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THE SUPPLY CHAIN CASH-FLOW BULLWHIP EFFECT

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by

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ABSTRACT

We theorize that just like supply chains experience the bullwhip effect (BWE), they also experience the cash-flow bullwhip effect (CFB). CFB is the phenomenon of amplification of working capital variance in the upstream direction of the supply chains. High variance in working capital can cause financial distress to a firm and its trading partners in the supply chain and can reduce supply chain's financial sustainability. A high CFB is indicative of a firm raising more capital than required to meet customer demand. Such situations increase operating costs and exacerbate the financial strain of firms with large weighted average cost of capital (WACC). A firm with large CFB and large WACC borrows more than the required amount of cash to support operations that too at a higher price. First, we propose an analytical model for cash-flow bullwhip to characterize working capital variance propagation in a serial supply chain. We use this model to study the relationship of procurement lead time, payment lead time, and demand autocorrelation with CFB in a serial supply chain. Second, we empirically investigate the existence of CFB and its association with company-level attributes by using a sample of 782 U.S. public companies during 2010–2019. We find that 31% of retailing, 25% of wholesaling, and 80% of manufacturing industries experience CFB. Furthermore, we find that a firm's CFB is related to firm size, payment behavior, procurement and payment lead times, demand autocorrelation, demand seasonality, and liquidity. Insights from this empirical research can inform key efficiency and sustainability responses at firm, industry, and government levels. Firms can use this knowledge to reduce

financial distress experienced by their supply chain and identify supply chain partners who could benefit from cash infusion. At industry level, this knowledge can be used to benchmark how fair and financially sustainable are the payment and inventory policies of the comprising firms. Finally, it can be used to inform trade and commerce policy and regulation formation at the government level. Third, we use simulation modeling to examine the effects of stochastic lead times and information sharing on CFB in serial supply chain. We also perform a comparative analysis of CFB and BWE between serial, convergent, divergent, con-div, and general supply chain topologies. Results reveal a significant difference between the CFB and BWE experienced by various topologies.

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Chapter 1 INTRODUCTION

1.1 Background

A supply chain is an interlinkage of entities that work together to get goods (products/material) from producers to customers and cash from customers to producers. The flow of material and cash in supply chains is facilitated by the flow of information between supply chain entities. Figure 1-1 illustrates a simple supply chain wherein material flows from suppliers to manufacturers, from manufacturers to wholesalers, from wholesalers to retailers, and finally from retailers to customers. Cash flows in the opposite direction from customers to suppliers. Information flows both ways in the supply chain. The flow of material, cash, and information keep the supply chain running.

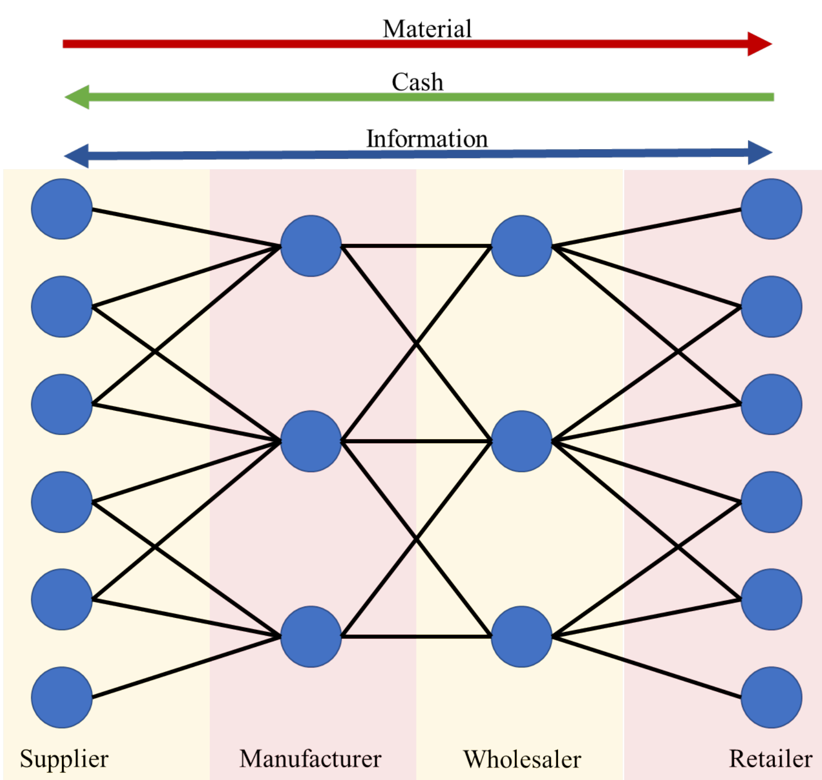

Figure 1-1 Supply chain network

Distortions in material, information, and cash flows induce the bullwhip effect in supply chains. Initially described by Forrester (1961), the supply chain bullwhip effect (BWE) is the amplification of demand distortion in the upstream direction of the supply chain. It is the phenomenon of minor variations in demand at the customer end, causing significant distortions in the orders upstream supply chain entities receive from downstream partners (Lee et al. 1997a, b). Figure 1-2 illustrates the BWE. Evidence suggests that BWE plays a pivotal role in making operational decisions like setting up and shutting down machines, idling and overtime in the workload, hiring and firing of the workforce, desired inventory level. It has negative consequences like difficulty in forecasting and scheduling and poor supplier/customer relationships (Wang and Disney 2016).

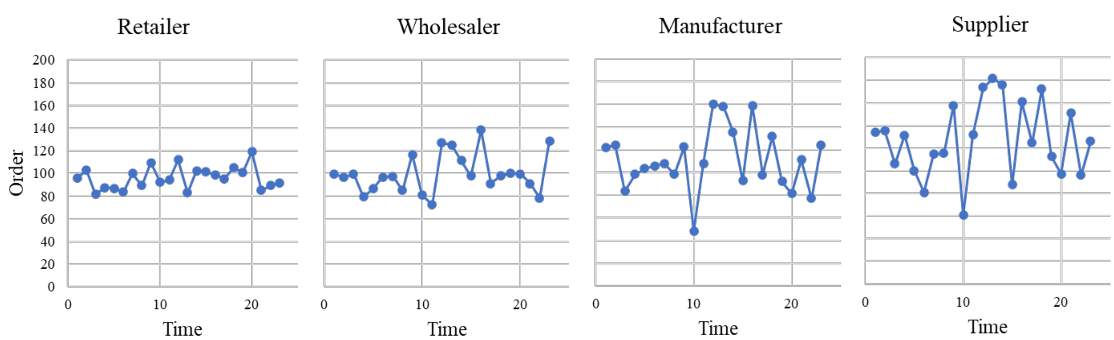

Figure 1-2 Supply chain bullwhip effect

Tangsucheeva and Prabhu (2013) hypothesized that just like material flow variations cause BWE, financial flow variations cause the cash-flow bullwhip effect in supply chains. According to Tangsucheeva and Prabhu (2013), the cash-flow bullwhip effect is the phenomenon of amplification of the cash conversion cycle in the upstream direction of the supply chain. They quantify the cash-flow bullwhip effect experienced by a supply chain entity as:

$$CFB = \frac{var(CCC)}{var(Customer\ Demand)} \tag{1}$$

where, CCC is the entity's cash conversion cycle.

We found a caveat in Tangsucheeva and Prabhu's (2013) characterization of cash-flow bullwhip and hence propose the following formula of measuring the cash-flow bullwhip effect experienced by a supply chain entity:

$$CFB = \frac{var(Working\ Capital)}{var(Customer\ Demand)}. \tag{2}$$

A discussion on the caveat mentioned above is presented in Chapter 2. This research aims to bring supply chain researchers' and practitioners' attention to the cash-flow bullwhip effect.

1.2 Motivation

As seen earlier, the three vital flows in any supply chain are the material, information, and cash flows. Material and information flows in supply chains have received much attention by way of research on the bullwhip effect. In the supply chain literature, we see that BWE has been studied using 3 major approaches: (i) Analytical modeling (Agrawal et al. 2009, Chen et al. 2000, Dejonckheere et al. 2003, 2004, Zhang 2004), (ii) Simulation modeling (Chatfield et al. 2009, Ojha et al. 2019), and (iii) Empirical investigation (Bray and Mendelson 2012, Cachon et al. 2007, Jin et al. 2017, Zhu et al. 2020). However, cash flows and the associated cash-flow bullwhip effect have not received much attention in the supply chain literature (Tangsucheeva and Prabhu 2013, Tsai 2008).

Cash is a crucial asset for operating a business. It is the most liquid asset and can be used immediately, when required, to take actions like buying goods (material), buying equipment, clearing debt, paying dividends and salaries. Proper cash and working capital management allow companies to stay afloat in times of economic slowdowns and provides an opportunity for business expansion during times of economic growth (Tangsucheeva and Prabhu 2013). Inefficient cash and working capital management is a sign of financial unsustainability. Our motivation to study the cash-flow bullwhip effect stemmed from the importance of cash in supply chains' financial sustainability and the dearth of literature on the cash-flow bullwhip effect. Understanding how working capital variations and the associated CFB effect propagate in supply chains can inform financial sustainability decisions and policy formation at firm, industry, and government levels.

For example, Consider the food supply chain. In 2012 farm sector had a working capital of \$165 billion, but only \$56.9 billion in 2019. Debt in the farm sector has been increasing since the 1990s. It ballooned from about \$131 billion in 1990 to \$415.7 billion in 2019 (USDA ERS). Over the last five years, large financial institutions have significantly shrunken their agricultural load. Because of which small American farmers have been forced to take high-interest loans outside traditional banks to stay in business (Bunge and Maltais, 2019). Exploration of CFB and using the developed knowledge to inform industry and government policy formation can contribute in ensuring the financial sustainability of the food supply chain. Large players in the food supply chain could use CFB measures to identify small agribusiness that could benefit from cash infusion to buy seeds, fertilizers and fuel for the next season.

1.3 Research Objectives

As seen earlier, the ultimate goal of this research is to bring supply chain researchers' and practitioners' attention to the cash-flow bullwhip effect. Our research objectives are to:

1. Propose a new measure of the cash-flow bullwhip effect that can determine if supply chain entities are amplifying or attenuating the material and financial variations they experience.
2. Develop an analytical framework to study cash-flow bullwhip in a serial supply chain and analyze how procurement lead time, payment lead time, payment batching, and demand information sharing affect cash-flow bullwhip.
3. Use empirical research to search for the existence of the cash-flow bullwhip effect in U.S. supply chains.
4. Use empirical methods to study the relationship between company-level attributes and the cash-flow bullwhip that U.S. companies experience.
5. Propose a simulation modeling framework to study cash-flow bullwhip in various supply chain topologies, viz., serial, convergent, divergent, con-div, and general topologies.
6. Use simulation modeling to study the effect of stochastic procurement lead times, stochastic payment lead times, and demand information sharing on the cash-flow bullwhip experienced by the serial supply chain.
7. Use simulation modeling to study the propagation of cash-flow bullwhip in various supply chain topologies under a demand shock.

1.4 Dissertation outline

The remainder of the chapter is organized as follows. Chapter 2 proposes an analytical framework for studying the cash-flow bullwhip effect in a multi-echelon serial supply chain. Specifically, we parametrize the cash-flow bullwhip effect in serial supply chains by including procurement lead time, payment lead time, and customer demand autocorrelation. Chapter 3 investigates the existence of the cash-flow bullwhip effect and the traditional bullwhip effect using financial data from a sample of 782 U.S. public companies between the years 2010-2019. Further, we also explore the relationship between the cash-flow bullwhip experienced by companies with company-level attributes like company size, procurement, and payment lead times, and predictability in demand seasonality, to name a few. A simulation study to study the relationship between cash-flow bullwhip, demand information sharing, stochastic procurement lead time, stochastic payment lead times and choice of cash-flow forecasting algorithm is performed in Chapter 4. Additionally, the simulation model is used to study the magnitude and speed of propagation of cash-flow bullwhip in various supply chain topologies. Finally, the research conclusions and directions for future research are presented in Chapter 5.

Chapter 2 SUPPLY CHAIN CASH-FLOW BULLWHIP EFFECT: AN ANALYTICAL APPROACH

Abstract

This chapter studies cash-flow bullwhip effect (CFB), the phenomenon of amplification of working capital variance in supply chains. High variance in working capital can cause financial distress to a firm and its trading partners in the supply chain. We propose an analytical model for cash-flow bullwhip to characterize working capital variance propagation in a multi-echelon serial supply chain. The end-customer demand is assumed to be a first-order autoregressive process. All echelons use order up-to inventory replenishment policy. Specifically, we parameterize the CFB model by including demand autocorrelation, procurement lead time, and payment lead times. We show that CFB exists for non-zero procurement and payment lead times even when end-customer demand is shared with all echelons. The longer the procurement lead time the higher an organization's cash-flow bullwhip. The larger the difference between an organization's payment lead time and its customer's payment lead time, the larger the organization's CFB. We show that if a supply chain echelon enforces shorter payment lead time on customers and longer payment lead times on suppliers, it increases the cash-flow bullwhip of all three entities involved, the echelon itself, its customers, and suppliers. Numerical analysis of specific test cases shows that payment batching and sharing end-customer demand information can reduce cash-flow bullwhip by up to 49.5% and 53.7%,

respectively. Finally, we empirically measure the cash-flow bullwhip experienced by 786 companies over the years 2010-2019. 65% of companies in the sample amplify working capital variance. Our results urge caution when negotiating procurement lead times with suppliers and payment terms with customers and suppliers. An organization should jointly consider its procurement lead time, payment lead time, location in the serial supply chain, customer's payment lead time, and demand autocorrelation when exploring ways to reduce its cash-flow bullwhip.

2.1 Introduction

A supply chain problem that has drawn significant attention is the concept of the bullwhip effect (BWE). It represents the amplification of demand distortion in the upstream direction of supply chains. Amplification of demand distortion can potentially cause instability and increase operational costs (Zhang 2004).

BWE in the supply chain literature is studied using one of the following approaches: (i) Analytical modeling (Agrawal et al. 2009, Chen et al. 2000, Dejonckheere et al. 2004, Zhang 2004), (ii) Simulation modeling (Chatfield et al. 2009, Ojha et al. 2019), and (iii) Empirical investigation (Bray and Mendelson 2012, Cachon et al. 2007, Jin et al. 2017, Zhu et al. 2020). Chen et al. (2000) characterize BWE experienced by echelon k as follows:

$$BWE_k = \frac{var(q^{(k)})}{var(d)} \tag{2.1}$$

where $var[\cdot]$ represents the variance function of a random variable, $q^{(k)}$ represents the ordering process of echelon k, and d is the demand process of the end-customer. Random variables in both the numerator and the denominator in Equation (2.1) represent some form of demand. The random variable in numerator represents echelon k's demand for goods from the immediate upstream echelon, and the one in denominator represents the end-customer's demand for goods from the most downstream supply chain echelon. Therefore, echelon k is said to be amplifying supply chain demand distortion if $BWE_k > 1$ and attenuating demand distortion if $BWE_k < 1$.

The bullwhip effect concerns itself only with the flow of goods, a requisite but not the sole type of flow in supply chains. Goods flow downstream in the supply chain, and parallelly cash flows upstream. Supply chain cash flow is as crucial as material flow. Access to sufficient cash is essential for keeping supply chain operations running. Tangsucheeva and Prabhu (2013) coin the term "Cash-flow Bullwhip" to represent the phenomenon of amplification of financial distortions in supply chains. They propose that the cash-flow bullwhip effect experienced by echelon k of a supply chain can be quantified as follows:

$$CFB_{k,TP} = \frac{var\left(CCC^{(k)}\right)}{var(d)} = \frac{var\left(DIO^{(k)} + DSO^{(k)} - DPO^{(k)}\right)}{var(d)} \tag{2.2}$$

where $CCC^{(k)}$ is echelon k's cash conversion cycle (measured in days), d is the demand process of the end-customer; and $DIO^{(k)}$, $DSO^{(k)}$, and $DPO^{(k)}$ are echelon k's days of inventory outstanding, days sales outstanding, and days payables outstanding, respectively. Cash conversion cycle measures the number of days it takes for an organization to convert its investments in inventory into cash flow from sales of the finished product. Note that unlike the metric for BWE_k in Equation (2.1), $CFB_{k,TP}$ in Equation (2.2) is not a ratio of variance of random variables with the same units. $CCC^{(k)}$ is measured in days, and D is measured in units of goods. Therefore, it cannot be said that echelon k is amplifying financial distortion if $CFB_{k,TP} > 1$ and attenuating financial distortion if $CFB_{k,TP} < 1$.

Tangsucheeva and Prabhu (2013) derive the $CFB_{k,TP}$ metric for a multi-echelon serial supply chain in which a first-order autoregressive process describes the end-customer demand, echelons use order up-to inventory replenishment policy, and use moving average method to forecast lead time demand. They show that $CFB_{k,TP}$ is increasing in procurement lead time and decreasing in moving average period length. There are two shortcomings in Tangsucheeva and Prabhu's (2013) analytical model of cash-flow bullwhip. First, as seen before, $CFB_{k,TP}$ does not show if a certain echelon k is either amplifying or attenuating financial distortions. Second, $CFB_{k,TP}$ does not take into consideration the payment terms between the echelons of the supply chain.

To address the first shortcoming of Tangsucheeva and Prabhu (2013), we propose a new metric for quantifying cash-flow bullwhip, which is given as follows:

$$
\begin{aligned}
CFB_k &= \frac{var\left(WC^{(k)}\right)}{var(d)} \\
&= \left.\begin{bmatrix} var\left(Cash^{(k)}\right) + var\left(Invt^{(k)}\right) + var\left(AR^{(k)}\right) + var\left(AP^{(k)}\right) \\ +2Cov\left(Cash^{(k)}, Invt^{(k)}\right) + 2Cov\left(Cash^{(k)}, AR^{(k)}\right) \\ -2Cov\left(Cash^{(k)}, AP^{(k)}\right) \\ +2Cov\left(Invt^{(k)}, AR^{(k)}\right) - 2Cov\left(Invt^{(k)}, AP^{(k)}\right) \\ -2Cov\left(AR^{(k)}, AP^{(k)}\right) \end{bmatrix}\middle/ var\left(d^{(k,\$)}\right)\right.
\end{aligned}
\tag{2.3}
$$

where $WC^{(k)}$ is echelon k's working capital, $d^{(k,\$)}$ the end-customer demand process (measured in monetary terms with respect to echelon k); and $Cash^{(k)}$, $Invt^{(k)}$, $AR^{(k)}$, and

$AP^{(k)}$ are echelon k's cash on hand, inventory (in monetary terms), accounts receivable, and accounts payable, respectively. Here, $AR^{(k)}$ and $AP^{(k)}$ correspond only to the accounts receivable and accounts payable emanating from the operations of buying and selling inventory. Like BWE_k, CFB_k is a ratio of variance of random variables that have the same units. Both $WC^{(k)}$ and $D^{(\$)}$ are measured in monetary terms. $WC^{(k)}$ is the measure of echelon k's ability to keep operations running, that is, its ability to meet end-customer demand, $D^{(\$)}$. Therefore, it can be said that echelon k is amplifying working capital distortion if $CFB_k > 1$ and attenuating working capital distortions if $CFB_k < 1$. To address the second shortcoming in Tangsucheeva and Prabhu's (2013) model of the cash-flow bullwhip, we propose an analytical model for CFB_k that takes into consideration payment terms in addition to procurement lead time.

In the current chapter we build a mathematical model for CFB_k in a multi-echelon serial supply chain where the end-customer demand is a first-order autoregressive process, echelons use order up-to inventory replenishment policy, mean squared error (MSE) optimal scheme to forecast lead time demand, and end-customer demand information is accessible to each echelon. The use of MSE-optimal forecasting scheme ensures that the contribution of forecasting errors to CFB_k is minimized. Moreover, we empirically test the existence of cash-flow bullwhip in US companies. Using a sample of 786 firms, we find that 510 companies amplify while 276 attenuate working capital distortions.

Two significant contributions of this chapter are: (i) the proposal of a new expression of measuring material and financial distortions experienced by echelon k of a supply chain, CFB_k, and (ii) the expression of CFB_k as a function of k, procurement lead time, payment lead times, and end-customer demand process parameters.

The organization of the chapter is as follows. In Section 2.2 we discuss the supply chain model studied in this chapter. After deriving the formulas of CFB_k for $k = 1$ and $k \geq 2$ in Section 2.3, we briefly explore some properties of CFB_k in Section 2.4. In Section 2.5, we perform an empirical analysis to measure the cash-flow bullwhip experienced by a sample of 786 companies. Finally, Section 2.6 provides conclusive remarks and directions for future work.

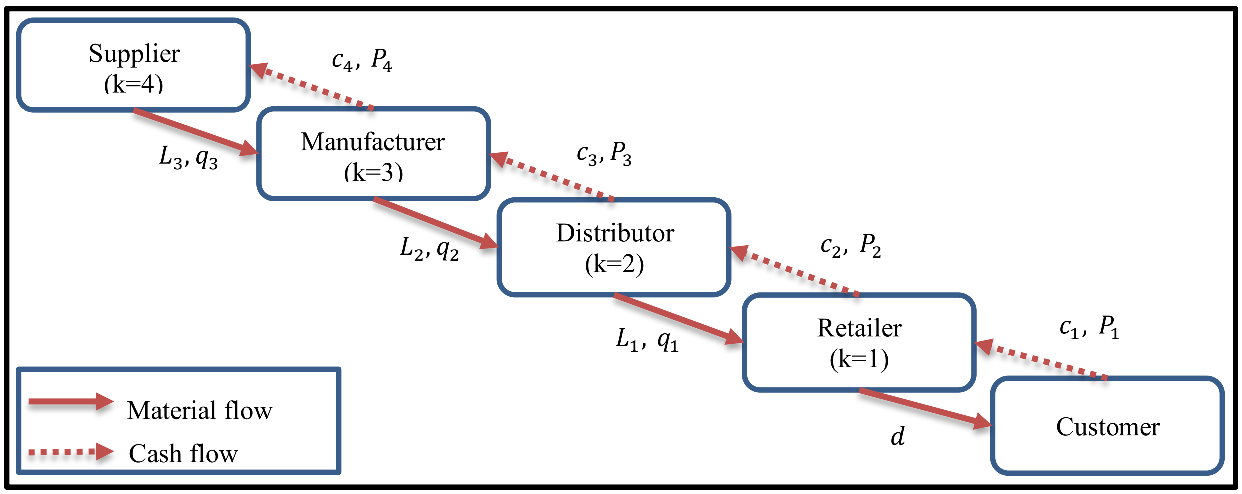

Figure 2-1 Structure of a serial supply chain

2.2 Supply Chain Model

Consider the supply chain structure illustrated in Figure 2-1. It constitutes of 4 echelons, $k \in \{1,2,3,4\}$. Retailer, represented by $k = 1$, is the most downstream echelon in the supply chain. Supplier, represented by $k = 4$, is the most upstream supply chain echelon. We assume that this supply chain maintains a single-item inventory, and echelon $k = 1$ shares end-customer demand information with every other echelon in the supply chain at the end of each epoch.

2.2.1 Sequence of Events

Each echelon $k \in \{1,2,3,4\}$ to meet the demand for material from echelon $k - 1$, replenishes its inventory stock from echelon $k + 1$ on a fixed time interval. For the ease of modeling, we assume that all shortages are backlogged.

At the beginning of time epoch t, echelon k carries over the inventory it ended epoch $t - 1$ with. Demand observed by echelon k in epoch t brings down its inventory level. At the end of epoch t, echelon k reviews its inventory position and places an order of size q_k with echelon $k + 1$. Orders placed by echelon k in epoch t are delivered in epoch $t + L_k$. L_k is the procurement lead time experienced by echelon k. Echelon k pays the amount c_{k+1} for each unit of goods it purchases from echelon $k + 1$. The payment is completed based on agreed-upon payment terms between the echelons. Payment for goods bought by echelon k during epoch t is made in epoch $t + P_k$. P_k is the agreed-upon permissible delay in payment which echelon k grants to echelon $k - 1$. Henceforth, permissible delays in payment are referred to as payment lead times. For simplicity, we assume that fractional payments for goods purchased are not allowed.

2.2.2 End-Customer Demand Process

Echelon $k = 1$ experiences end-customer demand described by a first order-autoregressive, henceforth called AR(1), process. The AR(1) end-customer demand process is expressed as follows:

$$d_t = \mu_d + \rho d_{t-1} + \epsilon_t \quad t = 1,2,3,\ldots \tag{2.4}$$

where d_t is the end-customer demand in epoch t, μ_d is a non-negative constant, $|\rho| < 1$ is the correlation coefficient, and ϵ_t is an independently and identically distributed random variable that follows normal distribution with mean 0 and variance σ_ϵ^2. $|\rho| < 1$ ensures that the demand process is stationary and the following properties hold (Box et al. 2008):

$$E[d_t] = \frac{\mu_d}{1-\rho}, \tag{2.5}$$

$$var[d_t] = \frac{\sigma_\epsilon^2}{1-\rho^2} \tag{2.6}$$

where $E[\cdot]$ and $var[\cdot]$ represent the mean and variance functions of a random variable.

Varying the value of ρ between -1 and 1 allows us to model various kinds of demand processes. For $\rho = 0$, the demand process is normally distributed with mean 0 and variance σ_ϵ^2. For $-1 < \rho < 0$, the demand process is negatively correlated and exhibits oscillatory behavior. Finally, when $0 < \rho < 1$ holds, the demand process is positively correlated and exhibits a sequence of meandering observations.

2.2.3 Forecasting Process

As mentioned in Section 2.1, we assume that each echelon in the supply chain uses an MSE-optimal forecasting scheme. An MSE-optimal forecast minimizes the mean squared errors in the forecast. Since the demand process is AR(1), the MSE-optimal demand forecast for epoch $t+i$ made in epoch t is given as follows (Wei 2005):

$$\hat{d}_{t+i|H_t} = \mu_d + \rho^i(d_t - \mu_d) \tag{2.7}$$

where H_t is the demand history up to epoch t,

$$H_t = \{d_t, d_{t-1}, \ldots, d_3, d_2, d_1\}. \tag{2.8}$$

Now, the MSE-optimal lead time demand forecast for echelon k made at the end of time epoch t can be written as:

$$\hat{F}_{t|H_t}^{(k,L_k)} = \hat{d}_{t+1|H_t} + \hat{d}_{t+2|H_t} + \cdots + \hat{d}_{t+L_k|H_t} \tag{2.9}$$

$$= L_k\mu_d + d_t\sum_{i=1}^{L_k}\rho^i - \mu_d\sum_{i=1}^{L_k}\rho^i$$

2.2.4 Order Quantity

Let $q_t^{(k)}$ and $y_t^{(k)}$ be the order quantity and order up-to point of echelon k at the end of time epoch t. Conservation of material flow implies that

$$q_t^{(k)} = y_t^{(k)} - y_{t-1}^{(k)} + q_t^{(k-1)}. \tag{2.10}$$

The order up-to level is the sum of forecasted lead time demand and inventory safety stock and is given as follows:

$$y_t^{(k)} = \hat{F}_{t|H_t}^{(k,L_k)} + z\hat{\sigma}_{t|H_t}^{(L_k)} \tag{2.11}$$

where z is a constant chosen to meet desired service level and $\hat{\sigma}_{t|H_t}^{(L_k)}$ is the standard deviation of lead time forecast error. Substituting Equation (2.11) in Equation (2.10) we get

$$q_t^{(k)} = \hat{F}_{t|H_t}^{(k,L_k)} - \hat{F}_{t-1|H_{t-1}}^{(k,L_k)} + z\left(\hat{\sigma}_{t|H_t}^{(L_k)} - \hat{\sigma}_{t-1|H_{t-1}}^{(L_k)}\right) + q_t^{(k-1)}. \tag{2.12}$$

Zhang (2004) shows that $\hat{\sigma}_{t|H_t}^{(L_k)} = \hat{\sigma}_{t-1|H_{t-1}}^{(L_k)}$. Therefore, we have

$$\begin{aligned} q_t^{(k)} &= \hat{F}_{t|H_t}^{(k,L_k)} - \hat{F}_{t-1|H_{t-1}}^{(k,L_k)} + q_t^{(k-1)} \\ &= \sum_{i=1}^{L_k}\rho^i\,(d_t - d_{t-1}) + q_t^{(k-1)} \end{aligned} \tag{2.13}$$

For $k = 1$, $q_t^{(k-1)} = d_t$ and therefore,

$$q_t^{(1)} = \frac{\rho - \rho^{L_1+1}}{1-\rho}(d_t - d_{t-1}) + d_t \tag{2.14}$$

Using Equations (2.13) and (2.14) the generalized equation for $q_t^{(k)}$ is given as follows:

$$q_t^{(k)} = \frac{\rho}{1-\rho}(d_t - d_{t-1})\left(k - \sum_{i=1}^{k} \rho^{L_i}\right) + d_t \tag{2.15}$$

2.2.5 Inventory

The inventory level at echelon k at the end of time epoch t is the difference in the total goods that flow in and out of echelon k up to epoch t. Therefore, the inventory level at echelon k at the end of epoch t is given as follows:

$$I_t^{(k)} = I_{int}^{(k)} + \sum_{i=1}^{t} q_{i-L_k}^{(k)} - \sum_{i=1}^{t} q_i^{(k-1)} \tag{2.16}$$

where $I_{int}^{(k)}$ is the initial inventory at echelon k.

For $k = 1$, Equation (2.16) can be rewritten using Equation (2.14) as:

$$\begin{aligned} I_t^{(1)} = I_{int}^{(1)} + d_{t-L_1}\left(\frac{\rho - \rho^{L_1+1}}{1-\rho}\right) \\ - \sum_{i=0}^{L_1-1} d_{t-i}. \end{aligned} \tag{2.17}$$

For $k \geq 2$, Equation (2.16) can be rewritten using Equation (2.15) as:

$$I_t^{(k)} = I_{int}^{(k)} + \left[\left(k - \sum_{j=1}^{k} \rho^{L_j}\right)\frac{\rho}{1-\rho} d_{t-L_k} + \sum_{i=1}^{t} d_{i-L_k}\right] - \left[\left(k - 1 - \sum_{j=1}^{k-1} \rho^{L_j}\right)\frac{\rho}{1-\rho} d_t + \sum_{i=1}^{t} d_i\right] \tag{2.18}$$

Equations (2.17) and (2.18) represent inventory as the number of units. To convert $I_t^{(k)}$ for $k = 1,2, \dots, K$ to monetary terms, $I_t^{(k)}$ is multiplied with C_{k+1}, the unit cost echelon k paid to purchase goods from echelon $k+1$. Therefore, inventory in monetary terms at echelon k at the end of time epoch t is given as follows:

$$Invt_t^{(k)} = c_{k+1} I_t^{(k)} \tag{2.19}$$

2.2.6 Accounts Receivable, Accounts Payable, and Cash

Accounts receivable at echelon k in time epoch t is the amount echelon $k-1$ owes to the former in epoch t. Assuming the payment terms agreement between echelons k and $k-1$ require the latter to make payments for goods bought in epoch t in epoch $t + P_k$, the accounts receivable at echelon k can be represented as follows:

$$AR_t^{(k)} = c_k \left(\sum_{i=1}^{P_k} q_{t-i}^{(k-1)}\right). \tag{2.20}$$

Accounts payable at echelon k in epoch t is the amount it owes to echelon $k+1$ in epoch t. Assuming the payment terms agreed between echelons k and $k+1$ require the former to make payments for goods bought in epoch t in epoch $t + P_{k+1}$, the accounts payable at echelon k can be represented as follows:

$$AP_t^{(k)} = c_{k+1}\left(\sum_{i=1}^{P_{k+1}} q_{t-i}^{(k)}\right). \tag{2.21}$$

The cash position of organizations is subject to tax laws, organizations' operating (payment of salaries, buying and selling goods, paying and receiving interest on long term debts, etc.), financial (paying dividends, stock sales and purchase, etc.), and investing activities (Buying and selling non-current assets, loaning capital to other organizations, etc.). Based on these factors, organizations determine the optimal cash position they need to maintain. In this chapter, we assume that every echelon k holds an optimal cash position, $Cash^{(k)^*}$. In case of a cash surplus, echelon k invests the surplus in securities, and in case of a cash shortage, echelon k sells securities to raise enough cash to bring the cash position up to $Cash^{(k)^*}$. Therefore, the cash position of echelon k at the end of time epoch t is:

$$Cash_t^{(k)} = Cash^{(k)^*} \text{ for } t = 1,2,\ldots \tag{2.22}$$

In the next section, a closed-form expression of CFB_k for $k = 1,2,\ldots,K$ for the supply chain model presented in Section 2.2 is derived.

2.3 Cash-flow Bullwhip

The demand process described in Section 2.2 represents the number of inventory items the end-customer demands from echelon $k = 1$. But according to Equation (2.3), demand needs to be specified in monetary terms. Since echelon k buys goods at the unit price of c_{k+1}, the end-customer demand in monetary terms as seen by echelon k can be written as:

$$d^{(k,\$)} = c_{k+1}d \tag{2.23}$$

Now using Equations (2.19 – 2.22), the bullwhip effect experienced by echelon $k = 1$

is given by:

$$CFB_1 = \frac{var\left(Cash^{(1)} + Invt^{(1)} + AR^{(1)} - AP^{(1)}\right)}{var(d^{(1,\$)})}$$

$$= L_1 + \frac{2L_1\rho(1-\rho)+2\rho\left(\rho^{L_1}-1\right)}{(1-\rho)^2} + \frac{c_1^2}{c_2^2(1-\rho)^2}\left(P_1(1-\rho^2) + 2\rho(\rho^{P_1}-1)\right) -$$

$$\frac{1}{(1-\rho)^2}\left(P_2(1-\rho^2) + 2\rho(\rho^{P_2}-1)\right) + \left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)\left[\frac{2}{1-\rho}\left(1 + \rho^{L_1+P_2+1} -\right.\right.$$

$$\rho^{L_1+1} - \rho^{P_2}\right) + 2\left(\frac{(\rho-\rho^{L_1+1})}{1-\rho}\left(\rho^{|L_1-P_2-1|} - \rho^{L_1-1}\right) + \frac{\rho\left(1-\rho-\rho^{L_1-2}\right)+1}{1-\rho} - \quad (2.24)$$

$$\sum_{i=0}^{L_1-1}\rho^{|P_2+1-i|} - \sum_{i=1}^{P_2}\rho^{|L_1-i|}\right) - \frac{(\rho-\rho^{L_1+1})}{1-\rho} + \frac{2c_1}{c_2}\left(\sum_{i=1}^{P_1}\rho^{|L_1-i|} +\right.$$

$$\left.\left.\sum_{i=1}^{P_1}\rho^{|P_2+1-i|} + \frac{\rho^{P_1-1}}{1-\rho}\right)\right] - \frac{2c_1}{c_2}\sum_{i=0}^{L_1-1}\sum_{j=1}^{P_1}\rho^{|i-j|} + 2\sum_{i=0}^{L_1-1}\sum_{j=1}^{P_2}\rho^{|i-j|} -$$

$$\frac{2c_1}{c_2}\sum_{i=1}^{P_2}\sum_{j=1}^{P_1}\rho^{|i-j|}$$

and cash-flow bullwhip effect experienced by echelon $k \geq 2$ is given by:

$$CFB_k = \frac{var\left(Cash^{(k)} + Invt^{(k)} + AR^{(k)} - AP^{(k)}\right)}{var(d^{(k,\$)})}$$

$$= L_k\left(1 + 2\sum_{i=1}^{L_k-1}\rho^i\right) + \frac{3\rho^2}{(1-\rho)^2}\left(k - \sum_{j=1}^{k}\rho^{L_j}\right)^2 - 2\sum_{i=1}^{L_k-1}i\rho^i + \frac{\rho^2}{(1-\rho)^2}\left(k -\right.$$

$$\left.1 - \sum_{j=1}^{k-1}\rho^{L_j}\right)^2\left(1 + 2\frac{c_k^2}{c_{k+1}^2}\right) + \sum_{i=0}^{1}\left[\frac{P_{k+i}c_{k+i}^2}{c_{k+1}^2}\left(1 + 2\sum_{j=1}^{P_{k+i}-1}\rho^j -\right.\right.$$

$$\left.\left.\frac{2}{P_{k+i}}\sum_{j=1}^{P_{k+i}-1}j\rho^j\right)\right] + \frac{2\rho}{1-\rho}\left(-\left(k - \sum_{j=1}^{k}\rho^{L_j}\right)\sum_{i=1}^{L_k}\rho^i - \left(k - \sum_{j=1}^{k}\rho^{L_j}\right)\left(k - 1 -\right.\right. \quad (2.25)$$

$$\left.\left.\sum_{j=1}^{k-1}\rho^{L_j}\right)\frac{\rho^{L_k+1}}{1-\rho} + \left(k - 1 - \sum_{j=1}^{k-1}\rho^{L_j}\right)\left(1 + \sum_{i=1}^{L_k-1}\rho^i\right)\right) + \frac{2c_k}{c_{k+1}}\frac{\rho}{(1-\rho)}\left[\frac{\rho}{(1-\rho)}\left(k -\right.\right.$$

$$\left.\sum_{j=1}^{k}\rho^{L_j}\right)\left(k - 1 - \sum_{j=1}^{k-1}\rho^{L_j}\right)\left(\rho^{L_k-1} - \rho^{|L_K-P_k-1|}\right) + \left(k -\right.$$

$$\left.\sum_{j=1}^{k}\rho^{L_j}\right)\sum_{i=1}^{P_k}\rho^{|L_k-i|} - \left(k - 1 - \sum_{j=1}^{k-1}\rho^{L_j}\right)\left(1 + \rho + \sum_{i=1}^{P_k}\rho^i + \sum_{i=1}^{L_k-2}\rho^i -\right.$$

$\sum_{i=0}^{L_k-1}\rho^{|P_k+1-i|}\Big)-\frac{\rho}{(1-\rho)}\big(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\big)^2(\rho-\rho^{P_k+1})-$

$\frac{(1-\rho)}{\rho}\Big(\sum_{i=0}^{L_k-1}\sum_{j=1}^{P_k}\rho^{|i-j|}\Big)\Big]-\frac{2\rho}{(1-\rho)}\Big[\frac{\rho}{1-\rho}\big(k-\sum_{j=1}^{k}\rho^{L_j}\big)^2\Big(\rho^{L_k-1}-$

$\rho^{\left|L_{-P_{k+1}}-1\right|}\Big)+\big(k-\sum_{j=1}^{k}\rho^{L_j}\big)\big(\sum_{i=1}^{P_{k+1}}\rho^{|L_k-i|}+\sum_{i=0}^{L_k-1}\rho^{|P_{k+1}+1-i|}-$

$\sum_{i=1}^{L_k-2}\rho^{i}-\rho-1\big)-\frac{(1-\rho)}{\rho}\sum_{i=0}^{L_k-1}\sum_{j=1}^{P_{k+1}}\rho^{|i-j|}-\frac{\rho^2(1-\rho^{P_{k+1}})}{(1-\rho)}\big(k-1-$

$\sum_{j=1}^{k-1}\rho^{L_j}\big)\big(k-\sum_{j=1}^{k}\rho^{L_j}\big)-\big(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\big)\sum_{i=1}^{P_{k+1}}\rho^{i}\Big]-\frac{2c_k^2}{c_{k+1}^2}\frac{\rho}{(1-\rho)}\big(k-$

$1-\sum_{j=1}^{k-1}\rho^{L_j}\big)\Big[\frac{\rho^{P_k+1}}{1-\rho}\big(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\big)+\rho^{P_k}-1\Big]-\frac{2c_k}{c_{k+1}}\frac{\rho}{(1-\rho)}\Big[\frac{\rho}{(1-\rho)}\big(k-$

$1-\sum_{j=1}^{k-1}\rho^{L_j}\big)\big(k-\sum_{j=1}^{k}\rho^{L_j}\big)\big(1-\rho^{P_{k+1}}-\rho^{P_k}+\rho^{|P_{k+1}-P_k|}\big)+\big(k-1-$

$\sum_{j=1}^{k-1}\rho^{L_j}\big)\big(1+\sum_{i=1}^{P_{k+1}-1}\rho^{i}-\sum_{i=1}^{P_{k+1}}\rho^{P_k+1-i}\big)+\big(k-\sum_{j=1}^{k}\rho^{L_j}\big)\Big(1+$

$\sum_{i=1}^{P_k-1}\rho^{i}-\sum_{i=1}^{P_k}\rho^{P_{k+1}+1-i}+\frac{(1-\rho)}{\rho}\sum_{i=1}^{P_k}\sum_{j=1}^{P_{k+1}}\rho^{|i-j|}\Big)\Big]-\frac{2\rho}{(1-\rho)}\big(k-$

$\sum_{j=1}^{k-1}\rho^{L_j}\big)\Big[\frac{\rho}{(1-\rho)}\big(k-\sum_{j=1}^{k}\rho^{L_j}\big)\rho^{P_{k+1}}+\rho^{P_{k+1}}-1\Big]$

See Appendix A and B for the complete derivation of Equations (2.24) and (2.25), respectively.

2.4 Numerical Analysis

Having derived the analytical solutions of CFB_k, we briefly explore some of its properties that will be useful in understanding CFB_k in a serial supply chain. Specifically, we study the association of CFB_k with demand autocorrelation, supply chain echelon, procurement lead time, payment lead times, and end-customer demand information-sharing scheme.

2.4.1 Cash-flow Bullwhip v/s Echelon

Figure 2-2 depicts the relationship of CFB_k with k and ρ for $c_1=c_2=c_3=1$ and $L_1=$

$L_2 = L_3 = P_1 = P_2 = P_3 = 0$. Setting the costs to one and procurement and payment lead times to zero ensures they do not contribute towards amplifying CFB_k, allowing us to purely study the association between CFB_k, ρ, and k. We observe that in a supply chain with no procurement and payment lead times, $CFB_k = 0\ \forall\ k \in \{1,2, \dots, K\}$.

Figure 2-3 depicts the relationship between CFB_k, k, and ρ for $c_1 = c_2 = c_3 = 1$ and $L_1 = L_2 = P_1 = P_2 = P_3 = 2$. The following observations are made:

1. For $\rho > 0$, CFB_k is more significant
2. For $\rho > 0$, $CFB_k < CFB_{k+1}$
3. CFB_k reaches a peak for $\rho \geq 0.5$ and then recedes as $\rho \to 1$

Based on these observations, it is inferred that for non-zero procurement and payment lead times $CFB_k > 0\ \forall\ k \in \{1,2, \dots, K\}$. Additionally, for $\rho \geq 0$, $CFB_{k-1} \leq CFB_k \leq CFB_{k+1}$. Meaning for $\rho \geq 0$ and non-zero procurement and payment lead times, working capital distortions amplify as one moves upstream in the supply chain.

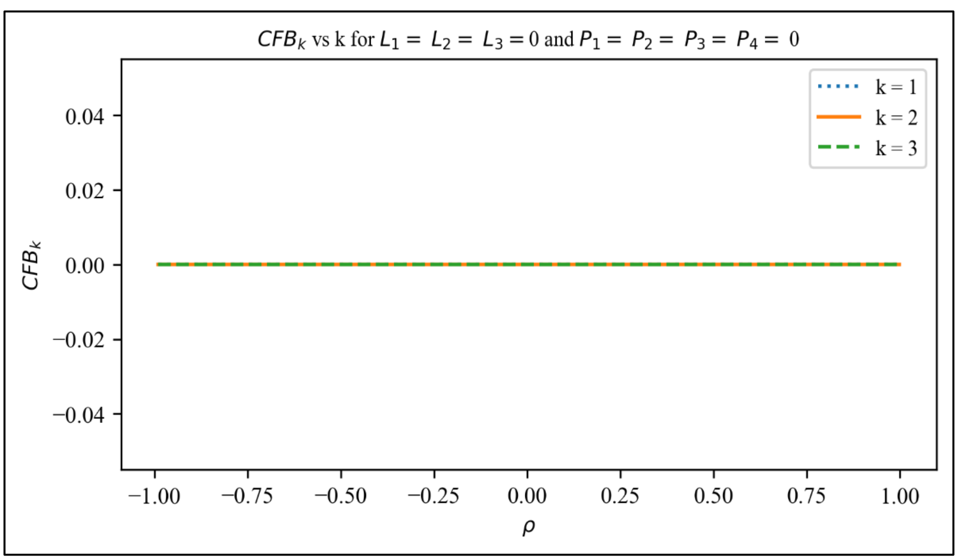

Figure 2-2 Cash-flow bullwhip experienced by echelons of a serial supply chain for zero lead times

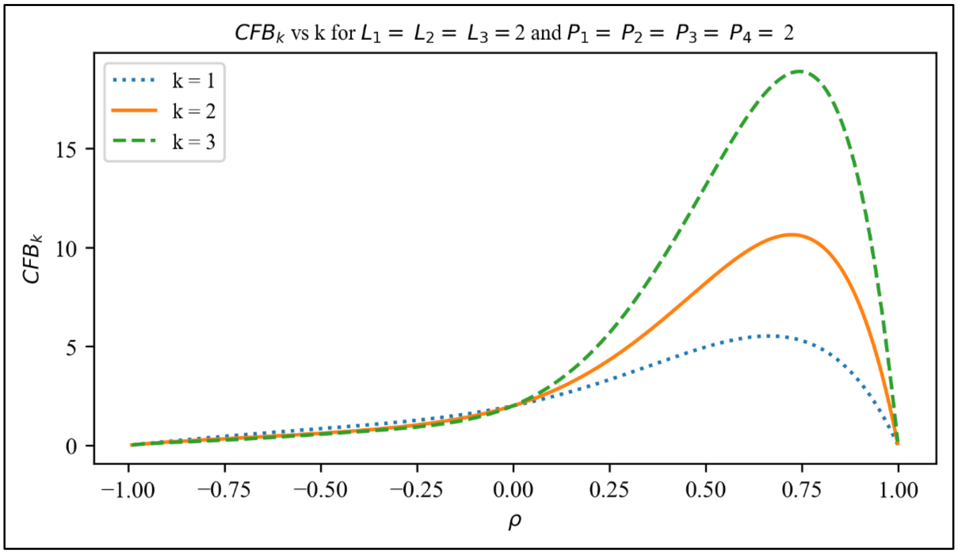

Figure 2-3 Cash-flow bullwhip experienced by echelons of a serial supply chain for non-zero lead times

2.4.2 Cash-flow Bullwhip v/s Procurement Lead time

Figure 2-4 depicts CFB_k as a function of demand autocorrelation (ρ) for procurement lead time, $L_k = 0,1,2,3,4$. For the ease of exposition, k is set to 2, $P_1 = P_2 = P_3 = 0$, and $c_1 = c_2 = c_3 = 1$. Setting payment lead times to zero ensures that their contribution towards CFB_k is zero, allowing us to purely study the association of CFB_k with procurement lead times and demand autocorrelation. We make the following observations about CFB_k:

1. For $L_k = 0$ and $-1 < \rho < 1$, the contribution of procurement lead time to CFB_k is zero
2. For $0 < \rho < 1$, the contribution of procurement lead time towards CFB_k is more significant
3. Longer the procurement lead time, the higher its contribution towards CFB_k
4. Contribution of procurement lead time towards CFB_k reaches a peak for $0 < \rho < 1$ and then recedes as $\rho \to 1$

Other values of k showed similar results.

Based on these observations, we infer that when payment lead times are zero, reducing procurement lead time reduces CFB_k.

Figure 2-5 shows the relationship of the traditional bullwhip effect (BWE) with demand autocorrelation (ρ) and procurement lead time (L_k). A visual comparison between Figure 2-4 and Figure 2-5 shows that CFB and BWE behave differently for the same values of demand autocorrelation, procurement lead time, and payment lead time.

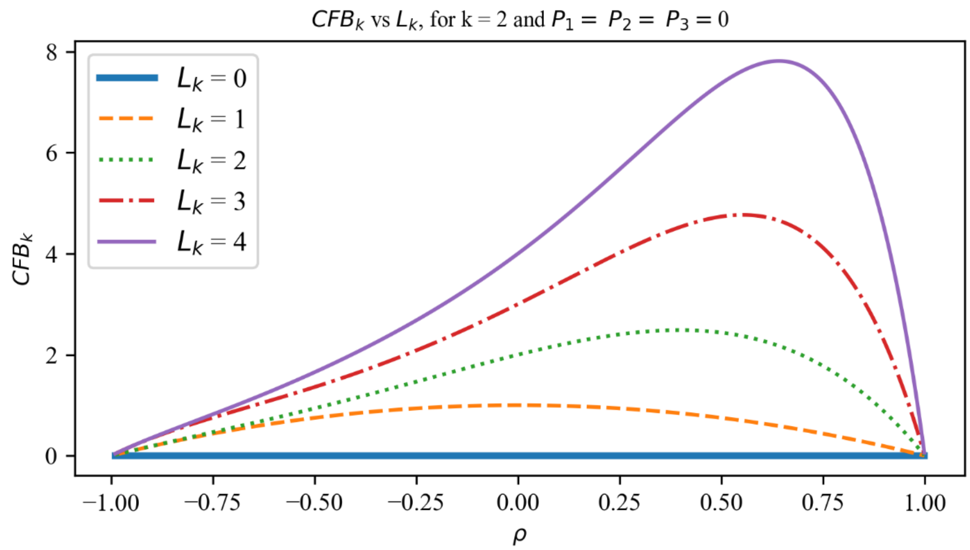

Figure 2-4 Relationship between CFB, demand autocorrelation, and procurement lead time

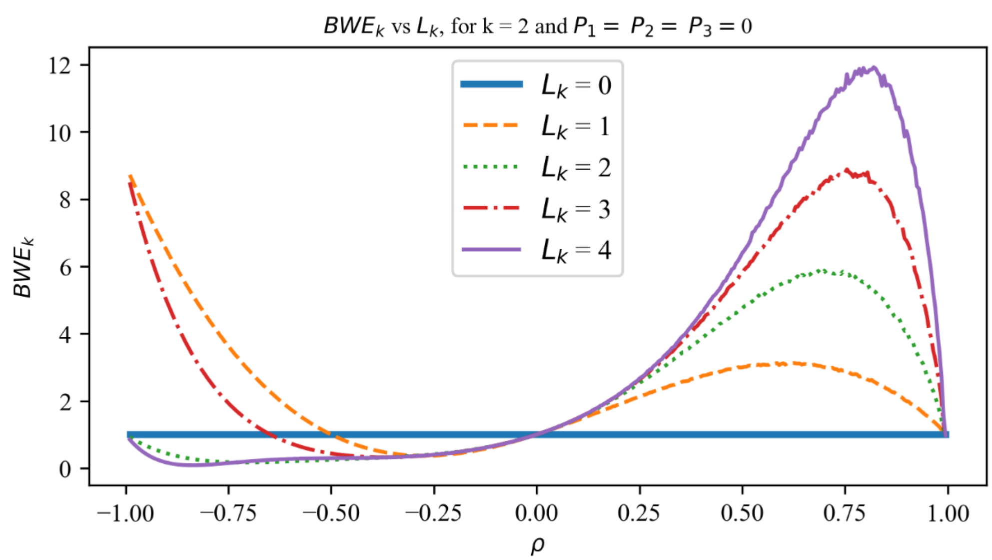

Figure 2-5 Relationship between BWE, demand autocorrelation, and procurement lead time

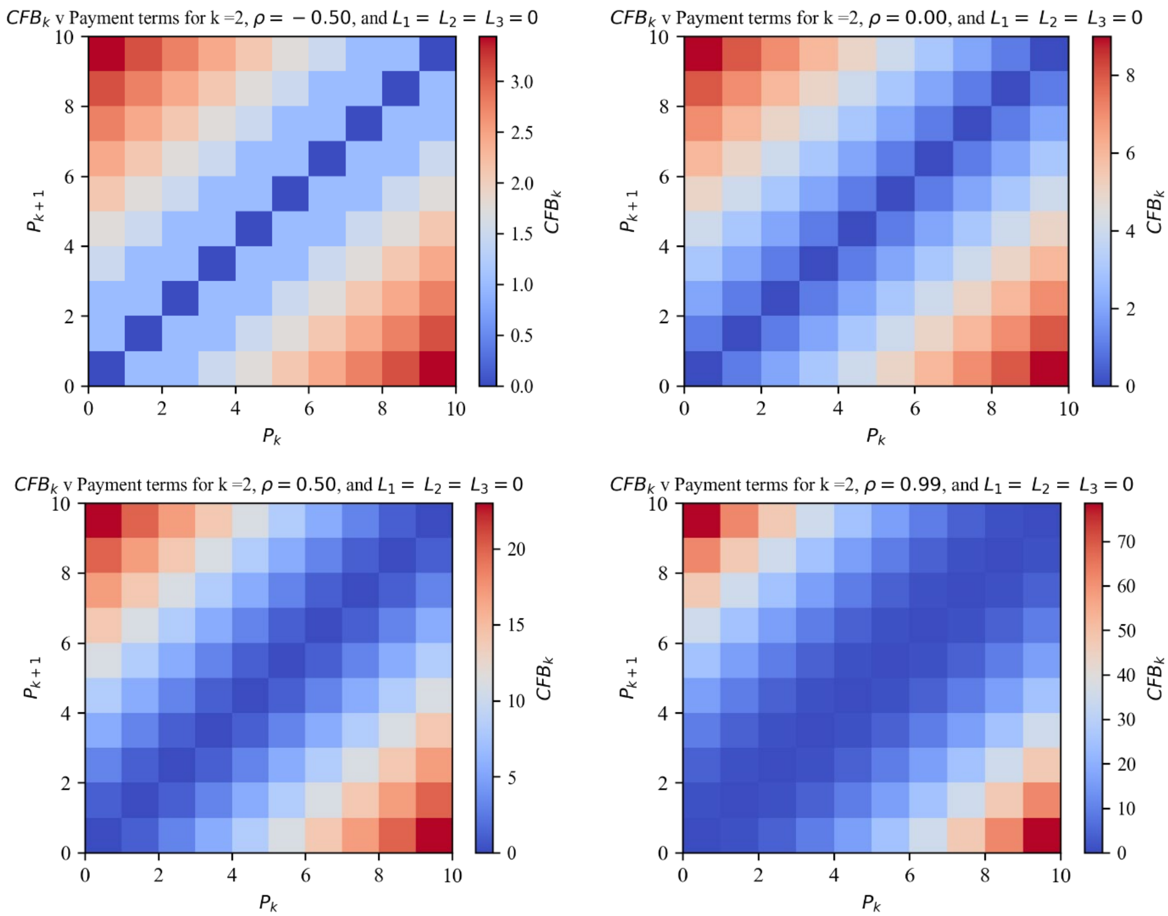

Figure 2-6 Relationship between CFB, demand autocorrelation, and payment lead times

2.4.3 Cash-flow Bullwhip v/s Payment lead times

Figure 2-6 depicts CFB_k for $k = 2$, $c_1 = c_2 = c_3 = 1$, and $L_1 = L_2 = 0$ as a function of demand autocorrelation (ρ), P_k and P_{k+1}. Setting $L_1 = L_2 = 0$ ensures that procurement lead time has no contribution towards CFB_k amplification. This allows us to purely study the association of CFB_k with payment lead times and demand autocorrelation. The following observations are made:

1. Contribution of payment lead times towards CFB_k is minimum when $P_k = P_{k+1}$

2. Ceteris paribus, the contribution of payment lead times towards CFB_k is increasing in ρ
3. For $P_k > P_{k+1}$, the contribution of payment lead times towards CFB_k is increasing in P_k
4. For $P_{k+1} > P_k$, the contribution of payment lead times towards CFB_k is increasing in P_{k+1}

Other values of k showed similar results.

Based on these observations, it is inferred that when procurement lead time is zero, to minimize payment lead times' contribution to CFB_k echelon k should negotiate payment terms with echelons $k-1$ and $k+1$ so that $P_k = P_{k+1}$.

2.4.4 Cash-flow Bullwhip v/s Procurement v/s Payment lead times

In Sections 2.4.2 and 2.4.3, the associations of CFB_k with procurement and payment lead times are studied individually. These associations are studied by setting either the procurement or payment lead times to zero. However, non-zero procurement and payment lead times are the norm in real supply chains rather than the exception. In this section, the association of procurement and payment lead times with CFB_k is studied jointly.

Figure 2-7 illustrates the relationship of CFB_k with L_k, P_{k+1}, and ρ for $k = 2$, $P_k = 5$, and $c_1 = c_2 = c_3 = 1$. The following observations are made:

1. Shorter procurement lead times, ceteris paribus, does not guaranty lower CFB_k
2. P_{k+1} values closer to P_k, ceteris paribus, does not guaranty lower CFB_k

Based on these observations, it is inferred that the association of CFB_k with procurement lead ($L_k > 0$) and payment lead times ($P_k > 0$ and $P_{k+1} > 0$) is rather more complex than seen in Sections 2.4.2 and 2.4.3, where either procurement or payment lead times are set to 0. From a managerial perspective, efforts to reduce CFB_k by reducing L_k and altering payment terms so that $P_k = P_{k+1}$ can be misleading, especially when the manager has limited knowledge of the end-customer demand process.

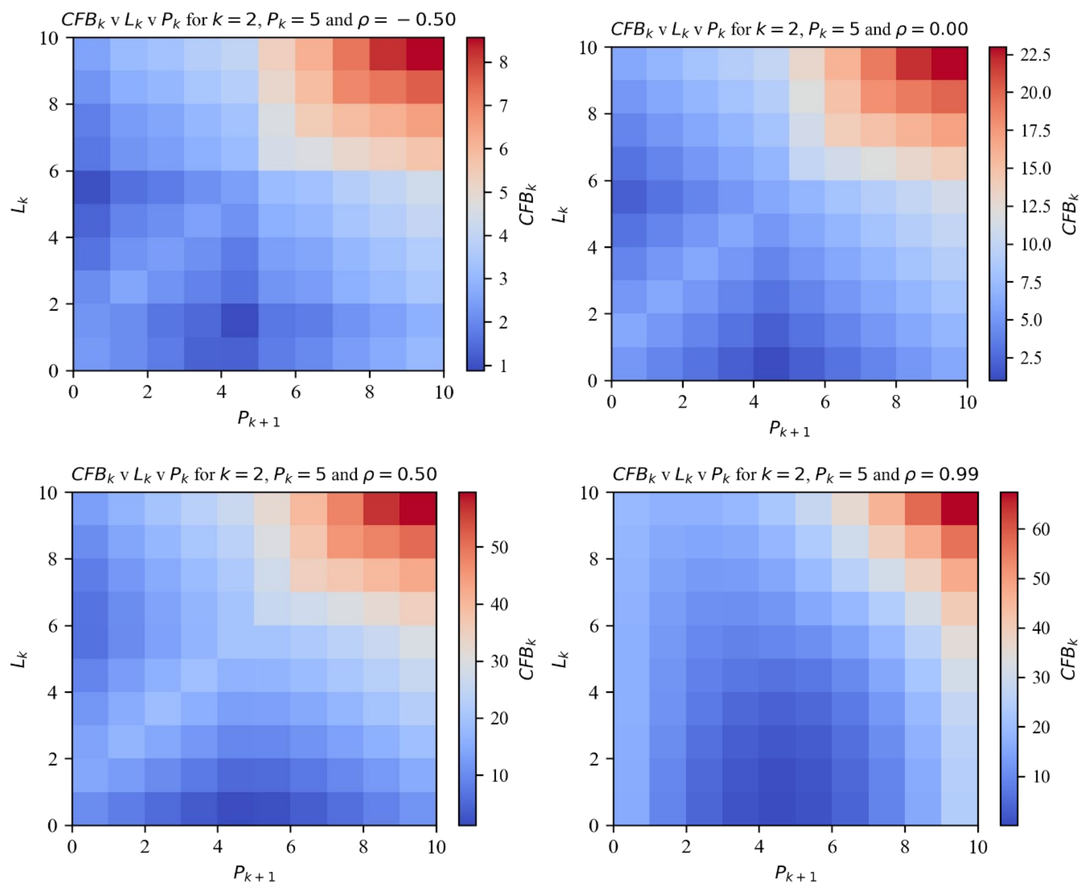

Figure 2-7 Relationship between CFB, demand autocorrelation, procurement lead time and payment lead times

2.4.5 What if an echelon has unbalanced payment terms?

Larger firms can have an outsized influence on their supply chain partners by extending payment terms to suppliers, enforce shorter payment terms on customers, and may also have unbalanced inventory policies that push risk on to smaller firms in the supply chain

(Hofmann and Kotzab 2010). Enforcing shorter payment terms on customers and longer payment terms of suppliers allows an echelon to reduce cash conversion cycle and free up extra cash. Figure 2-8 illustrates two scenarios. In the baseline scenario, all echelons $k = 1,2,3,4,5$ make payments to their respective supplier in 3 epochs, that is, $P_1 = P_2 = P_3 = P_4 = P_5 = 3$. In the unbalanced scenario, echelon $k = 3$, through its supply chain clout enforces echelon $k = 2$ to make payments in 1 epoch and increases the payment term it has with echelon $k = 4$ to 5 epochs.

Figure 2-8 shows that under the unbalanced scenario, the cash-flow bullwhip experienced by echelons $k = 2,3,4$ is greater than the cash-flow bullwhip that they experience in the baseline scenario. From a managerial perspective, enforcing unbalanced payment terms on customers and suppliers not only increases their cash-flow bullwhip effect but also that of the enforcing echelon.

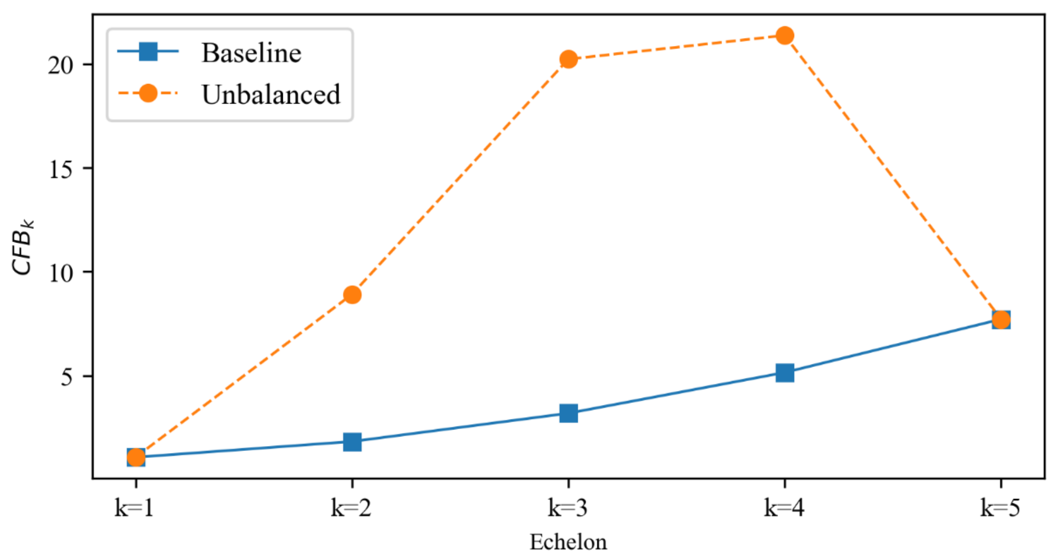

Figure 2-8 Cash-flow bullwhip experienced by various echelons of a serial supply chain under the baseline and unbalanced scenarios

2.4.6 What if payments are batched?

Some companies impose end-of-week or end-of-month as payment terms for their suppliers. Following the end-of-week payment terms, a company makes payments for all orders placed during a week at the end of the week. Similarly, a company following the end-of-month payment terms makes payments for all orders placed during a month, at the end of the month. In such scenarios, payments to suppliers arrive in batches rather than following the demand structure with a delay.

Assume that every echelon in the serial supply chain, including the end-customer, imposes end-of-B-epochs as payment terms for their supplier. Now echelon k's working capital at the end of epoch t can be written as:

$$
\begin{aligned}
WC_t^{(k)} &= Invt_t^{(k)} + AR_t^{(k)} - AP_t^{(k)} \\
&= Invt_t^{(k)} \\
&\qquad + c_k \left[q_t^{(k-1)} \mathbb{I}_1 + \left(q_t^{(k-1)} + q_{t-1}^{(k-1)} \right) \mathbb{I}_2 + \cdots \right. \\
&\qquad \left. + \left(q_t^{(k-1)} + q_{t-1}^{(k-1)} + \cdots + q_{t-B+1}^{(k-1)} \right) \mathbb{I}_B \right] \\
&\qquad - c_{k+1} \left[q_t^{(k)} \mathbb{I}_1 + \left(q_t^{(k)} + q_{t-1}^{(k)} \right) \mathbb{I}_2 + \cdots + \left(q_t^{(k)} + q_{t-1}^{(k)} + \cdots + q_{t-B+1}^{(k)} \right) \mathbb{I}_B \right]
\end{aligned}
$$

where $\mathbb{I}_\tau \ \forall \tau \in [1,2, \dots, B-1]$ are indicator variables defined as follows:

$$
\mathbb{I}_\tau = \begin{cases} 1, \tau \ mod \ B = \tau \\ 0, otherwise \end{cases}
$$

and $\mathbb{I}_B$ too is an indicator variable defined as:

$$
\mathbb{I}_B = \begin{cases} 1, \tau \ mod \ B = 0 \\ 0, otherwise \end{cases}.
$$

All other variables have the same meaning as defined earlier.

Intuition suggests that compared to the model described in Sections 2.2 and 2.3, the variance of AR, AP and WC under the payment batching scheme will be higher. Meaning the cash-flow bullwhip experienced under the payment batching scheme will be higher than that experienced under the payment lead time scheme (PLT) described in Section 2.2. This, however, is not true. If an echelon k and its customer, echelon $k-1$, both use the batching scheme then the covariance between $AR^{(k)}$ and $AP^{(k)}$ is more than enough to compensate for the rise in variances of $AR^{(k)}$ and $AP^{(k)}$. See Table 2-1 and Equation (2.3) for further explanation.

Table 2-1 reports the variance and covariance components that together determine the variance of $WC^{(k)}$ for $k = 2$ under various combinations of payment schemes followed by echelons $k = 1$ and 2. For all values of ρ listed in Table 2-1, when both $k = 1$ and $k = 2$ follow payment batching scheme (batch-batch), the cash-flow bullwhip experienced by echelon $k = 2$ is smaller than or equal to that experienced when both echelons follow payment lead time scheme (PLT-PLT). PLT-batch scheme represents the condition when echelon $k = 1$ follows PLT scheme, and $k = 2$ follows payment batching scheme. The batch-PLT scheme represents the opposite of PLT-batch scheme. For all values of ρ listed in Table 2-1, cash-flow bullwhip experienced by echelon $k = 2$ under the PLT-batch and batch-PLT schemes is greater than experienced under the PLT-PLT and batch-batch schemes. Based on results in Table 2-1, for echelon $k = 2$ and $P_1 = P_2 = B = 7$ the switch from PLT-PLT scheme to batch-batch scheme can reduce cash-flow bullwhip by up to 49.5%.

Table 2-1 Components of cash-flow bullwhip experienced by echelon $k = 2$ under various payment schemes

ρ	Pay Scheme	var(Invt)	var(AR)	var(AP)	cov(Invt,AR)	cov(Invt,AP)	cov(AR,AP)	var(WC)	CFB
-0.99	PLT-PLT	199.1	5050.7	4676.3	-4.7	-6.6	4859.8	210.4	0.0
	Batch-Batch		13070.1	12849.7	-183.8	-180.0	12957.7	195.8	0.0
	PLT-Batch		5050.7	12849.7	-4.7	-180.0	-2571.0	23592.1	4.7
	Batch-PLT		13070.1	4676.3	-183.8	-6.6	-2572.9	22736.9	4.5
-0.75	PLT-PLT	188.6	360.6	254.2	-79.2	-83.0	285.3	240.6	1.1
	Batch-Batch		13303.7	13203.3	-155.7	-126.6	13232.6	172.3	0.8
	PLT-Batch		360.6	13203.3	-79.2	-126.6	91.1	13665.4	59.9
	Batch-PLT		13303.7	254.2	-155.7	-83.0	63.5	13474.2	59.1
-0.5	PLT-PLT	218.8	371.4	314.7	-133.8	-125.3	330.0	228.0	1.7
	Batch-Batch		18029.0	17967.2	-181.0	-160.1	17984.4	204.4	1.5
	PLT-Batch		371.4	17967.2	-133.8	-160.1	144.6	18320.9	138.0
	Batch-PLT		18029.0	314.7	-181.0	-125.3	110.7	18229.8	137.3
0	PLT-PLT	400.3	713.2	713.2	-303.7	-303.7	713.2	400.3	4.0
	Batch-Batch		40372.3	40372.3	-330.3	-330.3	40372.3	400.3	4.0

ρ	Pay Scheme	var(Invt)	var(AR)	var(AP)	cov(Invt,AR)	cov(Invt,AP)	cov(AR,AP)	var(WC)	CFB
	PLT-Batch		713.2	40372.3	-303.7	-330.3	304.6	40929.7	413.0
	Batch-PLT		40372.3	713.2	-330.3	-303.7	304.6	40823.3	411.9
0.5	PLT-PLT	985.0	2344.8	2810.4	-756.7	-1021.8	2460.5	1749.6	13.1
	Batch-Batch		161283.2	161700.3	-791.3	-913.6	161390.5	1432.2	10.7
	PLT-Batch		2344.8	161700.3	-756.7	-913.6	928.1	163487.9	1225.7
	Batch-PLT		161283.2	2810.4	-791.3	-1021.8	1344.8	162850.2	1221.0
0.75	PLT-PLT	1683.7	6708.3	9052.1	-1221.4	-2242.3	7038.4	5409.1	23.7
	Batch-Batch		642486.7	644184.6	-1397.5	-2002.8	642727.0	4111.7	18.0
	PLT-Batch		6708.3	644184.6	-1221.4	-2002.8	2695.5	648748.3	2845.8
	Batch-PLT		642486.7	9052.1	-1397.5	-2242.3	4333.4	646245.5	2834.8
0.99	PLT-PLT	2969.3	2.87E+06	2.70E+06	-3709.8	-7140.5	2.78E+06	23898.9	0.4
	Batch-Batch		4.00E+08	4.00E+08	-1839.6	-4552.5	4.00E+08	15984.7	0.3
	PLT-Batch		2.87E+06	4.00E+08	-3709.8	-4552.5	1.55E+06	4.00E+08	7310.2
	Batch-PLT		4.00E+08	2.70E+06	-1839.6	-7140.5	1.56E+06	4.00E+08	7307.6

2.4.7 What if end-customer demand information is not shared?

Consider that echelon $k = 1$ does not share end-customer demand information with echelons $k \geq 2$. In such a situation, an echelon $k \geq 2$ at time epoch t makes demand forecasts based on $H_t^{(k-1)}$, the history of orders echelon k received from echelon $k-1$ up to epoch t. $H_t^{(k-1)}$ can be written as follows:

$$H_t^{(k-1)} = \{q_t^{(k-1)}, q_{t-1}^{(k-1)}, \ldots, q_1^{(k-1)}\}. \tag{2.26}$$

Alwan et al. (2003) show that if echelon $k = 1$ experiences AR(1) demand and uses an MSE-optimal forecasting scheme, then the order quantity process of all echelons are autoregressive-moving-average processes with terms 1 and 1, ARMA(1,1). That is, $q^{(k)}$ $\forall k \geq 1$ are ARMA(1,1) processes. Since $q^{(k)}$ is an ARMA(1,1) process, order quantity of echelon k at epoch t can be written as follows:

$$q_t^{(k)} = \mu_d + \rho q_{t-1}^{(k)} - \theta \epsilon_{t-1} + \epsilon_t, \tag{2.27}$$

where θ is the moving average term of order 1 and is given by:

$$\theta = \frac{\rho - \rho^{L_k}}{1 - \rho^{L_k+1}}, \tag{2.28}$$

and all other terms have the same meaning as previously defined in the chapter.

Alwan et al. (2003) further show that echelon k's MSE-optimal lead time demand forecast determined using $H_t^{(k-1)}$ in time epoch t is given by:

$$\hat{Q}_{t|H_t^{(k-1)}}^{(k,L_k)} = \beta(\rho, \mu_d, L_k) + \frac{\rho(1-\rho^{L_k})}{1-\rho} q_t^{(k-1)} - \theta \frac{\rho(1-\rho^{L_k})}{1-\rho} \epsilon_t, \tag{2.29}$$

where $\beta(\rho, \mu_d, L_k)$ is a constant. The interested reader is directed to Alwan et al. (2.2003) for further discussion on $\beta(\rho, \mu_d, L_k)$. Conservation of material flow implies:

$$q_t^{(k)} = \hat{Q}^{(k,L_k)}_{t|H_t^{(k-1)}} - \hat{Q}^{(k,L_k)}_{t-1|H_{t-1}^{(k-1)}} + q_t^{(k-1)}. \tag{2.30}$$

Now, using Equations (2.29) and (2.30), the order quantity of echelon k in time epoch t in the absence of end-customer demand information can be written as:

$$q_t^{(k)} = \frac{\rho(1-\rho^{L_k})}{1-\rho}\left(q_t^{(k-1)} - q_{t-1}^{(k-1)}\right) - \theta\frac{\rho(1-\rho^{L_k})}{1-\rho}(\epsilon_t - \epsilon_{t-1}) + q_t^{(k-1)}. \tag{2.31}$$

Next, the cash-flow bullwhip of echelon k at time epoch t in the absence of end-customer demand information is given by:

$$CFB_{k,INS} = \frac{var\left(Invt^{(k)} + AR^{(k)} - AP^{(k)}\right)}{var(d^{(k,\$)})}$$

$$= \frac{var\begin{pmatrix} c_{k+1}I_{int}^{(k)} + c_{k+1}\sum_{i=1}^{t} q_{i-L_k}^{(k)} - c_{k+1}\sum_{i=1}^{t} q_i^{(k-1)} \\ +c_k\sum_{i=1}^{P_k} q_{t-i}^{(k-1)} - c_{k+1}\sum_{i=1}^{P_{k+1}} q_{t-i}^{(k)} \end{pmatrix}}{var(d^{(k,\$)})} \tag{2.32}$$

where $q_t^{(k)}$ is given by Equation (2.31).

Figure 2-9 illustrates the cash-flow bullwhip experienced by echelon $k = 2$ when end-customer demand information is shared (IS) and when it is not shared (INS). The curves in Figure 2-9 are generated numerically using Equations (2.25) and (2.32) for various values of ρ. The following observations are made:

1. For $-1 < \rho \leq 0$, $CFB_k \leq CFB_{k,INS}$
2. For $0 < \rho < \rho^*$, $CFB_{k,INS} \leq CFB_k$
3. For $\rho^* \leq \rho^* < 1$, $CFB_k \leq CFB_{k,INS}$.

Based on the observations, it is inferred that $CFB_k \leq CFB_{k,INS}$ for $\rho \in (-1,0] \cup [\rho^*, -1)$ where ρ^* is a function of $c_k, c_{k+1}, P_k, P_{k+1}$, and L_k. Finding the exact closed-form solution of ρ^* would require determining the analytical equation of $CFB_{k,INS}$, which is out of the scope of this chapter. It should be noted that the maximum absolute difference in CFB_k and $CFB_{k,INS}$ when $\rho \in (0, \rho^*]$ compared to the maximum absolute difference in CFB_k and $CFB_{k,INS}$ when $\rho \in (-1,0] \cup [\rho^*, 1)$ is very small. Meaning for a wide range of values of ρ, CFB_k and $CFB_{k,INS}$ are comparable and for $\rho \in [\rho^*, 1)$, $CFB_k < CFB_{k,INS}$. Similar results are observed for $k > 2$. In Figure 2-9, the maximum difference in CFB_k and $CFB_{k,INS}$ occurs when $\rho = 0.91$. At this point CFB_k is 53.7% smaller than $CFB_{k,INS}$. For $k > 3$ (not shown in Figure 2-9), the maximum difference in CFB_k and $CFB_{k,INS}$ occurs when $\rho = 0.94$ and at that point CFB_k is 96.4% smaller than $CFB_{k,INS}$.

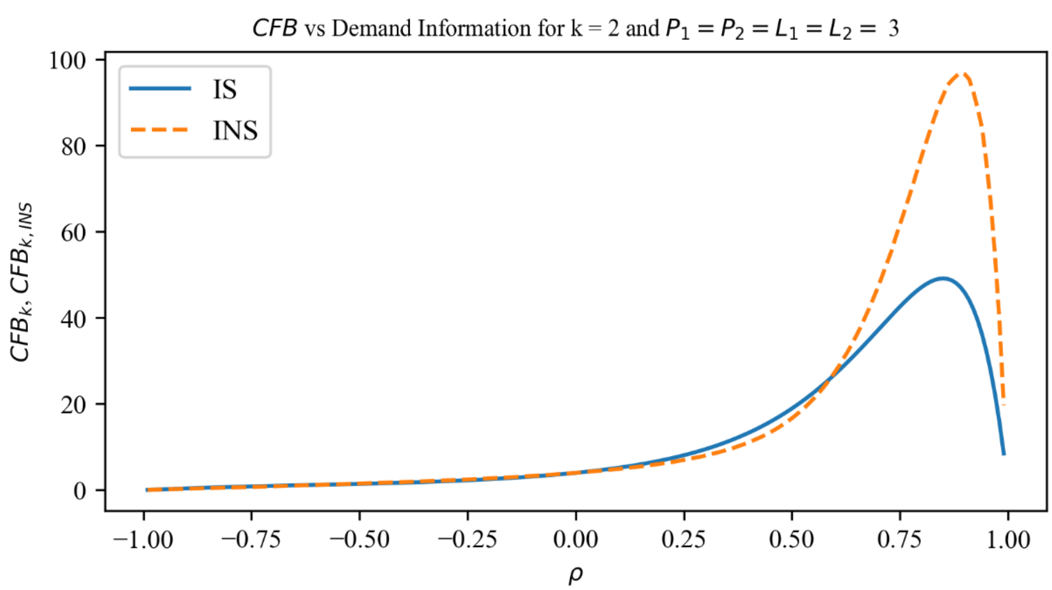

Figure 2-9 Relationship between CFB, demand autocorrelation and end-customer demand information sharing scheme

2.5 Empirical Observation

The discussion on an analytical model of cash-flow bullwhip presented in Sections 2.2 and 2.3 poses a vital question: do real-world supply chain entities experience the cash-flow bullwhip effect? To answer this question, we empirically measure the cash-flow bullwhip experienced by a sample of companies. Our sample comprises Compustat US companies for the years 2010 through 2019. We exclude companies not classified as manufacturers, wholesalers, or retailers. Therefore, the sample only consists of manufacturers (NAICS 31-33), wholesalers (NAICS 42), and retailers (NAICS 44-45). Also, we exclude companies from the sample that have missing data points in the cost of goods sold (COGS), cash, inventory, trade receivables, or trade payables series. Trade receivables and payables represent the accounts receivable and payable emanating from selling/buying material (goods). Finally, we exclude from the sample companies that are not publicly traded for more than one calendar quarter in the period 2010-2019. The final sample consists of 786 companies.

Table 2-2 reports the descriptive statistics of the sample. We use the method described in Chapter 3 for data transformations and calculation of cash-flow bullwhip experienced by companies in the sample. Note that the analytical model presented in Sections 2.2 and 2.3 assumes that the cash position emanating from buying/selling material is constant. COMPUSTAT, however, does not report the cash position associated with buying/selling material. Instead, it reports the overall cash position for each company, which is the sum of cash position emanating from operational (buying/selling material), investing, and financial activities. Therefore, we calculate two types of cash-flow bullwhip measures for each company. The first measure, $CFB_{(o,i,f)}$, includes the cash position (operating +

investing + financial activities) in determining the working capital, while the second measure, $CFB_{(o)}$, assumes that the operating cash position is always constant. Therefore, the two measures of cash-flow bullwhip for any company, $comp$ in sample, can be written as:

$$CFB_{(o,i,f)}^{comp} = \frac{var(Cash^{comp} + Invt^{comp} + TradeReceivables^{comp} - TradePayables^{comp})}{var(COGS)} \tag{2.33}$$

$$CFB_{(o)}^{comp} = \frac{var(Invt^{comp} + TradeReceivables^{comp} - TradePayables^{comp})}{var(COGS)} \tag{2.34}$$

Table 2-3 reports the summary of cash-flow bullwhip experienced by companies in the sample. The mean $CFB_{(o,i,f)}^{comp}$ is 23.3. Out of the 786 companies in the sample, 606 (77%) experience $CFB_{(o,i,f)}^{comp}$ greater than 1. The mean $CFB_{(o)}^{comp}$ is 2.95. 510 (65%) of the 786 companies in the sample experience $CFB_{(o)}^{comp}$ greater than 1.

Table 2-2 Descriptive statistics of sample data

	Cash	Inventory	Trade Receivables	Trade Payables	COGS
count	33728	33728	33728	33728	33728
mean	716.80	884.54	975.36	757.87	1269.69
std	2537.70	3107.81	4230.61	3183.85	5505.45
min	0.00	0.00	0.00	0.01	-44.96
25%	13.62	23.38	18.58	10.02	21.84
50%	74.54	129.89	118.32	61.85	136.84

75%	333.72	518.42	465.10	287.37	538.03
max	53484.68	56656.26	87192.11	67062.75	104920.00

All figures are in million USD

Table 2-3 Summary of cash-flow bullwhip by companies in the sample

	$CFB_{(o,i,f)}^{comp}$	$CFB_{(o)}^{comp}$
count	786	786
mean	23.34	2.96
std	45.05	3.42
min	0.27	0.21
25%	1.10	0.72
50%	4.12	1.62
75%	16.57	3.58
max	170.93	13.18

In Table 2-3, we observe that according to both metrics, $CFB_{(o,i,f)}^{comp}$ and $CFB_{(o)}^{comp}$, of the cash-flow bullwhip effect, a majority of the companies in the sample amplify the working capital distortions. These results indicate that amplification of working capital distortions in supply chains is a real phenomenon. The reader should note that the results in Table 2-3 do not prove that the working capital distortions are strictly increasing as one moves upstream in the supply chain.

2.6 Conclusion

The supply chain bullwhip effect (BWE) is concerned with the material flow distortions in supply chains. The distortions in material flow also cause distortions in cash-flow. In this chapter, we propose a new metric for cash-flow bullwhip effect. More specifically, we focus on building an analytical model of cash-flow bullwhip for echelon k in a serial supply chain where (i) end-customer demand is an AR(1) process, (ii) end-customer demand information is shared with every echelon in the supply chain, (iii) each echelon uses an order up-to inventory policy, and (iv) each echelon uses an MSE-optimal lead time demand forecasting scheme. We show that cash-flow bullwhip experienced by echelon k (denoted by CFB_k) is related to k, demand autocorrelation parameter (ρ), echelon k's procurement lead time (L_k), the payment lead time echelon k experiences in receiving payments from echelon $k-1$ (denoted by P_k), and the payment lead time echelon k takes to make payments to echelon k (denoted by P_{k+1}).

We find that when the procurement and payment lead times are zero, there is no working capital distortion in the supply chain, i.e., cash-flow bullwhip experienced by every echelon is 0. For non-zero values of lead times and $0 < \rho < 1$, cash-flow bullwhip increases as one moves upstream in the supply chain. Meaning working capital distortion amplifies along the supply chain. When payment lead times are zero, higher the echelon k's procurement lead time (L_k), the higher the cash-flow bullwhip experienced by echelon k. When procurement lead time is zero, the higher the difference in P_k and P_{k+1}, the higher the cash-flow bullwhip experienced by echelon k. However, when the procurement and payment lead times are non-zero, the relationship between CFB_k is quite complex and is defined by Equations (2.24) and (2.25) for $k = 1$ and $k \geq 2$, respectively. We show that for a wide range of ρ, end-customer demand information sharing reduces the cash-flow bullwhip that echelons experience. We empirically show that a majority of the 786 companies in our sample amplify working capital distortion. Our results indicate that the cash-flow bullwhip is a real phenomenon. Our analysis shows that if an echelon forces shorter payments terms on its customers and longer payment terms on its suppliers, then the cash-flow bullwhip experienced by all three the echelon, its customers, and its suppliers increases.

We also numerically study the effect of payment batching on cash-flow bullwhip. We observe that cash-flow bullwhip under the batch-batch scheme is smaller than or equal to that experienced under the PLT-PLT scheme. Also, the cash-flow bullwhips experienced under the PLT-batch and batch-PLT schemes are greater than that experienced under the PLT-PLT and batch-batch schemes. That is, mimicking its customer's payment scheme reduces an echelon's cash-flow bullwhip.

The findings of this chapter are qualified because of the following limitations: (i) real-world supply chains do not necessarily have a serial structure, (ii) end-customer demand cannot always be modeled as an AR(1) process, and (iii) supply chain echelons do not always employ order up-to level inventory policy, and (iv) supply chain echelons tend to make payments in batches. In the future, research can be generalized in various directions to bridge the gaps stated above. First, characterize CFB_k for complex supply chain networks. Second, it would be interesting to see what happens to CFB_k when the end-customer demand process has a more general specification like ARMA(p, q). Third, characterize CFB_k when supply chain echelons use more general inventory replenishment policies like the (s, S) policy. Fourth, analytically study the effect of payment batching on

CFB_k. Moreover, finally, perform empirical analysis to study the association between cash-flow bullwhip, procurement lead time, payment lead time, and demand autocorrelation.

Chapter 3 SUPPLY CHAIN CASH-FLOW BULLWHIP EFFECT: AN EMPIRICAL INVESTIGATION

Abstract

Just like the bullwhip effect (BWE) is the amplification of order variance along a supply chain, the cash-flow bullwhip effect (CFB) is the amplification of working capital variance along a supply chain. High CFB can lead to inefficiency in working capital and lead to financial distress. We investigate the existence of CFB and its association with BWE by using a sample of 782 U.S. public companies during 2010–2019. We find that 31% of retailing, 25% of wholesaling, and 80% of manufacturing industries experienced CFB. Furthermore, we find that: (i) larger firms experience smaller CFB, (ii) firms with conservative payment policy experience smaller CFB and BWE, (iii) firms with high liquidity ratio have smaller CFB, (iv) predictability in demand seasonality is associated with smaller CFB and BWE, (v) high lead time is associated with larger CFB and BWE, and (vi) higher demand autocorrelation is associated with larger CFB and BWE. Finally, we use data from automotive and semiconductor companies to analyze the CFB experienced by automotive and semiconductor supply chains. Insights from this new knowledge on the association of CFB and BWE with firm-attributes can inform key decisions—at the firm level, industry level, or government policy level.

3.1 Introduction

Access to sufficient working capital (WC) is vital for all firms in the global economy. Inefficient management of WC leads to bankruptcy. As a result, it has been the focus of numerous studies from a supply chain perspective. However, most studies have been centered around WC management and optimization (e.g., Peng & Zhou, 2019; Song et al., 2020; Huang et al., 2020). Little attention has been given to the variance of working capital in supply chain entities and the drivers of this effect.

An import financial metric that is affected by variance in WC is the operating cash-flow. Operating cash-flow measures the amount of cash a firm generates through its business operations. Insufficient positive cash-flow can hinder a firm's operations. In such cases, the firm may require external financing to keep operations running. The relationship between operating cash-flow and working capital can be expressed as:

$$\begin{aligned} &Operating\ Cash\ Flow \\ &\qquad = Operating\ Income + Depreciation - Taxes \\ &\qquad + Change\ in\ Working\ Captial \end{aligned} \tag{3.1}$$

Based on Equation (3.1), as WC's variance increases, the variance of Operating Cash-flow increases. Sufficiently high variance in Operating Cash-flow can lead to a firm having to need external financing to maintain operations. Such scenarios are of concern to individual firms and their supply chain partners. Therefore, it is crucial to study WC variance propagation in supply chains.

Tangsucheeva & Prabhu (2013) hypothesized that just like supply chains experience the bullwhip effect (BWE) in their material (goods) flow, they concurrently experience a cash-flow bullwhip effect which is characterized by amplification of cash conversion cycle

(CCC) variability as one moves upstream in the supply chain. BWE is defined as

$$BWE = \frac{var(Order\ Quantity)}{var(Demand)} \tag{3.2}$$

where $Order\ Quantity$ and $Demand$, both are either measured in monetary units (e.g., $Order\ Quantity = \$20{,}000$ and $Demand = \$19{,}500$) or as counts of units of goods (e.g., Order Quantity = 10,000 units of goods, and Demand = 11,000 units of goods). Therefore, when a firm's $BWE > 1$, the firm is experiencing demand variance amplification, and when $BWE < 1$, it is experiencing demand variance attenuation.

Tangsucheeva & Prabhu (2013) define cash-flow bullwhip as:

$$CFB\text{-}T = \frac{var(CCC)}{var(Demand)} = \frac{var\left(\frac{Inventory}{COGS} + \frac{Accounts\ Receivables}{Revenue} - \frac{Accounts\ Payable}{COGS}\right)}{var(Demand)} \tag{3.3}$$

where, $COGS$ is the cost of goods sold. A caveat in Tangsucheeva & Prabhu's (2013) formulation of cash-flow bullwhip is that it compares variances of two different units of measurements. CCC is measured in time units (e.g., CCC = 35 days), whereas Demand is measured in monetary units or as counts of units of goods demanded (e.g., Demand = 120,000,000 units of goods). Therefore, it is not possible to use a firm's $CFB\text{-}T$ value to infer if it is amplifying or attenuating financial variances. Therefore, we propose a new formulation for cash-flow bullwhip, by replacing CCC in Tangsucheeva & Prabhu's (2013) formulation of cash-flow bullwhip with WC. This new formulation ensures that the numerator and denominator both represent the variance of entities measured in monetary units. We define cash-flow bullwhip as:

$$CFB = \frac{var(WC)}{var(Demand)} \\ = \frac{var(Inventory + Cash + Accounts\ Receivable - Accounts\ Payable)}{var(Demand)} \tag{3.4}$$

Whenever CFB value of an industry/firm is greater than one, we say that the industry/firm is experiencing WC variance amplification. And when the value is less than 1, we say that it is experiencing WC variance attenuation.

Recall that in Chapter 2, Figure 2-4 and Figure 2-5 show that CFB and BWE behave differently for the same values of demand autocorrelation, procurement lead time, and payment lead time. Therefore, we believe there is merit not only in measuring an entity's BWE but also its CFB, especially if the stakeholders are interested in studying the entity's financial sustainability.

Based on the type of entities in the numerator of Equation (3.4), CFB can be broken down into 2 main components: Inventory Bullwhip Effect (IBE) and Payment Bullwhip Effect (PBE). IBE is the ratio of inventory variance to demand variance, and PBE is the ratio of cash and payments variance to demand variance. IBE and PBE are given as follows:

$$IBE = \frac{var(Inventory)}{var(Demand)} \tag{3.5}$$

$$PBE = \frac{var(Cash +\ Accounts\ Receivable - Accounts\ Payable)}{var(Demand)} \tag{3.6}$$

Our objective in this chapter is two-fold. First, to quantify the supply chain bullwhip effects (BWE, CFB, IBE, and PBE) experienced across industries using recent firm-level financial data from the Compustat database accessed from Wharton Research Data Services. Second, to identify the association between CFB and firm-level variables.

Through this econometric study, we empirically demonstrate how firm and supply chain partners' attributes influence the bullwhip effects experienced by firms. Understanding this effect and its drivers can support the managerial decision-making process.

We use quarterly data of 782 firms from Q1-2010 to Q4-2019. Of these, 42 are retailers, 33 are wholesalers, and 707 are manufacturers. Each of these retailing, wholesaling, and manufacturing firms has a North American Industrial Classification System (NAICS) code which shows the industry the firm operates in. This chapter uses 4-digit NAICS codes to classify firms into various industries. Based on these 4-digit codes, the 42 retailing firms operate in 13 different retailing industries, the 33 wholesaling firms in 8 wholesaling industries, and the 707 manufacturing firms in 78 different manufacturing industries. We find that 3 of the 13 retailing industries, 2 of the 8 wholesaling industries, and 62 of the 78 manufacturing industries experience CFB greater than 1.

Our second contribution is finding and quantifying the relationship between various firm-level variables and the magnitude of CFB firms experience. Based on the analytical model of cash-flow bullwhip by Tangsucheeva & Prabhu (2013), we identify several firm attributes that could potentially influence the CFB experienced by a firm and build hypotheses for us to test. For example, (i) theory predicts that as payment and procurement lead times increase, the CFB increases; (ii) intuition suggests that predictable seasonality in demand decreases BWE and CFB; (iii) observation of supply chains suggests that larger firms have an outsized influence on their suppliers by extending payment terms to suppliers and having unbalanced inventory policies (Peng and Zhou, 2019), and hence large firms should experience less CFB. A detailed discussion of all our hypotheses on the association between firm-level variables and CFB is given in Section 3.4. Specifically, we test the association between CFB and firm attributes like firm size, payment policy, liquidity ratio, predictability of seasonality in demand, procurement lead time, production lead time, payment lead time, and autocorrelation in demand. We find that all these attributes significantly affect the CFB, IBE, and PBE experienced by a firm. Further, BWE too is affected by all these attributes but firm size and liquidity ratio.

We also illustrate how the bullwhip effects propagate in the U.S. automotive supply chain. We investigate if drivers of bullwhip effects that we identify in Section 3.4 also affect the automotive supply chain bullwhip effects. We find that original equipment manufacturers (viz., Daimler Ag, Honda Motor Co Ltd., Nissan Motor Co Ltd., etc.), on average, experience smaller CFB than their supply chain partners like automobile dealers and automobile parts suppliers. It is also found that CFB experienced by a firm in the automotive supply chain is associated with its payment policy, seasonality ratio, and lead time.

Analytical models of BWE by Chen et al. (2000) and cash-flow bullwhip by Tangsucheeva & Prabhu (2013) were built for single product types and specific echelons of the supply chain. These models account for the effects of lead-time, forecasting method, and demand pattern of a single type of product on the bullwhip effects experienced by a firm in a specific echelon. That is, they represent only the effects that product-level operational decisions have on bullwhip experienced by a firm. They do not model the effect of aggregation of demand and inventory across product lines, aggregation of payment policy across suppliers, aggregation of trade receivables across customers, firm size, or any other tactical and strategic decisions endogenous to the firm on BWE and CFB. It could be said that Chen et al. (2000) and Tangsucheeva & Prabhu (2013) treat the firm as a blackbox that keeps firm-level effects hidden and only shows the product-level effects. This chapter uses firm-level data to analyze if insights from product-level models are consistent with firm-level data. By exploring this link empirically, we contribute to supply chain literature by showing how operational decisions and firm-level practices affect a firm's bullwhip effects.

This chapter brings to the fore a concept largely unnoticed by supply chain researchers and managers. It offers several fruitful directions for future research that might shed light on prescriptions to mitigate WC-induced distress in supply chains.

The rest of the chapter is organized as follows. In Section 3.2, we review the literature on related research in econometrics, supply chain, and operations management. In Section 3.3, we describe the data used in the study. In Section 3.4, we define the method used to quantify CFB and formulate hypotheses to be tested. In Section 3.5, we perform the analysis. It covers three areas: (i) magnitude of bullwhip effects experienced by various industries of the U.S. economy, (ii) identification of the drivers of bullwhip effects, and (iii) bullwhip effects in the automotive and semiconductor supply chains. Finally, Section 3.7 concludes the chapter by discussing the results, limitations of this study, and directions for future work.

3.2 Literature Review

Many analytical and empirical studies have contributed to the BWE literature. When it comes to CFB, there are some analytical studies but no empirical studies (to the best of our knowledge). This chapter aims to empirically study the CFB, BWE, IBE, and PBE in the U.S. supply chains. In this section, we first review the empirical contributions to the BWE literature and then review the analytical contributions to the CFB literature.

3.2.1 Measuring the Bullwhip

In supply chain and operations management literature, BWE has been extensively studied using various approaches, viz., (i) analytical modeling (e.g., Chen et al., 2000; Dai et al., 2016; Towill et al., 2017), (ii) simulation modeling (e.g., Chatfield et al., 2004; Dominguez et al., 2014; Ojha et al., 2019; Dolgui et al., 2020), (iii) empirical quantification of BWE (e.g., Cachon et al., 2007; Bray & Mendelson, 2012; Shan et al., 2014; Udenio et al., 2015; Zhu et al., 2020), and (iv) laboratory experiments (e.g., Wu & Katok, 2006; Croson et al., 2014; Sterman & Dogan, 2015). The empirical approach of studying BWE can be further split into (i) single firm case studies (e.g., Akkermans & Voss, 2013; Duan et al., 2015; Pastore et al., 2019) and (ii) multi-firm and economy-wide studies (e.g., Cachon et al., 2007; Bray & Mendelson, 2012; Shan et al., 2013; Mackelprang & Malhotra, 2015; Isaksson & Sifert, 2016; Zhu et al., 2020).

According to Bray & Mendelson (2012), single firm case studies of BWE might experience a publication bias that favors results that point to the existence of BWE. That is, published case studies on BWE will feature firms that indeed experience BWE. Due to this pitfall of single firm case studies, Cachon et al. (2007) and Bary & Mendelson (2012) used data from a broad sample of industries and firms, respectively, to study BWE.

Cachon et al. (2007) searched for the BWE in various industries of the U.S. economy over January 1992 to February 2006 using data obtained from the U.S. Census Bureau and the Bureau of Economic Analysis (BEA). The advantage of using Census and BEA data is that it is cataloged monthly. Monthly industry-level data has a finer temporal granularity compared to quarterly data. Census and BEA data, however, do not have much cross-sectional granularity, i.e., they do not give any insights into firm-level effects. This is why Cachon et al. (2007) pointed out that "it is possible that firms exhibit the bullwhip effect, but the industry does not" (p. 477). They found that: (i) most retailing and manufacturing industries do not exhibit BWE, while the wholesaling industries do; (ii) smaller the predictability in demand seasonality of an industry, the more likely the industry is to amplify order variance and increase its BWE; (iii) industries that experience large seasonality in demand tend to smooth order variance decreasing the BWE they experience.

Bray & Mendelson (2012) addressed the shortcoming of less cross-sectional granularity in Cachon et al. (2007) by using quarterly firm-level financial data from Compustat. The use of quarterly firm-level financial data affords expansive cross-sectional granularity but sacrifices temporal granularity. They studied the BWE experienced by 4,689 public U.S. companies over 1974-2008. They found that while about two-thirds of the firms in the sample experience BWE, its magnitude greatly varies across firms. The caveat in Bray & Mendelson (2012) is that they estimate bullwhip across firms and not across supply chains.

Chiang et al. (2016) empirically examined the impact of several aspects of demand forecasting on the BWE experienced by a U.S. automotive firm. They used monthly data of units sold by Chevrolet between 1991-2008. Chiang et al. (2016) found that the choice of demand forecasting method leads to BWE. Moreover, the smaller the variation in lead time and demand forecast, the smaller is the BWE experienced by a supply chain entity.
Pastore et al. (2019) studied the BWE in the European automotive spare parts supply chain to shed light on how demand variability propagates in different product groups. They used data from a five-echelon supply chain that handles 30,000 different SKUs. Their results

indicate that the European automobile spare parts supply chain experiences BWE, and the effect is larger for fast-moving products than it is for slow-moving products.

3.2.2 Cash-flow Bullwhip Effect

While BWE has received extensive attention in the literature, far lesser studies have focused on the dynamics and variations in supply chains' working capital flow. Tsai (2008) provided insights into the behavior of cash-flow risk with respect to trade terms and lead times. The analytical model of cash-flow risk developed by Tsai (2008) showed that cash-strapped firms that aggressively push for lower cash conversion cycle (CCC) increase their cash-flow risk in doing so.

Cash-flow bullwhip effect was first characterized by Tangsucheeva & Prabhu (2013) as the ratio of variance(CCC) and variance(Demand). Tangsucheeva & Prabhu (2013) provided an analytical formula to quantify the CFB experienced by various supply chain entities of a serial supply chain. This analytical formula of CFB parametrized: demand autocorrelation, lead time, and the moving window size used to forecast demand.

3.3 Data

This section describes the data used for our study and the transformations we apply to it. Public companies are required to provide financial statements and operational data. This data is reported following the generally accepted accounting principles (GAAP) and is available in the Compustat database.

We use Compustat data containing 40 time points between calendar quarters Q1-2010 and Q4-2019 for each firm in our sample. The fiscal quarters of firms do not always align with calendar quarters. Therefore, to temporally align data from all the firms, we use calendar quarters. Since our study is focused on supply chains, we only use the data entries that correspond to retailing, wholesaling, and manufacturing firms (NAICS 44-45, 42, and 31-33, respectively). Entries corresponding to all other industries are dropped from the data. We also omit from our sample the firms that have missing values for cost of goods sold (COGS), cash, trade payables, trade receivables, or inventory (total). We also drop firms that were not public for at least one calendar quarter between Q1-2010 and Q4-2019. We end up with 782 firms in our sample. The 2019 cutoff allows us to ignore the effect of COVID-19 related supply chain disruption (starting Q1-2020) on CFB, BWE, IBE, and PBE.

The reader should note that the Compustat database reports WC numbers for each firm, but we do not use them to calculate CFB. WC numbers in financial statements are based on assets and liabilities emanating from three types of firm activities: operating, investing, and financing activities. Since we are only interested in the flow of goods and cash as a result of the sale/purchase of goods, we calculate a firm's WC for a given quarter as follows:

$$WC = Cash + Inventory + Trade\ Receivables\ (AR) - Trade\ Payables (AP) \tag{3.7}$$

It should also be noted that we use total inventory numbers without breaking them down into raw materials, work in process, and finished goods inventories. We do not perceive the loss of granularity when using total inventory numbers as an issue because we wish to study the effect of aggregate firm-level variables on CFB and its components.

As seen in Equations (3.2), (3.4), (3.5) and (3.6), the calculation of BWE, CFB, IBE, and PBE requires information on demand variability. Here, when we say demand, we mean the demand imposed by the downstream customers on the firm and not by the final consumer at the end of the supply chain. Compustat does not report quarterly demand data for any firm. Therefore, as a proxy for a firm's quarterly demand, we use the quarterly cost of goods sold (COGS). Sales series can also be used as a proxy for demand but the caveat in its use is that sales includes profit. The profit margins vary not only between industries, but also between companies within the same industry. Therefore, we choose COGS as a proxy for demand.

Most firms receive orders (demand) in a volatile manner, but since customers are willing to wait for delivery, firms smooth the flow of goods to customers (Cachon et al., 2007). This means that the variance of COGS is less than or equal to the variance of demand. Therefore, the use of var(COGS) in place of var(Demand) in Equations (3.2) and (3.4)–(3.6) could potentially inflate the bullwhip effects experienced by an industry/firm. To check how reliable is the use of COGS as a proxy for demand, we perform a robustness test in Section 3.6.

When measuring BWE, we also need the variance of order quantity. Order quantity can be seen as the quantity of goods that flow into a firm in a given quarter. Since Compustat does not directly report order quantity numbers, we use a measure called "purchases" as a proxy for order quantity. Therefore, BWE experienced by a firm is given as:

$$BWE = \frac{var(purchases)}{var(COGS)} \tag{3.8}$$

For each firm *i*, the purchases it makes in quarter *t*, $purchases_{it}$ is given as:

$$purchases_{it} = COGS_{it} + Inventory_{it} - Inventory_{it-1} \tag{3.9}$$

where, $COGS_{it}$ and $Inventory_{it}$ are the cost of goods sold and inventory of firm *i* in quarter *t*.

Based on the discussion so far, we need the following series of each firm to calculate CFB, BWE, IBE, and PBE: Cash, inventory trade receivables, trade payables, COGS, and purchases. Before we calculate the bullwhips for each industry and firm, we transform each series by (i) applying the first difference operator and (ii) winsorizing the top and bottom 1%. The first transformation detrends our series, and the second dampens the effect of significant outliers. Detrending is essential because the data series span over ten years (40 quarters), and a firm could observe a stochastic trend (growth, decline, or both) in these years. Such a stochastic trend would affect the bullwhip measures. We are interested in measuring the variance of data series about stochastic trends and not the variance of data series itself. Therefore, if the data series have trends, they need to be detrended. To check for non-stationarity in the data series, we perform the Augmented Dickey-Fuller test. This test's null-hypothesis is that a given data series has a unit root, i.e., it is not stationary. The test results show that of the 782 firms in the sample, 85 firms reject the null hypothesis for WC (Cash + Inventory + Trade Receivables – Trade Payables) series and 117 firms for the COGS series.

It should be noted that the Augmented Dickey-Fuller test has a high Type-I error rate. We conclude that most series have a trend. Therefore, we detrend all data series by applying the first difference. Figure 3-1 & Figure 3-2 show how removing stochastic trends from Apple Inc.'s data series allows us to study the variance of COGS, WC, and Purchases about the trend.

While we detrend the data to remove the effect of stochastic trends from the data series, we choose not to adjust them seasonally. This decision is in accordance with the arguments made by Cachon et al. (2007): (i) “firms must produce to meet demand, not seasonally adjusted demand," and (ii) "seasonality provides a strong motivation to smooth production" (p. 465–466). We believe these arguments can also be extended to working capital. Therefore, it can be said that firms need to maintain enough working capital to meet operational requirements, not seasonally adjusted operational requirements.

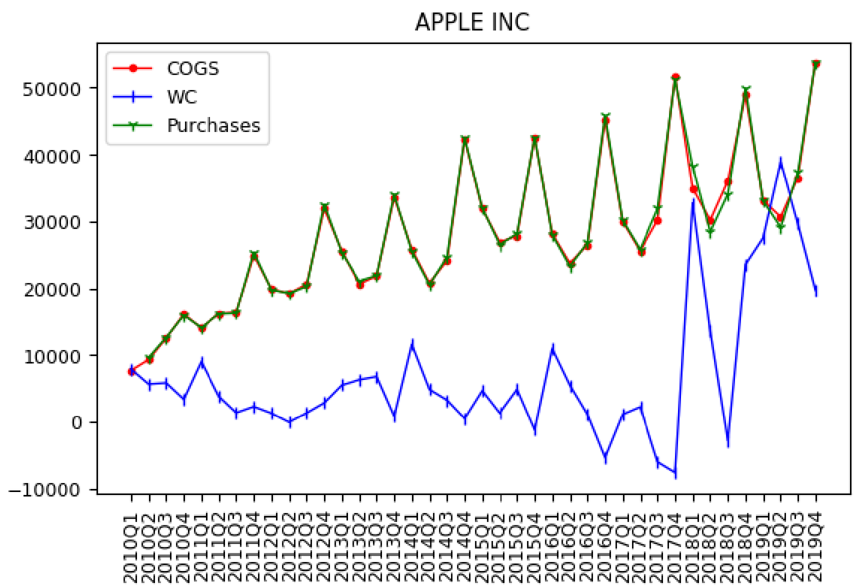

Figure 3-1 Apple Inc's data series for the period 2010Q1-2019Q4

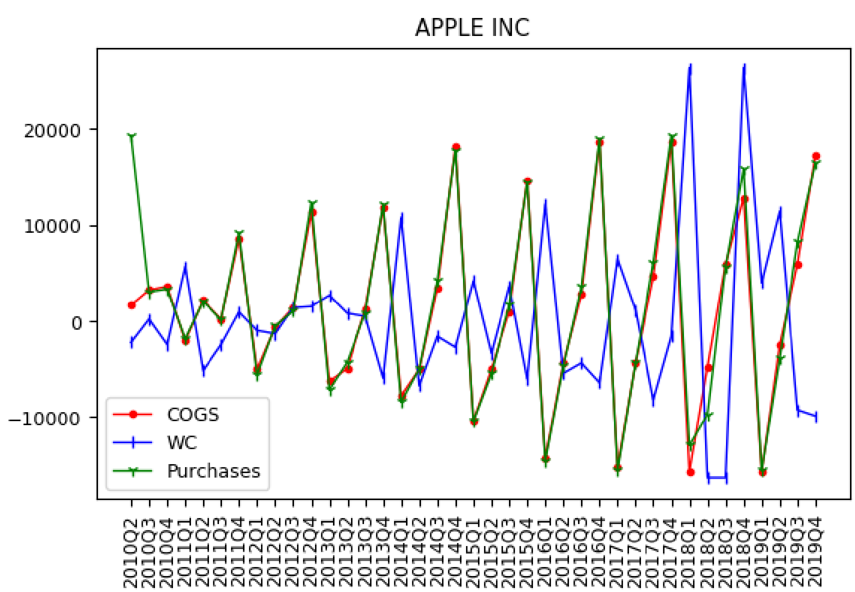

Figure 3-2 Apple Inc's detrended data series for the period 2010Q1-2019Q4

3.4 Measures and Hypotheses

We base our hypotheses on the relationship of bullwhip effects with firm-level variables based primarily on analytical models for BWE (by Chen et al., 2000) and CFB (by Tangsucheeva & Prabhu, 2013; Chapter 2), and on intuition gained from supply chain literature broadly. Some of our hypotheses might turn out to be wrong because of the reason discussed in Section 3.1 viz., analytical models for BWE and cash-flow bullwhip do not take into consideration the effects of demand and inventory aggregation across product lines, aggregation of payment policy across suppliers, aggregation of trade receivables across customers, firm size, or any other firm-level parameter controlled by tactical and strategic decisions.

As discussed in Section 3.1, larger firms can have an outsized influence on their supply chain partners. They do this by extending payment terms to suppliers, enforcing shorter payment terms on customers, and having an unbalanced inventory policy. Such behavior pushes risk onto smaller firms in the supply chain (Hofmann and Kotzab 2010). These small firms then do the same with even smaller supply chain partners. Also, vendors are willing to hold inventory for larger firms, i.e., larger firms can leverage the concept of vendor-managed inventory to keep their financials clean. Large firms can also pool risk and take advantage of economies of scale by aggregating demand across products, time, and locations. This further reduces the uncertainties they experience. Owing to these reasons, we hypothesize that:

Hypothesis 1: CFB and its components are negatively associated with firm size.

We use the log of average COGS as a proxy of firm *i*'s size, i.e.,

$$firm\ size_i = log\big(mean(COGS_i)\big) \tag{3.10}$$

The AP (trade payables) and AR (trade receivables) levels of firms reveal how well they are managing their cash position. Large AR indicates that a firm is not able to recover cash owed to it quickly. On the other hand, large AP indicates that the company is using others' cash to run its own operations. We define a firm's payment policy parameter (α) as the ratio of its AP and AR. The larger a firm's α, the more conservative the firm's payment policy. Over the period Q1-2010 to Q3-2020, Apple Inc.'s mean payment policy parameter was $\alpha_{Apple} = 2.26$, that of Chevron Corporation was $\alpha_{Chevron} = 1.01$, and that of KLA Corporation was $\alpha_{KLA} = 0.22$. Of these three firms, Apple Inc. has the most conservative payment policy and KLA Corporation has the most lenient payment policy. Apple Inc.'s conservative payment policy means that it is able to recover money owed to it quickly and runs its own operations on borrowed money. We believe that firms like Apple Inc. that have a conservative payment policy are better at managing cash and therefore hypothesize that:

Hypothesis 2: CFB and its components are negatively associated with payment policy parameter.

We measure firm *i*'s payment policy as follows:

$$\alpha_i = \frac{mean(AP_i)}{mean(AR_i)} = \frac{mean(trade\ payables_i)}{mean(trade\ receivables_i)} \tag{3.11}$$

We define liquidity ratio as the ratio of cash on hand to inventory. Our intuition suggests that a firm that manages WC efficiently (and consequently has a small CFB) should be able to maintain a high liquidity ratio. A high liquidity ratio is a sign of a firm being able not to let cash be stuck in inventory. This can be achieved by making supply chain partners hold inventory by adopting vendor-managed inventory, forcing short payment terms on customers and extended payment terms on suppliers. Therefore, we hypothesize that:

Hypothesis 3: CFB and its components are negatively associated with liquidity ratio.

We define firm *i*'s liquidity ratio as follows:

$$LR_i = \frac{mean(Cash\ on\ hand_i)}{mean(Inventory_i)} \tag{3.12}$$

High seasonality in demand might motivate firms to adopt a level production strategy. Depending on which industry a firm operates in, it may or may not choose to smooth production. But intuition suggests that capacity constraints incentivize firms to smooth production. Cachon and Schmidt (2007) empirically show this to be the case. It is our intuition that smooth production corresponds to a smooth order quantity. Assuming procurement and payment lead times remain constant, we can say that smooth production leads to smoothening of purchases, inventory level, AR, AP, and hence WC. Thus, we hypothesize that:

Hypothesis 4: CFB and its components are negatively associated with seasonality ratio.

We adopt the formula for seasonality ratio as defined by Cachon et al. (2007), which is given as:

$$SR_i = \frac{Var(COGS_i) - Var(Seasonally\ adjusted\ COGS_i)}{Var(COGS_i)} \tag{3.13}$$

where $Var(Seasonally\ adjusted\ COGS_i)$ is the variance of seasonally adjusted COGS series of firm i. Break $COGS_i$ into 4 sub-series: $COGS_{i,Q1}$, $COGS_{i,Q2}$, $COGS_{i,Q3}$, and $COGS_{i,Q4}$ each represents the cost of goods sold in Q1, Q2, Q3, and Q4, respectively, between Q1-2010 and Q4-2019. Now, the seasonally adjusted value of the cost of goods sold of firm i in time period t is given by:

$$Seasonally\ Adjusted\ COGS_{i,t} = \begin{cases} \dfrac{COGS_{i,t} * mean(COGS_i)}{mean(COGS_{i,Q1})}, if\ t \in COGS_{i,Q1} \\ \dfrac{COGS_{i,t} * mean(COGS_i)}{mean(COGS_{i,Q2})}, if\ t \in COGS_{i,Q2} \\ \dfrac{COGS_{i,t} * mean(COGS_i)}{mean\left(COGS_{i,Q3}\right)}, if\ t \in COGS_{i,Q3} \\ \dfrac{COGS_{i,t} * mean(COGS_i)}{mean(COGS_{i,Q4})}, if\ t \in COGS_{i,Q4} \end{cases} \tag{3.14}$$

The larger the seasonality ratio, the larger is the seasonality in demand and therefore, the larger the motivation to smooth production and WC.

Chen et al. (2000) showed that as a firm's procurement lead time increases, the BWE it experiences increases. The same was shown to be true for CFB in Chapter 2. As procurement lead time increases, the CFB experienced by a firm increases. Firm-level data for procurement lead time (L) is not publicly available. It should be noted that for any given firm, the procurement lead time varies based on component and supplier. Consequently, we use the mean Days Payable Outstanding (DPO) of a firm as a proxy for the lead time (LT) it experiences. Firm i's mean DPO is calculated as follows:

$$LT_i = DPO_i = \frac{365}{4 \times \dfrac{mean(COGS_i)}{mean(AP_i)}} \tag{3.15}$$

It should be noted that DPO represents not only procurement lead time but also the payment lead time. Payment lead time is the time a firm takes to pay for the material it bought from its suppliers. Therefore, we hypothesize that:

Hypothesis 5: CFB and its components are positively associated with procurement and payment lead times.

Tangsucheeva & Prabhu (2013) studied the cash-flow bullwhip effect in a serial supply chain with a single product, constant payment and procurement lead times, constant payment behavior, and demand D following an AR(1) process. The demand in period *t* is given by:

$$D_t = d + \rho D_{t-1} + \epsilon_t \tag{3.16}$$

where d is the demand level constant, ρ is the demand correlation such that $|\rho| \leq 1$, and ϵ_t is the error term for period *t*. ϵ_t is an independent and identically distributed random variable that follows a normal distribution with mean 0 and variance σ^2. Equation (3.14) of Tangsucheeva & Prabhu (2013) shows that $var(Inventory)$, $var(AR)$, and $var(AP)$ are increasing in ρ. Therefore, we hypothesis that:

Hypothesis 6: CFB and its components are positively associated with demand autocorrelation.

It should be noted that Equation (3.14) of Tangsucheeva & Prabhu (2013) is based on the assumption that there is no seasonality in demand. Therefore, to test Hypothesis 6 we use seasonally adjusted COGS to calculate demand autocorrelation.

Chen et al. (2000) showed that as one moves upstream in the serial supply chain, material flow variance increases. Parallelly, Tangsucheeva & Prabhu (2013) and Chapter 2 show that CCC and WC variance increases upstream in the serial supply chain. Real-world supply chains however, are not serial but rather are complex networks. In our sample of 782 firms, not all manufacturing firms supply finished goods exclusively to wholesalers. Manufacturers can sell their finished products to other manufacturers, wholesalers, or retailers directly. The same is true for wholesalers and retailers in our sample. This means the firms in the sample do not form a serial supply chain, the kind studied by Chen et al. (2000), Tangsucheeva & Prabhu (2013) and in Chapter 2 but rather are entities in complex supply networks. Therefore, instead of hypothesizing that retailers experience the least bullwhip effects and the manufacturers the highest, we hypothesize that:

Hypothesis 7: CFB and its components experienced by retailers, wholesalers, and manufacturers are different.

Table 3-1 presents descriptive statistics for all firms, retailers, wholesalers, and manufacturers in the sample. On average, retailers have the most conservative payment policy parameter (2.14) and wholesalers the most lenient (0.68). Manufacturers, on average, have the highest liquidity ratio (0.95), while wholesalers have the lowest (0.28). Seasonality ratio, on average, is highest for retailers (0.20) and lowest for manufacturers (0.10). Demand autocorrelation parameter is highest for wholesalers (0.64) and lowest for retailers (0.56).

Table 3-1. Descriptive statistics of variables of interest (Q1-2010 to Q4-2019)

All firms (N = 782)	Mean	Std. dev.	10th percentile	50th percentile	90th percentile
Company size (million dollars)	622.55	1108.37	4.57	145.27	2015.43
Payment policy parameter (α)	0.77	0.63	0.27	0.56	1.53
Liquidity ratio (LR)	0.89	0.94	0.06	0.57	2.23
Seasonality ratio (SR)	0.11	0.13	0.01	0.05	0.33
Lead time (LT)	54.10	27.58	23.56	47.77	93.30

Demand autocorrelation (ρ)	0.58	0.22	0.22	0.65	0.82
Retailing firms (N = 42)	Mean	Std. dev.	10th percentile	50th percentile	90th percentile
Company size (million dollars)	1527.87	1574.04	58.53	961.47	4215.71
Payment policy parameter (α)	2.14	0.97	0.40	2.82	2.82
Liquidity ratio (LR)	0.37	0.49	0.03	0.18	0.66
Seasonality ratio (SR)	0.20	0.18	0.02	0.12	0.49
Lead time (LT)	42.10	26.14	18.80	38.87	74.37
Demand autocorrelation (ρ)	0.56	0.22	0.27	0.55	0.82
Wholesaling firms (N = 33)	Mean	Std. dev.	10th percentile	50th percentile	90th percentile
Company size (million dollars)	971.54	1159.15	15.19	477.39	2488.83
Payment policy parameter (α)	0.68	0.25	0.36	0.67	1.01
Liquidity ratio (LR)	0.28	0.64	0.03	0.11	0.34
Seasonality ratio (SR)	0.13	0.15	0.01	0.08	0.39
Lead time (LT)	43.09	18.04	21.46	39.34	63.80
Demand autocorrelation (ρ)	0.64	0.19	0.39	0.66	0.85
Manufacturing firms (N = 707)	Mean	Std. dev.	10th percentile	50th percentile	90th percentile
Company size (million dollars)	552.48	1046.35	4.04	123.70	1713.81
Payment policy parameter (α)	0.69	0.52	0.27	0.54	1.24
Liquidity ratio (LR)	0.95	0.96	0.07	0.65	2.37
Seasonality ratio (SR)	0.10	0.13	0.01	0.05	0.31
Lead time (LT)	55.33	27.77	25.37	48.57	96.74
Demand autocorrelation (ρ)	0.58	0.22	0.22	0.65	0.81

3.5 Analysis

Our analysis is split into two sections. The first section aims to quantify the CFB, BWE, IBE, and PBE experienced by various industries. The second section explores the association between various firm-level variables and the bullwhip effects firms experience.

3.5.1 Quantifying the Bullwhip Effects Across Industries

To measure the bullwhip effects experienced by various industries, we first aggregate the firm-level Compustat data by 4-digit NAICS codes to generate industry-level data; then transform (first differencing and winsorizing) the data; and finally calculate CFB, BWE, IBE, and PBE experienced by each industry following the methodology discussed in Section 3.3. Table 3-2 reports the bullwhip experienced by each industry in the sample over 2010–2019. The bullwhip numbers reported in this table are calculated using seasonally unadjusted data series. To check if Var(COGS) is significantly different than Var(WC), Var(Purchases), Var(Inventory), and Var(Payment), we perform the adjusted Brown-Forsythe (ABF) test of homogeneity of variance. Table 3-2 presents p-values for the same. The null hypothesis of the ABF test is that the variances of data series are the same. For $p < 0.1$, we reject the null hypothesis and consider the difference in the data series' variances to be statistically significant.

CFB greater than one is indicative of an industry amplifying WC variance, and BWE greater than one is indicative of an industry amplifying order quantity (purchases) variance. In Table 3-2 we see that in the retailing sector, 15.4%, 38.5%, 0%, and 30.8% of industries experience CFB, BWE, IBE, and PBE values greater than 1. These percentages only represent the industries for which the ABF p-value < 0.1. In the wholesaling sector, 0%, 12.5%, 0%, and 0% industries experience CFB, BWE, IBE, and PBE greater than 1.

Finally, in the manufacturing sector, 48.1%, 27.8%, 2.5%, and 39.2% of industries experience CFB, BWE, IBE, and PBE greater than 1.

Values of bullwhip effects experienced by each industry using seasonally adjusted data are reported in Table C1 in Appendix C. To seasonally adjust the data series, we use the same method used to seasonally adjust the COGS series shown in Equation (3.14). Rejecting the ABF test's null hypothesis for $p < 0.1$, we get the following results from Table C1 from Appendix C. In retailing sector, 38.5%, 46.2%, 15.4%, and 30.8% industries experience CFB, BWE, IBE, and PBE values greater than 1. In wholesaling sector, 0%, 50.0%, 0%, and 0% industries experience CFB, BWE, IBE, and PBE greater than 1. In manufacturing sector, 58.2%, 40.5%, 6.3%, and 45.6% industries experience CFB, BWE, IBE, and PBE greater than 1. The use of seasonally adjusted data inflates the bullwhip effects across all industries of retailing, wholesaling, and manufacturing sectors. This inflation could be attributed to the fact that industries account for seasonality in demand when determining ways to smooth purchases and WC levels.

Table 3-2 Magnitude of CFB, BWE, IBE, and PBE experienced by major industries.

	CFB	p-value*	BWE	p-value*	IBE	p-value*	PBE	p-value*
Retailers								
Automobile Dealers	0.89	0.790	1.44	0.478	0.69	0.552	0.03	0.076
Automotive Parts, Accessories, & Tire Stores	0.58	0.309	2.69	0.097	0.69	0.058	1.12	0.935
Furniture Stores	1.97	0.115	3.42	0.008	0.75	0.191	4.42	0.001
Electronics & Appliance Stores	2.93	0.022	3.16	0.005	1.33	0.609	2.65	0.061
Grocery Stores	0.03	0.000	1.26	0.616	0.01	0.000	0.03	0.000
Health & Personal Care Stores	0.28	0.887	1.48	0.608	0.13	0.348	0.34	0.970
Gasoline Stations	0.06	0.015	1.10	0.832	0.02	0.000	0.06	0.017

	CFB	p-value*	BWE	p-value*	IBE	p-value*	PBE	p-value*
Clothing Stores	0.45	0.071	1.75	0.745	0.50	0.216	0.25	0.217
Shoe Stores	0.72	0.165	2.31	0.051	2.03	0.148	1.21	0.740
Jewelry, Luggage, & Leather Goods Stores	6.46	0.000	0.56	0.157	1.13	0.744	10.41	0.000
Sporting Goods, Hobby, & Musical Instrument Stores	0.23	0.000	0.91	0.462	0.86	0.313	0.57	0.023
Department Stores	0.19	0.000	1.45	0.050	1.11	0.167	1.81	0.018
General Merchandise Stores Warehouse Clubs	0.14	0.000	0.54	0.037	0.33	0.002	0.20	0.000
Wholesalers								
Motor Vehicle & Motor Vehicle Parts Wholesalers	0.73	0.645	1.33	0.340	1.43	0.888	0.40	0.731
Lumber & Other Construction Materials Wholesalers	0.59	0.015	2.21	0.152	0.42	0.001	0.26	0.000
Professional & Commercial Equipment Wholesalers	0.18	0.013	1.44	0.445	0.12	0.007	0.02	0.002
Metal & Mineral (except Petroleum) Wholesalers	1.29	0.158	4.57	0.000	0.62	0.243	0.21	0.000
Household Appliances & Electronic Goods Wholesalers	0.52	0.002	2.19	0.228	0.19	0.000	0.15	0.000
Hardware, Plumbing & Heating Equipment Wholesalers	0.21	0.002	1.17	0.217	0.12	0.000	0.15	0.001
Machinery, Equipment, & Supplies Wholesalers	4.04	0.271	1.77	0.309	1.39	0.859	0.88	0.574
Miscellaneous Durable Goods Merchant Wholesalers	0.27	0.048	1.00	0.949	0.09	0.003	0.10	0.007
Manufacturing								
Grain & Oilseed Milling	0.32	0.127	1.20	0.528	0.25	0.017	0.11	0.002
Sugar & Confectionery Product Manufacturing	1.62	0.522	0.62	0.233	0.49	0.140	0.97	0.407
Fruit & Vegetable Preserving & Food Manufacturing	1.46	0.297	2.36	0.005	0.81	0.590	0.80	0.212
Dairy Product Manufacturing	0.85	0.911	2.56	0.177	0.53	0.538	0.12	0.221
Bakeries & Tortilla Manufacturing	2.44	0.205	2.45	0.506	0.62	0.378	0.82	0.753
Other Food Manufacturing	0.97	0.646	2.31	0.110	1.25	0.376	0.28	0.604
Beverage Manufacturing	25.47	0.000	1.34	0.307	0.30	0.057	24.87	0.000
Tobacco Manufacturing	18.41	0.000	15.26	0.000	3.84	0.000	15.38	0.000
Fiber, Yarn, & Thread Mills	0.97	0.869	2.11	0.031	0.38	0.009	1.11	0.907
Fabric Mills	2.79	0.151	2.89	0.003	0.95	0.876	4.02	0.001
Textile Furnishings Mills	5.68	0.040	5.74	0.039	1.05	0.852	1.56	0.496
Apparel Knitting Mills	2.24	0.101	1.58	0.726	0.88	0.264	0.63	0.024

	CFB	p-value*	BWE	p-value*	IBE	p-value*	PBE	p-value*
Cut & Sew Apparel Manufacturing	4.47	0.002	1.37	0.040	1.43	0.792	2.96	0.000
Apparel Accessories & Other Apparel Manufacturing	3.60	0.001	3.75	0.000	1.58	0.196	6.94	0.000
Footwear Manufacturing	4.88	0.258	4.37	0.395	0.73	0.349	2.18	0.379
Other Leather & Allied Product Manufacturing	12.85	0.020	1.08	0.907	2.42	0.558	8.17	0.002
Sawmills & Wood Preservation	6.54	0.001	2.49	0.091	0.22	0.001	5.74	0.001
Veneer, Plywood, & Wood Product Manufacturing	9.41	0.000	0.57	0.015	0.26	0.000	9.04	0.001
Other Wood Product Manufacturing	0.69	0.401	5.72	0.346	0.23	0.022	0.21	0.069
Pulp, Paper, & Paperboard Mills	1.00	0.371	2.23	0.236	0.11	0.112	0.64	0.401
Converted Paper Product Manufacturing	4.56	0.033	2.20	0.123	0.84	0.819	1.58	0.132
Printing & Related Support Activities	1.04	0.583	0.83	0.268	0.13	0.000	0.69	0.229
Petroleum & Coal Products Manufacturing	0.55	0.418	1.17	0.730	0.09	0.043	0.45	0.371
Basic Chemical Manufacturing	1.23	0.355	1.80	0.051	0.28	0.001	0.73	0.583
Resin, Rubber, & Synthetic Fibers Manufacturing	13.96	0.001	4.07	0.001	3.54	0.788	6.01	0.000
Pesticide, Fertilizer, & Chemical Manufacturing	9.49	0.001	4.89	0.019	1.72	0.521	4.26	0.002
Pharmaceutical & Medicine Manufacturing	40.73	0.002	1.84	0.256	3.66	0.391	21.36	0.000
Paint, Coating, & Adhesive Manufacturing	1.16	0.774	1.16	0.949	0.71	0.134	0.30	0.221
Soap, & Cleaning Compound Manufacturing	2.65	0.000	1.17	0.708	0.57	0.829	1.35	0.001
Other Chemical Product & Preparation Manufacturing	3.38	0.237	1.05	0.899	0.28	0.000	2.05	0.663
Plastics Product Manufacturing	3.42	0.001	1.14	0.510	0.50	0.557	2.59	0.002
Rubber Product Manufacturing	2.18	0.043	0.89	0.899	1.02	0.924	0.67	0.097
Clay Product & Refractory Manufacturing	1.52	0.323	1.32	0.620	0.50	0.010	2.10	0.105
Glass & Glass Product Manufacturing	1.92	0.074	1.69	0.741	0.63	0.439	0.60	0.652
Cement & Concrete Product Manufacturing	0.69	0.887	1.43	0.677	0.02	0.013	0.52	0.981
Lime & Gypsum Product Manufacturing	0.94	0.387	1.16	0.297	0.22	0.001	1.36	0.820
Other Nonmetallic Mineral Product Manufacturing	4.45	0.000	2.82	0.089	0.56	0.160	4.70	0.000
Iron & Steel Mills & Ferroalloy Manufacturing	1.55	0.128	2.01	0.161	0.72	0.287	0.68	0.245
Steel Product Manufacturing from Purchased Steel	18.50	0.084	1.19	0.456	4.60	0.570	6.25	0.012
Alumina & Aluminum Production & Processing	2.27	0.014	2.20	0.205	0.73	0.125	2.64	0.018

	CFB	p-value*	BWE	p-value*	IBE	p-value*	PBE	p-value*
Nonferrous Metal (except Al) Production & Processing	3.32	0.061	4.63	0.082	1.32	0.178	3.28	0.021
Forging & Stamping	1.66	0.099	4.46	0.024	0.71	0.233	1.56	0.128
Cutlery & Handtool Manufacturing	5.80	0.005	1.05	0.956	0.79	0.124	4.36	0.001
Architectural & Structural Metals Manufacturing	3.71	0.369	1.94	0.614	0.44	0.007	1.81	0.865
Boiler, Tank, & Shipping Container Manufacturing	2.43	0.039	0.65	0.027	0.33	0.001	2.00	0.161
Hardware Manufacturing	4.56	0.000	3.22	0.087	0.80	0.402	5.72	0.000
Spring & Wire Product Manufacturing	11.43	0.075	1.51	0.016	1.72	0.470	5.32	0.024
Machine Shops; & Screw, Nut, & Bolt Manufacturing	3.54	0.001	3.00	0.022	0.59	0.196	2.47	0.013
Other Fabricated Metal Product Manufacturing	2.96	0.048	2.00	0.133	0.90	0.231	0.84	0.250
Agriculture & Construction Machinery Manufacturing	2.64	0.322	1.78	0.425	1.00	0.092	0.95	0.113
Industrial Machinery Manufacturing	23.03	0.017	1.93	0.390	1.97	0.904	12.15	0.013
Commercial Industry Machinery Manufacturing	5.91	0.000	2.52	0.441	0.06	0.020	5.90	0.000
HVAC & Refrigeration Equipment Manufacturing	0.64	0.747	2.45	0.446	0.15	0.090	0.26	0.441
Metalworking Machinery Manufacturing	14.55	0.000	3.39	0.028	1.87	0.088	11.10	0.003
Engine & Transmission Equipment Manufacturing	0.38	0.004	0.72	0.023	0.29	0.001	0.46	0.016
Other General Purpose Machinery Manufacturing	5.47	0.013	2.22	0.243	1.14	0.616	2.19	0.377
Computer & Peripheral Equipment Manufacturing	1.05	0.613	0.93	0.617	0.37	0.011	0.58	0.389
Communications Equipment Manufacturing	1.12	0.696	1.59	0.425	0.05	0.000	0.89	0.815
Audio & Video Equipment Manufacturing	0.96	0.767	2.50	0.046	0.46	0.024	1.55	0.425
Semiconductor & Electronic Component Manufacturing	15.02	0.068	2.92	0.170	1.00	0.568	8.39	0.078
Navigational & Electromedical Manufacturing	17.41	0.000	1.40	0.526	1.35	0.643	8.00	0.000
Manufacturing Magnetic & Optical Media	2.48	0.839	1.02	0.980	0.26	0.001	3.38	0.293
Electrical Equipment & Appliance Manufacturing	0.33	0.002	1.46	0.347	0.08	0.000	0.29	0.001
Electric Lighting Equipment Manufacturing	6.63	0.002	4.94	0.112	0.30	0.001	6.49	0.002
Household Appliance Manufacturing	0.38	0.014	0.85	0.464	0.25	0.004	0.17	0.003
Electrical Equipment Manufacturing	5.32	0.179	1.86	0.566	0.40	0.066	2.92	0.394
Other Electrical Equipment & Component Manufacturing	4.07	0.050	1.34	0.502	0.84	0.661	1.44	0.070
Motor Vehicle Manufacturing	5.71	0.657	1.25	0.558	0.52	0.108	2.70	0.981

	CFB	p-value*	BWE	p-value*	IBE	p-value*	PBE	p-value*
Motor Vehicle Body & Trailer Manufacturing	0.31	0.002	3.65	0.357	0.17	0.000	0.21	0.002
Motor Vehicle Parts Manufacturing	0.90	0.605	1.50	0.381	0.19	0.000	0.34	0.097
Aerospace Product & Parts Manufacturing	2.26	0.555	2.87	0.112	0.49	0.001	1.00	0.620
Railroad Rolling Stock Manufacturing	4.84	0.222	9.38	0.263	4.97	0.896	1.67	0.438
Ship & Boat Building	1.51	0.372	3.32	0.020	0.38	0.006	1.39	0.459
Other Transportation Equipment Manufacturing	7.79	0.197	0.76	0.101	0.24	0.000	7.11	0.118
Household & Institutional Furniture Manufacturing	1.75	0.390	3.00	0.029	1.33	0.512	0.44	0.886
Office Furniture (including Fixtures) Manufacturing	1.53	0.048	2.83	0.320	0.13	0.004	1.35	0.014
Other Furniture Related Product Manufacturing	0.82	0.933	2.83	0.319	0.09	0.000	0.57	0.249
Medical Equipment & Supplies Manufacturing	25.07	0.000	3.69	0.037	4.40	0.245	21.70	0.000
Other Miscellaneous Manufacturing	3.10	0.057	0.72	0.979	0.33	0.006	2.45	0.064
Farming								
Fruit & Tree Nut Farming	0.86	0.528	1.75	0.689	0.27	0.029	0.51	0.870
Other Crop Farming	0.91	0.562	6.02	0.001	3.06	0.163	3.06	0.013

*p-value of Brown-Forsythe test for equivalence of variance.

3.5.2 Firm-level Variables and the Bullwhip Effects

Next, we move our attention to identifying the drivers of bullwhip effects in supply chains. To do this, we test the hypotheses presented in Section 3.4 using regression analysis. Instead of using data aggregated over industries, we use firm-level data. This allows us to study the association between bullwhip effects and firm-level variables. Hypotheses 1–7 are tested by regressing CFB, BWE, IBE, and PBE on company size, payment policy parameter, liquidity ratio, seasonality ratio, lead time, demand autocorrelation parameter, and firm type (retailer, wholesaler, or manufacturer). We use multiplicative regression models instead of additive regression models because the former have higher adjusted R-squared values, and therefore, have larger explanatory power. The regression models we fit are:

$$\log(CFB_i) = a + b_1 \log\big(mean(COGS_i)\big) + b_2 \log(\alpha_i) + \mathrm{b}_3\log(LR_i) + \mathrm{b}_4\log(SR_i) + \mathrm{b}_5\log(LT_i) + \mathrm{b}_6\log(\rho_i) + c_1 Retailer_i + c_2 Wholesaler_i + \epsilon_i \tag{3.17}$$

$$\log(BWE_i) = a + b_1 \log(COGS_i) + b_2 \log(\alpha_i) + \mathrm{b}_3\log(LR_i) + \mathrm{b}_4\log(SR_i) + \mathrm{b}_5\log(LT_i) + \mathrm{b}_6\log(\rho_i) + c_1 Retailer_i + c_2 Wholesaler_i + \epsilon_i \tag{3.18}$$

$$\log(IBE_i) = a + b_1 \log(COGS_i) + b_2 \log(\alpha_i) + \mathrm{b}_3\log(LR_i) + \mathrm{b}_4\log(SR_i) + \mathrm{b}_5\log(LT_i) + \mathrm{b}_6\log(\rho_i) + c_1 Retailer_i + c_2 Wholesaler_i + \epsilon_i \tag{3.19}$$

$$\log(PBE_i) = a + b_1 \log(COGS_i) + b_2 \log(\alpha_i) + \mathrm{b}_3\log(LR_i) + \mathrm{b}_4\log(SR_i) + \mathrm{b}_5\log(LT_i) + \mathrm{b}_6\log(\rho_i) + c_1 Retailer_i + c_2 Wholesaler_i + \epsilon_i \tag{3.20}$$

where CFB_i, BWE_i, IBE_i, and PBE_i are the CFB, BWE, IBE, and PBE effects experienced by firm i over the time period Q1-2010 to Q4-2019. α_i, LR_i, SR_i, and LT_i are calculated using Equations (3.11–3.15). ρ_i is the autocorrelation parameter of the deseasonalized COGS series. b_j for j ∈ {1,2, … ,6} are the regression coefficients of continuous predictor variables and c_k for $k \in \{1,2\}$ are the coefficients of firm type dummy variables. The dummy variables $Retailer_i$ and $Wholesaler_i$ represent whether a firm is a retailer, wholesaler, or manufacturer. ϵ_i additively includes firm-specific effects and random noise in the model. We call these models multiplicative because the independent variables in them are in a multiplicative form before log transformation.

Regression models presented in Equations (3.17–3.20) are not only fit over the entire sample but also individually over retail, wholesale, and manufacturing sectors. Fitting regression models over individual sectors allows us to see how the independent variables are related to bullwhip effects within specific segments of supply chains and whether the hypotheses hold therein. The coefficients of these regression models are given in Table 3-3 . F-statistic for all but two models are significant. For models with a significant F-statistic, the adjusted R-square (%) values are in the range [19, 67]. Models where log(COGS) is significant support Hypothesis 1 that large firms experience lower CFB and its components. We find that a 1% increase in COGS is, on average, associated with a 0.14% decrease in CFB. This effect is the strongest for retailers, where a 1% increase in COGS is associated with a 0.32% decrease in CFB. Whereas for manufacturers, the effect is the weakest. A 1% increase in COGS of manufacturers is associated with only a 0.14% decrease in CFB.

Models where log(α) is significant support Hypothesis 2 that firms with larger α (more conservative payment policy) experience lower CFB. In Table 3-3, we find that a 1% increase in payment policy parameter (α) is, on average, associated with 1%, 0.23%, 0.61%, and 0.81% decrease in CFB, BWE, IBE, and PBE, respectively.

Models where log(BWE) and log(IBE) are the dependent variables and where log(LR) is significant support a part of Hypothesis 3 that BWE and IBE are positively associated with liquidity ratio. When it comes to models where log(CFB) and log(PBE) are the dependent variables, Hypothesis 3 is rejected. We find that a 1% increase in liquidity ratio is, on average, associated with 0.46% increase in CFB and PBE and with 0.21% decrease in IBE.

The regression coefficient of seasonality ratio (SR) is negative in all models. Therefore, all models support Hypothesis 4 that as seasonality ratio increases, CFB and its components decrease. We find that a 1% increase in seasonality ratio is, on average, associated with a 0.24%, 0.26%, 0.15%, and 0.18% decrease in CFB, BWE, IBE, and PBE, respectively. For retailers and wholesalers, a 1% increase in seasonality ratio is, on average, associated with a 0.7% and 0.73% decrease in CFB, respectively. For manufacturers, a 1% rise in seasonality ratio is associated only with a 0.21% decrease in CFB. When it comes to BWE, a 1% rise in retailer's and wholesaler's seasonality ratio is, on average, associated with a 0.63% and 53% decrease in BWE, respectively. In comparison, a 1% rise in a manufacturer's seasonality ratio is, on average, associated with only a 0.23% decrease in its BWE. Compared to manufacturers, retailers and wholesalers are in a better position to smooth WC and purchases when demand seasonality is high.

All models where regression coefficients of lead time (LT) and demand autocorrelation parameter (ρ) are significant support Hypotheses 5 and 6, that CFB and its components are positively associated with lead time and demand autocorrelation parameter. In Table 3-3 , we see that compared to all other independent variables, lead time (LT) has the largest effect on CFB. 1% increase in lead time is, on average, associated with a 1.33% increase in CFB. This suggests that a firm that intends to decrease its CFB should start with reducing its lead time. Here, lead time is the sum of procurement and payment lead time. Reduction in payment lead time, ceteris paribus, will decrease α (increased leniency in payment policy). We saw earlier in the section that the smaller the α, the larger is the CFB. Therefore, to reduce CFB, a firm should first decrease its procurement lead time. To further reduce CFB, it should explore the possibility of lowering payment lead time. Decreasing payment lead time would be beneficial only when the subsequent decrease in CFB more than compensates for the rise in CFB that the decrease in α would cause.

The coefficients of the dummy variables Retailer and Wholesaler are not significant for all models. The only model where both are significant is where the dependent variable is log(CFB). This indicates that the CFB experienced by retailers, wholesalers, and manufacturers are significantly different. However, the same cannot be said about BWE, IBE, and PBE.

Table 3-3 Regression coefficients from multiplicative models of CFB, BWE, IBE, and PBE

	log(CFB)				log(BWE)			
	All firms	Retailers	Wholesalers	Manufacturers	All firms	Retailers	Wholesalers	Manufacturers
Intercept	-3.69***	-3.53	-2.99	-3.54***	-0.36	0.38	-2.19	-0.25
Retailer	0.54*				0.55***			
Wholesaler	-0.6*				0.26			
log(COGS)	-0.14***	-0.32*	-0.2	-0.14***	-0.02	-0.17**	0.05	-0.02
log(α)	-1***	-0.58	-0.52	-0.96***	-0.23***	0.25	-0.14	-0.24***
log(LR)	0.46***	0.1	0.07	0.5***	-0.03	-0.36***	-0.04	-0.02
log(SR)	-0.24***	-0.7**	-0.73*	-0.21***	-0.26***	-0.63***	-0.56***	-0.23***
log(LT)	1.33***	1.3**	0.41	1.32***	0.15*	-0.22	0.29	0.15*
log(ρ)	0.27**	0.67	-0.65	0.25*	0.31***	-0.28	-0.39	0.34***
Adj R-squared (%)	44	39	12	41	27	67	67	25
F-statistic	78.37***	5.34***	1.72	82.28***	36.81***	14.59***	11.7***	40.33***
N	782	42	33	707	782	42	33	707
	log(IBE)				log(PBE)			
	All firms	Retailers	Wholesalers	Manufacturers	All firms	Retailers	Wholesalers	Manufacturers
Intercept	-3.53***	-5.06*	-3.88	-3.49***	-3.05***	-4.47**	-4.22	-2.85***
Retailer	0.37				0.09			
Wholesaler	-0.64**				0.1			
log(COGS)	-0.12***	-0.27	-0.15	-0.11***	-0.12***	-0.34*	0.02	-0.12***

$\log(\alpha)$	-0.61***	0.33	0.07	-0.68***	-0.81***	-0.23	-0.67	-0.82***
log(LR)	-0.21***	-0.69**	-0.47	-0.19***	0.46***	0.29	0.39	0.46***
log(SR)	-0.15***	-0.08	-0.56	-0.15***	-0.18***	-0.78***	-0.39	-0.15***
log(LT)	0.71***	1.13*	0.12	0.69***	1.3***	1.51***	1.18	1.28***
$\log(\rho)$	0.24**	0.02	-1.07	0.27***	0.24**	-0.12	-0.26	0.26**
Adj R-squared (%)	19	23	5	20	48	46	27	44
F-statistic	23.23***	3.03**	1.253	28.94***	91.36***	6.80***	2.96*	91.85***
N	782	42	33	707	782	42	33	707

***, **, and * denote statistical significance at p-value < 0.001, < 0.01 and < 0.05, respectively.

3.5.3 Bullwhip Effects in the Automotive Supply Chain

In Sections 3.5.1 and 3.5.2, we quantified the bullwhip effects experienced by various industries in the U.S. economy and identified the firm-level variables that drive the bullwhip effects that the firms experience. However, supply chain practitioners are interested in how the bullwhip effects propagate in their supply chain more than how they propagate across individual firms in disparate industries. To study a specific supply chain, we would need financial information from all entities in the supply chain. Such data is not easy to access because not all supply chain entities are public companies and are not obligated to make their financial data public. At best, publicly available financial data can be used to study the propagation of bullwhip effects in specific industries.

In this section, we study bullwhip effects in automotive supply chain (ASC). The way NAICS codes catalogs various ASC entities makes it easy to identify the retailers, original equipment manufacturers (OEMs), and parts/components suppliers involved in the ASC. Therefore, we choose to focus on it instead of any other supply chains like food, home appliances, etc., where the NAICS codes alone would not allow us to identify the types of firms involved in those supply chains.

Table 3-4 lists the firm names and their respective NAICS codes that we use to form the sample of firms in the ASCs. Based on each firm's NACIS code description, we classify them as one of the following supply chain stages: automobile dealer, OEM, or tier 1 supplier. Figure 3-3 illustrates the structure of the ASC. We use financial data from the companies listed in

Table 3-4 to model the supply chain shown in Figure 3-3.

Table 3-4 Automotive firms used to model the automotive supply chain

Firm name	NAICS code	NAICS description	Supply Chain Stage
Asbury Automotive Group Inc	441110	Automobile Dealers	Automobile Dealers
Autonation Inc	441110	Automobile Dealers	Automobile Dealers
Lithia Motors Inc	441110	Automobile Dealers	Automobile Dealers
Penske Automotive Group Inc	441110	Automobile Dealers	Automobile Dealers
Sonic Automotive Inc	441110	Automobile Dealers	Automobile Dealers
Daimler Ag	336111	Automobile Manufacturing	OEMs
Honda Motor Co Ltd	336111	Automobile Manufacturing	OEMs
Nissan Motor Co Ltd	336111	Automobile Manufacturing	OEMs
Tesla Inc	336111	Automobile Manufacturing	OEMs
Volkswagen Ag	336111	Automobile Manufacturing	OEMs
Astronics Corp	336320	Motor Vehicle Electronic Equipment Manufacturing	Tier 1 Suppliers
Kandi Technologies Group	336320	Motor Vehicle Electronic Equipment Manufacturing	Tier 1 Suppliers

Standard Motor Prods	336320	Motor Vehicle Electronic Equipment Manufacturing	Tier 1 Suppliers
Visteon Corp	336320	Motor Vehicle Electronic Equipment Manufacturing	Tier 1 Suppliers
China Automotive Systems Inc	336330	Motor Vehicle Steering and Suspension Components (except Spring) Manufacturing	Tier 1 Suppliers
American Axle & Mfg Holdings	336350	Motor Vehicle Transmission and Power Train Parts Manufacturing	Tier 1 Suppliers
Sypris Solutions Inc	336350	Motor Vehicle Transmission and Power Train Parts Manufacturing	Tier 1 Suppliers
Lear Corp	336360	Motor Vehicle Seating and Interior Trim Manufacturing	Tier 1 Suppliers
Shiloh Industries Inc	336370	Motor Vehicle Metal Stamping	Tier 1 Suppliers
Autoliv Inc	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers
Commercial Vehicle Group Inc	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers
Donaldson Co Inc	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers
Dorman Products Inc	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers
Gentex Corp	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers
Gentherm Inc	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers
Magna International Inc	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers
Modine Manufacturing Co	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers
Patrick Industries Inc	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers
Superior Industries Intl	336390	Other Motor Vehicle Parts Manufacturing	Tier 1 Suppliers

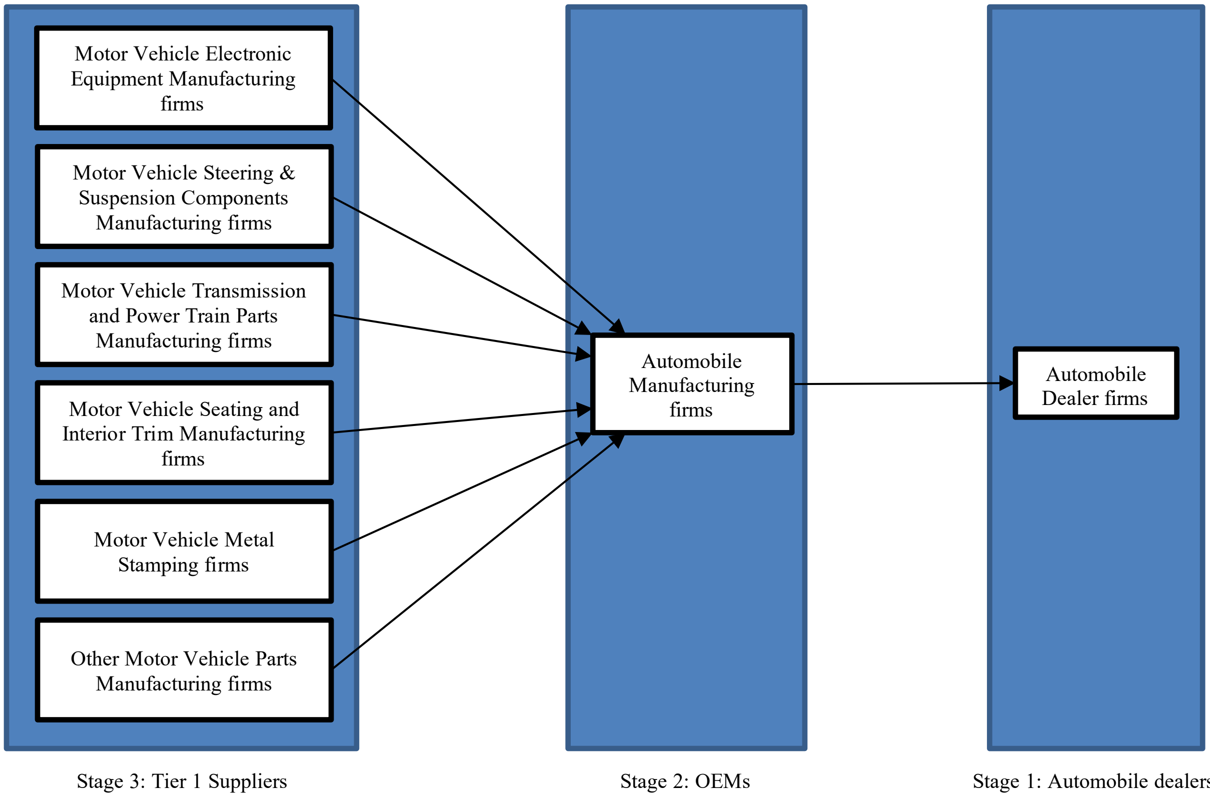

Figure 3-3 Structure of automotive supply chain

To study the bullwhip effects in ASC, we use the method discussed in Section 3.4. The only difference being that instead of using the complete sample of 782 firms, we use financial data from the 29 ASC firms listed in

Table 3-4 . First, we measure each firm's bullwhip effects and then check if the hypotheses presented in Section 3.4 hold true for the ASC. Note that in this section, we change Hypothesis 7 to:

Hypothesis 7: CFB and its components experienced by automobile dealers, OEMs, and Tier-1 suppliers are different.

Table 3-5 reports the descriptive statistics of interest from the sample of ASC firms between Q1-2010 and Q4-2019. Among the three supply chain stages, on average, OEMs experience the least CFB (1.73), BWE (1.91), and IBE (0.12). On average, automobile dealers experience the least PBE (0.53), and largest BWE (7.71), and IBE (0.56). Tier 1 suppliers, on average, experience the largest CFB (7.72) and PBE (9.34). All three stages' payment policy, on average, is smaller than one meaning all have a lenient payment policy. Automobile dealers' liquidity ratio is only 0.01, i.e., they carry ~100 times more inventory than they do cash. On the other hand, OEMs' and tier 1 suppliers' liquidity ratios are 0.90 and 0.69, respectively. Automobile dealers experience the shortest procurement + payment lead time (~8 days). OEMs and tier 1 suppliers experience procurement + payment lead times of ~60 days.

In Table 3-5, it is observed that OEMs, on average, do not experience the largest CFB, BWE, IBE, and PBE in the ASC. To bring forth this phenomenon, we construct box and whisker charts of the bullwhip effects experienced by the stages of ASC in Figure 3-4. OEMs have the smallest spread in CFB, BWE, and IBE among all stages. OEMs also have the smallest mean and median values of CFB, BWE, and IBE. This possibly means that OEMs can leverage: (i) their supply chain clout to push material and cash-flow variations onto tier 1 suppliers and automobile dealers and (ii) their size allows them to leverage economies of scale in order to reduce the bullwhip effects they experience.

Table 3-5 Descriptive statistics of variables of interest of automotive supply chain

Automobile Dealers (N = 5)	Mean	Std. dev.	10th percentile	50th percentile	90th percentile
CFB	1.73	2.01	0.59	0.69	3.75
BWE	7.71	3.43	4.44	6.83	11.34
IBE	0.56	0.22	0.36	0.55	0.79
PBE	0.53	0.55	0.18	0.35	1.07
Company size (million dollars)	2429.05	1265.79	1302.08	1924.80	3805.89

Payment policy parameter (α)	0.50	0.23	0.31	0.40	0.75
Liquidity ratio (LR)	0.01	0.01	0.00	0.01	0.02
Seasonality ratio (SR)	0.05	0.04	0.01	0.04	0.09
Lead time (LT)	8.01	3.86	4.99	5.92	12.36
Demand autocorrelation (ρ)	0.71	0.10	0.61	0.70	0.80
OEMs (N = 5)	Mean	Std. dev.	10th percentile	50th percentile	90th percentile
CFB	0.87	0.88	0.14	0.50	1.85
BWE	1.91	1.17	1.03	1.72	3.04
IBE	0.12	0.07	0.05	0.12	0.19
PBE	1.24	0.92	0.54	0.85	2.24
Company size (million dollars)	21021.80	12413.77	8617.27	20908.97	31660.16
Payment policy parameter (α)	0.51	0.39	0.29	0.35	0.89
Liquidity ratio (LR)	0.90	0.40	0.58	0.66	1.36
Seasonality ratio (SR)	0.13	0.13	0.06	0.08	0.25
Lead time (LT)	64.11	34.33	41.71	48.17	100.08
Demand autocorrelation (ρ)	0.32	0.19	0.19	0.26	0.52
Tier 1 Suppliers (N = 19)	Mean	Std. dev.	10th percentile	50th percentile	90th percentile
CFB	7.72	20.20	0.41	2.11	10.12
BWE	4.34	3.89	1.21	2.45	10.41
IBE	0.55	0.84	0.08	0.17	1.82
PBE	9.34	17.10	2.13	4.90	14.32
Company size (million dollars)	891.69	1788.02	75.86	199.02	2079.94

Payment policy parameter (α)	0.70	0.26	0.38	0.76	0.96
Liquidity ratio (LR)	0.69	0.66	0.03	0.46	1.58
Seasonality ratio (SR)	0.05	0.10	0.00	0.01	0.12
Lead time (LT)	58.08	33.27	25.31	51.05	94.47
Demand autocorrelation (ρ)	0.71	0.16	0.54	0.78	0.85

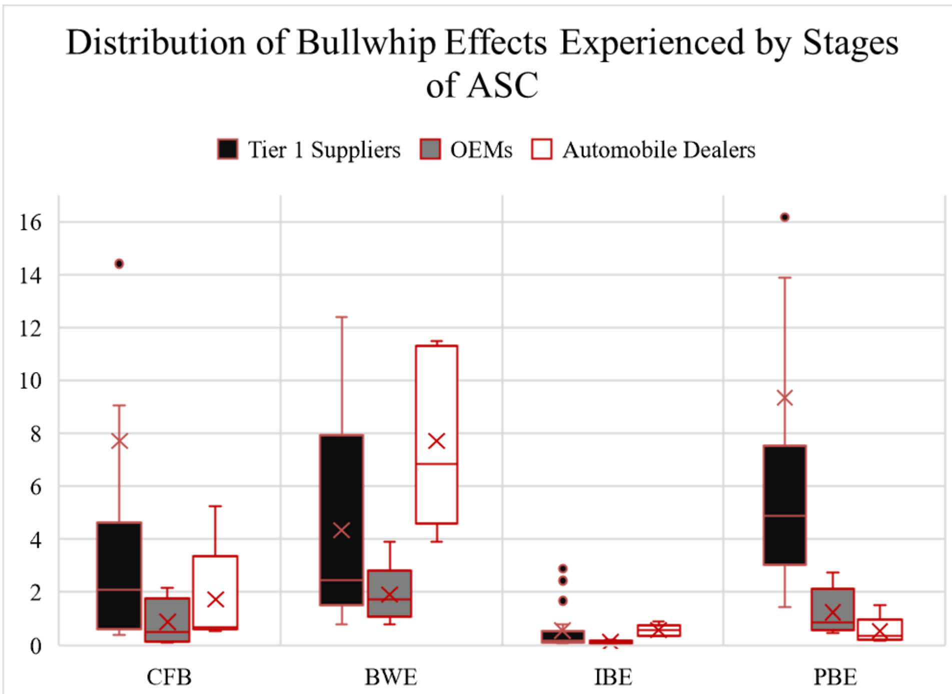

Figure 3-4 Distributions of the bullwhip effects experienced by the stages of automotive supply chain

To test Hypotheses 1–7 for ASC, we regress CFB, BWE, IBE, and PBE on company size, payment policy parameter, liquidity ratio, seasonality ratio, lead time, demand autocorrelation parameter, and supply chain stage (automobile dealer, OEM, or tier 1 supplier). We use the multiplicative regression models presented in Equations (3.17–3.20). The only difference here is that the dummy variables, $Retailer_i$ and $Wholesaler_i$ are replaced with OEM_i and $Tier\ 1\ Supplier_i$. Table 3-6 reports the regression coefficients for multiplicative models fit over ASC data. It should be noted that these models are fit using only 29 observations (5 automobile dealers, 5 OEMs, and 19 tier 1 suppliers) and, therefore, may not be reliable. Based on the regression coefficients in Table 3-6, we say that for ASC, CFB, on average, is: (i) negatively associated with payment behavior and seasonality ratio and (ii) positively associated with lead time. We also find that, on average, the difference in CFB experienced by automobile dealers, OEMs, and tier 1 suppliers is significant. For entities in ASC, BWE is negatively associated with seasonality ratio. IBE experienced by ASC entities is: (i) negatively associated with company size and seasonality ratio and (ii) positively associated with payment policy parameter (α) and lead time. On average, the difference in IBE experienced by automobile dealers, OEMs, and tier 1 suppliers is statistically significant. Finally, we observe that PBE in ASC is negatively associated with seasonality ratio.

Table 3-6 Regression coefficients of multiplicative models of automotive supply chain bullwhips

	log(CFB)	log(BWE)	log(IBE)	log(PBE)
Intercept	-3.85	-0.5	-4.61	-2.48
OEM	-4.21*	-0.89	-2.82*	-0.78
Tier 1 Supplier	-3.69**	-1.19	-2.81**	0.05
log(COGS)	-0.2	0.02	-0.26*	-0.15
log(α)	-2.2*	-0.93	2.46***	-0.88
log(LR)	0.22	-0.04	-0.11	0.15
log(SR)	-0.43*	-0.31**	-0.33**	-0.27*
log(LT)	1.82*	0.32	1.29*	0.94
log(ρ)	0.82	0.84	0.47	0.38
Adj R-squared (%)	46.6%	55.7%	62.4%	72%
F-statistic	4.056**	5.40**	6.82***	10.02***
N	29	29	29	29

***, **, and * denote statistical significance at p-value < 0.001, < 0.01 and < 0.05, respectively.

3.5.4 Bullwhip Effects in the Semiconductor Supply Chain

In this section, we study bullwhip effects in the semiconductor supply chain (SSC). From the Compustat database we build a sample of 238 companies involved in the semiconductor industry. The complete list of these companies is reported in Appendix C. Based on their NAICS code, these 238 companies can be put in the following categories: (i) Semiconductor Machinery Manufacturing (SMM), (ii) Semiconductor and Related Devices Manufacturing (SRDM), and (iii) Computer and Communications Manufacturing (CCM). We assume these 3 categories form a serial supply chain of the kind illustrated in Figure 3-5.

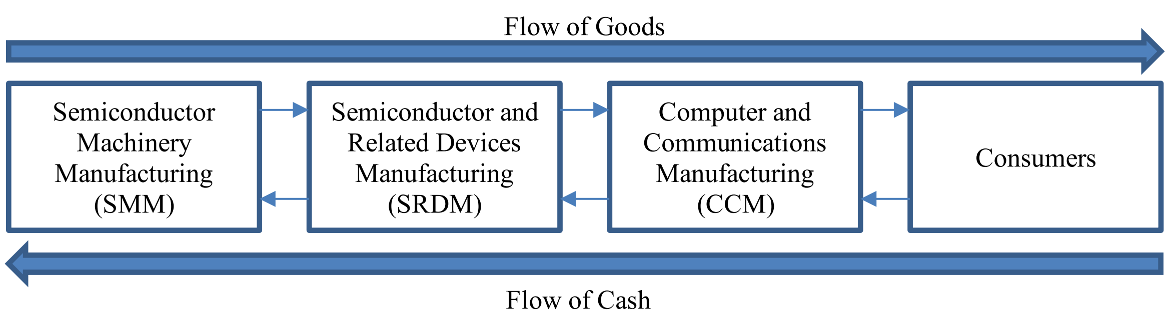

Figure 3-5 Structure of the semiconductor supply chain

To study the bullwhip effects in SSC, we use the method discussed in Sections 3.3 and 3.4. First, we measure each firm's bullwhip effects and then check if the hypotheses presented in Section 3.4 hold true for the ASC. Note that in this section, we change Hypothesis 7 to:

Hypothesis 7: CFB and its components experienced by SSM companies, SRDM companies, and CCM companies are different.

Table 3-7 reports the descriptive statistics of interest from the sample of SSC firms between Q1-2010 and Q4-2019. On average, SMMs experience the least CFB (2.89) and PBE (20.61). On average, SMMs experience the least BWE (2.26) and IBE (0.94). All three stages' payment policy, on average, is smaller than one meaning all have a lenient payment policy.

Table 3-7 Descriptive statistics of variables of interest of semiconductor supply chain

SMM (N = 13)	Mean	Std. dev.	25th percentile	50th percentile	75th percentile
CFB	2.89	2.98	0.95	2.10	2.78
BWE	2.98	4.86	1.36	1.90	2.17
IBE	1.02	1.52	0.41	0.60	0.83
PBE	20.61	27.78	1.93	12.37	26.30
Company size (million dollars)	231.47	471.38	24.26	57.86	90.19
Payment policy parameter (α)	0.44	0.11	0.37	0.40	0.50
Liquidity ratio (LR)	1.91	1.45	0.73	1.58	2.37
Seasonality ratio (SR)	0.09	0.15	0.01	0.04	0.11
Lead time (LT)	55.00	14.29	46.96	48.27	65.64
Demand autocorrelation (ρ)	0.72	0.16	0.58	0.70	0.87

SRDM (N = 105)	Mean	Std. dev.	25th percentile	50th percentile	75th percentile
CFB	4.27	4.71	1.15	2.98	5.36
BWE	3.32	3.90	1.24	2.19	3.64
IBE	1.60	2.04	0.49	1.02	1.78
PBE	105.81	316.38	5.65	16.54	73.40
Company size (million dollars)	294.13	562.71	14.83	62.84	288.37
Payment policy parameter (α)	0.96	2.02	0.46	0.63	0.87
Liquidity ratio (LR)	2.74	2.46	1.20	1.99	3.48
Seasonality ratio (SR)	0.09	0.12	0.02	0.05	0.10

Lead time (LT)	65.42	27.66	50.03	59.65	78.54
Demand autocorrelation (ρ)	0.75	0.24	0.67	0.83	0.91

CMM (N = 120)	Mean	Std. dev.	25th percentile	50th percentile	75th percentile
CFB	3.79	5.14	1.09	1.94	4.41
BWE	2.26	1.91	1.18	1.87	2.81
IBE	0.94	1.06	0.35	0.65	1.05
PBE	115.24	791.93	2.49	7.07	22.60
Company size (million dollars)	478.54	2746.58	6.12	21.76	101.40
Payment policy parameter (α)	0.72	1.42	0.34	0.50	0.68
Liquidity ratio (LR)	3.43	5.14	0.83	1.79	3.48
Seasonality ratio (SR)	0.12	0.16	0.02	0.06	0.15
Lead time (LT)	74.37	117.32	44.81	56.90	77.80
Demand autocorrelation (ρ)	0.76	0.24	0.73	0.83	0.91

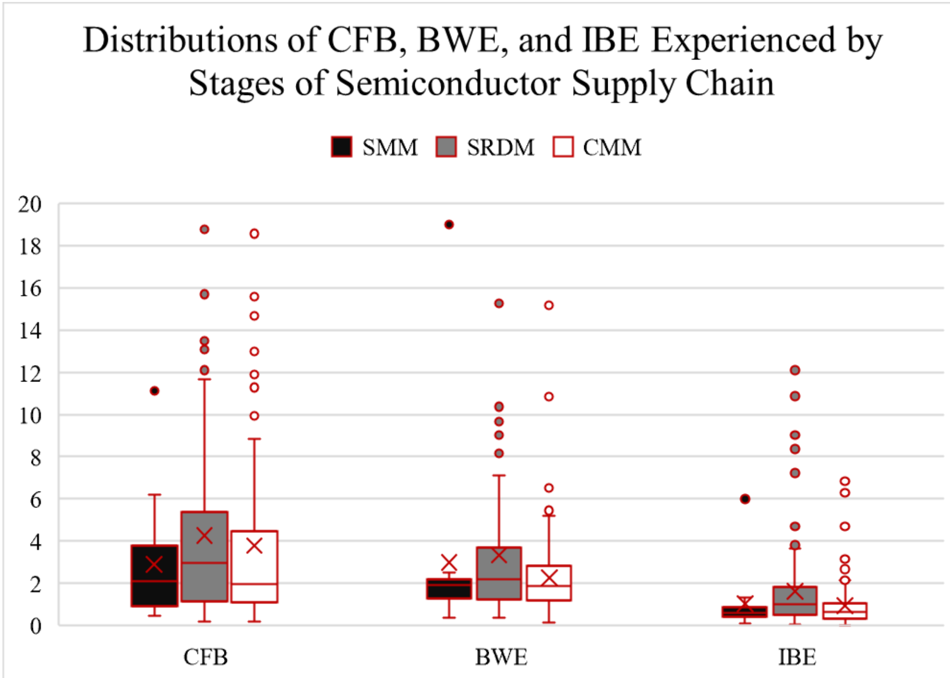

Figure 3-6 Distributions of the CFB, BWE, and IBE experienced by the stages of semiconductor supply chain

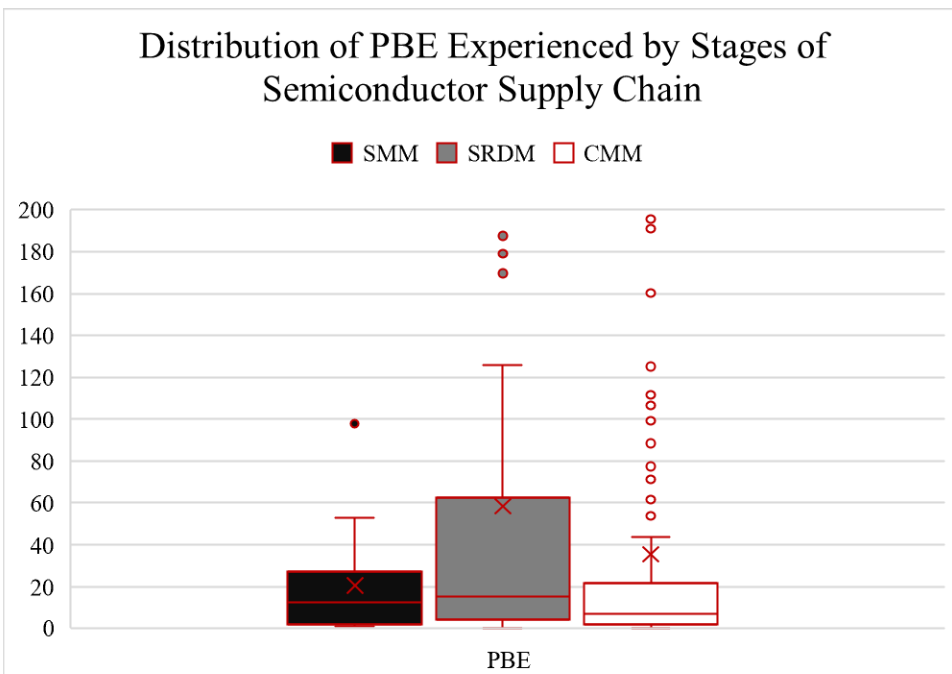

Figure 3-7 Distribution of PBE experienced by semiconductor supply chain

To test Hypotheses 1–7 for SSC, we regress CFB, BWE, IBE, and PBE on company size, payment policy parameter, liquidity ratio, seasonality ratio, lead time, demand autocorrelation parameter, and supply chain stage (SMM, SRDM, and CMM). We use the multiplicative regression models presented in Equations (3.17–3.20).

Table 3-8 reports the regression coefficients for multiplicative models fit over SSC data. Based on the regression coefficients in Table 3-8, we say that for SSC, CFB, on average, is: (i) negatively associated with company size, payment behavior, and seasonality ratio; and (ii) positively associated with lead time. We also find that, on average, the difference in CFB experienced by SMMs, SRDMs, and CMMs is significant. For entities in SSC, BWE is negatively associated with company size, payment behavior, and seasonality ratio; and positively associated with lead time and demand autocorrelation. IBE experienced by SSC entities is negatively associated with company size, payment behavior, liquidity ratio, and seasonality ratio; and positively associated with demand autocorrelation. On average, the difference in IBE experienced by SMMs, SRDMs, and CMMs is statistically significant. Finally, we observe that PBE in SSC is: (i) negatively associated with payment behavior, and seasonality ratio; and (ii) positively associated with liquidity ratio, lead time, and demand autocorrelation.

Table 3-8 Regression coefficients of multiplicative models of semiconductor supply chain bullwhips

	log(CFB)	log(BWE)	log(IBE)	log(PBE)
Intercept	-3.65***	-0.96	-1.67	-4.19**
SMM	0.51***	0.34***	0.66***	1.01***
SRDM	-0.2	-0.06	0	-0.28
log(COGS)	-0.09**	-0.06**	-0.13***	-0.07
log(α)	-1.32***	-0.38**	-0.5**	-1.95***
log(LR)	0.09	-0.01	-0.14*	0.59***
log(SR)	-0.06**	-0.05**	-0.06*	-0.08*

log(LT)	0.9***	0.35*	0.32	1.23***
log(ρ)	0.25	0.34**	0.46**	0.79**
Adj R-squared (%)	35.2%	13.6%	0.205	0.422
F-statistic	17.11***	5.66***	8.65***	22.65***
N	238	238	238	238

3.6 Robustness Checks

In this section, we study two potential sources of bias in our estimations: product aggregation and demand censoring. Table 3-9 and Table 3-10 summarize the results of robustness checks. These results are certainly not definitive; however, they show that we cannot reject the null hypothesis that there are no meaningful biases. That is, although the robustness checks cannot disprove the existence of the biases mentioned above, they increase our confidence in our results, as they do not suggest that any of them exist.

Table 3-9 Mean bullwhip measures across various aggregation levels

Aggregation Level	Mean CFB	Mean BWE	Mean IBE	Mean PBE
Product aggregation	46.34	5.50	1.07	48.64
Aggregation across 5-digit NAICS code	11.02	4.64	0.69	12.40
Aggregation across 4-digit NAICS code	11.01	4.51	0.66	12.18

Table 3-10 Mean BWE measures across period-start inventory quartiles

Subsample	Mean BWE
SUB Q1	1.91
SUB Q2	2.06
SUB Q3	2.14
SUB Q4	2.20

Product aggregation. In Section 3.5.1, our data aggregate across firms, and in Sections 3.5.2 to Section 3.5.4, our data aggregate across firm product offerings. Such data aggregation across firms and product offerings can bias BWE estimates (Chen and Lee 2012). As Bray and Mendelson (2012) show, this bias should work against our results in theory. Aggregation of data across firms and firm products dampens the bullwhip estimates. For the sake of completeness, we empirically check the effect of product aggregation on the bullwhip effects experienced by firms. We aggregate firms based on their 5-digit and 4-digit NAICS code to create a higher degree of aggregation. This aggregation scheme simulates aggregating across firms and products. We see that the mean bullwhip measures of the sample of 782 firms calculated in Section 3.5.2 is larger than that calculated using data aggregated using 5-digit and 4-digit NAICS codes (see Table 3-9). This shows that aggregation attenuates bullwhip measures. Meaning our calculations of bullwhip measures presented in Section 3.5 are not inflated, rather they are attenuated. The real bullwhip measures experienced by individual products in each firm must be higher than our estimates.

Censoring Bias. In Section 3.5, we use COGS as a proxy for demand. COGS, the minimum of demand and available inventory, is a censored variable. Such censoring can inflate bullwhip estimates by truncating demand, making it less variable. To check if censoring bias drives our bullwhip measures, we use the robustness test used by Bray and Mendelson (2012). We investigate whether stockouts relate to our bullwhip measures in order to check if demand censoring bias drives our results. Since data on stockouts is not available, we use period-start inventory level as a proxy. Since higher period-start inventory levels generally mean fewer stockouts, higher period-start inventory should be negatively correlated to stockouts. Hence if a censoring bias exists, there should be an inverse relationship between period-start inventory level and our measures of bullwhip effects. The sample of 782 companies if split into four subsamples based on period-start inventory level. Each company-quarter is evenly allocated to each subsample. SUB Q1 represents the subsample consisting of the first period-start inventory level quartile, SUB Q2 the second, SUB Q3 the third, and finally, SUB Q4 the fourth.

Results in Table 3-9 show that there is no censor bias signature in our measures of bullwhip effect. As period-start inventory levels increase (from SUB Q1 to SUB Q4), the mean BWE across subsamples does not decrease. More importantly, we find that BWE measure is the highest in SUB Q4, when stockouts and hence demand censoring should be least likely. However, we do not claim that this robustness claim is definitive since it hinges on the assumption that there is a negative relationship between period-start inventories and stockouts.

3.7 Conclusion

Supply chain literature has given a lot of attention to the traditional bullwhip effect, BWE, but the same cannot be said about CFB or the amplification of working capital variance upstream in supply chains. This chapter is a step in the direction of empirically discovering the CFB effect in supply chains and identifying its drivers. This chapter links CFB and the single product model for BWE (by Chen et al., 2000) with firm-level operational and financial variables. Our results indicate that industries experience the traditional BWE and parallelly also experience the CFB effect, which is caused by WC variance amplification. The results also suggest that CFB, IBE, and PBE experienced by a firm are associated with firm-level variables like firm size, payment policy parameter (or payment behavior), liquidity ratio, seasonality ratio, procurement, and payment lead times, and demand autocorrelation parameter. The findings suggest that as the firm size grows, the CFB, IBE, and PBE it experiences decreases. We also observe that firms with conservative payment behavior experience less CFB, BWE, IBE, and PBE. Conservative payment behavior might allow a firm to free up more cash for operations and push cash-flow uncertainties onto its suppliers, thereby reducing its own CFB. When it comes to demand seasonality, we find that firms that experience quarterly seasonality in demand smooth their working capital and purchases to reduce the CFB and BWE they experience. Our results also indicate that CFB is positively associated with lead time. We find that among all variables in the study, lead time has the most considerable impact on a firm's CFB. Finally, results also indicate that a firm's CFB, BWE, IBE, and PBE increase as the autocorrelation parameter of the demand it experiences increases.

We find that CFB and its components are also present in the ASC and SSC. CFB in ASC is associated with the following attributes: supply chain stage, payment policy parameter, seasonality ratio, and procurement and payment lead times. It is observed that OEMs, on average, experience the least CFB, BWE, and IBE in the ASC. We hypothesize that this could be due to the following reasons: (i) the size of OEMs allows them to take advantage of economies of scale to reduce production and purchase variations, and (ii) OEMs use their clout to push supply chain uncertainties on to tier 1 suppliers and automobile dealers. Future work can focus on testing these hypotheses and identifying other reasons (if any) due to which OEMs experience lesser bullwhip than other entities in the ASC.

Our results indicate that semiconductor companies experience financial and operational risks in the form of CFB and BWE. These effects experienced by semiconductor companies are associated with company size, lead-time, payment policy, liquidity ratio, demand seasonality, and demand autocorrelation. We also observe the CFB experienced by SRDM companies as smaller than CMM companies and BWE experienced by SRDM companies to be larger than that of CMM companies.

It would be remiss of us not to list the limitations of this chapter. This chapter uses data from Compustat, which only lists data of public companies. This means we are not looking at the entire world economy, let alone the U.S. economy. We further make the dataset smaller by (i) selecting only the companies that were public in all quarters between Q1-2010 and Q4-2019 and (ii) dropping companies that have one or more missing values in any field(s) of interest in their financial report. We used a final sample of 782 companies. This small sample (compared to the entire U.S. economy) is potentially subject to flaws like size bias and survivorship bias. Another limitation of this work is the use of imperfect proxies for demand, lead time (procurement + payment), magnitude of seasonality, and firm size. Future studies could explain why some of our hypotheses do not hold. The use of better proxies for various firm variables might help. Our model does not account for business cycles, competition, and supply chain complexities. These attributes of a company, too, can affect the magnitude of CFB (and components) it experiences. The inclusion of these attributes in the model could increase the latter's adjusted R-squared values.

Chapter 4 SUPPLY CHAIN CASH-FLOW BULLWHIP EFFECT: A SIMULATION APPROACH

Abstract

We use simulation model to examine the effects of stochastic procurement lead time, stochastic payment lead times, and information sharing on the cash-flow bullwhip experienced by a serial supply chain. We find that the procurement lead time variance, payment lead time variance, demand information sharing, and the choice of cash-flow forecasting algorithm have a statistically significant effect on the CFB experienced especially by the upstream echelons of the serial supply chain. We also use simulation modeling to perform a comparative analysis of the cash-flow bullwhip and traditional bullwhip effect between serial, convergent, divergent, con-div, and general supply chain topologies. To do this, we study cash-flow bullwhip in the abovementioned topologies under two demand processes: (i) stationary demand and (ii) impulse demand. The results reveal that there is a significant difference between the CFB experienced by convergent and divergent supply chains; serial and divergent supply chain; and general and divergent supply chain.

4.1 Introduction

4.1.1 Cash-flow Bullwhip Effect

First studied by Tangsucheeva and Prabhu (2013), the cash-flow bullwhip effect (CFB) is the amplification of material and financial flow distortions upstream in the supply chain from customers (most downstream entity) to suppliers (most upstream entity). CFB is analogous to the traditional bullwhip effect (BWE), amplification of order rate variance upstream in the supply chain.

Tangsucheeva and Prabhu (2013) define CFB as the ratio of the variance of an entity's cash conversion cycle (CCC) and the variance of customer demand (D), $var(CCC)/var(D)$. Using Tangsucheeva and Prabhu's (2013) definition of CFB, several authors have performed simulation studies to analyze CFB in supply chains. Goodarzi et al. (2017) use response surface methodology to study the impact of demand information sharing, rationing, and shortage gaming on $var(CCC)/var(D)$ experienced by various entities of a serial supply chain. Badakhshan et al. (2020) use the simulation-based optimization approach to determine values of forecast updating parameter; rationing and shortage gaming parameter; desired inventory level; and cost of material that minimize the $var(CCC)/var(D)$ experienced by various entities of a serial supply chain.

In Chapter 3, we show that Tangsucheeva and Prabhu's (2013) definition of CFB does not reveal whether a specific supply chain entity amplifies or attenuates the material and financial distortions that it experiences. To overcome this caveat, we propose a new definition of CFB experienced by an entity k given by:

$$\begin{aligned} CFB_k &= \frac{var\left(WC^{(k)}\right)}{var(d^{(k,\$)})} \\ &= \frac{var\left(C^{(k)} + I^{(k,\$)} + AR^{(k)} - AP^{(k)}\right)}{var(d^{(k,\$)})} \end{aligned} \tag{4.1}$$

where $WC^{(k)}$ is entity k's working capital, $d^{(k,\$)}$ the customer demand process (measured in monetary terms with respect to entity k); and $C^{(k)}$, $Invt^{(k,\$)}$, $AR^{(k)}$, and $AP^{(k)}$ are entity k's cash level, inventory (in monetary terms), accounts receivable, and accounts payable, respectively. This chapter uses the formula shown in Equation (4.1) to study the CFB experienced by the echelons of 5 different supply chain topologies.

4.1.2 Contribution to Literature

Our research is split into two parts. The first part uses a designed experiment to study the effect of several key supply chain parameters like procurement lead time, payment lead time, information sharing policy, and cash-flow forecasting algorithm on the CFB and BWE experienced by various echelons of a serial supply chain. The second part employs designed experiments to perform a comparative analysis between the CFB and BWE experienced by various supply chain topologies.

In the first part of our research, we create a 4-echelon serial supply chain simulation model to study CFB in serial supply chain. We employ a custom tool to aid in supply chain modeling. We run a series of experiments using the simulation model with experimental factors related to procurement lead-time variation, payment lead-time variation, information sharing, and cash flow forecasting algorithm. The purpose of these experiments is to gain insights into the relationship of these factors with CFB and BWE experienced by the serial supply chain. We wish to answer the following questions:

1. What effect does stochastic procurement and payment lead times have on CFB and BWE experienced by various echelons of a serial supply chain?
2. What is the extent to which information sharing helps reduce CFB and BWE in a serial supply chain?
3. How does the choice of cash flow forecasting algorithm affect CFB of echelons in a serial supply chain?

Chatfield et al. (2009) performed a similar study on the traditional bullwhip effect

(BWE) in serial supply chains. They show that procurement lead time, demand information sharing, and the quality of the shared information significantly affect the BWE experienced by various echelons of a serial supply chain.

Computational results reveal that all four factors, viz. procurement lead time, payment lead time, customer demand information sharing, type of cash flow forecasting algorithm significantly affect the CFB experienced by various echelons of a serial supply chain. Procurement lead time and demand information sharing are found to affect BWE significantly.

In the second part of this research, we create simulation models of 5 supply chain topologies, viz., serial, divergent, convergent, a mix of convergent and divergent (henceforth called con-div), and general supply chain topologies under various demand patterns proposed by Towill et al. (2007). The authors propose three lenses, viz., variance lens, shock lens, and filter lens, through which the BWE can be observed. Dominguez et al. (2014) studied BWE in serial and divergent supply chains under the variance and shock lens. Under the variance lens, the end customer demand is a stationary process. Under the shock lens, a sudden change in customer demand is introduced. The objective of introducing this shock in demand is to perform a “stress test” on the supply chain. We use the experimental framework proposed by Dominguez et al. (2014) to study CFB’s and BWE’s magnitude and speed of propagation in the 5 supply chain topologies mentioned above using the variance and shock lens.

Computational results reveal that the difference in CFB experienced by various topologies under the two lenses is significantly different. Under both lenses, divergent and con-div supply chains experience the highest CFB, and the convergent supply chain experiences the least CFB.

To the best of our knowledge, this is the first attempt in the open literature to study the following:

1. The impact of procurement lead time variations, payment lead time variations, and demand information sharing on the CFB experienced by the echelons of a serial supply chain
2. The impact of customer demand pattern (variance lens or shock lens) on CFB and BWE experienced by supply chains with the following topologies: serial, divergent, convergent, con-div, and general topology.
3. The speed at which CFB and BWE propagate through various supply chain topologies.

4.1.3 Organization of the Chapter

In Section 4.2, we discuss the 5 supply chain topologies that we study in this chapter. We present the supply chain material and cash flow logic used for simulation in Section 4.3. In Section 4.4, we explain the experimental designs we employ to study CFB and BWE. The results of the simulation experiments are presented in Section 4.6. Finally, Section 4.7 concludes the chapter by discussing the results, limitations of this study, and directions for future work.

4.2 Supply Chain Topologies

Figure 4-1 illustrate the various supply chain topologies that we study in this chapter. Each topology but the con-div topology has 4 echelons. The con-div topology has 5 echelons. We assume that each supply chain illustrated in Figure 4-1 maintains a single item inventory. The 4 echelons of serial, convergent, divergent, and general supply chain topologies are Retailer, Wholesaler, Manufacturer, and Supplier. The 5 echelons of the con-div supply chain topology are Retailer, Wholesaler, Manufacturer, Tier-1 Supplier, and Tier-2 Supplier. Material flows downstream from Suppliers (Tier-2 Suppliers in the con-div supply chain) towards Retailers and finally to Customers. Cash flows upstream from Customers to Retailers and finally to Suppliers (Tier-2 Suppliers in the con-div supply chain).

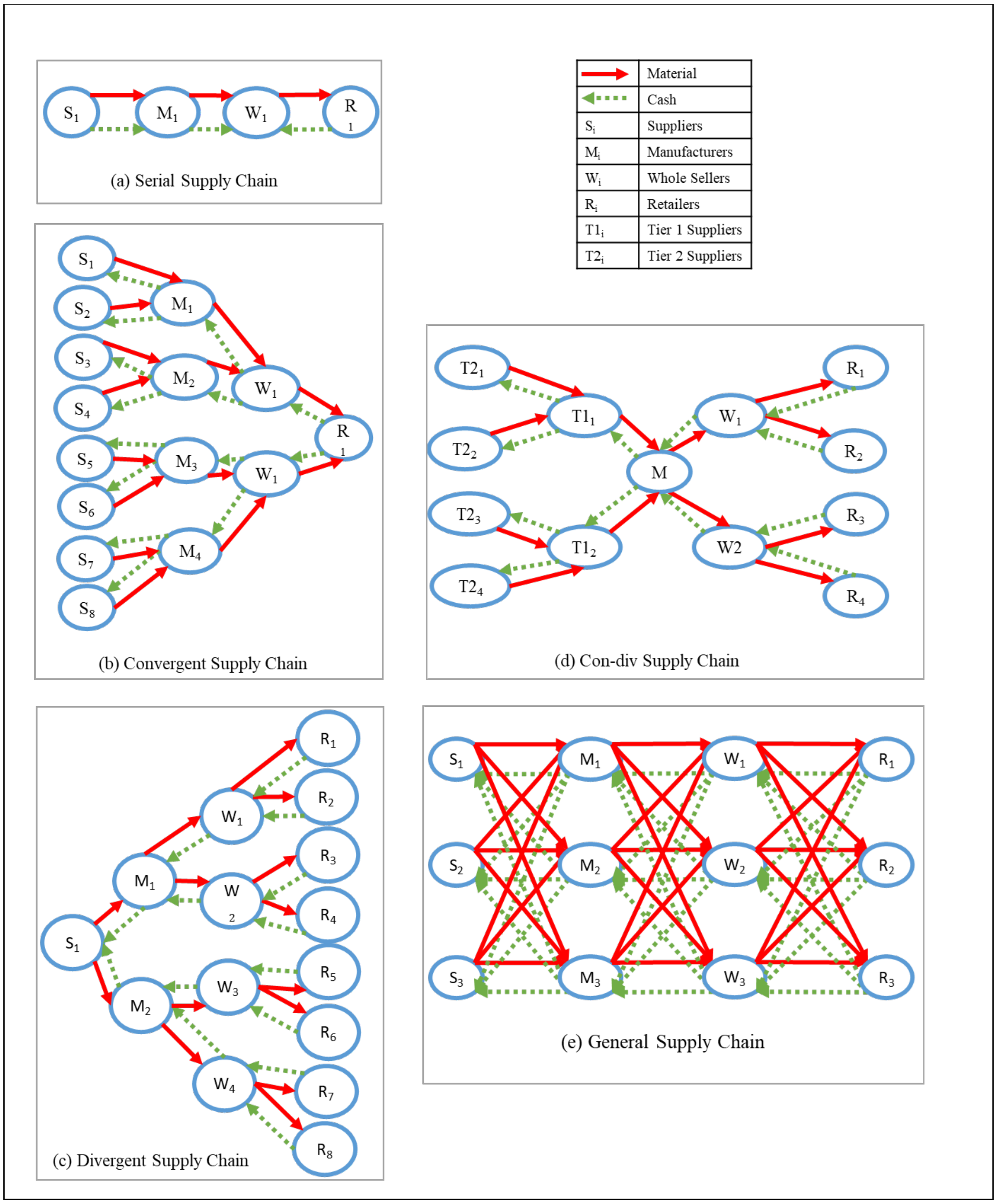

Figure 4-1 Supply chain topologies

4.2.1 Serial Supply Chain

The serial supply chain, shown in Figure 4-1, constitutes 4 echelons, $k \in \{1,2,3,4\}$. Retailer, represented by $k = 1$, is the most downstream echelon in the supply chain. Supplier, represented by $k = 4$, is the most upstream supply chain echelon. Each entity in the serial supply chain does business with only one entity downstream and one entity upstream. Every echelon k ∈ {1,2,3,4} receives material from echelon k+1 and cash from echelon k-1.

4.2.2 Divergent Supply Chain

Unlike the serial supply chain, each entity in the divergent supply chain (shown in Figure 4-1) does business with 2 entities downstream and one entity upstream. Each entity of the divergent supply chain receives material from exactly one entity in the immediate upstream echelon and delivers material to exactly 2 entities in the immediate downstream echelon. Each entity of the divergent supply chain receives cash from the 2 downstream entities it delivered the material to and pays cash to 1 upstream entity that delivered the material.

4.2.3 Convergent Supply Chain

Each entity of the convergent supply chain supplies material to one entity in the immediate downstream echelon, and itself sources material from 2 entities in the echelon immediately upstream. Based on the demand for material that a given entity is experiencing, it determines an order quantity. This order quantity is split into two halves and is assigned to two echelons upstream. Say, entity W_1's (see Figure 4-1) order quantity at the end of a business period is 100 units of material. W_1 would place an order for 50 units with M_1 and 50 units with M_2. Cash flows in the opposite direction of the flow of material. Entities receive cash from one entity downstream and pay cash to two entities upstream. Meaning,

W_1 receives cash from R_1 and pays cash to M_1 and M_2.

4.2.4 Con-Div Supply Chain

Con-div supply chain is a mix of convergent and divergent supply chain topologies. The first half of the con-div supply chain is convergent, and the second half is divergent. The con-div supply chain in Figure 4-1 can be thought of as an automotive supply chain wherein 4 Tier-2 Suppliers supply raw materials to 2 Tier-1 Suppliers. The Tier-1 Suppliers (equivalent of Suppliers in serial, divergent, and convergent supply chains) use the raw materials to build automobile components and ship them to the OEM (Manufacturer). The OEM assembles the automobiles and ships them to 2 Distribution Centers (Wholesalers), which then ship the automobiles to 4 Dealerships (Retailers). The convergent half of the supply chain in Figure 4-1 starts at the Tier-2 Suppliers and ends at the OEM. The divergent half starts at the OEM and ends at the Dealerships. Material and cash flow through these halves as they do in convergent and divergent supply chains.

4.2.5 General Supply Chain

The general supply chain, shown in Figure 4-1, has 4 echelons like the serial supply chain. Each echelon has 3 entities. Each entity in every echelon sources material from all 3 entities in the echelon immediately upstream. At the end of each business period, each entity splits its orders using predetermined proportions between the 3 entities upstream to it. Based on the order quantity assigned to the 3 entities upstream, each echelon pays the respective cash owed to the former.

4.3 Supply Chain Logic

This section discusses the logic that drives customer demand and material and cash flows in the simulation models that we build. Let (i, j) represent entity i in echelon j of a supply chain.

4.3.1 Material Flow and Information Sharing

To model the events related to material flow and information sharing, we adapt the supply chain characteristics described in Chatfield et al. (2009) and Dominguez et al. (2014) as follows:

Customer Demand. Customer demand in period t, D_t, is assumed to be normally distributed with mean μ_D and variance σ_D^2, represented as $N(\mu_D, \sigma_D^2)$.

Procurement Lead Time. The procurement lead time, $L_t^{(i,j)}$, experienced by (i,j) is assumed to be a stationary, identically, and independently distributed gamma random variable with mean $\mu_{L_t^{(i,j)}}$ which we estimate by $\bar{L}^{(i,j)}$, and variance $\sigma^2_{L_t^{(i,j)}}$ that we estimate by $s^2_{L^{(i,j)}}$.

Lead time demand. Let $X_t^{(i,j)}$ be the demand observed by (i,j) during the period t to $L_t^{(i,j)}$. $X_t^{(i,j)}$ has mean $\mu_{X^{(i,j)}}$ that we estimate by $\bar{X}^{(i,j)}$, and variance $\sigma^2_{X^{(i,j)}}$ that we estimate by $s^2_{X^{(i,j)}}$.

Ordering Policy and Inventory. We assume that each entity in the supply models we study follows a simple order-up-to inventory policy in which the order-up-to point of (i,j) at the end of period t, $y_t^{(i,j)}$, is estimated from the observed demand as follows:

$$y_t^{(i,j)} = \bar{X}^{(i,j)} + z s_{X^{(i,j)}} \tag{4.2}$$

where z is the safety factor. We assume $z = 2$ (service level of 97.72%).

The order quantity of (i,j) at the end of period t is given by:

$$O_t^{(i,j)} = y_t^{(i,j)} - y_{t-1}^{(i,j)} + D_t^{(i,j)} \tag{4.3}$$

where $D_t^{(i,j)}$ is the demand observed by (i,j) in the period t.

The inventory level at (i,j) at the end of period t is the difference in the total goods that flow in and out of the entity up to period t. Therefore, the inventory level at (i,j) at the end of period t is given as follows:

$$I_t^{(i,j)} = I_{int}^{(i,j)} + \sum_{i=1}^{t} O_{i-L_{t(i,j)}}^{(i,j)} - \sum_{i=1}^{t} D_i^{(i,j)} \tag{4.4}$$

Information Sharing. Our experiments model two information scenarios: (i) the Retailers share customer demand information with all entities in the supply chain, and (ii) the Retailers do not share the customer demand with any other entity. Under the first scenario, all entities use the knowledge of customer demand to forecast the lead time demand. Under the second scenario, the absence of customer demand information forces entities to rely only on the demand they observe from the entities downstream to forecast the lead time demand.

When the customer demand information is shared with every entity in the supply chain, $\bar{X}^{(i,j)}$ is given by:

$$\bar{X}^{(i,j)} = \bar{L}^{(i,j)} \times \bar{D} \tag{4.5}$$

where $\bar{D}$ is the 15-period moving average of customer demand. When the customer demand information is not shared, $\bar{X}^{(i,j)}$ is given by:

$$\bar{X}^{(i,j)} = \bar{L}^{(i,j)} \times \bar{D}^{(i,j)} \tag{4.6}$$

where $\bar{D}^{(i,j)}$ is the 15-period moving average of demand (i,j) experiences from downstream entities.

4.3.2 Cash Flow

Descriptions of the notations used in this sub-section are presented in Table 4-1.

Table 4-1 Notation descriptions for cash-flow

Symbol	Description
$\mathbb{N}$	Set of echelons in supply chain
$\mathbb{N}_i$	Set of entities in echelon $i \in \mathbb{N}$
(i,j)	Entity $j \in \mathbb{N}_i$ in echelon $i \in \mathbb{N}$
$cp^{(i,j)}$	The price at which (i,j) buys material from upstream entities
$sp^{(i,j)}$	The price at which (i,j) sells material to downstream entities
$P_t^{(i,j)}$	$(i,j)'$s payment decision at the end of period t
$DC_{out,t}^{(i,j)}$	$(i,j)'$s desired cash outflow at the end of period t
$DC^{(i,j)}$	$(i,j)'$s desired cash level
$C_t^{(i,j)}$	$(i,j)'$s cash level at the end of period t
$C_{in,t}^{(i,j)}$	Cash that flowed into (i,j) in period t
$AP_t^{(i,j)}$	$(i,j)'$s accounts payable at the end of period t
$AR_t^{(i,j)}$	$(i,j)'$s accounts receivable at the end of period t
$FC_{in,t}^{(i,j)}$	$(i,j)'$s forecast of cash-inflow at period t
$Invst_t^{(i,j)}$	$(i,j)'$s investment in assets at the end of period t
$\beta^{(i,j)}$	$(i,j)'$s cash control aggressivity measure
$\gamma^{(i,j)}$	$(i,j)'$s cash surplus investment strategy

Payment Lead time. We assume that there is a stochastic lead time associated with the payment of accounts payable, just like there is one associated with the procurement of goods. We call this lead time the payment lead time. Say, if (i,j) in period t has the payment lead time $PLT_t^{(i,j)}$, in period t, (i,j) will attempt to clear its accounts payable from $PLT_t^{(i,j)}$ periods ago. That is, in period t, (i,j) will attempt to pay off $AP_{t-PLT_t^{(i,j)}}^{(i,j)}$. We assume that $PLT_t^{(i,j)}$ is a stationary, identically, and independently distributed gamma random variable with mean $\mu_{PLT_t^{(i,j)}}$ and variance $\sigma_{PLT_t^{(i,j)}}^2$.

Payment Policy. We assume that each supply chain entity (i,j) wants to maintain a constant stock of cash, $DC^{(i,j)}$. Each entity channels the cash inflows that accumulate in every period towards investing activities and paying its upstream partners. The sum of payments made by (i,j) to its upstream partners at the end of period t is non-negative and is given by:

$$P_t^{(i,j)} = MIN\left(AP_{t-PLT_t^{(i,j)}}^{(i,j)}, \gamma^{(i,j)} DC_{out,t}^{(i,j)}\right) \tag{4.7}$$

where

$$DC_{out,t}^{(i,j)} = MAX\left(0, FC_{in,t}^{(i,j)} - \beta^{(i,j)} \underbrace{\left(DC^{(i,j)} - C_{t-1}^{(i,j)}\right)}_{Cash\,Gap}\right) \tag{4.8}$$

The cash inflow forecast at period t is generated using the exponential smoothing technique. A high $\beta^{(i,j)}$ indicates (i,j) has an aggressive policy to shrink the discrepancy in desired cash level and cash level. A high $\gamma^{(i,j)}$ is indicative of (i,j) giving more importance to using surplus cash for investing activities than for paying upstream partners. That is, (i,j) is willing to devote only $\left(1-\gamma^{(i,j)}\right)$ fraction of its desired cash outflow towards settling outstanding payments to its upstream partners. The amount of surplus cash invested in assets by (i,j) at the end of period t is non-negative and is given by:

$$Invst_t^{(i,j)} = DC_{out,t}^{(i,j)} - P_t^{(i,j)}. \tag{4.9}$$

Therefore, $(i,j)'$s cash level at the end of period t is given by:

$$C_t^{(i,j)} = C_{t-1}^{(i,j)} - P_t^{(i,j)} - Invst_t^{(i,j)} + C_{in,t}^{(i,j)}. \tag{4.10}$$

Working Capital. The working capital of (i,j) in period t is given by:

$$WC_t^{(i,j)} = C_t^{(i,j)} + AR_t^{(i,j)} - AR_t^{(i,j)} + cp^{(i,j)} \times I_t^{(i,j)}. \tag{4.11}$$

Demand in monetary terms. As seen in Equation (4.1), the calculation of CFB of an entity requires demand in monetary terms with respect to that entity. The demand in monetary terms for (i,j) is given by:

$$D_t^{(i,j,\$)} = sp^{(i,j)} \times D_t \tag{4.12}$$

4.4 Simulation Model Verification

We verify our simulation model by comparing observed bullwhip measures to those from the analytical work of Chen et al. (2000) on BWE and analytical work presented in Chapter 2 on CFB. For the purpose of verification, we use the serial supply chain simulation model because the analytical models presented by Chen et al. (2000) and in Chapter 2 are for serial supply chains.

Comparison with Chen et al. (2000). To make a direct comparison with the analytical results of Chen et al. (2000), we make adjustments to our simulation model to make it consistent with the assumptions of Chen et al. (2000). First, we set $z = 0$, $\rho = 0$, and $L + R = 4 + 1 = 5$ (see Chatfield et al. (2009) for discussion on R). Secondly, negative order quantities at the customer end are allowed. Thirdly, demand information is assumed to be not shared by the retailer with other entities in the serial supply chain. As seen in Table 4-2 our results for BWE are in close agreement with the analytical work of Chen et al. (2000).

Table 4-2 Our simulation vs. Chen et al. (2000) with no information sharing: BWE

Model	Retailer	Wholesaler	Manufacturer	Supplier
Chen et al.	1.89	3.57	6.74	12.73
Our Simulation Model	1.81	3.14	6.54	12.48

Demand rate ~ $N(50,20^2)$. The simulation was run for 50 replications of 10000 time periods of which the first 200 periods constituted the warm-up period

Table 4-3 Our simulation vs. analytical model (from Chapter 2): CFB

Model	Retailer	Wholesaler	Manufacturer	Supplier
Analytical Model (Chapter 2)	4.66	7.65	12.25	18.48
Our Simulation Model (Scenario 1)	5.18	9.01	15.42	24.47
Our Simulation Model (Scenario 2)	5.08	9.25	15.91	26.89

Demand rate ~ $N(50,20^2)$. The simulation was run for 50 replications of 10000 time periods of which the first 200 periods constituted the warm-up period

Comparison with Chapter 2. Recall that the analytical model of CFB presented in Chapter 2 assumes that the cash level of each entity in the serial supply chain remains constant. Therefore, to compare the CFB measures of the simulation model with that of the analytical model presented in Chapter 2, we need to make certain adjustments to the simulation model. We assume that there is always enough cash to pay account payables (perpetual cash sufficiency), and we do not include cash level in working capital calculations. Not including cash level in working capital calculations is equivalent to assuming the cash level is always constant, just like in the analytical model presented in

Chapter 2. We also compare the analytical model with a simulation model where the assumption of perpetual cash sufficiency is dropped, and cash level is included in working capital calculations.

In Table 4-3, we see that the simulated CFB measures of scenario 1, where perpetual cash sufficiency is assumed, are greater than the measures of the analytical value. The reason for this discrepancy is the use of simple moving average method for demand forecast generation in the simulation model. The analytical model for CFB in Chapter 2 assumes that echelons use MSE-optimal method for demand forecast generation, which is a more accurate method of forecasting and therefore causes smaller CFB. The simulated CFB measures of scenario 2, where perpetual cash sufficiency is not assumed, are greater than the CFB measures of the Scenario 1. There are two reasons for CFB measures in scenario 2 to be greater. First is the inclusion of variable cash level in working capital calculations. Second reason is that the removal of assumption of perpetual cash sufficiency causes AP and AR levels in scenario 2 to fluctuate more vehemently than they do in scenario 1. Cash insufficiency at buyers can cause them to make payments later than the payment lead time. This causes AP levels of buyers and AR levels of sellers to have higher variances than they would have had in scenario 1.

4.5 Experimental Designs

4.5.1 Experiment 1: Impact of Stochastic Lead times, Information Sharing, and Cash-flow forecasting algorithm on CFB and BWE

To measure the impact of stochastic procurement lead times, stochastic payment lead times, information sharing, and cash-flow forecasting algorithm on CFB and BWE in the serial supply chain, we design a factorial experiment with the 4 factors: the coefficient of variation (c.v.) of procurement lead time; the c.v. of payment lead time; weather customer demand is shared or not; and if exponential smoothing or Stochastic Financial Analytics (SFA) algorithm, developed by Tangsucheeva and Prabhu (2014), is used to make cash-flow forecasts. For the designed experiment, we assuming that SFA is run on the last day of each month. Table 4-4 reports the factors and their levels that are employed in Experiment 1.

Table 4-4 Factors and their levels used in Experiment 1

Factor	Level	Description
L	1	c.v. = 0
	2	c.v. = 0.25
	3	c.v. = 0.50
	4	c.v. = 0.75
PLT	1	c.v. = 0
	2	c.v. = 0.25
	3	c.v. = 0.50
	4	c.v. = 0.75
Information Sharing	1	Customer demand information is not shared
	2	Customer demand information is shared

Factor	Level	Description
Cash-flow forecasting algorithm	1	Exponential Smoothing
	2	Stochastic Financial Analysis (SFA (1-Month))

Modifying the experimental procedure proposed in Chatfield et al. (2009), we run a full-factorial experiment on these factors resulting in 64 factor combinations (4 levels of stochastic procurement lead time × 4 levels of stochastic procurement lead time × 2 levels of information sharing × 2 levels of cash-flow forecasting algorithm). Every simulation model run entails customer demand generation and material and cash flow between the 4 echelons of the serial supply chain illustrated in Figure 4-1. Each factor combination is replicated 30 times and has a simulation run length of 700 periods. The first 200 periods are used as a warm-up period and hence dropped from the analysis.

The end customer demand for this experiment is normally distributed with a mean of 50 and a variance of 20. The means of procurement and payment lead times are fixed at 12-time units. The variance values are changed depending on the c.v. value required by experimental runs. We assume that each echelon sells material at a price 10% higher than what it paid for it. $\beta^{(i,j)}\ \forall\ i \in \mathbb{N}, j \in \mathbb{N}_i$ is assumed to be 0.5 and $\gamma^{(i,j)}\ \forall\ i \in \mathbb{N}, j \in \mathbb{N}_i$ is assumed to be 0.99. Since the serial supply chain has only one entity in each echelon, $\mathbb{N}_i = [1]\ \forall\ i \in \mathbb{N}$.

In this experiment, we track the following response variables for each entity in the serial supply chain:

1. $CFB^{(i,1)} = var(WC^{(i,1)})/var(sp^{(i,1)} \times D)$
2. $BWE^{(i,1)} = var(O^{(i,1)})/var(D)$

4.5.2 Experiment 2: CFB and BWE under the Two Lenses

The objective of experiment 2 is to study CFB in serial, divergent, convergent, con-div, and general supply chain topologies under the variance and shock lenses. Simulation models for each topology follow the supply chain logic discussed in Section 4.3. Similar to experiment 1, the simulation run length for experiment 2 is 700 periods. The first 200 periods represent the system warm-up period and hence are dropped from the analysis.

Experiment 2 is split into 2 parts. In the first part, we analyze CFB under the variance lens. Studying CFB under variance lens allows us to measure CFB's magnitude and propagation velocity through various supply chain topologies. In the second part, we study CFB under the shock lens. The shock lens allows us to see how long various supply chain topologies take to recover from a demand shock.

Experiment 2.1: Variance Lens

Under the variance lens, the end customer demand follows $N(50,20)$ for all 700 periods. Each supply chain topology (Figure 4-1) is simulated 30 times. The mean values of procurement and payment lead times are fixed at 2-time units, and the variance values are fixed at 1. We assume that each echelon sells material at a price 10% higher than what it paid for it. All entities in a given echelon i are assumed to sell material at the same price, $sp^{(i)}$. $\beta^{(\boldsymbol{i},\boldsymbol{j})}$ $\forall\ i \in \mathbb{N}, j \in \mathbb{N}_i$ for all topologies is assumed to be 0.5 and $\gamma^{(\boldsymbol{i},\boldsymbol{j})}$ $\forall\ i \in \mathbb{N}, j \in \mathbb{N}_i$ is assumed to be 0.99. Consistent with Dominguez et al. (2014), we assume that the Retailers do not share customer demand with other entities in the supply chain and all entities use exponential smoothing to forecast cash-flows.

In this experiment, we track the following response variables for each echelon $i \in \mathbb{N}$ in the 5 supply chain topologies that we simulate:

1. CFB_i for $t \in [350,700]$
2. CFB_i-slope for $t \in [350,700]$
3. BWE_i for $t \in [350,700]$
4. BWE_i-slope for $t \in [350,700]$

CFB_i is the cash flow bullwhip experienced by echelon i. Depending on the supply chain topology, the number of entities in echelon i, $n(\mathbb{N}_i)$, could be 1, 2, 3, 4, or 8. The cash-flow bullwhip experienced by echelon i is given by:

$$CFB_i = \frac{var\left(\sum_{j\in\mathbb{N}_i} WC^{(i,j)}\right)}{var\left(sp^{(i)} \times \sum_{j\in\mathbb{N}_1} D^{(1,j)}\right)} \tag{4.13}$$

where $\mathbb{N}_1$ is the set of Retailers and $D^{(1,j)}$ is the customer demand experienced by Retailer $j \in \mathbb{N}_1$.

The CFB_i-slope is a measure of the speed of propagation of CFB through a supply chain. The higher the CFB_i-slope, the faster the propagation of material and financial variations through the supply chain. CFB_i-slope is calculated by performing a linear regression on CFB_i using i as an independent variable and is given by:

$$CFB_i\text{-slope} = \frac{n(\mathbb{N})\sum_{k=1}^{n(\mathbb{N})}(k \times CFB_k) - \sum_{k=1}^{n(\mathbb{N})} k \sum_{k=1}^{n(\mathbb{N})} CFB_i}{n(\mathbb{N})\sum_{k=1}^{n(\mathbb{N})} k^2 - \left(\sum_{k=1}^{n(\mathbb{N})} k\right)^2} \tag{4.14}$$

The BWE experienced by echelon i is given by:

$$BWE_i = \frac{var\left(\sum_{j\in\mathbb{N}_i} O^{(i,j)}\right)}{var\left(\sum_{j\in\mathbb{N}_1} D^{(1,j)}\right)} \tag{4.15}$$

The BWE_i-slope is a measure of the speed of propagation of BWE through a supply chain and is given by:

$$BWE_i\text{-slope} = \frac{n(\mathbb{N})\sum_{k=1}^{n(\mathbb{N})}(k \times BWE_k) - \sum_{k=1}^{n(\mathbb{N})} k \sum_{k=1}^{n(\mathbb{N})} BWE_k}{n(\mathbb{N})\sum_{k=1}^{n(\mathbb{N})} k^2 - \left(\sum_{k=1}^{n(\mathbb{N})} k\right)^2} \tag{4.16}$$

Experiment 2.2: Shock Lens

The experimental setup used in this experiment is the same as the one used in Experiment 2.1. The only differences are in the end customer demand process and response metrics that we track. The end customer demand process follows $N(50,20)$ for $t \in [0,349]$ and $N(100,20)$ for $t \in [350,750]$. Time $t = 350$ is when the demand shock is introduced and is called impulse time. Our objective is to measure various supply chain topologies' temporal response (time to recover from demand shock). To measure this temporal response to demand shock, we adapt the method proposed by Dominguez et al. (2014) as follows.

Each simulation run is split into 9 sections:

1. Warm-up period: $t \in [0,199]$
2. T0: $t \in [200,349]$
3. T1: $t \in [350,400]$
4. T2: $t \in [350,450]$
5. T3: $t \in [350,500]$
6. T4: $t \in [350,550]$
7. T5: $t \in [350,600]$
8. T6: $t \in [350,650]$
9. T7: $t \in [350,700]$

For each echelon $i \in \mathbb{N}$ in the 5 supply chain topologies that we simulate, we measure:

1. CFB_i for [T0-T7] and $t \in [350{,}700]$
2. CFB_i-slope for $t \in [350{,}700]$
3. BWE_i for [T0-T7] and $t \in [350{,}700]$
4. BWE_i-slope for $t \in [350{,}700]$

4.6 Numerical Results

4.6.1 Results of Experiment 1

For exposition, we present results for the Manufacturer in the serial supply chain. Results for the Retailer, Wholesaler, and Supplier are reported in Appendix D. We present the analysis of variance (ANOVA) output for the Manufacturer in Table 4-5, Table 4-6, and Table 4-7. In Table 4-5, the response variable is $varWC^{(i=Manufacturer,1)}$; in Table 4-6, it is $CFB^{(i=Manufacturer,1)}$; and in Table 4-7, it is $BWE^{(i=Manufacturer,1)}$.

Table 4-5 ANOVA results for variance of working capital at the manufacturer

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	3.49394E+18	5.54594E+16	68.55	0.000
Linear	8	2.38811E+18	2.98514E+17	368.99	0.000
A	3	8.17693E+15	2.72564E+15	3.37	0.018
B	3	1.33874E+16	4.46248E+15	5.52	0.001
C	1	9.74792E+17	9.74792E+17	1204.92	0.000
D	1	1.39176E+18	1.39176E+18	1720.32	0.000
2-Way Interactions	22	1.02359E+18	4.65270E+16	57.51	0.000
A*B	9	1.94695E+16	2.16327E+15	2.67	0.004
A*C	3	1.07692E+16	3.58974E+15	4.44	0.004
A*D	3	8.65069E+15	2.88356E+15	3.56	0.014
B*C	3	1.60412E+16	5.34706E+15	6.61	0.000

Source	DF	Adj SS	Adj MS	F-Value	p-Value
B*D	3	1.25627E+16	4.18756E+15	5.18	0.001
C*D	1	9.56101E+17	9.56101E+17	1181.82	0.000
3-Way Interactions	24	6.49946E+16	2.70811E+15	3.35	0.000
A*B*C	9	1.76015E+16	1.95572E+15	2.42	0.010
A*B*D	9	1.98083E+16	2.20092E+15	2.72	0.004
A*C*D	3	1.14583E+16	3.81945E+15	4.72	0.003
B*C*D	3	1.61265E+16	5.37550E+15	6.64	0.000
4-Way Interactions	9	1.72407E+16	1.91564E+15	2.37	0.012
A*B*C*D	9	1.72407E+16	1.91564E+15	2.37	0.012
Error	1856	1.50152E+18	8.09011E+14		
Total	1919	4.99547E+18			

Table 4-6 ANOVA results for CFB at the manufacturer

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	4.88998E+13	7.76187E+11	67.12	0.000
Linear	8	3.34118E+13	4.17648E+12	361.17	0.000
A	3	1.06181E+11	35393729426	3.06	0.027
B	3	1.81376E+11	60458586125	5.23	0.001
C	1	1.36935E+13	1.36935E+13	1184.16	0.000
D	1	1.94308E+13	1.94308E+13	1680.30	0.000
2-Way Interactions	22	1.43510E+13	6.52318E+11	56.41	0.000
A*B	9	2.68294E+11	29810416911	2.58	0.005
A*C	3	1.40693E+11	46897758389	4.06	0.005
A*D	3	1.13071E+11	37690225910	3.26	0.021
B*C	3	2.31043E+11	77014488705	6.66	0.000
B*D	3	1.69171E+11	56390291757	4.88	0.002

Source	DF	Adj SS	Adj MS	F-Value	p-Value
C*D	1	1.34287E+13	1.34287E+13	1161.27	0.000
3-Way Interactions	24	8.98777E+11	37449048877	3.24	0.000
A*B*C	9	2.42736E+11	26970705860	2.33	0.013
A*B*D	9	2.73482E+11	30386936324	2.63	0.005
A*C*D	3	1.50504E+11	50167879945	4.34	0.005
B*C*D	3	2.32055E+11	77351584521	6.69	0.000
4-Way Interactions	9	2.38153E+11	26461489728	2.29	0.015
A*B*C*D	9	2.38153E+11	26461489728	2.29	0.015
Error	1856	2.14625E+13	11563865288		
Total	1919	7.03623E+13			

Table 4-7 ANOVA results for BWE at the manufacturer

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	21085435	334689	1048.05	0.000
Linear	8	18964138	2370517	7423.08	0.000
A	3	2777701	925900	2899.38	0.000
B	3	752	251	0.78	0.502
C	1	16185412	16185412	50683.26	0.000
D	1	273	273	0.86	0.355
2-Way Interactions	22	2097476	95340	298.55	0.000
A*B	9	2316	257	0.81	0.611
A*C	3	2091883	697294	2183.52	0.000
A*D	3	198	66	0.21	0.892
B*C	3	422	141	0.44	0.724
B*D	3	2491	830	2.60	0.051
C*D	1	165	165	0.52	0.472

Source	DF	Adj SS	Adj MS	F-Value	p-Value
3-Way Interactions	24	14113	588	1.84	0.008
A*B*C	9	1917	213	0.67	0.739
A*B*D	9	9225	1025	3.21	0.001
A*C*D	3	258	86	0.27	0.848
B*C*D	3	2713	904	2.83	0.037
4-Way Interactions	9	9708	1079	3.38	0.000
A*B*C*D	9	9708	1079	3.38	0.000
Error	1856	592703	319		
Total	1919	21678138			

Impact of Stochastic Procurement Lead Times on $varWC^{(i,1)}$, $CFB^{(i,1)}$ and $BWE^{(i,1)}$

We find that level of procurement lead time variance has a statistically significant (p<0.005) impact on $varWC^{(i,1)}$ and $CFB^{(i,1)}$ for $i \in \{Retailer, Wholesaler\}$. Procurement lead time variation is found to have statistically significant impact on $BWE^{(i,1)}$ for $i \in \{Retailer, Wholesaler, Manufacturer, Supplier\}$. ANOVA outputs shown in Table 4-5, Table 4-6, and Tables D-1 to D-3 (in Appendix D) also suggest that the two-way interactions between procurement lead time variance and payment lead time variance has a statistically significant effect on $varWC^{(i,1)}$ for $i \in \{Retailer, Wholesaler, Manufacturer, Supplier\}$.

The 2-way interaction between procurement lead time variance and information sharing is found to have a statistically significant effect on $varWC^{(i,1)}$ and $CFB^{(i,1)}$ for $i \in \{Wholesaler, Manufacturer, Supplier\}$, and $BWE^{(i,1)}$ for $i \in \{Retailer,$

$Wholesaler,\ Manufacturer,\ Supplier\}$. The impact of this interaction is substantial, especially at the upper echelons. For example, when L c.v. = 0.25 and demand information is not shared, the mean $CFB^{(i=Manufacturer,1)}$ is 204268.2 but when demand information is shared ceteris paribus the mean $CFB^{(i=Manufacturer,1)}$ is only 18588.3, a reduction of 91%. The mean $BWE^{(i=Manufacturer,1)}$ when L c.v. = 0.25 and demand information is not shared is 150.2, but when L c.v. = 0.25 and demand information is shared, it is only 20.3, a reduction of 86%.

We observe that when demand information is shared and exponential smoothing is used to forecast cash-flows, the $CFB^{(i,1)}$ and $BWE^{(i,1)}$ experienced by the echelons increases as the c.v. of procurement lead time increases. This effect for the Manufacturer is illustrated in Figure 4-2 and Figure 4-3. For example, as the c.v. of procurement lead time increases from 0 to 0.25 to 0.50 to 0.75, the mean $CFB^{(i=Manufacturer,1)}$ increases from 1748.7 to 1802.6 to 2018.8 to 2371.3. Similarly, as the c.v. of procurement lead time increases from 0 to 0.25 to 0.50 to 0.75, the mean $BWE^{(i=Manufacturer,1)}$ increases from 20.0 to 20.4 to 24.85 to 32.7.

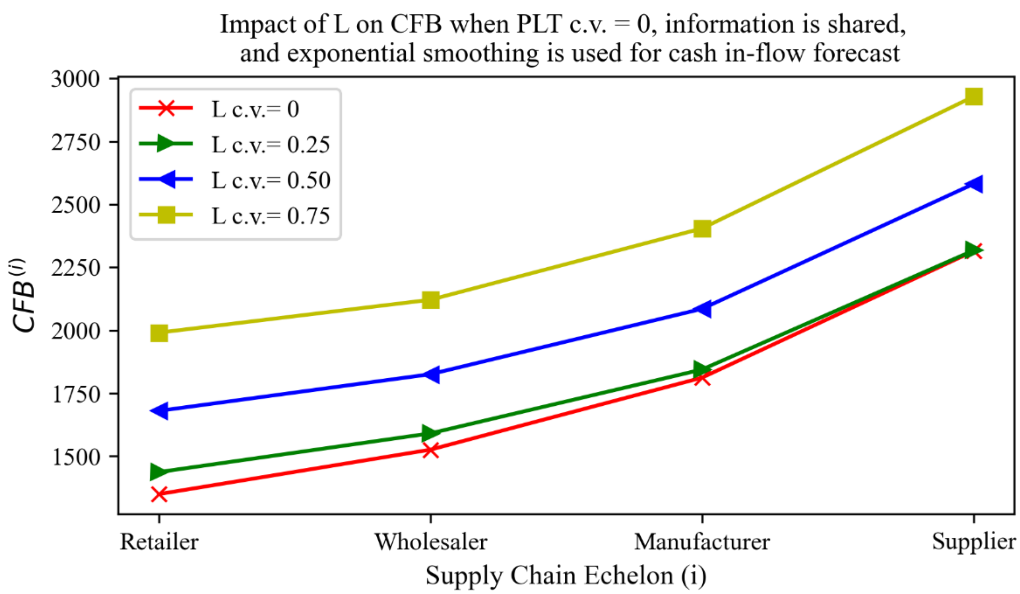

Figure 4-2 Impact of procurement lead time on CFB

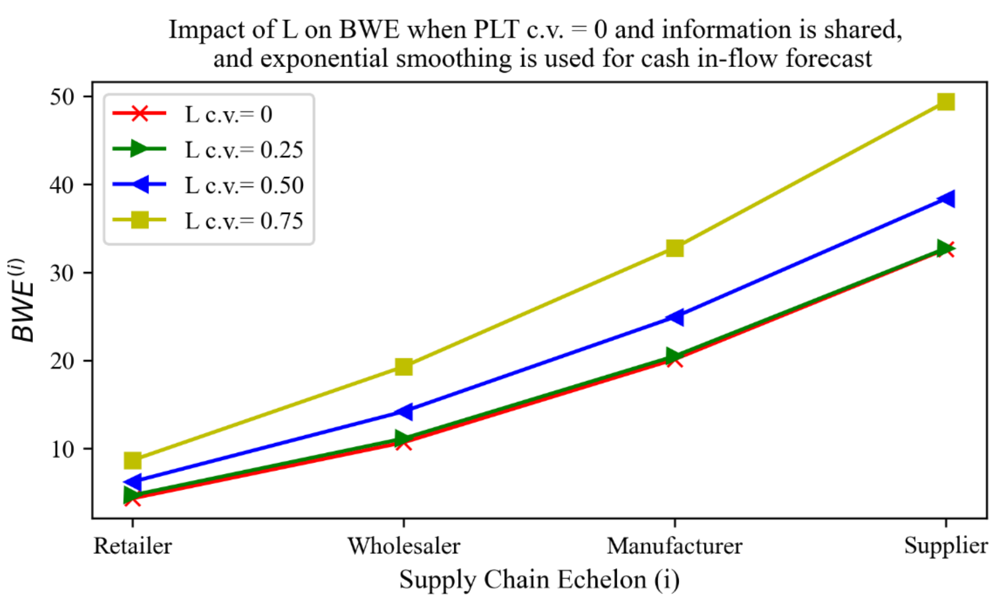

Figure 4-3 Impact of procurement lead time on BWE

Impact of Stochastic Payment Lead Times on $varWC^{(i,1)}$, $CFB^{(i,1)}$ and $BWE^{(i,1)}$

We find that level of payment lead time variance has a statistically significant (p<0.005) impact on $varWC^{(i,1)}$ and $CFB^{(i,1)}$ for $i \in \{Retailer, Wholesaler, Manufacturer, Supplier\}$. The lack of statistically significant effect of level of payment lead time variation on $BWE^{(i,1)}$ is justified by the fact that the simulation logic presented in Section 4.3 does not define any kind of relationship between payment lead time (PLT) and order quantity (O). PLT and O are independent of each other, and therefore, so are PLT and $BWE^{(i,1)}$.

The two-way interactions between: (i) payment lead time variance and procurement lead time variance, (ii) payment lead time and cash-flow forecasting algorithm have a statistically significant impact on $varWC^{(i,1)}$ and $CFB^{(i,1)}$ for $i \in \{Retailer, Wholesaler, Manufacturer, Supplier\}$. When PLT c.v. = 0.25 and demand information is not shared, the mean $CFB^{(i=Manufacturer,1)}$ is 202334.7 but when demand information is shared ceteris paribus the mean $CFB^{(i=Manufacturer,1)}$ is only 33095.1, a reduction of 74%.

The three-way interaction between payment lead time, information sharing, and cash-flow forecasting algorithm has a statistically significant effect on $varWC^{(i,1)}$ and $CFB^{(i,1)}$ for $i \in \{Manufacturer, Supplier\}$. That is, the interaction between these three factors has a significant effect only on the variance of WC and CFB experienced by echelons higher upstream in the serial supply chain.

In Figure 4-4, we observe that when L c.v. = 0, information is shared and exponential smoothing cash-flow forecasting algorithm is used the mean $CFB^{(i,1)}$ experienced by any given stage of the serial supply chain is larger than the $CFB^{(i,1)}$ experienced by entities that are downstream to it. Unlike the phenomenon observed in Figure 4-2, rise in PLT c.v. for a given echelon i does not always result in a rise in $CFB^{(i,1)}$. For example, the average $CFB^{(i=Manufacturer,1)}$ values in Figure 4-4 for PLT c.v. = 0.25, 0.50, and 0.75 are 3608.0, 3929.1, and 3701.1, respectively. We see that the $CFB^{(i=Manufacturer,1)}$ for PLT c.v = 0.75 is smaller than that observed for PLT c.v. = 0.50. Recall that the PLT process is assumed to follow gamma distribution. As PLT c.v. increases, the skewness of PLT increases. For PLT c.v. = 0.00, 0.25, 0.50, and 0.75, the skewness measures of PLT are 0.00, 0.48, 1.07, and 1.55, respectively. That is, as PLT c.v. increases, the PLT process gets increasingly more skewed to the right and therefore has a larger density of PLT values closer to 0 than PLT processes that have smaller c.v. values. The larger density of smaller PLT values in PLT processes with high c.v. contribute towards reducing the CFB, while the large variation caused by high c.v. contributes towards increasing CFB. The combination of these 2 opposing effects results in the type of behavior seen in Figure 4-4.

Figure 4-5 shows that payment lead time variance has no effect on $BWE^{(i,1)}$ for $i \in \{Retailer,\ Wholesaler,\ Manufacturer,\ Supplier\}$.

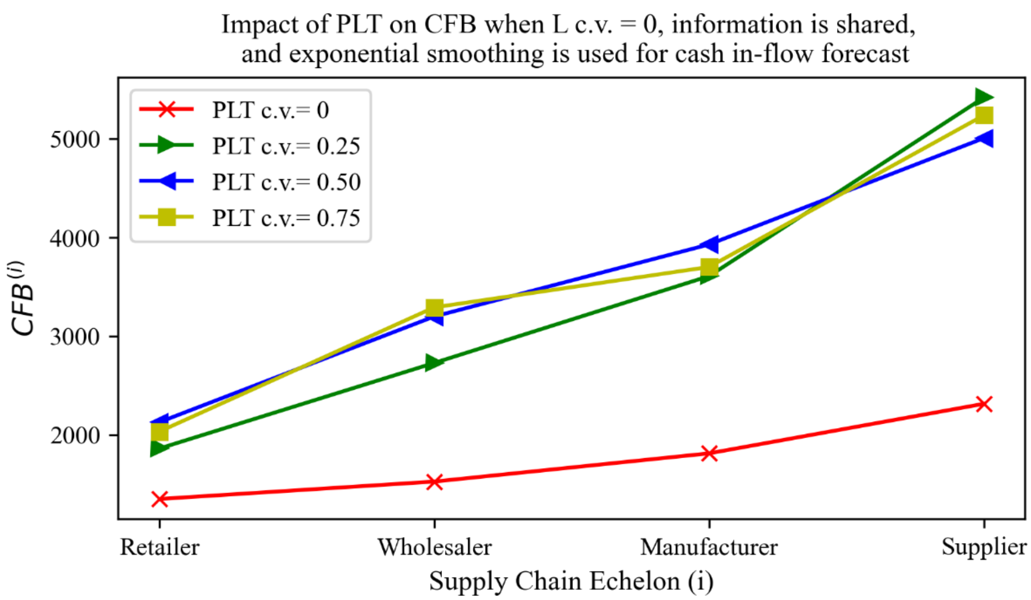

Figure 4-4 Impact of payment lead time on CFB

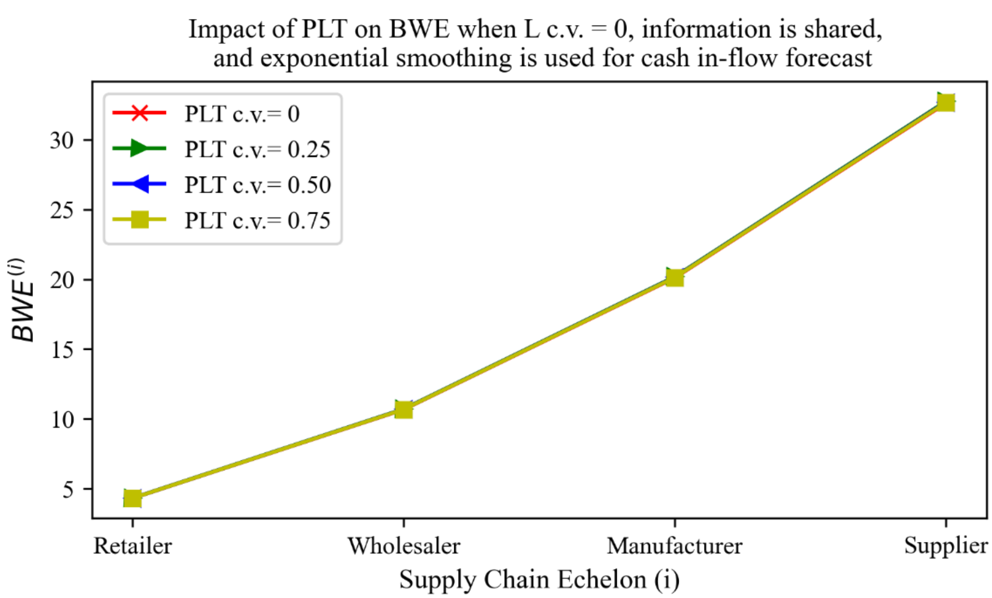

Figure 4-5 Impact of procurement lead time on BWE

Impact of Information Sharing on $varWC^{(i,1)}$, $CFB^{(i,1)}$ and $BWE^{(i,1)}$

We find that sharing demand information with all echelons of the supply chain does not eliminate $varWC^{(i,1)}$, $CFB^{(i,1)}$ and $BWE^{(i,1)}$ for i = Retailer, Wholesaler, Manufacturer, and Supplier. However, we do find that information sharing reduces the $varWC^{(i,1)}$, $CFB^{(i,1)}$ and $BWE^{(i,1)}$ of especially the upstream echelons of the serial supply chain. The same is illustrated in Figure 4-6 and Figure 4-7. Based on the ANOVA outputs listed in Table 4-5, Table 4-6, Table 4-7, and Tables D-1 to D-9 (in Appendix D), we find that information sharing has a statistically significant impact on $varWC^{(i,1)}$, $CFB^{(i,1)}$ and $BWE^{(i,1)}$ for all echelons save the Retailer. The exception of Retailer is expected because the information sharing only affects the lead time demand forecasts of echelons upstream of Retailer. The Retailer has access to the customer demand information whether it is shared or not.

We see that the mean $CFB^{(i=Wholesaler,1)}$ and $BWE^{(i=Wholesaler,1)}$ when information is not shared are 54183.6 and 34.5, respectively. When information is shared, these numbers drop to 16074.6 and 13.7, an improvement of 70% and 60%, respectively.

We find that the two-way interaction between information sharing and cash-flow forecasting algorithm has a statistically significant effect on $varWC^{(i,1)}$ and $CFB^{(i,1)}$ for $i =$ Wholesaler, Manufacturer, and Supplier. When demand information is not shared and SFA cash-flow forecasting algorithm is used, the mean $CFB^{(i=Manufacturer,1)}$ is 372973.3 but when demand information is shared ceteris paribus the mean $CFB^{(i=Manufacturer,1)}$ is only 36809.0, a reduction of 90%. When demand information is not shared and exponential smoothing cash-flow forecasting algorithm is used, the mean $CFB^{(i=Manufacturer,1)}$ is 4513.0 but when demand information is shared ceteris paribus the mean $CFB^{(i=Manufacturer,1)}$ is 2872.3, a reduction of 36%.

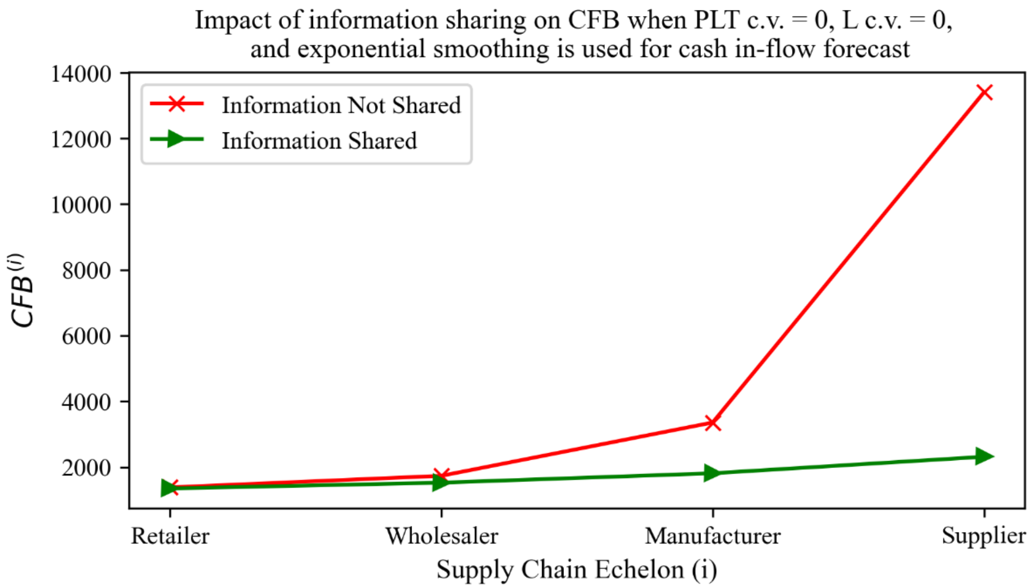

Figure 4-6 Impact of information sharing on CFB

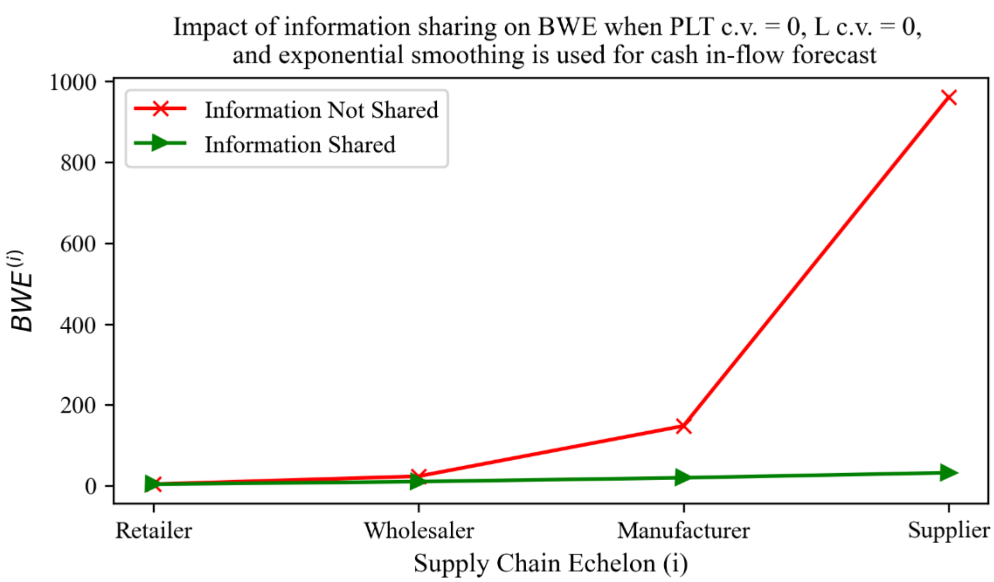

Figure 4-7 Impact of information sharing on BWE

Impact of Cash-flow Forecasting Algorithm on $varWC^{(i,1)}$, $CFB^{(i,1)}$ and $BWE^{(i,1)}$

ANOVA outputs in Table 4-5, Table 4-6, and Tables D-1 to D-3 (in Appendix D) show that cash-flow forecasting algorithm type has a statistically significant effect on $varWC^{(i,1)}$ and $CFB^{(i,1)}$ i = Retailer, Wholesaler, Manufacturer, and Supplier.

Figure 4-8 illustrates a comparison between the exponential smoothing algorithm, SFA (1-Month), SFA (1-Week), and SFA (1-Day) algorithms for cash-flow forecasting when PLT c.v. = 0, L c.v. = 0, and demand information is shared. As discussed earlier, SFA (1-Month) corresponds to the policy of using SFA at the end of each month. SFA (1-Week) and SFA (1-Day) correspond to the policies of running SFA at the end of each week and the end each day, respectively. Note that SFA (1-Week) and SFA (1-Day) are not included in the designed experiment as levels of the factor “Cash-flow forecasting algorithm”.

We see that for all echelons $i =$ Retailer, Wholesaler, Manufacturer, and Supplier, SFA policies result in higher $CFB^{(i,1)}$compared to exponential smoothing. This observation holds for all combinations of various levels of the factors: L, PLT, and information sharing. Figure 4-9 shows the average forecast error (%) of the various forecasting methods at various echelons. We see that exponential smoothing has the lowest absolute average forecast error percentage across all echelons of the serial supply chain. The higher forecast accuracy of exponential smoothing compared to SFA policies results in lower CFB for all echelons.

The choice of cash-flow forecasting algorithm has no statistically effect on $BWE^{(i,1)}$. This is expected because the simulation logic presented in Section 4.3 does not relate cash-flow forecasts and cash level with material order quantity. The lack of any kind of effect of the choice of cash-flow forecasting algorithm on $BWE^{(i,1)}$ is illustrated in Figure 4-10.

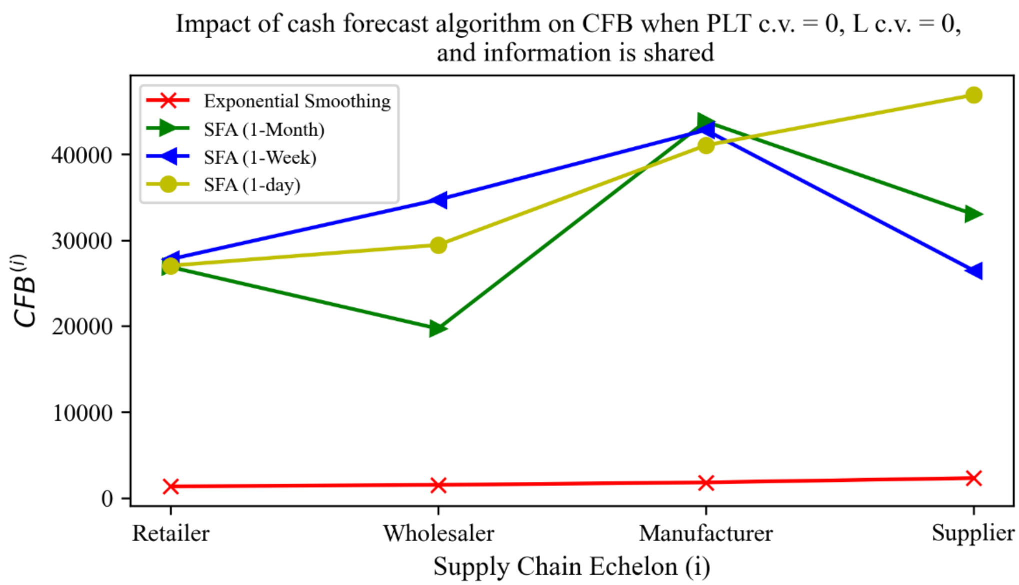

Figure 4-8 Impact of cash-flow forecasting algorithm on CFB

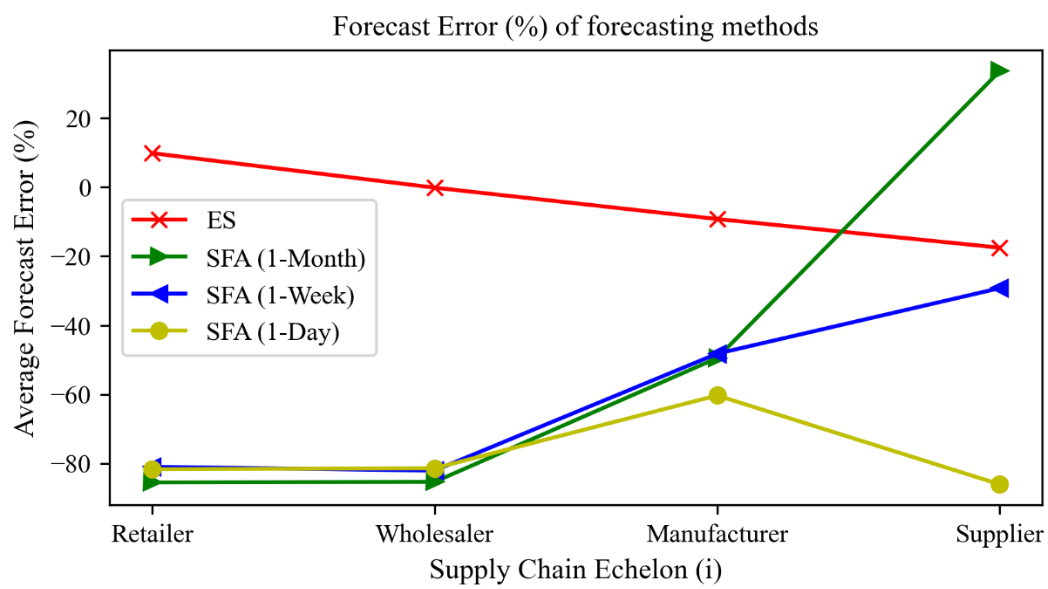

Figure 4-9 Average forecast error percentage of various cash-flow forecasting methods at various echelons

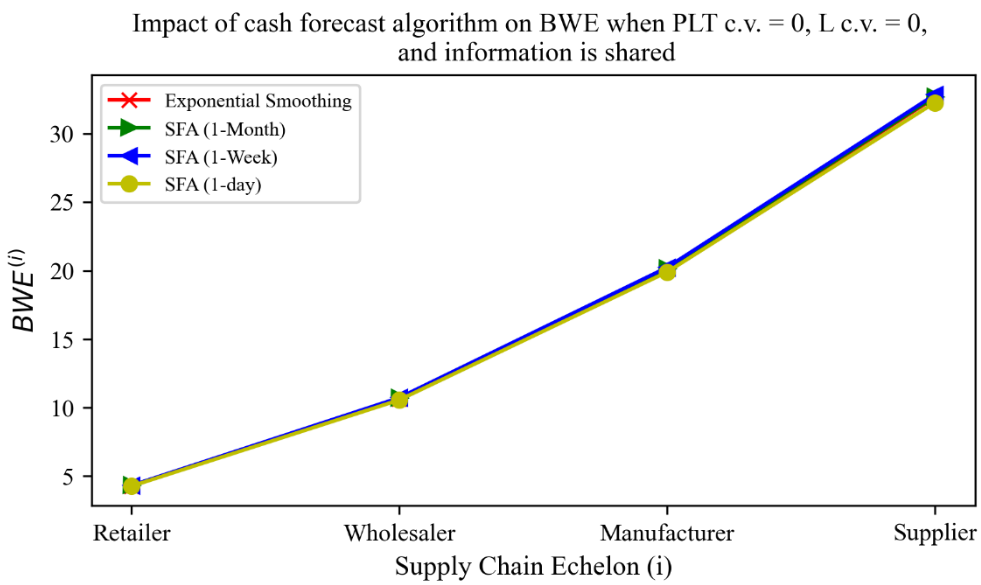

Figure 4-10 Impact of cash-flow forecasting algorithm on BWE

4.6.2 Results of Experiment 2

Table 4-8, Table 4-9, and Figure 4-11 report the CFB_i, CFB_i-slope, BWE_i, and BWE_i-slope measured in Experiments 2.1 and 2.2. Under the variance lens $CFB_{i=Retailer}$ of all topologies are comparable to each other. The CFB_i of the topologies start diverging from Wholesaler onwards. Among the 5 topologies, the convergent supply chain has the lowest CFB_i for all 4 echelons. In the convergent supply chain, there is just one entity in the Retailer echelon. This one entity splits its order (O) and payments (P) between 2 entities upstream in the Wholesaler echelon. These 2 Wholesalers split their O and P among 4 entities upstream in the Manufacturer echelon, which in turn split their O and P among 8 entities in the Supplier echelon. Essentially, each echelon of a convergent supply chain experiences the same CFB_i as their immediate downstream echelon does. This is seen in Figure 4-11, where the line representing the CFB_i of the convergent supply chain is almost flat.

The second smallest CFB_i values are experienced by the general and the serial supply chains. The con-div and divergent supply chains experience the highest cash-flow bullwhip effect. For echelons $i =$ Retailer, Wholesaler, and Manufacturer the CFB_i experienced by con-div and divergent supply chains are comparable. But for $i =$ Supplier, CFB_i experienced by con-div supply chain is significantly smaller than that by the divergent supply chain. $CFB_{i=Supplier}$ of the con-div supply chain is smaller than that of the divergent supply chain because, in the con-div supply chain, the supply chain structure between the Manufacturer and Supplier echelons is convergent.

In the divergent supply chain, the Supplier echelon has to deal with variations in demand and cash coming from 8 customer markets at the end of the supply chain. Whereas in the convergent supply chain, the Supplier echelon has to deal with demand and cash coming from only 1 customer market. Since the echelons of the divergent supply chain have to deal with variations coming from more customer markets, they experience a larger CFB_i and BWE_i compared to supply chains that have to deal with lesser customer markets.

As seen in Figure 4-11, the observations made above hold under the shock lens too. The only difference is that under the shock lens, CFB_i for $i =$ Retailer, Wholesaler, Manufacturer, and Supplier experienced by each supply chain topology is higher than what it does under the variance lens. The bad performance of the divergent supply chain under the variance and shock lens is well summarized by its CFB_i-slope which are 367.61% and 653.38% higher than the convergent supply chain's CFB_i-slope.

Under the variance lens, the $BWE_{i=Retailer}$, $BWE_{i=Wholesaler}$, $BWE_{i=Manufacturer}$ and $BWE_{i=Supplier}$ of all topologies are statistically not very different, being the highest for divergent supply chain and the lowest for the general supply chain. However, under the shock lens $BWE_{i=Manufacturer}$ and $BWE_{i=Supplier}$ of the topologies are statistically different. On average, the lowest BWE_i is experienced by the convergent supply chain, and the divergent supply chain experiences the highest. The bad performance of the divergent supply chain under the shock lens is well summarized by its BWE_i-slope which is 58.34% higher than convergent supply chain's BWE_i-slope.

Table 4-8 CFB and CFB-slope in topologies under the variance and shock lenses

Lens	Topology	CFB_i				CFB_i-slope
		Retailer	Wholesaler	Manufacturer	Supplier	
Variance	Serial	12.13 ± 0.5553	14.249 ± 0.6571	17.775 ± 0.9679	22.581 ± 1.0112	36.856 ± 1.4796
	Divergent	12.032 ± 0.4597	22.679 ± 0.9068	44.785 ± 1.7025	86.017 ± 4.2606	107.163 ± 3.9635
	Convergent	12.088 ± 0.6101	10.177 ± 0.381	10.399 ± 0.3542	12.736 ± 0.4152	22.917 ± 0.6586
	Con-Div	11.554 ± 0.3607	13.817 ± 0.5958	17.141 ± 0.6915	21.097 ± 0.9635	48.971 ± 1.8893
	General	11.59 ± 0.4453	22.066 ± 1.1688	42.881 ± 1.8915	34.596 ± 1.7106	35.000 ± 1.1265
Shock	Serial	36.258 ± 1.5235	41.721 ± 1.9429	47.938 ± 1.8700	58.393 ± 2.265	99.417 ± 3.0447
	Divergent	35.995 ± 1.4465	70.029 ± 2.401	148.469 ± 7.6502	298.396 ± 11.3893	363.009 ± 12.2527
	Convergent	35.372 ± 1.9548	23.223 ± 0.9169	21.100 ± 1.1267	23.95 ± 1.2223	48.184 ± 2.0185
	Con-Div	33.725 ± 2.0497	43.234 ± 2.5501	47.296 ± 2.3343	57.573 ± 3.1474	152.79 ± 6.6286
	General	36.346 ± 1.9241	73.081 ± 3.3175	152.995 ± 9.5225	104.49 ± 5.4243	98.475 ± 4.3912

Table 4-9 BWE and BWE-slope in topologies under the variance and shock lenses

Lens	Topology	BWE_i				BWE_i-slope
		Retailer	Wholesaler	Manufacturer	Supplier	
Variance	Serial	1.326 ± 0.0194	1.854 ± 0.0503	2.760 ± 0.1051	4.318 ± 0.2160	6.117 ± 0.2555
	Divergent	1.310 ± 0.0152	1.863 ± 0.0340	2.847 ± 0.0905	4.584 ± 0.1961	6.383 ± 0.2145
	Convergent	1.314 ± 0.0225	1.796 ± 0.0491	2.628 ± 0.0999	4.064 ± 0.1932	5.809 ± 0.2360
	Con-Div	1.290 ± 0.0188	1.758 ± 0.0408	2.520 ± 0.0793	3.796 ± 0.1268	6.284 ± 0.2725
	General	1.304 ± 0.0193	1.847 ± 0.0453	2.780 ± 0.0936	4.213 ± 0.1781	5.510 ± 0.1657
Shock	Serial	1.505 ± 0.0381	2.280 ± 0.0681	3.444 ± 0.1307	5.413 ± 0.2536	7.610 ± 0.3050
	Divergent	1.525 ± 0.0357	2.535 ± 0.0842	4.462 ± 0.1989	8.474 ± 0.3684	10.775 ± 0.4200
	Convergent	1.506 ± 0.0322	2.138 ± 0.0558	3.119 ± 0.0940	4.722 ± 0.1643	6.805 ± 0.2100
	Con-Div	1.479 ± 0.0350	2.260 ± 0.0605	3.442 ± 0.1292	5.410 ± 0.2261	10.387 ± 0.5006
	General	1.509 ± 0.0416	2.551 ± 0.0856	4.528 ± 0.1722	7.093 ± 0.3369	7.594 ± 0.2767

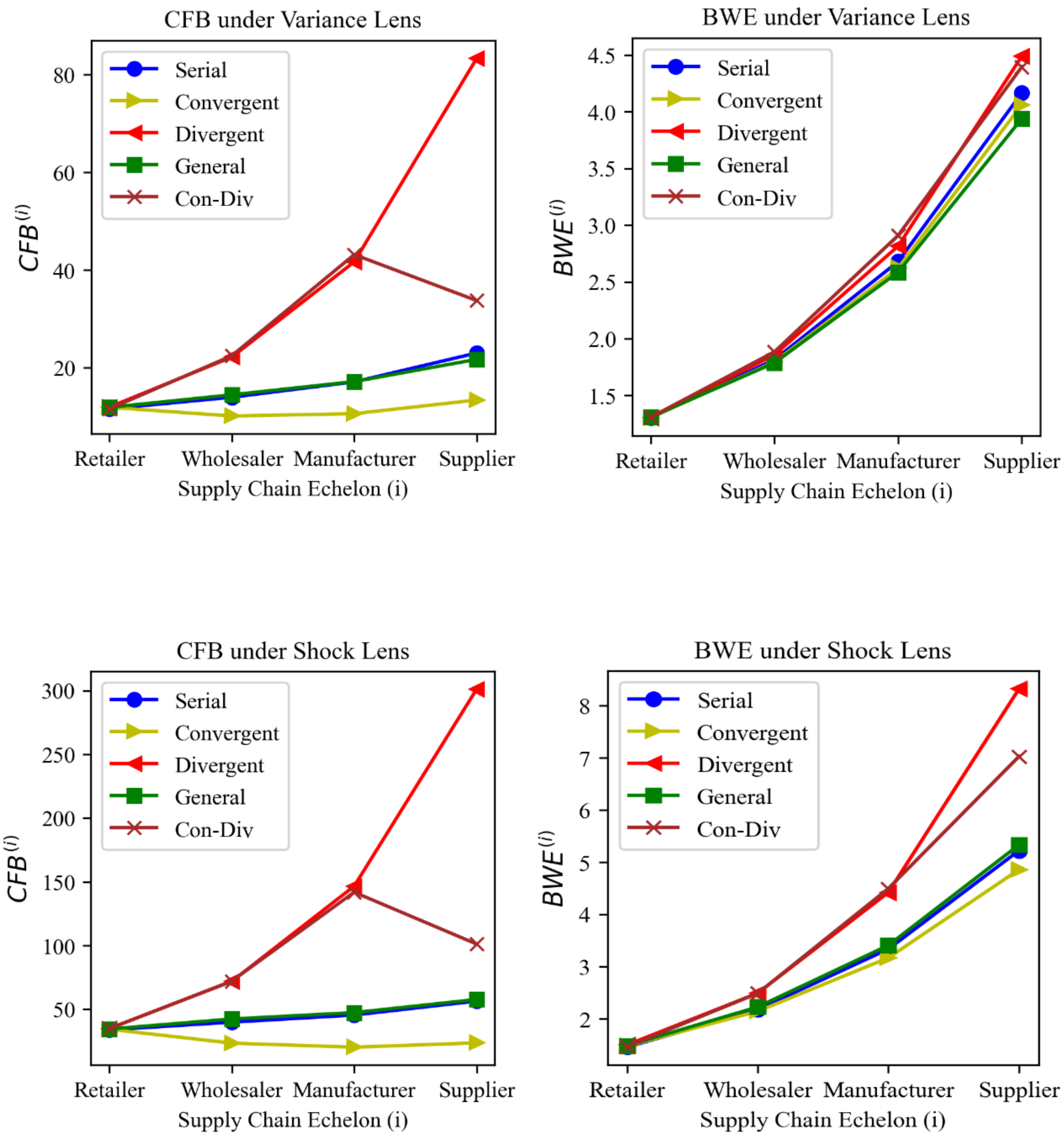

Figure 4-11 CFB and BWE in topologies under the variance and shock lenses

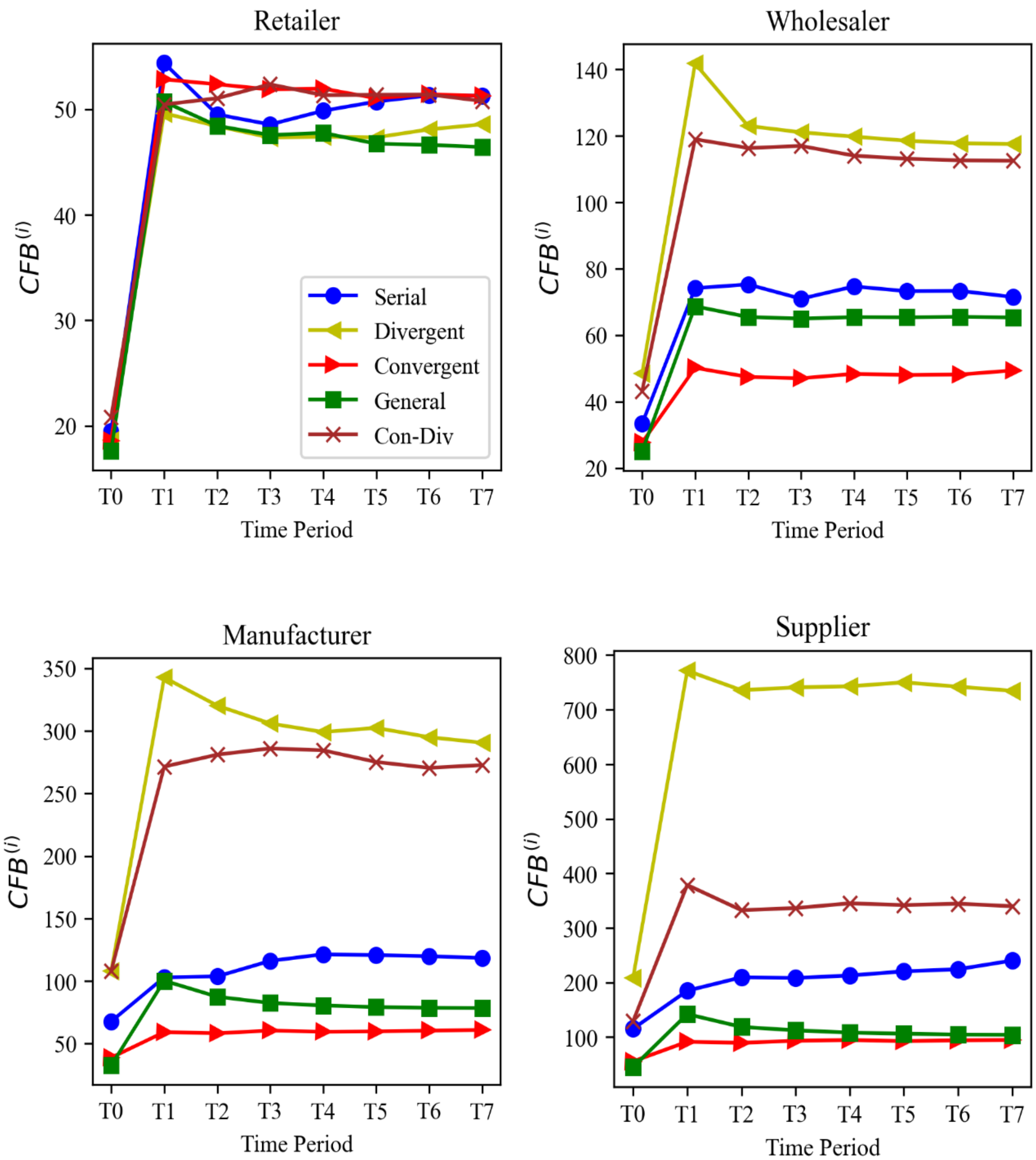

Figure 4-12 CFB in topologies over various time periods

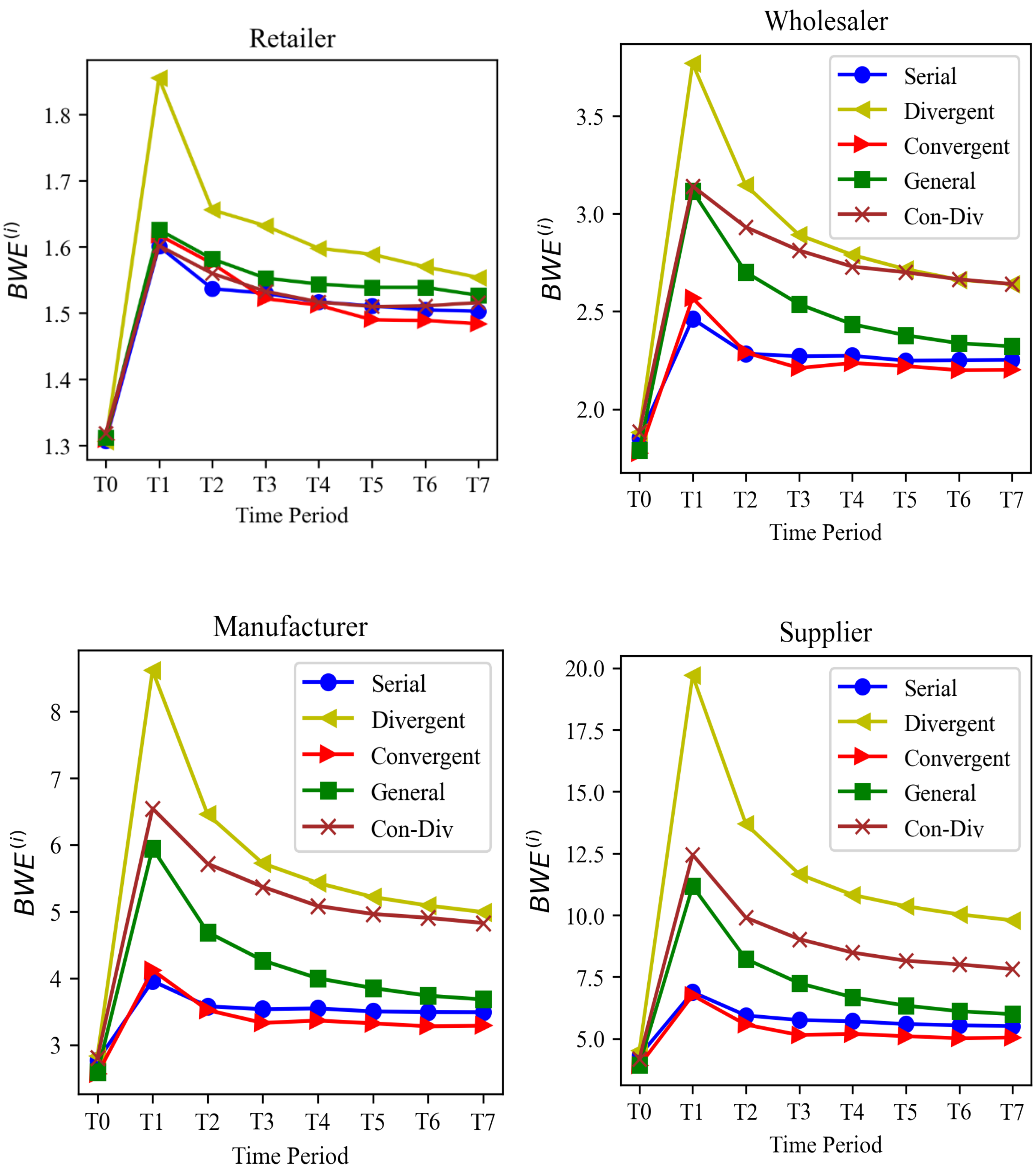

Figure 4-13 BWE in topologies over various time periods

Figure 4-12 and Figure 4-13 show the evolution of CFB_i and BWE_i over time for each echelon in the 5 supply chain topologies. We observe that:

1. Under an unexpected demand shock, entities across all supply chain topologies react by immediately increasing their order quantity to meet the sudden rise in

demand and then gradually reduce the variation of order quantity over time. Sudden rise in order quantity at the impulse time increases the CFB_i and BWE_i of entities across all supply chain topologies.

2. Like the variance lens, under the shock lens too the convergent supply chain experiences the smallest CFB_i for i = Wholesaler, Manufacturer, and Supplier echelons over periods T1-T7. The divergent supply chain experiences the largest CFB_i for all echelons over periods T1-T7.
3. Save the convergent supply chain, the CFB_i of all other topologies increases as we move upstream. For example, in the divergent supply chain in period T1, $CFB_{i=Retailer} = 54.36$, $CFB_{i=wholesaler} = 98.25$, $CFB_{i=manufacturer} = 285.02$, and $CFB_{i=supplier} = 456.00$.
4. For entities across all topologies, BWE_i is maximum during period T1. BWE_i at T1 experienced by each supply chain topology increases as we move upstream in the topology. For example, in the divergent supply chain in period T1, $BWE_{i=Retailer} = 1.44$, $BWE_{i=wholesaler} = 3.32$, $BWE_{i=manufacturer} = 9.09$, and $BWE_{i=supplier} = 19.85$.
5. Among the 5 topologies, the divergent supply chain has the highest BWE_i for i = Retailer, Wholesaler, Manufacturer, and Supplier over periods T1-T7.
6. Over time, the BWE_i starts receding as echelons adopt a new order process to meet the new customer demand process, $N(100,20)$. However, the same cannot be said about CFB_i. CFB_i for periods T1-T7 does not show a clear downward trend in most cases. For example, $CFB_{i=Wholesaler}$ in the general supply chain

is the maximum in period T3, $CFB_{i=Manufacturer}$ in the serial supply chain is the maximum in period T7.

4.7 Conclusions

Literature review reveals that much research has not been done on the phenomena of cash-flow bullwhip in supply chains. Of the limited open literature on the topic, only 2 papers (Badakhshan et al. 2020, Goodarzi et al. 2017) employ simulation methodology to study cash-flow bullwhip in supply chains. These 2 papers use Tangsucheeva and Prabhu's (2013) definition of cash-flow bullwhip, which, as seen in Chapter 2, does not reveal if a certain supply chain entity amplifies or attenuates material and financial flow variations. Our chapter proposes a simulation framework of studying cash-flow bullwhip and the traditional bullwhip in 5 different supply chain topologies under the variance lens and shock lens.

In Experiment 1, we posed the following questions about cash-flow bullwhip in a serial supply chain:

1. How do stochastic procurement and payment lead times affect cash-flow bullwhip?
2. How does customer demand information sharing affect cash-flow bullwhip?
3. How does the choice of cash-flow forecasting algorithm affect cash-flow bullwhip?

The results indicate that the procurement lead time variance has a statistically significant effect on the cash-flow bullwhip experienced by the serial supply chain. The larger the variance of procurement lead time, the larger is the cash-flow bullwhip experienced by the serial supply chain. We find that payment lead variance has a statistically significant effect on the cash-flow bullwhip. We also find that demand information sharing reduces the cash-flow bullwhip experienced, especially by the upstream entities; and the use of SFA to forecast cash-flows increases the CFB experienced by the serial supply chain.

In Experiment 2, we posed the following questions:

1. How different are the magnitudes of CFB_i and BWE_i in the 5 supply chain topologies?
2. How long do various supply chain topologies take to recover from a demand shock?

The results indicate that under the variance lens, the CFB_i experienced by the convergent supply chain, on average, is the smallest among the 5 topologies. CFB_i experienced by the serial and general supply chains are statistically similar. On average, the divergent supply chain experiences the largest CFB_i. The BWE_i experienced by the 5 supply chains under the variance lens are statistically very similar. Under the shock lens, the divergent supply chain experiences the largest CFB_i and BWE_i.

In the future, this research can be expanded in various directions. First, explore how customer demand processes other than the normal distribution affect CFB_i and BWE_i of various supply chain topologies. Second, perform simulation experiments to study the effects of β (cash control aggressivity measure) and γ (cash surplus investment strategy) on CFB_i. In this chapter, β and γ were held constant at 0.5 and 0.99, respectively. Third, use a simulation-based optimization approach to determine strategies for reducing CFB_i in various supply chain topologies.

Chapter 5 CONCLUSIONS AND FUTURE DIRECTIONS

This chapter concludes the findings of this dissertation and provides directions for future research.

Chapter 2 proposes a new metric to quantify the cash-flow bullwhip effect experienced by supply chain entities. Unlike Tangsucheeva and Prabhu's (2013) cash-flow bullwhip metric, the new metric can identify if a certain entity is amplifying or attenuating the material and financial flow distortions it is experiencing. An analytical model to study the cash-flow bullwhip (using the new metric) in a serial supply chain is proposed in Chapter 2. The analytical model assumes that the customer demand is an order-1 autoregressive process; all entities use a mean-squared error optimal forecasting policy and follow the order up-to inventory policy. We show that cash-flow bullwhip experienced by every entity of a serial supply chain is related to the entity's echelon (position in the supply chain), procurement lead time, payment lead time it experiences from its customers, and payment lead time it implements on suppliers.

We find that in the absence of procurement and payment lead times, i.e. when the lead times are zero, the cash-flow bullwhip experienced by every echelon of the serial supply chain is zero. For non-zero values of lead times, the cash-flow bullwhip experienced by entities in a serial supply chain can be determined using Equations 2.24 and 2.25. Numerical studies on the effect of: (i) not sharing customer demand information, and (ii) payment batching on cash-flow bullwhip are also performed. We find that demand information sharing reduces the cash-flow bullwhip experienced by supply chain entities under a wide range of demand autocorrelation values. We also find that mimicking customer's payment policy reduces the cash-flow bullwhip experienced by an entity.

The findings of Chapter 2 are qualified because of the following limitations: (i) real-world supply chains do not necessarily have a serial structure, (ii) customer demand cannot always be modeled as an AR(1) process, (iii) supply chain echelons do not always employ order up-to level inventory policy, and (iv) supply chain echelons tend to make payments in batches.

Chapter 3 presents an empirical investigation of the cash-flow bullwhip effect in U.S. supply chains and identifies its drivers. Specifically, we use financial data from 2010-2019 of 782 U.S. public companies spread across 100 different industries. We find that 31% of the retailing, 25% of wholesaling, and 80% of the manufacturing firms in our sample experience cash-flow bullwhip greater than 1. We also measure the inventory bullwhip effect (IBE) and the payment bullwhip effect (PBE) along with the cash-flow bullwhip effect.

Regression analysis to study the effect of company-level attributes on bullwhip effects reveals that: (i) larger firms experience smaller CFB, IBE, and PBE; (ii) firms with conservative payment policy experience smaller BWE, CFB, IBE, and PBE; (iii) firms with high liquidity ratio have smaller CFB, (iv) predictability in demand seasonality is associated with smaller CFB and BWE, (v) high lead time is associated with larger CFB and BWE, and (vi) higher demand autocorrelation is associated with larger BWE, CFB, IBE, and PBE. We find that among all variables in the study, lead time has the most considerable impact on a firm's CFB.

Finally, we study the bullwhip effects in the automotive supply chain (ASC). We find that CFB in ASC is associated with the following company-level attributes: supply chain stage, payment policy parameter, seasonality ratio, and procurement and payment lead times. We observe that automotive OEMs, on average, experience the least CFB, BWE, and IBE in the ASC. We hypothesize that this could be due to the following reasons: (i) the size of OEMs allows them to take advantage of economies of scale to reduce production and purchase variations, and (ii) OEMs use their clout to push supply chain uncertainties on to tier 1 suppliers and automobile dealers.

The limitations of the analysis presented in Chapter 3 are as follows. First, using financial data from a small (compared to the entire U.S. economy) set of public companies is potentially subject to flaws like size and survivorship biases. Secondly, we use imperfect proxies for demand, demand seasonality, and lead times.

Chapter 4 proposes a simulation framework of studying the cash-flow bullwhip effect in supply chains of 5 topologies, viz, serial, divergent, convergent, con-div, and general. The analysis in Chapter 4 is split into 2 sections.

In the first section, we perform a designed experiment to study the effect level of variance of stochastic procurement lead time, level of variance of stochastic payment lead time, demand information sharing, and the choice of cash-flow forecasting algorithm on the cash-flow bullwhip experienced by various echelons of the serial supply chain. We find that procurement lead time variance, payment lead variance, demand information sharing, and the choice of cash-flow forecasting algorithm have a statistically significant effect on the cash-flow bullwhip. Several two-way and three-way interactions of the above-mentioned factors also have a statistically significant effect on the CFB experienced by the echelons of the serial supply chain.

The second section studies the cash-flow bullwhip effect in 5 supply chain topologies under the variance and shock lenses. The variance lens allows us to study the propagation of cash-flow bullwhip when the customer demand is a stationary process. The shock lens allows us to study cash-flow bullwhip when there is a sudden rise in customer demand.

Results indicate that under the variance lens, the CFB experienced by the convergent supply chain, on average, is the smallest among the 5 topologies. CFBs experienced by the serial and general supply chains are statistically similar. On average, the divergent supply chain experiences the largest CFB. The BWE experienced by the 5 supply chains under the variance lens are statistically very similar. Under the shock lens, the divergent supply chain experiences the largest CFB and BWE, and the convergent supply chain experiences the least. Temporal analysis reveals that demand impulse suddenly increases the BWE and CFB experienced by all topologies. However, over time, BWE starts reducing as supply chain entities smooth their order quantities to meet the new demand process. CFB, however, does not necessarily decrease as time passes after the demand shock.

The work presented in Chapters 3-5 offers several fruitful directions for future research. The analytical framework presented in Chapter 3 can be generalized in the following directions in the future. First, characterize CFB for supply chain topologies that are more complex than the serial supply chain. Some topologies that could be explored in the future are convergent, divergent, con-div, general topologies. Second, it would be interesting to see what happens to CFB when the customer demand process has a more general specification like an autoregressive-moving-average model with p autoregressive terms and q moving-average terms, $ARMA(p, q)$. Third, characterize CFB for supply chain echelons that use more general inventory replenishment policies like the (s,S) policy. Fourth, build an analytical model to study the effect of payment batching on CFB.

In the future, empirical research on CFB presented in Chapter 4 can be extended to include privately-owned companies. Including a reasonably large number of privately-owned companies in the sample will remove the size and survivorship bias associated with the sample used in Chapter 4. In work presented in Chapter 4, we use the cost of goods sold (COGS) to proxy demand. In the future, the use of actual demand data series to calculate the CFB experienced by companies should be considered. Attention should be turned towards probing data from linear supply chains (FMCG, Apparel supply chains, etc.) to understand the phenomenon of CFB better.

The research presented in Chapter 4 can be expanded in the following directions in the future. First, explore how more general customer demand processes like $ARMA(p,q)$ affect CFB and BWE of various supply chain topologies. Second, perform simulation experiments to study the effects of β (cash control aggressivity measure) and γ (cash surplus investment strategy) on CFB. Third, use a simulation-based optimization approach to determine strategies for reducing CFB in various supply chain topologies.

Appendix A. CFB FORMULA FOR ECHELON 1

$$WC_t^{(1)} = Cash_t^{(1)} + Invt_t^{(1)} + AR_t^{(1)} - AP_t^{(1)} \tag{A1}$$

Now using Equations (2.17) and (2.19-2.21), we can rewrite Equation (A1) as follows:

$$\begin{aligned} WC_t^{(1)} = Cash_t^{(1)} + c_2 I_{int}^{(1)} + \ c_2\left[d_{t-L_1}\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right) - \sum_{i=0}^{L_1-1} d_{t-i}\right] \\ + c_1\left(\sum_{i=1}^{P_1} d_{t-i}\right) - c_2\left(\sum_{i=1}^{P_2} q_{t-i}^{(1)}\right) \end{aligned} \tag{A2}$$

Using Equation (2.15), $\sum_{i=1}^{P_2} q_{t-i}^{(1)}$ can be expanded as follows:

$$\begin{aligned} \sum_{i=1}^{P_2} q_{t-i}^{(1)} &= \sum_{i=1}^{P_2}\left[d_{t-i} + \ \frac{(1-\rho^{L+1})}{1-\rho}(d_{t-i} - d_{t-i-1})\right] \\ &= \sum_{i=1}^{P_2} d_{t-i} + \left(\frac{\rho-\rho^{L+1}}{1-\rho}\right)\left(d_{t-1} - d_{t-P_2-1}\right) \end{aligned} \tag{A3}$$

Now, Equation (A2) can be written as:

$$\begin{aligned} WC_t^{(1)} = Cash_t^{(1)} + c_2 I_{int}^{(1)} - c_2 \sum_{i=0}^{L_1-1} d_{t-i} + c_2 d_{t-L_1}\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right) \\ - c_2 d_{t-1}\left(\frac{\rho-\rho^{L+1}}{1-\rho}\right) \\ + c_2 d_{t-P_2-1}\left(\frac{\rho-\rho^{L+1}}{1-\rho}\right) + c_1 \sum_{i=1}^{P_1} d_{t-i} - c_2 \sum_{i=1}^{P_2} d_{t-i} \end{aligned} \tag{A4}$$

Now CFB_1 is given by:

$$CFB_1 = var\left(WC_t^{(1)}\right)/var\left(d^{(1,\$)}\right)$$

$$= \frac{\left[\begin{array}{c} c_2^2 var\left(I_{int}^{(1)}\right) + c_2^2 var\left(\sum_{i=0}^{L_1-1} d_{t-i}\right) + c_2^2 var\left(\frac{\rho-\rho^{L_1+1}}{1-\rho} d_{t-L_1}\right) \\ +c_2^2 var\left(\frac{\rho-\rho^{L_1+1}}{1-\rho} d_{t-1}\right) + c_2^2 var\left(\frac{\rho-\rho^{L_1+1}}{1-\rho} d_{t-P_2-1}\right) \\ +c_1^2 var\left(\sum_{i=1}^{P_1} d_{t-i}\right) - c_2^2 var\left(\sum_{i=1}^{P_2} d_{t-i}\right) \\ -2c_2^2 \frac{\rho-\rho^{L_1+1}}{1-\rho} cov\left(\sum_{i=0}^{L_1-1} d_{t-i}, d_{t-L_1}\right) + 2c_2^2 \frac{\rho-\rho^{L_1+1}}{1-\rho} cov\left(\sum_{i=0}^{L_1-1} d_{t-i}, d_{t-1}\right) \\ -2c_2^2 \frac{\rho-\rho^{L_1+1}}{1-\rho} cov\left(\sum_{i=0}^{L_1-1} d_{t-i}, d_{t-P_2-1}\right) - 2c_1 c_2 cov\left(\sum_{i=0}^{L_1-1} d_{t-i}, \sum_{i=1}^{P_1} d_{t-i}\right) \\ +2c_2^2 cov\left(\sum_{i=0}^{L_1-1} d_{t-i}, \sum_{i=1}^{P_2} d_{t-i}\right) - 2c_2^2 \left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)^2 cov\left(d_{t-L_1}, d_{t-1}\right) \\ +2c_2^2 \left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)^2 cov\left(d_{t-L_1}, d_{t-P_2-1}\right) + 2c_2^2 \frac{\rho-\rho^{L_1+1}}{1-\rho} cov\left(d_{t-L_1}, \sum_{i=1}^{P_1} d_{t-i}\right) \\ -2c_2^2 \frac{\rho-\rho^{L_1+1}}{1-\rho} cov\left(d_{t-L_1}, \sum_{i=1}^{P_2} d_{t-i}\right) - 2c_2^2 \left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)^2 cov\left(d_{t-1}, d_{t-P_2-1}\right) \\ -2c_1 c_2 \frac{\rho-\rho^{L_1+1}}{1-\rho} cov\left(d_{t-1}, \sum_{i=1}^{P_1} d_{t-i}\right) + 2c_2^2 \frac{\rho-\rho^{L_1+1}}{1-\rho} cov\left(d_{t-1}, \sum_{i=1}^{P_2} d_{t-i}\right) \\ +2c_1 c_2 \frac{\rho-\rho^{L_1+1}}{1-\rho} cov\left(d_{t-P_2-1}, \sum_{i=1}^{P_1} d_{t-i}\right) - 2c_2^2 \frac{\rho-\rho^{L_1+1}}{1-\rho} cov\left(d_{t-P_2-1}, \sum_{i=1}^{P_2} d_{t-i}\right) \\ -2c_1 c_2 cov\left(\sum_{i=1}^{P_1} d_{t-i}, \sum_{i=1}^{P_2} d_{t-i}\right) \end{array}\right]}{c_2^2 var(d)} \tag{A5}$$

Simplifying Equation (A5) results in:

$$
\begin{aligned}
CFB_1 = {} & L_1 + 2L_1 \sum_{i=1}^{L_1-1} \rho^i - 2\sum_{i=1}^{L_1-1} i\rho^i + \left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)^2 + 2\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)^2 \\
& + \frac{c_1^2}{c_2^2} P_1 \\
& + 2\frac{c_1^2}{c_2^2} P_1 \sum_{i=1}^{P_1-1} \rho^i - 2\frac{c_1^2}{c_2^2} \sum_{i=1}^{P_1-1} i\rho^i + P_2 + 2P_2 \sum_{i=1}^{P_2-1} \rho^i - 2\sum_{i=1}^{P_2-1} i\rho^i \\
& - 2\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)\sum_{i=1}^{L_1} \rho^i \\
& + 2\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)\left(1+\rho+\sum_{i=1}^{L_1-2} \rho^i\right) - 2\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)\sum_{i=1}^{L_1} \rho^{|P_2+1-i|} \\
& - 2\frac{c_1}{c_2}\sum_{i=0}^{L_1-1}\sum_{j=1}^{P_1} \rho^{|i-j|} \\
& + 2\sum_{i=0}^{L_1-1}\sum_{j=1}^{P_2} \rho^{|i-j|} + 2\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)^2 \left(\rho^{|L_1-P_2-1|} - \rho^{L_1-1}\right) \\
& + 2\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)\left(\frac{c_1}{c_2}\sum_{i=1}^{P_1} \rho^{|L_1-i|} - \sum_{i=1}^{P_2} \rho^{|L_1-i|}\right) \\
& - 2\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)\Bigg[\rho^{P_2}\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right) + \frac{c_1}{c_2}\left(1+\sum_{i=1}^{P_1-1} \rho^i - \sum_{i=1}^{P_1-1} \rho^{|P_2+1-i|}\right) - 1 \\
& - \sum_{i=1}^{P_2-1} \rho^i + \sum_{i=1}^{P_2} \rho^i\Bigg] - 2\frac{c_1}{c_2}\sum_{i=1}^{P_1}\sum_{j=1}^{P_2} \rho^{|i-j|}
\end{aligned}
\tag{A6}
$$

Simplifying the summation expressions in Equation (A6) results in:

$$CFB_1 = L_1 + \frac{2L_1\rho(1-\rho)+2\rho\left(\rho^{L_1}-1\right)}{(1-\rho)^2} + \frac{c_1^2}{c_2^2(1-\rho)^2}\left(P_1(1-\rho^2)+2\rho(\rho^{P_1}-1)\right)$$

$$-\frac{1}{(1-\rho)^2}\left(P_2(1-\rho^2)+2\rho(\rho^{P_2}-1)\right)$$

$$+\left(\frac{\rho-\rho^{L_1+1}}{1-\rho}\right)\begin{bmatrix} \frac{2}{1-\rho}\left(1+\rho^{L_1+P_2+1}-\rho^{L_1+1}-\rho^{P_2}\right) \\ +2\begin{pmatrix} \frac{\left(\rho-\rho^{L_1+1}\right)}{1-\rho}\left(\rho^{|L_1-P_2-1|}-\rho^{L_1-1}\right) \\ +\frac{\rho\left(1-\rho-\rho^{L_1-2}\right)+1}{1-\rho} \\ -\sum_{i=0}^{L_1-1}\rho^{|P_2+1-i|}-\sum_{i=1}^{P_2}\rho^{|L_1-i|} \end{pmatrix} \\ -\frac{\left(\rho-\rho^{L_1+1}\right)}{1-\rho}+\frac{2c_1}{c_2}\left(\sum_{i=1}^{P_1}\rho^{|L_1-i|}+\sum_{i=1}^{P_1}\rho^{|P_2+1-i|}+\frac{\rho^{P_1}-1}{1-\rho}\right) \end{bmatrix} \tag{A7}$$

$$-\frac{2c_1}{c_2}\sum_{i=0}^{L_1-1}\sum_{j=1}^{P_1}\rho^{|i-j|}+2\sum_{i=0}^{L_1-1}\sum_{j=1}^{P_2}\rho^{|i-j|}-\frac{2c_1}{c_2}\sum_{i=1}^{P_2}\sum_{j=1}^{P_1}\rho^{|i-j|}$$

Appendix B. CFB FORMULA FOR ECEHLONS 2 AND ABOVE

$WC_t^{(k)}$ for $k \geq 2$ is given by:

$$WC_t^{(k)} = Cash_t^{(k)} + Invt_t^{(k)} + AR_t^{(k)} - AP_t^{(k)} \tag{B1}$$

Using Equations (2.15) and (2.18-2.21), (B1) can be written as follows:

$$\begin{aligned}
WC_t^{(k)} &= Cash_t^{(k)} + c_{k+1} I_{int}^{(k)} + c_{k+1}\left(k - \sum_{j=1}^{k} \rho^{L_j}\right)\frac{\rho}{1-\rho} d_{t-L_k} \\
&- c_{k+1}\left(k - 1 - \sum_{j=1}^{k-1} \rho^{L_j}\right)\frac{\rho}{1-\rho} d_t - c_{k+1}\sum_{i=0}^{L_k - 1} d_{t-i} \\
&+ c_k \frac{\rho}{1-\rho}\left(k - 1 - \sum_{j=1}^{k-1} \rho^{L_j}\right)\left(d_{t-1} - d_{t-P_k-1}\right) + c_k \sum_{i=1}^{P_k} d_{t-i} \\
&- c_{k+1} \frac{\rho}{1-\rho}\left(k - \sum_{j=1}^{k} \rho^{L_j}\right)\left(d_{t-1} - d_{t-P_{k+1}-1}\right) - c_{k+1} \sum_{i=1}^{P_{k+1}} d_{t-i}
\end{aligned} \tag{B2}$$

Now CFB_k for $k \geq 2$ is given by:

$$\begin{aligned}
CFB_k &= var\left(WC_t^{(k)}\right) / var\left(d^{(k,\$)}\right) \\
&= \frac{V + C1 + C2 + C3 + C4 + C5 + C6 + C7 + C8}{var\left(d^{(k,\$)}\right)}
\end{aligned} \tag{B3}$$

where

$$V = var\left(c_{k+1}I_{int}^{(k)}\right) + var\left(c_{k+1}\left(k - \sum_{j=1}^{k}\rho^{L_j}\right)\frac{\rho}{1-\rho}d_{t-L_k}\right)$$

$$+var\left(c_{k+1}\frac{\rho}{1-\rho}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)d_t\right) + var\left(c_{k+1}\sum_{i=0}^{L_k-1}d_{t-i}\right)$$

$$+var\left(c_k\frac{\rho}{1-\rho}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\left(d_{t-1}-d_{t-P_k-1}\right)\right) \tag{B4}$$

$$+var\left(c_k\sum_{i=1}^{P_k}d_{t-i}\right)var\left(c_{k+1}\frac{\rho}{1-\rho}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\left(d_{t-1}-d_{t-P_{k+1}-1}\right)\right)$$

$$+var\left(c_{k+1}\sum_{i=1}^{P_{k+1}}d_{t-i}\right)$$

$$C1 = -2c_{k+1}^2\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\frac{\rho^2}{(1-\rho)^2}cov\left(d_{t-L_k},d_t\right)$$

$$-2c_{k+1}^2\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\frac{\rho}{1-\rho}cov\left(d_{t-L_k},\sum_{i=0}^{L_k-1}d_{t-i}\right)$$

$$+2c_kc_{k+1}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\frac{\rho^2}{(1-\rho)^2}cov\left(d_{t-L_k},d_{t-1}\right)$$

$$-2c_kc_{k+1}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\frac{\rho^2}{(1-\rho)^2}cov\left(d_{t-L_k},d_{t-P_k-1}\right) \tag{B5}$$

$$+2c_kc_{k+1}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)cov\left(d_{t-L_k},\sum_{i=1}^{P_k}d_{t-i}\right) - 2c_{k+1}^2\Big(k -$$

$$\sum_{j=1}^{k}\rho^{L_j}\Big)^2\frac{\rho^2}{(1-\rho)^2}cov\left(d_{t-L_k},d_{t-1}\right) + 2c_{k+1}^2\Big(k -$$

$$\sum_{j=1}^{k}\rho^{L_j}\Big)^2cov\left(d_{t-L_k},d_{t-P_{k+1}-1}\right)$$

$$C2 = 2c_{k+1}^2\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\frac{\rho}{1-\rho}cov\left(d_t,\sum_{i=1}^{L_k-1}d_{t-i}\right)$$

$$-2c_kc_{k+1}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)^2\frac{\rho^2}{(1-\rho)^2}cov(d_t,d_{t-1})$$

$$+2c_kc_{k+1}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)^2\frac{\rho^2}{(1-\rho)^2}cov\left(d_t,d_{t-P_k-1}\right) \tag{B6}$$

$$-2c_kc_{k+1}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\frac{\rho}{1-\rho}cov\left(d_t,\sum_{i=1}^{P_k}d_{t-i}\right)$$

$$+2c_{k+1}^2\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\frac{\rho^2}{(1-\rho)^2}cov(d_t,d_{t-1})$$

$$-2c_{k+1}^2\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\frac{\rho^2}{(1-\rho)^2}cov\left(d_t,d_{t-P_{k+1}-1}\right)$$

$$+2c_{k+1}^2\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\frac{\rho}{1-\rho}cov\left(d_t,\sum_{i=1}^{P_{k+1}}d_{t-i}\right)$$

$$\begin{aligned}C3 = & -2c_k c_{k+1}\frac{\rho}{1-\rho}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)cov\left(\sum_{i=0}^{L_k-1}d_{t-i}, d_{t-1}\right)\\ &+2c_k c_{k+1}\frac{\rho}{1-\rho}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)cov\left(\sum_{i=0}^{L_k-1}d_{t-i}, d_{t-P_k-1}\right)\\ &-2c_k c_{k+1}\,cov\left(\sum_{i=0}^{L_k-1}d_{t-i}, \sum_{i=1}^{P_k}d_{t-i}\right)\\ &+2c_{k+1}^2\frac{\rho}{1-\rho}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)cov\left(\sum_{i=0}^{L_k-1}d_{t-i}, d_{t-1}\right)\\ &-2c_{k+1}^2\frac{\rho}{1-\rho}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)cov\left(\sum_{i=0}^{L_k-1}d_{t-i}, d_{t-P_{k+1}-1}\right)\\ &+2c_{k+1}^2\,cov\left(\sum_{i=0}^{L_k-1}d_{t-i}, \sum_{i=1}^{P_{k+1}}d_{t-i}\right)\end{aligned} \tag{B7}$$

$$\begin{aligned}C4 = & -2c_k^2\frac{\rho^2}{(1-\rho)^2}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)^2cov\left(d_{t-1},d_{t-P_k-1}\right)\\ &+2c_k^2\frac{\rho}{1-\rho}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)cov\left(d_{t-1},\sum_{i=1}^{P_k}d_{t-i}\right)\\ &-2c_k c_{k+1}\frac{\rho^2}{(1-\rho)^2}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)cov(d_{t-1},d_{t-1})\\ &+2c_k c_{k+1}\frac{\rho^2}{(1-\rho)^2}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)cov\left(d_{t-1},d_{t-P_{k+1}-1}\right)\\ &-2c_k c_{k+1}\frac{\rho}{1-\rho}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)cov\left(d_{t-1},\sum_{i=1}^{P_{k+1}}d_{t-i}\right)\end{aligned} \tag{B8}$$

$$\begin{aligned}C5 = & -2c_k^2\frac{\rho}{1-\rho}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)cov\left(d_{t-P_k-1},\sum_{i=1}^{P_k}d_{t-i}\right)\\ &+2c_k c_{k+1}\frac{\rho^2}{(1-\rho)^2}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)cov\left(d_{t-P_k-1},d_{t-1}\right)\end{aligned} \tag{B9}$$

$$-2c_k c_{k+1}\frac{\rho^2}{(1-\rho)^2}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)cov\left(d_{t-P_k-1},d_{t-P_{k+1}-1}\right)$$

$$+2c_k c_{k+1}\frac{\rho}{1-\rho}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)cov\left(d_{t-P_k-1},\sum_{i=1}^{P_{k+1}}d_{t-i}\right)$$

$$C6=-2c_k c_{k+1}\frac{\rho}{1-\rho}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)cov\left(\sum_{i=1}^{P_k}d_{t-i}\,,d_{t-1}\right)$$

$$+2c_k c_{k+1}\frac{\rho}{1-\rho}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)cov\left(\sum_{i=1}^{P_k}d_{t-i}\,,d_{t-P_{k+1}-1}\right) \qquad \text{(B10)}$$

$$-2c_k c_{k+1}cov\left(\sum_{i=1}^{P_k}d_{t-i}\,,\sum_{i=1}^{P_{k+1}}d_{t-i}\right)$$

$$C7=-2c_{k+1}^2\frac{\rho^2}{(1-\rho)^2}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)^2 cov\left(d_{t-1},d_{t-P_{k+1}-1}\right)$$

$$+2c_{k+1}^2\frac{\rho}{1-\rho}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)cov\left(d_{t-1},\sum_{i=1}^{P_{k+1}}d_{t-i}\right) \qquad \text{(B11)}$$

$$C8=-2c_{k+1}^2\frac{\rho}{1-\rho}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)cov\left(d_{t-P_{k+1}-1},\sum_{i=1}^{P_{k+1}}d_{t-i}\right) \qquad \text{(B12)}$$

Simplifying Equations (B4-B12) and substituting them in Equation (B3) results in:

$$CFB_k=L_k\left(1+2\sum_{i=1}^{L_k-1}\rho^i\right)+\frac{3\rho^2}{(1-\rho)^2}\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)^2-2\sum_{i=1}^{L_k-1}i\rho^i+$$

$$\frac{\rho^2}{(1-\rho)^2}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)^2\left(1+2\frac{c_k^2}{c_{k+1}^2}\right)+\sum_{i=0}^{1}\left[\frac{P_{k+i}c_{k+i}^2}{c_{k+1}^2}\left(1+2\sum_{j=1}^{P_{k+i}-1}\rho^j-\right.\right.$$

$$\left.\left.\frac{2}{P_{k+i}}\sum_{j=1}^{P_{k+i}-1}j\rho^j\right)\right]+\frac{2\rho}{1-\rho}\left(-\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\sum_{i=1}^{L_k}\rho^i-\left(k-\sum_{j=1}^{k}\rho^{L_j}\right)\left(k-1-\right.\right.$$

$$\left.\left.\sum_{j=1}^{k-1}\rho^{L_j}\right)\frac{\rho^{L_k+1}}{1-\rho}+\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\left(1+\sum_{i=1}^{L_k-1}\rho^i\right)\right)+\frac{2c_k}{c_{k+1}}\frac{\rho}{(1-\rho)}\left[\frac{\rho}{(1-\rho)}\left(k-\right.\right. \qquad \text{(B13)}$$

$$\left.\sum_{j=1}^{k}\rho^{L_j}\right)\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\left(\rho^{L_k-1}-\rho^{|L_K-P_k-1|}\right)+\left(k-\right.$$

$$\left.\sum_{j=1}^{k}\rho^{L_j}\right)\sum_{i=1}^{P_k}\rho^{|L_k-i|}-\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)\left(1+\rho+\sum_{i=1}^{P_k}\rho^i+\sum_{i=1}^{L_k-2}\rho^i-\right.$$

$$\left.\sum_{i=0}^{L_k-1}\rho^{|P_k+1-i|}\right)-\frac{\rho}{(1-\rho)}\left(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\right)^2\left(\rho-\rho^{P_k+1}\right)-$$

$$\frac{(1-\rho)}{\rho}\Big(\sum_{i=0}^{L_k-1}\sum_{j=1}^{P_k}\rho^{|i-j|}\Big)\Big] - \frac{2\rho}{(1-\rho)}\Big[\frac{\rho}{1-\rho}\Big(k-\sum_{j=1}^{k}\rho^{L_j}\Big)^2\Big(\rho^{L_k-1} -$$

$$\rho^{\left|L_{-P_{k+1}}-1\right|}\Big) + \Big(k-\sum_{j=1}^{k}\rho^{L_j}\Big)\Big(\sum_{i=1}^{P_{k+1}}\rho^{|L_k-i|}+\sum_{i=0}^{L_k-1}\rho^{|P_{k+1}+1-i|}-\sum_{i=1}^{L_k-2}\rho^{i} -$$

$$\rho-1\Big) - \frac{(1-\rho)}{\rho}\sum_{i=0}^{L_k-1}\sum_{j=1}^{P_{k+1}}\rho^{|i-j|} - \frac{\rho^2\left(1-\rho^{P_{k+1}}\right)}{(1-\rho)}\Big(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\Big)\Big(k -$$

$$\sum_{j=1}^{k}\rho^{L_j}\Big) - \Big(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\Big)\sum_{i=1}^{P_{k+1}}\rho^{i}\Big] - \frac{2c_k^2}{c_{k+1}^2}\frac{\rho}{(1-\rho)}\Big(k-1-$$

$$\sum_{j=1}^{k-1}\rho^{L_j}\Big)\Big[\frac{\rho^{P_k+1}}{1-\rho}\Big(k-1-\sum_{j=1}^{k-1}\rho^{L_j}\Big)+\rho^{P_k}-1\Big] - \frac{2c_k}{c_{k+1}}\frac{\rho}{(1-\rho)}\Big[\frac{\rho}{(1-\rho)}\Big(k-1-$$

$$\sum_{j=1}^{k-1}\rho^{L_j}\Big)\Big(k-\sum_{j=1}^{k}\rho^{L_j}\Big)\Big(1-\rho^{P_{k+1}}-\rho^{P_k}+\rho^{|P_{k+1}-P_k|}\Big)+\Big(k-1-$$

$$\sum_{j=1}^{k-1}\rho^{L_j}\Big)\Big(1+\sum_{i=1}^{P_{k+1}-1}\rho^{i}-\sum_{i=1}^{P_{k+1}}\rho^{P_k+1-i}\Big)+\Big(k-\sum_{j=1}^{k}\rho^{L_j}\Big)\Big(1+$$

$$\sum_{i=1}^{P_k-1}\rho^{i}-\sum_{i=1}^{P_k}\rho^{P_{k+1}+1-i}+\frac{(1-\rho)}{\rho}\sum_{i=1}^{P_k}\sum_{j=1}^{P_{k+1}}\rho^{|i-j|}\Big)\Big] - \frac{2\rho}{(1-\rho)}\Big(k-$$

$$\sum_{j=1}^{k-1}\rho^{L_j}\Big)\Big[\frac{\rho}{(1-\rho)}\Big(k-\sum_{j=1}^{k}\rho^{L_j}\Big)\rho^{P_{k+1}}+\rho^{P_{k+1}}-1\Big]$$

Appendix C. BULLWHIP EXPERIENCED BY MAJOR INDUSTRIES

Table C-1. Magnitude of CFB, BWE, IBE, and PBE Experienced by Major Industries. Note: The bullwhip magnitudes here are calculated using data that has been detrended, deseasonalized, and winsorized.

	CFB	p-value*	BWE	p-value*	IBE	p-value*	PBE	p-value*
Retailers								
Automobile Dealers	0.91	0.890	1.49	0.286	0.73	0.815	0.02	0.079
Automotive Parts, Accessories, & Tire Stores	2.45	0.005	3.85	0.012	2.80	0.427	5.62	0.001
Furniture Stores	6.02	0.000	5.88	0.001	1.63	0.193	10.05	0.000
Electronics & Appliance Stores	9.66	0.000	10.03	0.000	2.54	0.008	8.32	0.000
Grocery Stores	0.24	0.001	1.41	0.398	0.05	0.000	0.22	0.002
Health & Personal Care Stores	0.29	0.511	1.47	0.462	0.13	0.140	0.34	0.819
Gasoline Stations	0.05	0.001	1.16	0.881	0.02	0.000	0.06	0.001
Clothing Stores	0.51	0.045	2.47	0.985	0.52	0.082	0.19	0.073
Shoe Stores	0.81	0.939	3.27	0.008	0.86	0.794	0.56	0.416
Jewelry, Luggage, & Leather Goods Stores	21.08	0.000	5.20	0.000	6.01	0.000	30.26	0.000
Sporting Goods, Hobby, & Musical Instrument Stores	2.21	0.033	2.95	0.162	1.63	0.182	1.58	0.184
Department Stores	0.76	0.875	0.68	0.838	0.50	0.430	1.40	0.231
General Merchandise Stores Warehouse Clubs	0.97	0.701	3.41	0.038	0.18	0.002	1.18	0.898
Wholesalers								
Motor Vehicle & Motor Vehicle Parts Wholesalers	0.76	0.662	1.34	0.321	1.43	0.822	0.35	0.741
Lumber & Other Construction Materials Wholesalers	0.98	0.785	4.16	0.002	0.70	0.135	0.39	0.030
Professional & Commercial Equipment Wholesalers	0.23	0.020	1.54	0.469	0.15	0.006	0.03	0.001
Metal & Mineral (except Petroleum) Wholesalers	1.27	0.707	4.64	0.010	0.71	0.243	0.22	0.000
Household Appliances & Electronic Goods Wholesalers	0.91	0.061	3.22	0.086	0.34	0.000	0.28	0.000
Hardware, Plumbing & Heating Equipment Wholesalers	1.45	0.386	9.69	0.004	1.06	0.584	1.48	0.445
Machinery, Equipment, & Supplies Wholesalers	4.13	0.141	1.76	0.205	1.37	0.967	0.91	0.756
Miscellaneous Durable Goods Merchant Wholesalers	0.30	0.010	1.32	0.802	0.10	0.000	0.11	0.000
Manufacturing								

Table C-1. Magnitude of CFB, BWE, IBE, and PBE Experienced by Major Industries. Note: The bullwhip magnitudes here are calculated using data that has been detrended, deseasonalized, and winsorized.

	CFB	p-value*	BWE	p-value*	IBE	p-value*	PBE	p-value*
Grain & Oilseed Milling	0.41	0.101	1.40	0.243	0.32	0.007	0.15	0.000
Sugar & Confectionery Product Manufacturing	1.85	0.333	0.77	0.105	0.53	0.062	0.96	0.376
Fruit & Vegetable Preserving & Food Manufacturing	1.82	0.018	2.86	0.001	0.95	0.551	0.97	0.771
Dairy Product Manufacturing	0.84	0.804	2.87	0.034	0.53	0.515	0.11	0.214
Bakeries & Tortilla Manufacturing	2.09	0.054	2.57	0.115	0.56	0.729	0.73	0.377
Other Food Manufacturing	1.09	0.394	2.63	0.044	1.42	0.561	0.31	0.849
Beverage Manufacturing	21.26	0.000	1.48	0.344	0.34	0.029	20.98	0.000
Tobacco Manufacturing	42.06	0.000	30.75	0.000	7.32	0.000	34.62	0.000
Fiber, Yarn, & Thread Mills	1.50	0.551	1.82	0.204	0.56	0.016	1.84	0.329
Fabric Mills	4.54	0.031	4.35	0.001	1.17	0.574	4.77	0.002
Textile Furnishings Mills	8.95	0.015	9.55	0.029	1.62	0.417	2.76	0.140
Apparel Knitting Mills	2.57	0.058	2.87	0.051	1.78	0.214	1.03	0.887
Cut & Sew Apparel Manufacturing	5.98	0.000	1.90	0.035	1.73	0.439	3.40	0.000
Apparel Accessories & Other Apparel Manufacturing	9.89	0.001	9.21	0.000	2.71	0.046	11.32	0.000
Footwear Manufacturing	5.03	0.106	6.97	0.018	0.76	0.198	2.22	0.216
Other Leather & Allied Product Manufacturing	18.80	0.002	1.36	0.757	3.20	0.274	10.82	0.000
Sawmills & Wood Preservation	6.23	0.003	3.31	0.117	0.38	0.043	5.66	0.008
Veneer, Plywood, & Wood Product Manufacturing	7.76	0.000	0.81	0.228	0.49	0.011	7.92	0.000
Other Wood Product Manufacturing	0.75	0.282	6.24	0.036	0.25	0.002	0.23	0.011
Pulp, Paper, & Paperboard Mills	1.02	0.652	2.42	0.052	0.10	0.016	0.65	0.879
Converted Paper Product Manufacturing	4.58	0.018	2.04	0.232	0.86	0.692	1.56	0.148
Printing & Related Support Activities	2.05	0.087	1.47	0.340	0.18	0.004	1.50	0.050
Petroleum & Coal Products Manufacturing	0.45	0.185	1.20	0.724	0.10	0.003	0.35	0.133
Basic Chemical Manufacturing	1.23	0.374	1.72	0.021	0.28	0.001	0.73	0.544
Resin, Rubber, & Synthetic Fibers Manufacturing	13.55	0.003	4.01	0.001	3.49	0.851	5.31	0.000
Pesticide, Fertilizer, & Chemical Manufacturing	12.14	0.000	6.23	0.004	2.28	0.253	4.94	0.001
Pharmaceutical & Medicine Manufacturing	41.52	0.001	2.44	0.055	3.73	0.394	21.70	0.000
Paint, Coating, & Adhesive Manufacturing	1.38	0.660	1.38	0.991	0.88	0.165	0.33	0.170

Table C-1. Magnitude of CFB, BWE, IBE, and PBE Experienced by Major Industries. Note: The bullwhip magnitudes here are calculated using data that has been detrended, deseasonalized, and winsorized.

	CFB	p-value*	BWE	p-value*	IBE	p-value*	PBE	p-value*
Soap, & Cleaning Compound Manufacturing	2.43	0.000	1.22	0.394	0.58	0.833	1.22	0.000
Other Chemical Product & Preparation Manufacturing	3.56	0.219	1.12	0.812	0.29	0.000	2.18	0.797
Plastics Product Manufacturing	3.49	0.000	1.75	0.377	0.52	0.162	2.59	0.000
Rubber Product Manufacturing	2.16	0.022	0.95	0.740	1.09	0.800	0.57	0.059
Clay Product & Refractory Manufacturing	1.57	0.151	1.26	0.418	0.51	0.023	2.12	0.087
Glass & Glass Product Manufacturing	1.81	0.004	1.85	0.438	0.65	0.557	0.55	0.139
Cement & Concrete Product Manufacturing	0.74	0.886	1.54	0.556	0.03	0.002	0.56	0.915
Lime & Gypsum Product Manufacturing	2.87	0.118	4.41	0.316	0.41	0.005	3.02	0.081
Other Nonmetallic Mineral Product Manufacturing	5.31	0.000	2.88	0.025	0.50	0.165	5.01	0.000
Iron & Steel Mills & Ferroalloy Manufacturing	1.47	0.323	2.34	0.045	0.91	0.629	0.61	0.160
Steel Product Manufacturing from Purchased Steel	20.50	0.022	1.24	0.296	4.95	0.127	6.92	0.003
Alumina & Aluminum Production & Processing	2.22	0.013	2.21	0.195	0.71	0.142	2.51	0.016
Nonferrous Metal (except Al) Production & Processing	4.21	0.006	2.98	0.062	1.65	0.505	4.39	0.004
Forging & Stamping	1.56	0.052	4.66	0.008	0.66	0.266	1.53	0.053
Cutlery & Handtool Manufacturing	6.07	0.002	1.00	0.902	0.83	0.255	4.46	0.000
Architectural & Structural Metals Manufacturing	3.84	0.315	2.00	0.467	0.46	0.008	1.85	0.726
Boiler, Tank, & Shipping Container Manufacturing	6.27	0.000	2.81	0.307	0.84	0.742	6.52	0.000
Hardware Manufacturing	17.22	0.000	15.80	0.001	3.36	0.001	18.47	0.000
Spring & Wire Product Manufacturing	11.39	0.018	1.46	0.041	1.71	0.249	5.40	0.010
Machine Shops; & Screw, Nut, & Bolt Manufacturing	4.07	0.004	2.66	0.024	1.03	0.691	3.08	0.024
Other Fabricated Metal Product Manufacturing	2.96	0.040	2.28	0.071	0.90	0.193	0.84	0.249
Agriculture & Construction Machinery Manufacturing	2.62	0.207	1.90	0.370	0.94	0.150	0.92	0.237
Industrial Machinery Manufacturing	22.91	0.001	2.64	0.068	1.98	0.778	12.06	0.001
Commercial Industry Machinery Manufacturing	5.06	0.000	1.95	0.337	0.05	0.010	4.87	0.000
HVAC & Refrigeration Equipment Manufacturing	0.64	0.619	2.69	0.116	0.13	0.014	0.26	0.124
Metalworking Machinery Manufacturing	18.70	0.000	4.60	0.015	2.66	0.021	13.42	0.001
Engine & Transmission Equipment Manufacturing	0.53	0.000	0.60	0.000	0.36	0.000	0.55	0.000
Other General Purpose Machinery Manufacturing	5.82	0.002	2.55	0.204	1.21	0.526	2.38	0.319

Table C-1. Magnitude of CFB, BWE, IBE, and PBE Experienced by Major Industries. Note: The bullwhip magnitudes here are calculated using data that has been detrended, deseasonalized, and winsorized.

	CFB	p-value*	BWE	p-value*	IBE	p-value*	PBE	p-value*
Computer & Peripheral Equipment Manufacturing	1.09	0.460	0.97	0.404	0.35	0.002	0.59	0.191
Communications Equipment Manufacturing	1.31	0.769	1.68	0.198	0.06	0.000	1.02	0.630
Audio & Video Equipment Manufacturing	1.51	0.497	2.71	0.057	0.50	0.016	2.22	0.110
Semiconductor & Electronic Component Manufacturing	15.32	0.044	2.31	0.223	1.02	0.410	8.56	0.072
Navigational & Electromedical Manufacturing	17.34	0.000	1.67	0.378	1.37	0.860	7.94	0.000
Manufacturing Magnetic & Optical Media	2.09	0.866	1.13	0.941	0.04	0.000	2.34	0.856
Electrical Equipment & Appliance Manufacturing	0.31	0.002	1.41	0.278	0.05	0.000	0.27	0.001
Electric Lighting Equipment Manufacturing	15.82	0.000	12.57	0.021	0.71	0.437	15.24	0.000
Household Appliance Manufacturing	0.40	0.000	0.90	0.272	0.26	0.000	0.16	0.000
Electrical Equipment Manufacturing	5.42	0.068	2.35	0.338	0.39	0.024	3.02	0.250
Other Electrical Equipment & Component Manufacturing	4.04	0.015	1.68	0.392	0.83	0.814	1.42	0.026
Motor Vehicle Manufacturing	5.69	0.373	1.27	0.621	0.51	0.122	2.70	0.748
Motor Vehicle Body & Trailer Manufacturing	0.34	0.000	3.50	0.174	0.18	0.000	0.23	0.000
Motor Vehicle Parts Manufacturing	0.89	0.568	1.69	0.266	0.19	0.000	0.34	0.059
Aerospace Product & Parts Manufacturing	2.82	0.176	2.83	0.048	0.62	0.005	1.26	0.814
Railroad Rolling Stock Manufacturing	4.57	0.054	8.01	0.010	4.36	0.327	1.62	0.179
Ship & Boat Building	1.54	0.376	2.99	0.076	0.31	0.002	1.46	0.457
Other Transportation Equipment Manufacturing	9.71	0.088	0.78	0.144	0.25	0.000	8.82	0.043
Household & Institutional Furniture Manufacturing	1.79	0.291	1.76	0.157	1.35	0.698	0.44	0.992
Office Furniture (including Fixtures) Manufacturing	1.34	0.002	3.10	0.142	0.13	0.013	1.13	0.000
Other Furniture Related Product Manufacturing	1.07	0.129	3.47	0.146	0.13	0.009	0.79	0.369
Medical Equipment & Supplies Manufacturing	24.19	0.000	3.94	0.020	4.64	0.093	20.28	0.000
Other Miscellaneous Manufacturing	3.71	0.087	0.73	0.468	0.37	0.000	2.92	0.129
Farming								
Fruit & Tree Nut Farming	0.82	0.320	2.32	0.526	0.29	0.010	0.42	0.886
Other Crop Farming	0.98	0.779	5.55	0.001	2.63	0.075	2.31	0.019

*p-value of Brown-Forsythe test for equivalence of variance.

C-2. Semiconductor firms used in Section 3.5.4

Firm name	NAICS code	Supply Chain Stage
LAM RESEARCH CORP	333242	SMM
APPLIED MATERIALS INC	333242	SMM
VEECO INSTRUMENTS INC	333242	SMM
BROOKS AUTOMATION INC	333242	SMM
AXCELIS TECHNOLOGIES INC	333242	SMM
FSI INTL INC	333242	SMM
BESI-BE SEMICONDUCTOR INDS	333242	SMM
MATTSON TECHNOLOGY INC	333242	SMM
CYMER INC	333242	SMM
TRIO-TECH INTERNATIONAL	333242	SMM
ULTRATECH INC	333242	SMM
AIXTRON SE	333242	SMM
KULICKE & SOFFA INDUSTRIES	333242	SMM
MONOLITHIC POWER SYSTEMS INC	334413	SRDM
BROADCOM INC	334413	SRDM
MICROCHIP TECHNOLOGY INC	334413	SRDM
MERCURY SYSTEMS INC	334413	SRDM
STR HOLDINGS INC	334413	SRDM
IPG PHOTONICS CORP	334413	SRDM
ULTRA CLEAN HOLDINGS INC	334413	SRDM
QORVO INC	334413	SRDM
NVIDIA CORP	334413	SRDM
DIODES INC	334413	SRDM
SILICON LABORATORIES INC	334413	SRDM
INTERSIL CORP -CL A	334413	SRDM
GSI TECHNOLOGY INC	334413	SRDM
MARVELL TECHNOLOGY GROUP LTD	334413	SRDM

Firm name	NAICS code	Supply Chain Stage
CYPRESS SEMICONDUCTOR CORP	334413	SRDM
SYNAPTICS INC	334413	SRDM
INTEGRATED DEVICE TECH INC	334413	SRDM
AMKOR TECHNOLOGY INC	334413	SRDM
JINKOSOLAR HOLDING CO	334413	SRDM
SPREADTRUM COMMUNICATNS -ADR	334413	SRDM
ALPHA AND OMEGA SEMICONDUCTO	334413	SRDM
ON SEMICONDUCTOR CORP	334413	SRDM
O2MICRO INTERNATIONAL LTD	334413	SRDM
IKANOS COMMUNICATIONS INC	334413	SRDM
ANALOG DEVICES	334413	SRDM
TRINA SOLAR LTD	334413	SRDM
ANADIGICS INC	334413	SRDM
PHOTRONICS INC	334413	SRDM
MICRON TECHNOLOGY INC	334413	SRDM
CIRRUS LOGIC INC	334413	SRDM
RUBICON TECHNOLOGY INC	334413	SRDM
KOPIN CORP	334413	SRDM
LSI CORP	334413	SRDM
SKYWORKS SOLUTIONS INC	334413	SRDM
TAIWAN SEMICONDUCTOR MFG CO	334413	SRDM
INTEL CORP	334413	SRDM
PERICOM SEMICONDUCTOR CORP	334413	SRDM
QUALCOMM INC	334413	SRDM
MAXLINEAR INC	334413	SRDM
TEXAS INSTRUMENTS INC	334413	SRDM
POWER INTEGRATIONS INC	334413	SRDM
INFINEON TECHNOLOGIES AG	334413	SRDM
INTEGRATED SILICON SOLUTION	334413	SRDM
OMNIVISION TECHNOLOGIES INC	334413	SRDM

Firm name	NAICS code	Supply Chain Stage
ATMEL CORP	334413	SRDM
NXP SEMICONDUCTORS NV	334413	SRDM
SEMTECH CORP	334413	SRDM
API TECHNOLOGIES CORP	334413	SRDM
NVE CORP	334413	SRDM
NETLIST INC	334413	SRDM
ALLIANCE FIBER OPTIC PRODUCT	334413	SRDM
FAIRCHILD SEMICONDUCTOR INTL	334413	SRDM
STMICROELECTRONICS NV	334413	SRDM
PMC-SIERRA INC	334413	SRDM
XILINX INC	334413	SRDM
QUICKLOGIC CORP	334413	SRDM
MICROSEMI CORP	334413	SRDM
CELESTICA INC	334413	SRDM
JAZZ TECHNOLOGIES INC	334413	SRDM
SILICON IMAGE INC	334413	SRDM
AU OPTRONICS CORP	334413	SRDM
SUPERTEX INC	334413	SRDM
SPIRE CORP	334413	SRDM
HITTITE MICROWAVE CORP	334413	SRDM
ADVANCED MICRO DEVICES	334413	SRDM
APPLIED MICRO CIRCUITS CORP	334413	SRDM
IXYS CORP	334413	SRDM
LINEAR TECHNOLOGY CORP	334413	SRDM
JA SOLAR HOLDINGS CO LTD	334413	SRDM
MEMSIC INC	334413	SRDM
SPANSION INC	334413	SRDM
VISHAY PRECISION GROUP INC	334413	SRDM
VITESSE SEMICONDUCTOR CORP	334413	SRDM
LATTICE SEMICONDUCTOR CORP	334413	SRDM

Firm name	NAICS code	Supply Chain Stage
ENTROPIC COMMUNICATIONS INC	334413	SRDM
BROADCOM CORP	334413	SRDM
PIXELWORKS INC	334413	SRDM
GIGPEAK INC	334413	SRDM
FREESCALE SEMICONDUCTOR LTD	334413	SRDM
LIGHTING SCIENCE GROUP CORP	334413	SRDM
ADVANCED PHOTONIX INC -CL A	334413	SRDM
ACTIONS SEMICNDCTR LTD -ADR	334413	SRDM
EVOLUCIA INC	334413	SRDM
HIMAX TECHNOLOGIES INC	334413	SRDM
GT ADVANCED TECHNOLOGIES INC	334413	SRDM
MAXIM INTEGRATED PRODUCTS	334413	SRDM
AUTHENTEC INC	334413	SRDM
EXAR CORP	334413	SRDM
CHINA SUNERGY CO LTD	334413	SRDM
ALTERA CORP	334413	SRDM
CANADIAN SOLAR INC	334413	SRDM
MICREL INC	334413	SRDM
AXT INC	334413	SRDM
VOLTERRA SEMICONDUCTOR CORP	334413	SRDM
SILICONWARE PRECISION INDS	334413	SRDM
RAMTRON INTERNATIONAL CORP	334413	SRDM
GLOBAL-TECH ADV INNOVATIONS	334413	SRDM
INTL RECTIFIER CORP	334413	SRDM
LOGIC DEVICES INC	334413	SRDM
STANDARD MICROSYSTEMS CORP	334413	SRDM
MICROPAC INDUSTRIES INC	334413	SRDM
PLX TECHNOLOGY INC	334413	SRDM
MINDSPEED TECHNOLOGIES INC	334413	SRDM
FIRST SOLAR INC	334413	SRDM

Firm name	NAICS code	Supply Chain Stage
TRIQUINT SEMICONDUCTOR INC	334413	SRDM
AVAYA INC	334220	CCM
FORTINET INC	334118	CCM
ZEBRA TECHNOLOGIES CP -CL A	334118	CCM
ELECTRONICS FOR IMAGING INC	334118	CCM
VIASAT INC	334220	CCM
STRATASYS LTD	334118	CCM
SCIENTIFIC GAMES CORP	334118	CCM
ARUBA NETWORKS INC	334210	CCM
CALAMP CORP	334220	CCM
SHORETEL INC	334210	CCM
ASTRONOVA INC	334118	CCM
ZOOM TELEPHONICS INC	334210	CCM
ARRIS INTERNATIONAL PLC	334220	CCM
SILICOM LTD	334118	CCM
AVIAT NETWORKS INC	334220	CCM
INFINERA CORP	334118	CCM
APPLE INC	334220	CCM
LOGITECH INTERNATIONAL SA	334118	CCM
DSP GROUP INC	334220	CCM
ECHOSTAR CORP	334220	CCM
EXTREME NETWORKS INC	334210	CCM
VIAVI SOLUTIONS INC	334210	CCM
ECHELON CORP	334210	CCM
VERIFONE SYSTEMS INC	334118	CCM
WIRELESS TELECOM GROUP INC	334220	CCM
CHYRONHEGO CORP	334220	CCM
RADISYS CORP	334118	CCM
NOKIA CORP	334220	CCM
DIEBOLD NIXDORF INC	334118	CCM

Firm name	NAICS code	Supply Chain Stage
INNOVATIVE SOLTNS & SUPP INC	334118	CCM
DIGI INTERNATIONAL INC	334210	CCM
COMTECH TELECOMMUN	334220	CCM
TELLABS INC	334210	CCM
EMCORE CORP	334220	CCM
CHECKPOINT SYSTEMS INC	334290	CCM
EMC CORP/MA	334112	CCM
SMART TECHNOLOGIES INC	334118	CCM
PLANTRONICS INC	334210	CCM
DATARAM CORP - OLD	334112	CCM
AUDIOCODES LTD	334210	CCM
MITEL NETWORKS CORP	334210	CCM
LEXMARK INTL INC -CL A	334118	CCM
MOTOROLA SOLUTIONS INC	334220	CCM
PCTEL INC	334220	CCM
RADWARE LTD	334118	CCM
XPLORE TECHNOLOGIES CORP	334111	CCM
XYRATEX LTD	334112	CCM
WESTELL TECH INC -CL A	334210	CCM
VICON INDUSTRIES INC	334290	CCM
RIVERBED TECHNOLOGY INC	334210	CCM
NETAPP INC	334112	CCM
TELULAR CORP	334220	CCM
CALIX INC	334210	CCM
CPI INTERNATIONAL HLDG CORP	334290	CCM
MICROWAVE FILTER CO INC	334220	CCM
SEAGATE TECHNOLOGY PLC	334112	CCM
ALLOT LTD	334210	CCM
HAUPPAUGE DIGITAL INC	334118	CCM
FRANKLIN WIRELESS CORP	334210	CCM

Firm name	NAICS code	Supply Chain Stage
COMMUNICATIONS SYSTEMS INC	334210	CCM
STEC INC	334112	CCM
CERAGON NETWORKS LTD	334220	CCM
LANTRONIX INC	334210	CCM
OCZ TECHNOLOGY GROUP INC	334112	CCM
DOT HILL SYSTEMS CORP	334112	CCM
QLOGIC CORP	334118	CCM
GILAT SATELLITE NETWORKS LTD	334220	CCM
POWERWAVE TECHNOLOGIES INC	334220	CCM
INSEEGO CORP	334210	CCM
IDENTIV INC	334118	CCM
VIEWCAST.COM INC	334220	CCM
CLEARONE INC	334220	CCM
ZHONE TECHNOLOGIES INC	334210	CCM
EROOMSYSTEM TECHNOLOGIES INC	334118	CCM
RISK(GEORGE) INDUSTRIES INC	334290	CCM
WESTERN DIGITAL CORP	334112	CCM
TRANSACT TECHNOLOGIES INC	334118	CCM
LOJACK CORP	334290	CCM
PERFORMANCE TECHNOLOGIES INC	334210	CCM
OVERLAND STORAGE INC	334112	CCM
NETGEAR INC	334220	CCM
CISCO SYSTEMS INC	334210	CCM
DRAGONWAVE INC	334220	CCM
BK TECHNOLOGIES CORP	334220	CCM
POLYCOM INC	334210	CCM
VERSUS TECHNOLOGY INC	334290	CCM
TECHNOLOGY MONITORING SOLTNS	334220	CCM
ON TRACK INNOVATIONS	334118	CCM
EZCHIP SEMICONDUCTOR LTD	334118	CCM

Firm name	NAICS code	Supply Chain Stage
ONESPAN INC	334290	CCM
MAXAR TECHNOLOGIES INC	334220	CCM
TELEFONAKTIEBOLAGET LM ERICS	334220	CCM
ANDREA ELECTRONICS CORP	334220	CCM
PROCERA NETWORKS INC	334210	CCM
MAGAL SECURITY SYSTEMS	334290	CCM
PAR TECHNOLOGY CORP	334118	CCM
INFOSONICS CORP -OLD	334220	CCM
ADTRAN INC	334210	CCM
ANAREN INC	334220	CCM
INTL LOTTERY & TOTALIZATOR	334118	CCM
BROCADE COMMUNICATIONS SYS	334118	CCM
ELECTRONIC SYSTEM TECH INC	334220	CCM
SOCKET MOBILE INC	334220	CCM
SILICON GRAPHICS INTL CORP	334111	CCM
LOCATION BASED TECHNOLOGIES	334220	CCM
INTERMEC INC	334118	CCM
INTERPHASE CORP	334210	CCM
MERU NETWORKS INC	334210	CCM
ACME PACKET INC	334210	CCM
CRAY INC	334111	CCM
TECHNICAL COMMUNICATIONS CP	334220	CCM
ENTORIAN TECHNOLOGIES INC	334111	CCM
NAPCO SECURITY TECH INC	334290	CCM
UNIVERSAL SECURITY INSTRUMNT	334290	CCM
COBRA ELECTRONICS CORP	334220	CCM
VISCOUNT SYSTEMS INC	334290	CCM
NETWORK EQUIPMENT TECH INC	334210	CCM
PHAZAR CORP	334220	CCM
DITECH NETWORKS INC	334220	CCM

Firm name	NAICS code	Supply Chain Stage
ARC WIRELESS SOLUTIONS INC	334220	CCM

Appendix D. ANOVA TABLES

Table D-1 ANOVA Results for $varWC^{(i,1)}$ at the Retailer

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	1.44246E+17	2.28962E+15	21.95	0.000
Linear	8	1.05770E+17	1.32213E+16	126.77	0.000
A	3	4.19267E+15	1.39756E+15	13.40	0.000
B	3	2.35760E+16	7.85865E+15	75.35	0.000
C	1	1.63780E+14	1.63780E+14	1.57	0.210
D	1	7.78381E+16	7.78381E+16	746.31	0.000
2-Way Interactions	22	3.28375E+16	1.49261E+15	14.31	0.000
A*B	9	4.41116E+15	4.90129E+14	4.70	0.000
A*C	3	1.07952E+14	3.59840E+13	0.35	0.793
A*D	3	3.72420E+15	1.24140E+15	11.90	0.000
B*C	3	2.94341E+14	9.81135E+13	0.94	0.420
B*D	3	2.41423E+16	8.04744E+15	77.16	0.000
C*D	1	1.57529E+14	1.57529E+14	1.51	0.219
3-Way Interactions	24	5.17412E+15	2.15588E+14	2.07	0.002
A*B*C	9	4.03689E+14	4.48544E+13	0.43	0.920
A*B*D	9	4.36819E+15	4.85354E+14	4.65	0.000
A*C*D	3	9.20100E+13	3.06700E+13	0.29	0.830
B*C*D	3	3.10234E+14	1.03411E+14	0.99	0.396
4-Way Interactions	9	4.63994E+14	5.15549E+13	0.49	0.879
A*B*C*D	9	4.63994E+14	5.15549E+13	0.49	0.879
Error	1856	1.93576E+17	1.04298E+14		
Total	1919	3.37822E+17			

Table D-2 ANOVA Results for $varWC^{(i,1)}$ at the Wholesaler

Model	63	5.20725E+17	8.26547E+15	28.68	0.000
Linear	8	3.42036E+17	4.27545E+16	148.36	0.000
A	3	2.69567E+16	8.98558E+15	31.18	0.000
B	3	2.34503E+16	7.81677E+15	27.12	0.000
C	1	7.37523E+16	7.37523E+16	255.92	0.000
D	1	2.17877E+17	2.17877E+17	756.02	0.000
2-Way Interactions	22	1.49296E+17	6.78620E+15	23.55	0.000
A*B	9	5.88532E+15	6.53924E+14	2.27	0.016
A*C	3	1.68557E+16	5.61857E+15	19.50	0.000
A*D	3	2.57597E+16	8.58657E+15	29.80	0.000
B*C	3	3.41843E+15	1.13948E+15	3.95	0.008
B*D	3	2.42796E+16	8.09319E+15	28.08	0.000
C*D	1	7.30977E+16	7.30977E+16	253.65	0.000
3-Way Interactions	24	2.75528E+16	1.14803E+15	3.98	0.000
A*B*C	9	1.85335E+15	2.05927E+14	0.71	0.696
A*B*D	9	5.85327E+15	6.50363E+14	2.26	0.016
A*C*D	3	1.64990E+16	5.49966E+15	19.08	0.000
B*C*D	3	3.34718E+15	1.11573E+15	3.87	0.009
4-Way Interactions	9	1.83979E+15	2.04421E+14	0.71	0.701
A*B*C*D	9	1.83979E+15	2.04421E+14	0.71	0.701
Error	1856	5.34875E+17	2.88187E+14		
Total	1919	1.05560E+18			

Table D-3 ANOVA Results for $varWC^{(i,1)}$ at the Supplier

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	1.04082E+17	1.65209E+15	15.39	0.000
Linear	8	5.54875E+16	6.93594E+15	64.59	0.000
A	3	2.67719E+14	8.92397E+13	0.83	0.477
B	3	2.96406E+15	9.88020E+14	9.20	0.000
C	1	6.32712E+15	6.32712E+15	58.92	0.000
D	1	4.59286E+16	4.59286E+16	427.72	0.000
2-Way Interactions	22	2.43010E+16	1.10459E+15	10.29	0.000
A*B	9	4.47942E+15	4.97714E+14	4.64	0.000
A*C	3	3.08010E+15	1.02670E+15	9.56	0.000
A*D	3	7.29916E+14	2.43305E+14	2.27	0.079
B*C	3	1.31228E+16	4.37428E+15	40.74	0.000
B*D	3	2.46392E+15	8.21305E+14	7.65	0.000
C*D	1	4.24774E+14	4.24774E+14	3.96	0.047
3-Way Interactions	24	2.31006E+16	9.62524E+14	8.96	0.000
A*B*C	9	1.16095E+15	1.28994E+14	1.20	0.290
A*B*D	9	4.49371E+15	4.99301E+14	4.65	0.000
A*C*D	3	4.51728E+15	1.50576E+15	14.02	0.000
B*C*D	3	1.29286E+16	4.30955E+15	40.13	0.000
4-Way Interactions	9	1.19289E+15	1.32543E+14	1.23	0.269
A*B*C*D	9	1.19289E+15	1.32543E+14	1.23	0.269
Error	1856	1.99300E+17	1.07381E+14		
Total	1919	3.03382E+17			

Table D-4 ANOVA Results for $CFB^{(i,1)}$ at the Retailer

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	9.24638E+11	14676799412	21.38	0.000
Linear	8	6.78022E+11	84752735144	123.48	0.000
A	3	26411120890	8803706963	12.83	0.000
B	3	1.51342E+11	50447298801	73.50	0.000
C	1	826831074	826831074	1.20	0.273
D	1	4.99442E+11	4.99442E+11	727.64	0.000
2-Way Interactions	22	2.09411E+11	9518660457	13.87	0.000
A*B	9	27774470197	3086052244	4.50	0.000
A*C	3	843365475	281121825	0.41	0.746
A*D	3	23332805037	7777601679	11.33	0.000
B*C	3	1864588419	621529473	0.91	0.438
B*D	3	1.54801E+11	51600440688	75.18	0.000
C*D	1	793978861	793978861	1.16	0.282
3-Way Interactions	24	33455604708	1393983530	2.03	0.002
A*B*C	9	3260606272	362289586	0.53	0.855
A*B*D	9	27499511431	3055501270	4.45	0.000
A*C*D	3	717263907	239087969	0.35	0.790
B*C*D	3	1978223099	659407700	0.96	0.410
4-Way Interactions	9	3750347030	416705226	0.61	0.792
A*B*C*D	9	3750347030	416705226	0.61	0.792
Error	1856	1.27394E+12	686389509		
Total	1919	2.19858E+12			

Table D-5 ANOVA Results for $CFB^{(i,1)}$ at the Wholesaler

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	4.90254E+12	77818164473	28.54	0.000
Linear	8	3.22320E+12	4.02899E+11	147.76	0.000
A	3	2.55878E+11	85292691328	31.28	0.000
B	3	2.18742E+11	72913925755	26.74	0.000
C	1	6.97100E+11	6.97100E+11	255.66	0.000
D	1	2.05148E+12	2.05148E+12	752.38	0.000
2-Way Interactions	22	1.40436E+12	63834625003	23.41	0.000
A*B	9	51862477577	5762497509	2.11	0.026
A*C	3	1.61600E+11	53866527349	19.76	0.000
A*D	3	2.44144E+11	81381444105	29.85	0.000
B*C	3	30521607292	10173869097	3.73	0.011
B*D	3	2.25995E+11	75331830423	27.63	0.000
C*D	1	6.90238E+11	6.90238E+11	253.15	0.000
3-Way Interactions	24	2.57315E+11	10721478190	3.93	0.000
A*B*C	9	17953018228	1994779803	0.73	0.680
A*B*D	9	51518520010	5724280001	2.10	0.027
A*C*D	3	1.57877E+11	52625757361	19.30	0.000
B*C*D	3	29966666250	9988888750	3.66	0.012
4-Way Interactions	9	17671978009	1963553112	0.72	0.691
A*B*C*D	9	17671978009	1963553112	0.72	0.691
Error	1856	5.06064E+12	2726639144		
Total	1919	9.96319E+12			

Table D-6 ANOVA Results for $CFB^{(i,1)}$ at the Supplier

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	2.11212E+12	33525765905	15.78	0.000
Linear	8	1.12386E+12	1.40482E+11	66.11	0.000
A	3	4702629285	1567543095	0.74	0.530
B	3	62719259945	20906419982	9.84	0.000
C	1	1.34608E+11	1.34608E+11	63.35	0.000
D	1	9.21826E+11	9.21826E+11	433.83	0.000
2-Way Interactions	22	4.95182E+11	22508287757	10.59	0.000
A*B	9	91469977451	10163330828	4.78	0.000
A*C	3	58911425521	19637141840	9.24	0.000
A*D	3	14909186630	4969728877	2.34	0.072
B*C	3	2.67027E+11	89008903263	41.89	0.000
B*D	3	52957608727	17652536242	8.31	0.000
C*D	1	9907422526	9907422526	4.66	0.031
3-Way Interactions	24	4.67709E+11	19487872186	9.17	0.000
A*B*C	9	25516512384	2835168043	1.33	0.214
A*B*D	9	90359918635	10039990959	4.73	0.000
A*C*D	3	88943267784	29647755928	13.95	0.000
B*C*D	3	2.62889E+11	87629744556	41.24	0.000
4-Way Interactions	9	25375734620	2819526069	1.33	0.217
A*B*C*D	9	25375734620	2819526069	1.33	0.217
Error	1856	3.94374E+12	2124858572		
Total	1919	6.05586E+12			

Table D-7 ANOVA Results for $BWE^{(i,1)}$ at the Retailer

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	5944.34	94.35	370.12	0.000
Linear	8	5930.42	741.30	2907.83	0.000
A	3	5927.01	1975.67	7749.76	0.000
B	3	1.92	0.64	2.51	0.057
C	1	1.06	1.06	4.17	0.041
D	1	0.43	0.43	1.67	0.196
2-Way Interactions	22	7.89	0.36	1.41	0.099
A*B	9	2.91	0.32	1.27	0.248
A*C	3	3.53	1.18	4.61	0.003
A*D	3	0.17	0.06	0.22	0.885
B*C	3	0.38	0.13	0.49	0.688
B*D	3	0.84	0.28	1.09	0.350
C*D	1	0.07	0.07	0.27	0.603
3-Way Interactions	24	4.98	0.21	0.81	0.721
A*B*C	9	1.84	0.20	0.80	0.613
A*B*D	9	2.37	0.26	1.03	0.413
A*C*D	3	0.15	0.05	0.20	0.896
B*C*D	3	0.62	0.21	0.81	0.488
4-Way Interactions	9	1.05	0.12	0.46	0.903
A*B*C*D	9	1.05	0.12	0.46	0.903
Error	1856	473.16	0.25		
Total	1919	6417.50			

Table D-8 ANOVA Results for $BWE^{(i,1)}$ at the Wholesaler

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	355431	5642	734.62	0.000
Linear	8	319774	39972	5204.73	0.000
A	3	112760	37587	4894.18	0.000
B	3	23	8	1.01	0.389
C	1	206982	206982	26951.18	0.000
D	1	8	8	1.09	0.297
2-Way Interactions	22	35085	1595	207.66	0.000
A*B	9	47	5	0.68	0.727
A*C	3	34958	11653	1517.31	0.000
A*D	3	7	2	0.31	0.821
B*C	3	6	2	0.25	0.863
B*D	3	65	22	2.84	0.037
C*D	1	1	1	0.18	0.669
3-Way Interactions	24	350	15	1.90	0.005
A*B*C	9	45	5	0.66	0.748
A*B*D	9	214	24	3.09	0.001
A*C*D	3	11	4	0.46	0.713
B*C*D	3	80	27	3.47	0.015
4-Way Interactions	9	223	25	3.23	0.001
A*B*C*D	9	223	25	3.23	0.001
Error	1856	14254	8		
Total	1919	369685			

Table D-9 ANOVA Results for $BWE^{(i,1)}$ at the Supplier

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	63	955312865	15163696	1080.52	0.000
Linear	8	864406915	108050864	7699.42	0.000
A	3	95243401	31747800	2262.26	0.000
B	3	8803	2934	0.21	0.890
C	1	769148249	769148249	54807.45	0.000
D	1	6462	6462	0.46	0.497
2-Way Interactions	22	89817325	4082606	290.92	0.000
A*B	9	76363	8485	0.60	0.794
A*C	3	89597805	29865935	2128.17	0.000
A*D	3	12340	4113	0.29	0.830
B*C	3	6911	2304	0.16	0.921
B*D	3	118108	39369	2.81	0.038
C*D	1	5798	5798	0.41	0.520
3-Way Interactions	24	647456	26977	1.92	0.005
A*B*C	9	72980	8109	0.58	0.816
A*B*D	9	440764	48974	3.49	0.000
A*C*D	3	13831	4610	0.33	0.805
B*C*D	3	119881	39960	2.85	0.036
4-Way Interactions	9	441169	49019	3.49	0.000
A*B*C*D	9	441169	49019	3.49	0.000
Error	1856	26046446	14034		
Total	1919	981359310			

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VITA

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