ESSAYS IN SUPPLY CHAIN MANAGEMENT

by

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ABSTRACT

Supply chain management involves coordination and collaboration among organizations at different echelons of a supply chain. This dissertation explores two challenges to supply chain coordination: trade promotion (sales incentive offered by a manufacturer to its downstream customers, e.g., distributors or retailers) and bullwhip effect (a phenomenon of amplification of demand variability from downstream echelons to upstream echelons in the supply chain). Trade promotion represents one of the most important elements of the marketing mix and accounts for about 20% of manufacturers' revenue. However, the management of trade promotion remains in a relatively under-researched state, especially for nongrocery products. This dissertation describes and models the effectiveness of trade promotion for healthcare products in a multiechelon pharmaceutical supply chain. Trade promotion is identified in the literature as a cause of the bullwhip effect, which has long been of interest to both researchers in academia and industrial practitioners. This dissertation develops a framework to decompose the conventional inter-echelon bullwhip measure into three intra-echelon bullwhips, namely, the shipment, manufacturing, and order bullwhips, and explores the empirical relationship between the bullwhip and the time duration over which it is measured. This dissertation also analyzes the potential bias in aggregated bullwhip measurement and examines various driving factors of the bullwhip effect. Theoretical and managerial implications of the findings are discussed.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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CHAPTER 1

INTRODUCTION

There has been an increasing recognition of the importance of supply chain management in the past decade. More and more organizations consider supply chain management as a core competitive strategy. A supply chain is a set of organizations that interact to transform raw materials into finished products and deliver them to customers. Each organization in the supply chain is linked by one or more upstream and downstream flows of material, information, and finance. The material flow includes the transformation and movement of goods and materials. It generally goes from an upstream organization to a downstream organization. The information flow involves order transmission and delivery status update. The financial flow consists of payment schedules, credits terms, and incentive programs. The information and finance flows can move both upstream and downstream. Supply chain management is the coordination and integration of these three flows both within and among organizations in the supply chain to achieve a sustainable competitive advantage. It requires a conscious effort by all supply chain organizations to run the supply chain in an efficient way.

Supply chain performance depends on the actions taken by all organizations in the supply chain; one weak link can have a negative effect on every other organization in the chain. While all organizations in the supply chain support in principle the objective of maximizing the total profit of the supply chain, each organization's primary objective is to maximize its own profit. An action that maximizes one organization's profit might not maximize its upstream supplier's or downstream customer's profit. There are incentive conflicts among independent organizations in the supply chain. Each organization's self-serving behavior can lead to tremendous inefficiencies. Organizations in the supply chain can benefit from better alignment of incentives and operational coordination. In this dissertation, we study two issues related to supply chain coordination: trade promotion and bullwhip effect.

Trade promotions are special incentive programs offered by manufacturers to their supply chain partners (e.g., distributors and retailers). They take various forms such as direct price discounts, display allowance, free case offers, off-invoice allowance, volume discounts, and slotting allowance. Globally, manufacturers spend more than $500 billion on trade promotions every year. In consumer product goods industry, trade spending represents about 19% of manufacturers' revenue compared with advertising's 7.5% (Nielsen, 2014). A recent three-year (2012-2014) industry analysis finds that more than 50% of the trade promotion events worldwide did not break even in 2014 (Nielsen, 2015). Trade promotion efficiency is rated as the top issue by 99% of manufacturers in the A.C. Nielsen 2002 Trade Promotion Practice Study. The success of trade promotions is contingent on whether manufacturers and their downstream partners can forge a coordinated strategy that eliminates forward buying and ineffective spending. Trade promotion management remains in a relatively under-researched state (Donthu & Poddar, 2011; Nielsen, 2014). One topic that has not yet obtained sufficient attention is about effects of trade promotions for nongrocery products (van Heerde & Neslin, 2008). In this dissertation, we describe and model the effectiveness of trade promotion for healthcare products, and make a contribution to the literature on trade promotions.

Trade promotion is identified in the literature as a source of the bullwhip effect (Lee et al., 1997a; Sodhi, Sodhi, & Tang, 2014). In a seminal paper, Lee et al. (1997a) define the bullwhip effect as "the phenomenon where orders to the supplier tend to have larger variance than sales to the buyer (i.e., demand distortion), and the distortion propagates upstream in an amplified form (i.e., variance amplification)" (p. 546). The bullwhip effect is costly to all organizations of the supply chain, but particularly to upstream organizations that receive the most distorted order information. The bullwhip effect results from the interactions among organizations at different echelons of the supply chain, so an organization is not able to mitigate the bullwhip effect by itself. It must recognize the underlying causes and try to achieve better coordination with its upstream and downstream members. The identification and management of the bullwhip effect is a significant advancement in supply chain management in the past two decades. A commonly used bullwhip measure in previous studies is the ratio of variability in a firm's orders placed with its supplier to the variability in its demand (the orders the firm receives from its customers). While the conventional bullwhip measure is informative and useful for determining what happens across a firm in the supply chain, numerous actions inside the firm contribute to its conventional bullwhip measure. We develop a framework to decompose the conventional bullwhip measure into three intra-echelon bullwhips, namely, the shipment, manufacturing, and order bullwhips. This simple and readily-implementable framework enables the firm to keep track of its internal bullwhip and to reduce the variability in its product flow streams.

Although there is a growing literature of empirical studies on the bullwhip effect, there are several challenges in empirical estimation of the effect. First, theoretical analysis uses information-based definition of bullwhip measure, which compares order variance with demand variance (Lee et al., 1997a). Most empirical studies employ material-based definition, which compares the variance of order receipts with that of sales. These two definitions differ in concept and are not necessarily a good approximation of each other. Hence, empirical studies on the bullwhip effect using material-based definition may not have a direct bearing on the theoretical models that use information-based definition. Second, analytical models define the bullwhip effect based on a single product and order decision period. Due to data availability issues, most empirical studies measure the bullwhip effect based on aggregated products and aggregated time to a month or longer. Measuring the bullwhip effect in terms of aggregate data may cause potential biases in estimation (Chen & Lee, 2012). Whether aggregation amplifies, preserves, or dampens the bullwhip effect is an important question to explore. Third, the bullwhip effect is a supply chain phenomenon. Bullwhip effect estimation requires information such as order and demand data from each echelon along the supply chain to keep track of individual products. It is a formidable task to collect this information. To the best of our knowledge, no prior work manages to do this. In this dissertation, we address these empirical challenges by analyzing a proprietary dataset from a multiechelon pharmaceutical supply chain and make the following contributions to the literature. First, we measure the bullwhip effects based on both information flows and material flows, and compare them with each other. Second, we explore the impact of product aggregation and temporal aggregation on the bullwhip effect. Third, we examine some drivers of the bullwhip effect such as price fluctuation, replenishment lead time, and inventory, which have not been fully verified in prior empirical literature.

This dissertation contains three main chapters, with each chapter corresponding to a different aspect of trade promotion management and bullwhip effect control. Each chapter is independent for the most part and can be read separately. We briefly summarize these three chapters below.

In Chapter 2, we describe and model the effectiveness of trade promotion in a multiechelon pharmaceutical supply chain. We analyze how distributors behave when trade promotions are offered. We find that distributors heavily forward buy during promotion period and seldom pass through promotions to consumers. Overall consumer demand associated with the trade promotions doesn't increase, making trade promotions unprofitable for manufacturers. Our results show that the manufacturer does not exhibit a bullwhip effect and distributors exhibit the effect for the products that receive trade promotions. We observe that the manufacturer and several distributors face sales spikes during the final month of a fiscal quarter (hockey stick phenomenon). This sales surge together with the bullwhip effect can cause substantial problems in production planning and inventory control. We discuss theoretical contributions and managerial implications of our findings.

Researchers exploring the bullwhip effect and its impact on supply chain performance utilize the conventional bullwhip measure, that is, the ratio of variance in the stream of orders placed to suppliers to variance in demand stream. In Chapter 3, we develop a framework to decompose this conventional inter-echelon bullwhip measure into three intra-echelon bullwhips, namely, the shipment, manufacturing, and order bullwhips. We define the shipment bullwhip as the variance in shipments (sales) relative to demand, the manufacturing bullwhip as the variance in manufacturing output relative to shipments, and the order bullwhip as the variance in orders placed relative to manufacturing. We demonstrate that the conventional bullwhip is the product of each of these three intra-echelon bullwhips. Moreover, using monthly, industry-level U.S. Census Bureau data, we characterize the magnitude of these intra-echelon bullwhips across industries, examine correlations between them, and identify factors that may be associated with industry differences. We also explore the empirical relationship between the bullwhip and the time duration over which it is measured (e.g., quarterly versus monthly) along with the impact of the time period's start date. For example, our data suggest a quarterly start date of February 1 yields a higher bullwhip measure than does a January 1 start date. Importantly, the decomposition framework provides guidance to firms seeking to better manage their shipping, manufacturing, and ordering activities.

In Chapter 4, we investigate the bullwhip effect in a multiechelon pharmaceutical supply chain. Specifically, we estimate the bullwhip effect at the stock keeping unit (SKU) level, analyze the bias in aggregated measurement of the bullwhip effect, and examine various driving factors of the bullwhip effect. We find that both manufacturer and distributors exhibit an intensive bullwhip effect, but the bullwhip effect at the manufacturer is less severe than that at distributors. Furthermore, we observe increasing demand variability from distributors to manufacturer. The bullwhip measurement based on orders (information flow) is larger than that based on order receipts (material flow). Data aggregation across products or over long time periods tends to mask the bullwhip effect in some cases. We find that products that have a flatter demand are more likely to exhibit the

bullwhip effect, and that price variation, replenishment lead time, and inventory are three main factors associated with the bullwhip effect. Managerial implications of the findings are discussed.

CHAPTER 2

TRADE PROMOTION AND ITS CONSEQUENCES

2.1 Introduction

Trade promotions are special incentive programs offered by manufacturers to distributors/retailers. They take various forms such as direct price discounts, display allowance, volume discounts, and bonus case offers. In this chapter, trade promotions are referred to as temporary price discounts. Dreze and Bell (2003) report that the U.S. consumer packaged goods industry spends approximately $75 billion annually on trade promotions. The large magnitude of this number becomes more obvious when compared with the total money spent on advertising that is approximately $37 billion. According to Ailawadi et al. (1999), trade promotions overall account for 52% of the total money spent on advertising and promotion. They represent a significant percentage of the marketing mix budget. However, trade promotions remain under-researched (Donthu & Poddar, 2011). One topic that has not yet obtained sufficient attention is the effect of trade promotions for nongrocery products (van Heerde & Neslin, 2008). By using a proprietary dataset in the healthcare industry, we fill the gap and make a contribution to the literature on trade promotions.

Manufacturers offer trade promotions with the hope that distributors will pass through some of the incentives to customers so as to increase sales. Distributors respond to price discounts offered by the manufacturers in three ways: first, they will purchase products from manufacturers who offer discounts instead of competing manufacturers who do not; second, they may forward buy, that is, order more products from the manufacturers than they need to meet current demand and hold inventory; third, they may pass through the discounts to customers in some form of distributor promotions. In any case, we expect to see a larger order during manufacturer promotion period. Manufacturers are very concerned about distributors' behavior during sales promotion. If the distributors just forward buy and do not pass through promotions, or pass through only a small part of the promotions, what manufacturers achieve is to sell more units at a lower price. These units could have been sold at regular price in the near future. Therefore, manufacturers do not benefit from promotions. Trade promotion efficiency is rated as the top issue by 99% of manufacturers in the A.C. Nielsen 2002 Trade Promotion Practice Study. This chapter explicitly examines how distributors respond to price discounts and provides insights for manufacturers.

In the past two decades, a significant advancement in supply chain management is the identification and management of the bullwhip effect. In a seminal paper, Lee et al. (1997a) define the bullwhip effect as "the phenomenon where orders to the supplier tend to have larger variance than sales to the buyer (i.e., demand distortion), and the distortion propagates upstream in an amplified form (i.e., variance amplification)" (p. 546). The mismatch between demand and production leads to supply chain inefficiency. Lee et al. (1997a) identify trade promotion as a source of the bullwhip effect. Most theoretical studies on bullwhip effect analyze this effect in a single product model setting, but most empirical studies use aggregate data (e.g., Cachon et al., 2007; Bray & Mendlson, 2012). Measuring bullwhip effect in terms of aggregate data causes potential biases (e.g., Chen & Lee, 2012; Jin et al., 2015b). In contrast, we report the tests of the bullwhip effect in a supply chain at the product level and in fine time buckets such as monthly as defined in analytical papers. So our results avoid aggregation biases and therefore make important contributions to the literature.

One issue directly related to trade promotion or distributor promotion is promotion timing. In practice, manufacturers and/or distributors often offer promotions at the end of sales period in order to reach sales targets. In the literature, the resulting last-period sales spike is referred to as the hockey stick phenomenon. Hockey stick sales pattern is one of the most harmful problems in the supply chain management and contributes to triggering the bullwhip effect (Singer et al., 2009). Graham et al. (2005) and Roychowdhury (2006) find that managers select operational activities (e.g., offering price discounts at the end of the quarter) that sacrifice long-time value to manipulate earnings to meet earnings benchmarks. Earnings management may mislead some shareholders about the underlying economic performance of the firm (Healy & Wahlen, 2009). One goal of this chapter is to document hockey stick phenomenon in recent firm/product-level data from a proprietary dataset in the healthcare industry.

The rest of this chapter is organized as follows. Section 2.2 provides a brief survey on the related literature. Research objectives are stated in section 2.3. Section 2.4 summarizes empirical context and data. In section 2.5, we discuss the econometric models used in estimation. We present our results in section 2.6. Section 2.7 offers some concluding comments.

2.2 Literature Review

There are three streams of literature related to our study: trade promotions, bullwhip effect, and hockey stick phenomenon. There is a huge body of literature on trade promotions. Interested readers are referred to comprehensive reviews by Blattberg et al. (1995), Raju (1995), and Donthu and Poddar (2011). We only discuss the papers that are relevant to our study. Researchers attempt to measure the profit impact of trade dollars (Mohr & Low, 1993) and have long questioned whether trade promotions are profitable to the manufacturer (Chevalier & Curhan, 1976; Kruger, 1987; Lucas, 1996). Kopp and Greyser (1987) and Quelch (1983) investigate both the long- and short-term impacts of trade promotions. Manufacturers blame retailers for taking advantage of trade promotions but not providing benefits to end consumers (Chevalier & Curhan, 1976), which would increase the profits of only the retailers at the expense of manufacturers. Coughlan et al. (2006) and Kotler and Keller (2006) argue that retailer's forward buying is a consequence of trade promotions, which helps the retailer but hurts the manufacturer. Desai et al. (2010) show that the retailer in a bilateral monopoly model will forward buy when trade promotion is offered by the manufacturer. Retailers admit that they use trade promotions to shore up their profits (Kumar et al., 2001). Abraham and Lodish (1990) find that only 16% of trade promotion deals are profitable for the manufacturer based on incremental sales through retailer warehouses compared to the manufacturers' allowances, lost margin, and cost of discounts. Overall, trade promotions appear to be a losing proposition for manufacturers. Our findings in this chapter are consistent with this conclusion. In a seminal paper, Blattberg and Levin (1987) present an integrated model to describe the interrelationships among the manufacturer, retailers, and consumers. Their model consists primarily of two equations: retailer orders as a function of inventory and trade promotion, and consumer sales as a function of retailer promotion. By using Nielsen bimonthly data on manufacturer shipments, retail sales, and information on trade deals and advertising, they estimate the effectiveness and profitability of trade promotions. In terms of conceptual modelling structure, our econometric model is similar to theirs. We come up with a more complex model, use alternative proxy variables, and estimate the model using advanced techniques. The difference is that we get more accurate estimates. Also our dataset contains more detailed information (e.g., monthly sales numbers) that is not available to Blattberg and Levin, eliminating many of the data problems they encounter. For example, there is no need to develop monthly sales numbers from bimonthly sales using linear extrapolation.

Bullwhip effect has been widely studied in economics and operations management literature since Forrester (1961) first identified the effect in a series of case studies. Economists discuss supply chain volatility in terms of production smoothing. A firm can use inventory as a buffer to smooth its production in response to demand fluctuations. Maintaining production at a relatively stable level is less costly than varying the production level, possibly either because the production cost function is convex or because changing the rate of production is expensive. Production smoothing enables the firm to exploit economies in production and maximize total profits. This argument suggests that production is less volatile than demand. However, the majority of the empirical studies show the opposite result: production is more variable than demand (e.g., Blanchard, 1983; Miron & Zeldes, 1988; Rossana, 1998). To explain the discrepancies, several researchers (e.g., Caplin, 1985; Blinder, 1986; Kahn, 1987) have shown that production is actually more variable than demand under certain inventory policies and demand structure. Lee et al. (1997a) approach the bullwhip phenomenon from a managerial perspective as opposed to a macroeconomics aspect and popularize the term in the operations management literature. In a seminal paper (1997a), these same authors define the bullwhip effect in supply chain context and analyze four sources of the effect: demand signal processing, price fluctuation, order batching, and rationing game. There is a growing operations management literature of the analytical studies on the bullwhip effect after the work of Lee et al. (1997a) (e.g., Cachon, 1999; Chen et al., 2000; Gilbert, 2005; Chen & Lee, 2012). Many researchers from operations management field have conducted empirical investigation on the bullwhip effect. Anderson et al. (2000) and Terwiesch et al. (2005) report the existence of the bullwhip effect in machine tool industry and semiconductor supply chain, respectively. Fransoo and Wouters (2000) discuss several important issues in measuring the bullwhip effect, and find that the bullwhip effect exists at different echelons in two food supply chains in the Netherlands. By using monthly data on 3,754 SKUs from the distribution center of a supermarket chain in Spain, Lai (2005) finds that 80% of the total SKUs show bullwhip effect and order batching is the main cause. Cachon et al. (2007) use monthly sales and inventory data from the U.S. Census Bureau and the Bureau of Economic Analysis to search for the bullwhip effect in a wide panel of industries. They find that retail industries and most manufacturing industries do not exhibit a bullwhip effect, but wholesale industries exhibit the effect. Our results at the product level are consistent with those at the industry level by Cachon et al. (2007). By using firm-level quarterly data from Compustat, Bray and Mendelson (2012) find that two thirds of 4,689 public U.S. companies bullwhip and information transmission lead time contributes to the effect.

As a common phenomenon observed in practice, hockey stick phenomenon has been reported in the literature by several researchers. Sterman (1992) shows that even though automobile manufacturers demand the parts at a constant pace for their assembly lines, the orders placed to suppliers at the end of each month exceed many times the orders placed during the month. Hammond (1994) reports a similar situation for Barilla SpA, the largest pasta manufacturer in Italy. While pasta consumption is relatively constant, the order pattern of one of its wholesalers has peaks at the end of each month. Bradley and Arntzen (1999) report this situation for an electronics manufacturer at the end of each quarter, and describe it as a self-induced pattern driven by the company's business practices and by customers who have learned to watch for end-of-quarter deals. Our findings provide some evidence for hockey stick phenomenon in healthcare industry. Theoretical models that have been employed to study this phenomenon are based on noncooperative game theory (Singer et al., 2009), agency theory (Chen, 2000), and dynamic stochastic models (Sohoni et al., 2010). Hockey stick phenomenon is associated with other effects in the accounting and economics literature such as channel stuffing, sales manipulation, forward selling, earnings management, and fiscal year end effect (Chapman & Steenburgh, 2011; Cohen et al., 2008; Lai et al., 2011). Oyer (1998) shows the fiscal year end sales pattern: sales at the industry level of a large panel of manufacturing firms are 2.7% higher in the fourth fiscal quarter and 4.8% lower in the first fiscal quarter than they are in the second or third quarter. Oyer discusses how managerial incentives may cause the observed fiscal year end effects. Our econometric modelling approach is closely related to the pioneering work by Oyer. But our study focuses on end-of-quarter effect rather than fiscal year end effect.

2.3 Research Objectives

The primary objective of this chapter is to explore how downstream members in a three-echelon supply chain respond to manufacturer's price discounts. Figure 2.1 shows factors that influence the offering of discounts and the response to the discounts. We discuss these factors below from the perspective of manufacturer, distributor, and practitioner, respectively.

The Manufacturer's Perspective: The main reason that a manufacturer offers a discount is to increase sales volume. The willingness of a manufacturer to run trade promotions depends on several factors. The first one is inventory. When a manufacturer is burdened with excess inventory, there are many financial drawbacks such as increased holding cost, reduced profits, and adverse impact on cash flow. The manufacturer can use promotions to liquidate excess inventory and shift inventory holding cost to the distributors (Cui et al., 2008). The more inventory the manufacturer holds, the more likely it offers discounts. Inventory positively affects the manufacturer's offering of a discount. The second factor is financial report's timing (end of the fiscal quarter). Managers may take various actions (e.g., temporary price reductions) to boost sales prior to the end of the fiscal quarter to meet sales target or earnings benchmarks. Graham et al. (2005) find that 78% of 400 managers surveyed admit to take economic actions that sacrifice long-term value to manage earnings. Roychowdhury (2006) find that managers choose operational activities to manipulate earnings to meet earnings thresholds, so promotions have a positive relationship with the fiscal quarter end. We expect to see that sales are higher at the end of the fiscal quarter (hockey stick phenomenon). The third factor is capacity utilization. Low capacity utilization incurs higher fixed costs per unit, and therefore reduces profit. It indicates that there is a lack of market demand and portrays a negative image of management. When experiencing low capacity utilization, the manufacturer will be more likely to offer promotions to stimulate demand in order to keep the utilization at the appropriate level. Promotions have a negative association with capacity utilization.

The Distributor's Perspective: The distributor responds to promotions in three ways. First, the distributor will purchase from manufactures who provide promotions rather than from competing manufacturers who do not. This affects manufacturers' market share: Market share of manufacturers who offer discounts increases, and that of those who do not decreases. Second, since the purpose of the trade promotion is to get the distributor to offer the practitioners a price discount and therefore increase sales, the distributor will pass through (some) promotions and increase its inventories in anticipation of increased sales to practitioners. Third, the distributor will forward buy and hold inventory in order to take advantage of the discounts and save purchasing cost. Forward buying benefits the distributor at the expense of the manufacturer: The distributor buys at reduced costs, but the manufacturer has a lower sales revenue because there is no overall increase in practitioner demand to compensate for the discounted price. In any of three cases aforementioned, trade promotions increase orders placed by the distributor. When a distributor decides how much to order in each period to meet demand for its products, inventory on hand must be taken into account. Higher inventory level causes the distributor to order less to avoid additional holding cost. The distributor evaluates trade-off between savings from the promotion and extra inventory costs. The distributor's inventory negatively affects its response to the discount. As in the manufacturer's case, the distributor's willingness to provide practitioners with discounts depends on inventory and fiscal quarter end. The distributor's inventory positively affects the distributor's own offering of a discount, as does the distributor's own fiscal quarter end.

The Practitioner's Perspective: When distributors pass through trade promotions to the practitioners or offer practitioners their own promotions, the practitioners react in the following three ways: First, they purchase from distributors who provide discounts rather than from those who do not. This causes distributors' market share to shift. Second, the practitioners may purchase more units than usual and consume them at a higher rate. Consumption responds to promotions because promotions have the ability to increase practitioners' inventory level. Higher inventory levels mean fewer stockouts. The practitioners have more chances to consume the product. Both behavioral and economic theory provide supporting evidence that high inventory can increase usage rate (Ailawadi & Neslin, 1998). Third, the practitioners may forward buy. As in the distributor's case, the practitioner's inventory negatively affects its response to the distributor's discount.

The second objective of this chapter is to investigate the impact of trade promotions. Trade promotion is identified as a cause of the bullwhip effect (Lee et al. 1997a). We empirically test whether the bullwhip effect exists. If so, how severe is the effect? We also calculate the financial cost of the bullwhip effect. Following the original definition of the bullwhip effect by Lee et al. (1997a), we define

$$Bullwhip\ Ratio = \frac{V[Order]}{V[Demand]} \tag{2.1}$$

where $V[\,]$ is the variance operator. The numerator and denominator are the variance of order series and demand series of a single product. Order can be interpreted as production in manufacturing setting. We say that the bullwhip effect is exhibited by a product when the ratio is greater than 1. Given that trade promotion is recognized as a source of the bullwhip effect, we expect that bullwhip ratio is greater than 1 for products that receive promotions.

2.4 Empirical Context and Data

Our empirical analysis is based on a proprietary dataset in the healthcare industry. The dataset consists of one manufacturer and six nation-wide distributors (A-F). The structure of the supply chain and of the data is shown in Figure 2.2. The manufacturer produces consumable products that all medical practitioners in this specialty use, and has a lion's share of the market. These products are applied to patients in medical practitioner's office and have a shelf life of approximately 18 months. The manufacturer may periodically offer price discounts to its distributors to meet sales targets, for example, at the end of the manufacturer's fiscal quarter. In turn, a distributor may pass through some of the discounts to its customers. Also the distributor may offer its own promotions to meet sales targets at the end of its fiscal quarter.

We collect monthly data on 31 stock keeping units (SKUs) over the period between January 2010 and June 2014. The frequency of the data (monthly) matches the frequency of decisions by the manufacturer and distributors, so the data do not have the "time-disaggregation bias" identified by Kahn (1992), and are suitable for appropriate supply chain cost assessment (Chen & Lee, 2012). The entire product category is made up of these 31 SKUs. Specifically, the following data are used to perform empirical analysis: manufacturer's production, manufacturer's sales (shipments to distributors), distributors' orders, distributors' sales, manufacturer's wholesale price, and manufacturer's price discounts. Table 2.1 presents summary statistics by distributor for the orders, sales, and price variables used in our study. SKUs 1-11 are carried by all distributors. SKUs 12-15, 16-19, 20-23, 24-26, 27-28, and 29-31 are carried only by distributors A-F, respectively. Manufacturer offers price discounts for 2 SKUs (SKUs 1 and 2), which account for 40% of the total sales. All 31 SKUs have annual wholesale price increase. Quantities are expressed in physical units rather than dollar amounts. This avoids measurement and accounting problems associated with inventory evaluation (Lai, 2005). Over the entire sample period, manufacturer offers ten discounts, five discounts, four discounts, four discounts, five discounts, and six discounts to distributors A-F, respectively. Among these thirty-four discounts, twenty-five occur at the end of manufacturer's fiscal quarter.

We do not have access to distributors' inventory data, so an estimate of inventories is made using the following relationship:

$$Inventory_t = Inventory_{t-1} + Production_t - \ Sales_t \tag{2.2}$$

where $Inventory_t$ denotes the net inventories at the end of period t. We use shipments received from manufacturer as a proxy for distributor's production. Since initial inventories are not available, we choose them so that each period's inventory is greater than or equal to zero. Thus, the inventory data used in model estimation are relative inventory. Blattberg and Levin (1987) use the same approach to set the starting inventory.

Figure 2.3 shows sales and orders of a distributor for a specific product. We observe that there are usually troughs in orders after a price discount ends, suggesting forward buying on the part of the distributor during the promotional period. If the distributor passes promotions on to practitioners, the sales pattern and order pattern will be close to each other. In Figure 2.3, the sales of the distributor have much less variability than the orders placed by the distributor. This implies that the distributor is buying for inventory and passes only some portion of the promotions on to practitioners. Figure 2.4 shows the total sales of a distributor. We see spikes towards the end of every quarter. Hockey stick phenomenon is prevalent.

2.5 Model Specification

In order to explore the impact of trade promotions and identify the presence or absence of the hockey stick effect, we propose four empirical models and describe them in detail below. Recall that manufacturer provides price discounts only for SKUs 1 and 2, which carried by all distributors, and some of the other 29 SKUs are not carried by every distributor. We analyze SKUs 1 and 2 separately from the remaining 29 SKUs. Specifically, Models I(a), I(b), and III apply to SKUs 1 and 2, and Models II and IV apply to SKUs 3-31.

2.5.1 Distributor Order Model

We regress the distributors' orders on explanatory variables with the following specification (Model I(a)) for SKUs 1 and 2:

$$\begin{aligned} Orders_{it} = \alpha_i + \beta_1 t + \beta_2 Wholesale_{it} + \gamma_i Discount_{it} \\ + \delta_i (Lagged\ Inventory)_{it} + \varepsilon_{it} \end{aligned} \tag{2.3}$$

where i and t refer to distributor and time, respectively. $Orders_{it}$ is the orders placed by distributor i in month t to the manufacturer. α_i is the time-invariant distributor-specific fixed effect for distributor i. t is a linear time trend. That is, t is 1 in the first month, 2 in the second month, and up to 54 in the last month. Manufacturer increases wholesale price once per year. When manufacturer increases price, what typically happens is that it sends out the price change notice 60 days before effective date and then distributors will react accordingly. For example, if the manufacturer plans for a January price increase, distributors may make a purchase in December, depending on how big the price increase is. A price increase is often preceded by an increase in orders. This can be modeled by having a dummy variable for the periods prior to the price increase times the percentage price changes. More specifically, if there is a 10% wholesale price increase for distributor i in July, $Wholesale_{it}$ will be 0 for July and 10% for May and June. To represent the magnitude of a promotion, $Discount_{it}$ is a percentage dollar discount for distributor i in month t. This percentage discount makes various trade promotions comparable over time. Since trade promotions increase orders, we expect γ_i to be positive. $(Lagged\ Inventory)_{it}$ is one period lagged inventory for distributor i in month t. Distributors usually use some form of inventory model to determine how much to order on a given promotion. We include lagged inventories in the model because last period's inventories influence the quantity to order in the present period. Inventories inversely affect orders, so δ_i is expected to have a negative sign. ε_{it} denotes the error term, which account for all of the order fluctuations that we cannot explain.

In order to demonstrate the robustness of the results from Model I(a), we estimate the alternative model specification for each distributor and product combination (Model I(b)):

$$\begin{aligned} Orders_t = \alpha + \beta_1 t + \beta_2 Wholesale_t + \gamma Discount_t \\ + \delta (Lagged\ Inventory)_t + \varepsilon_t \end{aligned} \tag{2.4}$$

Since not every distributor carries SKUs 3-31, we analyze each distributor and product combination separately by running the following regression model (Model II):

$$Orders_t = \alpha + \beta_1 t + \beta_2 Wholesale_t + \delta(Lagged\ Inventory)_t + \varepsilon_t \tag{2.5}$$

2.5.2 Distributor Sales Model

We perform regression analysis on distributors' sales using the following linear specification (Model III) for SKUs 1 and 2:

$$Sales_{it} = \alpha_i + \beta_1 t + \beta_2 Wholesale_{it} + \delta_i(QuarterEnd)_{it} + \gamma_i Discount_{it} + \varepsilon_{it} \tag{2.6}$$

where i and t refer to distributor and time, respectively. $Sales_{it}$ is the sales of distributor i to practitioners in month t. $Wholesale_{it}$ is exactly the same as in Model I(a). Since we do not know distributors' pricing information, we use manufacturer's annual wholesale price increase as a proxy for distributor's wholesale price change. $(QuarterEnd)_{it}$ is a dummy variable that equals one if the sales occur at the last month of a fiscal quarter and zero otherwise. We assume that the fiscal effects are the same in the first and second months of a fiscal quarter and use these as the base months. δ_i measures the amount by which distributor i's unit sales change, holding other factors constant, from the first two months of a fiscal quarter to the third one. If hockey stick phenomenon exists, δ_i is expected to have a positive sign.

Ideally, $Discount_{it}$ is a percentage dollar discount offered by distributor i in month t. Given that we do not collect information about distributor promotions, we use manufacturer promotions as a surrogate for distributor promotions. Since discounts may increase sales, γ_i is expected to have a positive sign.

For SKUs 3-31 that are not carried by all distributors, we run separate regressions for each distributor and product combination (Model IV):

$$Sales_t = \alpha + \beta_1 t + \beta_2 Wholesale_t + \delta(QuarterEnd)_t + \varepsilon_t \qquad (2.7)$$

The data used in analysis are stationary because the Dickey-Fuller test suggests that there is no unit root in each data series. Since our data contain observations across distributors and months, it is likely that the variance of errors varies across distributors and errors for different observations are correlated within a distributor. We estimate Models I(a) and III by fixed effect (FE) method with cluster-robust standard errors that are robust to arbitrary heteroskedasticity and arbitrary serial correlation (see Wooldridge, 2010, Chapter 10). We estimate Models I(b), II, and IV by ordinary least squares (OLS) with Newey-West standard errors (see Greene, 2008, Chapter 19). The error structure is assumed to be heteroskedastic and AR(1) autocorrelated.

2.6 Results

In Tables 2.2 and 2.3, we report estimates of Models I(a) and I(b). Among these two models, the coefficients on $Discount$ for distributors A, B, E, and F are positive and statistically significant across products, indicating that distributors A, B, E, and F place a significantly larger order during promotional period. While these distributors seem to behave consistently with distributors described in previous literature (i.e., wholesaler or retailer increases its orders placed to the manufacturer when a trade promotion is offered (e.g., Srinivasan et al., 2004)), other distributors do not. Specifically, the coefficients on $Discount$ for distributors C and D have varying signs and different levels of significance across models. Clearly, not all distributors respond to the price discounts. The coefficients on $Lagged\ Inventory$ for all distributors are negative and statistically significant across products in two models, indicating that higher inventory level is associated with lower order quantity. This is consistent with our expectation: Inventory inversely affects order.

Estimates of Model II are shown in Table 2.4. The coefficients on $Wholesale$ are positive and statistically significant for almost all products carried by distributor A, but not for products carried by other distributors. Only distributor A responds to wholesale price increase. In general, the coefficients on $Lagged\ Inventory$ are negative and statistically significant, indicating that inventory is negatively associated with orders.

Table 2.5 shows estimates of Model III. Columns (1)-(3) and (4)-(6) are for SKU 1 and SKU 2, respectively. In columns (1) and (4), the coefficients on $Discount$ are positive and statistically significant for distributor F, indicating that distributor F has significantly higher sales for SKUs 1 and 2 during manufacturer promotion period. This implies that distributor F passes through trade promotions to practitioners. But we do not know the pass-through rate. Orders placed by practitioners to distributors and shipments from distributors to practitioners may occur in different months. Given that we only have shipments data, it is likely that some distributors pass through trade promotions, but the shipments occur in the next month rather than in the same month as manufacturer promotions. In columns (2) and (5), we use one period lagged discount variable. The coefficients on this variable are positive and statistically significant for distributors A and B. These two distributors have significantly higher sales for SKUs 1 and 2 one month later after manufacturer promotions. This implies that distributors A and B probably pass through trade promotions. In columns (3) and (6), we use lagged discount for distributors A and B, and use discount for the remaining distributors. The results show that distributors A, B, and F may pass through promotions for SKUs 1 and 2. Across columns (1)-(6), the coefficients on $QuarterEnd$ are positive and statistically significant for distributors B, C, D, E, and F. The hockey stick effect exists at most distributors. If we compare the coefficients on $Discount$ for distributors A, B, E, and F in Model I(a) with those in Model III, we find that the magnitude of the coefficients in Model I(a) is much larger than that in Model III, indicating that most of the incremental units sold by the manufacturer during promotion period are not the incremental units sold by distributors. Distributors A, B, E, and F forward buy and build inventories at lower costs when trade promotions occur. The distributors pocket the discount promotions without passing the benefits to the practitioners or with passing through a small part of the benefits. This result is consistent with the findings in the literature that trade promotions are not profitable for manufacturers (e.g., Abraham & Lodish, 1990).

Parameter estimates of Model IV are reported in Table 2.6. The coefficients on $QuarterEnd$ are positive and statistically significant for 10 out of 13 products carried by distributor B and 7 out of 12 products carried by distributor D. The coefficients on $QuarterEnd$ are positive but not significant for the remaining 5 products carried by distributor D. These results indicate that distributors B and D have higher sales in the last month of a fiscal quarter than they do in the first two months.

In Table 2.7, we report the bullwhip ratios. The bullwhip ratio for the manufacturer is equal to variance in production stream divided by variance in demand stream. Since we do not have distributors' demand data, we use sales as a proxy for demand. This will not inflate bullwhip estimates because distributors in our dataset usually carry enough inventory and stockouts rarely occur. The bullwhip ratio for distributors is equal to variance in order stream divided by variance in sales stream. At the SKU level, the substantial bullwhip effect exists at each distributor. The average ratio is 49.81 (ranging from 3.85 to 216.97), much higher than those reported in the previous literature. However, the bullwhip effect is not exhibited by manufacturer, indicating that the manufacturer makes production smoother than demand. This result is aligned well with production smoothing hypothesis. Our findings are consistent with those obtained by Cachon et al. (2007) at industry level.

Many firms use market share as a key indicator of their relative success in market competitiveness. From the information we collect from several distributors, we know that the distribution of health care products is highly competitive and these distributors actually compete with each other. The product category in our dataset is mature and the primary demand doesn't increase over sample periods. If a distributor passes through trade promotions to practitioners or boosts sales at the quarter end, its market share will increase. Table 2.8 presents the correlation coefficients between distributors' market share and trade promotion. There is a significant positive association between market share of distributors B and F and manufacturer's discounts for SKUs 1 and 2. This implies that distributors B and F probably pass through trade promotions. The result is consistent with that from Model III. In Table 2.9, we report the correlation coefficients between distributors' market share and their fiscal quarter ends. Market share of distributors B, D, and F has a significantly positive relationship with fiscal quarter ends for SKUs 1 and 2. This result is consistent with the hockey stick effect identified in Model III.

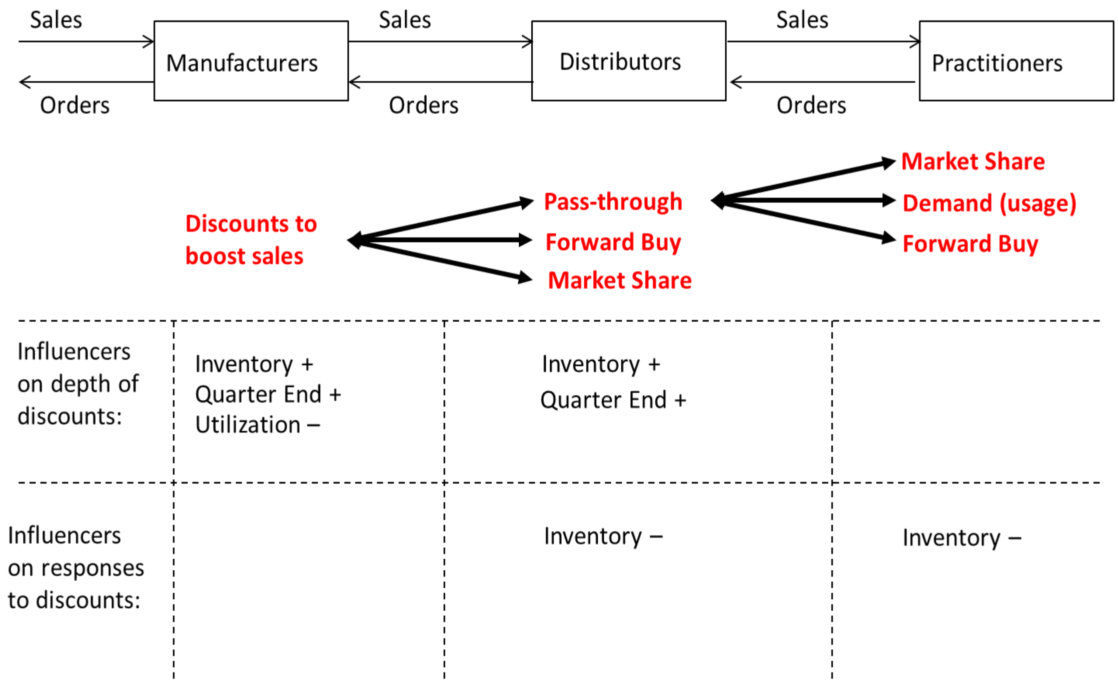
Trade promotions cause forwarding buying, which inflates inventories and therefore raises certain costs. We seek to estimate the added inventory costs resulting from promotions for manufacturer and distributors. In order to do this, we need to compare the actual inventories with those (hypothetical inventories) that would be carried if there was no promotion. When calculating the hypothetical inventory, we assume that manufacturer and distributors implement base stock inventory model (also called the order-up-to model) and maintain 99% service level. From our interviews with management of the manufacturer and public information of several distributors, we think these assumptions are reasonable approximations to real life situations. By using the analytical model developed by Moinzadeh (1997), we estimate that the carrying costs on inventories that include storage, insurance, handling, and capital charges are about 15% per year. We use Model III to forecast what the distributors' sales would have been in the absence of the discounts. Then we calculate the hypothetical inventory level at distributors and manufacturer. Table 2.10 shows the yearly added costs caused by promotions. The cost to the manufacturer is over one million dollars and represents 3.21% of total sales of the products affected. The costs to several distributors represent more than 1% of total sales. The cost to the supply chain is about two million dollars. Moreover, these substantial amounts account for only a part of the total costs of trade promotions. We do not try to quantify other expenses such as higher administrative and selling costs to operate increasingly complex procurement and sales programs, the costs of the time spent on design and evaluation of trade deals, and higher production costs due to uneven scheduling. These costs of promotions may equal or exceed the costs that we have estimated. Trade promotions incur high costs for both manufacturer and distributors and impair the efficiency of the supply chain.

2.7 Conclusion

Trade promotions are the most important promotional tool for manufacturers. It is reported in A.C. Nielsen 2002 Trade Promotion Practices Study that trade promotion spending accounts for 16% of gross sales. Conventional wisdom in marketing holds that (1) trade promotions are the main culprit behind retailer forwarding buying and (2) manufacturers are hurt by forward buying. Our results are consistent with this wisdom. By using a proprietary dataset in the healthcare industry, we find that some distributors do forward buy when offered wholesale price discounts and pass through only a small part of discounts to practitioners, causing trade promotions not to pay for manufacturers. Given the huge expenditure on trade promotions, we encourage marketing managers to re-examine the components of their promotion programs. In fact, our discussions with managers of the manufacturer reveal that they are suspicious of the effectiveness of periodic discounts and plan to implement a new pricing scheme that excludes the discounts. To the best of our knowledge, our study is the first empirical study on the effects of trade promotions for health care products.

We observe hockey stick phenomenon at the manufacturer and several distributors. The resulting sales surge causes substantial difficulty in production planning, transportation, and inventory management. Both trade promotion and hockey stick phenomenon contribute to triggering the bullwhip effect, which is one of the most harmful problems in the supply chain management. We find that all distributors exhibit an intensive bullwhip effect, lowering supply chain efficiency. One leading cause of the hockey stick phenomenon is salesperson and executive compensation contracts, which induce these agents to manipulate prices and influence the timing of sales. Our results provide practicing managers with a good starting point to think about their incentive schemes.

Since there are only two products in our dataset that receive price discounts, this limits the generalizability of our findings to the larger class of products. We do not collect information about distributor promotions, so we have to use an alternative variable as a measure of distributor activity. The availability of distributor promotion data in the future will enhance the models developed in this chapter and give more accurate model estimates.



Note: "+" and "–" denote positive and negative effects, respectively.

Figure 2.1: Factors Influencing Promotions

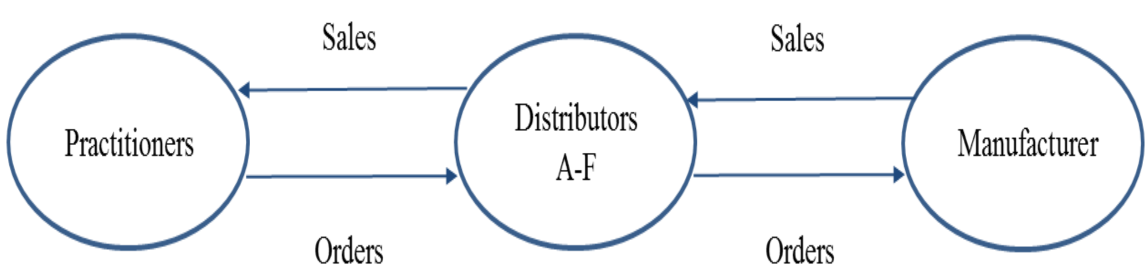


Figure 2.2: Structure of Supply Chain and Data

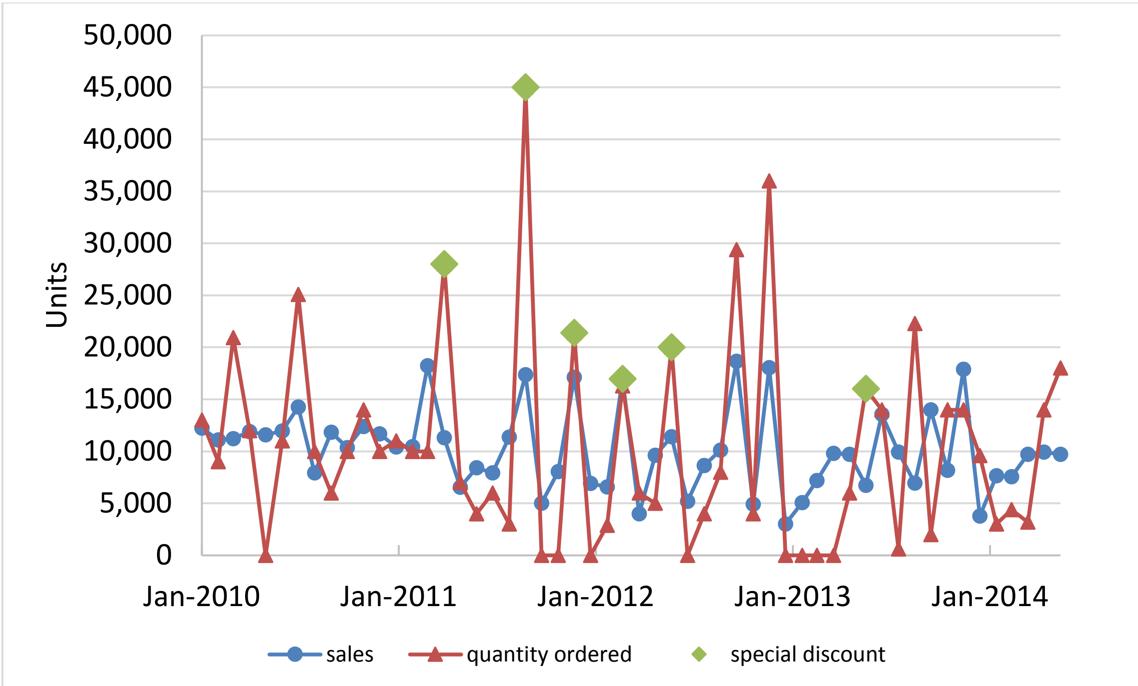


Figure 2.3: Sales and Orders of SKU 2 Carried by Distributor F

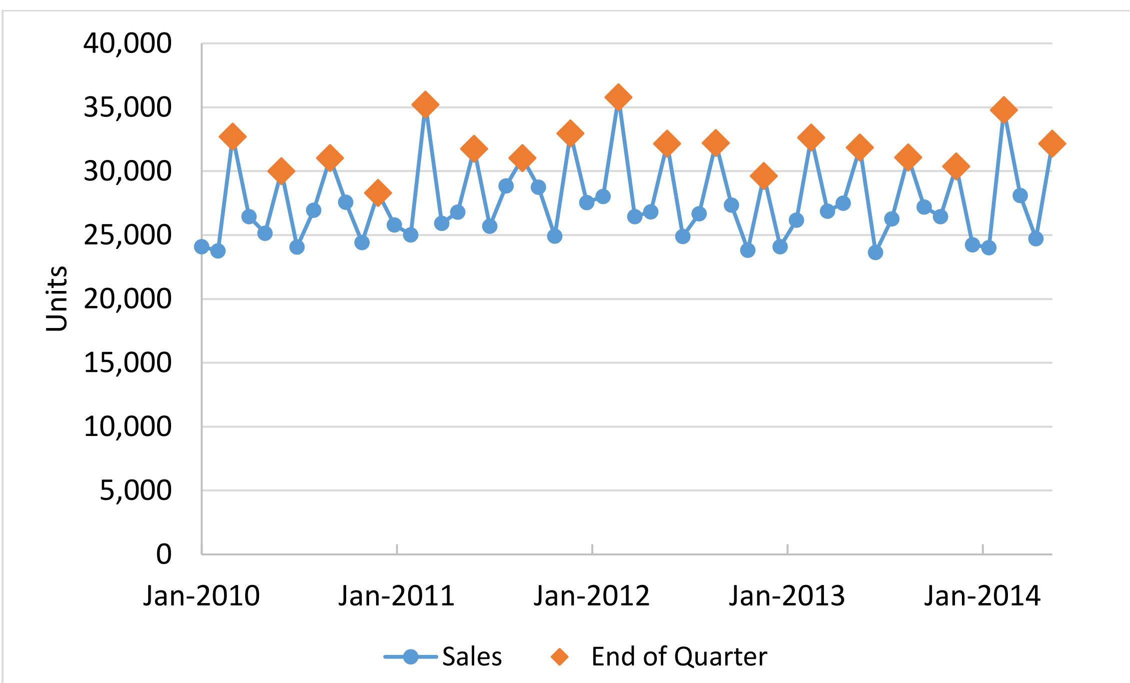


Figure 2.4: Total Sales of Distributor D

Table 2.1: Summary Statistics of the Orders, Sales, and Price Variables

		mean	standard deviation	min	max
Distributor A	Sales	9699	20431	2	88510
	Orders	13179	41712	-7	411240
Distributor B	Sales	5104	10038	8	43999
	Orders	6321	14241	-22	104860
Distributor C	Sales	1969	4781	1	31207
	Orders	2706	6339	-20	63240
Distributor D	Sales	2289	4187	-3	16992
	Orders	2969	6534	-225	53000
Distributor E	Sales	838	1437	1	5903
	Orders	2055	3592	-13	20800
Distributor F	Sales	2008	3556	-160	18660
	Orders	2562	5201	20	45000
Discount		5.46%	0.02	4.00%	8.60%
Wholesale price % change		5.70%	0.03	1.01%	10.10%

Note: negative numbers represent returns.

Table 2.2: Estimates of Model I(a)

	(1) SKU1	(2) SKU2
wholesale_a	327.7***	3,274***
	(0.286)	(15.30)
wholesale_b	352.3***	1,866***
	(1.357)	(16.35)
wholesale_c	10.98	67.72***
	(7.323)	(7.258)
wholesale_d	347.3***	804.5***
	(0.422)	(16.81)
wholesale_e	37.85***	210.6***
	(0.349)	(5.246)
wholesale_f	94.87***	367.3***
	(4.250)	(12.03)
discount_a	1,712***	11,837***
	(7.959)	(44.44)
discount_b	1,149***	7,143***
	(8.840)	(72.69)
discount_c	24.46**	-263.0***
	(6.676)	(56.50)
discount_d	134.9***	636.8***
	(10.88)	(32.03)
discount_e	150.1***	664.0***
	(3.285)	(18.73)
discount_f	525.1***	2,613***
	(1.730)	(6.555)
lagged_inv_a	-0.483***	-0.407***
	(0.00979)	(0.00558)
lagged_inv_b	-0.335***	-0.384***
	(0.0397)	(0.0150)
lagged_inv_c	-0.278**	-0.119***
	(0.0910)	(0.0142)
lagged_inv_d	-0.185***	-0.178***
	(0.00396)	(0.0408)
lagged_inv_e	-0.768***	-0.710***
	(0.148)	(0.139)
lagged_inv_f	-0.433***	-0.539***
	(0.0293)	(0.0162)
linear_trend	19.64	18.26
	(14.36)	(79.60)
Constant	2,887***	21,861***
	(260.5)	(1,976)
Observations	324	324
R-squared	0.393	0.399

Table 2.2 Continued

	(1) SKU1	(2) SKU2
Number of distributor	6	6
Distributor FE	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.3: Estimates of Model I(b)

	(1) SKU1_A	(2) SKU2_A	(3) SKU1_B	(4) SKU2_B	(5) SKU1_C	(6) SKU2_C
wholesale	328.9	3,202	350.0*	1,898	20.82	60.90
	(517.1)	(4,193)	(207.4)	(1,365)	(50.62)	(207.7)
discount	1,745***	12,046***	1,163***	6,998***	15.49	-316.1
	(526.9)	(4,212)	(205.0)	(1,361)	(16.63)	(286.6)
lagged_inv	-0.524***	-0.434***	-0.402***	-0.354***	-0.155**	-0.132**
	(0.151)	(0.125)	(0.136)	(0.115)	(0.0624)	(0.0517)
linear_trend	79.28	393.7	43.86	-140.1	0.355	-56.53**
	(62.94)	(419.3)	(27.33)	(120.2)	(5.907)	(24.79)
Constant	6,369***	49,699***	5,719***	40,484***	998.7***	7,141***
	(1,194)	(10,680)	(937.0)	(7,622)	(144.8)	(932.6)
Observations	54	54	54	54	54	54
R-squared	0.406	0.413	0.388	0.369	0.081	0.230

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.3 Continued

	(7) SKU1_D	(8) SKU2_D	(9) SKU1_E	(10) SKU2_E	(11) SKU1_F	(12) SKU2_F
wholesale	346.6**	782.2**	37.66	209.2	100.5	374.8
	(167.5)	(386.4)	(23.88)	(137.9)	(109.9)	(902.2)
discount	116.7	594.3	151.9**	659.0**	522.8***	2,609***
	(147.6)	(955.8)	(72.82)	(289.6)	(66.54)	(616.7)
lagged_inv	-0.192***	-0.232**	-0.687***	-0.747***	-0.394***	-0.529***
	(0.0508)	(0.104)	(0.121)	(0.111)	(0.114)	(0.142)
linear_trend	-4.401	-87.52	11.81***	39.55*	0.599	-31.67
	(9.922)	(57.31)	(3.839)	(20.59)	(8.385)	(53.86)
Constant	1,712***	13,867***	827.5***	4,934***	1,906***	16,257***
	(408.0)	(2,552)	(191.4)	(1,068)	(341.3)	(3,016)
Observations	54	54	54	54	54	54
R-squared	0.303	0.150	0.399	0.392	0.547	0.487

Table 2.4: Estimates of Model II

	(1) SKU 3_A	(2) SKU 4_ A	(3) SKU 5_ A	(4) SKU 6_ A	(5) SKU 7_A	(6) SKU 8_ A
wholesale	9.968	8.788	38.48	39.25***	102.6***	14.26***
	(11.37)	(11.23)	(23.04)	(11.20)	(27.77)	(3.955)
lagged_inv	-0.172	-0.319**	-0.112	-0.212***	-0.222***	-0.210***
	(0.140)	(0.143)	(0.122)	(0.0566)	(0.0344)	(0.0601)
linear_trend	-1.921	-3.311**	-10.60**	1.179	0.754	-0.381
	(1.198)	(1.411)	(4.966)	(0.902)	(1.796)	(0.402)
Constant	176.3***	246.6***	554.3**	109.8***	335.6***	71.79***
	(43.73)	(50.36)	(253.0)	(36.00)	(61.30)	(11.16)
Observations	36	36	36	54	54	54
R-squared	0.131	0.193	0.266	0.453	0.517	0.462

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4 Continued

	(7) SKU 9_ A	(8) SKU 10_ A	(9) SKU 11_ A	(10) SKU 12	(11) SKU 13	(12) SKU 14
wholesale	359.6***	57.69**	3.813	212.8***	1,241***	447.6***
	(101.6)	(21.96)	(19.82)	(67.55)	(411.8)	(127.6)
lagged_inv	-0.244***	-0.0699	0.640	-0.392**	-0.458***	-0.330***
	(0.0547)	(0.0587)	(0.520)	(0.180)	(0.0996)	(0.0707)
linear_trend	13.24	-1.391	-22.82	2.179	38.84	18.71
	(9.518)	(2.868)	(15.25)	(6.035)	(27.62)	(14.61)
Constant	1,197***	358.4**	262.7	1,593***	6,940***	2,631***
	(244.0)	(144.2)	(171.2)	(448.7)	(1,129)	(457.4)
Observations	54	54	30	54	54	54
R-squared	0.479	0.177	0.144	0.416	0.432	0.476

	(13) SKU 15	(14) SKU 3_B	(15) SKU 4_ B	(16) SKU 5_ B	(17) SKU 6_ B	(18) SKU 7_ B
wholesale	14,827***	-2.192	0.650	0.821	13.05***	16.71*
	(4,338)	(4.074)	(3.331)	(2.830)	(4.766)	(9.519)
lagged_inv	-0.412***	-0.61***	-0.869***	-1.186***	-0.766***	-0.684***
	(0.0783)	(0.206)	(0.163)	(0.211)	(0.139)	(0.112)
linear_trend	198.2	0.594	1.588*	2.329*	5.402***	8.243***
	(352.5)	(0.981)	(0.795)	(1.238)	(1.426)	(1.628)
Constant	68,584***	240.2***	306.3***	459.9***	274.0***	625.2***
	(13,055)	(60.27)	(39.98)	(57.51)	(39.08)	(79.45)
Observations	54	36	36	36	54	54
R-squared	0.459	0.264	0.380	0.572	0.442	0.433

Table 2.4 Continued

	(19) SKU 8_ B	(20) SKU 9_ B	(21) SKU 10_ B	(22) SKU 11_ B	(23) SKU 16	(24) SKU 17
wholesale	0.930	41.05	1.088	-10.68**	39.00**	262.7**
	(2.506)	(31.08)	(21.79)	(4.216)	(18.37)	(122.8)
lagged_inv	-0.338***	-0.783***	-0.289**	-0.106	-0.452***	-0.425**
	(0.0784)	(0.260)	(0.140)	(0.0912)	(0.151)	(0.176)
linear_trend	1.214**	14.27*	25.97**	2.486	3.201	26.41
	(0.516)	(8.143)	(10.45)	(2.914)	(3.836)	(20.00)
Constant	79.26***	2,927***	104.3	82.12**	1,093***	5,382***
	(11.73)	(502.3)	(91.74)	(32.14)	(164.9)	(975.2)
Observations	54	54	54	30	54	54
R-squared	0.227	0.349	0.098	0.083	0.242	0.232

	(25) SKU 18	(26) SKU 19	(27) SKU 3_C	(28) SKU 4_ C	(29) SKU 5_ C	(30) SKU 6_ C
wholesale	67.28**	2,880***	-1.061**	-2.435	1.149	2.477
	(31.00)	(944.3)	(0.414)	(1.844)	(2.294)	(1.653)
lagged_inv	-0.390**	-0.603***	-0.419***	-0.139*	-0.495***	-0.160*
	(0.160)	(0.173)	(0.102)	(0.0703)	(0.116)	(0.0805)
linear_trend	26.04**	363.5**	-0.0633	-0.286	-4.711***	0.0493
	(12.54)	(147.2)	(0.137)	(0.659)	(1.206)	(0.367)
Constant	1,511***	43,128***	19.66***	72.41**	259.3***	39.49***
	(254.6)	(6,797)	(4.085)	(26.56)	(49.73)	(14.17)
Observations	54	54	36	36	36	54
R-squared	0.271	0.356	0.214	0.138	0.259	0.075

Table 2.4 Continued

	(31) SKU 7_ C	(32) SKU 8_ C	(33) SKU 9_ C	(34) SKU 10_ C	(35) SKU 11_ C	(36) SKU 20
wholesale	1.731	-0.0191	0.211	-1.096	-1.370	11.55
	(1.763)	(0.277)	(4.072)	(1.452)	(2.606)	(7.138)
lagged_inv	-0.620***	-0.49***	-0.368***	-0.217*	-0.437*	-0.146**
	(0.104)	(0.121)	(0.106)	(0.114)	(0.223)	(0.0575)
linear_trend	-0.948***	-0.138*	-2.662**	0.140	-0.318	-3.148*
	(0.329)	(0.0774)	(1.012)	(0.248)	(0.711)	(1.732)
Constant	147.8***	18.12***	349.4***	35.75***	43.66	545.0***
	(19.19)	(3.986)	(58.84)	(7.908)	(26.07)	(70.55)
Observations	54	54	54	54	30	54
R-squared	0.318	0.220	0.243	0.070	0.171	0.252

	(37) SKU 21	(38) SKU 22	(39) SKU 23	(40) SKU 3_D	(41) SKU 4_ D	(42) SKU 5_ D
wholesale	43.72	8.494	277.8	-0.616	-0.982	2.717
	(68.06)	(22.39)	(665.7)	(12.66)	(3.139)	(10.11)
lagged_inv	0.0694*	-0.130*	-0.0472	-0.322***	-0.355**	-0.265***
	(0.0370)	(0.0763)	(0.0879)	(0.111)	(0.150)	(0.0810)
linear_trend	-42.9***	-5.462	-168.3	-5.086	-1.222	-4.813**
	(9.732)	(3.756)	(162.2)	(3.026)	(0.776)	(2.070)
Constant	2,924***	953.1***	23,761***	458.9***	135.4***	355.7***
	(450.0)	(165.3)	(3,065)	(118.5)	(37.08)	(69.62)
Observations	54	54	54	36	36	36
R-squared	0.221	0.131	0.103	0.154	0.130	0.177

Table 2.4 Continued

	(43) SKU 6_ D	(44) SKU 7_ D	(45) SKU 8_ D	(46) SKU 9_ D	(47) SKU 10_ D	(48) SKU 11_ D
wholesale	-2.793	4.380	0.121	6.364	1.813	13.53
	(3.784)	(5.418)	(1.538)	(30.42)	(4.835)	(11.15)
lagged_inv	-0.261**	-0.205**	-0.435***	-0.440***	-0.153	-0.118*
	(0.112)	(0.0956)	(0.100)	(0.114)	(0.104)	(0.0644)
linear_trend	4.118**	-0.952	1.684***	-28.19***	-0.320	-3.064
	(1.647)	(0.985)	(0.476)	(9.429)	(0.964)	(3.355)
Constant	130.3***	234.9***	60.89***	2,431***	213.2***	107.3
	(30.44)	(47.46)	(11.64)	(525.8)	(45.39)	(85.65)
Observations	54	54	54	54	54	30
R-squared	0.152	0.085	0.243	0.197	0.034	0.100

	(49) SKU 24	(50) SKU 25	(51) SKU 26	(52) SKU 3_E	(53) SKU 4_ E	(54) SKU 5_ E
wholesale	289.1**	57.13***	1,303**	-3.003	0.373	-0.116
	(122.1)	(18.46)	(605.9)	(2.125)	(0.599)	(2.092)
lagged_inv	-0.250***	-0.396***	-0.296***	-0.975***	-0.629***	-0.397
	(0.0611)	(0.0591)	(0.0925)	(0.197)	(0.149)	(0.243)
linear_trend	-13.07	1.652	-59.54	-0.256	0.0558	-3.859**
	(10.20)	(2.836)	(80.54)	(0.538)	(0.135)	(1.756)
Constant	2,417***	559.2***	17,880***	123.4***	23.71***	107.6**
	(518.1)	(108.0)	(3,517)	(24.02)	(5.045)	(48.39)
Observations	54	54	54	36	36	36
R-squared	0.325	0.385	0.190	0.420	0.288	0.297

Table 2.4 Continued

	(55) SKU 6_ E	(56) SKU 7_ E	(57) SKU 8_ E	(58) SKU 9_ E	(59) SKU 10_ E
wholesale	0.568	2.158	0.526	2.152	0.442
	(0.766)	(2.148)	(0.411)	(6.051)	(0.826)
lagged_inv	-0.615***	-0.785***	-0.752***	-0.793***	-0.625***
	(0.182)	(0.143)	(0.107)	(0.193)	(0.219)
linear_trend	0.931***	-0.0855	-0.355***	-3.086***	0.160**
	(0.291)	(0.347)	(0.0683)	(1.076)	(0.0748)
Constant	-3.510	86.58***	28.43***	403.1***	13.01***
	(2.920)	(14.15)	(3.828)	(69.48)	(3.635)
Observations	54	54	54	54	54
R-squared	0.314	0.369	0.436	0.287	0.174

	(60) SKU 27	(61) SKU 28	(62) SKU 3_F	(63) SKU 4_ F	(64) SKU 5_ F	(65) SKU 6_ F
wholesale	50.98	260.0	-7.145**	0.533	-2.375	30.84*
	(37.68)	(208.0)	(3.016)	(5.518)	(13.19)	(15.56)
lagged_inv	-0.79***	-0.850***	-0.225**	-0.284**	-0.290***	-0.0622
	(0.231)	(0.158)	(0.0876)	(0.113)	(0.0655)	(0.173)
linear_trend	8.067	-2.974	-3.336*	-3.654	-3.224	1.192
	(6.796)	(34.90)	(1.795)	(2.308)	(4.639)	(3.081)
Constant	1,527***	11,992***	255.7***	209.5***	498.5***	246.1**
	(298.2)	(2,167)	(55.60)	(72.99)	(83.14)	(98.67)
Observations	54	54	36	36	36	54
R-squared	0.324	0.391	0.130	0.255	0.268	0.170

Table 2.4 Continued

	(66) SKU 7_ F	(67) SKU 8_ F	(68) SKU 9_ F	(69) SKU 10_ F	(70) SKU 11_ F	(71) SKU 29
wholesale	8.264	-7.315	182.5**	-0.687	-8.115	39.14
	(13.64)	(7.998)	(74.55)	(7.233)	(7.078)	(62.03)
lagged_inv	-0.339**	-0.177**	-0.288*	-0.0391	-0.578***	-0.731***
	(0.140)	(0.0876)	(0.163)	(0.137)	(0.145)	(0.186)
linear_trend	-1.739	5.366*	-31.1***	2.059	6.857***	16.89***
	(1.771)	(3.148)	(9.571)	(3.308)	(2.382)	(4.947)
Constant	459.5***	26.56	3,183***	171.1***	95.90***	1,257***
	(86.20)	(32.50)	(614.0)	(53.03)	(28.02)	(214.9)
Observations	54	54	54	54	30	54
R-squared	0.180	0.101	0.287	0.017	0.469	0.280

	(72) SKU 30	(73) SKU 31
wholesale	8.920	367.4
	(15.92)	(309.1)
lagged_inv	-0.884***	-0.805***
	(0.251)	(0.137)
linear_trend	7.982*	195.4***
	(4.455)	(52.32)
Constant	549.8***	9,347***
	(126.3)	(1,166)
Observations	36	54
R-squared	0.339	0.393

Table 2.5: Estimates of Model III

	(1) SKU1	(2) SKU1	(3) SKU1
wholesale_a	-82.51***	-83.40***	-83.40***
	(0.277)	(0.0849)	(0.0849)
wholesale_b	14.02***	-5.780***	-5.780***
	(0.596)	(0.0203)	(0.0203)
wholesale_c	-6.844***	-5.054***	-6.831***
	(0.379)	(0.324)	(0.391)
wholesale_d	-5.984***	-1.788***	-5.971***
	(0.379)	(0.324)	(0.391)
wholesale_e	-3.955***	-6.055***	-3.949***
	(0.173)	(0.256)	(0.179)
wholesale_f	7.079***	-0.860***	7.083***
	(0.118)	(0.0837)	(0.122)
discount_a	-11.98*		
	(5.169)		
discount_b	75.01***		
	(4.075)		
discount_c	-11.08*		-10.89
	(5.357)		(5.536)
discount_d	-13.45*		-13.26*
	(5.357)		(5.536)
discount_e	11.77***		11.86***
	(2.629)		(2.717)
discount_f	82.95***		83.03***
	(2.335)		(2.413)
linear_trend	0.171	0.284	0.348
	(5.213)	(5.385)	(5.387)
QuarterEnd_a	-153.3***	-109.0***	-109.1***
	(18.43)	(4.924)	(4.926)
QuarterEnd_b	842.1***	714.7***	714.8***
	(9.782)	(6.657)	(6.660)
QuarterEnd_c	65.06***	52.04***	64.66***
	(11.66)	(6.609)	(12.04)
QuarterEnd_d	374.6***	347.7***	374.2***
	(11.66)	(6.609)	(12.04)
QuarterEnd_e	51.17***	53.28***	50.90***
	(8.014)	(7.808)	(8.281)
QuarterEnd_f	382.4***	483.6***	382.0***
	(11.46)	(8.374)	(11.84)
discount_lag_a		66.04***	66.07***
		(2.968)	(2.970)
discount_lag_b		89.06***	89.08***
		(1.566)	(1.566)

Table 2.5 Continued

	(1) SKU1	(2) SKU1	(3) SKU1
discount_lag_c		-8.439**	
		(2.484)	
discount_lag_d		-29.76***	
		(2.484)	
discount_lag_e		8.904***	
		(1.634)	
discount_lag_f		-32.87***	
		(0.383)	
Constant	2,241***	2,239***	2,228***
	(143.1)	(147.4)	(147.7)
Observations	324	324	324
R-squared	0.234	0.246	0.257
Number of distributor	6	6	6
Distributor FE	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(4) SKU2	(5) SKU2	(6) SKU2
wholesale_a	-605.6***	-619.1***	-619.1***
	(2.112)	(0.636)	(0.637)
wholesale_b	195.8***	125.3***	125.3***
	(4.545)	(0.152)	(0.152)
wholesale_c	-74.45***	-54.55***	-74.31***
	(2.887)	(2.431)	(2.936)
wholesale_d	-64.73***	-51.43***	-64.58***
	(2.887)	(2.431)	(2.936)
wholesale_e	-26.90***	-30.25***	-26.84***
	(1.320)	(1.921)	(1.343)
wholesale_f	175.3***	115.3***	175.4***
	(0.902)	(0.627)	(0.917)
discount_a	-275.8***		
	(39.41)		
discount_b	183.7***		
	(31.06)		
discount_c	-95.84*		-93.77*
	(40.84)		(41.53)

Table 2.5 Continued

	(4) SKU2	(5) SKU2	(6) SKU2
discount_d	-76.23		-74.15
	(40.84)		(41.53)
discount_e	12.60		13.61
	(20.04)		(20.38)
discount_f	498.2***		499.1***
	(17.80)		(18.10)
linear_trend	-54.05	-52.30	-52.03
	(39.75)	(40.34)	(40.41)
QuarterEnd_a	-686.2***	-868.2***	-868.4***
	(140.5)	(36.89)	(36.95)
QuarterEnd_b	5,318***	4,836***	4,836***
	(74.58)	(49.88)	(49.96)
QuarterEnd_c	432.9***	294.6***	428.3***
	(88.86)	(49.52)	(90.35)
QuarterEnd_d	2,504***	2,407***	2,499***
	(88.86)	(49.52)	(90.35)
QuarterEnd_e	178.2**	179.3**	175.1**
	(61.09)	(58.50)	(62.12)
QuarterEnd_f	2,236***	2,586***	2,232***
	(87.34)	(62.74)	(88.81)
discount_lag_a		371.8***	371.9***
		(22.24)	(22.28)
discount_lag_b		377.5***	377.6***
		(11.73)	(11.75)
discount_lag_c		-115.7***	
		(18.61)	
discount_lag_d		-67.61**	
		(18.61)	
discount_lag_e		18.86	
		(12.24)	
discount_lag_f		-482.6***	
		(2.869)	
Constant	16,708***	16,669***	16,563***
	(1,091)	(1,105)	(1,108)
Observations	324	324	324
R-squared	0.272	0.282	0.282
Number of distributor	6	6	6
Distributor FE	Yes	Yes	Yes

Table 2.6: Estimates of Model IV

	(1) SKU 3_A	(2) SKU 4_A	(3) SKU 5_A	(4) SKU 6_A	(5) SKU 7_A	(6) SKU 8_A
wholesale	-1.127	-1.109	-1.351	1.941	-1.786	1.516***
	(1.783)	(0.704)	(5.856)	(1.371)	(2.799)	(0.428)
QuarterEnd	-8.617	5.854	-37.09	7.438	-41.31**	-8.598**
	(6.420)	(9.250)	(35.54)	(9.692)	(16.57)	(3.718)
linear_trend	-0.527*	-1.661***	1.097	0.0449	0.158	-0.285**
	(0.286)	(0.350)	(1.533)	(0.363)	(0.555)	(0.114)
Constant	129.7***	169.1***	311.5***	129.2***	384.0***	66.94***
	(7.437)	(8.828)	(37.06)	(11.36)	(19.34)	(4.679)
Observations	36	36	36	54	54	54
R-squared	0.116	0.356	0.047	0.038	0.097	0.241

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(7) SKU 9_ A	(8) SKU 10_A	(9) SKU 11_A	(10) SKU 12	(11) SKU 13	(12) SKU 14	(13) SKU 15
wholesale	-3.377	-6.338	-25.26	-10.39	-95.7***	-42.65**	-1,064**
	(12.43)	(4.077)	(24.58)	(6.209)	(33.04)	(19.67)	(454.9)
QuarterEnd	-100.7**	-23.62	72.19	101.6*	227.5	164.4	5,303*
	(48.46)	(25.56)	(136.2)	(51.50)	(213.0)	(101.6)	(2,875)
linear_trend	-2.146	4.92***	-11.48	-1.737	0.823	-6.07***	1.447
	(1.552)	(1.052)	(8.218)	(1.179)	(5.374)	(1.563)	(49.47)
Constant	1542***	194***	303.1	1039***	6804***	2186***	69645***
	(53.47)	(35.10)	(184.0)	(43.24)	(206.8)	(63.43)	(1931)
Observations	54	54	30	54	54	54	54
R-squared	0.098	0.349	0.123	0.124	0.122	0.226	0.183

Table 2.6 Continued

	(14) SKU 3_B	(15) SKU 4_ B	(16) SKU 5_ B	(17) SKU 6_ B	(18) SKU 7_ B	(19) SKU 8_ B
wholesale	0.465	0.207	2.772**	-0.976	4.612*	-0.214
	(1.731)	(0.760)	(1.072)	(1.925)	(2.433)	(0.636)
QuarterEnd	42.71***	37.45***	47.47***	25.96*	81.98***	23.22***
	(11.25)	(9.277)	(10.14)	(12.98)	(18.39)	(6.545)
linear_trend	-0.0515	-0.566*	-1.473***	-1.356***	-1.305**	-0.333**
	(0.519)	(0.295)	(0.369)	(0.433)	(0.584)	(0.135)
Constant	106.7***	94.46***	149.6***	222.6***	406.1***	68.77***
	(10.85)	(6.037)	(8.313)	(15.20)	(16.48)	(4.855)
Observations	36	36	36	54	54	54
R-squared	0.345	0.466	0.563	0.255	0.342	0.346

	(20) SKU 9_ B	(21) SKU 10_ B	(22) SKU 11_ B	(23) SKU 16	(24) SKU 17	(25) SKU 18	(26) SKU 19
wholesale	0.775	0.860	0.497	2.251	11.72	3.805	72.17
	(4.893)	(4.823)	(1.153)	(2.826)	(10.52)	(4.741)	(68.79)
QuarterEnd	340***	80.35*	-1.244	162***	864***	216***	6,614***
	(52.39)	(41.57)	(5.399)	(27.13)	(130.7)	(26.56)	(888.3)
linear_trend	-9.2***	5.4***	1.55***	-3.36***	-9.137**	-6.5***	-81.50***
	(1.590)	(1.172)	(0.334)	(0.757)	(4.481)	(1.047)	(30.00)
Constant	1,747***	102.6**	12.63*	740.1***	3,980***	1,085***	32,211***
	(52.72)	(40.36)	(6.511)	(21.86)	(132.9)	(35.40)	(995.1)
Observations	54	54	30	54	54	54	54
R-squared	0.649	0.314	0.515	0.591	0.546	0.688	0.610

Table 2.6 Continued

	(27) SKU 3_C	(28) SKU 4_ C	(29) SKU 5_ C	(30) SKU 6_ C	(31) SKU 7_ C	(32) SKU 8_ C
wholesale	-0.257	-0.494	-0.437	1.819	0.845	-0.0237
	(0.282)	(0.355)	(1.318)	(1.217)	(0.936)	(0.137)
QuarterEnd	-1.616	10.23***	3.299	4.888	5.954	-0.458
	(2.043)	(3.046)	(8.163)	(6.114)	(5.122)	(1.151)
linear_trend	0.0192	-0.427***	-1.570***	-0.100	0.0228	-0.0101
	(0.0620)	(0.132)	(0.388)	(0.185)	(0.104)	(0.0346)
Constant	7.984***	34.69***	113.2***	28.50***	51.32***	5.965***
	(1.417)	(1.925)	(10.17)	(6.868)	(3.573)	(1.404)
Observations	36	36	36	54	54	54
R-squared	0.064	0.433	0.310	0.095	0.068	0.005

	(33) SKU 9_ C	(34) SKU 10_ C	(35) SKU 11_ C	(36) SKU 20	(37) SKU 21	(38) SKU 22	(39) SKU 23
wholesale	2.480	-1.2***	-2.051	-0.267	14.84	15.12	648.7**
	(2.218)	(0.412)	(1.796)	(3.079)	(38.39)	(10.03)	(270.4)
QuarterEnd	45.24***	-0.0422	11.47	-9.961	31.73	13.29	-574.0
	(15.12)	(4.177)	(10.54)	(14.11)	(181.0)	(55.33)	(1,447)
linear_trend	-1.91***	0.009	-0.507	-2.14***	-4.539	-4.09***	-58.95
	(0.358)	(0.099)	(0.557)	(0.434)	(5.433)	(1.215)	(57.92)
Constant	186.3***	21.79***	15.61	399.9***	2,410***	690.7***	18,063***
	(12.56)	(3.290)	(11.46)	(16.33)	(225.7)	(53.03)	(2,250)
Observations	54	54	30	54	54	54	54
R-squared	0.416	0.045	0.110	0.267	0.013	0.180	0.173

Table 2.6 Continued

	(40) SKU 3_D	(41) SKU 4_ D	(42) SKU 5_ D	(43) SKU 6_ D	(44) SKU 7_ D	(45) SKU 8_ D
wholesale	-0.155	-1.302*	-1.832	-3.263***	1.012	-0.461
	(2.565)	(0.768)	(1.218)	(1.179)	(2.277)	(0.330)
QuarterEnd	48.98*	5.835	31.98***	39.92***	22.64*	4.090
	(24.72)	(4.533)	(9.410)	(13.86)	(13.23)	(3.423)
linear_trend	-1.147	-0.143	-1.148***	2.375***	-0.0806	0.154
	(0.924)	(0.210)	(0.363)	(0.350)	(0.381)	(0.0969)
Constant	196.1***	52.44***	160.8***	30.14***	132.3***	20.89***
	(19.01)	(4.494)	(7.947)	(10.98)	(11.13)	(3.215)
Observations	36	36	36	54	54	54
R-squared	0.200	0.117	0.430	0.577	0.093	0.091

	(46) SKU 9_ D	(47) SKU 10_ D	(48) SKU 11_ D	(49) SKU 24	(50) SKU 25	(51) SKU 26
wholesale	-1.033	-0.737	-4.602	-7.366	-0.727	-85.55**
	(5.296)	(2.620)	(6.568)	(7.487)	(2.560)	(34.80)
QuarterEnd	187.7***	37.79**	21.48	265.4***	78.33***	2,700***
	(40.46)	(17.03)	(34.96)	(63.57)	(21.15)	(257.5)
linear_trend	-2.756**	0.291	-4.253*	0.366	-0.810*	28.58***
	(1.174)	(0.591)	(2.404)	(2.209)	(0.428)	(9.008)
Constant	837.1***	136.8***	99.30*	1,630***	413.6***	11,831***
	(32.28)	(17.16)	(57.55)	(65.42)	(15.55)	(272.1)
Observations	54	54	30	54	54	54
R-squared	0.382	0.087	0.169	0.287	0.277	0.685

Table 2.6 Continued

	(52) SKU 3_E	(53) SKU 4_ E	(54) SKU 5_ E	(55) SKU 6_ E	(56) SKU 7_ E	(57) SKU 8_ E
wholesale	-0.413	-0.510***	-0.777	0.0827	-0.328	0.432
	(0.536)	(0.165)	(0.872)	(0.311)	(0.444)	(0.288)
QuarterEnd	5.100	-1.426	-1.781	-2.484	-5.698*	-1.585
	(5.672)	(2.109)	(4.916)	(1.993)	(3.262)	(1.430)
linear_trend	0.324	0.0526	-1.860***	0.304***	-0.150	-0.135***
	(0.241)	(0.0727)	(0.204)	(0.0705)	(0.1000)	(0.0433)
Constant	29.17***	11.62***	56.00***	1.144	44.35***	10.81***
	(5.614)	(1.621)	(5.962)	(1.524)	(3.266)	(1.864)
Observations	36	36	36	54	54	54
R-squared	0.085	0.115	0.678	0.355	0.099	0.189

	(58) SKU 9_ E	(59) SKU 10_ E	(60) SKU 27	(61) SKU 28
wholesale	-1.183	-0.0697	17.07***	102.3***
	(1.226)	(0.194)	(5.786)	(22.61)
QuarterEnd	-8.336	0.756	49.70	280.6
	(9.263)	(1.543)	(35.65)	(231.4)
linear_trend	-0.766***	0.0721*	-1.740	-9.062
	(0.200)	(0.0368)	(1.449)	(6.918)
Constant	180.9***	6.196***	784.1***	4,413***
	(7.420)	(1.243)	(48.42)	(212.0)
Observations	54	54	54	54
R-squared	0.185	0.047	0.191	0.259

Table 2.6 Continued

	(62) SKU 3_F	(63) SKU 4_ F	(64) SKU 5_ F	(65) SKU 6_ F	(66) SKU 7_ F	(67) SKU 8_ F
wholesale	2.223	2.395	13.94*	14.62	4.450	5.616
	(2.692)	(2.331)	(7.498)	(13.59)	(7.590)	(7.750)
QuarterEnd	-9.789	4.638	61.50	22.94	46.93	16.53
	(12.35)	(18.01)	(44.94)	(57.49)	(42.27)	(29.33)
linear_trend	-0.130	-3.764**	-10.33***	0.155	-2.767**	3.321***
	(0.801)	(1.476)	(1.827)	(1.085)	(1.119)	(1.082)
Constant	129.0***	176.7***	436.9***	239.0***	334.2***	1.840
	(19.61)	(38.99)	(52.91)	(45.55)	(33.36)	(31.34)
Observations	36	36	36	54	54	54
R-squared	0.025	0.213	0.448	0.072	0.121	0.241

	(68) SKU 9_ F	(69) SKU 10_ F	(70) SKU 11_ F	(71) SKU 29	(72) SKU 30	(73) SKU 31
wholesale	141.3**	5.594	-7.379**	14.66	5.668	118.2*
	(61.40)	(7.895)	(3.585)	(21.90)	(5.540)	(65.76)
QuarterEnd	425.0	14.01	-19.70	187.1	-39.18	314.0
	(368.9)	(43.63)	(27.68)	(112.4)	(32.04)	(595.3)
linear_trend	-34.01***	0.501	-1.791*	4.404**	1.751	45.24***
	(5.395)	(0.975)	(0.987)	(1.778)	(1.682)	(13.73)
Constant	2,450***	155.7***	85.78***	808.1***	280.3***	6,681***
	(191.9)	(32.67)	(26.69)	(72.29)	(38.00)	(336.0)
Observations	54	54	30	54	36	54
R-squared	0.326	0.026	0.081	0.155	0.095	0.140

Table 2.7: Bullwhip Ratios

Bullwhip Ratio	Manufacturer	A-F	A	B	C	D	E	F
SKU 1	0.79	88.51	174.54	25.39	19.57	50.77	29.26	7.19
SKU 2	0.19	80.18	216.67	18.42	4.73	34.46	43.54	6.16
SKUs 1-2	0.17	85.13	216.97	19.23	5.33	36.12	41.75	6.22
SKUs 3-31	0.14	75.79	94.15	24.80	3.85	58.49	51.14	6.78

Table 2.8: Correlation between Distributors' Market Share and Trade Promotion

	SKU 1	SKU 2
Distributor A	0.15	0.13
Distributor B	0.44**	0.43**
Distributor C	-0.18	-0.12
Distributor D	-0.0093	0.02
Distributor E	0.14	0.09
Distributor F	0.37**	0.33**

Note. *** p<0.01, ** p<0.05, * p<0.1

Table 2.9: Correlation between Distributors' Market Share and Quarter Ends

	SKU 1	SKU 2
Distributor A	-0.33**	-0.27
Distributor B	0.498**	0.43**
Distributor C	0.15	0.09
Distributor D	0.66**	0.75**
Distributor E	0.15	0.04
Distributor F	0.46**	0.40**

Note. *** p<0.01, ** p<0.05, * p<0.1

Table 2.10: Added Inventory Costs due to Promotions

	Yearly Added Cost	Percent of Sales
Distributor A	$346,176	1.16%
Distributor B	$205,580	1.20%
Distributor C	$26,914	0.82%
Distributor D	$55,081	0.82%
Distributor E	$19,749	0.97%
Distributor F	$21,288	0.30%
Manufacturer	$1,296,138	3.21%
Total	$1,970,927	1.85%

CHAPTER 3

IN SEARCH OF INTRA-ECHELON BULLWHIPS

3.1 Introduction

Supply chain managers and operations researchers alike have invested considerable effort over the past several decades to better understand the bullwhip effect and mitigate its negative consequences. The seminal paper of Lee et al. (1997a) defines the bullwhip effect as “the phenomenon where orders to the supplier tend to have larger variance than sales to the buyer (i.e., orders distortion), and the distortion propagates upstream in an amplified form (i.e., variance amplification)” (p. 546). Researchers have explored the cause of the bullwhip phenomenon and proposed a variety of remedies (e.g., Lee et al., 1997a; Chen et al., 2000; Chen & Lee, 2012). Other researchers have focused on empirically measuring the level of the bullwhip in practice and testing for possible drivers of its magnitude (e.g., Bray & Mendelson, 2012; Cachon et al., 2007; Dooley et al., 2010; Duan et al., 2015; Fransoo & Wouter, 2000; Lai, 2005; Jin et al., 2015; Mackelprang & Malhotra, 2015; Shan et al., 2014; Zotteri, 2013).

The bullwhip definition noted above effectively looks across the firm, comparing the variability in the firm’s orders it places with its suppliers to the variability in the orders the firm receives from its customers. If the measure is greater than one then the bullwhip effect is said to exist, while if it is less than one then an antibullwhip exists. That is, the firm smooths rather than amplifies its order variability. This conventional bullwhip measure views the firm as one "entity" in the supply chain and constitutes an inter-firm bullwhip measure.

While the conventional bullwhip measure is informative and useful for determining what happens across a firm in the supply chain, numerous actions inside the firm contribute to its conventional bullwhip measure. By decomposing the firm's conventional inter-firm bullwhip measure into three intra-firm (component) bullwhips, we offer the firm a simple and readily-implementable framework to employ "in search of" its internal bullwhip, and to track and reduce the variability in its product flow streams.

The first bullwhip component in our framework is what we call the shipment bullwhip – it describes the variability in the firm's shipment (i.e., sales) stream relative to the stream of demand (i.e., orders received). Moving upstream within the firm, the second component is referred to as the manufacturing bullwhip – it measures the variability in the firm's manufacturing stream relative to its shipment stream. Next is the order bullwhip, defined as the variability in the stream of orders the firm places relative to the firm's manufacturing stream. Mathematically, we show that multiplying these three intra-firm bullwhips results in the conventional inter-firm bullwhip measure. That is, the conventional bullwhip measure is the product of the firm's shipment, manufacturing, and order bullwhips.

In the remainder of this chapter, inter-firm bullwhip and intra-firm bullwhip are referred to as inter-echelon bullwhip and intra-echelon bullwhip, respectively, to account for the possibility that some entity other than a firm (e.g., a division within a firm, an individual facility within a division, and an industry) is under investigation.

Using monthly, industry-level U.S. Census Bureau data, we proceed "in search of" the magnitude of each of intra-echelon bullwhips across industries, and we examine correlations between them. For example, we find that in some industries there is a very strong shipment antibullwhip (the shipment bullwhip measure is well below one, meaning shipments are much smoother than demands), while in other industries there is a significant shipment bullwhip (shipments are substantively more variable than demands). While our data are neither extensive nor informative enough to definitively assign cause and effect, we are able to make several observations regarding the differences in the industry characteristics. In general, we find that in industries where there is an antibullwhip in shipping, there is bullwhip created in manufacturing and/or ordering. However, industries that exhibit an antibullwhip in manufacturing also tend to order in a smoother stream than they manufacture (i.e., an antibullwhip in ordering). Our work therefore acts as a set of mini-case studies that can be used to motivate future research into what explains the observed disparity in intra-echelon bullwhips across industries. Although we report results based on industry-level data, the same analysis can also be performed at a less aggregate level (e.g., the divisional level, a product category level, and a product level).

In addition to offering managers a framework for monitoring intra-echelon bullwhips, we provide insight into the impact of their decisions regarding the bullwhip measurement time interval. Our results are consistent with Chen and Lee (2012) who propose that time aggregation tends to dampen the bullwhip (i.e., when the bullwhip ratio is above one, time aggregation reduces it). Moreover, we find new empirical evidence that suggests time aggregate tends to amplify the bullwhip ratio when an antibullwhip exists; time aggregation seems to cause the bullwhip ratio to converge to one. An additional contribution of our work is to demonstrate the importance of properly setting the starting point for the time aggregation interval. For example, while many retailers use a February 1 quarterly start date, we show that a start date of January 1 may be more appropriate for the purposes of bullwhip measurement.

In sum, our empirical observations provide additional insight into the factors managers should take into account when determining their shipment schedules (which impact their shipment bullwhip), when setting their manufacturing plans (which impact their manufacturing bullwhip), and when establishing their order quantities (which impact their order bullwhip). While other researchers have studied some of the internal factors that might influence the overall bullwhip, such as inventory stocking levels (e.g., Svensson, 2003) and manufacturing activities (e.g., Taylor, 1999), we contribute to this body of work by demonstrating how the intra-echelon bullwhips contribute to the overall inter-echelon bullwhip, both analytically and empirically.

The chapter proceeds as follows. In section 3.2 we explicitly lay out the bullwhip decomposition, showing how the shipment, manufacturing, and order bullwhips contribute to the overall (conventional) bullwhip measure. Next, in section 3.3 we develop hypotheses regarding whether we expect an intra-echelon bullwhip to be greater than or less than one (i.e., whether the bullwhip or antibullwhip predominates). We also hypothesize as to the effect of time aggregation and interval starting point. We describe our dataset in section 3.4, proceed to test our hypotheses in section 3.5, and summarize the results in section 3.6.

3.2 Bullwhip Decomposition

An ideal supply chain might be described as having a smooth flow of inventory throughout the chain. Every echelon would 1) receive a perfectly smooth demand stream from its downstream customers; 2) fulfill this demand stream with a perfectly-matched shipment (i.e., sales) stream; 3) manufacture in a smooth just-in-time fashion, shipping immediately on completion with no need for any finished goods inventory; 4) order raw materials (RM) from upstream suppliers at a smooth rate that exactly matches the manufacturing flow stream; and 5) receive raw materials (i.e., fulfillment of orders) from its supplier in just-in-time fashion so as to avoid the need for raw materials inventory. This would result in no variance in any flow stream anywhere in the supply chain, that is, no bullwhip (or smoothing). Note that in this description the upstream progression could be executed via a pull system – downstream demand pulls shipments, shipments pull manufacturing, and manufacturing pulls orders as one moves upstream in the supply chain.

Compared to this ideal, actual supply chains differ substantially, namely, there is virtually always some level of variability in each of the flow streams identified above. The framework we introduce in this chapter, as depicted in Figure 3.1, characterizes how the variability in each of these flow streams is either amplified or dampened when pulling the upstream flow. Note that our framework does not hinge on the use of a pull system. Instead, we use this terminology simply for convenience.

Starting at the upper left of Figure 3.1, an echelon at any point in the supply chain (which we refer to as the focal echelon) receives a demand stream that has variance denoted by V_D^F (the superscript *F* refers to the focal echelon, while the subscript *D* denotes that this parameter is the variance in the demand stream). Echelon *F* may choose not to (or may not be able to) fulfill demands immediately, so its shipment stream may not exactly match its demand stream (by "demand stream" we mean the stream of orders received). For example, the economy may suddenly get stronger, creating a surge in demand that echelon *F* cannot immediately fill via manufacturing output and/or inventory. Thus, the variance in echelon *F*'s shipment stream, which we denote by V_S^F (the superscript again denoting echelon *F* and the subscript *S* referring to the shipment stream), may differ from the variance in its demand stream, V_D^F. We define the variance ratio $\frac{V_S^F}{V_D^F}$ to be the echelon's ***shipment bullwhip***, and denote this bullwhip ratio by B_S^F. Note that the shipment bullwhip might indicate an amplification of the demand stream ($B_S^F = \frac{V_S^F}{V_D^F} > 1$) or a smoothing ($B_S^F < 1$).

If echelon *F* holds finished goods (FG) inventory at any point in time, then its manufacturing output stream will not necessarily match its shipment stream. For example, demand may be seasonal, and even if demand is fully known in advance, echelon *F* may find it optimal to smooth its output (overproduce and build up finished goods inventory in periods of slack demand and under-produce and ship from inventory in periods of high demand). If demand is uncertain, this further complicates echelon *F*'s decision making with regard to the manufacturing stream. The manufacturing stream may become even further disconnected from the shipment stream due to factors such as the desirability of batch manufacturing. In other words, there may be what we denote as a ***manufacturing bullwhip*** within the echelon, defined as $B_M^F = \frac{V_M^F}{V_S^F}$, where V_M^F denotes the variance in the manufacturing stream. The manufacturing bullwhip recognizes the fact that the manufacturing stream may differ from the shipment stream. Again, the manufacturing bullwhip may indicate an amplification ($B_M^F > 1$) or smoothing ($B_M^F < 1$).

Similarly, it may not be optimal for echelon F to order raw materials to exactly follow its manufacturing stream (i.e., for its order stream to follow its manufacturing stream). For example, an upstream echelon's supply may be uncertain or it may offer end-of-quarter discounts or have other promotions due to goods surpluses. Factors such as these may make it optimal for echelon F to alter its order stream as compared to the manufacturing stream (i.e., it may be optimal for an echelon to plan to hold raw materials inventory). We denote the variance in stream of orders that echelon F places by V_O^F, and define the ***order bullwhip*** as $B_O^F = \frac{V_O^F}{V_M^F}$, where V_O^F denotes the variance in the order stream. Similar to the above discussion, the order bullwhip may indicate an amplification ($B_O^F > 1$) or a smoothing ($B_O^F < 1$).

As previously noted, Lee et al. (1997a) effectively define the bullwhip as "order distortion." Accordingly, echelon F's overall, or "undecomposed," bullwhip ratio (which we will denote by B^F) is defined to be the variance in the orders echelon F places with its suppliers (V_O^F) divided by the variance in the orders received by echelon F from its customers (V_D^F). That is:

$$B^F = \frac{V_O^F}{V_D^F} = \left(\frac{V_S^F}{V_D^F}\right)\left(\frac{V_M^F}{V_S^F}\right)\left(\frac{V_O^F}{V_M^F}\right) = B_S^F\, B_M^F\, B_O^F \qquad (3.1)$$

Hereafter, when we use "bullwhip" as a stand-alone term, it will be used to mean the undecomposed bullwhip B^F, or its surrogate (see discussion on a surrogate bullwhip measure below). Note that equation (3.1) decomposes echelon F's inter-echelon bullwhip into three intra-echelon bullwhips. Starting from the downstream demand side of the echelon, the three intra-echelon bullwhips are the shipment bullwhip (variability in shipment flows as compared to demand), the manufacturing bullwhip (variability in manufacturing flows as compared to shipments), and the order bullwhip (variability in the flow of orders placed as compared to manufacturing flows). The same setup applies for echelon *F*'s supplier, one level upstream in the supply chain. Using a superscript of U to denote *F*'s upstream supplier, we have, analogous to equation (3.1), $B^U = \frac{V_O^U}{V_D^U} = \left(\frac{V_S^U}{V_D^U}\right)\left(\frac{V_M^U}{V_S^U}\right)\left(\frac{V_O^U}{V_M^U}\right) = B_S^U\, B_M^U\, B_O^U$.

In some previous studies, surrogate measures have been used to estimate the bullwhip, B^F. Since we also use these surrogate measures in a subset of our analysis, we describe these measures here. Specifically, because the dataset used by Cachon et al. (2007) does not include information for orders placed, they are unable to directly measure V_O^F. Instead, Cachon et al. (2007) calculate what they call "production," computed as the sales (i.e., shipments) plus the change in inventory. This production measure effectively represents the inflow of materials. We use the term "inflow" to reflect the quantity represented by shipments plus change in inventory, and denote the inflow variance by V_I^F and the inflow bullwhip by $B_I^F = \frac{V_I^F}{V_O^F}$. Note that we have already effectively defined the inflow bullwhip (it is not yet another bullwhip) because the inflows to the focal echelon are effectively equal to the shipments of the upstream supply chain echelon. That is, $V_I^F = V_S^U$, as shown in Figure 3.1. Also note from Figure 3.1 that orders placed by the focal echelon are effectively the demand (orders received) for the upstream echelon, so $V_O^F = V_D^U$. Thus, $B_I^F = B_S^U = \frac{V_I^F = V_S^U}{V_O^F = V_D^U}$. For some supply chains the Cachon et al. (2007) dataset includes the orders received so the authors can directly calculate V_D^F; in these cases, they use the measure $B_*^F = \frac{V_I^F}{V_D^F}$ as a surrogate for the bullwhip (we put an asterisk in the subscript of the undecomposed bullwhip measure to denote that it is a surrogate measure). Note that $B_*^F = \frac{V_I^F}{V_D^F} = B_S^F\, B_M^F\, B_O^F\, B_I^F = B^F\, B_I^F$. That is, the bullwhip surrogate B_*^F is equal to the conventional bullwhip measure B^F multiplied by the inflow bullwhip. For other supply chains their dataset also does not include data for orders received, so they use V_S^F as a surrogate measure for V_D^F and calculate this (surrogate) bullwhip as $B_{**}^F = \frac{V_I^F}{V_S^F} = B_M^F\, B_O^F\, B_I^F$ (the double asterisk is used to denote this particular surrogate bullwhip).

The decomposition of the conventional inter-echelon bullwhip measure B^F (or its surrogate) allows us to pinpoint where it is created within the echelon. Specifically, by looking at its three individual intra-echelon bullwhips, B_S^F, B_M^F, and B_O^F, we can identify whether the amplification (or smoothing) occurs in shipping, and/or manufacturing, and/or ordering. We next develop hypotheses regarding the direction and magnitude of these bullwhips and generate hypotheses regarding the time duration over which they should be measured and the duration starting point.

3.3 Hypothesis Development

We discuss factors plausibly associated with our measures of shipment, manufacturing, and order bullwhips. In addition to factors discussed below, which all assume echelon *F* is making decisions optimally (to maximize expected profit), there may be behavioral factors which lead to bullwhip amplification (or even possibly smoothing) (e.g., Bendoly et al., 2006; Croson & Donohue, 2006).

Because of factors such as batch production, production smoothing, and order batching (Lee et al., 1997a), it is possible that it is not optimal for the bullwhip ratio to equal one (the variance in the stream of orders placed may not be equal to the variance in the stream of demands). That is, there are a host of factors that may induce echelon F, when operating optimally, to amplify or dampen a shipment bullwhip, a manufacturing bullwhip, or an order bullwhip. The decision making becomes even more complex in a multiechelon supply chain, where one echelon's decisions impact both the upstream and downstream echelons. Most likely, identifying the optimal set of decisions given this complexity is not a tractable problem – and even if the optimal decisions could be identified so as to reduce costs (or increase revenues) within the supply chain, it will be problematic to determine how to share the benefit among the various echelons within the chain. However, the framework discussed herein is intended to help move echelon F one step closer to this ultimate objective by identifying the importance of tracking intra-echelon bullwhip effects and adjusting its supply chain based on these observed bullwhips.

3.3.1 Shipment Bullwhip Magnitude

First we examine the shipment bullwhip, defined for echelon F as $B_S^F = \frac{V_S^F}{V_D^F}$. There are several factors suggesting it may not be possible (or desirable) to always ship exactly per the demand stream. Some dynamics work in the direction of smoothing, and others work in the direction of variance amplification.

One factor that may (under certain conditions) tend to smooth shipments relative to demand is an inventory constraint. If inventory holding costs are significant, then it may not be cost-effective to hold enough inventory to fill all the demand peaks. On the other hand, the inventory constraint may (under other circumstances) actually work to amplify shipments relative to demands. Take the case where demands arrive in a relatively smooth pattern, while manufacturing produces in batches. In this case, if inventory is not sufficient to fill the demand, then shipments will have to wait until a batch of goods is manufactured, at which point the whole batch (or a significant fraction of it) will be shipped. Thus, shipments will appear to be "clumpy" when compared to the smooth demand stream.

Analytically, Chen and Lee (2012) show that, under their assumptions, the variance of sales (shipments, in our terminology) is less than that of demand. The intuition is that shipments (assumed to be equal to the minimum of demand and on-hand inventory) is a truncated variable, so inventory censoring makes shipments appear less variable. This result implies that the shipment bullwhip is less than one. Thus, we propose the following hypothesis which enables us to test which theory prevails:

HYPOTHESIS 1 (H1). The shipment bullwhip is less than one.

3.3.2 Manufacturing Bullwhip Magnitude

If there are significant fixed costs in manufacturing, or if it is expensive to change the rate of manufacturing output, then it may be desirable to produce at a constant, steady pace as compared to following the ups and downs of demand (or more specifically, the ups and downs of shipments) – the capacity requirement if manufacturing at a smooth output rate is equal to the average demand rate, while the capacity requirement if following the peaks and valleys of demand is the highest demand rate. This will tend to smooth manufacturing relative to shipments, leading to a manufacturing bullwhip of $B_M^F = \frac{V_M^F}{V_S^F} < 1$.

On the other hand, echelon F may tend to amplify manufacturing variability as compared to shipment variability if the firm produces periodically in large batches rather than manufactures continuously. Echelon F will produce in relatively large batches and then ship from inventory, resulting in relatively more smooth shipments as compared to manufacturing.

We hypothesize that the forces behind manufacturing smoothing predominate, given the extensive work in this area by economists (e.g., Fair, 1989; Blinder & Maccini, 1991; Ramey & West, 1999) and the analytical and empirical work of operations management researchers (e.g., Klein, 1961; Cachon et al., 2007; Bray & Mendelson, 2015).

HYPOTHESIS 2 (H2). The manufacturing bullwhip is less than one.

3.3.3 Order Bullwhip Magnitude

Echelon *F* may tend to smooth orders relative to manufacturing output in an attempt to smooth deliveries of raw materials (e.g., it may have docking or "port" capacity constraints). In addition, it may face pressure from suppliers to buy in a steady stream, to facilitate lean operations practices, for example. This would lead to order smoothing, with $B_O^F = \frac{V_O^F}{V_M^F} < 1$.

However, it is plausible that other factors may influence the variability of orders relative to that of manufacturing output. For example, the supplier may insist on a minimum order quantity which exceeds the quantity echelon *F* might otherwise purchase. Also, order batching can be a routine part of echelon *F*'s purchase decision process due to economies of scale in purchasing associated with factors such as volume discounts and transportation (e.g., truckload shipments). An upstream echelon may offer periodic or sporadic price promotions to increase sales volume (shipments) and liquidate excess inventory, which encourage bulk purchases. The previous literature has reported that temporary price promotions can lead to forward buys and holding of raw materials inventory (e.g., Blattberg & Levin, 1987; Jin et al., 2015b). Given that both order batching and price promotions imply that the order stream is more volatile than the manufacturing stream, we offer the following hypothesis:

HYPOTHESIS 3 (H3). The order bullwhip is greater than one.

3.3.4 Impact of Duration of the Time Interval on the Bullwhip

When empirically measuring the bullwhip effect, researchers need to determine an appropriate time interval (e.g., weekly, monthly, or quarterly) over which to aggregate the flow values which are then used in calculations of the variances of orders, shipments, and manufacturing output. Previous studies (e.g., Fransoo & Wouters, 2000; Cachon et al., 2007; Chen & Lee, 2012) suggest that the proper aggregation across time should depend on the specific problem under investigation. Chen and Lee (2012) develop an analytical model to show that "aggregating data over relatively long time periods can mask the bullwhip effect" (p. 772). More specifically, they show that for a first-order autoregressive moving average (ARMA (1, 1)) demand process, the temporally aggregated bullwhip ratio will approach one in the limit as the aggregation period increases. Furthermore, they show that if the bullwhip ratio is greater than one, then the ratio will decrease monotonically to one as the aggregated time period increases. These results suggest that measuring the variance ratio over a longer time period tends to attenuate the bullwhip (or antibullwhip) effect, leading to the following hypothesis.

HYPOTHESIS 4 (H4). If the bullwhip ratio is greater than one then time aggregation decreases the ratio, while if it is less than one then time aggregation increases the ratio.

The smoothing that is hypothesized to occur with aggregation over longer time intervals may be related to seasonality in data series. To illustrate this possibility, consider the monthly sales data shown in Figure 3.2 – this plot is representative of sales data across 45 Wal-Mart stores for the period February 2010 to October 2012 (Kaggle, 2015). Note the seasonality in the data; longer time aggregation intervals have the potential to combine a maximal demand with a lesser demand (or a minimal demand with a greater demand), thereby reducing the variance. Assuming the seasonality propagates upstream, the variance of the upstream flow stream is also diminished, so the impact of seasonality on the bullwhip will depend on which flow (upstream or downstream) exhibits the most seasonality.

HYPOTHESIS 5 (H5). Seasonality will result in a higher (lower) aggregated bullwhip ratio when the upstream flow is less (more) seasonal than the downstream flow.

3.3.5 Impact of the Starting Point of the Time Interval on the Bullwhip

Managers must not only choose the duration of the time interval over which they measure their bullwhips, they must also set the starting point of that interval. Assume for the moment that echelon *F* decides it is most appropriate to use quarterly time durations to measure and track its bullwhip. Does it matter whether they start the quarter at January 1 versus February 1 versus March 1? (These three start dates effectively cover all possibilities since we do not consider starting mid-month.)

For all 45 Wal-Mart stores referenced in the Kaggle (2015) dataset, we find that the variance in the quarterly sales series when starting the quarter in February is less than that with a January start (see Figure 3.2 for sales at a typical store). This stems from the observation that December is the highest sales month, while January is the lowest sales month. Grouping the peak and valley into the same quarter partially balances the difference. Since the variance of sales is the denominator of the bullwhip ratio B_{**}^{F}, quarterly aggregation based on a start in February (Nov/Dec/Jan quarter) or March (Dec/Jan/Feb quarter) might be expected to result in a higher bullwhip ratio as compared to a start in January (Oct/Nov/Dec quarter).

Furthermore, a review of quarterly reports from Wal-Mart, Costco, Target, and Kohl's suggests that inflows (which in this case roughly equates to receipt of the goods to be sold) typically lead sales by one quarter – knowing that sales will peak in quarter four (knowing the seasonality pattern), these retailers prepare by over-producing (i.e., by increasing inflows) in the third quarter. Assuming inflows (or manufacturing, in the case of a manufacturer) leads sales (shipments) by one month, the inflow peak occurs in November and the trough occurs in December, suggesting that inflows would be smoothest (have the least variance) with the Nov/Dec/Jan (Feb start) and Oct/Nov/Dec (Jan start) quarters as compared to the Dec/Jan/Feb (March start) quarters. Since the variance of inflows is the numerator of the bullwhip ratio B_{**}^{F}, quarterly aggregation based on a start in March (Dec/Jan/Feb quarter) might be expected to result in a higher bullwhip ratio as compared to a start in January (Oct/Nov/Dec quarter) or February (Nov/Dec/Jan quarter).

Regarding previous empirical analysis in this regard, Bray and Mendelson (2012) argue that different time aggregation schemes will yield different results for any particular firm, but do not find a general effect.

HYPOTHESIS 6 (H6). For quarterly data, a February or March starting month results in a higher bullwhip than a January starting month.

3.4 Data

Our analysis uses the same monthly, industry-level U.S. Census Bureau data as used by Cachon et al. (2007). These data are from January 1992 to February 2006 and cover 8 retail, 21 wholesale, and 86 manufacturing industries (we, as do Cachon et al., 2007, exclude some Census data to avoid possible duplication – some overlap occurs across the industries because some data within one industry code may be aggregated into another industry code). We do not incorporate post-2006 data in our analysis (our data range is from 1992 to 2006) since Dooley et al. (2010) find that firms responded differently to the economic recession of 2007-2009. Given that we use industry data, the superscript *F* will denote the focal industry.

The Census reports monthly sales (i.e., shipments, in the terminology of this chapter) and inventories for each industry. The industry's inflow number in a given month t is calculated as the shipments in that month plus the change in inventory (that month's inventory minus last month's inventory): $Inflow_t = Shipments_t + Inv_t - Inv_{t-1}$, where Inv_t denotes the inventory in month t. This inflow number effectively represents incoming shipments received from the upstream suppliers, that is, it is the upstream shipment quantity. From these inflow numbers we calculate the inflow variance, V_I^F.

We divide manufacturing industries into three sets of data; A, B, and C (see Table 3.1). The A dataset includes 52 industries (A1 through A52) for which data are available for both demand and shipments (sales). For these industries we can calculate V_D^F and V_S^F, and thus B_S^F. The B dataset includes 23 industries (B1 through B23) for which there are shipment data but no demand data. The C dataset includes 11 durable goods manufacturing industries (C1 through C11) for which, again, there are shipment data but not demand (we separate durable goods from other industries given that results may differ).

The Census does not report orders placed for any industries. Since we have the demand (but not order placement) numbers for the A dataset, we calculate the surrogate (nondecomposed) bullwhip as $B_*^F = \frac{V_I^F}{V_D^F} = B_S^F\, B_M^F\, B_O^F\, B_I^F$. For the B and C datasets, since we do not have demand or order placement data, we report the surrogate bullwhip $B_{**}^F = \frac{V_I^F}{V_S^F} = B_M^F\, B_O^F\, B_F^I$.

The U.S. Census reports materials-and-supplies inventory (we infer this to mean raw materials, RM), work-in-process inventory (WIP), and finished goods inventory (FG) for 24 manufacturing industries (10 in the A dataset, 11 in B, and 3 in C). In our tables, we identify these 24 industries by underscoring the letter-number identifier, for example, A6 Computer and Electronic Products, B1 Apparel, and C11 Wood Products. For each of these 24 industries we infer the manufacturing series from its shipments, WIP, and FG, by assuming the WIP consists of half-finished product: $Manufacturing_t = Shipments_t + (FG_t - FG_{t-1}) + 0.5(WIP_t - WIP_{t-1})$. Thus, for these 24 "underscored" industries, we can calculate V_M^F, and hence, we can determine the manufacturing bullwhip $B_M^F = \frac{V_M^F}{V_S^F}$.

For the 10 underscored industries included in the A data subset (A6, A16, A21, A22, A24, A29, A40, A44, A49, and A50), we use U.S. Bureau of Economic Analysis (BEA) Input-Output data to identify the source and magnitude of the materials consumed by each industry and then infer the orders. Thus, for these 10 industries, we have the full decomposition of the bullwhip, B_S^F, B_M^F, and B_O^F. While this is a relatively limited dataset, it offers us the unique opportunity to test a number of hypotheses regarding intra-echelon bullwhips.

The demand and shipment series are margin-adjusted to convert into cost dollar units for inventory valuations. Demand, shipment, and inventory series are price-index-adjusted so that changes over time are not influenced by inflation. The demand, shipment, manufacturing, and inflow series are logged and first-differenced to remove the time trend. (See Cachon et al. (2007) for details regarding, and the rationale behind, these adjustments to the data.)

The inflow and demand series will probably exhibit some cyclical variation known as seasonality. We use the seasonality ratio developed by Cachon et al. (2007) to quantify the seasonality:

$$Seasonality\ Ratio = \frac{V[Data\ Series] - V[Deseasonalized\ Data\ Series]}{V[Data\ Series]} \quad (3.2)$$

where the data series can be either the inflow series or the demand series. The deseasonalized data series is the residuals from regressing data series on 11 monthly dummy variables. The seasonality ratio represents the fraction of variance that can be explained by seasonality.

3.5 Results and Discussion

Hypotheses presented in section 3.3.1 through section 3.3.5 are tested in section 3.5.1 through section 3.5.6. These results inform our quests “in search of” intra-echelon bullwhips. Results also suggest the need for managers to proceed “in search of” their own internal bullwhips.

3.5.1 Shipment Bullwhip Magnitude

Table 3.2 shows the shipment bullwhips for the A dataset: the 52 manufacturing industries for which both sales and demand data are available. The monthly results are evenly split in the sense that 26 bullwhip ratios are less than one and 26 are one or greater. However, a plot of the data in Figure 3.3 shows a cluster of industries (on the right) with very low shipment bullwhips (the *y*-value divided by the *x*-value); these industries smooth shipments relative to demand. The average ratio indicates smoothing and the t-test result is similarly consistent with H1.

It is instructive to look more closely at characteristics of those industries with larger-than-average shipment bullwhip and antibullwhip outcomes. First, consider the antibullwhipping industries. As an example, we plot in Figure 3.4 the shipments versus demand for industry A47: Ships and Boats (total). Figure 3.4 shows it is not uncommon to get a spike in demand that is double the average. The other industries in Figure 3.3 that exhibit strong antibullwhip shipment ratios (with shipment bullwhip ratios < 0.5) are a couple of defense-related industries; A12: Defense Aircraft and Parts and A45: Search and Navigation Equipment Mfg Defense, along with A37: Nondefense Aircraft and Parts, and A46: Search and Navigation Equipment Mfg Nondefense. These industries appear likely to operate in make-to-order fashion, producing only after orders are confirmed. Given the fixed costs in these heavy-equipment industries, it would be cost prohibitive for the industry to build capacity equal to the abnormally-high peak demand, so customers who order during a demand spike will presumably have to wait for delivery (shipment) of their order.

Conversely, Figure 3.5 shows an example of the shipments versus demand for an industry with a strong shipment bullwhip, A20: Electronic Computer Manufacturing. Note the spike in demand every third month, along with an even higher spike in shipments during that same month. The spikes occur in March, June, October, and December – that is, at what is (for the majority of firms) the end of the quarter. Thus, these results illustrate the hockey stick phenomenon, where sales spike in the last month of the quarter, presumably in an effort to meet quarterly financial expectations (Bradley & Arntzen, 1999; Singer et al., 2009). The high depreciation rates of computer equipment (something on the order of 50% per year) result in an extremely high holding cost, so computer manufacturers are hesitant to overbuild when producing in make-to-stock fashion. Figure 3.5 suggests that at the end of the quarter, however, they rush to build so as not to lose any end-of-quarter sales opportunities. Interestingly, inventory numbers (not shown here) suggest they end the quarter with their lowest monthly inventory, so (as shown in Figure 3.5) in the next month (the first month of the quarter) they fall short on shipments as compared to demand. A further possible factor leading to the end-of-quarter rush is that customers may place regular unfirm orders in the earlier months of the quarter but not make actual purchases until receiving end-of-quarter discounts from their supplier. What makes these actions more tenable in A20 (Electronic Computer Manufacturing) as compared to A47 (Ships and Boats) is that the fixed costs of capacity, and other costs of quickly ramping manufacturing up and down, are presumably much lower in A20.

These results suggest that it is too simplistic to suggest that firms should (or do) either amplify or smooth shipments relative to demand. Instead, there appear to be factors that can push the firm in one direction or the other, depending on industry characteristics.

3.5.2 Manufacturing Bullwhip Magnitude

For the 24 industries for which we can calculate the manufacturing bullwhip (based on monthly data), only five have $B_M^F > 1$ (see Tables 3.3, 3.4, and 3.5). The manufacturing bullwhip ratio is statistically significantly less than one, suggesting that industries generally smooth manufacturing relative to shipments. This is consistent with the manufacturing smoothing hypothesis in the economics literature, as discussed in section 3.3. H2 is supported.

While smoothing predominates in manufacturing, three of the 24 industries have manufacturing bullwhips greater than 1.05. These industries and their manufacturing bullwhip ratios are: B3: Beverage and Tobacco Products (1.19); A24: Furniture and Related Products (1.19), and B15: Petroleum and Coal Products (1.84). Characteristics of these industries are that they have highly cyclical demand (demand in peak months is roughly 25% higher than in slack months), but even more cyclical manufacturing (manufacturing tracks demand relatively closely, but accentuates the peaks and valleys). For example, in the B3 industry (Beverage and Tobacco) we find peak consumption occurs in the summer months, with a trough in January-February. In the A24 industry (Furniture) we find dips in July and December, and heavy demand during August through October and a lower peak in March. For the B15 industry (Petroleum and Coal) we find heavy consumption during the summer months of May through August and low demand in the winter months of December to March. In all three industries manufacturing output in the peak month (lowest month) is about 3% higher (3% lower) than shipments, except for B3 where manufacturing is 12% lower in December.

Factors that may in part drive the manufacturing bullwhip in some industries are plant shutdowns during summer and extended holidays, along with weather conditions that facilitate higher summer output and/or lower winter output. Another factor may be lack of storage capacity – for example, coal can be expensive to store due to space requirements, so unexpected spikes in demand may need to be met with short-term bursts in output (e.g., Mining Congress Journal, 1922). This may be exacerbated by customers who rely on the spot market for purchasing coal rather than entering into longer-term contracts (Murray, 1982).

3.5.3 Order Bullwhip Magnitude

The Census does not report the orders placed by an industry to its supplier, so we are not able to directly calculate the order bullwhip. But we use BEA Input-Output data to infer the orders placed and then calculate the order bullwhips for the ten A industries, as shown in Table 3.3 and Figure 3.6. We find that the order bullwhip ratio is less than one for six out of the ten industries; H3 is not supported. Industries with the highest order bullwhips were (order bullwhip numbers are given in parentheses) A44: Primary Metals (1.16) and A40: Nondurable Goods Total (1.12).

Figure 3.6 consolidates the decomposition results for the ten A industries. Not surprisingly, given the above discussions, the greatest tendency for smoothing occurs in manufacturing (rather than shipping or ordering). Somewhat surprisingly, ordering tends to also result in an antibullwhip. Shipments can exhibit extreme smoothing, although some industries instead amplify (amplification may be associated with the hockey stick phenomenon).

3.5.4 Correlation between the Intra-Echelon Bullwhips

Using a system dynamics simulation model, and calibrating the model with data from an auto assembly plant, Klug (2013) finds that the bullwhip ratio at one echelon within a firm is negatively correlated with the one at the next echelon. On the other hand, there are scenarios where bullwhip ratios at consecutive echelons are positively correlated. For example, the more a firm smooths its manufacturing relative to shipments, the more it may be able to operate in just-in-time fashion, ordering raw materials directly as it uses them, indicating that the manufacturing bullwhip is positively correlated with the order bullwhip. How intra-echelon bullwhips are correlated may be resolved empirically.

The intra-echelon bullwhips are plotted against each other in Figure 3.7; see Table 3.3 for details and statistical results for the 10-industry study of the A industries. Again using the convention of starting downstream and moving upstream in the supply chain, in all cases, we plot the downstream bullwhip as the "independent variable" on the *x*-axis and the upstream bullwhip as the "dependent variable" on the *y*-axis. There is a negative but not significant association between the manufacturing and shipment bullwhips. In the lower-left frame of Figure 3.7 we plot the shipment bullwhip on the *x*-axis against $B_M^F B_O^F B_I^F$ on the *y*-axis, that is, the product of the manufacturing, order, and inflow bullwhips. This plot shows a negative relationship; if smoothing is induced in shipping, then amplification tends to occur upstream, and vice versa.

This suggests that when firms smooth the shipments, they tend to create a bullwhip in manufacturing and/or ordering. Possibly, the shipment is less volatile than demand due to a lack of finished goods inventory that would be needed to immediately fill demand. This causes manufacturing to scramble to produce, creating a bullwhip in manufacturing, which in turn induces the firm to place large orders of raw materials and therefore creates a bullwhip in ordering. In short, when the firm chooses not to ship in a stream duplicating the demand stream, the firm is more likely to manufacture and/or order raw materials in a more variable fashion as compared to the way it ships. It may be a conscious decision to smooth shipments relative to demand, or it may be a suboptimal outcome and one that antagonizes the customer. Similarly, we cannot say definitively that is a bad thing to amplify the manufacturing and order streams relative to the shipment stream. However, our results point to the need for firms to consciously analyze their shipment, manufacturing, and order streams and to make sure they communicate and coordinate their shipment, manufacturing, and ordering decisions with their customers and suppliers as appropriate.

If smoothing (amplifying) happens in manufacturing, then the upstream bullwhip component (i.e., order bullwhip) tends to also smooth (amplify), as shown in the middle-top frame of Figure 3.7. So the order bullwhip is positively associated with the manufacturing bullwhip. Further supporting evidence is shown in the lower-right frame of Figure 3.7; if smoothing (amplifying) occurs in manufacturing, then the upstream bullwhip $B_O^F B_I^F$ tends to also smooth (amplify). The rationale for this relationship needs further study.

If a firm induces a bullwhip in its orders, resulting in high variability in demand for the upstream firm, this upstream firm may have a hard time following the peaks and valleys with its shipments (which become the inflow to the focal firm). This suggests that the inflow bullwhip is negatively associated with the order bullwhip, as shown in the upper-right frame of Figure 3.7.

3.5.5 Impact of Duration of the Time Interval on the Bullwhip

In order to explore the impact of time aggregation, we proceed by simply aggregating the monthly data for each industry into quarterly, semiannual, and yearly data. Bullwhip ratios calculated using monthly, quarterly, semiannual, and yearly data are called monthly, quarterly, semiannual, and yearly bullwhip ratios, respectively (quarterly, semiannual, and yearly results are calculated using January as the starting month). Tables 3.2, 3.4, and 3.5 report the bullwhip ratios based on different time aggregation schemes for A, B, and C datasets, respectively. Figure 3.8 plots the bullwhip ratios for the A, B, and C data series (excluding one outlier data point). We notice that, for bullwhippers, aggregation tends to dampen the bullwhip – observe that for a bullwhip ratio greater than one the trendline falls below the 1:1 diagonal (the aggregated quarterly bullwhip is less than the monthly bullwhip for 19 out of 28 of the industries that have a monthly bullwhip greater than one). On the other hand, if the industry was an antibullwhipper (i.e., it was a "smoother") on a monthly basis (that is, if the bullwhip ratio is less than one on a monthly basis) then aggregation to a quarterly level tends to amplify the bullwhip (in this case, the trendline falls above the 1:1 diagonal and the aggregated quarterly bullwhip is greater than the monthly bullwhip for 39 out of 58 of the industries that have a monthly bullwhip less than one). In other words, in both situations aggregations tend to push the bullwhip closer to a "neutral" value of one. While previous research has similarly shown the dampening effect on the bullwhip, an added contribution of our work is to show the converse "dampening" effect on the antibullwhip.

Retailer and wholesaler results are given in Tables 3.6 and 3.7, respectively. Wholesalers are generally bullwhippers when using monthly data, but we find that the bullwhip ratio is generally dampened when using quarterly and yearly data. Retailers are generally smoothers using monthly data, but we find that six out of nine become slight bullwhippers on a yearly base. Table 3.8 summarizes the results across all industries. All of the statistically significant results point to time aggregation decreasing the bullwhip ratio if the bullwhip ratio is greater than one before aggregation, or point to time aggregation increasing the bullwhip ratio if the bullwhip ratio is less than one before aggregation. H4 is supported.

Seasonality, to a large extent, may cause the differences between the monthly and quarterly (semiannual and yearly) bullwhip ratios. More specifically, it is differences in the way seasonality manifests itself in inflow of materials versus demand. Before delving into statistical findings regarding the seasonality measure, we use Figure 3.9 to motivate the intuition. First look at the upper-left frame of Figure 3.9. Industry A22: Fabricated Metal Products is neither a bullwhipper nor a smoother if one uses monthly data – it had a bullwhip ratio of 1.01. Each data point for "Inflow" indicates whether inflows in that month increase relative to inflows in the previous month (technically, each data point is the average monthly first difference between the log of inflows in that month versus the previous month – this technique follows Cachon et al. (2007)). It is similar for demand. For this industry the inflow and demand graphs track nearly one-to-one. The inflow and demand series exhibit a similar degree of seasonality; the seasonality ratios are 0.69 and 0.65, respectively. The monthly data are aggregated into quarterly data in the upper-right frame in Figure 3.9. The resulting bullwhip ratio is 1.06, and the graphs of inflow and demand again track nearly one-to-one.

Next look at the middle pair of graphs in Figure 3.9 for the wholesale industry W5:

Drugs and Druggists' Sundries. First, note that the monthly bullwhip ratio is 4.15, while quarterly ratio is 2.88. Next note a spike in inflow every third month, coinciding with the end of each quarter (assuming a January fiscal year start), along with a dip in every month prior (and generally following) the spike. There is also a demand spike in March and December, along with a dip before and after the spike. The seasonality ratios for the inflow and demand series are 0.67 and 0.46, respectively, so inflow exhibits a higher degree of seasonality than demand. When the monthly data are aggregated into quarterly data, each spike tends to be muted because it is aggregated with a dip. Since inflow is more seasonal than demand, the inflow series has more spikes to be muted, and thus, the reduction in variance due to aggregation is greater than for the demand series. The more dampened number is in the numerator of the bullwhip ratio, helping explain why the quarterly bullwhip ratio is lower.

The reverse happens with the retail industry R5: Furniture, Home Furnishings, Electronics, and Appliance Stores as shown in the bottom frame of Figure 3.9. The monthly bullwhip ratio is 0.63, while quarterly ratio is 1.02. There is a big demand spike in December (and lesser spikes in March and August). The December spike is followed by a plummeting January demand. There are inflow spikes in March and October, along with dips before and after the spikes. Since demand shows a higher degree of seasonality than inflow (seasonality ratios are 0.97 and 0.71, respectively), the demand series tends to be more dampened under data aggregation than the inflow series. The more muted number is in the denominator of the bullwhip ratio, so it increases the bullwhip number.

These three representative cases suggest that if seasonality of inflow is more (less) pronounced than that of demand, the bullwhip ratio aggregated over long time periods tends to be lower (higher). We test whether this result holds for other industries. As shown in Table 3.9, the majority of industries across manufacturing, retail, and wholesale sectors show a higher (lower) bullwhip ratio when inflow is less (more) seasonal than demand. For wholesalers we find that the negative association between these two ratios is statistically significant, supporting H5. The associations for manufacturers and retailers likewise directionally support H5.

3.5.6 Impact of the Starting Point of the Time Interval on the Bullwhip

Roughly two-thirds of U.S. public traded firms start their fiscal year in January (Wikipedia, 2015), so this has been used as the baseline in calculating quarterly, semiannual, and yearly results. We repeat our analysis with a February or March start and obtain qualitatively similar results to those reported in sections 3.5.1-3.5.5. However, for many industries, a start of the fiscal year in February yields a quite dramatic increase in the bullwhip ratio as compared to starting in January (see Table 3.10, and Figure 3.10). Starts in either February or March yield statistically significant results for the A and C datasets of manufacturers (as compared to a January start), offering support for H6. As discussed in section 3.3.5, it appears this can be caused by "artificial" smoothing of the demand peaks and valleys of the Christmas and postholiday season under the February and March quarterly starts. As shown in Table 3.10, H6 is generally supported across all datasets including retailers and wholesalers (although not universally).

3.6 Summary

We develop a framework to decompose the inter-echelon bullwhip measure into three intra-echelon bullwhips which we denote as the shipment, manufacturing, and order bullwhips. While much of the empirical work to-date has focused on bullwhip phenomenon across the firm, our framework allows us to empirically measure the magnitudes of these three intra-echelon bullwhips. We conduct this empirical analysis using the Census data, which aggregates firms into industries – thus, the following observations describe general trends rather than firm-specific results.

With regard to the three intra-echelon bullwhips, we find over 10% of the industries exhibit an extreme degree of smoothing in shipping (e.g., A47: Ships and Boats, with B_S^F=0.08), while others (about one-half) exhibit amplification of shipments relative to demands. In manufacturing we primarily observe the presence of an antibullwhip (manufacturing tends to proceed in a smoother fashion than shipping), however exceptions exist. Ordering also tends to smooth, but the trend is not universal.

Thus overall, we find smoothing predominates for all three intra-echelon bullwhips – shipment, manufacturing, and ordering. However, just as we find it instructive to look intra-firm instead of just across firms, we also find our work acts as a set of mini-case studies in that it identifies some characteristics of industries which exhibit behavior that diverges from the mean performance. For example, industries that exhibit a high shipment bullwhip seem to suffer from the hockey stick phenomenon – or is "suffer" the right word (possibly the behavior is optimal)? Conversely, industries that benefit from an extreme level of shipment smoothing appear to be those where orders are clumpy and customers are amenable to waiting, such that goods can be manufactured in make-to-order fashion –

or is “benefit from” the right word (possibly the firm would be better served by delivering more closely to the order date)? Somewhat surprising is the presence of a manufacturing bullwhip in some industries (presumably, some firms) which already exhibit a high degree of demand (and subsequently, shipment) variability – why do firms set manufacturing schedules that amplify this shipment variability even further? It may be due in part to climate (winter vs summer) and also due to Christmas and summer plant shutdowns. Also somewhat surprising is that firms that smooth manufacturing tend to further smooth orders, and vice versa. Again, by identifying these patterns, our research serves to motivate future research to further explore these propositions.

With regard to time aggregation, similar to other researchers (e.g., Chen & Lee, 2012) we find it tends to dampen the bullwhip if the ratio is greater than one at the shorter time aggregation level, but a new finding is that it amplifies the bullwhip if the ratio is less than one. Further, we show how seasonality may play a role in the differences between bullwhip ratios at various levels of temporal aggregation. Regarding the starting point of the time interval, an implication of our work for managers is that they should avoid masking the true bullwhip – masking occurs when peaks and valleys of a flow stream are aggregated into the same time bucket. For example, retailers should measure the quarterly bullwhip with a January start date, rather than February.

Managerial implications of our work are summarized in the following advice that we might offer managers: 1) Track your intra-echelon bullwhips. We know of few managers who break down their flow streams in the manner we suggest – managers need to know exactly where variability (or smoothing) is induced within their firm (and by implication, into their supply chain). 2) Pick an appropriate time interval over which to track your bullwhips, and an appropriate starting point for this interval (see above paragraph). 3) Understand what drives each of the intra-echelon bullwhips. The manufacturing bullwhip may be driven by the weather (e.g., higher output may be achievable in warm-weather months) or conversely, the firm may be able to achieve a manufacturing antibullwhip by implementing lean operations. But managers should understand the drivers of each of the intra-echelon bullwhips within their firm – and more broadly, their supply chain. 4) Rigorously track each intra-echelon bullwhip with an eye toward continuously driving it down, in an effort to achieve the "ideal" as described at the outset of section 3.2.

Many complex factors contribute to the challenge facing managers in attempting to match supply with demand across a distributed supply chain. Understanding and managing the bullwhip effect is a complex and difficult task. Our work demonstrates the value of measuring and tracking various intra-echelon bullwhip effects in addition to the overall inter-echelon bullwhip. Specifically, our approach to decomposing the bullwhip provides guidance to firms seeking to better manage their shipping, manufacturing, and ordering activities.

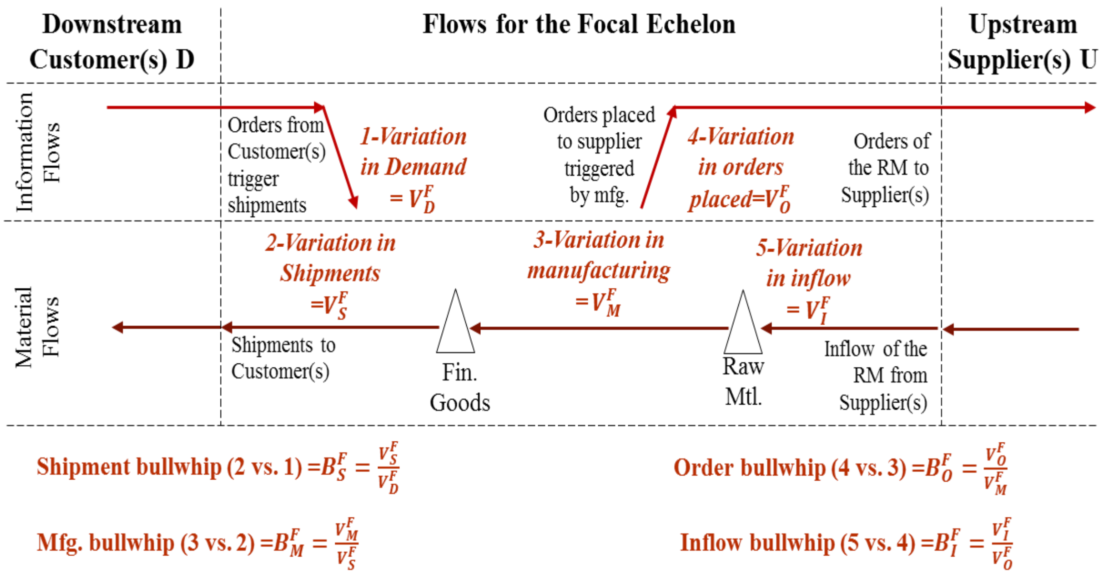


Figure 3.1: Decomposing Inter-Echelon Bullwhip into Intra-Echelon Bullwhips

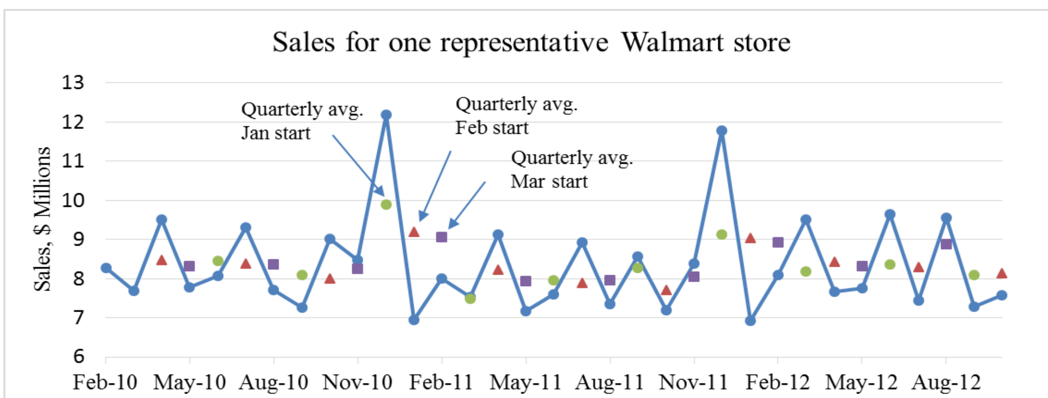


Figure 3.2: Grouping Dec and Jan into Same Quarter Dampens Variability

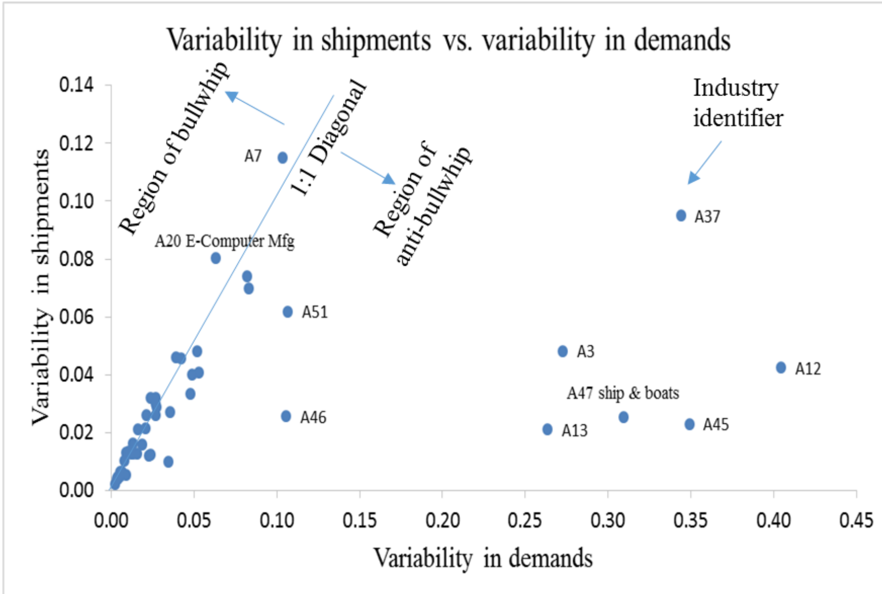


Figure 3.3: Shipment Bullwhip (Ratio=*Y/X*) for the A dataset

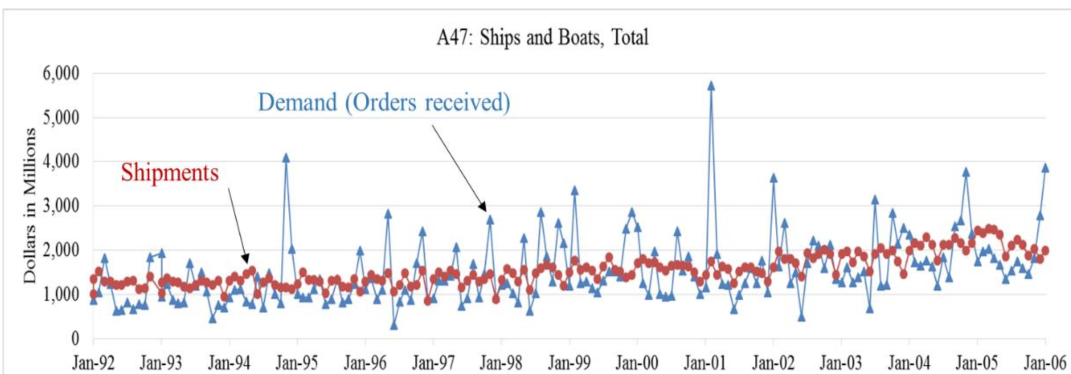


Figure 3.4: Smoothing of Shipments in A47: Ships and Boats

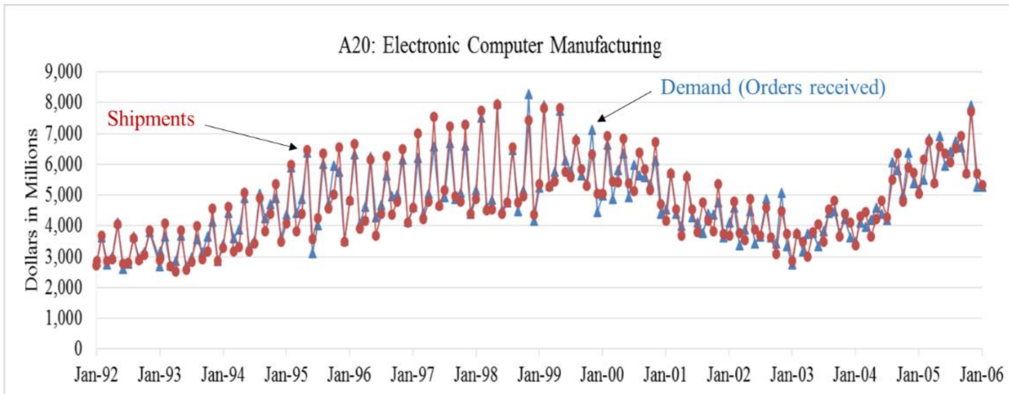


Figure 3.5: Shipment Bullwhip in A20: E-Computer Manufacturing.

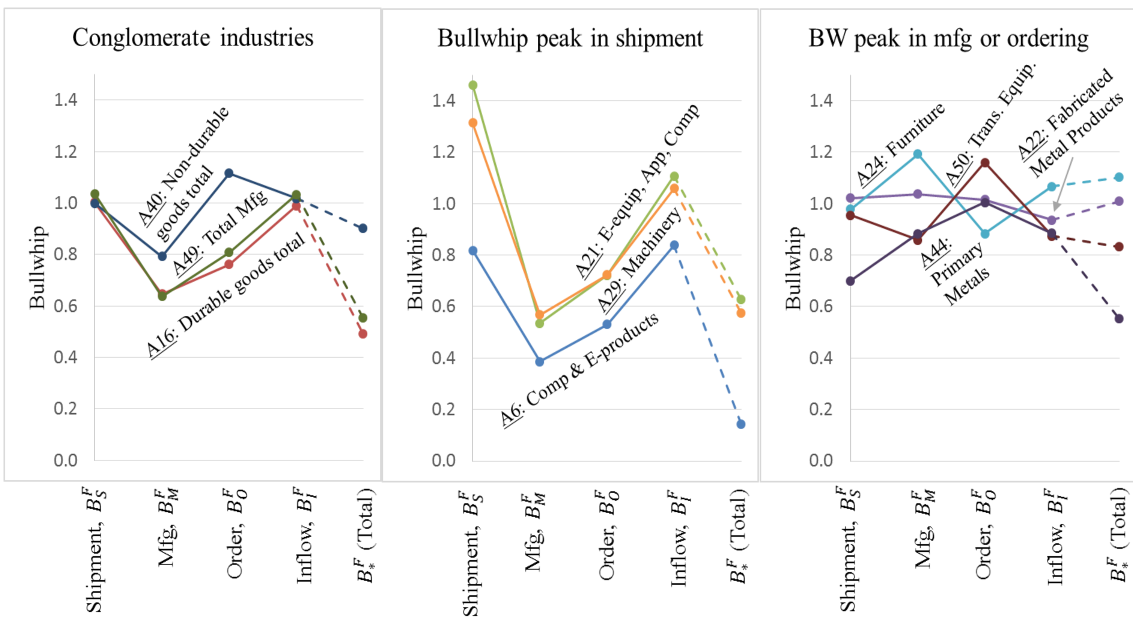


Figure 3.6: Individual Intra-Echelon Bullwhips by Industries

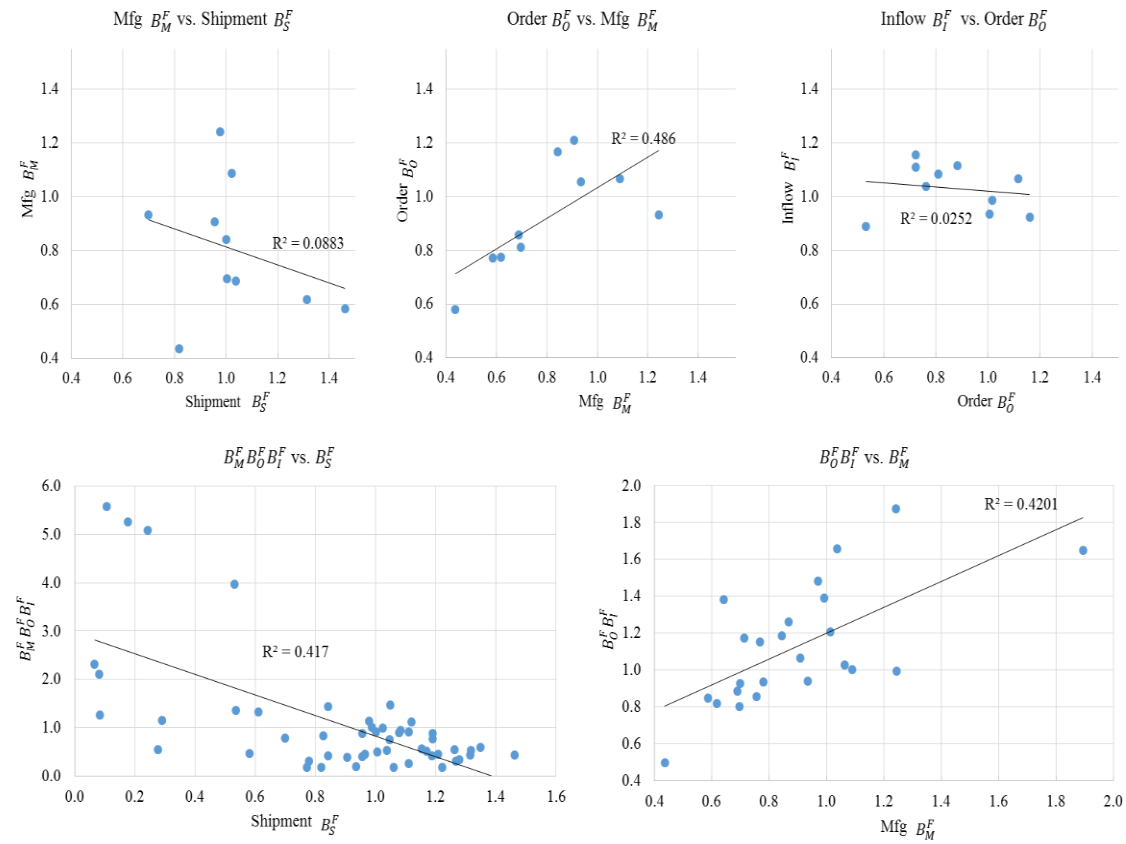


Figure 3.7: Relationships among Individual Intra-Echelon Bullwhips

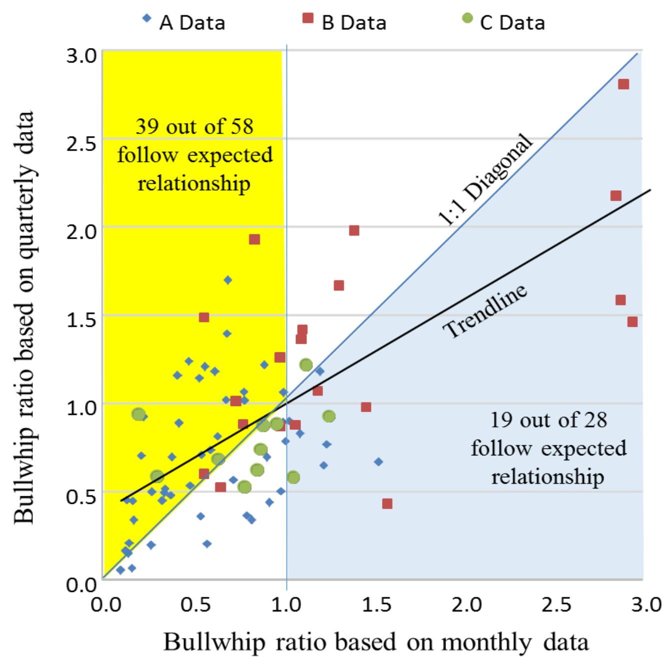


Figure 3.8: Time Aggregation Dampens the Bullwhip and the Antibullwhip

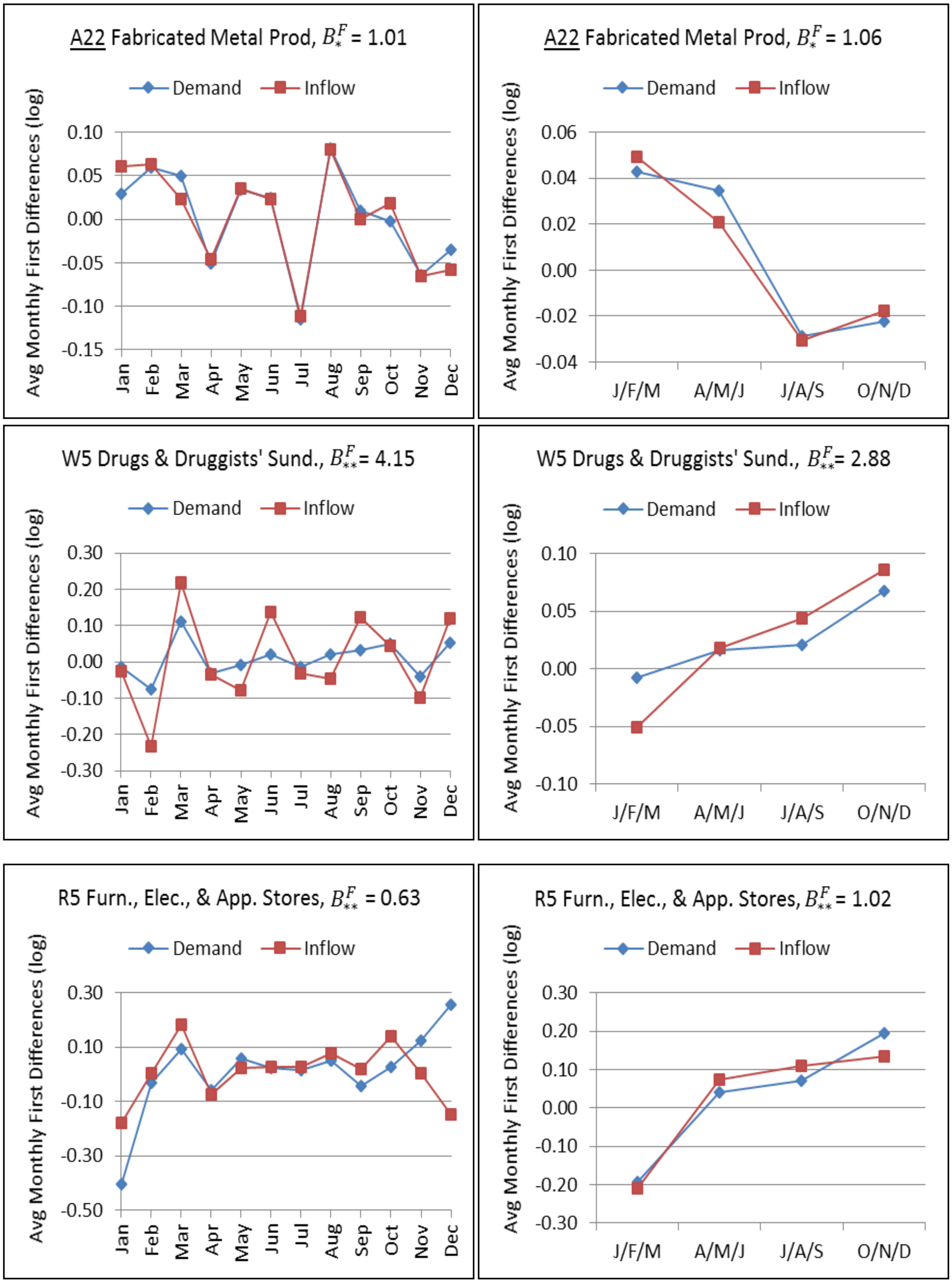


Figure 3.9: Impact of Seasonality on Aggregated Bullwhip Ratio

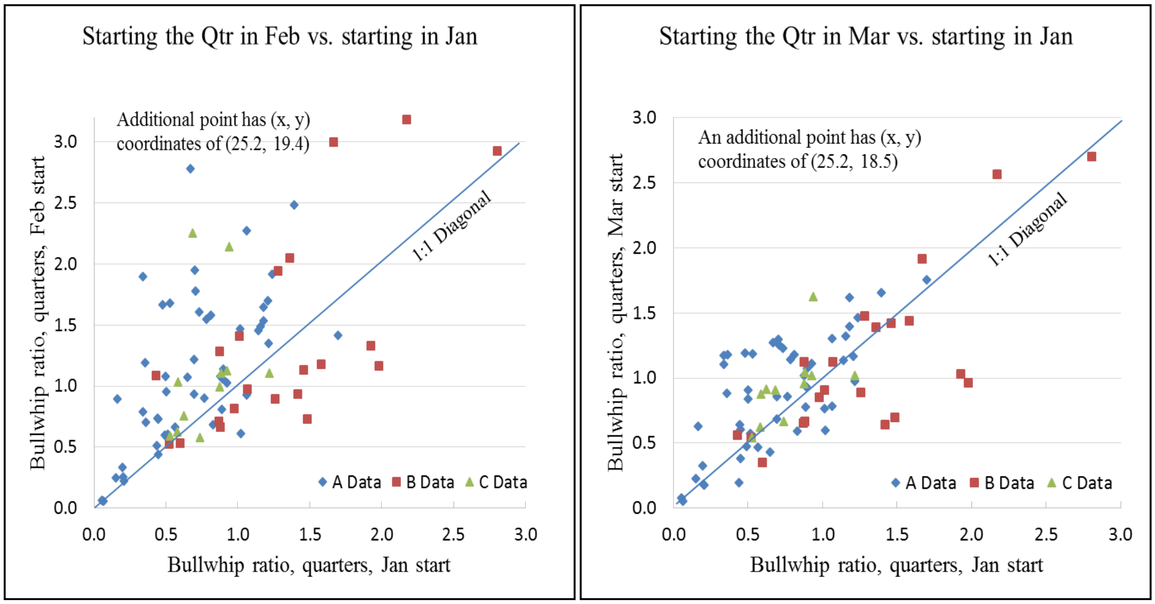


Figure 3.10: Impact of Different Quarterly Starts on Bullwhip Ratios for Manufacturers

Table 3.1: Information Available in the Dataset

		Manufacturing Set (number of industries)						Retail	Wholesale
Variance	Flow Stream	A (52)	$\underline{A}$ (10)	B (23)	$\underline{B}$ (11)	C (11)	$\underline{C}$ (3)	(8)	(21)
V_D^F	Demand	X	X						
V_S^F	Shipment	X	X	X	X	X	X	X	X
V_M^F	Manufacturing		X		X		X		
V_O^F	Orders placed		X						
V_I^F	Inflow	X	X	X	X	X	X	X	X

Table 3.2: Results for the A Dataset

		Bullwhip: B_*^F				Seasonality ratios		Bullwhip: B_{**}^F				Shipment bullwhip: B_S^F			
Code	Industry	Month	Qtr	6 Mo.	Year	Inflow	Demand	Month	Qtr	6 Mo.	Year	Month	Qtr	6 Mo.	Year
A1	All Manufacturing with Unfilled Orders	0.38	0.48	1.22	0.87	0.80	0.83	0.40	0.80	2.49	1.29	0.96	0.59	0.49	0.68
A2	Aluminum and Nonferrous Metal Products	0.99	0.50	0.62	0.93	0.64	0.54	1.01	1.06	1.06	1.19	0.99	0.47	0.58	0.78
A3	Communications Equipment Manufacturing, Defense	0.93	0.44	0.26	0.41	0.17	0.31	5.26	4.37	3.44	1.90	0.18	0.10	0.07	0.22
A4	Communications Equipment Manufacturing, Nondefense	0.35	0.51	0.79	0.80	0.20	0.73	0.39	0.79	1.18	1.27	0.91	0.65	0.67	0.63
A5	Communications Equipment, Total	0.35	0.49	0.77	0.76	0.23	0.75	0.41	0.80	1.19	1.25	0.84	0.62	0.65	0.61
A6	Computer and Electronic Products	0.14	0.45	0.91	1.07	0.65	0.95	0.17	0.75	1.12	1.48	0.82	0.60	0.81	0.73
A7	Computers and Related Products	0.28	0.50	0.99	1.25	0.74	0.92	0.25	0.76	0.98	1.23	1.11	0.66	1.01	1.02
A8	Construction Machinery Manufacturing	0.73	0.56	0.95	1.08	0.53	0.32	1.36	1.04	1.17	1.28	0.54	0.54	0.81	0.84
A9	Construction Supplies	1.25	0.77	1.80	1.28	0.60	0.75	1.12	0.66	2.09	1.32	1.12	1.16	0.86	0.97
A10	Consumer Durable Goods	1.01	0.89	1.08	1.04	0.90	0.90	0.91	0.90	1.39	1.16	1.11	0.99	0.78	0.89
A11	Consumer Goods, Total	1.02	0.78	1.00	0.98	0.83	0.88	0.94	0.71	1.11	1.05	1.08	1.10	0.90	0.94
A12	Defense Aircraft and Parts	0.58	0.20	0.32	0.86	0.07	0.29	5.57	2.67	2.39	2.17	0.10	0.08	0.13	0.40
A13	Defense Capital Goods	0.17	0.06	0.21	0.54	0.13	0.50	2.10	2.14	2.95	3.54	0.08	0.03	0.07	0.15
A14	Durable Excluding Defense	0.60	0.73	1.32	1.03	0.88	0.88	0.51	0.72	2.15	1.30	1.17	1.02	0.61	0.79
A15	Durable Excluding Transportation	0.42	1.16	1.63	1.27	0.78	0.91	0.33	0.72	1.96	1.40	1.28	1.61	0.83	0.91
A16	Durable Goods Total	0.49	0.53	1.32	0.99	0.88	0.88	0.49	0.69	2.38	1.31	1.00	0.77	0.55	0.76
A17	Electric Lighting Equipment Manufacturing	0.43	0.89	1.46	1.07	0.49	0.67	0.44	1.22	1.74	1.45	0.96	0.73	0.84	0.74
A18	Electrical Equipment Manufacturing	0.70	1.70	1.38	1.02	0.32	0.58	0.53	2.57	2.57	1.30	1.32	0.66	0.54	0.79
A19	Electromedical, Measuring, and Control Instrument Mfg	0.48	1.24	2.08	1.03	0.49	0.77	0.41	2.20	3.08	1.47	1.19	0.56	0.68	0.70
A20	Electronic Computer Manufacturing	0.39	0.70	1.35	1.33	0.51	0.73	0.31	1.18	1.37	1.34	1.27	0.59	0.99	0.99
A21	Electronic Equipment, Appliances and Components	0.63	1.18	2.12	1.13	0.65	0.77	0.43	0.88	1.74	1.24	1.46	1.33	1.22	0.91
A22	Fabricated Metal Products	1.01	1.06	1.12	0.88	0.69	0.65	0.99	1.27	3.45	1.24	1.02	0.83	0.33	0.71
A23	Ferrous Metal Foundries	1.21	1.18	1.47	0.92	0.80	0.68	1.44	1.36	1.58	1.10	0.84	0.87	0.93	0.84
A24	Furniture and Related Products	1.10	0.83	1.46	1.73	0.65	0.60	1.13	1.51	1.46	1.83	0.98	0.55	1.00	0.94
A25	Household Appliance Manufacturing	0.69	1.39	2.96	0.96	0.51	0.46	0.55	1.21	3.21	1.22	1.26	1.15	0.92	0.79
A26	Industrial Machinery Manufacturing	0.23	0.93	1.01	0.90	0.18	0.46	0.30	1.64	1.66	1.46	0.78	0.56	0.61	0.62
A27	Information Technology Industries	0.17	0.44	0.92	0.97	0.74	0.95	0.18	0.62	1.03	1.33	0.93	0.71	0.89	0.73
A28	Iron and Steel Mills and Ferroalloy and Steel Products Mfg	0.81	0.36	0.41	1.91	0.25	0.44	1.32	1.32	1.09	1.75	0.61	0.27	0.37	1.09
A29	Machinery	0.57	1.21	1.80	1.26	0.63	0.73	0.44	0.94	1.90	1.38	1.31	1.29	0.95	0.91
A30	Manufacturing Excluding Defense	0.64	0.81	1.41	1.12	0.84	0.88	0.56	0.63	1.95	1.26	1.15	1.29	0.72	0.89
A31	Manufacturing Excluding Transportation	0.54	1.14	1.40	1.33	0.74	0.90	0.45	0.69	1.37	1.37	1.21	1.66	1.02	0.97
A32	Material Handling Equipment Manufacturing	0.33	0.45	0.72	1.17	0.39	0.48	1.16	1.48	1.30	1.37	0.29	0.30	0.55	0.86
A33	Metalworking Machinery Manufacturing	0.79	1.01	1.17	1.26	0.25	0.66	0.59	0.55	0.87	1.22	1.35	1.83	1.35	1.03
A34	Mining, Oil and Gas Field Machinery Manufacturing	2.10	3.08	1.59	0.67	0.30	0.20	3.96	10.22	4.19	1.28	0.53	0.30	0.38	0.52
A35	Motor Vehicle Bodies, Trailers and Parts	1.04	0.90	1.06	1.15	0.91	0.88	0.88	0.82	0.94	1.14	1.19	1.09	1.13	1.01
A36	Motor Vehicles and Parts	0.97	0.88	1.07	1.04	0.91	0.90	0.90	0.84	1.01	1.08	1.08	1.05	1.05	0.96
A37	Nondefense Aircraft and Parts	0.15	0.15	0.32	0.57	0.20	0.28	0.54	0.59	1.88	1.28	0.28	0.25	0.17	0.44
A38	Nondefense Capital Goods	0.18	0.34	1.03	0.80	0.75	0.86	0.17	0.48	1.95	1.27	1.06	0.70	0.53	0.63
A39	Nondefense Capital Goods Excluding Aircraft	0.22	0.70	1.56	1.16	0.78	0.92	0.18	0.63	1.80	1.37	1.22	1.11	0.86	0.85
A40	Nondurable Goods Total	0.90	1.22	1.10	1.27	0.61	0.80	0.90	1.22	1.10	1.27	1.00	1.00	1.00	1.00
A41	Other Durable Goods	0.92	0.69	0.98	1.30	0.78	0.78	0.77	0.69	0.86	1.49	1.19	1.00	1.14	0.87
A42	Other Electronic Component Manufacturing	0.69	1.02	0.80	0.92	0.16	0.36	0.84	1.27	1.24	1.68	0.83	0.80	0.64	0.55
A43	Photographic Equipment Manufacturing	1.54	0.67	0.88	1.19	0.40	0.49	1.47	0.55	0.88	1.23	1.05	1.22	1.00	0.96
A44	Primary Metals	0.83	0.34	0.39	1.10	0.59	0.63	0.87	0.86	0.85	1.28	0.96	0.39	0.45	0.86
A45	Search and Navigation Equipment Mfg Defense	0.15	0.21	0.38	0.87	0.21	0.42	2.31	2.50	3.05	2.99	0.07	0.08	0.13	0.29
A46	Search and Navigation Equipment Mfg Nondefense	1.23	0.65	1.06	0.82	0.16	0.30	5.09	8.71	4.62	2.31	0.24	0.07	0.23	0.35
A47	Ships and Boats, Total	0.10	0.05	0.12	0.19	0.35	0.21	1.26	1.26	1.75	0.77	0.08	0.04	0.07	0.24
A48	Total Capital Goods	0.13	0.16	1.03	0.75	0.73	0.84	0.17	0.44	1.97	1.30	0.77	0.37	0.52	0.58
A49	Total Manufacturing	0.55	0.71	1.43	1.13	0.84	0.89	0.53	0.63	2.06	1.26	1.04	1.13	0.69	0.89
A50	Transportation Equipment	0.55	0.36	1.14	1.01	0.89	0.74	0.79	0.73	1.39	0.98	0.70	0.49	0.82	1.03
A51	Turbines, Generators, & Other Power Transmission Equip	0.27	0.20	0.10	0.09	0.41	0.58	0.47	0.60	2.34	1.53	0.58	0.33	0.04	0.06
A52	Ventilation, Heating, Air-Cond, and Refrig Equip Mfg	0.79	1.06	1.38	1.82	0.55	0.53	0.76	1.12	2.96	1.57	1.05	0.95	0.47	1.16
	Average:	0.65	0.75	1.09	1.02			1.06	1.44	1.87	1.43	0.89	0.74	0.67	0.75
	Ratio > 1:	10	14	31	29			15	23	46	50	26	17	10	7
	Ratio < 1:	42	38	21	23			37	29	6	2	26	35	42	45
	T Statistics	-2.65***	-3.21***	-5.88***	-5.08***							-2.17**	-4.28***	-7.13***	-7.01***

*** p<0.01, ** p<0.05, * p<0.1

Table 3.3: Individual Intra-Echelon Bullwhips for 10 Industries in A Dataset

Code	Industry	Shipment B_S^F	Mfg. B_M^F	Order B_O^F	Inflow B_I^F
A6	Computer and Electronic Products	0.82	0.39	0.53	0.84
A16	Durable Goods Total	1.00	0.65	0.76	0.99
A21	Electronic Equipment, Appliances and Components	1.46	0.54	0.72	1.11
A22	Fabricated Metal Products	1.02	1.04	1.02	0.94
A24	Furniture and Related Products	0.98	1.19	0.88	1.07
A29	Machinery	1.31	0.57	0.72	1.06
A40	Nondurable Goods Total	1.00	0.79	1.12	1.02
A44	Primary Metals	0.96	0.86	1.16	0.87
A49	Total Manufacturing	1.04	0.64	0.81	1.03
A50	Transportation Equipment	0.70	0.88	1.01	0.89
	T Statistics	0.42	-3.17***	-1.99**	-0.62
		B_M^F vs. B_S^F	B_O^F vs. B_M^F	B_I^F vs. B_O^F	
	Correlation	-0.30	0.69**	-0.17	

*** p<0.01, ** p<0.05, * p<0.1

Table 3.4: Results for the B Dataset

		Bullwhip: B_{**}^F				Seasonality ratios		Mfg.
Code	Industry	Monthly	Quarterly	Semiann.	Yearly	Inflow	Sales	B_M^F
B1	Apparel	0.57	0.60	0.34	1.62	0.71	0.88	0.65
B2	Basic Chemicals	0.74	1.01	1.57	1.07	0.28	0.73	0.66
B3	Beverage and Tobacco Products	2.17	3.37	4.04	0.63	0.28	0.42	1.19
B4	Beverage Manufacturing	3.04	1.28	2.01	1.10	0.39	0.80	
B5	Consumer Nondurable Goods	1.11	1.36	1.05	1.55	0.64	0.75	
B6	Dairy Product Manufacturing	0.85	1.93	2.06	1.13	0.45	0.70	
B7	Food Products	1.32	1.67	2.50	1.09	0.71	0.81	0.92
B8	Grain and Oilseed Milling	2.90	2.81	1.78	1.05	0.61	0.44	
B9	Leather and Allied Products	0.79	0.88	0.98	2.89	0.16	0.68	0.59
B10	Meat, Poultry and Seafood Product Processing	1.08	0.87	1.00	1.07	0.49	0.54	
B11	Paint, Coating and Adhesive Manufacturing	1.47	0.98	2.44	0.93	0.60	0.64	
B12	Paper Products	0.99	1.26	1.20	1.09	0.30	0.56	0.82
B13	Paperboard Container Manufacturing	1.40	1.98	1.65	1.18	0.19	0.56	
B14	Pesticide, Fertilizer & Other Ag. Chemical Mfg	0.66	0.52	0.55	1.18	0.62	0.81	
B15	Petroleum and Coal Products	2.95	1.46	0.96	1.19	0.22	0.40	1.84
B16	Petroleum Refineries	2.88	1.58	1.06	1.13	0.20	0.37	
B17	Pharmaceutical and Medicine Manufacturing	2.86	2.17	1.87	1.30	0.16	0.52	
B18	Plastics and Rubber Products	0.99	0.87	1.40	1.38	0.59	0.78	1.01
B19	Printing	1.59	0.43	0.29	1.42	0.50	0.76	0.99
B20	Pulp, Paper, and Paperboard Mills	1.20	1.07	1.04	1.34	0.20	0.34	
B21	Textile Products	1.12	1.42	2.52	1.66	0.62	0.83	0.96
B22	Textiles	0.57	1.48	2.36	1.00	0.78	0.89	0.70
B23	Tobacco Manufacturing	3.09	25.22	16.56	0.90	0.22	0.21	
	Average:	1.58	2.44	2.23	1.26			
	Ratio > 1:	15	16	18	19			
	Ratio < 1:	8	7	5	4			

Table 3.5: Results for the C Dataset

		Bullwhip: B^F_{**}				Seasonality ratios		Mfg.
Code	Industry	Monthly	Quarterly	Semiann.	Yearly	Inflow	Sales	B^F_M
C1	Audio and Video Equipment Mfg.	0.86	0.62	0.79	1.94	0.31	0.68	
C2	Automobile Manufacturing	0.90	0.87	1.08	1.05	0.89	0.91	
C3	Battery Manufacturing	1.06	0.58	0.49	1.28	0.49	0.76	
C4	Computer Storage Device Mfg.	0.20	0.94	1.00	1.02	0.49	0.95	
C5	Farm Machinery and Equipment Mfg.	0.88	0.74	0.81	1.13	0.51	0.68	
C6	Heavy Duty Truck Manufacturing	1.13	1.22	1.19	1.09	0.67	0.66	
C7	Light Truck and Utility Vehicle Mfg.	0.97	0.88	1.05	1.02	0.87	0.87	
<u>C8</u>	Miscellaneous Products	0.65	0.68	2.79	1.38	0.58	0.88	0.73
<u>C9</u>	Nonmetallic Mineral Products	0.79	0.53	0.63	1.01	0.60	0.75	0.72
C10	Other Computer Peripheral Equip. Mfg.	0.31	0.58	0.69	1.16	0.75	0.92	
<u>C11</u>	Wood Products	1.26	0.93	2.43	1.51	0.60	0.75	0.94
	Average:	0.82	0.78	1.18	1.24			
	Ratio > 1:	3	1	5	11			
	Ratio < 1:	8	10	6	0			

Table 3.6: Bullwhip Ratios for Retail Industries

		Bullwhip: B^F_{**}				Seasonality ratios	
Code	Industry	Monthly	Quarterly	Semiann.	Yearly	Inflow	Sales
	Retail Total	0.50	0.67	1.03	0.99	0.82	0.95
R1	Building Material and Garden Equip. & Supplies Dealers	0.94	0.55	1.58	1.62	0.74	0.81
R2	Clothing and Clothing Accessory Stores	0.35	0.23	0.56	1.52	0.82	0.99
R3	Department Stores	0.34	0.33	0.83	0.96	0.89	0.99
R4	Food and Beverage Stores	0.98	1.56	1.78	1.05	0.86	0.89
R5	Furniture, Home Furnishings, Electronics & Appliance Stores	0.63	1.02	1.40	1.45	0.71	0.97
R6	General Merchandise Stores	0.29	0.33	0.80	1.26	0.88	0.97
R7	Motor Vehicle and Parts Dealers	1.86	0.50	0.70	1.03	0.66	0.59
R8	Total (excl. motor vehicle and parts dealers)	0.34	0.53	0.97	1.07	0.87	0.97
	Average:	0.69	0.63	1.07	1.22		
	Ratio > 1:	1	2	4	7		
	Ratio < 1:	8	7	5	2		

Table 3.7: Bullwhip Ratios for Wholesale Industries

		Bullwhip: B^F_{**}				Seasonality ratios	
Code	Industry	Monthly	Quarterly	Semiann.	Yearly	Inflow	Sales
	Total	1.143	1.366	1.671	1.169	0.64	0.64
W1	Apparel,Piece Goods,and Notions	1.235	0.895	0.942	1.623	0.47	0.76
W2	Beer, Wine, and Distilled Alcoholic Beverages	0.572	0.581	0.345	1.122	0.54	0.81
W3	Chemicals and Allied Products	1.485	0.989	1.430	1.071	0.27	0.46
W4	Computer and Computer Peripheral Equip. & Software	1.011	1.164	1.000	0.953	0.74	0.83
W5	Drugs and Druggists' Sundries	4.152	2.884	3.532	1.098	0.67	0.46
W6	Durable Goods	0.869	0.799	0.745	1.208	0.60	0.69
W7	Electrical and Electronic Goods	0.990	1.019	0.863	1.282	0.37	0.65
W8	Farm Product Raw Materials	3.450	3.240	6.633	0.826	0.66	0.48
W9	Furniture and Home Furnishings	1.450	1.165	0.635	1.192	0.40	0.62
W10	Grocery and Related Products	1.393	1.398	1.346	1.177	0.59	0.65
W11	Hardware, and Plumbing and Heating Equip. & Supplies	1.167	0.805	1.062	1.482	0.33	0.56
W12	Lumber and Other Construction Materials	1.114	0.697	0.668	1.430	0.55	0.61
W13	Machinery, Equipment, and Supplies	1.241	1.125	3.022	1.344	0.53	0.66
W14	Metals and Minerals, for example, Petroleum	1.497	1.242	1.436	1.446	0.48	0.55
W15	Miscellaneous Durable Goods	1.145	0.933	0.841	1.231	0.41	0.65
W16	Miscellaneous Nondurable Goods	1.419	0.567	0.426	1.087	0.39	0.63
W17	Motor Vehicle and Motor Vehicle Parts and Supplies	1.109	0.949	1.854	1.062	0.30	0.68
W18	Nondurable Goods	1.609	2.802	5.950	1.192	0.64	0.58
W19	Paper and Paper Products	1.672	1.469	1.167	0.898	0.51	0.54
W20	Petroleum and Petroleum Products	1.355	1.382	1.036	1.058	0.36	0.46
W21	Professional and Commercial Equipment and Supplies	1.068	1.378	1.079	1.001	0.69	0.75
	Average:	1.461	1.311	1.713	1.180		
	Ratio > 1:	19	13	14	19		
	Ratio < 1:	3	9	8	3		

Table 3.8: T-Test Statistics for Bullwhip Ratio Time Aggregation Comparisons

	Month vs. Quarter		Qtr. vs. Semi-ann		Semi-ann vs. Year		Month vs. Semi-ann		Month vs. Year	
	>1	<1	>1	<1	>1	<1	>1	<1	>1	<1
A Data	1.10	-2.91***	-1.27	-7.89***	3.93***	-3.93***	-0.01	-5.91***	1.13	-9.78***
B Data	-0.78	-1.85**	0.75	-1.21	1.78**	-3.62**	-0.74	-2.21**	3.35***	-2.83**
C Data	NA	-0.31	NA	-1.88**	1.76*	-3.25**	NA	-1.51*	NA	-3.75***
Retail	NA	-0.97	NA	-4.74***	0.92	-2.56**	NA	-8.64***	NA	-5.98***
Wholesale	1.52*	NA	-1.60	-1.02	2.33**	-10.87***	-1.01	4.71	1.85**	-4.96**

*** p<0.01, ** p<0.05, * p<0.1

NA = not applicable due to sample size of less than four.

> 1 covers scenarios where the bullwhip ratio > 1 at the shorter time interval.

< 1 covers scenarios where the bullwhip ratio < 1 at the shorter time interval.

B^F_* for A Data; B^F_{**} for others.

Table 3.9: Impact of Seasonality on Aggregated Bullwhip Ratio

	Monthly vs. Quarterly	Quarterly vs. Yearly	Monthly vs. Semiannually	Monthly vs. Yearly
Manufacturing	57%	67%	58%	71%
Retail	67%	78%	100%	100%
Wholesale	41%	73%	23%	55%
Total	55%	69%	55%	70%

The numbers in the table show the fraction of industries that have a lower (higher) aggregated bullwhip ratio when inflow is more (less) seasonal than demand.

Table 3.10: T-Test Statistics for Bullwhip Comparisons for Different Fiscal Year Starts

	Jan ≠ Feb	Jan ≠ Mar	Feb ≠ Mar
A Data	-4.84***	-2.52***	5.22***
B Data	0.62	1.62*	3.34***
C Data	-2.06**	-2.09**	1.53*
Retail	-0.46	-2.48**	-2.47**
Wholesale	-0.75	-0.35	0.20

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

B_*^F for A Data; B_{**}^F for others.

CHAPTER 4

BULLWHIP EFFECT IN A PHARMACEUTICAL SUPPLY CHAIN

4.1 Introduction

A significant advancement in supply chain management in the past three decades is the identification and management of the bullwhip effect. In a seminal paper, Lee et al. (1997a) define the bullwhip effect as "the phenomenon where orders to the supplier tend to have larger variance than sales to the buyer (i.e., demand distortion), and the distortion propagates upstream in an amplified form (i.e., variance amplification)" (p. 546). The bullwhip effect has been observed in many firms and industries: Barilla's pasta supply chain (Hammond, 1994), machine tool industry (Anderson et al., 2000), European convenience foods supply chain (Fransoo & Wouters, 2000), a supermarket chain in Spain (Lai, 2005), Philips electronics (De Kok et al., 2005), semiconductor equipment industry (Terwiesch et al., 2005), and U.S. industries (Cachon et al., 2007).

The bullwhip effect leads to significant supply chain inefficiencies such as excessive capital investment in inventory, mismatched production schedules, poor customer service, lost revenues, misguided capacity planning, and additional transportation costs (e.g., Sterman, 1989; Lee et al., 1997b; Jin et al., 2015a). As a result, taming the bullwhip has attracted much attention from both researchers and practitioners. For example, Lee et al. (1997a) identify four causes of the bullwhip effect and suggest several strategies to mitigate its detrimental impact.

Although there is a growing literature of empirical studies on the bullwhip effect, there are several challenges in empirical investigation of the effect. First, Chen and Lee (2012) point out that two major definitions of bullwhip effect measurement have been used in the literature: information-based definition and material-based definition. The information-based definition originating from Lee et al. (1997a) compares order variance with demand variance. It has been widely used in theoretical analysis. The material-based definition that is used in most empirical studies compares the variance of order receipts with that of sales. These two definitions differ in concept and are not necessarily good approximations of each other. Hence, empirical studies on bullwhip effect using material-based definition may not have a direct bearing on the theoretical models that use information-based definition. Second, analytical analysis of the bullwhip effect is usually based on a single product and order decision period. However, due to data availability issues, most empirical studies measure the bullwhip effect based on aggregated products and aggregated time to a month or longer. Measuring the bullwhip effect in aggregate data may cause potential biases in estimation (Chen & Lee, 2012). Whether aggregation amplifies, preserves, or dampens the bullwhip effect is an important question to explore. For example, if the data aggregation masks the bullwhip effect, then the managers who make financial planning and investment decisions based on quarterly or yearly firm-level data will probably overlook the severity of monthly product-level bullwhip effect. But it is monthly information at product level that defines much of a firm's operations management. Third, the bullwhip effect is a phenomenon on the entire supply chain. Bullwhip effect estimation requires information such as order and demand data from each echelon along the supply chain to keep track of individual products. It is a formidable task to collect this information. To the best of our knowledge, no prior work manages to do this.

We address these empirical challenges by analyzing a proprietary dataset collected from a multiechelon pharmaceutical supply chain and make the following contributions to the literature. First, we measure the bullwhip effect based on information flows and compare it with that based on material flows. Second, we report the bullwhip effect in a supply chain at the product level and in fine time buckets such as monthly as defined in analytical papers. Third, we explore how data aggregation affects the bullwhip measurement. Specifically, we investigate whether product aggregation and temporal aggregation preserve or mask the bullwhip effect. Fourth, we measure the bullwhip effect across different echelons of a supply chain, rather than across a compilation of individual firms or industries. Fifth, we examine some drivers of the bullwhip effect such as price fluctuation, replenishment lead time, and inventory.

Our key findings are the following: (1) Distributors exhibit a prevalent and intensive bullwhip effect. (2) Manufacturer exhibits a less intensive bullwhip effect than distributors and makes production smoother than demand for some products. (3) The bullwhip measure based on order receipt variance underestimates the one based on order variance. (4) Products that have a flatter demand are more likely to exhibit the bullwhip effect. (5) Product aggregation and time aggregation tend to mask the bullwhip effect in some cases. (6) Price variation, inventory, and replenishment lead time are three prominent factors related to the bullwhip effect.

The rest of this chapter is organized as follows. Section 4.2 provides a brief survey of the related literature. Section 4.3 outlines our hypotheses. Section 4.4 summarizes empirical context and data. We present our analysis in section 4.5. Section 4.6 offers some concluding comments.

4.2 Literature Review

Since Forrester (1961) first identifies the bullwhip effect in a series of case studies, the phenomenon has been widely studied in the economics and operations management literatures. In general, the economics literature on supply chain variability precedes the work in operations management. Economists discuss supply chain volatility in terms of production smoothing hypothesis, which states that a firm can use inventory as a buffer to smooth its production relative to its sales. This argument suggests that production is less volatile than demand. Production smoothing is desirable for a firm if it is less costly to maintain production at a relatively stable level than to vary the production level, possibly because the production cost function is convex or because changing the rate of production is expensive. Although the intuition behind production smoothing is simple and fascinating, the majority of the empirical studies show the opposite result: Production is more variable than sales (e.g., Blinder, 1981; Blanchard, 1983; Miron & Zeldes, 1988; Krane & Braun, 1991; Kahn, 1992; Rossana, 1998). To explain the discrepancy between theory and observation, some economists (e.g., Fair, 1989; Ghali, 1987) argue that there are problems with the data used in the empirical analysis of production smoothing: Data are measured in monetary units rather than physical units and are seasonally adjusted. Other economists (e.g., Caplin, 1985; Blinder, 1986; Kahn, 1987) argue that there are problems with the theory itself, and show that production is actually more variable than sales under certain inventory policies and demand structures.

Lee et al. (1997a) approach the bullwhip phenomenon from a managerial perspective as opposed to a macroeconomics aspect and popularize the term in the operations management literature. In a seminal paper (1997a), these same authors define the bullwhip effect in supply chain context and identify four causes of the effect: demand signal processing, price fluctuation, order batching, and rationing game. There is a growing operations management literature of the theoretical studies on the bullwhip effect after the work of Lee et al. (1997a). Cachon (1999) show that order variance of retailers can be reduced when the retailers' order interval is lengthened or when their batch size is reduced. Chen et al. (2000) quantify the bullwhip effect in a two-stage supply chain that is due to the effects of demand forecasting and order lead times, and show that information sharing can reduce, but not completely eliminate, the bullwhip effect. Chen and Lee (2012) develop a general modeling framework to explain various observations in previous empirical studies and show that data aggregation across products or over long time periods masks the bullwhip effect. Many researchers from operations management discipline have conducted empirical investigations on the bullwhip effect. Hammond (1994) reports large fluctuations of weekly orders in Barilla's pasta supply chain. Anderson et al. (2000) find substantial volatility in the machine tool industry and attribute it to the bullwhip effect. Fransoo and Wouters (2000) discuss several important issues in measuring the bullwhip effect and find the existence of the bullwhip effect at different echelons in two food supply chains in the Netherlands. Terwiesch et al. (2005) find that the semiconductor equipment industry is more volatile than the personal computer industry. Lai (2005), using monthly data on 3,754 stock keeping units (SKUs) from the distribution center of a supermarket chain in Spain, finds that 80% of the total SKUs show the bullwhip effect and order batching is a main driver of the effect. Cachon et al. (2007) analyze the bullwhip effect using a wide panel of U.S. industries and find that retail industries and most manufacturing industries do not exhibit a bullwhip effect, but wholesale industries exhibit the effect. Bray and Mendelson (2012) examine the bullwhip effect in a sample of 4,689 public U.S. firms, and find that two-thirds of firms show the bullwhip effect and information transmission lead time contributes to the effect. Shan et al. (2014) investigate the bullwhip effect in China using a dataset of over 1,200 public companies from 2002 to 2009, and find that more than two-thirds of the companies experience the bullwhip effect.

Our study fits within the stream of empirical studies, but it differs from the previous works in several ways. First, we use monthly and item-level data, whereas most of prior studies use aggregate data at firm/industry level and at monthly/quarterly level. These finer levels of data, which define much of a firm's operations management, enable us to explore the impact of data aggregation on the bullwhip effect measurement. Second, we obtain order information that is not available in previous studies. We measure the bullwhip effect based on information flow (order) and compare it with the one based on material flow (order receipt). By doing this, we empirically test the analytical results derived by Chen and Lee (2012) and investigate the difference between information-based bullwhip definition that is widely used in theoretical studies and material-based definition that is used in most empirical studies. Third, we collect item-level data for all firms in a linear supply chain, and therefore we can make comparisons across different echelons of the supply chain, whereas prior works are generally not able to construct linear supply chains and have to study firms or industries without knowing their customers or suppliers. We are not aware of any work that manages to keep track of individual products through the supply chain. Our results have a direct bearing on the original bullwhip effect defined by Lee et al. (1997a).

4.3 Bullwhip Effect Measurement and Hypotheses

We use the terms “demand,” “sales,” “order,” and “order receipt” for a typical firm in the remainder of this chapter. Their meanings are as follows: demand refers to the order received by the firm from its customers; sales refers to the shipments from the firm to its customers; order refers to the order placed by the firm to its suppliers; order receipt refers to the shipment received by the firm from its suppliers. Following the original definition of the bullwhip effect by Lee et al. (1997a), we define

$$Bullwhip\ Ratio = \frac{V[Order]}{V[Demand]} \tag{4.1}$$

where $V[\,]$ is the variance operator. The numerator and denominator are the variance of order series and demand series of a single product or a group of products. We say that the bullwhip effect is exhibited when the ratio is greater than one. As described before, this definition is based on information flow. Due to data availability, some researchers use order receipt as a proxy for order and use sales as a proxy for demand (e.g., Bray & Mendelson, 2012; Cachon et al., 2007; Shan et al., 2014). If the order receipt information is not available, it is inferred from the inventory and sales data. The resulting bullwhip ratio is material-based bullwhip measure.

Chen and Lee (2012) argue that bullwhip measurement based on information flow (order) may be different from the measurement based on material flow (order receipt). These two measurements account for different levels of decision effects. The order information is an input to the decision process, but the order receipt information is the outcome of the decision process. The bullwhip effect based on material flow is the consequence of that based on information flow. Chen and Lee (2012) show analytically that the variance of order receipt sequence is less than that of order sequence. The intuition is that the downstream orders are truncated by the upstream order-fulfillment capacity, so the order receipt stream appears less variable. Using the order receipt data as a proxy for the order data will underestimate the original order variance. We therefore formulate the following hypothesis:

HYPOTHESIS 1 (H1). The bullwhip ratio based on order receipt variance is lower than that based on order variance.

Researchers in economics and operations management have explored the impact of data aggregation across products. Caplin (1985) shows that aggregation across products preserves the bullwhip effect under (S, s) inventory policy no matter the correlation structure of demand. Fransoo and Wouters (2000) show that the same basic data can lead to different bullwhip measurements, dependent on the sequence of aggregation. Cachon et al. (2007) write that "Whether aggregation preserves or masks the bullwhip effect or production smoothing depends on the correlation of production and demand across the units being aggregate (firms, products, etc.) and on the particular causes of amplification in place" (p. 477). Using a theoretical model, Chen and Lee (2012) give a rigorous treatment of the product aggregation issue, and show that the bullwhip effect tends to be masked under product aggregation. We propose the following hypothesis:

HYPOTHESIS 2 (H2). The bullwhip ratio is smaller at the group/family level than at the individual product level.

In theoretical studies on the bullwhip effect, researchers derive the bullwhip measure through specific assumptions on the order and demand distribution function. However, there is usually no information on the distribution function when researchers conduct empirical investigations on the bullwhip effect. We need to determine an appropriate time window (e.g., weekly, monthly, or quarterly) to calculate the variances of order and demand. Fransoo and Wouters (2000) suggest that the appropriate aggregation over time should depend on the specific problem under study. Chen and Lee (2012) argue that it is important to measure bullwhip effect at the appropriate time unit for supply chain cost assessment purposes. Chen and Lee (2012) develop an analytical model to demonstrate that "aggregating data over relatively long time periods can mask the bullwhip effect" (p. 772). More specifically, they show that under a first-order autoregressive moving average (ARMA (1, 1)) demand model, if the bullwhip ratio is greater than one, then the ratio will decrease monotonically to one as the aggregated time period increases. Thus, we propose the following hypothesis:

HYPOTHESIS 3 (H3). The bullwhip ratio decreases as the aggregation time period increases.

Lee et al. (1997a) define the bullwhip effect as a supply chain phenomenon where the demand variability increases from downstream echelons to upstream echelons. Empirical findings are mixed. Hammond (1994) reports large fluctuations of order quantities in Barilla's pasta supply chain. Lee et al. (1997b) observe amplified volatility in orders in diaper supply chain of Procter and Gamble and in Hewlett-Pachard's printer supply chain. However, Cachon et al. (2007) find that retail industries and most manufacturing industries do not exhibit the bullwhip effect, but the wholesale industries exhibit the effect. Furthermore, they observe that manufacturing industries (upstream echelon) do not experience greater demand variance than retail industries (downstream echelon). We construct a linear supply chain from our unique dataset and explore whether the demand variability amplifies along this three-echelon supply chain. We therefore test the following hypothesis:

HYPOTHESIS 4 (H4). The firm at upstream stage experiences a larger demand variability than that at downstream stage.

Price fluctuation is identified as a cause of the bullwhip effect in prior literature. Blinder (1986) proposes the cost shocks as an explanation for the empirical observation that industry-level production is more volatile than sales. Lee et al. (1997a) analytically show that manufacturer's wholesale price variation generates the bullwhip effect for the retailer. Sodhi et al. (2014) incorporate stochastic purchase price into economic order quantity model and show that price variance is positively related to the bullwhip effect. Manufacturer's trade promotion (i.e., wholesale price discounts) is one form of price variation. When manufacturer offers discounts to the retailer, the retailer will evaluate the trade-off between purchase cost and inventory cost. If the end consumer demand becomes flatter, indicating that the demand is very predictable, the retailer can easily compare the marginal saving with the marginal holding cost of an extra unit. So there is more room for the retailer to stockpile in order to take advantage of manufacturer's discounts. When the end consumer demand becomes more variable, the cost evaluation will be more complicated and imply more risk because the demand tends to be unpredictable. It is less likely for the retailer to make a risky inventory investment in this scenario; thus, the retailer's order more closely follows consumer demand. Zotteri (2013) shows that the bullwhip effect is larger for the products that have a relatively stable retail demand. The manufacturer in our dataset provides periodic discounts to the distributors, so we expect to observe similar results. We formulate the following hypotheses:

HYPOTHESIS 5 (H5). The bullwhip ratio is positively associated with price variation.

HYPOTHESIS 6 (H6). The bullwhip ratio is negatively associated with the demand variability.

Forrester (1961) identifies that the delay in information and material flow (i.e., lead time) is a source of demand amplification. By using an inventory model with constant replenishment lead time l and autoregressive demand process ($D_t = \alpha + \rho D_{t-1} + \epsilon_t$), Lee et al. (1997a) derive the bullwhip ratio as follows:

$$Bullwhip\ Ratio = 1 + \frac{2\rho(1-\rho^{l+1})(1-\rho^{l+2})}{1-\rho} \tag{4.2}$$

They argue that the bullwhip ratio increases in the lead time, as do Agrawal et al. (2009), Chen et al. (2000), and Steckel et al. (2009). These authors all assume that replenishment lead time is constant. Modelling lead time as a random variable is more approximate to the uncertainty of real-life logistics. Chatfield et al. (2004), Duc et al. (2008), and Kim et al. (2006) show that order variability increases with variability of lead time. The behavioral experiment conducted by Ancarani et al. (2013) supports this result. We test the following hypothesis:

HYPOTHESIS 7 (H7). There is a positive association between the bullwhip ratio and replenishment lead time.

Inventory is an important factor related to the bullwhip effect. For example, when distributors decide how much to order in each period to meet demand for their products, inventory on hand must be taken into account. Manufacturer's price discounts induce distributors to forward buy and thus result in bullwhip effect. But a higher inventory level causes distributors to order less to avoid additional holding cost, resulting in a lower bullwhip effect. Experimental studies identify managers' bounded rationality and sub-optimal decisions as a behavioral cause of the bullwhip effect (e.g., Sterman, 1989; Croson & Donohue, 2006). Over-reaction to demand changes is one of the managers' errors in decision making for inventory replenishment. Waston and Zheng (2008) show that manager's overreaction to demand signals can result in an increase in volatility of the system's replenishment orders. If a firm carries high inventory, the managers will be less likely to place an inflated order when seeing a demand spike. Hence, inventory helps mitigate the bullwhip effect. Baganha and Cohen (1998) develop an analytical model to show that inventories can have a stabilizing effect on the replenishment orders. Bray and Mendelson (2012) analytically illustrate that "the firm can reduce the bullwhip effect by increasing product shelf life: a longer shelf life means a lower holding cost, which means the firm carries a higher safety stock, which in turn means it reacts more calmly to demand spikes" (p. 863). We use inventory to sales ratio (inventory ratio for short) to compare inventory levels among SKUs and distributors. Our next hypothesis is as follows:

> HYPOTHESIS 8 (H8). The inventory ratio is negatively associated with the bullwhip ratio.

4.4 Empirical Context and Data

We use a proprietary dataset from a multiechelon pharmaceutical supply chain for our empirical analysis. To the best of our knowledge, no prior empirical studies on the bullwhip effect have the data at the same granularity level as ours. The dataset consists of one manufacturer and six nation-wide distributors (A-F). The structure of the supply chain and of the data is shown in Figure 4.1. This supply chain structure matches the one that is widely used in theoretical studies on the bullwhip effect (e.g., Lee et al., 1997a; Cachon, 1999). The manufacturer produces consumable products that all medical practitioners in this specialty use, and has a lion's share of the market. These products are used on patients in medical practitioners' office and have a shelf life of approximately 18 months. In order to meet sales targets, the manufacturer may periodically offer price discounts to its distributors, for example, at the end of the manufacturer's fiscal quarter.

We collect monthly data on 31 SKUs between January 2010 and June 2014. Since the frequency of the data (monthly) matches the frequency of order decisions made by the manufacturer and distributors, the data avoid the "time-disaggregation bias" identified by Kahn (1992), and are suitable for appropriate supply chain cost assessment (Chen & Lee, 2012). The entire product category is made up of these 31 SKUs. SKUs 1-11 are carried by all distributors. SKUs 12-15, 16-19, 20-23, 24-26, 27-28, and 29-31 are carried only by distributors A-F, respectively. Manufacturer offers price discounts for 2 SKUs (SKUs 1 and 2), which account for 40% of the total sales. All 31 SKUs have annual wholesale price increase. Specifically, we use the following data to conduct empirical analysis: manufacturer's production, manufacturer's sales (distributors' order receipts), manufacturer's raw material orders to the suppliers, manufacturer's raw material receipts from the suppliers, distributors' orders (manufacturer's demand), and distributors' sales. In general, sales is a censored variable and not the same as demand because it is equal to the minimum of demand and inventory on hand. Both our interview with the industry expert and public information from the distributors show that distributors' sales almost exactly match the orders from the practitioners. Hence, it is reasonable to assume for our dataset that distributors' sales are equivalent to their demand. Table 4.1 presents summary statistics by distributor for the orders and sales variables used in our study. We do not have access to the inventory data at distributors, so we estimate inventories using the following relationship:

$$Inventory_t = Inventory_{t-1} + Order\ Receipt_t - \ Sales_t \tag{4.3}$$

where $Inventory_t$ denotes the net inventories at the end of period t. Since initial inventories are not available, we choose them so that each period's inventory is greater than or equal to zero. Thus, the inventory data used in our analysis are relative inventory. Similar approach has been used by Blattberg and Levin (1987). We measure quantities in physical units rather than dollar amounts. This avoids measurement and accounting problems associated with inventory evaluation (Lai, 2005). The Dickey-Fuller test suggests that none of the data series presents a unit root, indicating that all data series are stationary. Therefore, we do not make any adjustment to each series. Figure 4.2 shows sales and orders of SKU 2 at distributor F. We observe that the distributor's sales have much less variability than its orders, indicating that the bullwhip effect exists. We notice that the distributor places significant large orders during price discount periods and there is usually a trough in orders after a price discount ends. This implies that the manufacturer's price promotions make the distributor's orders more volatile than its sales and therefore leads to the bullwhip effect.

4.5 Analysis

In Table 4.2, we report the bullwhip ratios at the SKU level. The substantial bullwhip effect exists at each distributor. The average ratio is 22.88 (ranging from 1.13 to 216.67), much higher than those reported in the previous literature. Not all SKUs at manufacturer exhibit the bullwhip effect, indicating that the manufacturer makes production smoother than demand to some extent. The magnitude of the bullwhip ratios is usually smaller at manufacturer than at distributors. The manufacturer (upstream firm) that is supposed to suffer more from the bullwhip effect actually experiences a less severe bullwhip effect than the distributors (downstream firm). Recall that manufacturer offers price promotions for SKUs 1 and 2. The bullwhip ratios of these two SKUs at six distributors are usually much larger than those of other SKUs, which implies that price variation is a possible cause of the bullwhip effect. The interesting thing is that SKUs 1 and 2 at manufacturer have bullwhip ratios less than one. Our discussions with managers of the manufacturer show that the factory operation prepares for the demand peaks caused by the price promotions and is able to fulfill these demands from inventory in most cases. Our findings at SKU level are similar to those obtained by Cachon et al. (2007) at industry level.

Table 4.3 shows the bullwhip ratios measured by order variance and order receipt variance for each SKU at distributors A-F. We find that the majority of SKUs at distributors A, B, D, E, and F have a higher bullwhip ratio measured by order variance than that measured by order receipt variance. Furthermore, paired t-tests (Table 4.4) show that distributors A, B, D, and E have a statistically significantly higher bullwhip ratio measured by variance of orders. We find strong evidence in support of H1. This result suggests that the bullwhip measure based on material flow underestimates the one based on information flow.

We report the results for product aggregation in Table 4.5. In order to create different degrees of aggregation, we merge similar products that are in the same group, and then merge products alike that are in the same family. Two products belong to a group if they have the common main chemical components with the same concentration. Two products are in a family if their primary chemical components are the same. The degree of aggregation over family is higher than that over group in our research context. Paired t-tests (Table 4.6) indicate that bullwhip ratios at group/family level are statistically significantly smaller than those at the SKU level for manufacturer and distributor C. There is some evidence in support of H2. We use results from prior theoretical studies on bullwhip effect to generate H2. All these analytical models assume some form of inventory model and demand structure. These assumptions seem not to be applicable to our study. Hence, we develop a two-product analytical model without making any specific assumption to further investigate the product aggregation issue. The model in given in the Appendix. We show that how the bullwhip ratios change under product aggregation depends on the relationship between covariance of orders and that of demand. We test our model using SKUs 1 and 2. The results are consistent with the model's predictions.

Tables 4.7 and 4.8 show the results for time aggregation. We measure the effect of temporal aggregation by increasing the level of aggregation from monthly, to quarterly, to semiannually. The bullwhip ratios become statistically significantly smaller as the level of time aggregation changes from monthly to semiannually for manufacturer, and distributors B and E. We find mild evidence in support of H3.

We report the bullwhip ratios along the entire supply chain in Table 4.9. Our unique dataset makes it possible to construct a linear supply chain, so we are able to make comparisons across different levels of the supply chain. The average bullwhip ratio is 28.59 (ranging from 0.13 to 132.17) for the entire supply chain, indicating that the bullwhip effect is prevalent. The majority of 31 SKUs have bullwhip ratios greater than one at distributors and manufacturer. T-test results show that manufacturer experiences a larger demand variance than the distributors. Hence, H4 is supported.

To test hypotheses H5-H8, we develop the following econometric model:

$$BullwhipRatio_{ij} = \beta_0 + \beta_1 SDPrice_{ij} + \beta_2 CVDemand_{ij} + \beta_3 Leadtime_{ij} + \beta_4 IR_{ij} + \sum_{i=A,\ldots,E} \gamma_i Distributor_i + \varepsilon_{ij} \tag{4.4}$$

Where i denotes distributor, and j denotes SKU. There are four explanatory variables with each corresponding to a hypothesis. $SDPrice$ is the standard deviation of wholesale price. In order to control for the range of price changes, we normalize the wholesale price using the formula $Price_{new} = \frac{Price - Price_{min}}{Price_{max} - Price_{min}}$. $CVDemand$ is the coefficient of variation of demand. $Leadtime$ is the average number of days between placing an order and receiving the ordered product. IR is the inventory ratio, which is calculated as the ratio of average inventory to average sales. We include dummy variables $Distributor_i$ to control for fixed distributor effect. The variance inflation factor values for all explanatory variables are between 1.43 and 2.26, which are lower than the cutoff value of 10 (Wooldridge, 2009). Multicollinearity is not a problem. Estimation results are presented in Table 4.10.

The coefficient for $SDPrice$ is positive and significant, indicating that a greater price variation is correlated with a higher bullwhip ratio. H5 is supported. This finding provides empirical support to the analytical work by Lee et al. (1997a) and Sodhi et al. (2014). The coefficient for $CVDemand$ is negative and significant, indicating that a higher demand variability is correlated with a lower bullwhip ratio. We find strong evidence to support H6. When demand becomes more predictable, the bullwhip effect is more likely to occur. Table 4.11 shows the correlation coefficients between bullwhip ratio and coefficient of variation of demand. All coefficients are negative and those for distributors D, E, and F are statistically significant.

As shown in Table 4.10, the coefficient for $Leadtime$ is positive and significant. This implies that a longer order lead time is associated with a higher bullwhip ratio. We find strong evidence in support of H7. Table 4.12 shows the correlation coefficients between replenishment lead time and bullwhip ratio. We find that there is a positive association between bullwhip ratio and lead time for distributor A, B, D, and E. The coefficient for IR is negative and significant, indicating that a higher inventory is correlated with a lower bullwhip ratio. H8 is supported. We report the correlation coefficients between inventory ratio and bullwhip ratio for distributors in Table 4.13. We find that there is a statistically significantly negative association between inventory ratio and bullwhip ratio for distributors A, D, and F, and there is a negative but not significant relationship for distributor E.

A firm will not exhibit a bullwhip effect if it operates in a perfectly-matched fashion. That is, the firm's shipment (i.e., sales to customers) stream coincides with the demand (i.e., orders received from the customers) stream; the shipments come directly out of a just-in-time manufacturing stream, indicating that there is no need to hold finished goods inventory; the firm places raw material orders with its supplier by exactly following the manufacturing stream, and the supplier fulfills these orders instantaneously, resulting in no raw material inventory. If each firm along a supply chain uses the perfectly-matched strategy, the entire chain will not exhibit a bullwhip effect.

However, we find not only prevalent but also intensive bullwhip effects in our dataset. To better understand the bullwhip effect in a firm and along the supply chain, we break down the inter-firm bullwhip ratio into individual intra-firm bullwhips by following the bullwhip effect decomposition framework developed in Chapter 3. This decomposition helps one think about the relationships between various information and material flows that are involved in a firm's decision-making process. Figure 4.3 illustrates the framework in a two-echelon supply chain: a distributor (downstream) and a manufacturer (upstream). The distributor and the manufacturer are denoted as firms *D* and *U*, respectively. We organize our discussion around the manufacturer. Similar discussion is applicable to the distributor. Firm U receives a demand stream (orders from distributor) with variance V_D^U (the superscript refers to firm *U*, and the subscript *D* denotes that this is the variance of the demand stream). Due to constraints in manufacturing and inventory, firm *U* may not be able to fulfill demands immediately, so its shipment stream may not exactly match its demand stream. For example, the anticipation of economic boom causes customers to place orders too large to be filled instantly via inventory on hand and/or current manufacturing output. Thus, the variance of firm *U*'s shipment stream denoted by V_S^U (the superscript denotes firm *U* and the subscript *S* refer to the shipment) may differ from the variance of its demand stream. We define firm *U*'s shipment bullwhip as the variance ratio $\frac{V_S^U}{V_D^U}$, and denote this bullwhip ratio by B_S^U. That is, $B_S^U = \frac{V_S^U}{V_D^U}$. The shipment bullwhip indicates an amplification of the demand stream when $B_S^U > 1$ and a smoothing of the demand stream when $B_S^U < 1$.

Firm *U*'s manufacturing stream will not necessarily match its shipment stream due to various factors such as seasonal demand, convex manufacturing cost function, and batch manufacturing. For example, suppose firm *U* faces seasonal demand throughout the year. Then the firm may find that it is appropriate to smooth its manufacturing relative to its shipment by using finished goods inventory as a buffer with the following results: Produce at relatively stable rate, build inventory during periods of low demand, and draw down inventory in periods of high demand. In order to recognize the fact that the manufacturing stream may differ from the shipment stream, we define manufacturing bullwhip as $B_M^U = \frac{V_M^U}{V_S^U}$, where V_M^U denotes the variance in the manufacturing stream. The manufacturing bullwhip may indicate an amplification ($B_M^U > 1$) or a smoothing ($B_M^U < 1$).

Similarly, firm *U* may find that it is not optimal to order raw materials to exactly follow its manufacturing stream due to sales promotion, demand uncertainty, and order batching. For example, the firm's supplier may offer periodic discounts to boost sales or liquidate material surpluses. The firm can forward buy and hold raw material inventory to save purchase cost, resulting in a volatile order stream compared to manufacturing stream. To capture the discrepancy between order and manufacturing stream, we define the order bullwhip as $B_O^U = \frac{V_O^U}{V_M^U}$, where V_O^U denotes the variance in stream of orders that firm *U* places. Again, the order bullwhip may indicate an amplification ($B_O^U > 1$) or a smoothing ($B_O^U < 1$). For firm *D* (distributor) that performs no manufacturing, there is no intermediate manufacturing stream between the order stream and the shipment stream. So the order bullwhip becomes $B_O^D = \frac{V_O^D}{V_S^D}$.

The information-based full bullwhip ratio, which we denote by B^U, is defined as

$B^U = \frac{V_O^U}{V_D^U}$. We can write firm *U*'s full bullwhip ratio as the multiplicative effect of three intra-firm component bullwhips, namely shipment bullwhip, manufacturing bullwhip, and order bullwhip:

$$B^U = \frac{V_O^U}{V_D^U} = \left(\frac{V_S^U}{V_D^U}\right)\left(\frac{V_M^U}{V_S^U}\right)\left(\frac{V_O^U}{V_M^U}\right) = B_S^U * B_M^U * B_O^U \tag{4.5}$$

Due to data availability issues, some previous studies use a surrogate measure to estimate the bullwhip ratio B^U. For example, Cachon et al. (2007) do not have access to the orders and therefore use what they call "production" as a proxy for these orders, which is calculated as sales plus the change in inventory (i.e., the difference between ending and beginning inventory). This production stream represents the inflow of materials (i.e., order receipt). For a firm (such as a wholesaler) that performs no manufacturing, the production stream is directly equivalent to the inflow of finished goods. Since "production" may have various connotations, we will use the term "inflow" (order receipt) to represent the production stream and denote the inflow variance by V_I^U. We define the inflow bullwhip as $B_I^U = \frac{V_I^U}{V_O^U}$. Note that firm *D*'s inflow stream is actually shipment stream of firm *U*, so variance of firm *D*'s inflow stream (V_I^D) is equal to variance of firm *U*'s shipment stream (V_S^U). Also note that *U*'s demand stream is equal to *D*'s order stream, which implies that $V_O^D = V_D^U$. The measure $B_*^U = \frac{V_I^U}{V_D^U}$ is then used as a surrogate for the bullwhip ratio B^U (we put an asterisk in the subscript to denote that it is a surrogate measure). Note that $B_*^U = \frac{V_I^U}{V_D^D} = B_S^U * B_M^U * B_O^U * B_I^U$. That is, the proxy bullwhip ratio B_*^U is equal to the bullwhip ratio B^U multiplied by the inflow bullwhip. Bray and Mendelson (2012) and Shan et al. (2014) use sales and production (which we call inflow) as proxy variables for demand and orders, respectively. These authors calculate the material-based bullwhip ratio as $B_{**}^{U} = \frac{V_I^U}{V_S^U} = B_M^U * B_O^U * B_I^U$ (we use double asterisk in the subscript to denote this bullwhip ratio).

The above decomposition allows us to consider the bullwhip effect by looking at its individual components. For the distributors in our dataset, the shipment stream (i.e., sales to customers) is almost equivalent to the demand stream, indicating that $B_S^D = 1$. As we mentioned before, distributors do not perform manufacturing, so there is no manufacturing bullwhip and the order bullwhip becomes $B_O^D = \frac{V_O^D}{V_S^D}$. In short, the full bullwhip (B_*^D) of a distributor can be written as $B_*^D = B_O^D * B_I^D$. Table 4.14 shows distributors' individual intra-firm bullwhips. We find that the majority of SKUs at distributors A, B, D, and E have a smoother inflow stream compared to the order stream ($B_I^D < 1$). This implies that manufacturer smooths shipment stream relative to demand stream, resulting in a dampening effect on the distributor's full bullwhip. Conversely, most SKUs at distributor C and about half SKUs at distributor F have an amplifying inflow stream compared to order stream ($B_I^D > 1$), indicating that manufacturer's shipment bullwhip amplifies the distributor's full bullwhip. Manufacturer's individual intra-firm bullwhips are shown in Table 4.15. We find that manufacturer's shipment stream is smoother than its demand stream ($B_S^U < 1$) and its manufacturing stream is more volatile that its shipment stream ($B_M^U > 1$). Our interview with managers of the manufacturer helps explain why the firm exhibits such behaviors: 1) When manufacturer offers distributors price discounts, the distributors sometimes place a significant large order. So manufacturer will not be able to fulfill orders immediately and have to spread out shipments in the next few months. This makes shipment stream smoother that demand stream. 2) The firm uses batch manufacturing due to economy of scale, resulting in a more variable manufacturing stream compared to the shipment stream.

Each SKU contains only one main chemical component and there are a total of four main chemical components in our dataset. We denote these components by chemicals A, B, L, and M and calculate individual bullwhips for each chemical. The results are shown in Table 4.16. Since we are not able to keep track of the raw chemical material usage in the actual manufacturing process, we use imputed manufacturing (raw material receipt plus change in raw material inventory) for the order bullwhip. Distributors' order bullwhip is greater than one for each chemical. This suggests that distributors amplify demand variability. All chemicals at manufacturer have shipment bullwhip less than one, indicating that the manufacturer smooths shipment relative to demand. Manufacturer's order bullwhip is greater than one for each chemical. This implies that the manufacturer amplifies orders placed to its supplier relative to its manufacturing output. The manufacturing bullwhip is positively correlated with the shipment bullwhip and negatively correlated with the order bullwhip. The inflow bullwhip is negatively correlated with the order bullwhip.

4.6 Conclusion

The bullwhip effect is one of the central observations in economics and operations management and has drawn much attention from both academia and industry. There has been an extensive literature of theoretical studies on the bullwhip effect, but empirical studies are still limited due to data availability issues. By using a unique dataset from a multiechelon pharmaceutical supply chain, we are able to address several empirical challenges identified in the prior literature and make a contribution to the literature. In particular, we investigate the existence and magnitude of the bullwhip effect at SKU level, analyze the impact of data aggregation on the bullwhip measurement, and test a number of driving factors of the bullwhip effect.

We find that the bullwhip effect at SKU level is prevalent and intensive at distributors. Manufacturer (upstream) exhibits a less intensive bullwhip effect than distributors (downstream). The manufacturer does not suffer as much as we previously thought. But we do observe that the manufacturer has greater demand variance than the distributors. We find that the bullwhip ratio based on order variance is higher than that based on order receipt variance. The material-based bullwhip measure that is widely used in prior empirical studies underestimates the information-based measure. We observe that product aggregation and time aggregation tend to mask the bullwhip effect in some cases. We find that SKUs that have more predictable demands are more likely to exhibit the bullwhip effect. Manufacturer smooths production relative to demand for several SKUs, providing empirical support to production smoothing hypothesis. We find that most prominent factors related to the bullwhip effect are price variation, order lead time, and inventory.

Our study has some limitations. First, our data are from a single supply chain and for pharmaceutical products. This limits the generalizability of our findings to other industries and other types of products. We advocate caution in out-of-sample inferences. Second, similar to other empirical research, our study is only able to estimate associations rather than test for causality.

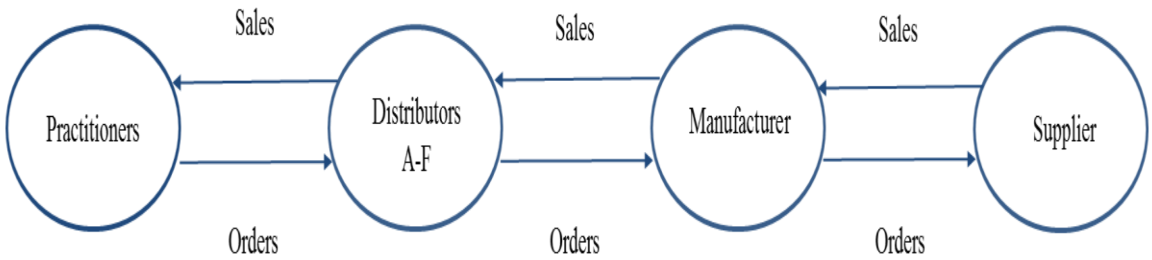


Figure 4.1: Supply Chain Structure

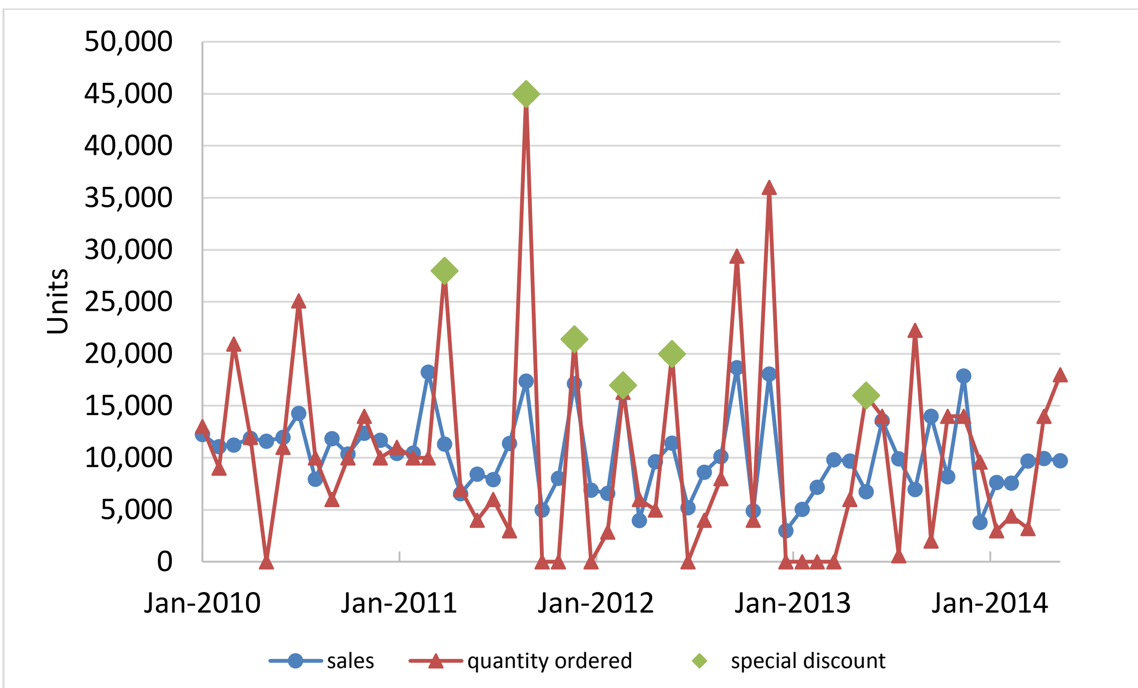


Figure 4.2: Sales and Orders of SKU 2 at Distributor F

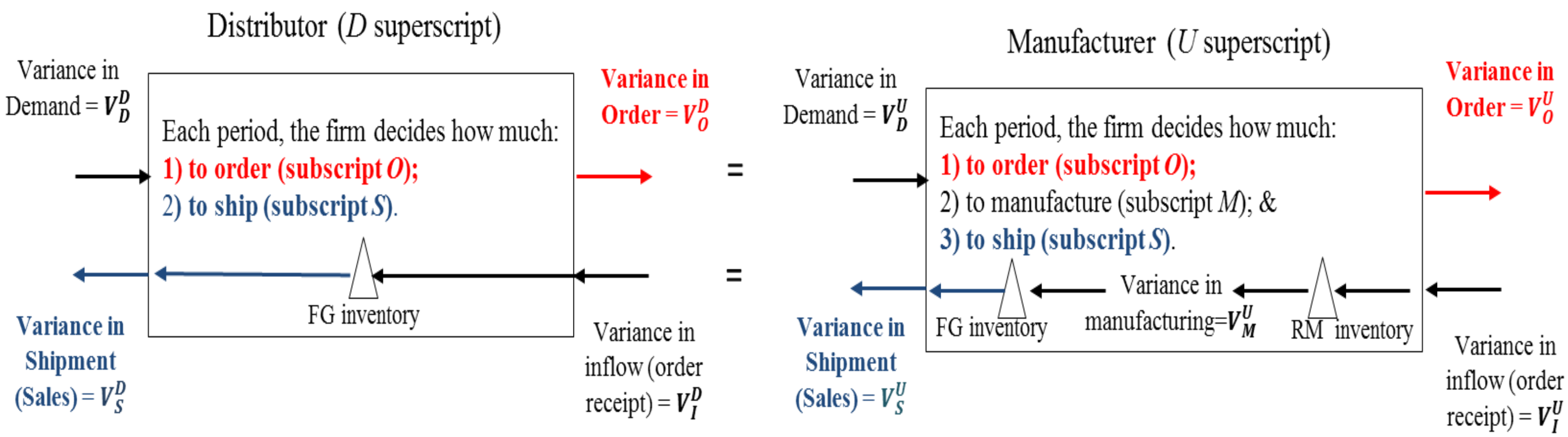


Figure 4.3: Breaking Down the Inter-Firm Bullwhip into Intra-Firm Bullwhips

Table 4.1: Summary Statistics of the Orders and Sales for Each Distributor

		mean	standard deviation	min	max
Distributor A	Sales	9699	20431	2	88510
	Orders	13179	41712	-7	411240
Distributor B	Sales	5104	10038	8	43999
	Orders	6321	14241	-22	104860
Distributor C	Sales	1969	4781	1	31207
	Orders	2706	6339	-20	63240
Distributor D	Sales	2289	4187	-3	16992
	Orders	2969	6534	-225	53000
Distributor E	Sales	838	1437	1	5903
	Orders	2055	3592	-13	20800
Distributor F	Sales	2008	3556	-160	18660
	Orders	2562	5201	20	45000

Note: negative numbers represent returns.

Table 4.2: Bullwhip Ratios at SKU Level

	Manufacturer	A	B	C	D	E	F
SKU 3	11.17	21.56	8.54	5.38	12.96	12.87	3.95
SKU 4	15.66	16.28	6.14	26.79	16.96	8.26	1.25
SKU 5	16.23	10.27	7.80	6.06	29.21	3.87	3.75
SKU 6	8.37	28.71	8.71	3.35	4.63	4.64	1.68
SKU 7	7.19	53.90	12.48	7.12	11.23	17.36	2.24
SKU 8	4.13	28.81	4.51	5.86	9.99	3.06	5.93
SKU 9	3.13	98.68	13.40	4.83	21.06	35.55	1.89
SKU 1	0.79	174.54	25.39	19.57	50.77	29.26	7.19
SKU 2	0.19	216.67	18.42	4.73	34.46	43.54	6.16
SKU 10	4.86	9.47	14.09	3.87	4.85	5.72	1.83
SKU 11	2.68	1.48	18.46	3.03	3.14		1.13
SKU 12	1.56	55.32					
SKU 13	0.74	81.22					
SKU 14	1.29	52.55					
SKU 15	0.13	92.62					
SKU 16	10.08			8.77			
SKU 17	5.11			2.58			
SKU 18	5.77			5.18			
SKU 19	1.43			4.18			
SKU 20	1.48					45.79	
SKU 21	0.89					48.31	
SKU 22	6.30		14.90				
SKU 23	2.33		21.67				
SKU 24	4.16		18.08				
SKU 25	0.43		28.30				
SKU 26	1.58				63.41		
SKU 27	2.79				36.00		
SKU 28	0.70				56.52		
SKU 29	2.89						5.23
SKU 30	4.15						7.14
SKU 31	1.08						7.73

For manufacturer: Bullwhip Ratio = V[Production]/V[Demand]
For distributors A-F: Bullwhip Ratio = V[Order]/V[Sales]

Table 4.3: Bullwhip Ratios Measured by Order Variance and Order Receipt Variance

Distributor A		
	V[Order]/V[Sales]	V[Order Receipt]/V[Sales]
SKU 3	21.56	18.75
SKU 4	16.28	14.57
SKU 5	10.27	8.83
SKU 6	28.71	24.76
SKU 7	53.90	36.02
SKU 8	28.81	19.47
SKU 9	98.68	63.64
SKU 1	174.54	67.23
SKU 2	216.67	92.48
SKU 10	9.47	11.34
SKU 11	1.48	1.00
SKU 12	55.32	31.30
SKU 13	81.22	30.15
SKU 14	52.55	32.80
SKU 15	92.62	24.02

Distributor B		
	V[Order]/V[Sales]	V[Order Receipt]/V[Sales]
SKU 3	8.54	10.68
SKU 4	6.14	4.21
SKU 5	7.80	7.06
SKU 6	8.71	7.04
SKU 7	12.48	13.01
SKU 8	4.51	4.51
SKU 9	13.40	10.62
SKU 1	25.39	15.52
SKU 2	18.42	12.02
SKU 10	14.09	8.37
SKU 11	18.46	16.37
SKU 22	14.90	11.52
SKU 23	21.67	13.68
SKU 24	18.08	14.12
SKU 25	28.30	11.81

Table 4.3 Continued

Distributor C		
	V[Order]/V[Sales]	V[Order Receipt]/V[Sales]
SKU 3	5.38	7.55
SKU 4	26.79	27.46
SKU 5	6.06	7.41
SKU 6	3.35	3.86
SKU 7	7.12	10.53
SKU 8	5.86	5.86
SKU 9	4.83	8.97
SKU 1	19.57	17.80
SKU 2	4.73	5.70
SKU 10	3.87	3.81
SKU 11	3.03	3.03
SKU 16	8.77	24.47
SKU 17	2.58	3.04
SKU 18	5.18	10.08
SKU 19	4.18	4.21

Distributor D		
	V[Order]/V[Sales]	V[Order Receipt]/V[Sales]
SKU 3	12.96	7.97
SKU 4	16.96	10.28
SKU 5	29.21	24.97
SKU 6	4.63	4.75
SKU 7	11.23	7.28
SKU 8	9.99	8.28
SKU 9	21.06	13.21
SKU 1	50.77	29.38
SKU 2	34.46	19.29
SKU 10	4.85	3.82
SKU 11	3.14	5.44
SKU 26	63.41	39.48
SKU 27	36.00	21.65
SKU 28	56.52	25.63

Table 4.3 Continued

Distributor E		
	V[Order]/V[Sales]	V[Order Receipt]/V[Sales]
SKU 3	12.87	10.33
SKU 4	8.26	7.44
SKU 5	3.87	3.87
SKU 6	4.64	4.42
SKU 7	17.36	14.84
SKU 8	3.06	2.59
SKU 9	35.55	31.74
SKU 1	29.26	25.06
SKU 2	43.54	35.26
SKU 10	5.72	4.24
SKU 20	45.79	40.12
SKU 21	48.31	42.43

Distributor F		
	V[Order]/V[Sales]	V[Order Receipt]/V[Sales]
SKU 3	3.95	4.68
SKU 4	1.25	1.28
SKU 5	3.75	3.98
SKU 6	1.68	1.31
SKU 7	2.24	2.59
SKU 8	5.93	5.79
SKU 9	1.89	1.92
SKU 1	7.19	6.87
SKU 2	6.16	5.64
SKU 10	1.83	1.82
SKU 11	1.13	1.21
SKU 29	5.23	3.09
SKU 30	7.14	5.28
SKU 31	7.73	7.17

Table 4.4: T-Test Statistics for Bullwhip Ratio Comparison

	T-Test Statistic
Distributor A	3.00***
Distributor B	3.28***
Distributor C	-2.02
Distributor D	3.55***
Distributor E	3.94***
Distributor F	1.51*

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.5: Product Aggregation of Bullwhip Effect

	Manufacturer		
	SKU	group	family
SKU 15	0.13	0.16	0.16
SKU 25	0.43	0.16	0.16
SKU 28	0.70	0.16	0.16
SKU 21	0.89	0.16	0.16
SKU 31	1.08	0.16	0.16
SKU 19	1.43	0.16	0.16
SKU 9	3.13	0.16	0.16
SKU 5	16.23	0.16	0.16
SKU 14	1.29	2.39	0.16
SKU 27	2.79	2.39	0.16
SKU 8	4.13	2.39	0.16
SKU 30	4.15	2.39	0.16
SKU 24	4.16	2.39	0.16
SKU 18	5.77	2.39	0.16
SKU 2	0.19	0.19	0.17
SKU 1	0.79	0.79	0.17
SKU 13	0.74	1.06	0.89
SKU 20	1.48	1.06	0.89
SKU 26	1.58	1.06	0.89
SKU 23	2.33	1.06	0.89
SKU 29	2.89	1.06	0.89
SKU 17	5.11	1.06	0.89
SKU 7	7.19	1.06	0.89
SKU 4	15.66	1.06	0.89
SKU 12	1.56	4.31	0.89
SKU 22	6.30	4.31	0.89
SKU 6	8.37	4.31	0.89
SKU 16	10.08	4.31	0.89
SKU 3	11.17	4.31	0.89
SKU 11	2.68	2.68	4.46
SKU 10	4.86	4.86	4.46

For manufacturer: Bullwhip Ratio = V[Production]/V[Demand]
For distributors A-F: Bullwhip Ratio = V[Order]/V[Sales]

Table 4.5 Continued

Distributor A			
	SKU	group	family
SKU 11	1.48	1.48	4.96
SKU 10	9.47	9.47	4.96
SKU 3	21.56	52.66	81.87
SKU 6	28.71	52.66	81.87
SKU 12	55.32	52.66	81.87
SKU 4	16.28	83.25	81.87
SKU 7	53.90	83.25	81.87
SKU 13	81.22	83.25	81.87
SKU 8	28.81	55.52	95.04
SKU 14	52.55	55.52	95.04
SKU 5	10.27	94.49	95.04
SKU 15	92.62	94.49	95.04
SKU 9	98.68	94.49	95.04
SKU 1	174.54	174.54	216.97
SKU 2	216.67	216.67	216.97

Distributor B			
	SKU	group	family
SKU 11	18.46	18.46	13.53
SKU 10	14.09	14.09	13.53
SKU 3	8.54	10.60	17.80
SKU 6	8.71	10.60	17.80
SKU 22	14.90	10.60	17.80
SKU 4	6.14	19.52	17.80
SKU 7	12.48	19.52	17.80
SKU 23	21.67	19.52	17.80
SKU 2	18.42	18.42	19.23
SKU 1	25.39	25.39	19.23
SKU 8	4.51	16.58	26.42
SKU 24	18.08	16.58	26.42
SKU 5	7.80	26.64	26.42
SKU 9	13.40	26.64	26.42
SKU 25	28.30	26.64	26.42

Table 4.5 Continued

Distributor C			
	SKU	group	family
SKU 17	2.58	2.58	2.70
SKU 7	7.12	2.58	2.70
SKU 4	26.79	2.58	2.70
SKU 6	3.35	8.16	2.70
SKU 3	5.38	8.16	2.70
SKU 16	8.77	8.16	2.70
SKU 11	3.03	3.03	2.93
SKU 10	3.87	3.87	2.93
SKU 19	4.18	4.17	4.16
SKU 9	4.83	4.17	4.16
SKU 5	6.06	4.17	4.16
SKU 18	5.18	5.18	4.16
SKU 8	5.86	5.18	4.16
SKU 2	4.73	4.73	5.33
SKU 1	19.57	19.57	5.33

Distributor D			
	SKU	group	family
SKU 11	3.14	3.14	4.23
SKU 10	4.85	4.85	4.23
SKU 2	34.46	34.46	36.12
SKU 1	50.77	50.77	36.12
SKU 6	4.63	9.77	50.68
SKU 3	12.96	9.77	50.68
SKU 7	11.23	59.42	50.68
SKU 4	16.96	59.42	50.68
SKU 26	63.41	59.42	50.68
SKU 8	9.99	35.72	56.07
SKU 27	36.00	35.72	56.07
SKU 9	21.06	55.29	56.07
SKU 5	29.21	55.29	56.07
SKU 28	56.52	55.29	56.07

Table 4.5 Continued

Distributor E			
	SKU	group	family
SKU 10	5.72	5.72	11.60
SKU 1	29.26	29.26	41.75
SKU 2	43.54	43.54	41.75
SKU 6	4.64	7.36	49.65
SKU 3	12.87	7.36	49.65
SKU 4	8.26	50.50	49.65
SKU 7	17.36	50.50	49.65
SKU 20	45.79	50.50	49.65
SKU 8	3.06	3.06	51.29
SKU 5	3.87	51.26	51.29
SKU 9	35.55	51.26	51.29
SKU 21	48.31	51.26	51.29

Distributor F			
	SKU	group	family
SKU 11	1.13	1.13	1.67
SKU 10	1.83	1.83	1.67
SKU 6	1.68	1.67	3.53
SKU 3	3.95	1.67	3.53
SKU 4	1.25	4.68	3.53
SKU 7	2.24	4.68	3.53
SKU 29	5.23	4.68	3.53
SKU 2	6.16	6.16	6.22
SKU 1	7.19	7.19	6.22
SKU 8	5.93	5.59	6.81
SKU 30	7.14	5.59	6.81
SKU 9	1.89	6.81	6.81
SKU 5	3.75	6.81	6.81
SKU 31	7.73	6.81	6.81

Table 4.6: T-test Statistics for Product Aggregation

	SKU -> Group	Group -> Family	SKU -> Family
Manufacturer	3.33***	3.92***	4.43***
Distributor A	-2.52**	-2.90***	-3.99***
Distributor B	-2.14**	-1.22	-2.52**
Distributor C	0.99	2.12**	2.22**
Distributor D	-2.47**	-1.29	-3.15***
Distributor E	-2.25**	-2.15**	-4.31***
Distributor F	-1.06	-0.55	-1.54*

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.7: Time Aggregation of Bullwhip Effect

	Manufacturer		
	monthly	quarterly	semi-annual
SKU 3	11.17	15.55	15.29
SKU 4	15.66	6.06	5.23
SKU 5	16.23	4.70	3.39
SKU 6	8.37	2.90	3.88
SKU 7	7.19	4.02	6.27
SKU 8	4.13	2.49	2.72
SKU 9	3.13	2.01	2.18
SKU 1	0.79	0.49	0.19
SKU 2	0.19	0.27	0.20
SKU 10	4.86	5.02	3.72
SKU 11	2.68	1.09	0.91
SKU 12	1.56	1.08	0.65
SKU 13	0.74	0.35	0.20
SKU 14	1.29	0.61	0.13
SKU 15	0.13	0.08	0.03
SKU 16	10.08	5.34	0.73
SKU 17	5.11	2.34	1.42
SKU 18	5.77	1.88	1.44
SKU 19	1.43	1.04	0.86
SKU 20	1.48	0.69	2.24
SKU 21	0.89	0.74	1.88
SKU 22	6.30	6.36	3.83
SKU 23	2.33	0.94	0.45
SKU 24	4.16	4.30	2.08
SKU 25	0.43	0.41	0.18
SKU 26	1.58	0.96	0.46
SKU 27	2.79	0.83	0.49
SKU 28	0.70	0.97	0.49
SKU 29	2.89	3.63	2.90
SKU 30	4.15	3.29	1.96
SKU 31	1.08	0.87	1.00

For manufacturer: Bullwhip Ratio = V[Production]/V[Demand]
For distributors A-F: Bullwhip Ratio = V[Order]/V[Sales]

Table 4.7 Continued

Distributor A			
	monthly	quarterly	semi-annual
SKU 3	21.56	17.56	18.76
SKU 4	16.28	9.36	6.00
SKU 5	10.27	15.37	10.62
SKU 6	28.71	31.05	24.92
SKU 7	53.90	146.64	137.18
SKU 8	28.81	26.71	16.84
SKU 9	98.68	158.95	141.74
SKU 1	174.54	94.20	61.07
SKU 2	216.67	330.29	269.14
SKU 10	9.47	5.23	2.34
SKU 11	1.48	1.05	0.89
SKU 12	55.32	117.24	185.44
SKU 13	81.22	217.06	277.62
SKU 14	52.55	77.13	106.81
SKU 15	92.62	175.15	928.13

Distributor B			
	monthly	quarterly	semi-annual
SKU 3	8.54	12.49	15.03
SKU 4	6.14	5.03	3.65
SKU 5	7.80	1.37	1.68
SKU 6	8.71	5.88	2.50
SKU 7	12.48	12.99	6.94
SKU 8	4.51	4.17	2.46
SKU 9	13.40	4.68	2.41
SKU 1	25.39	10.24	6.65
SKU 2	18.42	5.59	3.59
SKU 10	14.09	5.60	3.29
SKU 11	18.46	10.18	7.19
SKU 22	14.90	11.64	9.02
SKU 23	21.67	23.18	31.13
SKU 24	18.08	8.88	5.52
SKU 25	28.30	39.55	26.71

Table 4.7 Continued

Distributor C			
	monthly	quarterly	semi-annual
SKU 3	5.38	2.52	3.56
SKU 4	26.79	30.17	38.52
SKU 5	6.06	4.49	2.78
SKU 6	3.35	3.71	3.48
SKU 7	7.12	11.38	4.75
SKU 8	5.86	3.68	1.08
SKU 9	4.83	3.55	2.59
SKU 1	19.57	16.15	18.11
SKU 2	4.73	4.81	3.98
SKU 10	3.87	2.53	3.73
SKU 11	3.03	1.29	1.27
SKU 16	8.77	10.13	9.42
SKU 17	2.58	3.08	2.71
SKU 18	5.18	5.34	3.53
SKU 19	4.18	3.38	3.22

Distributor D			
	monthly	quarterly	semi-annual
SKU 3	12.96	23.49	52.13
SKU 4	16.96	64.16	53.02
SKU 5	29.21	32.23	25.92
SKU 6	4.63	2.38	1.64
SKU 7	11.23	10.70	13.43
SKU 8	9.99	14.50	14.35
SKU 9	21.06	21.55	28.16
SKU 1	50.77	108.39	95.96
SKU 2	34.46	107.20	111.42
SKU 10	4.85	2.96	2.73
SKU 11	3.14	1.01	0.55
SKU 26	63.41	164.58	110.51
SKU 27	36.00	64.82	56.97
SKU 28	56.52	123.40	75.53

Table 4.7 Continued

	Distributor E		
	monthly	quarterly	semi-annual
SKU 3	12.87	3.48	2.81
SKU 4	8.26	10.44	31.86
SKU 5	3.87	1.50	1.51
SKU 6	4.64	1.88	1.68
SKU 7	17.36	21.61	10.13
SKU 8	3.06	4.78	4.18
SKU 9	35.55	30.61	7.81
SKU 1	29.26	8.53	1.09
SKU 2	43.54	21.00	3.04
SKU 10	5.72	1.85	2.00
SKU 20	45.79	32.08	11.64
SKU 21	48.31	24.09	23.32

	Distributor F		
	monthly	quarterly	semi-annual
SKU 3	3.95	3.16	8.05
SKU 4	1.25	2.11	2.06
SKU 5	3.75	2.35	1.80
SKU 6	1.68	2.37	2.22
SKU 7	2.24	1.76	1.14
SKU 8	5.93	2.47	1.13
SKU 9	1.89	2.12	1.61
SKU 1	7.19	6.25	4.16
SKU 2	6.16	4.90	3.06
SKU 10	1.83	1.83	1.92
SKU 11	1.13	0.68	1.08
SKU 29	5.23	6.62	6.64
SKU 30	7.14	6.59	6.01
SKU 31	7.73	9.31	3.03

Table 4.8: T-Test Statistics for Time Aggregation

	Monthly -> Quarterly	Quarterly -> SemiAnnual	Monthly -> SemiAnnual
Manufacturer	2.87***	2.04***	3.28***
Distributor A	-2.17**	-1	-1.46*
Distributor B	2.22**	1.99**	3.18***
Distributor C	0.61	0.29	0.6
Distributor D	-2.95***	1.26	-3.09***
Distributor E	2.78***	1.45*	2.48**
Distributor F	0.94	0.99	1.44*

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.9: Bullwhip Ratios along the Supply Chain

	Distributors A-F	Manufacturer	Supply Chain
SKU 3	11.36	11.17	126.90
SKU 4	2.62	15.66	40.97
SKU 5	7.63	16.23	123.84
SKU 6	5.12	8.37	42.81
SKU 7	18.37	7.19	132.17
SKU 8	6.6	4.13	27.30
SKU 9	6.15	3.13	19.26
SKU 1	88.51	0.79	70.12
SKU 2	80.18	0.19	15.46
SKU 10	7.39	4.86	35.93
SKU 11	1.47	2.68	3.94
SKU 12	55.32	1.56	86.55
SKU 13	81.22	0.74	59.97
SKU 14	52.55	1.29	67.96
SKU 15	92.62	0.13	12.35
SKU 16	8.77	10.08	88.39
SKU 17	2.58	5.11	13.20
SKU 18	5.18	5.77	29.94
SKU 19	4.18	1.43	5.96
SKU 20	45.79	1.48	67.77
SKU 21	48.31	0.89	43.09
SKU 22	14.9	6.3	93.95
SKU 23	21.67	2.33	50.41
SKU 24	18.08	4.16	75.14
SKU 25	28.3	0.43	12.04
SKU 26	63.41	1.58	100.32
SKU 27	36	2.79	100.34
SKU 28	56.52	0.7	39.70
SKU 29	5.23	2.89	15.11
SKU 30	7.14	4.15	29.62
SKU 31	7.73	1.08	8.35
T Statistics	5.3***	4.14***	7.49***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
For manufacturer: Bullwhip Ratio = V[Production]/V[Demand]
For distributors A-F: Bullwhip Ratio = V[Order]/V[Sales]
For supply chain: Bullwhip Ratio = V[Manufacturer's Production]/V[Distributors' Sales]

Table 4.10: Estimation Results

	Bullwhip Ratio
SDPrice	561.0***
	(143.7)
CVDemand	-35.02***
	(5.684)
Leadtime	3.250***
	(1.009)
IR	-2.980*
	(1.603)
A	39.63***
	(12.58)
B	0.841
	(4.231)
C	6.350
	(4.848)
D	7.877
	(5.240)
E	15.39***
	(4.365)
Constant	-194.6***
	(51.08)
Observations	85
R-squared	0.516

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Bullwhip Ratio = V[Order]/V[Sales]

Table 4.11: Correlation between Coefficient of Variation of Demand and Bullwhip Ratio

	Correlation
Distributor A	-0.38
Distributor B	-0.30
Distributor C	-0.31
Distributor D	-0.48*
Distributor E	-0.80**
Distributor F	-0.54*

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Bullwhip Ratio = V[Order]/V[Sales]

Table 4.12: Correlation between Lead Time and Bullwhip Ratio

	Correlation
Distributor A	0.54**
Distributor B	0.44
Distributor C	-0.36
Distributor D	0.09
Distributor E	0.06
Distributor F	-0.24

*** p<0.01, ** p<0.05, * p<0.1
Bullwhip Ratio = V[Order]/V[Sales]

Table 4.13: Correlation between Inventory Ratio and Bullwhip Ratio

	Correlation
Distributor A	-0.47*
Distributor B	0.10
Distributor C	0.44
Distributor D	-0.65**
Distributor E	-0.49
Distributor F	-0.51*

*** p<0.01, ** p<0.05, * p<0.1
Bullwhip Ratio = V[Order]/V[Sales]

Table 4.14: Distributors' Intra-Firm Bullwhips

	Distributor A		
	B_*^D	B_O^D	B_I^D
SKU 3	18.75	21.56	0.87
SKU 4	14.57	16.28	0.89
SKU 5	8.83	10.27	0.86
SKU 6	24.76	28.71	0.86
SKU 7	36.02	53.90	0.67
SKU 8	19.47	28.81	0.68
SKU 9	63.64	98.68	0.64
SKU 1	67.23	174.54	0.39
SKU 2	92.48	216.67	0.43
SKU 10	11.34	9.47	1.20
SKU 11	1.00	1.48	0.68
SKU 12	31.30	55.32	0.57
SKU 13	30.15	81.22	0.37
SKU 14	32.80	52.55	0.62
SKU 15	24.02	92.62	0.26

	Distributor B		
	B_*^D	B_O^D	B_I^D
SKU 3	10.68	8.54	1.25
SKU 4	4.21	6.14	0.69
SKU 5	7.06	7.80	0.91
SKU 6	7.04	8.71	0.81
SKU 7	13.01	12.48	1.04
SKU 8	4.51	4.51	1.00
SKU 9	10.62	13.40	0.79
SKU 1	15.52	25.39	0.61
SKU 2	12.02	18.42	0.65
SKU 10	8.37	14.09	0.59
SKU 11	16.37	18.46	0.89
SKU 22	11.52	14.90	0.77
SKU 23	13.68	21.67	0.63
SKU 24	14.12	18.08	0.78
SKU 25	11.81	28.30	0.42

Table 4.14 Continued

	Distributor C		
	B_*^D	B_O^D	B_I^D
SKU 3	7.55	5.38	1.40
SKU 4	27.46	26.79	1.03
SKU 5	7.41	6.06	1.22
SKU 6	3.86	3.35	1.15
SKU 7	10.53	7.12	1.48
SKU 8	5.86	5.86	1.00
SKU 9	8.97	4.83	1.86
SKU 1	17.80	19.57	0.91
SKU 2	5.70	4.73	1.20
SKU 10	3.81	3.87	0.98
SKU 11	3.03	3.03	1.00
SKU 16	24.47	8.77	2.79
SKU 17	3.04	2.58	1.18
SKU 18	10.08	5.18	1.94
SKU 19	4.21	4.18	1.01

	Distributor D		
	B_*^D	B_O^D	B_I^D
SKU 3	7.97	12.96	0.61
SKU 4	10.28	16.96	0.61
SKU 5	24.97	29.21	0.85
SKU 6	4.75	4.63	1.03
SKU 7	7.28	11.23	0.65
SKU 8	8.28	9.99	0.83
SKU 9	13.21	21.06	0.63
SKU 1	29.38	50.77	0.58
SKU 2	19.29	34.46	0.56
SKU 10	3.82	4.85	0.79
SKU 11	5.44	3.14	1.74
SKU 26	39.48	63.41	0.62
SKU 27	21.65	36.00	0.60
SKU 28	25.63	56.52	0.45

Table 4.14 Continued

	Distributor E		
	B_*^D	B_O^D	B_I^D
SKU 3	10.33	12.87	0.80
SKU 4	7.44	8.26	0.90
SKU 5	3.87	3.87	1.00
SKU 6	4.42	4.64	0.95
SKU 7	14.84	17.36	0.85
SKU 8	2.59	3.06	0.84
SKU 9	31.74	35.55	0.89
SKU 1	25.06	29.26	0.86
SKU 2	35.26	43.54	0.81
SKU 10	4.24	5.72	0.74
SKU 20	40.12	45.79	0.88
SKU 21	42.43	48.31	0.88

	Distributor F		
	B_*^D	B_O^D	B_I^D
SKU 3	4.68	3.95	1.18
SKU 4	1.28	1.25	1.02
SKU 5	3.98	3.75	1.06
SKU 6	1.31	1.68	0.78
SKU 7	2.59	2.24	1.15
SKU 8	5.79	5.93	0.98
SKU 9	1.92	1.89	1.01
SKU 1	6.87	7.19	0.96
SKU 2	5.64	6.16	0.92
SKU 10	1.82	1.83	1.00
SKU 11	1.21	1.13	1.07
SKU 29	3.09	5.23	0.59
SKU 30	5.28	7.14	0.74
SKU 31	7.17	7.73	0.93

Table 4.15: Manufacturer's Intra-Firm Bullwhips

	Manufacturer	
	B_S^U	B_M^U
SKU 3	0.84	13.31
SKU 4	0.76	20.71
SKU 5	0.85	19.16
SKU 6	0.76	10.95
SKU 7	0.76	9.45
SKU 8	0.91	4.53
SKU 9	0.81	3.88
SKU 1	0.40	1.99
SKU 2	0.48	0.40
SKU 10	0.74	6.56
SKU 11	0.85	3.15
SKU 12	0.57	2.76
SKU 13	0.37	1.99
SKU 14	0.62	2.07
SKU 15	0.26	0.51
SKU 16	2.79	3.61
SKU 17	1.18	4.34
SKU 18	1.94	2.97
SKU 19	1.01	1.42
SKU 20	0.88	1.69
SKU 21	0.88	1.02
SKU 22	0.77	8.16
SKU 23	0.63	3.69
SKU 24	0.78	5.32
SKU 25	0.42	1.02
SKU 26	0.62	2.54
SKU 27	0.60	4.63
SKU 28	0.45	1.55
SKU 29	0.59	4.90
SKU 30	0.74	5.61
SKU 31	0.93	1.16

Table 4.16: Individual Intra-Firm Bullwhips by Chemical Components

	Distributors	Manufacturer			
	Order Bullwhip	Shipment Bullwhip	Manufacturing Bullwhip	Order Bullwhip	Inflow Bullwhip
Chemical A	85.13	0.46	0.37	3.38	0.29
Chemical B	8.23	0.74	6.57	1.08	1.03
Chemical L	77.65	0.33	0.48	7.46	0.12
Chemical M	49.71	0.46	1.98	6.36	0.25
		Shipment vs. Manufacturing	Manufacturing vs. Order	Order vs. Inflow	
Correlation		0.94	-0.73	-0.88	

*** p<0.01, ** p<0.05, * p<0.1

APPENDIX

We analytically show how bullwhip ratios change under data aggregation in a two-product case.

Product X: order $O_x = \{O_{x_1}, O_{x_2}, \dots, O_{x_n}\}$; demand $S_x = \{S_{x_1}, S_{x_2}, \dots, S_{x_n}\}$

Product Y: order $O_y = \{O_{y_1}, O_{y_2}, \dots, O_{y_n}\}$; demand $S_x = \{S_{y_1}, S_{y_2}, \dots, S_{y_n}\}$

Z is the one aggregated over products X and Y: order $O_z = \{O_{x_1} + O_{y_1}, O_{x_2} + O_{y_2}, \dots, O_{x_n} + O_{y_n}\}$; demand $S_z = \{S_{x_1} + S_{y_1}, S_{x_2} + S_{y_2}, \dots, S_{x_n} + S_{y_n}\}$

$$Bullwhip_x = \frac{Var(O_x)}{Var(S_x)}$$

$$Bullwhip_y = \frac{Var(O_y)}{Var(S_y)}$$

$$Bullwhip_z = \frac{Var(O_z)}{Var(S_z)} = \frac{Var(O_x + O_y)}{Var(S_x + S_y)} = \frac{Var(O_x) + Var\left(O_y\right) + 2Cov(O_x, O_y)}{Var(S_x) + Var\left(S_y\right) + 2Cov(S_x, S_y)}$$

Case 1: $Var\left(S_y\right) + 2Cov\left(S_x, S_y\right) > 0$ and $Var(S_x) + 2Cov\left(S_x, S_y\right) > 0$

If $\frac{Var\left(O_y\right)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} > \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} > \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_z > Bullwhip_x$ and $Bullwhip_z > Bullwhip_y$

$\left(\frac{Cov\left(O_x,O_y\right)}{Var(O_x)+Var\left(O_y\right)} > \frac{Cov\left(S_x,S_y\right)}{Var(S_x)+Var\left(S_y\right)}\right)$

If $\frac{Var\left(O_y\right)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} > \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} < \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_y > Bullwhip_z > Bullwhip_x$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} < \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} > \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_x > Bullwhip_z > Bullwhip_y$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} < \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} < \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_z < Bullwhip_x$ and $Bullwhip_z < Bullwhip_y$

($\frac{Cov(O_x,O_y)}{Var(O_x)+Var(O_y)} < \frac{Cov(S_x,S_y)}{Var(S_x)+Var(S_y)}$)

Case 2: $Var(S_y) + 2Cov(S_x,S_y) > 0$ and $Var(S_x) + 2Cov(S_x,S_y) < 0$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} > \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} < \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_z > Bullwhip_x$ and $Bullwhip_z > Bullwhip_y$

($\frac{Cov(O_x,O_y)}{Var(O_x)+Var(O_y)} > \frac{Cov(S_x,S_y)}{Var(S_x)+Var(S_y)}$)

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} > \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} > \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_y > Bullwhip_z > Bullwhip_x$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} < \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} < \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_x > Bullwhip_z > Bullwhip_y$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} < \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} > \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_z < Bullwhip_x$ and $Bullwhip_z < Bullwhip_y$

($\frac{Cov(O_x,O_y)}{Var(O_x)+Var(O_y)} < \frac{Cov(S_x,S_y)}{Var(S_x)+Var(S_y)}$)

Case 3: $Var(S_y) + 2Cov(S_x,S_y) < 0$ and $Var(S_x) + 2Cov(S_x,S_y) > 0$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} < \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} > \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_z > Bullwhip_x$ and $Bullwhip_z > Bullwhip_y$

($\frac{Cov(O_x,O_y)}{Var(O_x)+Var(O_y)} > \frac{Cov(S_x,S_y)}{Var(S_x)+Var(S_y)}$)

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} < \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} < \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_y > Bullwhip_z > Bullwhip_x$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} > \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} > \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_x > Bullwhip_z > Bullwhip_y$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} > \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} < \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_z < Bullwhip_x$ and $Bullwhip_z < Bullwhip_y$

($\frac{Cov(O_x,O_y)}{Var(O_x)+Var(O_y)} < \frac{Cov(S_x,S_y)}{Var(S_x)+Var(S_y)}$)

Case 4: $Var(S_y) + 2Cov(S_x,S_y) < 0$ and $Var(S_x) + 2Cov(S_x,S_y) < 0$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} < \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} < \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_z > Bullwhip_x$ and $Bullwhip_z > Bullwhip_y$

($\frac{Cov(O_x,O_y)}{Var(O_x)+Var(O_y)} > \frac{Cov(S_x,S_y)}{Var(S_x)+Var(S_y)}$)

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} < \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} > \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_y > Bullwhip_z > Bullwhip_x$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} > \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} < \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_x >$

$Bullwhip_z > Bullwhip_y$

If $\frac{Var(O_y)+2Cov(O_x,O_y)}{Var(S_y)+2Cov(S_x,S_y)} > \frac{Var(O_x)}{Var(S_x)}$ and $\frac{Var(O_x)+2Cov(O_x,O_y)}{Var(S_x)+2Cov(S_x,S_y)} > \frac{Var(O_y)}{Var(S_y)}$, then $Bullwhip_z <$ $Bullwhip_x$ and $Bullwhip_z < Bullwhip_y$

($\frac{Cov(O_x,O_y)}{Var(O_x)+Var(O_y)} < \frac{Cov(S_x,S_y)}{Var(S_x)+Var(S_y)}$)

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