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Bullwhip effect under substitute products

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ABSTRACT

Using a large-scale, product-level dataset collected from a supply chain dyad, we examine the effect of own and substitute products on a focal product's bullwhip effect and estimate the existence and magnitude of the bullwhip effect at the product level. We find that, under substitute products, the bullwhip effect is not only affected by a product's own factors but also by those of its substitute products. An increase in the number of own price changes is associated with a decrease in the bullwhip effect in terms of the direct effect but with an increase in the bullwhip effect in terms of the total effect, and increases in the number of price changes of substitute products and own stockouts are associated with increases in the bullwhip effect. The potential effects for own price changes, price changes of substitute products and own stockouts are as much as 59.51%, 95.06% and 66.11%. We also find that the bullwhip effect is prevalent and very intensive at the product level. We discuss the theoretical and managerial implications of the findings.

1. Introduction

In recent decades, a significant advancement in our understanding of supply chain management is the identification and management of the bullwhip effect (de Kok et al., 2005). The bullwhip effect refers to "the amplification of demand variability from a downstream site to an upstream site" (Lee et al., 2004, p. 1887). Research has shown that the bullwhip effect leads to tremendous supply chain inefficiencies such as excessive inventory investment, poor customer service, lost revenues, misguided capacity plans, ineffective transportation, and missed production schedules (Lee et al., 1997). While the bullwhip effect has generated attention among researchers and practitioners alike, companies have not yet succeeded in completely taming it (Lee et al., 2004; Songini, 2000; Wheatley, 2004; Wong et al., 2007).

Extensive modeling literature has focused on this phenomenon (e.g., Chen et al., 2000; Chen and Lee, 2009; Chen and Samroengraja, 2004; Lee et al., 1997; Metters, 1997). Building upon the theoretical work, a growing body of empirical studies has made efforts to detect and quantify the bullwhip effect and its driving forces (e.g., Bray and Mendelson, 2012; Cachon et al., 2007; Fransoo and Wouters, 2000; Klug, 2013; Lai, 2005; Taylor, 1999). Still, our understanding of the bullwhip effect is limited in several ways. First, empirical studies have used aggregate data or proxy data to measure the bullwhip effect; for example, prior studies have examined the bullwhip effect using aggregate data (e.g., Bray and Mendelson (2012) and Shan et al. (2013) at firm level; Cachon et al. (2007) at industry level), which may mask or dampen the estimation of the bullwhip effect (Caplin, 1985; Fransoo and Wouters, 2000; Lai, 2005) and shipment or delivery data to proxy order data because order information is not readily available (i.e., material flow-based bullwhip effects) (Chen and Lee, 2012). Second, analytical research on the bullwhip effect has generally considered a model setting for a single product (e.g., Chen et al., 2000; Lee et al., 1997); for example, Lee et al. (1997) assume that a single product is being managed and transacted between firms and compute the bullwhip effect for the product. In practice, however, firms such as retailers manage inventories and sales for multiple substitute products[1] simultaneously (e.g., kiwi juice vs. strawberry juice) (Kök and Fisher, 2007). Research has demonstrated that a product's demand is not only influenced by its inherent characteristics but also by the behaviors of its substitute products (Netessine and Rudi, 2003; Vulcano et al., 2012). As a result, a product's bullwhip effect may exhibit different magnitudes and properties in the presence of multiple substitute products. Few studies (including analytical and empirical studies) have considered substitute products when exploring the bullwhip

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[1] Substitute products are defined as those products where lowering the price of one product leads to a decrease in the sales of another (Shocker et al., 2004).

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effect. Clearly, addressing these issues can "improve our perspective on the phenomenon" (Bray and Mendelson, 2012, p. 874), thus making important contributions to the literature.

The objective of our research is to narrow these literature gaps. In particular, we use a large-scale dataset at the product (i.e., stock keeping unit) level from a large Chinese supermarket chain, including information from their supermarket stores and distribution center (i.e., a supply chain dyad) and examine the effect of own and substitute products in terms of price changes and stockouts on the focal product's bullwhip effect; that is, at this fine level of detail, we examine how the bullwhip effect reacts to price changes and stockouts across substitute products. Both price changes and stockouts are major factors in the context of product substitution and are identified in prior literature as potential driving factors of the bullwhip effect (e.g., Lee et al., 1997; Watson and Zheng, 2008). Also, at this fine level of detail, we estimate the existence and magnitude of the bullwhip effect.

Our product level estimation has several unique advantages. First, product level data allow us to delve into the routine operations and management practices of firms and uncover new evidence of the bullwhip effect that cannot be observed at the aggregate level, thus providing the finest level of evidence about the bullwhip effect. Furthermore, our estimation is a large-scale data analysis with over 700,000 observations and includes transactional and daily information for 487 products within 15 popular product categories over a 7-month period. Second, because the bullwhip effect is a supply chain phenomenon, its estimation requires information from both upstream and downstream parties in a supply chain dyad. Our data encompass demand and order information from both upstream and downstream parties in a supply chain dyad, allowing us to compute the bullwhip effect using the theoretical definition of the bullwhip effect as defined in modeling papers; that is, the ratio of order (to the upstream firm) variance to demand (to the downstream firm) variance.[2] Third, our data include information from multiple substitute products, thus enabling us to examine the effect not only from the focal product on its own but also from its substitute products, a perspective that resembles reality more closely but has been understudied.

Our key findings are that, under substitute products, the bullwhip effect is not only affected by a product's own factors but also by those of its substitute products. In particular, own price changes have a negative direct effect, but positive total effect, on the bullwhip effect, price changes of substitute products has a positive effect on the bullwhip effect, and own stockouts have a positive effect on the bullwhip effect. These effects are not only statistically significant but also economically significant. In addition, our findings provide further empirical evidence that the bullwhip effect is prevalent and very intensive at the product level. The average bullwhip effect ratio ranges from about 14.61 to 33.60 (based on first differenced bullwhip effect ratio), dependent on the time window by which the data are aggregated, which is much higher than ratios reported in the literature.

Our findings make original contributions to the literature in two important ways. First, our results are based on daily and product-level data with sales and order information from a supply chain dyad. Thus, our estimation of the bullwhip effect follows the theoretical definition of the bullwhip effect closely and provides new and complementary empirical evidence to the literature. Second, our analysis considers substitute products. This resembles real business practice since firms generally concurrently manage multiple substitute products. While some of the own effects have been explored in prior studies, the effects from substitute products have not been examined in the literature (including both analytical and empirical literature). Our results show, however, that the effects from substitute products are prevalent and significant, highlighting the important theoretical contributions of our study.

The rest of the paper is organized as follows. Section 2 discusses relevant literature and theory and develops a number of hypotheses. Section 3 presents empirical context and data. Section 4 presents empirical analysis and estimation results. Finally, Section 5 discusses the results, theoretical and managerial implications, research limitations, and future research.

2. Literature and hypotheses

2.1. The bullwhip effect

Three streams of research have studied the bullwhip effect. The first stream uses an analytical modeling approach and analyzes the causes and ways to mitigate the effect. The second stream uses data to empirically measure and examine the bullwhip effect and its driving factors. The third stream uses experiments to analyze behavioral issues related to the bullwhip effect. We summarize all three streams of literature.

In their seminal paper, Lee et al. (1997) identify four sources of the bullwhip effect – demand signal processing, rationing game, order batching, and price variation – and propose several ways to mitigate the bullwhip effect. Metters (1997) uses dynamic programming to quantify the magnitude of the bullwhip effect and shows that the relative importance of the bullwhip effect to a firm differs greatly depending on the specific business environment. Chen et al. (2000) further quantify the bullwhip effect within a two-stage supply chain and show that it may be reduced (albeit not eliminated) by information sharing. Chen and Lee (2009) analyze a supply chain with a general demand model and smoothing policy for order variability control and find that information sharing (combined with order postponement) can improve supply chain performance; however, order variability may amplify in some cases. Chen and Lee (2012) propose a general theoretical framework to explain various empirical observations and show that aggregating data over long time periods can mask the bullwhip effect.

In the stream of empirical literature, Anderson et al. (2000) find substantial volatility in the machine-tool industry and attribute this volatility to the bullwhip effect. Terwiesch et al. (2005) show that the semiconductor equipment (i.e., upstream) industry is more volatile than the personal computer (i.e., downstream) industry. Cachon et al. (2007) analyze a U.S. industry-level dataset and find that while wholesale industries exhibit bullwhip effects, retail industries do not, and seasonality attenuates the bullwhip effect. Bray and Mendelson (2012) examine the bullwhip effect using a sample of 4689 public firms from 1974 to 2008 and find that approximately two-thirds of firms experience the bullwhip effect; also, demand signals from short lead times (within three months), midrange lead times (three to nine months), and longer lead times (over nine months) contribute to the bullwhip effect. Fransoo and Wouters (2000) discuss potential issues when measuring the bullwhip effect empirically; also, when using data from two supply chains, they find the existence of the bullwhip effect at different supply chain echelons. Chen and Lee (2012) use a weekly, SKU-level dataset from a European retail store during a one-year period and demonstrate that bullwhip effect ratios decrease with the estimation time window for six products. Lai (2005) utilizes a monthly dataset containing 3754 SKUs from a Spanish supermarket chain to analyze the bullwhip effect and its drivers and finds a significant

[2] Since we measure the bullwhip effect at the downstream firm level throughout the paper, orders refer to the orders placed from the downstream firm to the upstream firm and demands and sales refer to the orders received by the downstream firm (from its customers).