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An empirical investigation on causes and effects of the Bullwhip-effect: Evidence from the personal care sector

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ABSTRACT

This paper analyses the empirical demand data for fast moving consumer goods to measure the Bullwhip-effect. The data consist of the sell-in from a large manufacturer to the retailers and the sell-out from a retailer to the consumers. Our findings show that the Bullwhip-effect can be substantial. Indeed, in more than 50% of the cases, the demand upstream (sell-in) is twice as variable as the demand downstream (sell-out). However, in other cases it can be negligible (and in one case, the demand upstream is slightly less variable than the demand downstream). So, while the Bullwhip-effect can be very large, it need not be so. Finally, we attempted to delve into the dynamics that generate a significant Bullwhip-effect and discovered that among the various causes that create the Bullwhip-effect discussed by Lee et al. (1997a), price fluctuations and forward buys driven by sales targets play a decisive role. We show that the flatter the final consumer demand (sell-out), the more room there is for the retailers to forward buy in order to take advantage of the deals offered by the manufacturer's sales force toward the end of the sales period. On the contrary, the more variable the final consumer demand, the less willing the retailer is to make a risky inventory investment and, thus, the more the retailer's orders closely follow consumer demand. This result at the product family level is very consistent with the results that Cachon et al. (2007) obtained at the company/industry level.

1. Introduction

Demand fluctuations are a significant problem for most practitioners, planners, demand managers and operations managers. Fluctuations make forecasting and inventory management more difficult and tend to increase inventory levels and decrease service levels.

These demand fluctuations are often not due to changes in the final consumer demand but rather are generated within the supply chain. For example, Procter and Gamble discovered that the fluctuations in diaper demand cannot be explained by the changes in consumer demand (let alone the end users' consumption, as those who have/had small children know very well) (see Lee et al., 1997a). In the classic Barilla case (Hammond, 1994), we also see a demand at the Barilla plant for pasta that has an impressive variability, while pasta consumption and demand in Italy is very flat, with very minor seasonal fluctuations. The classic Beer Game (Sterman, 1989) simulates this phenomenon, called the Forrester effect or the Bullwhip-effect, and it has been taught in business schools for decades. This phenomenon is relevant both for single companies that face an unnecessarily variable demand and for entire supply chains. In addition, the recent economic ups and downs are partially related to this issue. Banca d'Italia, 2010 argues that the 0.1% economic growth in the euro area for the first quarter of 2010 is due to 0.2% growth in inventory.

This relevant phenomenon deserves attention from academia, and, indeed, several researchers have devoted quite a bit of attention and effort to investigating it.

The first stream of research stems from economics literature, where the Bullwhip-effect has challenged the "production smoothing" hypothesis, which assumes that companies use inventories to make production smoother than demand. Several papers (for e.g. see Blanchard, 1983; Blinder, 1981) have shown that production is actually more variable than sales. Literature in this stream suggests that the analyses should measure demand and production in actual physical units, rather than in monetary terms (Fair, 1989) and that seasonality might play a decisive role (Ghali, 1987). Our paper actually analyses the seasonal data in unit terms and thus follows the suggestions of this stream of research.

The operations management literature has a different perspective and expects production (generally speaking, the upstream stages of the supply chain) to be more variable than the final consumer demand (see Forrester, 1958). In this stream, Lee et al. (1997a) provided the seminal work that defined the Bullwhip-effect and identified the root causes and remedies.

Some papers in the operations management literature are theoretical in nature and identify the causes and potential solutions, with a specific focus on information as a potential remedy for the Bullwhip-effect (Bourland et al., 1996; Lee et al., 1997b;

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Graves, 1999; Chen et al., 2000; Cachon and Fisher, 2000; Lee et al., 2000; Wharburton, 2004).

A second stream of research is more empirical. Some contributions use the classic Beer Game (Sterman, 1989; Steckel et al., 2004; Croson and Donohue, 2005; Croson and Donohue, 2006) or one of its variants (Anderson and Morrice, 2000) to create empirical data in a controlled environment and test hypothesis on the technical and behavioural causes of the Bullwhip-effect and its potential remedies.

Other contributions analyse data from natural experiments. Some authors provide evidence for the existence, size and consequences of the Bullwhip-effect in several companies (Mckenney and Clark, 1994; Hammond, 1994; Kelly, 1995), while others analyse entire industries (Blanchard, 1983; Anderson et al., 2000; Cachon et al., 2007). The latter group actually closely relates to the empirical analyses in our paper. Indeed, Cachon et al. not only measure the Bullwhip-effect but also investigate why it is different under different conditions. Interestingly, they find that the Bullwhip-effect is stronger in non-seasonal industries.

Our research fits within this stream of research, but rather than comparing entire industries, we compare the product families within a given supply chain, where fast moving consumer goods are manufactured by a major producer and distributed by a major retailer. Indeed, as suggested by Fransoo and Wouters, 2000, the degree of data aggregation matters when measuring the Bullwhip-effect.

2. Empirical context and data

We were able to collect demand data from the skin and personal care sector in Italy. The data refer to the products of the Italian subsidiary of a major manufacturer in the industry. The company operates in 130 countries and had 2009 sales of more than 17.000 M€. This large company has a very well-defined process for managing budgets and sales targets. As we will see later in this paper, this structured process plays a major role in generating the Bullwhip-effect.

The manufacturer sells through various channels, including retailers and distributors. The manufacturer records the orders collected from all customers. We call this variable the sell-in. Additionally, the manufacturer buys data on the sell-out of its products in a large retail chain. So, these data refer to the relationship with a single large retailer (one of the top three retailers in Italy by turnover). We will use these data as a proxy for the consumer demand for these products and name this variable the sell-out (Fig. 1).

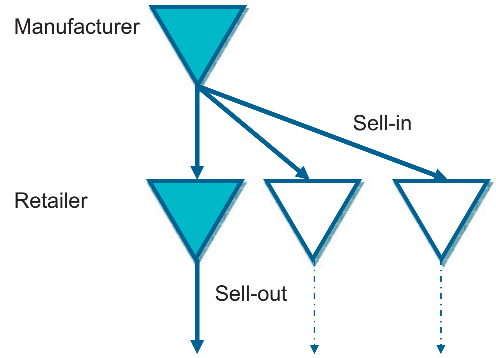

Fig. 1. Structure of the supply chain and of the data.

We investigate a two-echelon supply chain that sells fast moving consumer goods with a relatively long shelf life, and we observe demand at two levels: sell-in from the manufacturer to its clients and sell-out from a single retailer to consumers.

We were able to collect data on 9 product families from the company's assortment. In each product family, there are several items that share the same brand name and that differ in terms of fragrance or in terms of the benefits for the consumer (e.g., shampoos for dry hairs vs. shampoos against dandruff). The product families include solar cream (1), body and face cream (3), shampoo (2), hair gel (2), and colouring (1).

For this set of products, we were able to collect both upstream and downstream data in the supply chain. For the sell-in, we were able to observe the orders from all of the retailers at the weekly/product family level for one year. We were also able to collect information on the average price.

For the sell-out, we were able to collect the sales data of a large retailer in Italy at the weekly/product family level for one year. We will assume that, in this case, the sales data are a good proxy for demand data. Obviously, retailers (including this specific retailer) do stock out and, thus, demand differs from sales (see Corsten and Gruen, 2003). However, to make our assumptions work, we simply have to assume that stock-outs are somewhat constant over time and, thus, that there is a relatively constant relationship between the consumer demand and retail sales. Additionally, at the product family level, issues such as stock-outs and substitution are of a lesser concern because very often, when a product is stocked out, another product in the same product family is bought. In this case too, we were able to collect both data on units and average price and, thus, we can control for promotional demand.

These two sets of data are then augmented by insights from the managers at the manufacturer. We used these insights to double check our analyses of the hard data.

To provide the reader with a feeling for the dataset, we discuss the case of shampoos. Fig. 2 shows the dynamics of price and demand from the consumers to the retailers. We can see that as the price is reduced during promotions, the demand (sell-out) increases sharply.

Fig. 3 compares the sell-out pattern (i.e., the retail sales) of the two families of shampoos. They have a negative, though not significant, correlation (−9%). Indeed, in most cases, when one shampoo from a given brand is on promotion, often the other shampoos from the other brands are not promoted. Additionally, shampoo A (Coefficient of Variation[1] (*CV*) is 19%) has a more stable demand than shampoo B (*CV*=70%).

Fig. 4 compares the sell-in pattern for the same set of two shampoos. First, we can observe that this pattern is significantly more variable than the pattern shown in Fig. 3. It is surprising to note that there is a significant, positive correlation between the two products (82%). Additionally, we can note that the demand peaks tend to occur toward the end of the month, thus suggesting that some managerial process leads the demand for the two products to increase at the same given point in time. Indeed, when we investigated the issue with the manufacturer's managers, we discovered that the salespersons have monthly sales targets and so, apparently, there is a significant sales push toward the end of the month. Finally, the two patterns of sell-in show a similar degree of variability (*CV*=43% for shampoo A and *CV*=46% for shampoo B).

Our data set has the advantage of being very detailed, but it sets us some challenges and gives our research some limitations. First, the data have some limitations. We use the sell-out at this specific retailer as a proxy for the consumer demand of the whole market. While demand variability at this retailer is a very reasonable proxy of the demand variations in the supermarket channel, it could be a

[1] The Coefficient of Variation (CV) is the ratio between the standard deviation of a random variable and the expected value of a random variable and, thus, is a metric for variability. In this paper, we work on samples of data and use the sample standard deviation and the sample mean to compute the CV for all of the variables analysed in the paper.