Chapter book

"Impact of Demand Nature on the Bullwhip Effect. Bridging the Gap between Theoretical and Empirical Research"

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Chapter 1
Impact of Demand Nature on the Bullwhip Effect Bridging the Gap between Theoretical and Empirical Research

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Abstract The bullwhip effect (BE) consists of the demand variability amplification that exists in a supply chain when moving upwards. This undesirable effect produces excess inventory and poor customer service. Recently, several research papers from either a theoretical or empirical point of view have indicated the nature of the demand process as a key aspect to defining the BE. Nonetheless, they reached different conclusions. On the one hand, theoretical research quantified the BE depending on the lead time and ARIMA parameters, where ARIMA functions were employed to model the demand generator process. In turn, empirical research related nonlinearly the demand variability extent with the BE size. Although, it seems that both results are contradictory, this paper explores how those conclusions complement each other. Essentially, it is shown that the theoretical developments are precise to determine the presence of the BE based on its ARIMA parameter estimates. Nonetheless, to quantify the size of the BE, the demand coefficient of variation should be incorporated. The analysis explores a two-staged serially linked supply chain, where weekly data at SKU level from a manufacturer specialized in household products and a major UK grocery retailer have been collected.

Keywords Bullwhip Effect · Demand Forecasting · Supply Chain Management

1.1 Introduction

Since the beginning of the 20th century, one of the most interesting problems that Supply Chain Management has had to face is the bullwhip effect (BE) [10]. This

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phenomenon consists of demand variability amplification when moving from the consumer towards the supplier. These demand fluctuations might not be as a consequence of changes in the downstream demand but being generated within the supply chain. A typical example corresponds to the diaper demand shown by Procter and Gamble [12], where a stable end costumer demand became much more volatile in upstream supply chain members. This effect is of paramount importance for academics and practitioners given its harmful consequences in inventory levels and forecasting accuracy.

The research on the BE has been investigated on theoretical and empirical basis. From a theoretical perspective, the supply chain has been defined by assuming a certain underlying demand and a determined inventory policy. In reference [4] the BE is quantified by using moving average and exponential smoothing techniques for demand forecasting. In [14] forecasting procedures that minimize the expected mean-square forecast error are analyzed instead of exponential smoothing techniques. In this reference an expression for the BE is achieved, given a pre-defined demand process modeled by an ARIMA(p,d,q) [1] and an inventory policy defined by an Order-Up-To (OUT) level [5], [14]. Other theoretical approaches are focused on the influence of inventory control parameters on the BE [5].

Nonetheless, some authors claim that a theoretical analysis of the problem relies on restrictive assumptions to make it mathematically tractable and thus, they tend to be highly constrained versions of reality [2]. For example, they do not include the influence of promotional campaigns as price reductions, advertisements, etc., even when these aspects are accepted as main causes of the BE. In addition, since those factors are difficult to incorporate in statistical models, they are usually introduced into the forecasting process by managers that judgmentally adjust forecasts provided by a Forecasting Support System [8] and [16]. This judgmental forecasting approach is employed broadly in companies; in fact, in reference [7] a survey was conducted where, on average, 75% of the forecasts involved management judgment. Therefore, insights obtained from theoretical developments that do not include the aforementioned circumstances can be limited [2].

In order to overcome the theoretical analysis limitations, a second stream of research approaches the BE problem more empirically with data coming from different companies. Note that the BE may be analyzed by different levels of aggregation. In this sense, some authors investigate the BE on entire industries [3], where the strength of the BE is measured in industry-level U.S. data. Other authors analyze the BE at family level [17], where fast moving consumer goods are manufactured by a major producer and distributed by a major retailer in Italy. The latter reference found that if final consumer demand tends to be flat; the retailers are encouraged to forward buy in order to take advantage of possible manufacturer deals. On the contrary, if the final consumer demand is variable, the retailers orders closely follow consumer demand.

In summary, on the one hand, theoretical results suggest underlying end demand parameter estimates and lead time as the main factors to explain BE, on the other hand, empirical results found end demand variability as the key aspect to determine the BE.

This article links both perspectives and employs the coefficient of variation to set the limits under which the theoretical results can be applied. The results show that when the end demand coefficient of variation is low, the theoretical results defined by the underlying demand are not enough to quantify the BE. Nevertheless, when that coefficient of variation is higher, theoretical results can be a good approximation. Additionally, the nonlinear relationship described in [17] that relates the BE with the CV at family product level is also found in our dataset at SKU level.

The rest of the paper is organized as follows: Sect. 1.2 describes the case study; Sect. 1.3 states the main research objectives of the paper; Section IV discusses the empirical results and finally, Sect. 1.4 draws the main conclusions of the research.

1.2 Case Study

The supply chain system consists of a serially linked two-level supply chain, see Fig. 1.1. This supply chain comprises a flow of information represented by a dashed line from the market towards the manufacturer and a reverse one regarding materials represented by a solid line. Market sales and shipments from the manufacturer are the measured variables, indicated by the sensors in Fig. 1.1. Note that, unless company's fill rate is always 100%, either orders or sales do not reveal the true demand and they are only approximations [11].

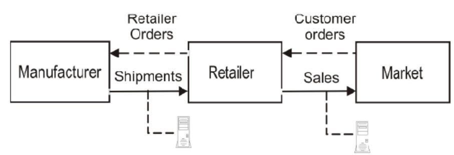

Fig. 1.1 Flow of material (solid line) and information (dashed line) for a two serially linked supply chain

Data from a manufacturing company specialized in household products have been collected. The data have been sampled weekly between October 2008 and October 2009. This manufacturing company provides products to one of the largest retailers in the UK. The data comprises shipments received by the retailer from the manufacturer, customer demand estimated by the retailer sales, as well as, promotional information.

The dataset under study comprises 16 Stock Keeping Units (SKU) with 52 observations per SKU. The average demand in each SKU ranges between 3,266.3 and 33,865.2 units, with the overall mean being 9,094.9 units. An example is depicted in Fig. 1.2, where retailer sales are in a dashed line and manufacturer shipments are in a solid line. Note that the shipments variability is higher than retailers one providing evidence of the BE.

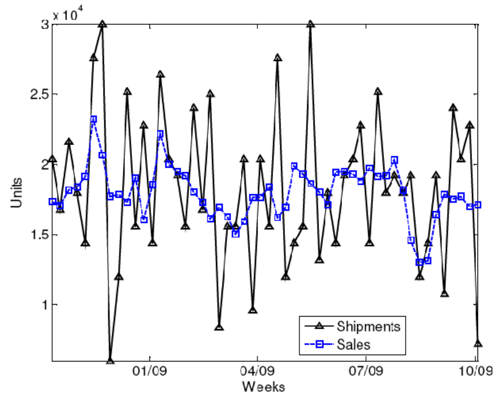

Fig. 1.2 Example of a SKU. Retailer sales are in a dashed line and shipments in a solid line

1.3 Research Questions

In this section, a set of key questions will be proposed in order to define the scope of the research. Firstly, since some papers doubt about the presence of the bullwhip effect [3], the first question is:
Q1: Is there any evidence of the bullwhip effect?

Here, it is important to define how the BE is measured. Different metrics will be shown in the next section to answer this question. Note that published papers show the BE under different levels of aggregation ranging from industries [3], to product families [17]. In this case study we calculate the BE for the lowest aggregation level, i.e. at SKU level. Assuming that the present dataset exhibited the presence of the bullwhip effect, the next question would be:
Q2: Is the bullwhip effect constant along SKUs for the same supply chain?

Despite the fact that theoretical and empirical research has aimed at the demand nature as one of the main factors to explain the bullwhip effect, there is a gap between conclusions achieved. On the one hand, theoretical works [13] conclude that different parameter values of demand processes modeled by ARIMA functions can produce the Bullwhip Effect or the Anti-Bullwhip Effect (ABE), according to which the variability of the orders placed upstream in the supply chain is lower than the variability of the demand itself. For instance, the results of their simulation show that for an AR(1) process, the BE will only take place when the autoregressive parameter is greater than zero. These results were corroborated analytically in [14]. On the other hand, an empirical analysis carried out in [17] shows that variability of the downstream demand is the main responsible to explain the different levels of BE. In order to shed some light into this, the next question is:
Q3: How the variability and the underlying demand process influence the bullwhip effect?

1.4 Empirical Results

In order to find out whether the considered dataset exhibit bullwhip effect (BE), firstly, we have to define how the BE can be measured. A possible way is to use the ratio of the coefficients of variation (CV) between the output supplier sales (shipments) and the input retailer sales [9]. Let the bullwhip ratio (BWR) be denoted by:

$$BWR = \frac{\sigma_s/\mu_s}{\sigma_r/\mu_r}, \tag{1.1}$$

where σ_i is the standard deviation and μ_i is the mean for i equal to supplier shipments (s) or retailer sales (r). Other conventional bullwhip measures use the ratio of the variance (or standard deviations) instead of the coefficient of variation. Note that those measures are equivalent as long as $\mu_s = \mu_r$. In our dataset this assumption has been corroborated. Thus, aforementioned measures are equivalent.

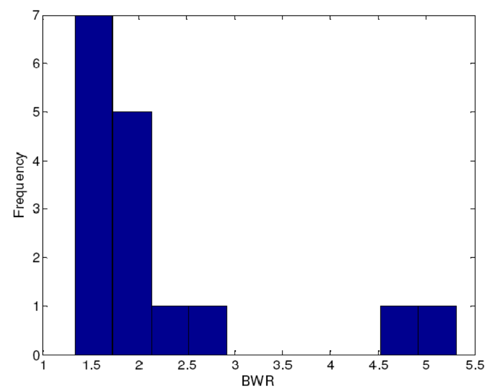

Fig. 1.3 Histogram of the bullwhip ratio

Fig. 1.3 shows the histogram of the BWR computed in the dataset. This figure shows a peak in the interval between 1.3 and 2. Interestingly, two SKUs achieve a BWR around 5. Therefore, we can answer the first two research questions given that there is empirical evidence of the BE presence since all the SKUs considered have a BWR greater than 1, as well as, the histogram shows that the BE is not constant but it possesses a variability that ranges from 1.3 to 5.3.

To find an explanation to that ample range of BWR, Fig. 1.4 and Fig. 1.5 depict the retailer sales and manufacturer shipments for the smallest and the largest BWR, respectively. Regarding the Fig. 1.4 (smallest BWR= 1.3), it is interesting to note a high variability demand due to the sales increase between 04/09 and 07/09 as a consequence of a promotion. According to Lee et al [12], price fluctuation is a source of BE, thus, we would have expected to obtain a high BWR. Conversely, the lowest BWR was achieved.

Fig. 1.5 shows a low variability retailer demand with a coefficient of variation equal to 0.08, however, the BWR is equal to 5.3. It is also interesting to point out

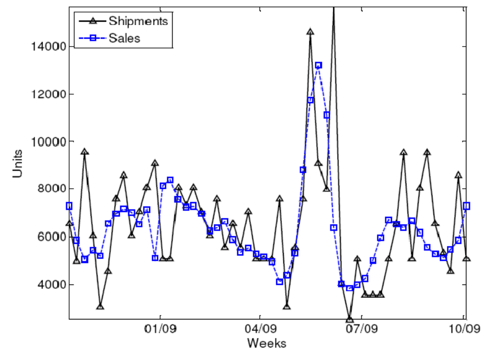

Fig. 1.4 SKU with the smallest BWR

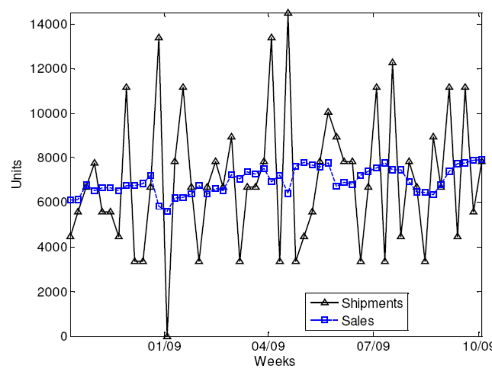

Fig. 1.5 SKU with the largest BWR

a remarkable increase of shipments before New Year. Furthermore, no promotional campaigns have been carried out for that SKU in the period under study.

Although these findings could seem controversial, in reference [17] a similar phenomenon was found in its case study based on Italy. They concluded that predictable demands of long shelf life products lead to higher BWR. The idea behind is that retailers who knew that its customer demand was stable were willing to invest on inventories in order to take advantage of the manufacturer sales force incentives to sell towards the end of the month. Unfortunately, in our case study we do not have manager information available to explain the reasons that drive the retailer to increase its orders variability when demand is relatively flat.

In order to find out whether the relationship found in [17] between the BE and downstream variability demand holds in our dataset, Fig. 6 shows a scatter plot between the retailer sales coefficient of variation CVr and the BWR. This plot exhibits a similar non-linear relationship found in Fig. 1.6 [17], which can be modeled by a potential function as follows:

$$\mathrm{BWR} = kCV_r^{\alpha}, \tag{1.2}$$

where k is a constant and α is the elasticity of the BWR with respect to CV_r . The estimation of both parameters results in $k = 0.47$ and $\alpha = -0.91$ (both statistically significant at 95% level). This means that 1% reduction of the coefficient of variation at retailer sales implies a 0.91% increase in the BE. The resulting function is also plotted in Fig. 1.6.

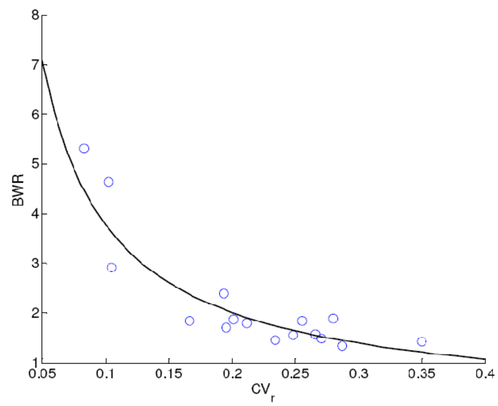

Fig. 1.6 Scatter plot between bullwhip ratio (BWR) and the retailer coefficient of variation (CV_r). It is also plotted in a solid line the fitted function defined in (1.2)

Other authors have developed expressions to quantify the BWR depending on the underlying demand process and the lead time (L). According to Box et al [1], a general ARIMA(p,d,q) process is described by:

$$\Phi_p(B)\nabla^d(D_t - \mu) = \Theta_q(B)\varepsilon_t, \tag{1.3}$$

where D_t is the end-customer's demand at period t. Polynomial $\Phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$ presents an $AR(p)$ (Autoregressive) process; polynomial $\Theta_q(B) = 1 - \vartheta_1 B - \vartheta_2 B^2 - \ldots - \vartheta_q B^q$ represents an $MA(q)$ (Moving Average) process; B is the backward shift operator $B^j \varepsilon_t = \varepsilon_{t-j}$; ∇ is de difference operator and $\nabla^d = (1 - B)^d$. In summary, (p,q) denote the order of an autoregressive and moving average process, respectively, and d the dth. difference of the original series. If $d = 0$, μ defines a neighborhood to which demand eventually returns. ε_t $(t = 1, 2, \ldots)$ are i.i.d. normally distributed random variables with mean 0 and variance σ^2.

Reference [14] quantified the BE measured by the ratio of variances when the demand follows an ARIMA(1,0,0) process such as:

$$B(L,\phi_1) = \frac{\sigma_s^2}{\sigma_r^2} = \frac{(1+\phi_1)(1-2\phi_1^{L+1}) + 2\phi_1^{L+2}}{1-\phi_1}, \tag{1.4}$$

where L is the lead time. The above expression means that the BE only occurs for $\phi_1 > 0$. Note that

$$\text{BWR} \approx \sqrt{B(L,\phi)}. \tag{1.5}$$

In reference [6] those results were expanded for the ARIMA(1,0,1) process providing the following expression:

$$B(L,\phi_1,\vartheta_1) = 1 + \frac{2(\phi_1-\vartheta_1)(1-\phi_1^L)(1-\phi_1^{L+1}-\phi_1\vartheta_1(1-\phi_1^{L-1}))}{(1-\phi_1)(1+\vartheta_1^2-2\phi_1\vartheta_1)}. \quad (1.6)$$

Here, the BE only occurs for $\phi_1 > \vartheta_1$. Previous expressions were validated by simulations in [13], where it was also found that an ARIMA(0,0,1) provides BE when $\vartheta_1 < 0$.

In order to corroborate the theoretical results, we have empirically identified the ARIMA process corresponding to the demands in our dataset by minimizing the normalized Bayesian Information Criterion (nBIC) such as:

$$n\mathrm{BIC} = \ln\left(\frac{\sum \hat{a}_t^2}{n}\right) + K\ln(n)/n, \quad (1.7)$$

where $\hat{a}_t$ are the residuals of the model; K is the number of parameters used and n is the number of residuals computed for the model. The best model is the one with the smallest nBIC value, [14]. The potential ARIMA models that can be selected by the previous algorithm are limited to ARIMA(1,0,0), ARIMA(0,0,1) and ARIMA(1,0,1), given that those models have available theoretical developments to be tested with our empirical dataset.

Table 1.1 Summary of identification and estimation results on the empirical dataset

ARIMA process	No. of series	% of series	Region	% estimates fall inside region
ARIMA(1,0,0)	9	56.25%	$\phi_1 > 0$	100%
ARIMA(0,0,1)	1	6.25%	$\vartheta_1 < 0$	100%
ARIMA(1,0,1)	6	37.5%	$\phi_1 > \vartheta_1$	100%

Table 1.1 shows the estimation results on the dataset. The first column indicates the ARIMA models under study. The second column counts the number of series that has been identified with a determined ARIMA model and the third column expresses it as a percentage. For instance, the ARIMA(1,0,0) has been identified 9 out of 16, i.e., a 56.25 %. The fourth column defines the parameters region that yields BE. Recall that all the SKUs considered yield BE, i.e., BWR > 1. Finally, the fifth column represents the percentage of SKUs that having BWR > 1, its parameter estimates fall inside the region defined in the fourth column. The first conclusion extracted from Table 1 is that the range of parameter values defined theoretically that provided BE were validated in our dataset. In other words, 100% of the parameter estimates fulfill the condition expressed in the 4th column. For instance, all the SKUs identified as an ARIMA(1,0,0) had a coefficient estimate $(\hat{\phi}_1)$ greater than zero. Interestingly, ARIMA(1,0,0) is the most frequent process in our dataset, followed by the ARIMA(1,0,1).

So far, we have empirically tested that theoretical results can determine whether a certain demand may produce the BE based on its demand parameterization. However, are the theoretical results precise enough to quantify the BE? To answer this question a comparison between the BE analytically and empirically computed has been carried out. Since the ARIMA(1,0,0) is the most frequent process in our dataset, we will test the precision of the theoretical findings expressed in (1.4) and (1.5). Fig. 1.7 shows the BWR against ϕ_1. The exact lead time is unknown in our dataset. To overcome such a limitation, we have plotted a shaded area that comprises lead times from 1 to 4 weeks. The BWR has been computed based on equations (1.4) and (1.5). In addition, the BWR empirically computed (see equation (1.1)) has also been plotted in the figure.

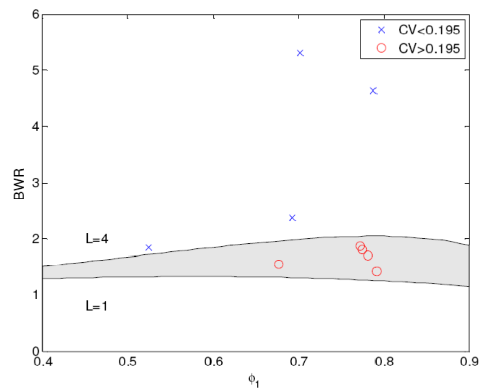

Fig. 1.7 Bullwhip ratio (BWR) against Autorregresive parameter (ϕ_1). Shaded area comprises the BWR analytically computed for lead times ranging from 1 to 4 weeks. Markers denote the BWR empirically computed

It can be seen that the magnitude of the BWR cannot only be explained by the parameter ϕ_1 and the lead time L. In order to find a reasonable explanation for the SKUs that are located out of the shaded area, we consider the empirical results previously found where the demand variability can partially explain the size of the BE. In the same figure, the SKUs with a $CV > 0.195$ have been plotted as blue crosses and those SKUs with a $CV < 0.195$ in red circles. Here, it seems that those SKUs with a high CV can be explained by using the theoretical formula in (1.4), whereas those with a low CV cannot.

The reasons behind the increase of the BE for low CV values are not totally understood and deserve further research. Author in [17] states that a flatter end demand encourages retailers to forward buy in order to take advantage of manufacturer deals usually often toward the end of the sales period to meet sales targets. In addition, it should be noted that the coefficient of variation may influence the use of a certain stock policy. In this sense, basic inventory theory suggests the use of deterministic inventory policies for low values of CV instead of stochastic inventory policies as the order-up-to.

1.5 Conclusion

Researchers and practitioners have devoted a great effort to study the BE given its harmful consequences. Two different streams can be distinguished from the operations management literature. On the one hand, theoretical analysis, which are based on initial assumptions about the underlying demand process and the stock policy, are considered to develop different expressions that quantify the BE. On the other hand, a more practical approach measure the bullwhip effect with actual data collected from different companies involved in the supply chain. Once the bullwhip measures are available, a deep analysis of causes is carried out. In principle both approaches are legitimate and they should converge to similar results, nonetheless, given the complexities associated to the system and/or particularities of each supply chain is expected to find some discrepancies. This work explores those differences at SKU level and proposes a framework to define the limits of application of theoretical results on the basis of real data coming from a case study. Summarizing, the variability of the end demand, which has been measured by means of the coefficient of variation, is the key factor. Firstly, a non-linear relationship between the BE and the end demand variability is statistically illustrated. Secondly, those SKUs with low variability do not fulfill the initial assumptions that support theoretical works and the resulting BE quantification is not precise. In turn, those SKUs with higher variability follow closely the expected magnitude of BE expected by the analytical expressions output. Further research should follow in at least two directions: i) given that our dataset did not contain SKUs with seasonal properties, the variability can be understood as a measure of forecastability. Thus, the use of forecastability rather than variability can significantly contribute to this area; and ii) these results should be expanded to other companies and at different levels of aggregation.

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