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# Quantification of Supply Chain Bullwhip Effect

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***Abstract***

*The bullwhip effect occurs when orders made to suppliers have a bigger variation than sales to the buyer. This is a major concern that businesses are working on eliminating, as it has numerous side effects, such as excessive inventory, stock-outs, insufficient production, increased costs, etc. The new study adds to the literature by demonstrating how to quantify and assess the bullwhip impact in any supply chain. The results provided here illustrate that when consumer demand is unstable, the bullwhip effect is magnified. This result was achieved by using the proposed formula, which was based on an explanation and graph of the traditional bullwhip effect. A stochastic simulation based on a case study that replicates the behavior of a generic supply chain in a real-world market was used to evaluate the formula.*

***Keywords:*** *Bullwhip, Supply Chain Management, Demand Uncertainty, Risk Evaluation*

## 1.0. Introduction

The bullwhip effect (BWE) is currently one of the principal challenges faced by supply chains. The BWE can be defined as "the phenomenon where orders to the supplier tend to have a larger variance than sales to the buyer (i.e., demand distortion), and the distortion propagates upstream in an amplified form" (Lee *et al.*, 1997). This effect is referred to as the BWE because, when the data is graphed, it forms an amplitude similar to the whip with all the increases and decreases. The BWE has numerous negative effects and leads to insufficient supply chains. It moves the supply chain performance level away from the efficiency frontier, as it increases the overall supply chain cost and decreases customer service levels (Almaktoom, 2017, 2019). This results in lower profitability. Lee *et al.* (1997) mentioned the following effects "excessive inventory investment, poor customer service, lost revenues, misguided capacity plans, ineffective transportation, and missed production schedules". The BWE has also been associated with many additional costs that can be massively reduced if the effect is mitigated or dealt with. Firms that experience the BWE usually need more capacity levels to deal with the fluctuation in demand. Additionally, these firms may experience more stock-outs during peak seasons and higher inventory levels during low-demand seasons, resulting in unstable costs throughout the year (Isaksson & Seifert, 2016; Alsaadi et al., 2016). The BWE proved its presence in every sector, including the service sector. According to Akkermans and Voss (2013), the BWE proved present in service supply chains because of fluctuations in demand. Demand fluctuation is a major challenge faced by operations and supply chain managers, planners, and forecasters (Almaktoom, 2023). It has an impact on every department in the

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business, as it increases inventory levels and reduces service levels. Consequently, supply chain managers are continually working on reducing the BWE by implementing solutions to improve their performance and mitigate the BWE.

This phenomenon has been gaining the academic interest of some scholars and has been studied across various industries. This topic was studied in economic literature, operations literature, etc. Many case studies and empirical studies prove the existence of the BWE; however, the effect still influences many supply chains, regardless of their size.

The main focus of this paper is to propose a different method to quantify and evaluate the BWE in any supply chain network. It will generate a mathematical measure for the BWE in various supply chains and demonstrate how the BWE may influence different stages in the supply chain. It contributes to the literature by providing evidence for the existence of the BWE. Furthermore, this paper will also give managers an insight into the magnitude of the effect and help them develop a better understanding of how to refrain from it.

To accomplish these objectives, a formula was proposed based on the definitions of the BWE. This formula measures the BWE at each stage and entity and assigns a percentage to it. The proposed formula was then applied through a case study using a stochastic simulation. The simulation will facilitate a means to experiment with the proposed formula in a manner that is similar to reality. First, the demand and order histories were simulated. Then, the formula was used to find the BWE for each entity through the simulated results.

The rest of the paper is divided as follows: In Section 2, a review of previous literature is provided, where background information is provided as well as some history behind the concept of the BWE and the causes of the BWE. Methods of evaluation are also included. Section 3 is the methodology section, where an overview of the methodology is provided and the developed model is explained and illustrated through a case study in Section 4. Finally, Section 5 concludes with final remarks and suggestions for future research.

## 2.0. Literature Review

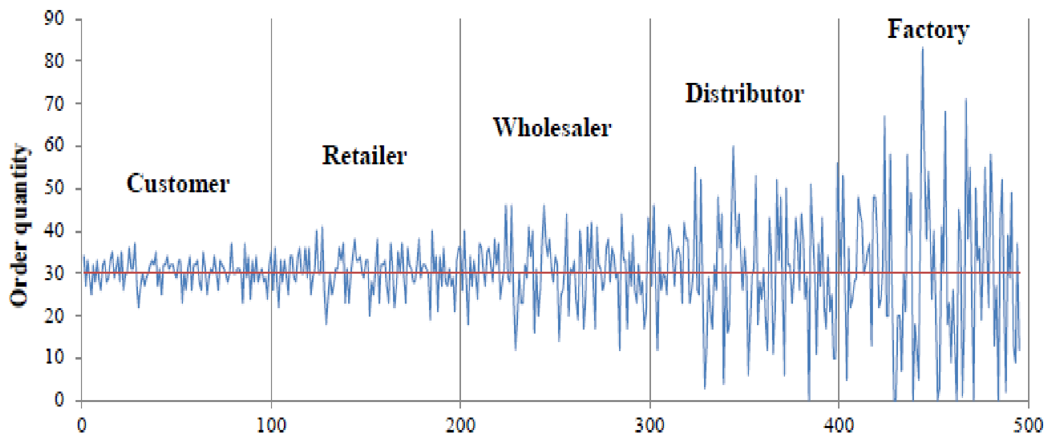
### 2.1. Background

The BWE existed for many years across different industries. It was initially known as the Forrester Effect because the first academic description of it is attributed to Forrester (1961), who tried to demonstrate the effect through system dynamics. The concept was later developed and appeared in multiple studies (de Kok *et al.*, 2005; Fisher *et al.*, 1994; Holweg *et al.*, 2005; Simon, 1952). Additionally, Sterman (1989) studied the BWE at the Massachusetts Institute of Technology (MIT) through the Beer Game, which is an experimental learning game that illustrates various challenges faced by supply chains. He interprets that the main cause of this effect is the irrationality of the players, and the same scenario applies to the practical business world.

The term “BWE” was further clarified when it was observed in Procter & Gamble (P&G) in the early 1990s. It was observed in the brand “Pampers”, which produces diapers for babies. The demand for diapers is relatively stable with slight fluctuations; however, drastic fluctuations appeared in the retail order to the wholesaler, and these fluctuations increased in later stages in the supply chain.

Lee *et al.* (1997) were among the first informative papers to discuss the BWE and give a clear overview of the phenomenon. The article provides evidence through a case study of a soup manufacturer and relates it to price fluctuations. (Lee *et al.*, 1997) measured the BWE by comparing the order variance with the demand variance, which captures the distortion of information that occurs upstream. Other empirical studies examine the difference between shipments, or order receipts, and sales. If the shipment data is unavailable, both sales and inventory data can be used to capture the essence (Blinder, 1986; Cachon *et al.*, 2007). The main idea behind the BWE is how an insignificant change in customer demand builds up and is magnified as it goes upstream in the supply chain, as shown in Figure 1.Shaban *et al.* (2015)

**Figure 1:** Graph of the BWE




To assess the BWE, Cannella *et al.* (2013) developed a two-criterion performance measurement system that assesses the satisfaction of customers and the efficiency of internal processes. Operational performance is measured by various KPIs, key performance indicators, including operational responsiveness, inventory stability, etc., and a new KPI: zero replenishment. On the other hand, customer satisfaction is measured by order fill rate and backlogs. This assessment also estimates the overall supply chain performance rather than a single supply chain stage or an internal supply chain.

## 2.2. Causes of the Bullwhip Effect

Various causes led to this phenomenon in supply chains. Bhattacharya and Bandyopadhyay (2011) categorized the causes into two groups: operational causes and behavioral causes. The first operational cause is poor communication and a lack of proper exchange of information (Dai *et al.*, 2017). When incomplete information moves along the supply chain, it creates misconceptions regarding current customer demand, and firms will interpret the received data differently to maximize their surplus and create benefits for their company. This cause can also be referred to as a lack of transparency. Lee and Whang (2000) summarized the main systems for information sharing as follows; point of sales data, sales forecasts, production or delivery schedules, order status, and inventory levels. This information can be shared both upstream and downstream and will facilitate collaboration with all supply chain members. The second operational cause is price fluctuation. Constant changes in prices and the introduction of promotions create an unsteady buying pattern because lower prices and promotions are incentives that drive customers to buy more. These promotions tend to increase supply chain costs and distort information as it moves through the supply chain.

Moreover, forecasting techniques have always been linked to the BWE. According to Lee *et al.* (1997), the demand-forecasting technique used by a firm has a massive impact on the BWE.

Firms must determine the most suitable method to ensure accurate demand planning (Towill *et al.*, 2007). The forecaster must take into account the available data to use and the type of demand, e.g., seasonal demand, trended demand, etc. Some researchers agreed that minimum mean squared error (MMSE) forecasting is capable of generating more precise results for demand processes (Alwan *et al.*, 2003; Hosoda & Disney, 2006; Zhang, 2004). Another factor that contributes to the BWE is time delays. (Towill, 1996) emphasized that any delay in material or information flow, both upstream and downstream, leads to demand amplification. Other researchers argued that lead times are a driving factor in BWE and that order variability increases with lead times (Agrawal *et al.*, 2009; F. Chen *et al.*, 2000; Lee *et al.*, 1997). Chaharsooghi and Heydari (2011) argued that lead times and BWE are irrelevant. They reached this conclusion by using a simulation to hold all other factors constant and just test the effect of lead times on the BWE. They found that it may influence inventory and somehow lead to uncertainty, but not to the BWE. Finally, replenishment or ordering policies are also reasons that may result in BWE (Boute, 2007; Jakšič & Rusjan, 2008).

Bhattacharya and Bandyopadhyay (2011) suggested three main behavioral causes that are linked to the BWE: neglecting time delays in making ordering decisions, lack of proper training, and fear of empty stock. Croson and Donohue (2003) pointed out that many supply chains ignore the time factor when planning their future orders, and thus any minor delay or variability in time automatically leads to BWE. According to Wu and Katok (2006), managers tend to overlook the fact that most employees need specific training, which leads to decision-making errors. These errors are somehow similar to the first, where decision makers ignore the time factor and cause errors. Finally, the fear of empty stock is the fear of stockouts, so managers tend to order excess quantities, claiming that they might run out of stock and lose customers.

### 2.3. Evaluation of Bullwhip Effect

In previous operations literature, some papers quantified the BWE. For example, Cachon *et al.* (2007) used industry-level data to detect the effect in the wholesale industry, while Bray and Mendelson (2012) used firm-level data to measure the effect. Both studies used data that connected the buyers and the suppliers, using single-echelon settings. Further research in this field was conducted by Isaksson and Seifert (2016), who introduced a novel way of quantifying the BWE across industries by using financial accounting data in a multi-echelon setting. They were able to study the demand variability in both upstream and downstream supply chain stages. The outcomes propose that the vastness of the BWE is more significant than previous estimations (Bray & Mendelson, 2012; Cachon *et al.*, 2007). Since some fields are more susceptible to the BWE, companies need to take that into account and measure the effects when required.

According to L. Chen and Lee (2012), for cost assessment purposes, measuring the BWE should be done at suitable times. The appropriate time varies based on the firm's position in the supply chain, whether it's upstream or downstream (Bahebshi & Almaktoom, 2019). When information sharing exists between upstream and downstream stages, the bullwhip measure must be deducted to ensure accuracy and reduce variability. They also found that the bullwhip ratio would increase when the upstream stages shortened their order fulfillment interval or replenishment lead times. Consequently, the performance improvement of the vendor-managed inventory program increases. Their analysis proposes that the aggregate planner's most likely disregard the BWE at the individual product level; most financial planning and investment decisions are taken based on the firm's aggregate data on a quarterly, or sometimes yearly, basis, thereby making the BWE more potent at the individual product level than the industry or firm level. Their research also suggests that time aggregation can reduce the effect.

Another study by Jin *et al.* (2017) had compatible conclusions. Moreover, Hussain *et al.* (2012) employed the Taguchi design of experiments and system dynamics simulation to quantify the relationship between the parameters of the supply chain and dynamic performance, including the BWE. They found that various parameters interact in multi-echelon supply chains, and altering the value of one parameter will lead to a change in other parameters as well; managers must take that into consideration when making decisions to avoid any complications. (Hussain *et al.*, 2012) also suggested that altering lead times and inventory errors would amend the order variance compared to other parameters. Nagaraja *et al.* (2015) further demonstrated the relation between the magnitude of the BWE, the lead time, and the seasonal lag through the use of the SARMA model. SARMA is a model that combines the autoregressive element (AR) and the moving average component (MA) with the seasonal element. The theory was applied to a single-item, two-stage supply chain that has an order-up-to-inventory policy. Their results suggest that the BWE can be considerably reduced if the lead time is less than the seasonal lag. If adjusting the lead time is not possible, then a fractional ordering policy would be more suitable for the firm, as suggested by Gaalman (2006).

## 3.0. Methodology

The methodology section describes the tools used and actions taken to investigate and analyze the research problem. Simulation modeling is a way to solve real-world problems efficiently and safely. It enables users to analyze problems and come up with better solutions. Recently, computer simulations have been widely used in business. Decision makers and business analysts often use computer simulation to better understand the operating characteristics of any given system, as it encapsulates the essence of any given scenario.

A simulation is a way to replicate the behavior of a real-world system using a mathematical model. The model usually represents the key characteristics or functions of the selected system, while the simulation represents the behavior of the model (Poole & Raftery, 2000). The model must have controllable variables, uncontrollable variables, and constraints that bind the system. The behaviors observed are a result of changes in these objects (Hale Feinstein *et al.*, 2002). The use of simulation, or mathematical models, is most appropriate when a user is trying to gain insight into a current or future situation. It is also used when an experiment is very expensive or too dangerous to implement in the real world.

A mathematical model is mainly built upon relations between different variables. When formulating a mathematical model, one must first consider the system they are trying to represent and then select the suitable model. To begin with, a deterministic model is one where all the sets of output are decided based on the models' parameters. This model is best used when the purpose is to understand the mechanism of a process or system (Choy *et al.*, 2009). Deterministic models are mainly used in scientific research and fields such as climate, populations, or other sciences such as chemistry (Kumar & Davidson, 1978; Khan et al., 2022). On the other hand, a stochastic model, also known as a probabilistic model, results in variables that change randomly based on given conditions. In this method, the output must be recorded, and the process is repeated several times to ensure accuracy. Each variable is described by a different value (Marchetti *et al.*, 2017). According to Gillespie (1977), stochastic simulation is the most accurate type of simulation; however, its disadvantage is that it is complex and highly computational.

For the current study, a stochastic simulation will be used to test the equation. This method was chosen for various reasons. First, since the main factor is demand and it is unstable and dynamic, a stochastic model will represent it in the most accurate way as it will create a projection that is based on a set of random values. Moreover, it will give an insight into the systems' behavior over a period of time with an appropriate level of detail. Furthermore, a computer simulation will permit the means to test and explore numerous scenarios and the effects of changing any variable. This can be done through a "what if" analysis. Finally, a virtual experiment must be used because real data is not accessible.

### 3.1. Modeling Bullwhip Effect

The BWE can be represented through the following equation:

$$BWE_{i,p}^{j,m,x} = [\left(\frac{Q_i^{j,m,x} - \left|Q_i^{(j,m,x-1)} - Q_i^{j,m,x}\right|}{D_i}\right) - 1] * 100$$

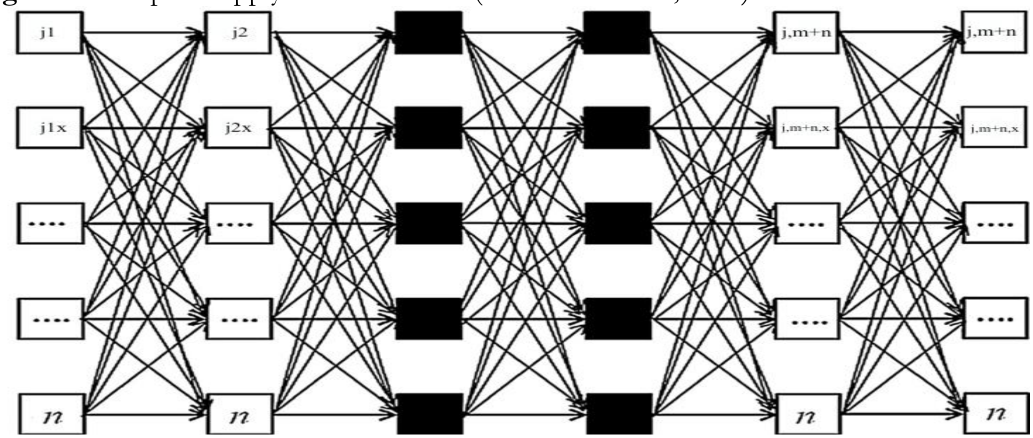
*Equation 1: The BWE*

The equation above is based upon the definition of the BWE and each variable denotes a component of the *BWE*. First, $Q_{i,p}^{j,m,x}$ is the quantity ordered, where $i$ is the period of time, and $p$ represents the product. While the $j$ exemplifies the entities of the supply chain, $m$ being the entity number, and $x$ is added in the case of parallel entities. Possible entities for this case may include; retailers, distributors, wholesalers, manufacturers, raw material suppliers, etc. $Q_{i,p}^{(j,m,x-1)}$ denoting the ordered quantity of the previous entity at a given time, for the same product. $D_{i,p}$ is the exact consumer demand without any additions, such as safety stocks or any other excess quantities. The difference between the ordered quantity of the current entity and the ordered quantity of the previous entity is in absolute value because the main objective is to find the magnitude of fluctuations in this case. Whatever the resulting value may be, it must be used as a positive number in the equation.

This formula encapsulates the BWE in a better manner, and it aims to represent a way to quantify the BWE. By using this formula, any entity in the supply chain can know the exact percentage of the actual demand that is covered. Since consumer demand constantly fluctuates, it is nearly impossible to ensure that it is 100% satisfied. A firm may be able to satisfy the demand but with a great excess quantity, or it may only cover a small fragment of the demand. If the result was positive, this means that the firm was able to satisfy the demand but had some excess. However, if the result was negative, it indicates that the firm was not able to cover the customers' demand. For example, if the result was 30% it indicates that the firm has 30%, more than the required quantity, but if the result was -40%, it implies that 40% of the demand was not covered. This formula uses historical data to help a company know how to cover demand with minimum losses. An enterprise may also use the mean of the previous year to assist it in planning and forecasting future demand.

This is the general formula that can be applied to different types of supply chains, no matter what structure they have. Supply chain types and sizes vary based on the type of product and the number of projects that move along the chain. It can even work with international and global supply chains. A firm can use their historical data to find the BWE for previous periods, and then use this information in their future estimates and forecasts. Each entity will benefit both from its own mistakes and from the mistakes of other entities in the supply chain. Every member or entity can find the exact percentage of the BWE that they might be experiencing and then work on reducing the effect. An example of a complex supply chain is provided in Figure 2 below.

**Figure 2:** Complex Supply Chain Network (Almaktoom *et al.*, 2014)



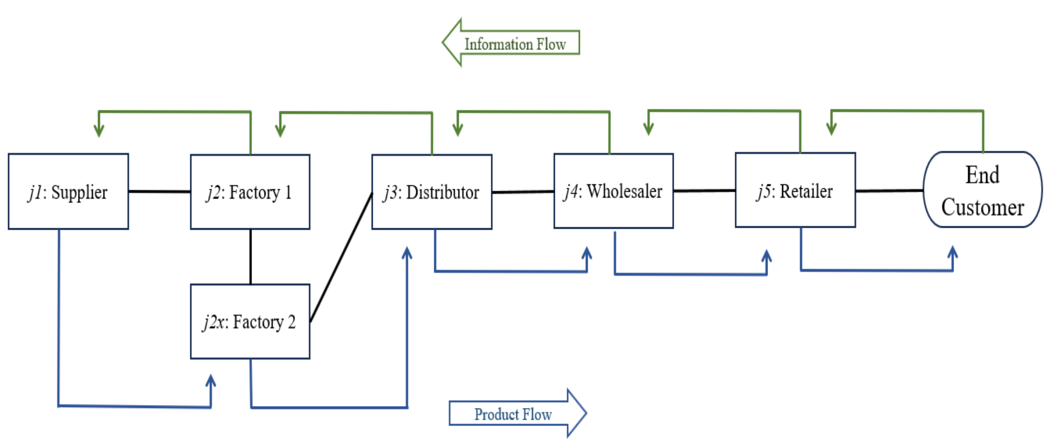

Since each supply chain has numerous products moving along it, the BWE percentage may vary. Since the end customer demand and the ordered quantities are the main variables in this formula, they will have the greatest influence on the results.

To ensure that this formula is applied correctly and that all supply chains benefit from, they must have proper sharing of information and data and ensure compliance by all supply chain members. Mitigating the BWE cannot be achieved without all members collaborating and working on the overall supply chain surplus rather than just the surplus of one entity in the supply chain.

## 4.0. Case Study

This case study presents a supply chain consists of five levels, as demonstrated in the figure below. The first level, *j1*, is the source of raw materials and the main supplier for the factories. There are two factories that work on producing the products; *j2* is the factory where the items are manufactured and *j2x* is the other factory where manufacturing is further completed and packed. *j3* is the distributor and *j4* represents the wholesaler that buys the products and resells them to different retailers. Finally, *j5* is the retailer where the products will be sold to the end customers. Each entity in this supply chain places its orders on a quarterly basis. Orders flow backwards and the product moves forward in the supply chain.

**Figure** 3: Supply Chain Diagram



To summarize, two products have been selected that move along the supply chain, *p1* and *p2*. The demand for *p1* is relatively stable, with mild fluctuations over time. On the other hand, the demand for *p2* fluctuates more often and is relatively unstable. The demand is recorded monthly and is then added to find the quarterly demand. Most entities in this chain do not share proper information with one another; however, after realizing that the BWE is an obstacle, they decided to appropriately share the required information with each other.

## 5.0. Findings

**Table 1:** Demand & Orders at Each Entity, Product 1

| $i$ | $D_i$ | $Q_{i,p1}^{j5}$ | $Q_{i,p1}^{j4}$ | $Q_{i,p1}^{j3}$ | $Q_{i,p1}^{j2}$ |
|---|---|---|---|---|---|
| 1 | 314 | 360 | 430 | 520 | 630 |
| 2 | 327 | 380 | 450 | 540 | 650 |
| 3 | 302 | 350 | 410 | 500 | 610 |
| 4 | 315 | 360 | 430 | 520 | 630 |
| 5 | 315 | 360 | 430 | 520 | 630 |
| 6 | 309 | 360 | 430 | 520 | 630 |
| 7 | 383 | 440 | 520 | 630 | 760 |
| 8 | 312 | 360 | 430 | 520 | 630 |
| 9 | 312 | 360 | 430 | 520 | 630 |
| 10 | 316 | 360 | 430 | 520 | 630 |
| 11 | 316 | 360 | 430 | 520 | 630 |
| 12 | 314 | 360 | 430 | 520 | 630 |
| 13 | 318 | 370 | 440 | 530 | 640 |
| 14 | 316 | 360 | 430 | 520 | 630 |
| 15 | 318 | 370 | 440 | 530 | 640 |
| 16 | 313 | 360 | 430 | 520 | 630 |
| 17 | 312 | 360 | 430 | 520 | 630 |
| 18 | 320 | 370 | 440 | 530 | 640 |
| 19 | 323 | 370 | 440 | 530 | 640 |
| 20 | 311 | 360 | 430 | 520 | 630 |

**Table 2:** Demand & Orders at Each Entity, Product 2

| $i$ | $D_i$ | $Q_{i,p2}^{j5}$ | $Q_{i,p2}^{j4}$ | $Q_{i,p2}^{j3}$ | $Q_{i,p2}^{j2}$ |
|---|---|---|---|---|---|
| 1 | 360 | 600 | 600 | 1280 | 2720 |
| 2 | 350 | 580 | 580 | 1230 | 2620 |
| 3 | 210 | 350 | 350 | 740 | 1570 |
| 4 | 320 | 530 | 530 | 1130 | 2400 |
| 5 | 230 | 380 | 380 | 810 | 1720 |
| 6 | 430 | 720 | 720 | 1530 | 3260 |
| 7 | 360 | 600 | 600 | 1280 | 2720 |
| 8 | 430 | 720 | 720 | 1530 | 3260 |
| 9 | 440 | 740 | 740 | 1570 | 3340 |
| 10 | 270 | 450 | 450 | 960 | 2040 |
| 11 | 350 | 580 | 580 | 1230 | 2620 |
| 12 | 360 | 600 | 600 | 1280 | 2720 |

| $i$ | $D_i$ | $Q_{i,p2}^{j5}$ | $Q_{i,p2}^{j4}$ | $Q_{i,p2}^{j3}$ | $Q_{i,p2}^{j2}$ |
|---|---|---|---|---|---|
| 13 | 420 | 700 | 700 | 1490 | 3170 |
| 14 | 410 | 680 | 680 | 1450 | 3090 |
| 15 | 420 | 700 | 700 | 1490 | 3170 |
| 16 | 360 | 600 | 600 | 1280 | 2720 |
| 17 | 410 | 680 | 680 | 1450 | 3090 |
| 18 | 340 | 570 | 570 | 1210 | 2580 |
| 19 | 290 | 480 | 480 | 1020 | 2170 |
| 20 | 410 | 680 | 680 | 1450 | 3090 |

The previous tables are results of the simulation. Table 1 is for the quantities from *p1* are displayed, and Table 2 is where the quantities for the product *p2* are shown. As previously mentioned, orders are made every quarter, and the data in the tables above is for 20 quarters, which translates into five years. In these tables, $i$ represents the given quarter, $D_i$ is the pure end customer demand, and $Q_{i,p}^{j5}$ is the quantity ordered by the retailer to the wholesaler. Since the demand fluctuates, the retailer usually keeps an additional 15% as safety stock. $Q_{i,p}^{j4}$ represents the quantity ordered by the wholesaler to the distributor and $Q_{i,p}^{j3}$ is the quantity ordered by the distributor to the manufacturer. Two factories were mentioned in the case study, but the order is received by factory *j2*, where the process begins, and both *j2* and *j2x* produce the exact same quantity. $Q_{i,p2}^{j2}$ is the quantity ordered by factory *j2* to the raw material suppliers. The formula has been applied between the following stages: *j2* and *j3*, *j3* and *j4*, and *j4* and *j5*. The results are presented in Tables 3 and 4, and Figures 4, 5, and 6.

**Table 3:** BWE, Product 1

| P1 | Average Orders/Quarter | Range | $BWE_{i,p1}^{j,m,x}$ |
|---|---|---|---|
| J5 | 366.5 | 90 | - |
| J4 | 436.5 | 110 | 15% |
| J3 | 527.5 | 130 | 37% |
| J2 | 638.5 | 150 | 44% |

**Table 4:** BWE, Product 2

| P2 | Average Orders/Quarter | Range | $BWE_{i,p1}^{j,m,x}$ |
|---|---|---|---|
| J5 | 358.5 | 230 | - |
| J4 | 597 | 390 | 14% |
| J3 | 1270.5 | 830 | 90% |
| J2 | 2703.5 | 1770 | 254% |

In the previous tables, the BWE formula was used to find the results. The average BWE per entity is the sum of BWE per period over the number of periods, 20 quarters in this case. The average was used to label each stage, as it gives an overview of the magnitude of the effect on the given entity. Additionally, the average order per quarter and the range were included to give a complete picture of the situation at each stage.

The average demand for *p1* is 318 units/quarter and the range is 81. These values start to increase as we go upstream in the supply chain. As presented in Table 3, the average orders per quarter, the range of orders, and the BWE increase as we proceed in the supply chain. So, later stages experience greater variances and more overstock. The greatest BWE is around 45%, which means that they are producing almost 50% extra units.

The average demand per quarter for *p2* is 311, and the quantity range is 196. As previously mentioned, *p2* experiences more fluctuations, and the result of that is visible in Table 4. The entities experience dramatic bullwhip results, especially *j4* with an average BWE of 254%. This percentage indicates that they have a huge order supply of *p2*, which is not really needed. The excess quantities may have a negative influence on the firm because they will increase holding costs, and if they are not used at the right time, they might go to waste.

**Figure 4**: Visual Representation of Quantities Ordered p1

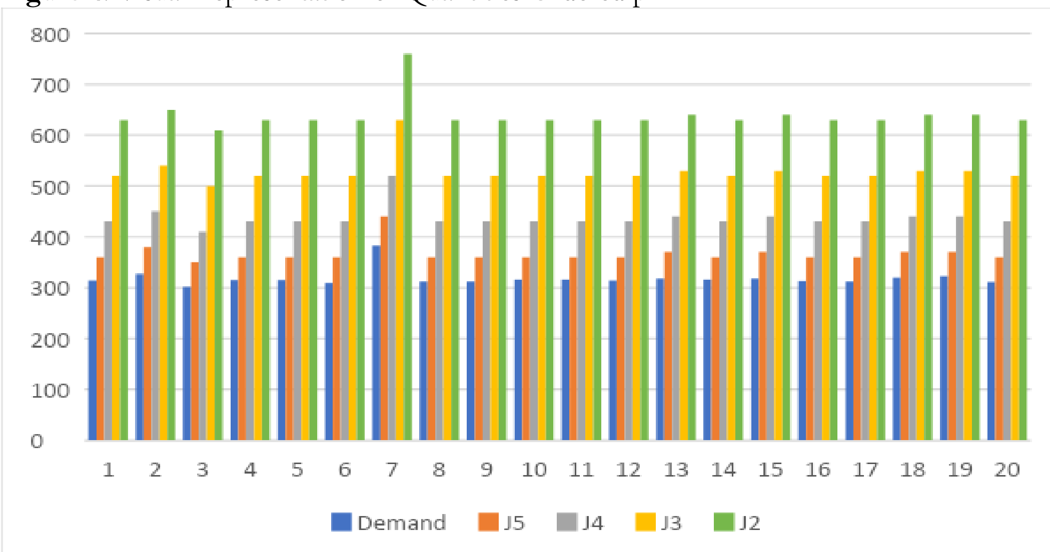
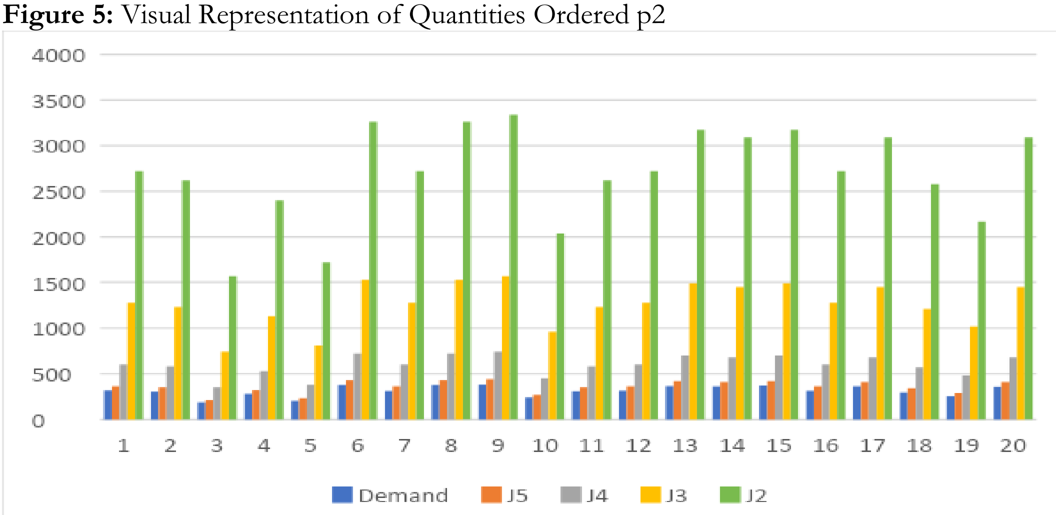



**Figure 5:** Visual Representation of Quantities Ordered p2




The previous figures graphically display the difference between the demand and the orders at each stage. In both products, entity *j2* experiences more BWE as compared to other stages.

The main drive that leads to this complication is basing production plans or orders solely on the demand from the next stage. In Figure 5, the entities *j2* and *j3* best exemplify the BWE and how much excess investment it results in. At these stages, the company has spent a huge amount of money and bought unwanted products. If the plans were based on end-customer demand, this problem might not have existed.

**Figure 6:** Comparison of Ordered Quantities for p1 & p2

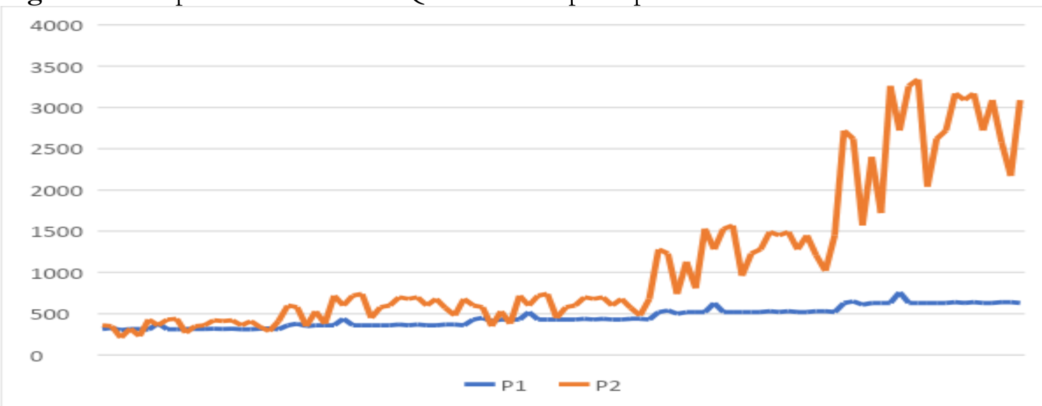



Figure 6 clearly reveals the difference between the BWE in both products. The graph starts with consumer demand and ends with the uppermost stage in the given supply chain, which is *j2*. It is visible that as we move away from the end customer, the effect is magnified. This graph completely illustrates the BWE definition, where raw demand influences the supply chain the most. The orders for *p1* demonstrate variation, but it is not as significant as it is in *p2*. This confirms that more variation leads to greater BWE.

## 6.0. Conclusion

The BWE is one of the main challenges faced by supply chains. It can influence any type of supply chain and may have a negative impact on both the supply chain and the entities involved. The BWE exists in every sector, but different sectors and fields may have diverse results and percentages of the effect. This research worked on quantifying the BWE and considered end consumer demand as a main factor in evaluation. To achieve the objectives of this research, a formula was developed and derived from the definition of the BWE. This formula has been applied to calculate the effects for previous periods using historical data. It can help demand planners, supply chain managers, decision-makers, and forecasters set a better plan for the coming time periods. It can be done by observing past or historical data and learning from previous mistakes, such as overstocks or stock-outs. Moreover, this measure can be used as a tool to demonstrate the significance of the BWE. A relationship was observed between the demand variance and the BWE, and the results indicate that as the variance in consumer demand increases, the BWE drastically increases as we move along the supply chain. The earliest stages of a supply chain may experience a BWE percentage of up to 250% each period.

The BWE is a chronic management disease that disturbs supply chains. Eliminating the effect is extremely challenging because it requires complete and sincere collaboration between supply chain members; however, it can be mitigated and reduced by adopting some techniques. First, they must ensure that they are all cooperating, which may require mutual decisions and contracts with clauses regarding information sharing. This will regulate the process and make it safer for all parties involved. Other policies, such as buying policies, must be considered as well. Besides that, the selected forecasting technique has great power over the future plan's accuracy; therefore, it is highly suggested to carefully choose the right method. Moreover, they must choose between a demand-driven and supply-driven supply chain to best suit their product. These decisions require long-term planning, as they might shape the strategies and objectives of a firm. Finally, each entity in the supply chain must ensure complete compliance and improve its operations to help one another. Implementing these tactics would benefit all parties and increase the supply chain surplus.

Although this research reached its aims and objectives, there are several limitations that future research could avoid and overcome. This was simulation-based research, which was implemented and tested through a case study with simulated results. Some products' data was not accessible due to the sensitivity of the required data. This study could be further improved if it were applied to more products from different industries. Future research suggestions are to conduct an empirical study to test the propositions above and to expand its horizons, which can also be done through the usage of data from different industries. Also, another suggestion would be to test the practices that would mitigate the BWE in a supply chain.

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