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Research Article

Quantifying the Bullwhip Effect in Supply Chains: A Stochastic Simulation Approach

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Abstract: The Bullwhip Effect (BWE) 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 on any supply chain. The results show that when consumer demand is unstable, the BWE is magnified. This was achieved by using the proposed formula which was based on an explanation and graph of the traditional BWE. 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 Effect (BWE), supply chain management, demand uncertainty, risk evaluation

MSC: 90B06, 90B50, 90C59

1. Introduction

The Bullwhip Effect (BWE) is currently one of the principal challenges faced by supply chains. It 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" [1]. This effect is referred to as the BWE because when the data is graphed, it forms an amplitude similar to a whip, with all its increases and decreases. The BWE has numerous negative effects and leads to inefficient 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 [2, 3]. This results in lower profitability. Lee et al. [1] 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 resources to deal with fluctuations 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 [4, 5]. The BWE has been observed in every sector, including the service sector. According to Akkermans et al. [6], it is also present in-service supply chains because of fluctuations in demand. Demand fluctuation is a major challenge faced by operations and supply chain managers, planners,

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and forecasters [7]. It has an impact on every department in the 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 it. Recent research has also explored mathematical and optimization-based approaches to supply chain dynamics using differential equations and heuristic methods. For example, Rarità et al. [8] introduced numerical schemes and genetic algorithms for the optimal control of continuous supply chain models, while Rarità [9] extended this idea by applying a genetic algorithm to optimize supply chain dynamics through processing velocity variations. Similarly, D'Arienzo et al. [10] applied differential equation models with a situation awareness strategy to supply networks in wine production, highlighting the effectiveness of advanced mathematical formulations in capturing bullwhip-related phenomena. This phenomenon has been gaining academic interest and it has been studied across various industries; for example, economic and operations literature, as well as in related fields. Many case studies and empirical studies demonstrate the existence of the BWE; however, this effect still influences many supply chains, regardless of their size.

The 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 of the supply chain. This paper also contributes to the literature by providing evidence for the existence of the BWE. Furthermore, it will also give managers an insight into the magnitude of the effect and help them develop a better understanding of how to mitigate the BWE.

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

The rest of the paper is divided as follows: In Section 2, a review of the previous literature is provided, including background information and some history on the concept of the BWE and its causes. The methods of evaluation are also included in this section. Section 3 outlines an overview of the methodology used, as well as an explanation and an illustration of the developed model. This model is illustrated through a case study in Section 4. Finally, Section 5 concludes with final remarks and recommendations for future research.

2. Literature review

2.1 *Background*

The BWE has existed for many years across different industries. It was initially known as the Forrester Effect because the first academic description of this phenomenon was attributed to Forrester (1961), who tried to demonstrate the effect through system dynamics. The concept was later developed and appeared in multiple studies [11–14]. Additionally, Sterman [15] studied the BWE at the Massachusetts Institute of Technology (MIT) through the Beer Game, which is an experiential learning game that illustrates various challenges faced by supply chains. He arguedthat the main cause of this effect was 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 at Procter & Gamble (P & G) in the early 1990s, with the brand "Pampers", which produces diapers for babies. The demand for diapers was relatively stable with slight fluctuations; however, drastic fluctuations appeared in the retail order from the wholesaler, and these fluctuations increased in later stages of the supply chain.

Lee et al. [1] were among the first informative researchers to discuss the BWE and give a clear overview of this phenomenon. The article provides evidence through a case study of a soup manufacturer and relates it to price fluctuations. They measured the BWE by comparing the order variance with the demand variance, which captures the distortion of information that occurs upstream. Other empirical studies examined the difference between shipments, order receipts, and sales. For example, if the shipment data are unavailable, both sales and inventory data can be used to capture the essence [16, 17]. The main idea behind the BWE is that an insignificant change in customer demand builds up and is magnified as it goes upstream in the supply chain, as shown in Figure 1 below.

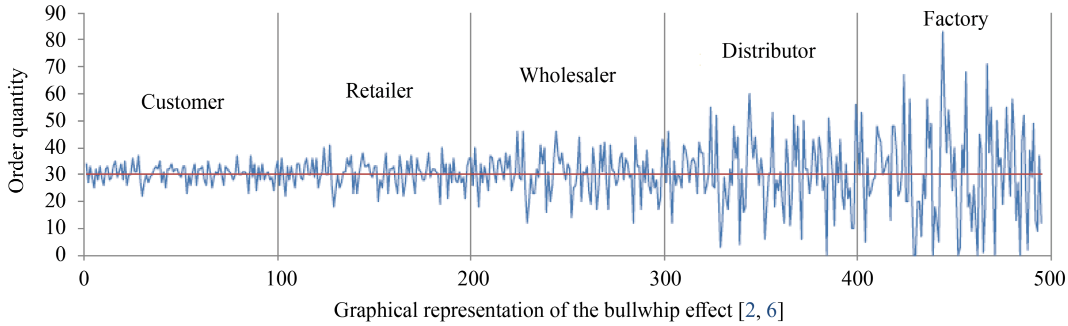

Figure 1. Graph of the BWE Shaban et al. [18]

To assess the BWE, Cannella et al. [19] developed a two-criterion performance measurement system that assesses the satisfaction of customers and the efficiency of internal processes. Operational performance was measured by various Key Performance Indicators (KPIs), including operational responsiveness, inventory stability, etc., and a new KPI: zero replenishment. On the other hand, customer satisfaction was measured at the order fill rate and backlogs. This assessment also estimated the overall supply chain performance rather than a single supply chain stage or an internal supply chain.

2.2 *Causes of the BWE*

Various causes have led to the BWE in supply chains. Bhattacharya et al. [20] categorized the causes into two groups: operational and behavioral. The first operational cause is poor communication and a lack of proper exchange of information [21]. When incomplete information moves along the supply chain, it creates misconceptions regarding current customer demand, and firms may 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 et al. [22] 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 to facilitate collaboration with all supply chain members. The second operational cause is price fluctuations. Constant changes in prices and the introduction of promotions can 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. [1], the demand-forecasting technique used by a firm has a massive impact on the BWE. Therefore, firms must determine the most suitable method to ensure accurate demand planning [23]. The forecaster must consider the available data being used and the type of demand, e.g., seasonal, trend, etc. In addition, some researchers agree that Minimum Mean Squared Error (MMSE) forecasting is capable of generating more precise results for demand processes [24–26]. Another factor that contributes to the BWE is time delays. Towill [23] emphasized that any delay in material or information flow, both upstream and downstream, can result in demand amplification. Other researchers argue that lead times are a driving factor in BWE and that order variability increases with them [1, 27, 28]. However, Chaharsooghi et al. [29] argued that lead times and the BWE are irrelevant. They used a simulation to hold all other factors constant and test only the effect of lead times on the BWE. They found that it may influence inventory and, in some cases, lead to uncertainty, but not to the BWE. Finally, replenishment or ordering policies are also factors that may cause BWE [30, 31].

Bhattacharya et al. [19] indicated three main behavioral causes linked to the BWE: neglecting time delays in making ordering decisions, lack of proper training, and fear of empty stock. Croson et al. [32] pointed out that many supply chains ignore the time factor when planning future orders, and thus any minor delay or variability in time automatically leads to

BWE. According to Wu et al. [33], managers tend to overlook the fact that most employees need specific training, which can lead to decision-making errors. These errors are 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 the BWE*

In the previous operations literature, some papers quantified the BWE. For example, Cachon et al. [17] used industry-level data to detect the effect in the wholesale industry, while Bray et al. [34] used firm-level data to measure this effect. Both studies used data that connected buyers and suppliers, in single-echelon settings. Further research in this field was conducted by Isaksson et al. [35], 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 demand variability in both upstream and downstream supply chain stages. Their results suggest that the magnitude of the BWE is more significant than previous estimations [17, 34]. Since some fields are more susceptible to the BWE, companies need to take that into account and measure the effects when required.

According to Chen et al. [36], 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 is upstream or downstream [37]. When information sharing exists between the upstream and downstream stages, the bullwhip measure must be adjusted to ensure accuracy and reduce variability. These authors also found that the bullwhip ratio increased when the upstream stages shortened their order fulfillment interval or replenishment lead times. Consequently, the performance of vendor-managed inventory programs improves. Their analysis suggests that aggregate planners are likely to disregard the BWE at the individual product level. Most financial planning and investment decisions are made 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 at the industry or firm level. Their research also indicates that time aggregation can reduce the effect. Another study by Jin et al. [38] had similar conclusions.

Moreover, Hussain et al. [39] employed the Taguchi design of experiments and system dynamics simulation to quantify the relationship between 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 can lead to a change in other parameters as well. Managers, therefore, must take these results into consideration when making decisions, to avoid complications. Hussain et al. [39] also indicated that altering lead times and inventory errors can change the order variance compared to other parameters. In addition, Nagaraja et al. [40] further demonstrated the relationship between the magnitude of the BWE, lead time, and seasonal lag through the use of the Seasonal Autoregressive Moving Average (SARMA) model. SARMA is a model that combines the Autoregressive (AR) element and the Moving Average (MA) component with the seasonal element. The theory was applied to a single-item, two-stage supply chain with 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. Moreover, if adjusting the lead time is not possible, then a fractional ordering policy would be more suitable for the firm, as recommended by Gaalman [41].

3. Methodology

This 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 offer better solutions. Recently, computer simulations have been widely used in business. Decision makers and business analysts often use computer simulations to better understand the operating characteristics of any given system, as they encapsulate the essence of different scenarios.

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 [42]. Moreover, this model must have controllable and uncontrollable variables, and constraints that bind the system. The behaviors observed are the result of changes in these variables [43]. 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 relationships between different variables. When developing a mathematical model, one must first consider the system being represented and then select the suitable model. To begin with, a deterministic model is one in which the outputs are fully determined based on the model's parameters. This model is best used when the purpose is to understand the mechanism of a process or system, as mentioned in Choy et al. [44]. In addition, deterministic models are mainly used in scientific research and fields such as climate, populations, or other sciences such as chemistry [45, 46]. On the other hand, a stochastic model, also known as a probabilistic model, produces variables that vary randomly based on the 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 [47]. According to Gillespie [48], stochastic simulation is the most accurate type of simulation; however, it has the disadvantage of being complex and highly computational.

For the current study, a stochastic simulation was used to test the equation. This method was chosen for various reasons. First, since the main factor is demand and this is unstable and dynamic, a stochastic model represents it in the most accurate way, as it creates a projection based on a set of random values. Moreover, it provides insights into the system's behavior over a period of time with an appropriate level of detail. Furthermore, a computer simulation allows the test and the exploration of numerous scenarios and the effects of changing any variable. This can be done through a "what if" analysis. Finally, a virtual experiment was used because real data were not accessible. To ensure robustness of results, multiple stochastic simulation runs were performed and the averaged outcomes were used in the analysis. This procedure follows standard practice in stochastic modeling and reduces the impact of random fluctuations on the final estimates.

3.1 *Modeling the BWE*

The BWE can be represented through the following equation:

$$\mathrm{BWE}_{i,\ p}^{j,\ m,\ x} = \left[\left(\frac{Q_i^{j,\ m,\ x} - \left|Q_i^{(j,\ m,\ x-1)} - Q_i^{j,\ m,\ x}\right|}{D_i}\right) - 1\right] \times 100. \tag{1}$$

This equation 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 the product, while 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. $Q_{i,\ p}^{(j,\ m,\ x\ -1)}$ denotes 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 taken as an absolute value because the main objective is to find the magnitude of fluctuations in this context. Whatever the resulting value is, it must be used as a positive number in the equation.

The formula above encapsulates the BWE more effectively and provides a means to quantify the BWE. By using it, any entity in the supply chain can determine 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 large surplus, or it may only cover a small fragment of the demand. If the result is positive, it means that the firm can satisfy the demand but with some excess. However, if the result is negative, it indicates that the firm cannot cover the customers' demand. For example, if the result is 30%, it indicates that the firm has 30% more than the required quantity, but if the result is -40%, it means that 40% of the demand is not covered. This formula uses historical data to help a company understand how to cover demand with minimum losses. An enterprise may also use the mean of the previous year to assist in planning and forecasting future demand.

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

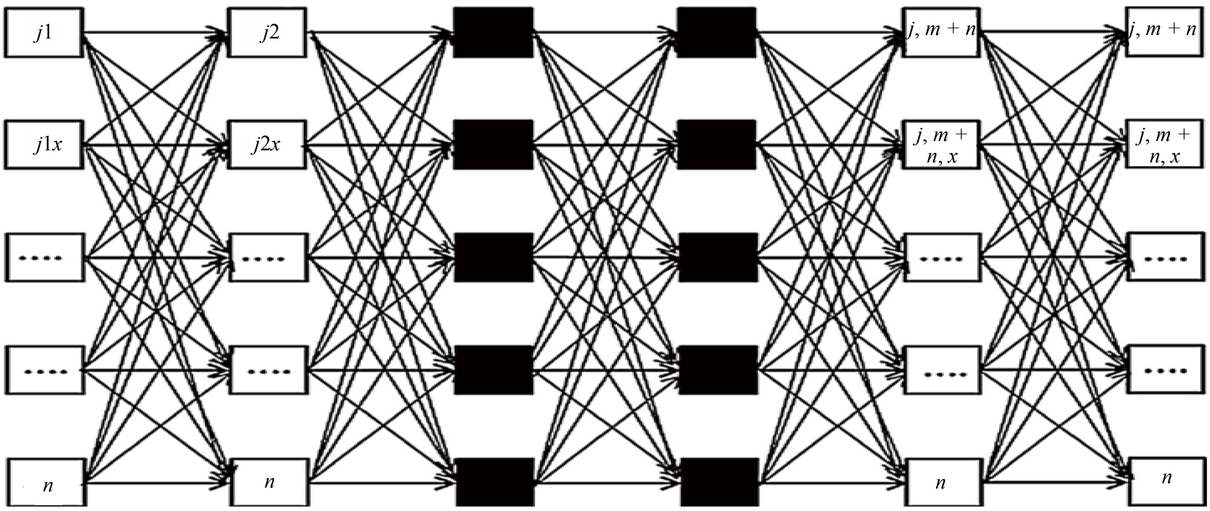

Figure 2. Complex supply chain network Almaktoom et al. [49]

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

To ensure that this formula is applied correctly and that all supply chains benefit from it, there must be proper sharing of information and data and full compliance from 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 within the supply chain.

4. Case study

This case study presents a supply chain consisting of five levels, as demonstrated in the Figure 3. The first level, $j1$, is the source of raw materials and the main supplier to the factories. There are two factories producing the products: $j2$, where the items are manufactured, and $j2x$, where manufacturing is completed and products are packed. Moreover, $j3$ 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 are sold to the end customers. Each entity in this supply chain places its orders on a quarterly basis. Orders flow upstream and the product moves downstream in the supply chain.

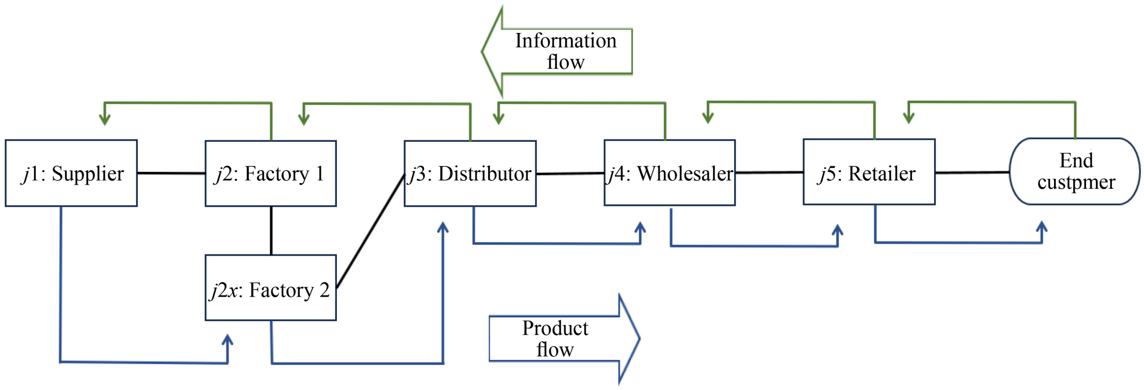

Figure 3. Supply chain diagram

To summarize, two products were 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 was recorded monthly and then aggregated to find the quarterly demand. Most entities in this chain do not share proper information with one another; however, after realizing that the BWE was an obstacle, they decided to appropriately share the required information with each other. This design choice highlights the role of information sharing in amplifying or mitigating the BWE. Initially, the lack of transparency magnified distortions, whereas later collaboration helped reduce variability across entities.

Table 1. Demand and 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

The previous tables are the results of the simulation. Table 1 shows the quantities from $p1$ that are displayed, and Table 2 shows the quantities for the product $p2$. As previously mentioned, orders are made every quarter, and the data in the tables above are 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. The 15% safety stock level reflects a common retail practice cited in industry reports and prior studies. This assumption adds realism to the simulation and also influences the resulting order variance, thereby reinforcing the observed bullwhip dynamics. $Q_{i,\ p}^{j4}$ 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 same quantity. $Q_{i,\ p2}^{j2}$ is the quantity ordered by factory $j2$ to the raw material suppliers. The formula was 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 in Figures 4-6.

Table 2. Demand and 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	1,280	2,720
2	350	580	580	1,230	2,620
3	210	350	350	740	1,570
4	320	530	530	1,130	2,400
5	230	380	380	810	1,720
6	430	720	720	1,530	3,260
7	360	600	600	1,280	2,720
8	430	720	720	1,530	3,260
9	440	740	740	1,570	3,340
10	270	450	450	960	2,040
11	350	580	580	1,230	2,620
12	360	600	600	1,280	2,720
13	420	700	700	1,490	3,170
14	410	680	680	1,450	3,090
15	420	700	700	1,490	3,170
16	360	600	600	1,280	2,720
17	410	680	680	1,450	3,090
18	340	570	570	1,210	2,580
19	290	480	480	1,020	2,170
20	410	680	680	1,450	3,090

In the previous tables, the BWE formula was used to calculate the results. The average BWE per entity was the sum of the BWE per period over the number of periods, 20 quarters in this case. The average labels 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 are included to give a complete picture of the situation at each stage.

Table 3. BWE-product 1

$P1$	Average orders/Quarter	Range	$\mathrm{BWE}_{i,\ p1}^{j,\ m,\ x}$
$J5$	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%
$J3$	1,270.5	830	90%
$J2$	2,703.5	1,770	254%

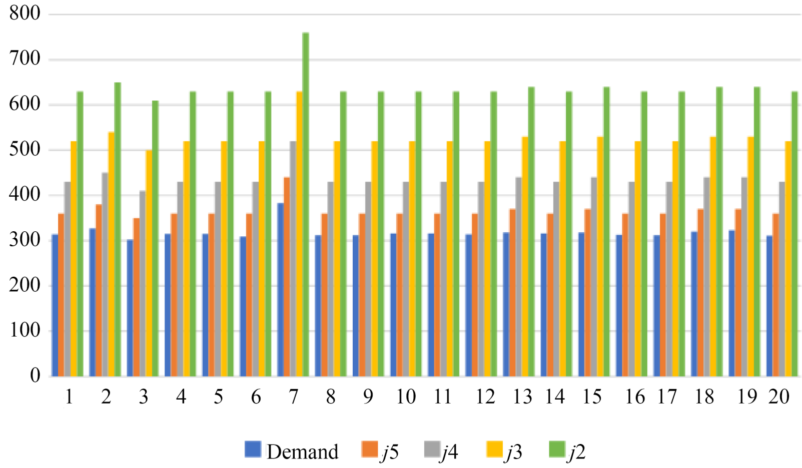

Figure 4. Visual representation of quantities ordered $p1$

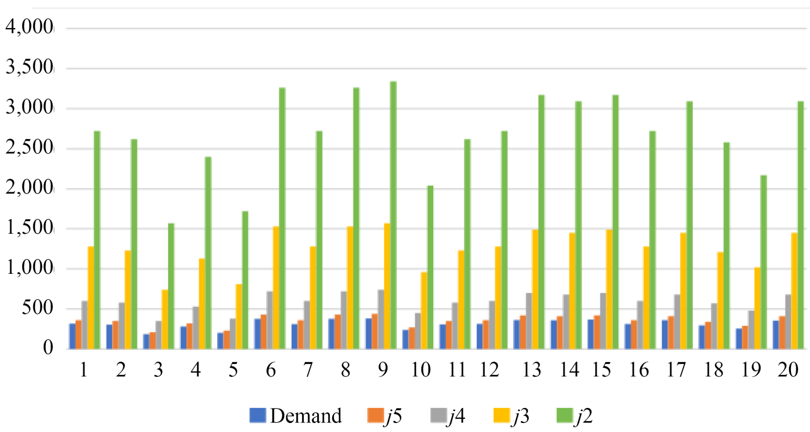

Figure 5. Isual representation of quantities ordered $p2$

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

The average demand per quarter for $p2$ was 311, and the quantity range was 196. As mentioned previously, $p2$ experiences more fluctuations and this is visible in Table 4 above. The entities experienced dramatic bullwhip results, especially $j4$ with an average BWE of 254%. This percentage indicates that they had a huge order supply of $p2$, which was not really needed. In addition, the excess quantities could have a negative influence on the firm because they would increase holding costs, and if they were not used at the right time, they could go to waste.

The previous figures graphically display the difference between demand and orders at each stage. In both products, entity $j2$ experiences more BWE than other stages. The main cause of this complication was basing production plans or orders solely on the demand from the next stage. In Figure 5 above, the entities $j2$ and $j3$ best exemplify the BWE and how much excess investment it caused. At these stages, the company spent a huge amount of money and bought unwanted products. If the plans had been based on end-customer demand, this problem would have been avoided.

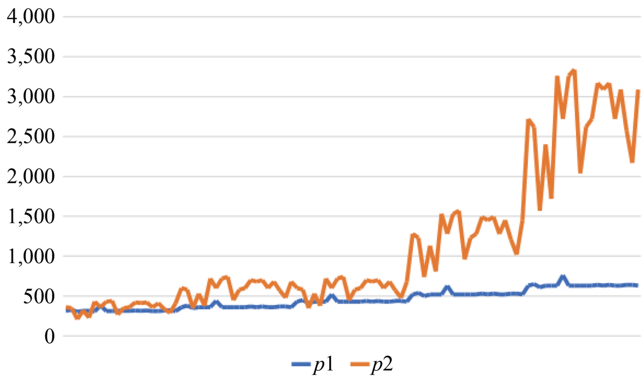

Figure 6. Comparison of ordered quantities for $p1$ and $p2$ (x-axis: different stages of supply chain)

Figure 6 gives comparison of Ordered Quantities for $p1$ and $p2$. The x-axis represents supply chain stages (end customer → retailer → wholesaler → distributor → manufacturer), while the y-axis illustrates the average ordered quantities per quarter. The figure illustrates how order variance amplifies upstream, with $p2$ (volatile demand) showing much stronger magnification than $p1$ (stable demand) This figure 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 was visible that as we move away from the end customer, the effect was magnified. In addition, this graph illustrates the BWE definition completely, where raw demand influences the supply chain the most. The orders for $p1$ demonstrate variation, but it was not as significant as that for $p2$. This confirms that more variation leads to greater BWE.

5. Discussion

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. In addition, the BWE exists in every sector, but different sectors and fields show different results and percentages of the effect. This research focused on quantifying the BWE and considered end consumer demand as a main factor in the evaluation. To achieve the objectives of this research, a formula was developed and derived from the definition of the BWE. This formula was applied to calculate the effects for previous periods using historical data. It can help demand planners, supply chain managers, decision-makers, and forecasters may develop better plans for the coming time periods. This can be done by observing past and 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 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. In fact, the earliest stages of a supply chain can experience a BWE percentage of up to 250% each period.

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

Beyond the present scope, future research avenues emerge. Empirical validation with real datasets across different industries are needed as they would strengthen the findings. Also, the proposed framework could be extended to explicitly incorporate cost, lead time, and inventory dynamics, which are critical for managerial decision making. These extensions would reinforce the practical relevance of the model and deepen its impact on supply chain management.

6. Conclusion

This study presents a practical formula for quantifying the bullwhip effect across multi-tier supply chains. By applying stochastic simulation, the research demonstrates how demand fluctuations and limited transparency contribute to inefficiencies. The proposed model offers a scalable tool for measuring demand magnification and guiding mitigation strategies.

The novelty lies in its adaptability to diverse supply chain structures and its ability to capture dynamic behavior under uncertainty. Future work may explore real-time data integration and advanced forecasting techniques to further reduce variability and enhance supply chain resilience.

Conflict of interest

The author declares no competing financial interest.

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