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Simulation-Based Analysis of the Bullwhip Effect in a Multi-Echelon Bottled Water Supply Chain

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ABSTRACT

This study investigates demand amplification, commonly known as the bullwhip effect, in a hypothetical three-echelon bottled-water supply chain comprising a retailer, distributor, and manufacturer. Due to the absence of empirical transaction data, weekly customer demand is generated using a seasonal Poisson process. Retailer and distributor ordering decisions are modeled using weekly order-up-to policies incorporating four-week moving-average forecasts, variable lead times, safety stock, order batching, and backordering. The simulation consists of 1,000 replications, each with a 52-week warm-up period followed by 208 weeks of analysis. The bullwhip effect (BE) is quantified as the ratio between the coefficients of variation (CVs) of outgoing orders and incoming demand. Under fixed proportional scaling, BE equals 1.000 at both supply-chain interfaces, indicating no amplification. In contrast, the policy-based simulation produces substantial demand amplification, with a median retailer-to-customer BE of 2.792 (95% simulation interval: 2.502–3.118) and a distributor-to-retailer BE of 1.857 (1.655–2.062). The cumulative distributor-to-customer variability ratio reaches 5.175 (4.570–5.936). These findings demonstrate that forecasting, replenishment policies, lead-time variability, safety stock, batching, and backordering can collectively amplify demand variability as orders move upstream. The results should be interpreted as evidence of the behavior of the specified simulation model rather than as a representation of any actual company or supply chain..

Keywords: *Bullwhip effect, discrete-time simulation, order-up-to policy, multi-echelon supply chain, synthetic demand.*

Introduction

The bullwhip effect (BE) occurs when replenishment orders become more variable as they move upstream through a supply chain. A retailer may receive fairly stable customer demand yet place uneven orders with its distributor. The distributor's orders to the manufacturer can fluctuate still more [1]. Recent evidence from U.S. manufacturing confirms that bullwhip remains relevant to production and inventory planning [2].

Established explanations include demand-signal processing, forecast updates, lead times, order batching, price changes, and rationing behavior [1], [3]. Brauch et al. group the wider literature into four categories: system structure, uncertainty, misaligned incentives, and cognitive limitations [4]. Laboratory research also shows that human ordering behavior can affect upstream costs [5]. These mechanisms may interact. A BE value alone therefore cannot identify its cause.

Amplified orders can complicate capacity planning and inventory control, increase expediting, and produce alternating shortages and excess stock [1], [4]. Recent network-design research also shows why order variability matters for planning decisions [6]. Information sharing and coordinated replenishment are common responses, but their value depends on the information available and how partners use it [7]. Studies of partial collaboration [8] and retail channels [9] examine this dependence in different supply-chain settings.

Measuring amplification requires a consistent definition. Fransoo and Wouters [10] use the coefficient of variation of an upstream output divided by that of its downstream input. This measure accounts for differences in average quantities between supply-chain stages. Multiplying every observation by a positive constant changes the mean and standard deviation in the same proportion, leaving the CV unchanged. Fixed multipliers can therefore increase absolute variance without increasing relative variability.

Indonesian studies have examined bullwhip in mineral-water distribution and vendor-managed inventory in industrial supply networks [11], [12]. These studies provide relevant context for consumer-goods distribution. They do not supply operational records for the network modelled here, so the present analysis makes no claim about an actual company.

Synthetic data can support supply-chain research when proprietary records are unavailable, provided that their purpose, assumptions, generation procedure, and limitations are clear [13]. Simulation also requires explicit model logic, control of random-number generation, and checks suited to its intended use [14]. This

study follows those principles in a hypothetical three-node bottled-water network serving a Yogyakarta-type market.

The study measures relative variability at two ordering interfaces: retailer orders sent to the distributor and distributor orders sent to the manufacturer. It does not measure manufacturer procurement or production orders, inventory costs, or total supply-chain efficiency. The research question is:

In the specified three-node simulation, how much is relative variability amplified in retailer and distributor replenishment orders, and how stable are the bullwhip ratios across repeated runs?

Research Methodology

Study Design and Scope

The model represents one bottled-water stock-keeping unit supplied through a retailer, a regional distributor, and a manufacturer. Customer demand reaches the retailer. Retailer replenishment orders then become the distributor's incoming demand, and distributor orders become the demand signal received by the manufacturer. No further manufacturer order stream is generated, so manufacturer outbound BE is not reported. The analysis is a simulation of this hypothetical setting.

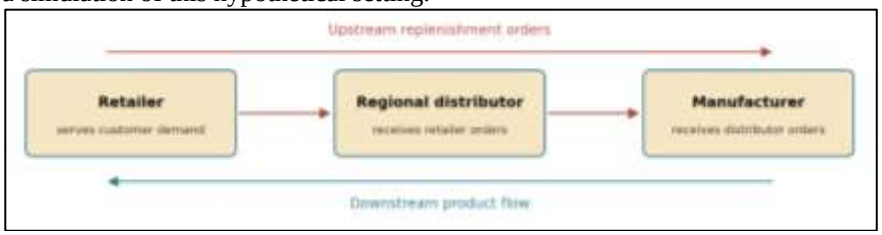


Figure 1. Simulated bottled-water supply-chain structure (retailer-distributor-manufacturer).

Synthetic Customer-Demand Process

The twelve monthly values retained from the submitted analysis serve as assumed seasonal mean demand inputs, as listed in Table 1. They are not observed sales. The profile repeats on a non-leap, 365-day calendar beginning on 1 January. Each week is assigned to the month containing its midpoint. If that month is j, its weekly mean equals the monthly mean M_j multiplied by 7 and divided by the number of days c_j in the month. Weekly customer demand D_t is drawn independently from a Poisson distribution:

$$D_t \sim Poisson(\lambda_t), \quad \lambda_t = 7M_j / c_j \tag{1}$$

The Poisson process produces nonnegative integer demand and random variation around the seasonal profile. This variation creates forecast discrepancies. The distribution is a stated scenario assumption; it has not been fitted to company transactions.

Table 1. Assumed monthly mean customer-demand inputs.

Month	Mean (ctn)	Month	Mean (ctn)	Month	Mean (ctn)
Jan	100	May	140	Sep	150
Feb	90	Jun	150	Oct	130
Mar	110	Jul	160	Nov	120
Apr	130	Aug	180	Dec	100

Note: The assumed monthly means total 1,560 cartons per year, or 130 cartons per month on average. These values are scenario inputs, not observed transactions.

Forecasting, Lead Time, Safety Stock, and Ordering Logic

Each echelon reviews inventory weekly. After receipts and incoming demand are processed at the end of week t, echelon e calculates a simple moving-average forecast from the four most recent incoming-demand observations. Moving-average forecasting and lead-time-based replenishment are established in analytical bullwhip models [3]. Later studies examine stochastic lead times [15], their interaction with demand patterns [16], and dependence between successive lead times [17]. These studies motivate the mechanisms considered here; they do not calibrate this scenario. The forecast is:

$$\hat{d}_{e,t} = (1/m) \sum_{i=0}^{m-1} d_{e,t-i}, \quad m = 4 \tag{2}$$

The echelon also calculates the sample standard deviation s(e,t) from the available observations in the same window. A prospective lead time L(e,t) is sampled independently at each weekly review and applies to any order placed that week. The review period is R = 1 week and the safety factor is z = 1.645. The target order-up-to level is:

$$S_{e,t} = \hat{d}_{e,t}(R + L_{e,t}) + z\, s_{e,t}\sqrt{(R + L_{e,t})} \tag{3}$$

Immediately before ordering, inventory position IP(e,t) equals on-hand inventory plus outstanding replenishments minus backorders. Unmet demand remains in the backlog. Orders arrive in full after the sampled lead time; the model assumes no capacity limits, partial shipments, or cancellations. Replenishment quantities are rounded upward to the batch size B_e:

$$Q_{e,t} = B_e \, ceil(max(0, S_{e,t} - IP_{e,t})/B_e) \quad (4)$$

Orders therefore depend on forecast revisions, inventory position, safety stock, the sampled lead time, and batch size. They are not fixed multiples of incoming demand. Table 2 lists the baseline parameters. Each echelon uses only its own incoming-demand history, following the decentralized information structure commonly examined in bullwhip research [18].

Table 2. Baseline simulation parameters and assumptions.

Parameter	Retailer	Distributor
Incoming signal	Customer demand	Retailer orders
Review period R	1 week	1 week
Forecast	4-week moving average	4-week moving average
Lead-time distribution	1 week (0.75); 2 weeks (0.25)	1 week (0.50); 2 weeks (0.50)
Safety factor z	1.645	1.645
Order batch B_e	5 cartons	10 cartons
Shortage handling	Backorder	Backorder
Information available	Own incoming-demand history	Own incoming-order history

All parameter values are scenario assumptions chosen to represent the replenishment mechanisms examined. They have not been calibrated to a named retailer, distributor, or manufacturer.

Bullwhip Metric and Decision Rule

The sample standard deviation and coefficient of variation of each signal X are calculated over the same n = 208 weeks after warm-up. The CV expresses variability relative to the signal mean:

$$CV(X) = s_x/\bar{X}, \quad s_x = \sqrt{[\sum_{t=1}^{n}(X_t - \bar{X})^2/(n-1)]} \quad (5)$$

Following the CV-ratio definition [10], local amplification is measured at each ordering interface. A separate cumulative ratio compares customer demand with distributor orders received by the manufacturer:

$$BE_R = CV(Q_R)/CV(D); \quad BE_D = CV(Q_D)/CV(Q_R); \quad BE_C = CV(Q_D)/CV(D) \quad (6)$$

The neutral value is 1.000. BE > 1 indicates amplification, BE = 1 unchanged relative variability, and BE < 1 smoothing. The former cutoff of 1.011 is not used. Lead-time-dependent bounds such as those derived by Chen et al. [3] apply to a specific variance-ratio measure and forecasting model. They cannot serve as a universal cutoff for the CV ratio.

Simulation Horizon, Reproduction, and Validation Checks

Each of the 1,000 replications covers 260 weeks. The first 52 weeks are discarded to reduce initialization effects, leaving 208 observations for analysis. Initial on-hand stock equals the first estimated order-up-to target. Random numbers are generated with NumPy 2.3.5 and its default PCG64 generator, using master seed 20260618. Independent child streams generate customer demand, retailer lead times, and distributor lead times. Figure 2 outlines the sequence.

Four checks were applied. First, the fixed-scaling benchmark Q_R = 1.10D and Q_D = 1.15Q_R gave BE_R = 1.000 and BE_D = 1.000, confirming that proportional scaling leaves the CV unchanged. Second, every order was nonnegative and an exact multiple of its specified batch size. Third, the inventory-balance identity held each week. Mean weekly flows after warm-up differed by only 0.0014 cartons between customer demand and retailer orders, and by 0.0015 cartons between retailer and distributor orders. Fourth, extending the discarded warm-up from 52 to 104 weeks changed the three median BE ratios by at most 0.46%. The 2.5th and 97.5th percentiles across replications form the reported 95% simulation intervals. These checks establish internal consistency; they do not replace external validation with operational records [14].

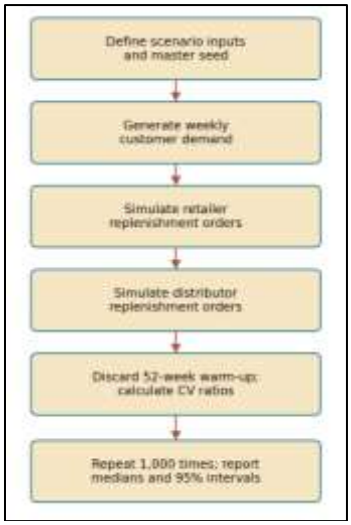


Figure 2. Reproducible simulation and analysis workflow.

The following example uses replication 451, selected as the run closest to the joint medians of the three BE measures. Customer demand has mean 29.9952 and sample standard deviation 7.7656 cartons, giving CV(D) ≈ 7.7656/29.9952 ≈ 0.2589. Retailer orders have mean 30.0000 and standard deviation 21.7862, so CV(Q_R) ≈ 0.7262 and BE_R ≈ 2.8050. Distributor orders have mean 29.9038 and standard deviation 40.1325, giving CV(Q_D) ≈ 1.3421. Thus, BE_D ≈ 1.3421/0.7262 ≈ 1.8480, and BE_C ≈ 1.3421/0.2589 ≈ 5.1838. Ratios are calculated from unrounded values; the intermediate values shown here are rounded.

Results and Discussion

Simulated Demand and Order Behavior

Across 1,000 replications, average weekly customer demand was 29.9417 cartons. Mean retailer and distributor orders were 29.9431 and 29.9446 cartons, respectively. Average flow was therefore nearly the same at each stage after warm-up. The amplification concerns order variability, rather than an imposed increase in average order quantity.

Figure 3 shows the final 52 weeks of replication 451. Customer demand varies around the seasonal profile. Retailer orders alternate between zero and larger batches, while distributor orders show still larger intermittent peaks as they respond to retailer orders. This run illustrates the pattern; the distributions across all replications provide the main numerical evidence.

Coefficient-of-Variation and Bullwhip Results

Table 3 presents the CV-based results. Retailer BE is 2.805 in the representative run and 2.792 at the replication median. Local distributor BE is 1.848 and 1.857, respectively. All four values exceed 1, indicating amplification at both ordering interfaces in the simulated baseline. The cumulative distributor-to-customer ratio is 5.184 in the representative run and 5.175 at the median.

Table 3. Corrected CV-based bullwhip results for representative replication 451 and 1,000-run summary.

Signal / comparison	Mean	SD	CV	BE: run 451; median [95% interval]	Interpretation
Customer demand	29.995	7.766	0.259	Baseline	Reference
Retailer orders / customer demand	30.000	21.786	0.726	2.805; 2.792 [2.502, 3.118]	Amplification
Distributor orders / retailer orders	29.904	40.133	1.342	1.848; 1.857 [1.655, 2.062]	Amplification
Distributor orders / customer demand	-	-	-	5.184; 5.175 [4.570, 5.936]	Cumulative amplification

Notes: Mean, SD, and CV refer to replication 451. In each BE cell, the first value is that run's ratio and the second is the median across 1,000 replications, followed by the 2.5th–97.5th percentile simulation interval. Means and SDs are in cartons per week; CV and BE are dimensionless. BE > 1 indicates amplification.

Both local 95% simulation intervals lie entirely above 1. Every replication also produced BE_R > 1 and BE_D > 1. Figure 4 shows the full distributions. The interpretation is consistent: both ordering interfaces

amplify relative variability under the stated assumptions, and distributor orders sent to the manufacturer have the greatest relative variability.

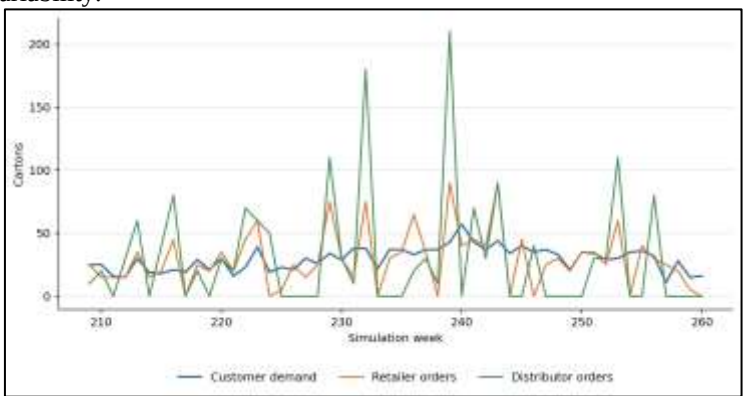


Figure 3. Final 52 weeks of representative replication 451 (cartons per week).

Interpretation of the Simulated Results

The fixed-scaling benchmark confirms that multiplying demand by a positive constant cannot establish CV-based amplification. In the policy model, forecasts, sampled lead times, safety-stock estimates, inventory position, and batch rounding jointly determine replenishment. These rules produce intermittent orders even when mean flow remains close to mean customer demand. Research on batching in retail distribution [19] and closed-loop supply chains [20] also links order patterns to replenishment settings.

The simulated pattern is consistent with research on forecast updating and lead time [3], [15]. Recent studies further show why forecast uncertainty [21], seasonality [22], and the forecasting method used for integer demand [23] matter when interpreting bullwhip. Work on proportional order-up-to policies [24], [25] and order smoothing [26] examines how forecast and replenishment choices interact. Studies of systems with material reuse likewise show the importance of the modelled supply-chain structure [27]. These findings provide context for the present model, rather than direct numerical benchmarks for it.

Interpretation remains limited to the simulation. Forecast updating, variable lead time, safety stock, and batching are specified model inputs; the order spikes are outputs of their combined operation. The experiment does not isolate each mechanism's contribution. It also does not establish that an actual retailer or distributor follows these policies, lacks demand visibility, holds conservative inventory, or experiences the reported BE values.

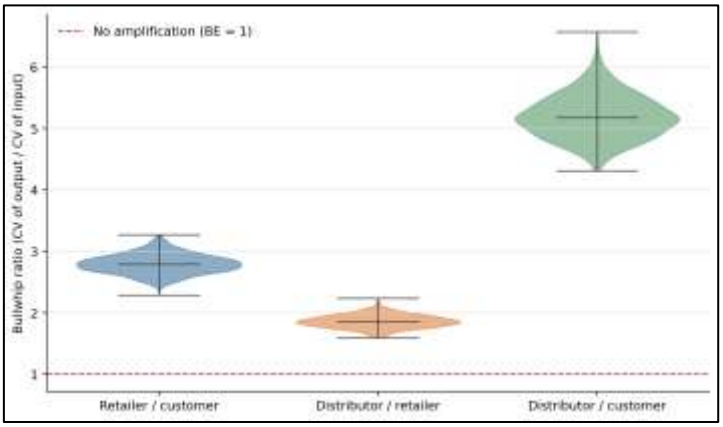


Figure 4. Distribution of corrected BE ratios across 1,000 replications.

Theory-Informed Managerial Implications

Access to customer demand, coordinated forecasting, smaller batches, and more stable lead times are potential options for reducing demand distortion [7]. Research on communication [28], downstream-demand inference [29], and forecasting methods and horizons [30] provides further grounds for testing such options. Vendor-managed inventory can also change information flows and replenishment decisions [12], [31]. Their benefits depend on the setting, including the demand process [16]. None of these alternatives was evaluated separately in the present experiment. They are literature-informed options for future testing, not verified remedies for this network or a named company.

The next practical step is to obtain weekly point-of-sale demand, replenishment orders, realized lead times, batch rules, inventory positions, and stockout records from participating firms. These records could support

parameter calibration and external validation. They would also allow the baseline to be compared with specific mitigation policies.

Conclusion

This study provides a reproducible simulation of a hypothetical multi-echelon bottled-water supply chain. It uses the coefficient-of-variation ratio consistently, with 1.000 as the neutral value. Fixed proportional scaling correctly gives no amplification. The replenishment model instead generates orders through forecast updates, variable lead times, safety stock, batch rules, and inventory position.

Median retailer-to-customer BE is 2.792, and median distributor-to-retailer BE is 1.857. Both local 95% simulation intervals remain above 1. The cumulative distributor-to-customer ratio is 5.175. These results answer the research question: both ordering interfaces amplify relative variability under the baseline assumptions, and this finding holds across the repeated runs.

The findings apply to the specified simulation. They do not measure actual company operations, identify empirical causes, or quantify inventory cost or overall supply-chain efficiency. The contribution is a reproducible demonstration of how the stated replenishment rules can generate upstream amplification. Future work should use operational data to calibrate and externally validate the model, then compare information sharing, smaller batches, more stable lead times, and alternative forecasts in explicitly defined scenarios.

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