Using Demand Uncertainty as a determinant for the Bullwhip Effect

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Bullwhip Effect

Bullwhip Effect

The Bullwhip effect is defined as the amplification of demand variance as one moves upstream in the supply chain.
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Retrieved from Trapero et al. (2012)
Consequences of the Bullwhip Effect

The Bullwhip effect results in:

- Mis-alignment of Production Schedules.
- Increased Inventory.
- Increase in Stock-outs and customer dissatisfaction.
- Improper use of capacity.
- Increase in Transportation Costs.
- To name a few...
Origins of the Bullwhip Effect (Lee et al., 1997)
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Using Demand Uncertainty as a determinant for the Bullwhip Effect
Bullwhip Measurement

In order to measure the Bullwhip Effect, the following ratio of variabilities is used (Chen et al., 2000):

\[
\text{BWR} = \frac{\text{Var}(\text{Orders})}{\text{Var}(\text{Demand})}
\]

Its interpretation is:
- \( \text{BWR} = 1 \) ⇒ No Bullwhip.
- \( \text{BWR} > 1 \) ⇒ Bullwhip exists.
- \( \text{BWR} < 1 \) ⇒ Anti-Bullwhip.

This falls in line with the definition of measuring the propagation of variability upstream.

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This falls in line with the definition of measuring the propagation of variability upstream.
Issues with the current measurement

• Empirical Studies report the Bullwhip as an over-estimated issue due to this measurement (see for e.g. Cachon et al., 2007).
• Does not reflect cost impacts.
• Concealed by both Temporal and Product Aggregation (Chen and Lee, 2012).
• Variance is only meaningful on stationary time series. It fails on series with trend, seasonality etc...

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Trending Demand

Nonstationary Demand: I(1)

Using Demand Uncertainty as a determinant for the Bullwhip Effect
Seasonal Demand

Seasonal Demand Example: Air Passengers Data

Using Demand Uncertainty as a determinant for the Bullwhip Effect
Promotional Demand

Retrieved from Trapero et al. (2014)
Other metrics have been proposed in the literature, such as:

- Inventory Variance Ratio (Disney and Towill, 2003).
- Time Varying Bullwhip Effect Metric (Trapero and Pedregal, 2016).
- An excellent summary can be found in Cannella et al. (2013).
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- Inventory Variance Ratio (Disney and Towill, 2003).
- Time Varying Bullwhip Effect Metric (Trapero and Pedregal, 2016).
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- This is where our research comes in!
Uncertainty

Definition
Forecast uncertainty refers to the unpredictability that arises in forecasting future demand.
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- It is captured by forecasting error metrics.
- Forecasting is one of the four origins of the Bullwhip Effect.
- Uncertainty is not Variability!
Uncertainty vs Variability

Demand Uncertainty: The random variation in the forecasting model, assuming the true demand is known!

Forecasting Uncertainty: How much is not captured by the forecasting method. It includes demand uncertainty and the effect of model mis-specification.

Demand variability: the fluctuations of demand around its mean.

Demand variability is forecasting uncertainty, if we use the average as a forecasting model.

These terms are often confused in the literature.

Forecast Uncertainty is a cost driver, not demand variability.

Using Demand Uncertainty as a determinant for the Bullwhip Effect
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Using Demand Uncertainty as a determinant for the Bullwhip Effect
Uncertainty vs Variability Example

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Using Demand Uncertainty as a determinant for the Bullwhip Effect
Error Metrics

The error metric we will look at is the Root Mean Squared Error (RMSE).

It is the conditional standard deviation of the forecast errors, provided they are homoscedastic.

In the literature, the term variance (standard deviation) is used to denote the unconditional variance (standard deviation), which is asymptotic.

From the Bias-Variance Decomposition, the MSE (RMSE) encapsulates the variance (standard deviation):

$$\text{MSE} = \text{Bias}^2 + \text{Variance} + \text{Irreducible Component}$$

Demand Uncertainty

Forecast Uncertainty
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Using Demand Uncertainty as a determinant for the Bullwhip Effect
RMSE link to cost
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Using Demand Uncertainty as a determinant for the Bullwhip Effect
Why RMSE?

- RMSE is fed into the calculation of Safety Stocks. For example, in an OUT policy, safety stocks are calculated as:

\[ SS_t = \hat{F}_t + L + \Psi - 1 + \alpha \sqrt{\sigma_t^2 + L} \]

- It is an actionable metric, i.e. actions can be taken in obtaining better forecasts, which is reflected in the metric.
- Captures the propagation of demand uncertainty.
- Accounts for the Lead Time over which decisions are made.
- Handles Nonstationarity, seasonality and promotions.
- Captures modelling uncertainty and mispecification.
- Improvements in the process will be reflected in the metric.
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Proposed Measure

Using Demand Uncertainty as a determinant for the Bullwhip Effect
Proposed Measure

RMSE ratio

We propose to measure the Bullwhip as the ratio of Root Mean Squared Error (RMSE) over Lead Time of Manufacturer to Retailer.

\[ \frac{\text{RMSE}}{\text{Lead Time}} \]
Proposed Measure

RMSE ratio

We propose to measure the Bullwhip as the ratio of Root Mean Squared Error (RMSE) over Lead Time of Manufacturer to Retailer.

The current metric we propose is:

$$RMSE_{Ratio} = \frac{RMSE_M}{RMSE_R}$$  (3)
RMSE Equations

In order to get the ratios:

1. Calculate the point forecasts and the point errors for both.
2. Calculate the Aggregate Forecasts and Errors over Lead-Time for both.
3. Calculate the RMSE of the Aggregate Errors for both.
4. Take the ratio of RMSE of Manufacturer to Retailer.
RMSE Equations

\[ RMSE_M = \sqrt{\frac{1}{(n_M - L_M + 1)} \sum_{t=1}^{n_M-L_M+1} \left( \sum_{i=1}^{L_M} d_t - \sum_{i=1}^{L_M} f_{t|t-L_M} \right)^2} \]  

(4)

\[ RMSE_R = \sqrt{\frac{1}{(n_R - L_R + 1)} \sum_{t=1}^{n_R-L_R+1} \left( \sum_{i=1}^{L_R} d_t - \sum_{i=1}^{L_R} f_{t|t-L_R} \right)^2} \]  

(5)

Using Demand Uncertainty as a determinant for the Bullwhip Effect
Information Sharing

• Proposed remedy to the Bullwhip Effect (Lee et al., 1997).
  • The manufacturer has access to the Point of Sales data, and bases his forecasts on demand rather than incoming orders.
  • In the context of demand uncertainty, this implies a reduction in MSE and RMSE.

• Its benefits are contested: theoretically, the value of Information Sharing depends on the process and parameters ((Babai et al., 2013, 2016; Teunter et al., 2018; Ali et al., 2012), while empirically it has appeared to benefit the manufacturer (Trapero et al., 2012).
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- Its benefits are contested: theoretically, the value of Information Sharing depends on the process and parameters ((Babai et al., 2013, 2016; Teunter et al., 2018; Ali et al., 2012), while empirically it has appeared to benefit the manufacturer (Trapero et al., 2012).
• From a forecasting perspective, it can result in a lower MSE.

\[ MSE_{IS} < MSE_{NIS} \implies RMSER_{IS} < RMSER_{NIS}. \]

• Under this logic, we expect that Information Sharing should reduce manufacturer costs and thus be beneficial.

• In this presentation, it is used as a forecasting scenario in the simulation.

• We will later (but not today) compare the Total Costs, Bullwhip Ratio and RMSE Ratios of sharing versus not sharing information.
Design

• Dyadic Supply Chain (1 Manufacturer and 1 Retailer).
• 3 Data Generating Processes from the ARIMA family:
  1. ARIMA(1,0,0)
  2. ARIMA(0,1,1)
  3. ARIMA(0,1,1)(0,1,1)
• Forecasting Methodology:
  Rolling Origin forecasts with automatic ARIMA fitting based on minimisation of the AIC.
• Inventory Policy:
  Periodic (R,S) inventory policy with \( R = 1 \) and unmet sales are backordered.
• Point of Sales vs No Information Sharing.

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Simulation Design

- For both, 3 deterministic values \{1, 3, 5\} of Lead Time + Review Period.
- 3 $\alpha$-service levels for both: \{90%, 95%, 99%\}
- 3 Order batching scenarios: No order batching, multiples of 10 and of 20.
- 3 Values for the model error noise: \{15, 25, 50\}.
- 500 Replications.
- The Bullwhip Ratio and RMSE Ratio are calculated at the Manufacturer’s level.
- 400 Observations (data split explained in the next slide)
Data Partition

Training Set:
- 100 points.
- Forecasting Models.

Inventory Burn-In:
- 200 points
- Inventory Simulation.
- Discard Initialisation Bias.

Test Set:
- 100 points.
- Results are estimated over these.
Two costs are considered: Backordering and Holding. They are calculated at the Manufacturer's level. Total Cost = $b \times \text{Backorders} + h \times \text{Excess Inventory}$. Despite the system working on a $\alpha$ Service Level, costs are approximated by a $\beta$ Service Level. The relationship between the two costs is: $b = (\beta_1 - \beta)h$. Using Demand Uncertainty as a determinant for the Bullwhip Effect.
Costs

1. Two costs are considered: Backordering and Holding.
2. These are calculated at the Manufacturer’s level.
3. Total Cost = $b \times \text{Backorders} + h \times \text{Excess Inventory}$.
4. Despite the system working on an $\alpha$ Service Level, costs are approximated by a $\beta$ Service Level.
5. The relationship between the two costs is:

\[
b = \left( \frac{\beta}{1 - \beta} \right) h \tag{6}
\]
Assessing the two measures
Assessing the two measures

- The objective of this paper is to address the cost impact.
- We will assess which of the two papers is more related to manufacturer costs.
- Fit 3 Linear Regression Models:
  1. Total Cost = f(Bullwhip Ratio)
  2. Total Cost = f(RMSE Ratio)
  3. Total Cost = f(Bullwhip Ratio, RMSE Ratio)
- The assessment will be based on the Akaike Information Criteria (AIC).
Terminology

- To separate the effect of Information Sharing from Non Information Sharing, we add a dummy, $d$, to each variable which codes whether it happens or not.
- RMSER = Root Mean Squared Error Ratio.
- BWR: Bullwhip Ratio.
- TC: Total Costs.
AIC Results

<table>
<thead>
<tr>
<th></th>
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The model with only RMSE ratio returns the lowest AIC across all processes!
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### \( R^2 \) Results

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- More variations in total costs is explained by using the RMSE ratio instead of the Bullwhip ratio.
- As the series is further away from stationarity, the value of the adjusted \( R^2 \) decreases for both ratios.
## R² Results

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- More variations in total costs is explained by using the RMSE ratio instead of the Bullwhip ratio.
- As the series is further away from stationarity, the value of the adjusted R² decreases for both ratios.
Conclusion

- The current Bullwhip Ratio possesses flaws.
- Uncertainty, captured by forecasting errors, is the cost driver.
- We propose to measure the propagation of uncertainty across the supply chain.
- our metric is more related to Total Costs than the Bullwhip Effect
Any Questions?
Conclusion

Any Questions?

A special thank you to Juan Ramon Trapero!


URL http://www.sciencedirect.com/science/article/pii/S0925527315001462


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