

Using Demand Uncertainty as a determinant for the Bullwhip Effect

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& Forecasting



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Bullwhip Effect

Bullwhip Effect

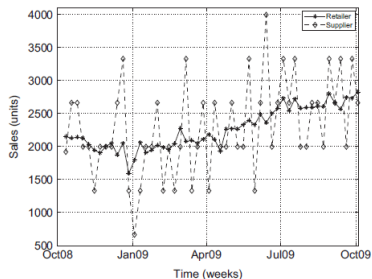
The Bullwhip effect is defined as the amplification of demand variance as one moves upstream in the supply chain.



Bullwhip Effect

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Retrieved from Trapero et al. (2012)

Consequences of the Bullwhip Effect

The Bullwhip effect results in:

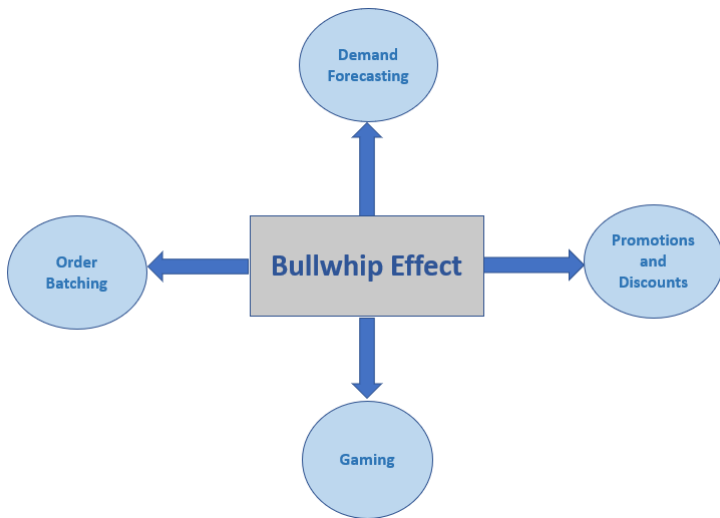
- Mis-alignment of Production Schedules.
- Increased Inventory.
- Increase in Stock-outs and customer dissatisfaction.
- Improper use of capacity.
- Increase in Transportation Costs.
- To name a few...



Origins of the Bullwhip Effect (Lee et al., 1997)



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Bullwhip Measurement



Bullwhip Measurement

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

$$BWR = \frac{Var(Orders)}{Var(Demand)} \quad (1)$$



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$$BWR = \frac{Var(Orders)}{Var(Demand)} \quad (1)$$

Its interpretation is:

- $BWR = 1 \implies$ No Bullwhip.
- $BWR > 1 \implies$ Bullwhip exists.
- $BWR < 1 \implies$ Anti-Bullwhip.

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



Issues with the current measurement



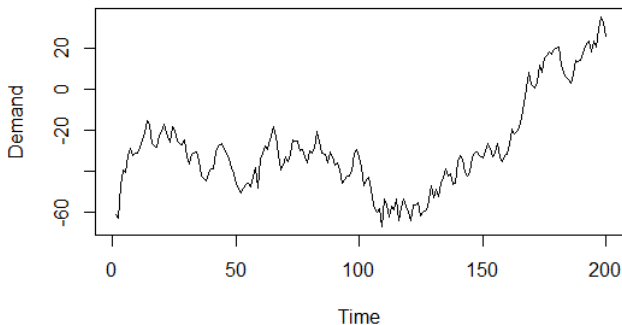
Issues with the current measurement

- 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...



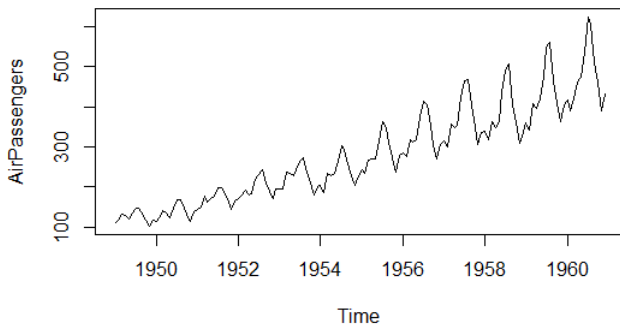
Trending Demand

Nonstationary Demand: I(1)

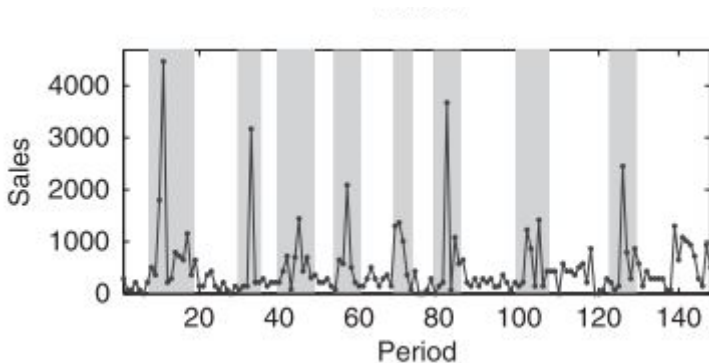


Seasonal Demand

Seasonal Demand Example: Air Passengers Data



Promotional Demand



Retrieved from Trapero et al. (2014)



Other metrics

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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Definition

Forecast uncertainty refers to the unpredictability that arises in forecasting future demand.

- 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



Uncertainty vs Variability

- Demand Uncertainty: The random variation in the forecasting model, assuming the **TRUE DEMAND** is known!



Uncertainty vs Variability

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Uncertainty vs Variability

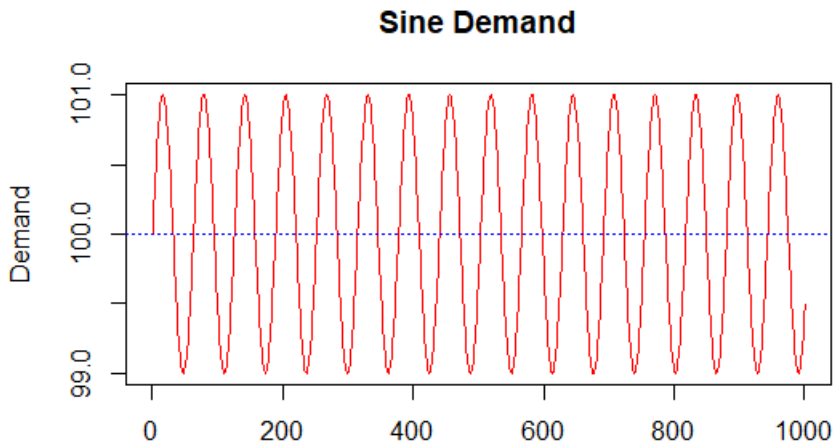
- Demand Uncertainty: The random variation in the forecasting model, assuming the **TRUE DEMAND** is known!
- Forecasting Uncertainty: How much is not captured by the forecasting method. It includes demand uncertainty and the effect of model mis-specification.
- Demand variability: the fluctuations of 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.



Uncertainty vs Variability Example



Uncertainty vs Variability Example



Error Metrics



Error Metrics

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- 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):

$$\text{MSE} = \text{Bias}^2 + \underbrace{\text{Variance} + \text{Irreducible Component}}_{\text{Demand Uncertainty}}$$

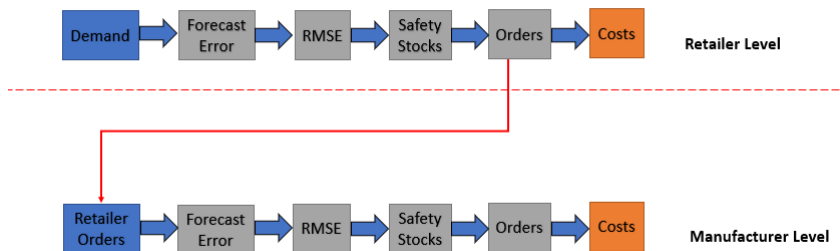
$$\underbrace{\hspace{15em}}_{\text{Forecast Uncertainty}}$$



RMSE link to cost



RMSE link to cost



Why RMSE?



Why RMSE?

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

$$SS = \hat{F}_{t+L} + \underbrace{\Psi_{\alpha}^{-1} \sqrt{\sigma_{t+L|t}^2}}_{\text{RMSE}} \quad (2)$$



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- 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 misspecification. Improvements in the process will be reflected in the metric.



Proposed Measure



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RMSE ratio

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



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The current metric we propose is:

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



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

$$RMSE_M = \sqrt{\frac{1}{(n_M - L_M + 1)} \sum_{t=1}^{n_M - L_M + 1} \left(\sum_{i=1}^{L_M} d_t - \sum_{i=1}^{L_M} f_{t|t-L_M} \right)^2} \quad (4)$$

$$RMSE_R = \sqrt{\frac{1}{(n_R - L_R + 1)} \sum_{t=1}^{n_R - L_R + 1} \left(\sum_{i=1}^{L_R} d_t - \sum_{i=1}^{L_R} f_{t|t-L_R} \right)^2} \quad (5)$$



Information Sharing



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).



Information Sharing

- From a forecasting perspective, it can result in a lower MSE.
- $MSE_{IS} < MSE_{NIS} \implies RMSE_{IS} < RMSE_{NIS}$.
- 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



Design

- Dyadic Supply Chain (1 Manufacturer and 1 Retailer).
- 3 Data Generating Processes from the ARIMA family:



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- 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.

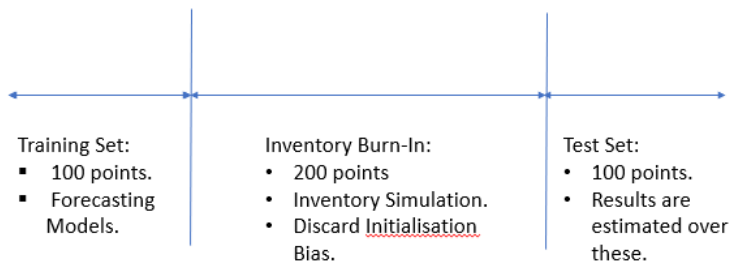


Simulation Design

- For both, 3 deterministic values $\{1, 3, 5\}$ of Lead Time + Review Period.
- 3 α -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



Costs



Costs

1. Two costs are considered: Backordering and Holding.
2. They 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 α Service Level, costs are approximated by a β Service Level.
5. The relationship between the two costs is:

$$b = \left(\frac{\beta}{1 - \beta} \right) h \quad (6)$$



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 = $f(\text{Bullwhip Ratio})$
 2. Total Cost = $f(\text{RMSE Ratio})$
 3. Total Cost = $f(\text{Bullwhip Ratio}, \text{RMSE Ratio})$
- 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.
- RMSE = Root Mean Squared Error Ratio.
- BWR: Bullwhip Ratio.
- TC: Total Costs.



AIC Results

	RMSER	BWR	RMSER,BWR
ARIMA(1,0,0)	<u>1st</u>	3rd	2nd
ARIMA(0,1,1)	<u>1st</u>	3rd	2nd
ARIMA(0,1,1)(0,1,1)	<u>1st</u>	3rd	2nd



AIC Results

	RMSE	BWR	RMSE,BWR
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The model with only RMSE ratio returns the lowest AIC across all processes!



R² Results

	RMSE	BWR
ARIMA(1,0,0)	96.29%	83.06%
ARIMA(0,1,1)	88.65%	66.44%
ARIMA(0,1,1)(0,1,1)	64.43%	49.52%



R² Results

	RMSE	BWR
ARIMA(1,0,0)	96.29%	83.06%
ARIMA(0,1,1)	88.65%	66.44%
ARIMA(0,1,1)(0,1,1)	64.43%	49.52%

- 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



Conclusion

Any Questions?



Conclusion

Any Questions?

A special thank you to Juan Ramon Trapero!



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