Lecture 3: Forecasting and Value of Information

TIØ4285 Production and Network Economics

Spring 2020

Norwegian University of Science and Technology

Outline

- Forecasting Methods
  - Qualitative methods
  - Quantitative methods
- The Value of Information

Forecasting

Forecasting

Basic Principles of Forecasting:

- The forecast is always wrong
- The longer the forecast horizon, the worse the forecast
- Aggregate forecasts are more accurate

Forecasting Methods

Forecasting methods can be split into four general categories:

- Judgment methods
- Market research methods
- Causal methods
- Time-series methods

Judgment Methods

- Panels of experts
  A group of experts is assembled in order to agree upon a forecast. It is assumed that sharing information and communicating allows for reaching a consensus.

- Delphi method
  A group of experts makes independent forecasts. The results of all forecasts is presented to the experts and they are asked to refine their forecasts based on the now available knowledge.
  The process is repeated a specified number of times or until the expert’s forecast are within a certain margin.

Market Research Methods

- Market testing
  Groups of potential customers are assembled and tested for their response to products. Their response is extrapolated to the whole market and used for estimating demand.
  When new models are launched in the automotive industry, potential customers are assembled to check their response to the planned design long before production starts.

- Market survey
  Customer response is estimated by gathering data from various potential customer groups. Data is usually collected through interviews, telephone-based surveys, written surveys, etc.

Causal Methods

Causal methods try to generate forecast based on data other than the data being predicted.

Using a causal forecasting method, you may try to forecast sales for the next three months based on

- inflation
- GNP
- advertising/marketing activities
- weather
- etc.

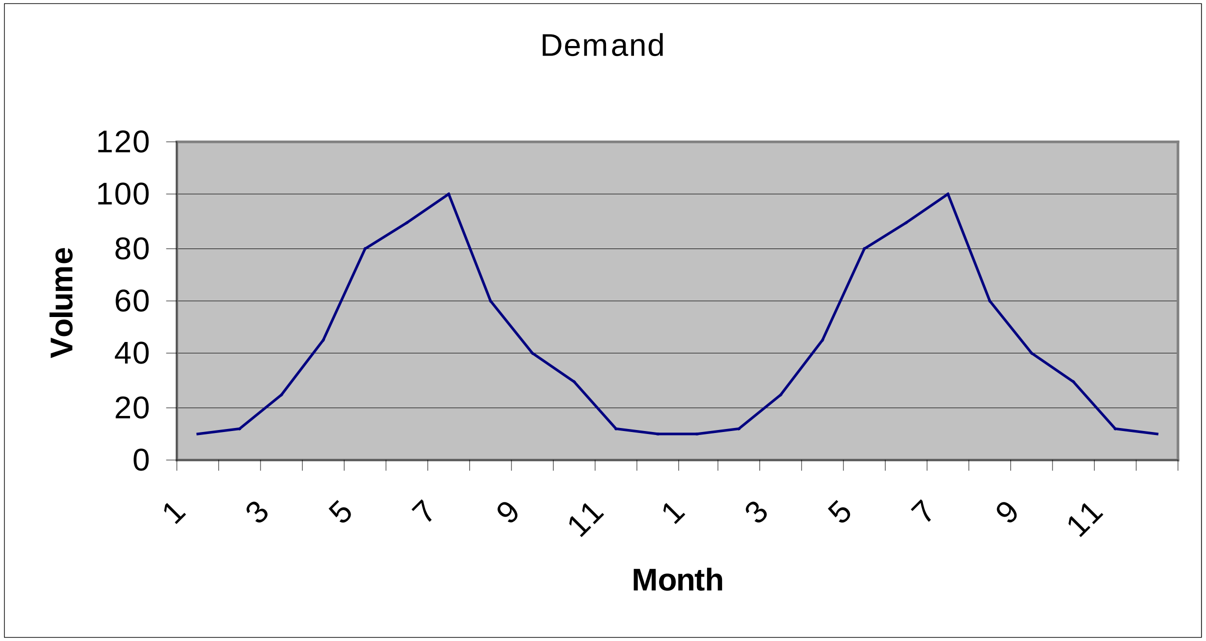
Time-Series Methods

- Time-series based methods use a variety of past data to estimate future data.

- Methods usually require stationary data series (no trends, no seasonality)

- Examples of time-series methods:
  - Last-Value forecasting
  - Averaging forecast
  - Moving average
  - Exponential smoothing
  - Methods for data with trends
  - Methods for seasonal data
  - etc.

Example of time series data



Last-Value forecasting

$$F_{t+1} = x_t$$

- Variance is large because of small sample size (1 data point)

- Worth considering if
  - Constant-level is not likely
  - World is changing so fast that most of the previous observations are irrelevant
  - Often called the naive method (by statisticians)
  - May be the only relevant value (under rapid changes)

Averaging Forecasting

$$F_{t+1} = \sum_{i=1}^{t} \frac{x_i}{t}$$

- Works ok if the process is stable
- Normally limited to young processes (i. e. processes with few observations)

Moving Average

$$F_{t+1} = \sum_{i=t-n+1}^{t} \frac{x_i}{n}$$

- Calculates the average of previous demand over a given number of time periods

- Every past demand point is weighted equally

- Determining the number of time periods *n* to calculate the average demand for is very important

- Only recent history and multiple observations

Exponential Smoothing

$$F_{t+1} = \alpha x_t + (1-\alpha)F_t$$
$$= \alpha x_t + \sum_i \alpha(1-\alpha)^i x_{t-i}$$

- α – smoothing constant (between 0 and 1)
- Forecast is a weighted average of the previous forecast and the last demand
- More recent value receive more weight than past values
- Similar to the Moving Average Forecast, but tracks changes in the process faster
- Lags behind a continuous trend
- Choice of the smoothing constant α (weight of the last demand) is important

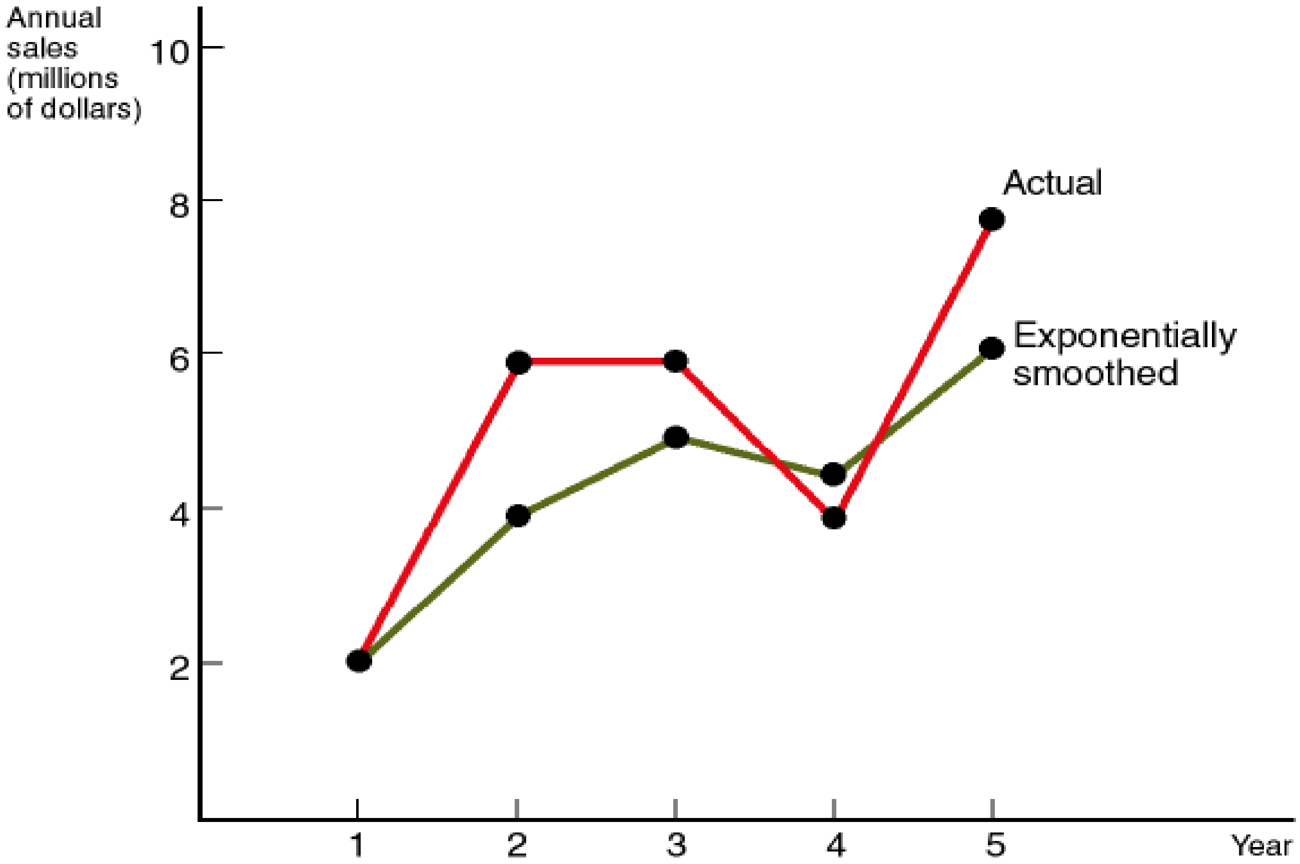


FIGURE 6.9 Sales of Firm, Actual and Exponentially Smoothed

Methods for Data with Trends

- Regression Analysis,
  tries to fit a straight line into data points. Thus, it's identifying linear trends.

- Holt's Method,
  combines the concepts of exponential smoothing with the ability to capture linear trends.

Box-Jenkins method

Box-Jenkins

- Alternative name: ARIMA method
- Box-Jenkins is a methodology for identifying, estimating, and forecasting ARIMA models
- ARIMA stands for “AutoRegressive Integrated Moving-Average"
  - Made up of sums of autoregressive and moving-average components
- Requires a large amount of data (historical observations of a variable)
- Iterative process

ARIMA models

- Describes a stochastic process or a model of one

- Explains the variable Y based only on the history of Y
  - No other explanatory variables
  - Not derived from economic theory

- An ARIMA process is stationary
  - mean, variance and autocorrelation structure do not change over time

ARIMA components

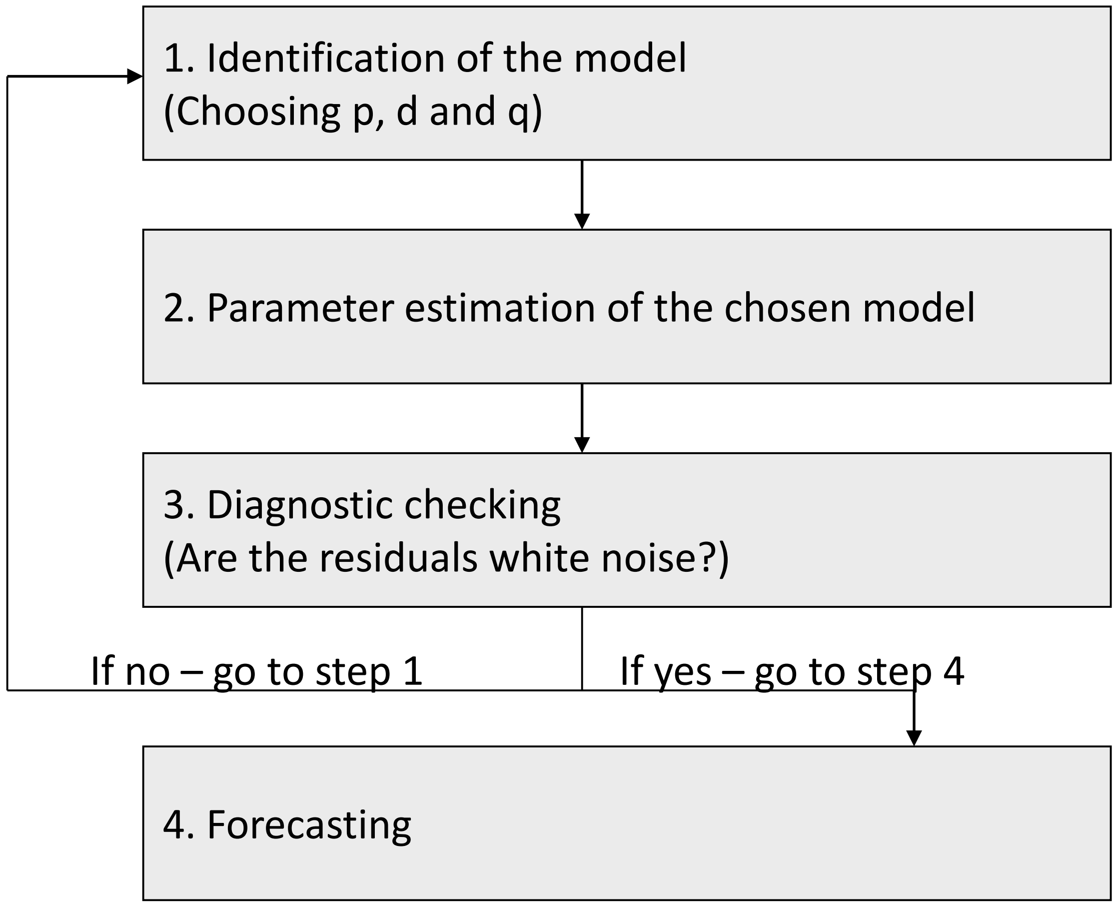
- AR (Autoregressive)
  - Process that can be described by a weighted sum of its previous values and a white noise error
  - AR(1): $Y_t = \alpha Y_{t-1} + \theta_t$
  - AR(p): $Y_t = \sum_{p=1}^{n} \alpha_p Y_{t-p} + \theta_t$
- MA (Moving Average)
  - Process that can be described by a constant plus a moving average of the current and past error terms
  - MA(1): $Y_t = \mu + \beta_t \theta_t$
  - MA(q): $Y_t = \mu + \sum_{n=0}^{q} \beta_{t-n} \theta_{t-n}$

ARIMA components (2)

- ARMA (p, q)
  - May be non-stationary (integrated)
    - Non-constant mean, variance or covariance
  - The *d*-differences of a time series that are integrated of order *d* is stationary
    - 1-differences of Y: $Y_t – Y_{t-1}$

- ARIMA (p, d, q)
  - *p* AR terms, integrated of order *d* and *q* MA terms

The Box-Jenkins Methodology



2. Parameter estimation

- Estimate the value of the *p* AR and the *q* MA parameters
  - Simple problems: use least squares method
  - Otherwise: nonlinear (in parameter) estimation methods
  - Done by several statistical packages
    - (SPSS, MiniTab, S-Plus, R,…..)

3. Diagnostic checking

- Test if the estimated model fits the historical data
- In particular: test if the residuals are white noise
  - If not – the model is not appropriate and a new one must be estimated
  - If they are – the model may be good and used for forecasting

4. Forecasting

- Use the model to forecast new values

- Can be used as a test of the goodness of the model
  - Out-of-sample tests
  - Cross validation

Conclusions

- Requires no economic theory
  - ÷ Cannot make use of any economic theory
  - \+ Cannot misuse economic theory/ make false assumptions
- Usually provides accurate forecasts
- Requires a large amount of data
- Only needs data for one variable

Regression analysis

- Applicable if causal link is strong
- Assume that a company's demand function can be written on the form

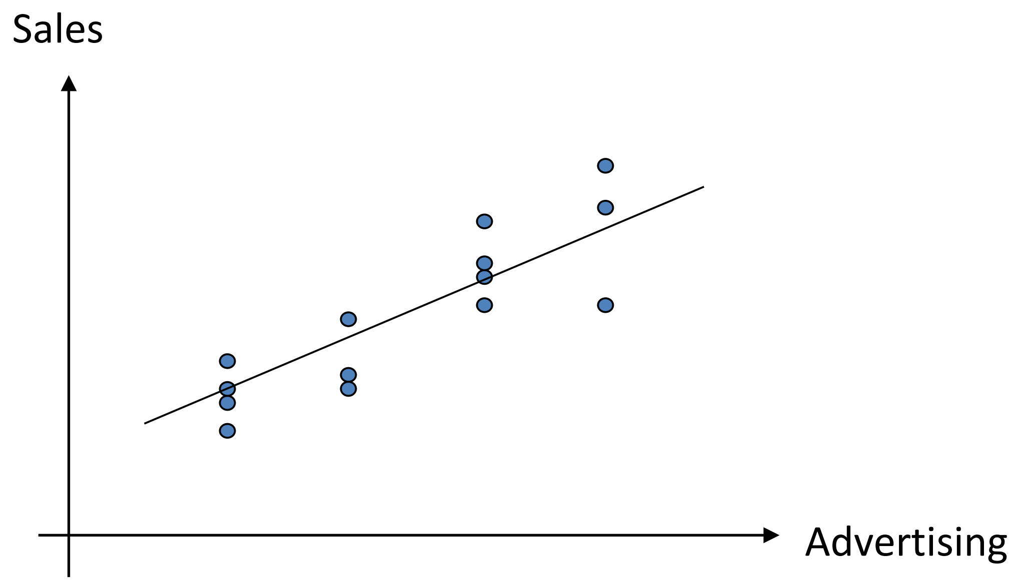
$$Y = A + B_1 x_1 + B_2 x_2 + B_3 I + B_4 P_r$$

- *Y* is the dependent variable
- x_1, x_2, I, P_r are examples of independent variables.
- We wish to estimate

$$A, B_1, B_2, B_3, B_4$$

  based on historical data

Population regression curve



- Line shows the value of E(Y|X)

$$Y = A + B_1 x_1$$

- The line is fitted so that squared deviation is minimized

Explained variance and the constant of determination

- Variance in dependent variable

$$\sum_{i=1}^{n}(Y_i - \bar{Y})^2$$

and

$$Y_i - \bar{Y} = (Y_i - \hat{Y}_i) + (\hat{Y}_i - \bar{Y})$$

- Explained variance

$$\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2$$

- Unexplained variance

$$\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

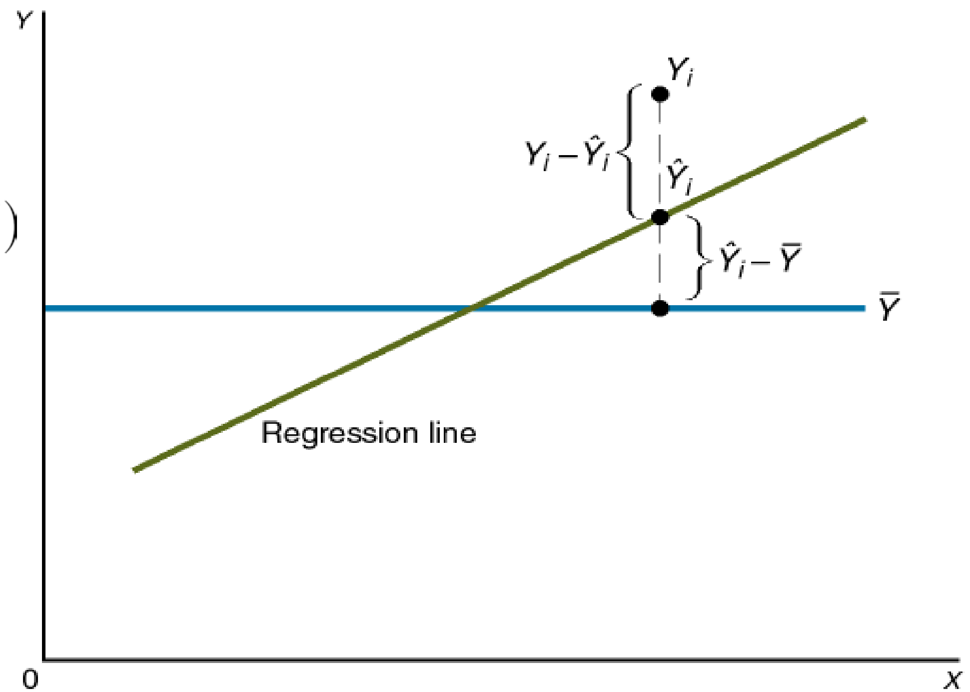


FIGURE 5.13 Division of $(Y_i - \bar{Y})$ into Two Parts: $(Y_i - \hat{Y}_i)$ and $(\hat{Y}_i - Y)$

Explained variance and the constant of determination

$$R^2 = 1 - \frac{\text{Variation not explained by regression}}{\text{Total variation}}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}$$

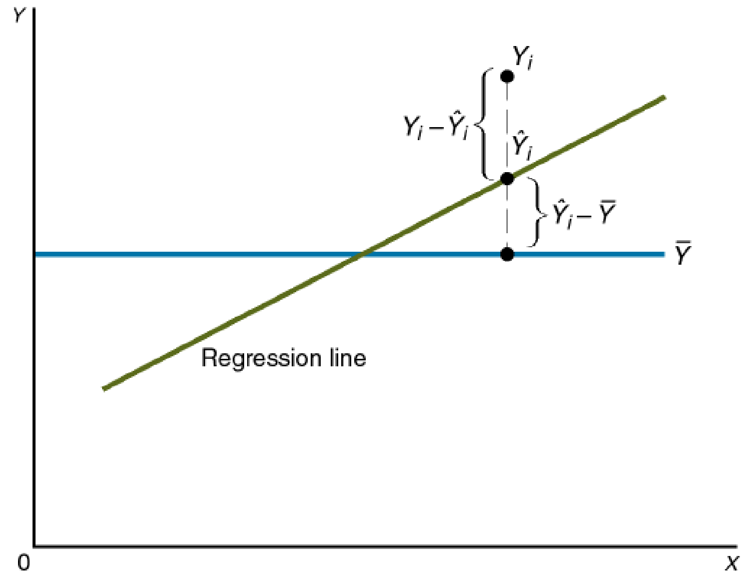


FIGURE 5.13 Division of $(Y_i - \bar{Y})$ into Two Parts: $(Y_i - \hat{Y}_i)$ and $(\hat{Y}_i - Y)$

Methods for Seasonal Data

Seasonal data has to be accounted for.

1. Calculate seasonal factor

$$\text{Seasonal factor} = \frac{\text{average for the period}}{\text{overall average}}$$

2. Calculate seasonally adjusted values

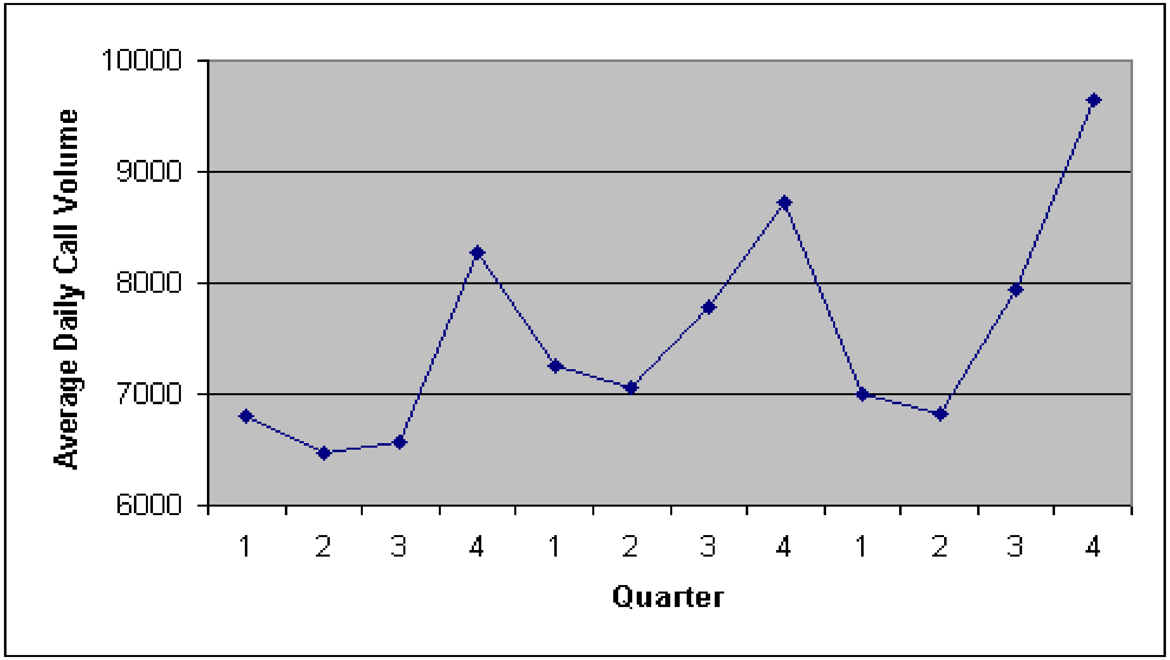
$$\text{Seasonal adjusted value} = \frac{\text{actual value}}{\text{seasonal factor}}$$

3. Select time-series forecasting method
4. Apply this method to the seasonally adjusted data
5. Multiply this forecast with the seasonal factor in order to get the next actual value

Example on Forecasting Seasonal Demand I

CCW's Average Daily Call Volume

Year	Quarter	Call Volume
1	1	6809
1	2	6465
1	3	6569
1	4	8266
2	1	7257
2	2	7064
2	3	7784
2	4	8724
3	1	6992
3	2	6822
3	3	7949
3	4	9650



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Example on Forecasting Seasonal Demand II

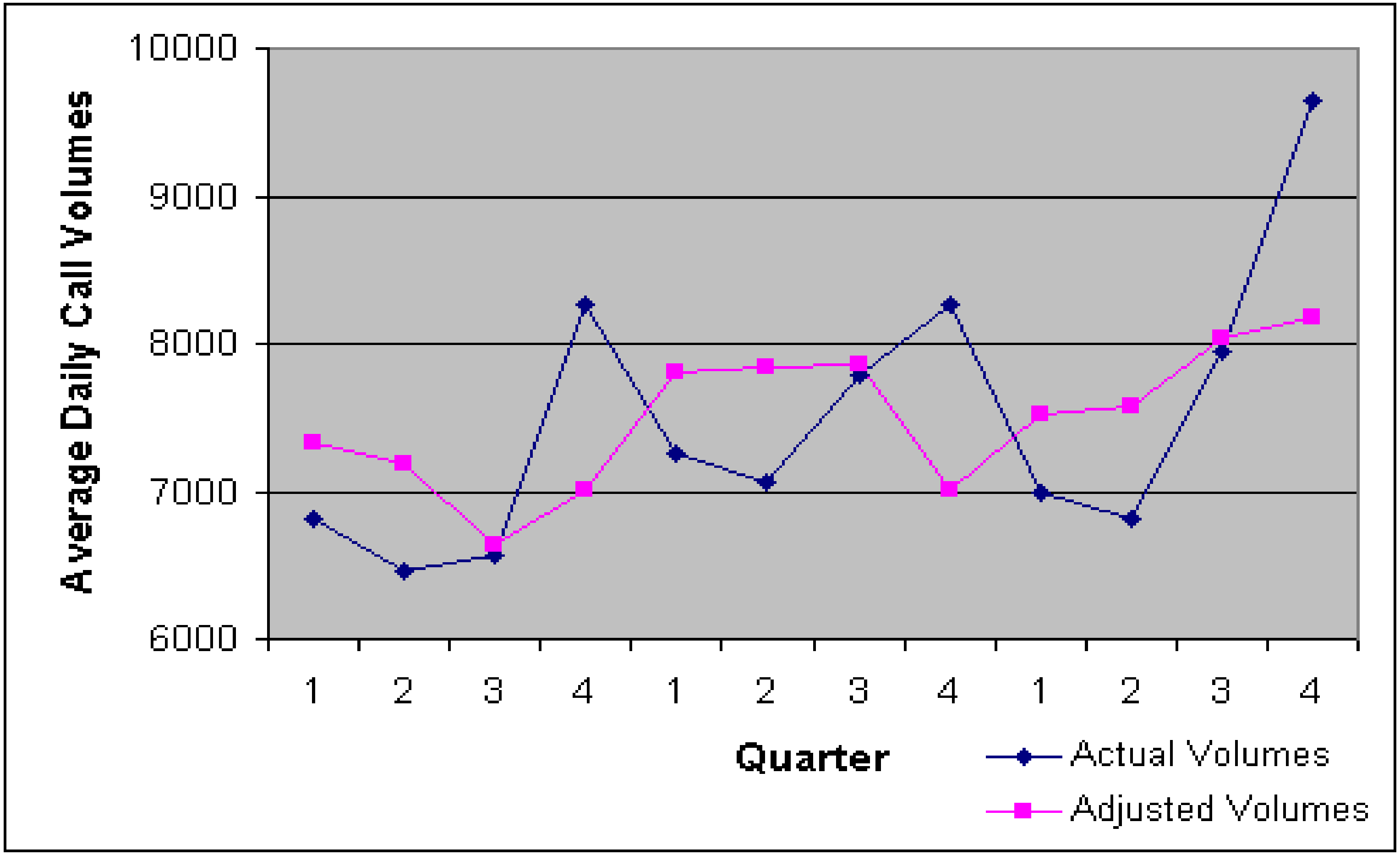
Calculating seasonal factors

Quarter	Three-Year Average	Seasonal Factor
1	7019	$\frac{7019}{7529} = 0.93$
2	6784	$\frac{6784}{7529} = 0.90$
3	7434	$\frac{7434}{7529} = 0.99$
4	8880	$\frac{8880}{7529} = 1.18$
Total=30117		
Average= $\frac{30117}{4} = 7529$		

Example on Forecasting Seasonal Demand III

Year	Quarter	Seasonal Factor	Actual Call Volume	Seasonally Adjusted Call Volume
1	1	0.93	6809	7322
1	2	0.90	6465	7183
1	3	0.99	6569	6635
1	4	1.18	8266	7005
2	1	0.93	7257	7803
2	2	0.90	7064	7849
2	3	0.99	7784	7863
2	4	1.18	8274	7012
3	1	0.93	6992	7518
3	2	0.90	6822	7580
3	3	0.99	7949	8029
3	4	1.18	9650	8178

Example on Forecasting Seasonal Demand III



Demand Forecasting and Scenario Generation

- Assume demand can be forecasted perfectly using an autoregressive process

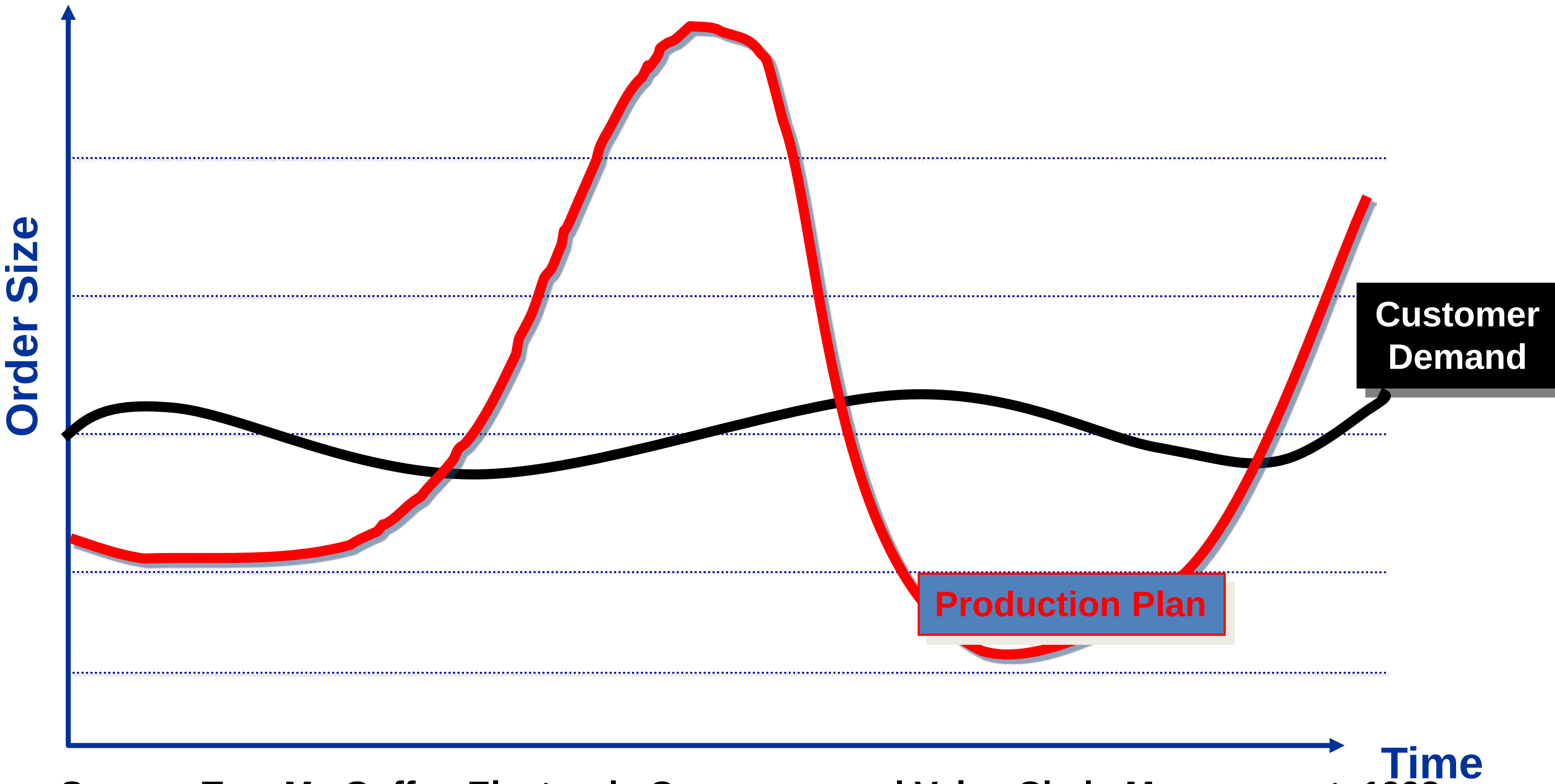
$$\hat{d}_{t+1} = \alpha + \sum_{i=1}^{N} \beta_i \cdot d_{t-i+1} + \varepsilon(\omega)$$

- But: The forecast is always wrong!
  - So there is an error term.

- Put all uncertainty in error term.
  - White noise $\rightarrow$ normal distribution with mean 0
  - Generate scenario tree for your error term and combine tree with forecasting model

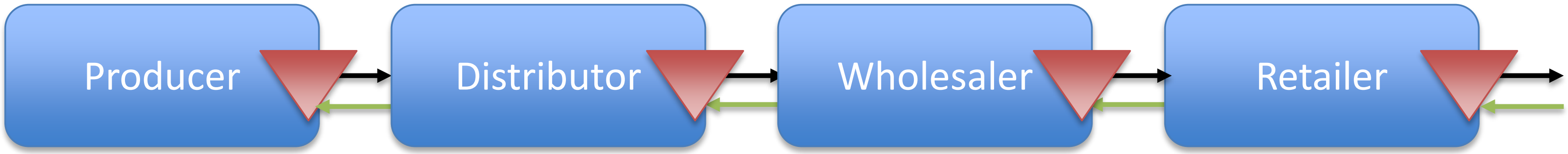
The Value of Information

The Dynamics of the Supply Chain

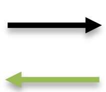


Source: Tom Mc Guffry, Electronic Commerce and Value Chain Management, 1998

The Supply Chain



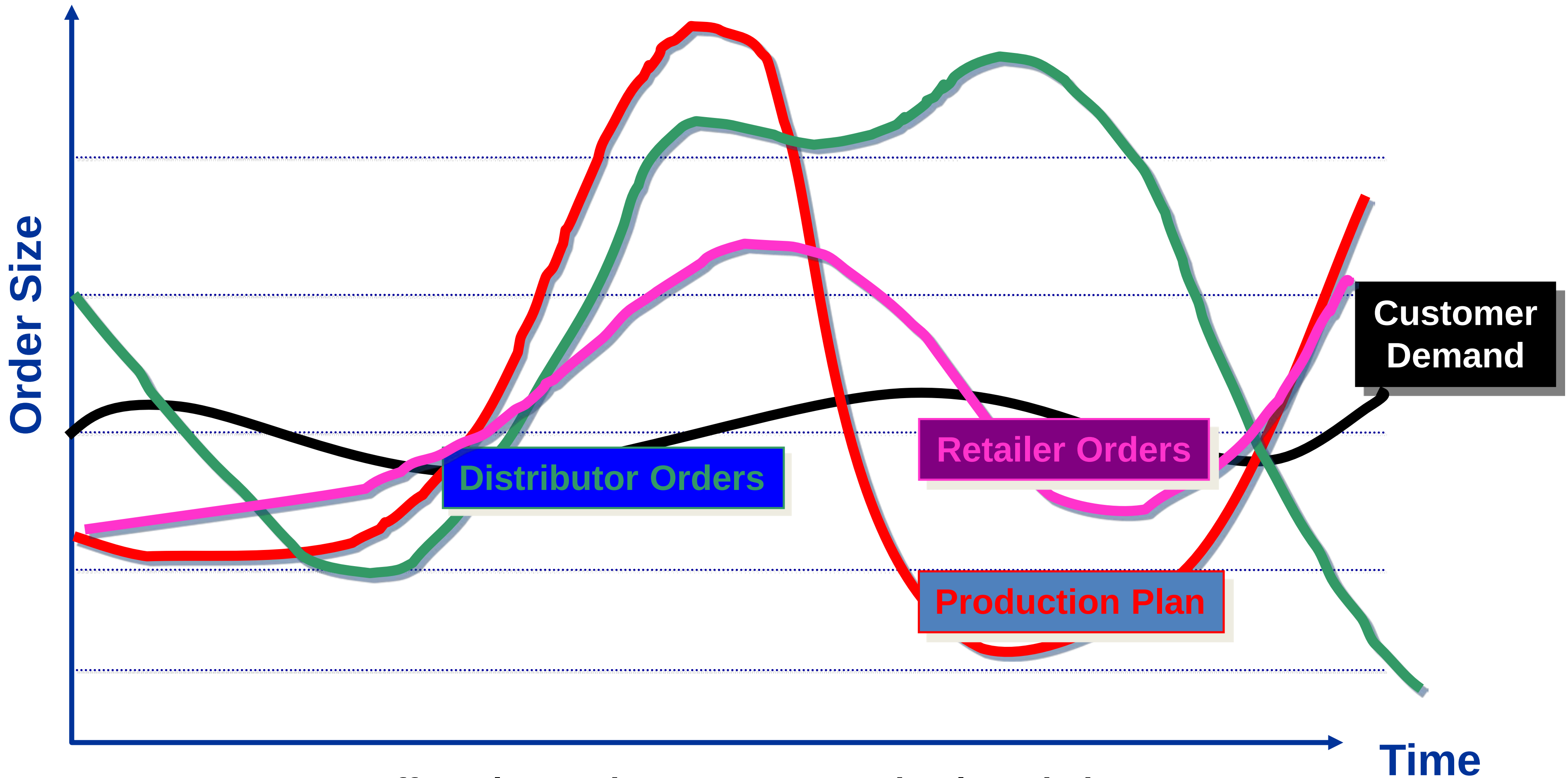
- Upstream receives orders from downstream actor



- Order is satisfied from stock or backlogged

- Leadtimes in both flow of goods <u>and</u> flow of information

The Dynamics of the Supply Chain



Source: Tom Mc Guffry, Electronic Commerce and Value Chain Management, 1998

What are the causes…

- For example
  - Promotional sales
  - Price fluctuations
  - Volume and transportation discounts
    - Batching
  - Inflated orders
  - Long cycle times
  - Demand forecasts
  - Lack of visibility of demand information

The Bullwhip Effect and its Impact on the Supply Chain

- Consider the order pattern of a single color television model sold by a large electronics manufacturer to one of its accounts, a national retailer.

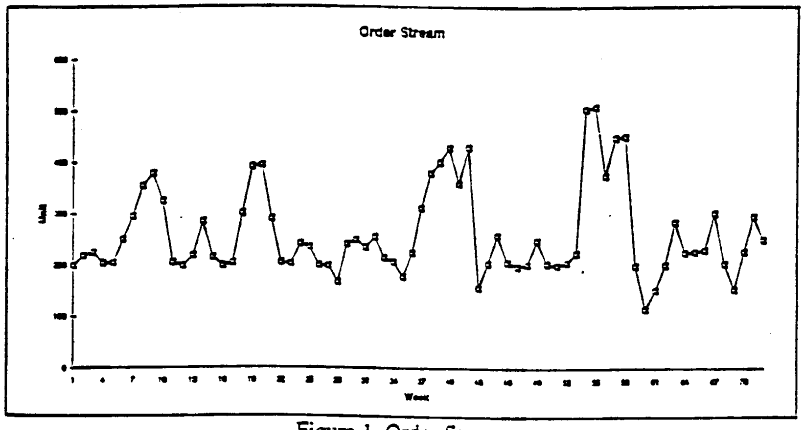


Figure 1. Order Stream

Huang at el. (1996), Working paper, Philips Lab

The Bullwhip Effect
and its Impact on the Supply Chain

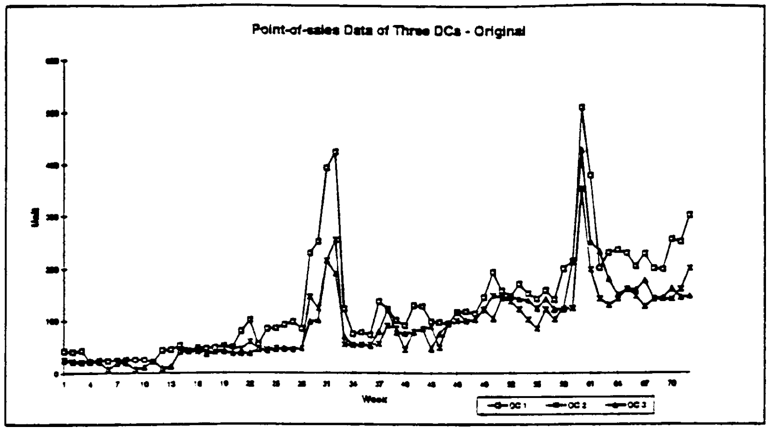


Figure 2. Point-of-sales Data-
Original

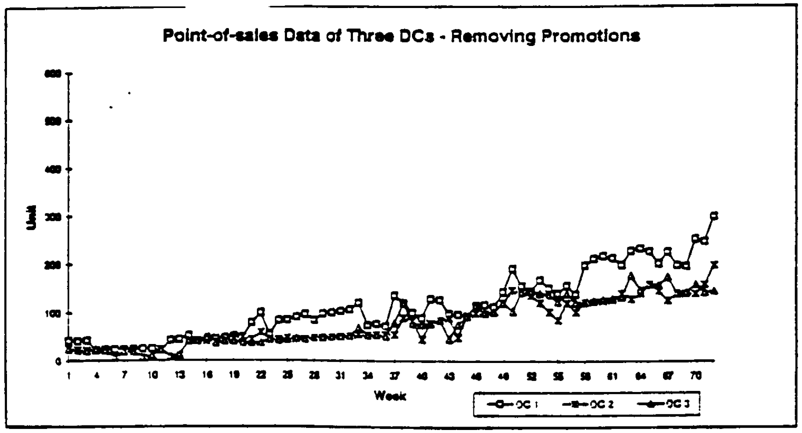


Figure 3. POS Data After Removing
Promotions

The Bullwhip Effect and its Impact on the Supply Chain

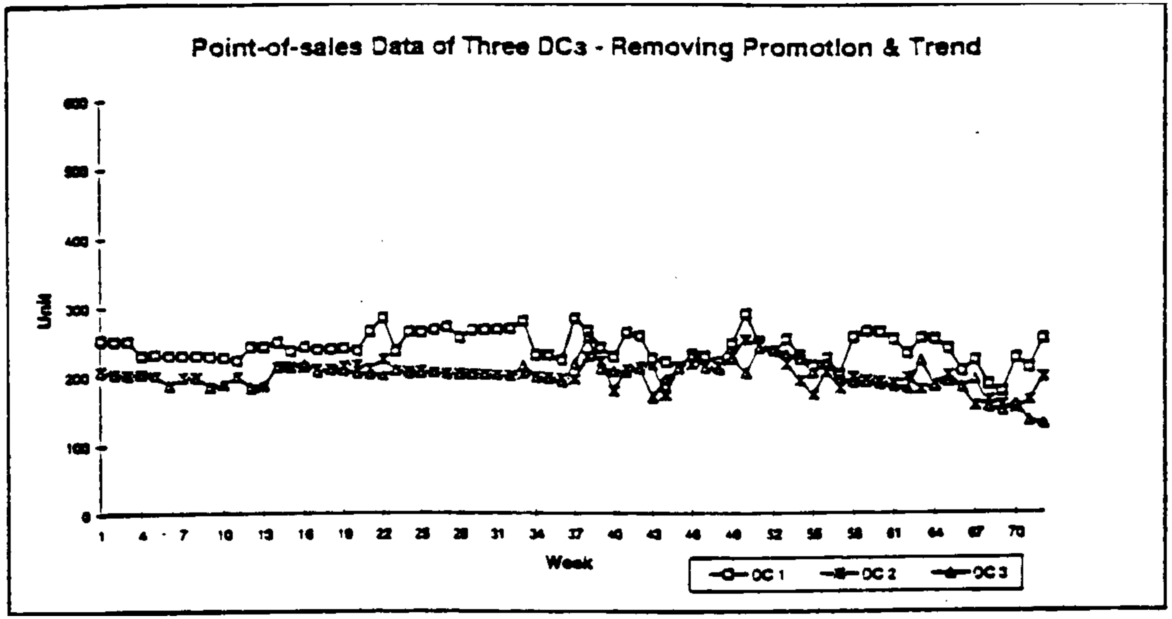
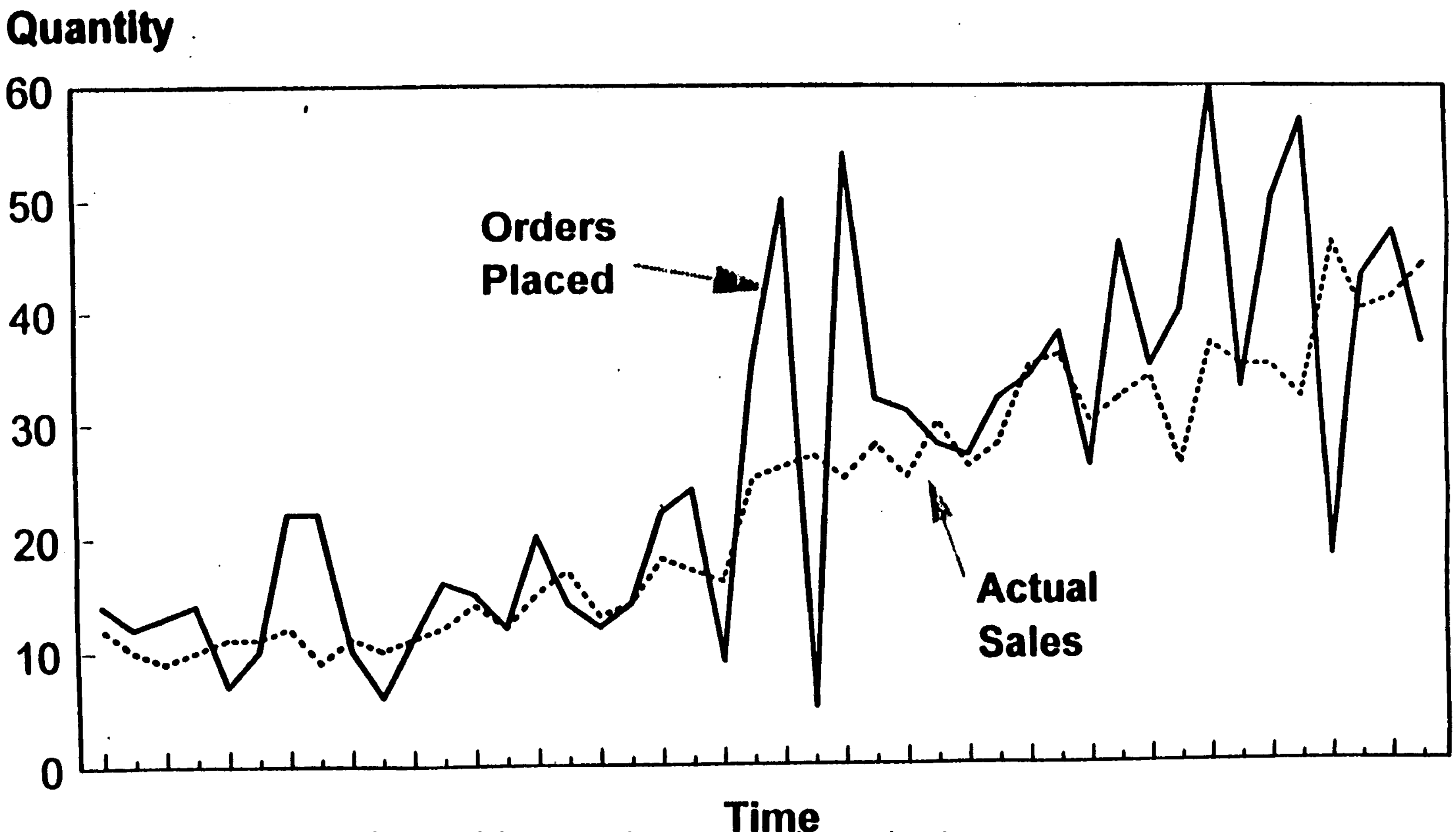


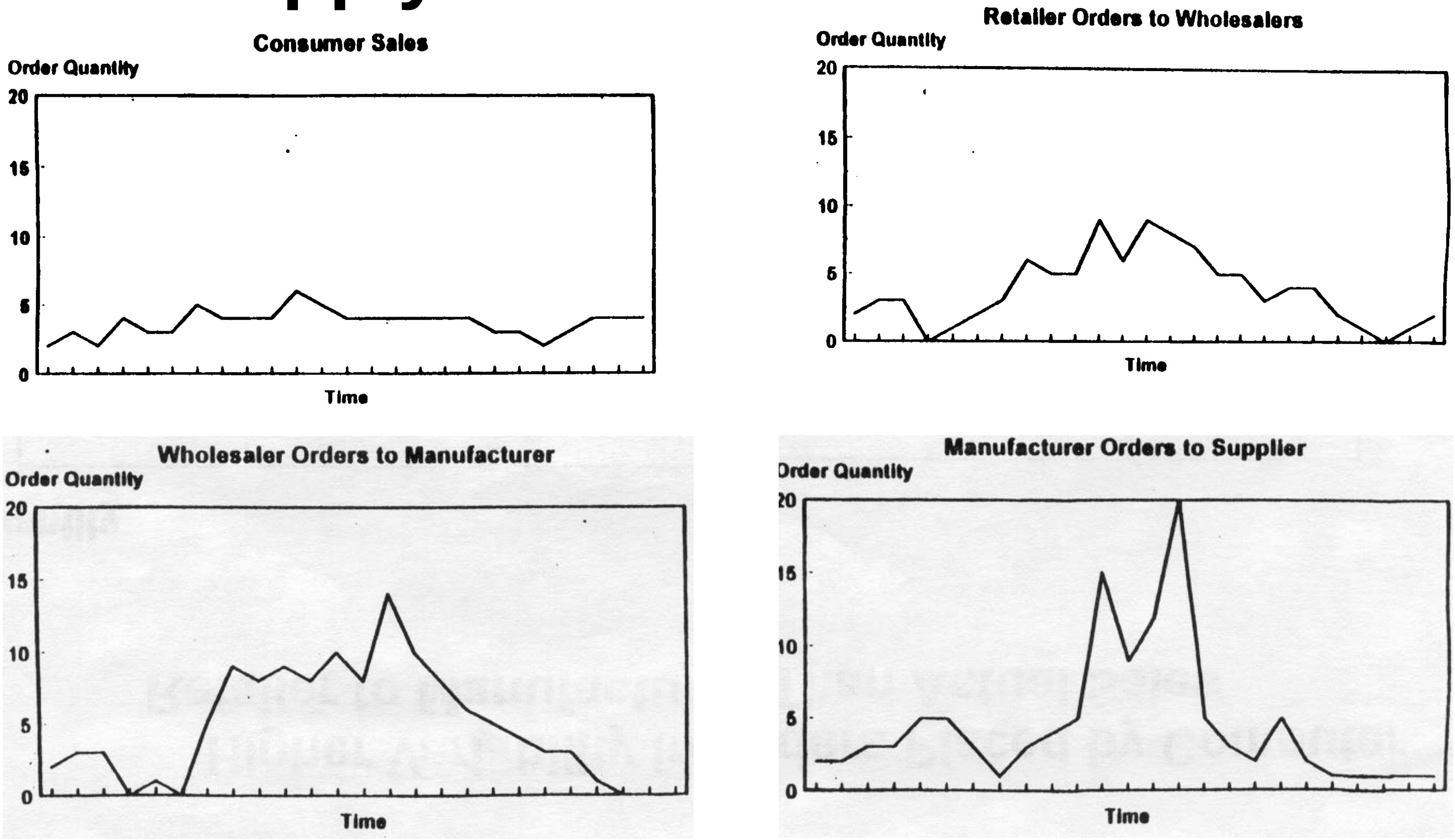
Figure 4. POS Data After Removing Promotion & Trend

Higher Variability in Orders Placed by Computer Retailer to Manufacturer Than Actual Sales



Lee, H, P. Padmanabhan and S. Wang (1997), Sloan Management Review

Increasing Variability of Orders up the Supply Chain



Lee, H, P. Padmanabhan and S. Wang (1997), Sloan Management Review

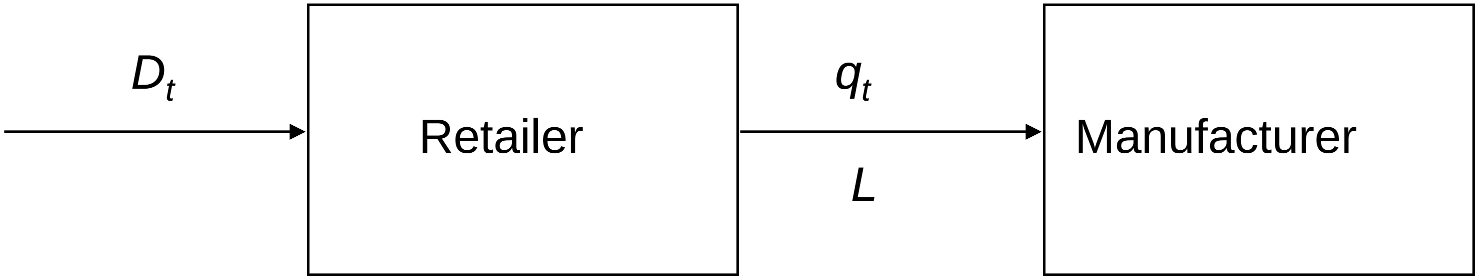
We Conclude ….

- Order Variability is amplified up the supply chain; upstream echelons face higher variability.

- What you see is not what they face.

What are the Causes….

- Single retailer, single manufacturer.
  - Retailer observes customer demand, D_t.
  - Retailer orders q_t from manufacturer.



Formulas

- Target inventory

$$y_t = \widehat{\mu}_t^L + z\widehat{\sigma}_t^L$$

$$\widehat{\mu}_t^L - \text{ estimate of mean leadtime demand}$$

$$\widehat{\sigma}_t^L - \text{ estimate of s.d. of forecasting error over leadtime demand}$$

$$z - \text{ service level parameter}$$

- Assume demand is

$$D_t = \mu + \rho D_{t-1} + \varepsilon_t$$

$$|\rho| < 1$$

Forecasting

- Moving average forecast

$$\widehat{\mu}^t = \frac{\sum_{i=1}^{p} D_{t-i}}{p}$$

$$\varepsilon_t = D_t - \widehat{\mu}_t$$

- Let q_t be the order quantity

$$q_t = y_t - y_{t-1} + D_{t-1}$$

(the difference in target inventory + demand)

$$\begin{aligned} q_t &= \widehat{\mu}_t^L - \widehat{\mu}_{t-1}^L + z\left(\widehat{\sigma}_t^L - \widehat{\sigma}_{t-1}^L\right) + D_{t-1} \\ &= \left(1 + \frac{L}{p}\right) D_{t-1} - \left(\frac{L}{p}\right) D_{t-p-1} + z\left(\widehat{\sigma}_t^L - \widehat{\sigma}_{t-1}^L\right) \end{aligned}$$

Variance of the orders

$$
\begin{aligned}
Var(Q_t) = &\left(1+\frac{L}{p}\right)^2 Var(D_{t-1}) + \left(\frac{L}{p}\right)^2 Var(D_{t-p-1}) \\
&- 2\left(\frac{L}{p}\right)\left(1+\frac{L}{p}\right) Cov(D_{t-1}, D_{t-p-1}) \\
&+ 2z\left(\frac{L}{p}\right)\left(1+\frac{L}{p}\right) Cov(D_{t-1}, \sigma_t^L) \\
&+ z^2 Var\left(\hat{\sigma}_t^L - \hat{\sigma}_{t-1}^L\right) \\
= &\left[1+\left(\frac{2L}{p}+\frac{2L^2}{p}\right)(1-\rho^p)\right] Var(D) \\
&+ 2z\left(1+\frac{2L}{p}\right) Cov\left(D_{t-1}, \sigma_t^L\right) \\
&+ z^2 Var\left(\hat{\sigma}_t^L - \hat{\sigma}_{t-1}^L\right)
\end{aligned}
$$

where

$$
Var(D) = \frac{\sigma^2}{1-\rho^2}, Cov(D_t, D_{t-p-1}) = \frac{\rho^p}{1-\rho^2}\sigma^2
$$

Variance of the orders

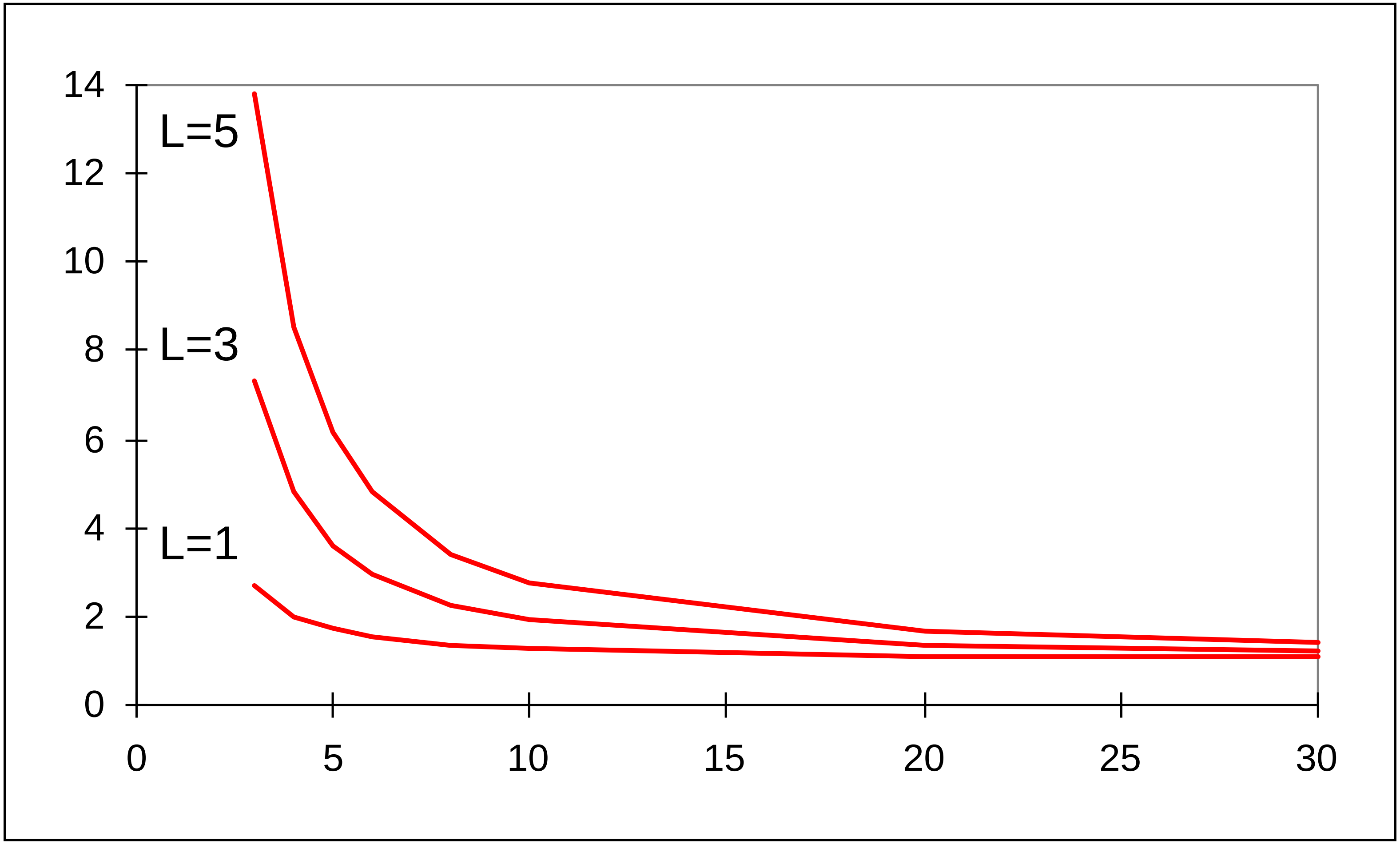
- For moving average forecasts and for the demand process we have assumed

$$Cov(D_{t-1}, \widehat{\sigma}_t^L) = 0$$

- Variance of orders placed by the retailer to the manufacturer (upstream unit), relative to variance in demand

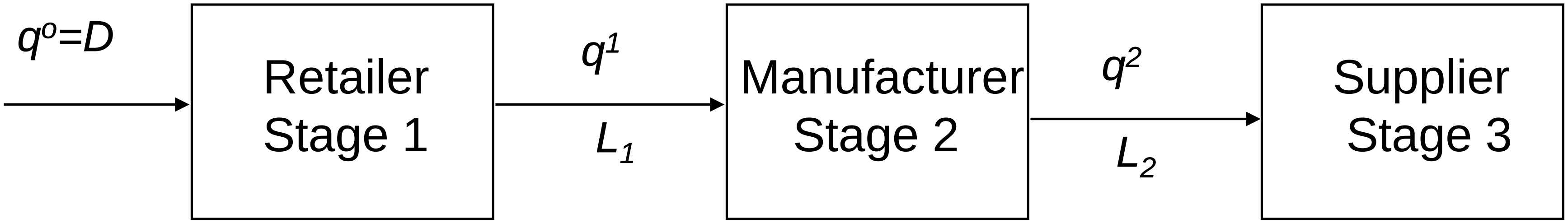
$$\frac{Var(q)}{Var(D)} \geq 1 + \frac{2L}{p} + \frac{2L^2}{p^2}$$

Var(q)/Var(D): For Various Lead Times (as a function of p)



Multi-Stage Supply Chains

- Consider a multi-stage supply chain:
  - Stage i places order qi to stage i+1.
  - Li is lead time between stage i and i+1.



Multistage centralised

- Each stage has complete information about the customer demand and uses the same estimate.
- The second level receives the orders from the first level and the demand forecast from the first level.
- The third level receives the order form the second level and the demand forecast from the first level
- ……….

$$\hat{\mu}_t = \frac{\sum_{i=1}^{p} D_{t-i}}{p}$$

Each stage k follow an order-up-to policy with target $(z = 0)$

$$y_t^k = L_k \hat{\mu}_t$$

Then

$$\frac{Var(q_t^k)}{Var(D)} \geq 1 + \left(\frac{2\sum_{i=1}^{k} L_i}{p} + \frac{2\left(\sum_{i=1}^{k} L_i\right)^2}{p^2} \right)$$

1) All demand information is centralized
2) Every stage of the supply chain uses the same forecast technique

Coping with the Bullwhip Effect

- Reduce Variability and Uncertainty
  - POS
  - Sharing Information
  - Year-round low pricing

- Reduce Lead Times
  - EDI
  - Cross Docking

- Alliance Arrangements
  - Vendor managed inventory
  - On-site vendor representatives

Distribution Strategies

- Warehousing
- Direct Shipping
  - No DC needed
  - Lead times reduced
  - “smaller trucks”
  - no risk pooling effects
- Cross-Docking

Cross Docking

- In 1979, Kmart was the king of the retail industry with 1891 stores and average revenues per store of $7.25 million

- At that time Wal-Mart was a small niche retailer in the South with only 229 stores and average revenues about half of those Kmart stores.

- Ten years later, Wal-Mart transformed itself; it has the highest sales per square foot, inventory turnover and operating profit of any discount retailer. Today Wal-Mart is the largest and highest profit retailer in the world.

The Bullwhip Effect: Managerial Insights

- Exists, in part, due to the retailer's need to estimateand update the mean and variance of demand.
- The increase in variability is an increasing function of the lead time.
- The more complicated the demand models and the forecasting techniques, the greater the increase.
- Centralized demand information can reduce the bullwhip effect, but will not eliminate it.