



# ***Models for Evaluating and Monitoring Efficiency of Supply Chain Networks***

Sri Talluri, Ph.D.

Hoagland-Metzler Endowed Professor

Professor of Operations and Supply Chain Management

The Eli Broad College of Business

Michigan State University



# Axia Institute at Michigan State University

- Established in Fall 2015 with support from Dow Chemical, Dow Corning, and multiple Midland based companies
- Emphasis is on collaborative solutions-focused research for a variety of industry problems
- Took over as the faculty director in Fall 2018
- Leverage the strengths of Supply Chain Management Department (ranked # 1 in the United States)



# Motivation

- Dow Chemical's focus on efficiency of supply chain networks:
  - Current methods mainly focusing on cost optimization
  - Evaluate supply chain network performance in a more holistic manner
  - Develop an approach for monitoring and improving network performance
  - Redesign trigger



# Performance Management

- Performance management literature (operations, engineering, and cost accounting) emphasizes the use of multiple measures (Kaplan and Norton 1996; Nanni et al. 1992; Adams et al. 1995)
- Kueng (2000) points that:
  - Performance is multidimensional and cannot be assessed by a single indicator and
  - Performance indicators are not independent (cost, quality, and time tradeoffs)
- SCOR model focuses on multiple supply chain metrics at strategic, tactical, and operational levels (Supply Chain Council 2004)



# Supply Chain Performance, Structure and Firm Performance

- Impact of supply chain responsiveness and uncertainty on firm performance ([Wagner et al. 2012](#))
- Supply chain flexibility (sourcing, manufacturing, logistics) and firm performance ([Sanchez and Perez 2005](#); [Merschmann and Thonemann 2011](#))
- Supply chain configurations (decentralized vs. centralized designs and direct vs. indirect shipments) and impact on performance ([Chiu and Kremer 2014](#); [Rosales et al. 2013](#))
- Supply chain network design with cost and reliability tradeoffs ([Yildiz et al. 2014](#)); cost and time tradeoffs ( [Arntzen et al. 1995](#))



# Contribution

- Given the emphasis on network design and its impact on multivariate performance:
  - We focus on developing an approach for effectively evaluating and monitoring the realized efficiency of supply chain networks based on multiple factors (**aggregated metric**)
  - Effectively consider interrelationships among factors (**tradeoffs**)
  - Assist in identifying any systematic trends/patterns in efficiency
  - Help trigger a network redesign need to improve performance



## Case Company Details & Data Gathering Efforts

- Multinational Chemical Corporation
- Identified a Business Unit with the assistance of Case Company Research Team
- Multiple on-site and conference call meetings with the Research Team and the Business Unit Management Team to finalize the factors to utilize in the study and related data requirements
- Significant amount of effort in data gathering- **multiple databases/systems**



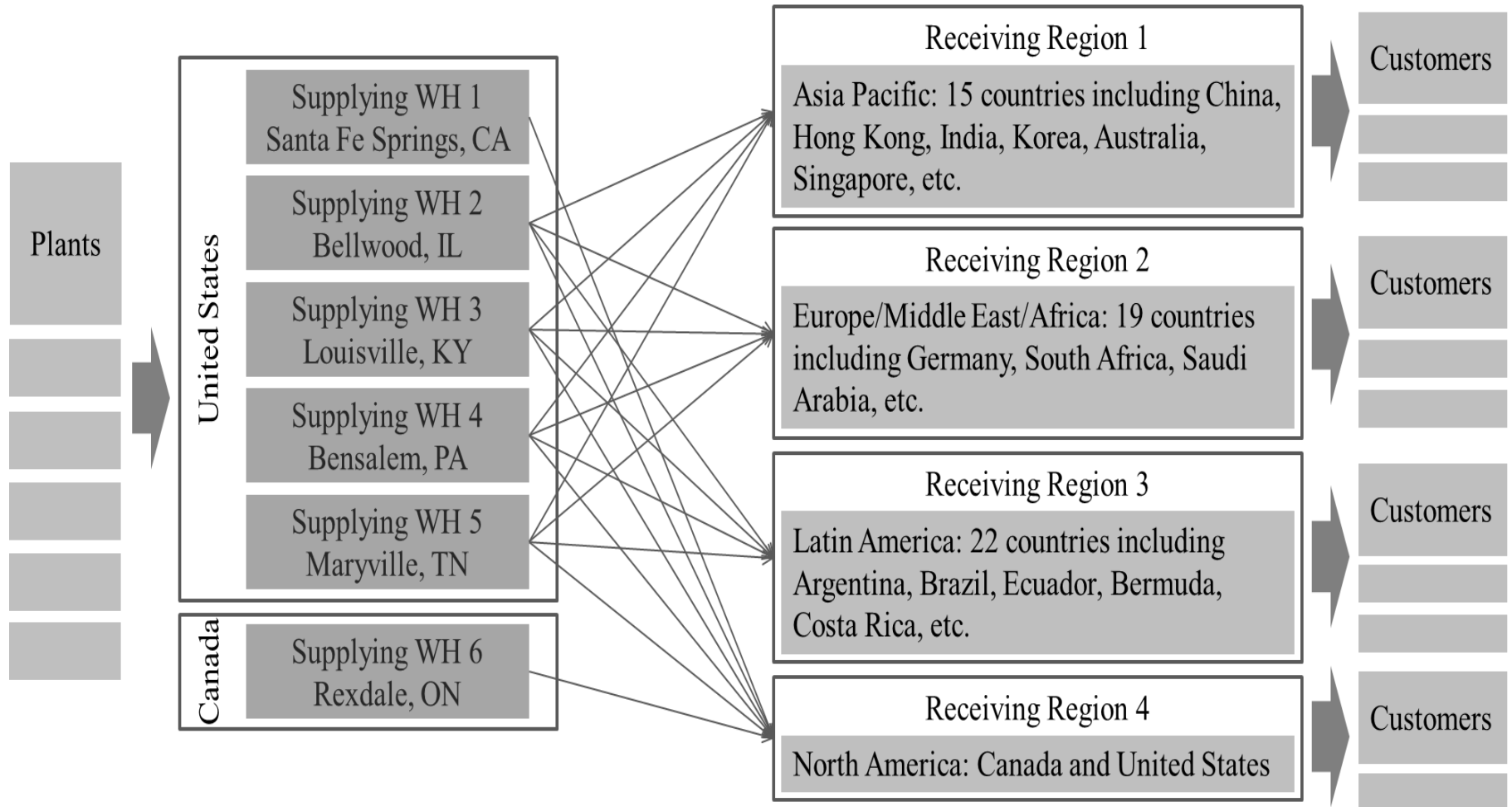
# Supply Chain Network Details

- Network:
  - 6 manufacturing plants
  - 6 warehouses
  - 869 customers
  - 699 products
- Dow's network optimization model:
  - Objective: Minimize transportation cost
  - Decisions: Reassign customers to existing warehouses





# Supply Chain Network Details





# Factors for Network Efficiency Analysis

- Inputs:
  - Total Inventory (\$)
  - Transportation Cost (\$/lb.)
- Outputs:
  - Customer Service Level (on-time delivery rate, %)
  - Throughput (sum of delivered net weight, lb.)



# Data

- Approximately 3 years of data
- Before Supply Chain Network (SCN) Optimization
  - 16 months
- After SCN Optimization
  - 17 months

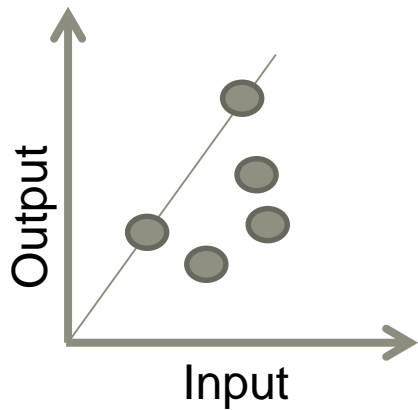


# Methodology

- Multi-factor productivity models - Data Envelopment Analysis
- Statistical Process Control methods
- Non-parametric statistical tests and clustering methods
- Extensions based on cross-efficiency models



# Efficiency Evaluation – CCR DEA Model



$$\begin{aligned}
 & \max \quad \frac{\sum_{k=1}^s v_k y_{kp}}{\sum_{j=1}^m u_j x_{jp}} \\
 & s.t. \quad \frac{\sum_{k=1}^s v_k y_{ki}}{\sum_{j=1}^m u_j x_{ji}} \leq 1, \quad \forall i \\
 & \quad v_k, u_j \geq 0 \quad \forall k, j
 \end{aligned}
 \quad \longrightarrow \quad
 \begin{aligned}
 & \max \quad \sum_{k=1}^s v_k y_{kp} \\
 & s.t. \quad \sum_{j=1}^m u_j x_{jp} = 1 \\
 & \quad \sum_{k=1}^s v_k y_{ki} - \sum_{j=1}^m u_j x_{ji} \leq 0, \quad \forall i \\
 & \quad v_k, u_j \geq 0 \quad \forall k, j
 \end{aligned}$$

where:  $p$  is the unit being evaluated;  $s$  represents the number of outputs;  $m$  represents the number of inputs;  $y_{ki}$  is the amount of output  $k$  provided by unit  $i$ ;  $x_{ji}$  is the amount of input  $j$  used by unit  $i$ ;  $v_k$  and  $u_j$  are the weights given to output  $k$  and input  $j$ , respectively.



## CCR DEA Model (Dual Form)

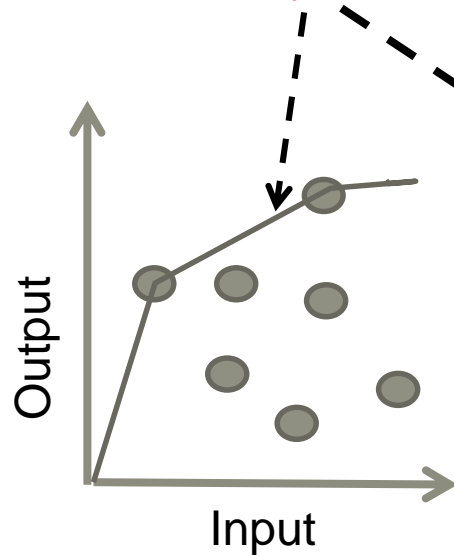
$$\begin{aligned} \min \quad & \theta \\ \text{s.t.} \quad & \sum_i \lambda_i x_{ji} \leq \theta x_{jp} \quad \forall j \\ & \sum_i \lambda_i y_{ki} \geq y_{kp} \quad \forall k \\ & \lambda_i \geq 0 \quad \forall i \end{aligned}$$

where:  $\theta$  represents the efficiency score of unit  $p$ ;  $\lambda$ s represent the dual variables that identify the benchmarks for inefficient units.



# Efficiency Evaluation - BCC DEA Model

new constraint  
(convexity)



$$\begin{aligned} \min \quad & \theta \\ \text{s.t.} \quad & \sum_i \lambda_i x_{ji} \leq \theta x_{jp} \quad \forall j \\ & \sum_i \lambda_i y_{ki} \geq y_{kp} \quad \forall k \\ & \sum_i \lambda_i = 1 \\ & \lambda_i \geq 0 \quad \forall i \end{aligned}$$

where:  $\theta$  represents the efficiency score of unit  $p$ ;  $\lambda$ s represent the dual variables that identify the benchmarks for inefficient units.



# Windows Analysis

- Temporal data in efficiency evaluation
- Network is treated as a different entity in each time period
- Network is compared to itself over time





# Individual Control Chart (X-Chart)

- Sample size of 1 (single efficiency score in each period)

Standard deviation

$$UCL = \bar{\bar{x}} + 3 \frac{\overline{MR}}{d_2}$$

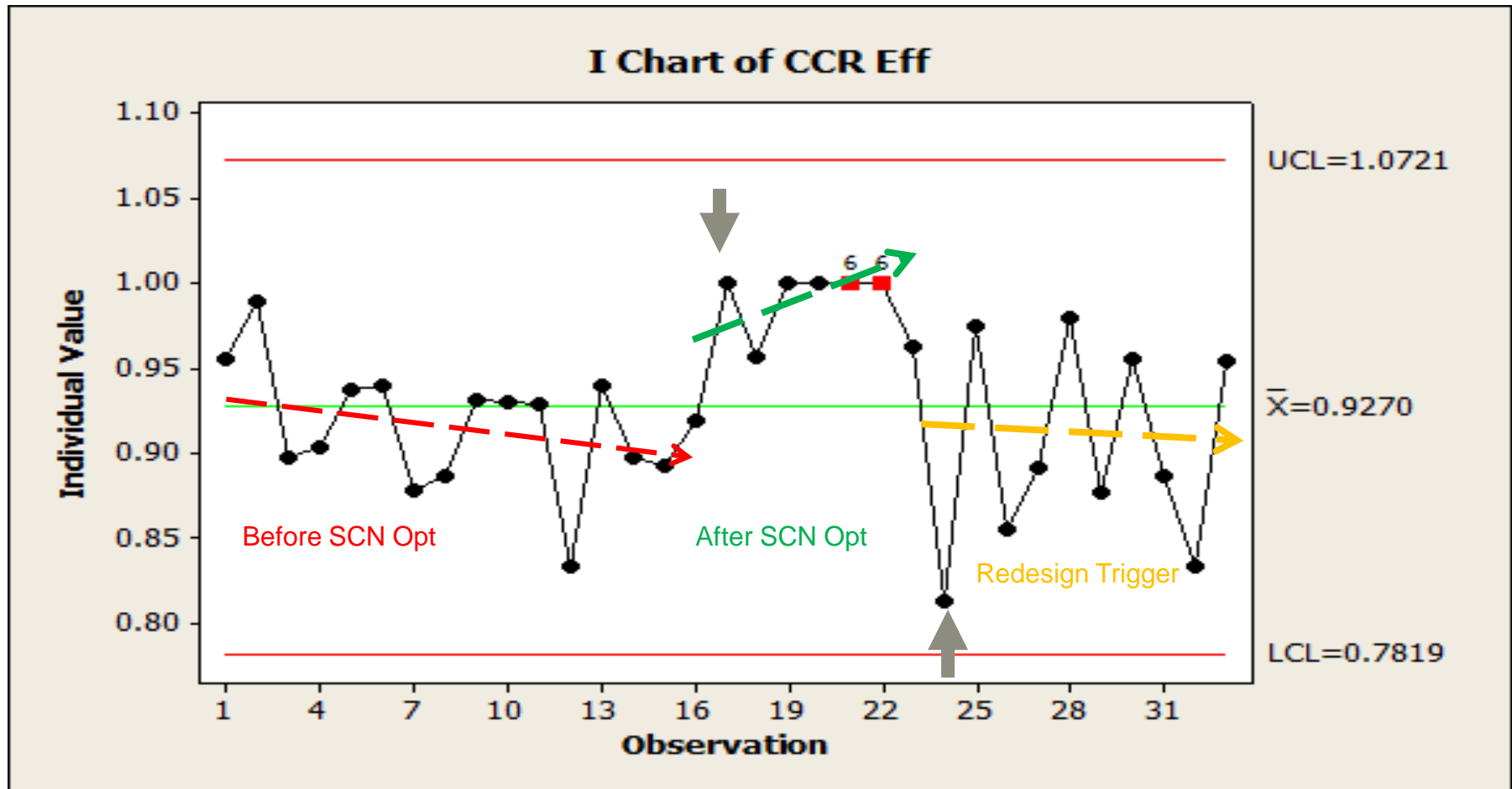
$$CL = \bar{\bar{x}}$$

$$LCL = \bar{\bar{x}} - 3 \frac{\overline{MR}}{d_2}$$

Where:  $\overline{MR} = \frac{\sum_{i=1}^m MR_i}{m}$

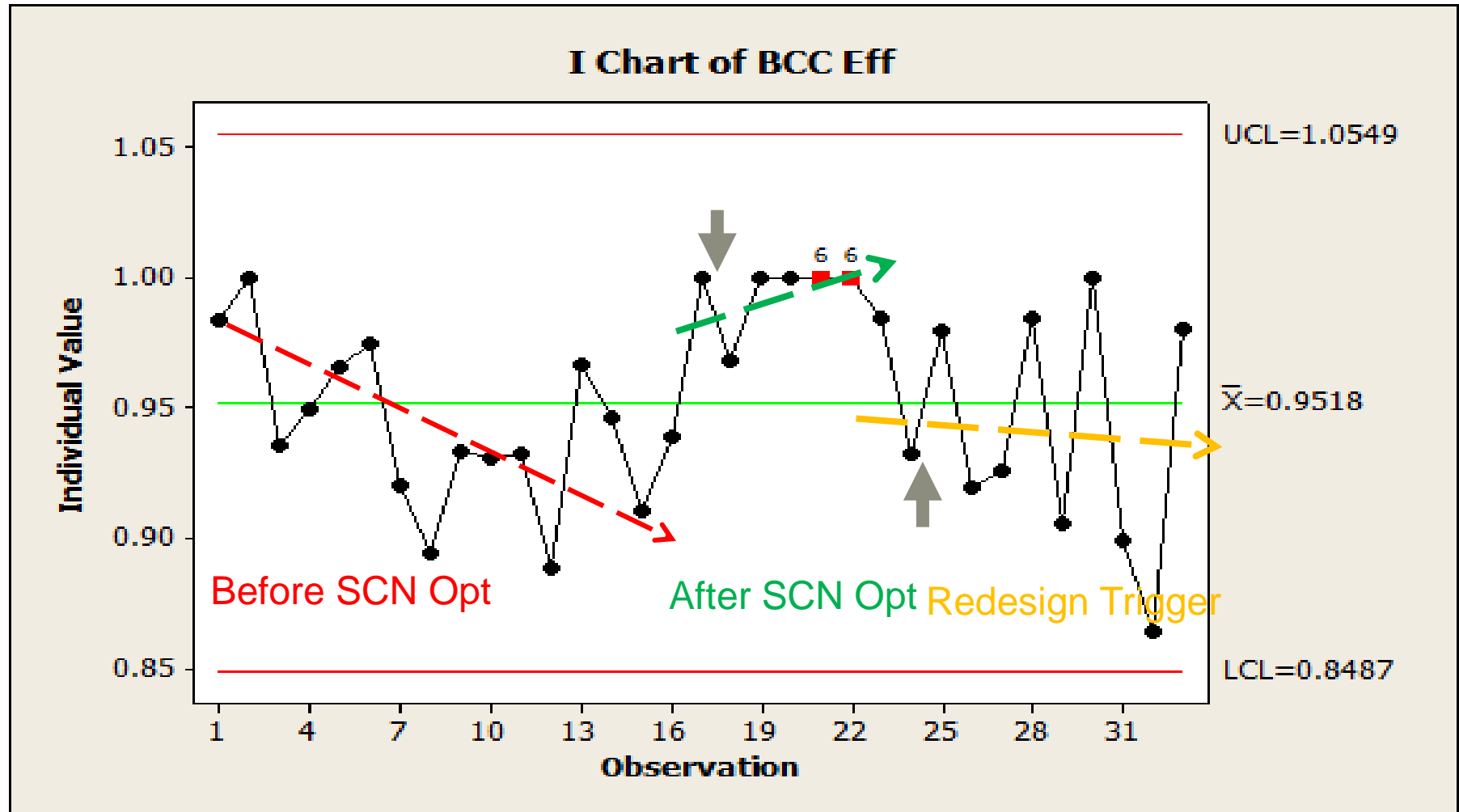


# Supply Chain Network Efficiency Results – Constant Returns to Scale





# Supply Chain Network Efficiency Results – Variable Returns to Scale





# Before and After Efficiency Differences – Mann Whitney Test

- Efficiency scores (normality issues)
- Nonparametric test for differences in distributions - Mann Whitney
- Hypotheses:
  - $H_0$ : *No difference in efficiency scores between the two segments of data*
  - $H_1$ : *Efficiency scores of one segment is higher than the other segment*



# Before and After Efficiency Differences – Mann Whitney Test 1

- After optimization CCR efficiency scores are statistically better than before optimization scores
  - $n_1 = 16, n_2 = 7, p\text{-value} = 0.0004^{***}$
- After optimization BCC efficiency scores are statistically better than before optimization scores
  - $n_1 = 16, n_2 = 7, p\text{-value} = 0.0011^{***}$



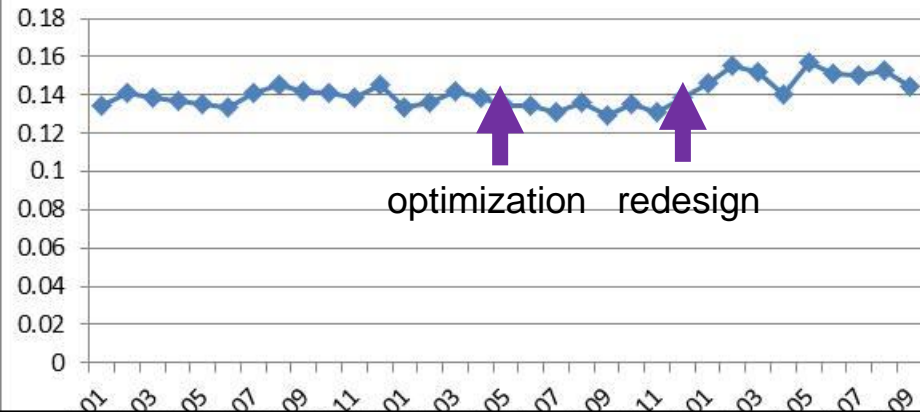
## Before and After Efficiency Differences – Mann Whitney Test 2

- After optimization CCR efficiency scores are statistically better than redesign trigger range scores
  - $n_1 = 7, n_2 = 10, p\text{-value} = 0.0029^{***}$
- After optimization BCC efficiency scores are statistically better than redesign trigger range scores
  - $n_1 = 7, n_2 = 10, p\text{-value} = 0.0112^{**}$

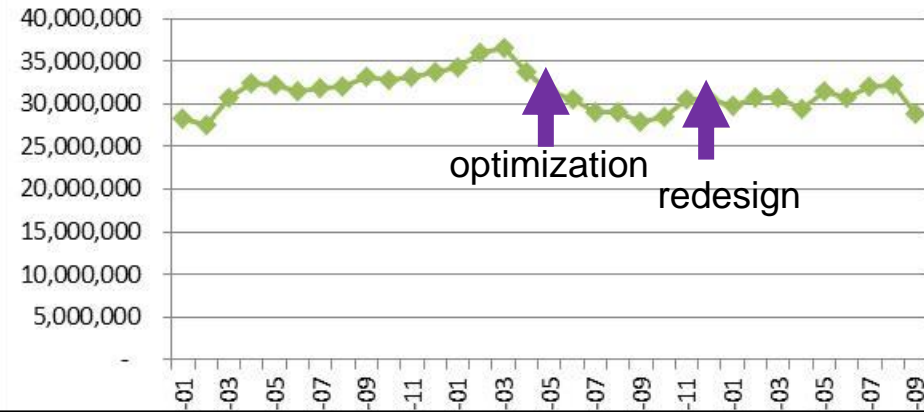


# Individual Factors

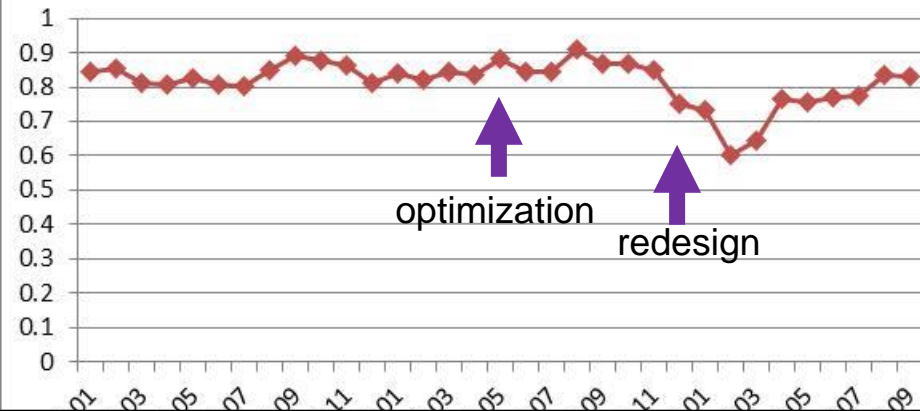
Transportation cost(\$/lb)



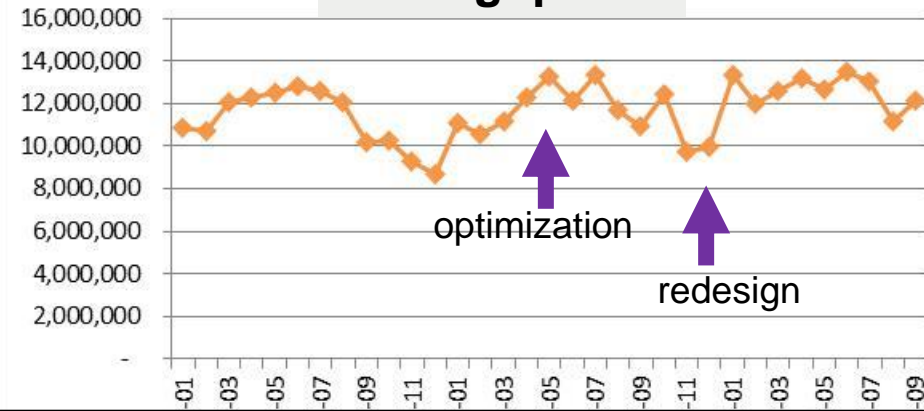
INV (\$)



CSL



Throughput





## Some Observations

- Each of the individual factors may be in control but the joint impact may show something different!
- After optimization: Transportation cost decreasing, inventory decreasing
- Redesign trigger: Transportation cost increasing, CSL decreasing, inventory increasing
  - Disruptions such as winter storm and the subsequent transportation capacity tightness might be a factors





# Impact of Disruptions

- The events include a wide range of failures:
  - Quality, transportation, inventory, production, documentation, and packaging issues
  - For each incident, the amount of products that were impacted was recorded. We used this information as a proxy for the size of the impact of the failure
- Hypotheses:
  - $H_0$ : *No difference in mean impacted product amounts between the two segments of data (Before SCN Opt vs. After SCN opt, Redesign Trigger vs. After SCM Opt)*
  - $H_1$ : *First segment results in a higher mean impacted product amounts than the second segment*



# Impact of Disruptions

- Failed to reject the Null Hypotheses in both cases (p-values of **0.17** and **0.13**, respectively)

	Mean	Std. Deviation
Before SCN Opt.	211427.1	46425.0
After SCN Opt.	183025.1	67329.4
Redesign Trigger	225537.6	54460.9

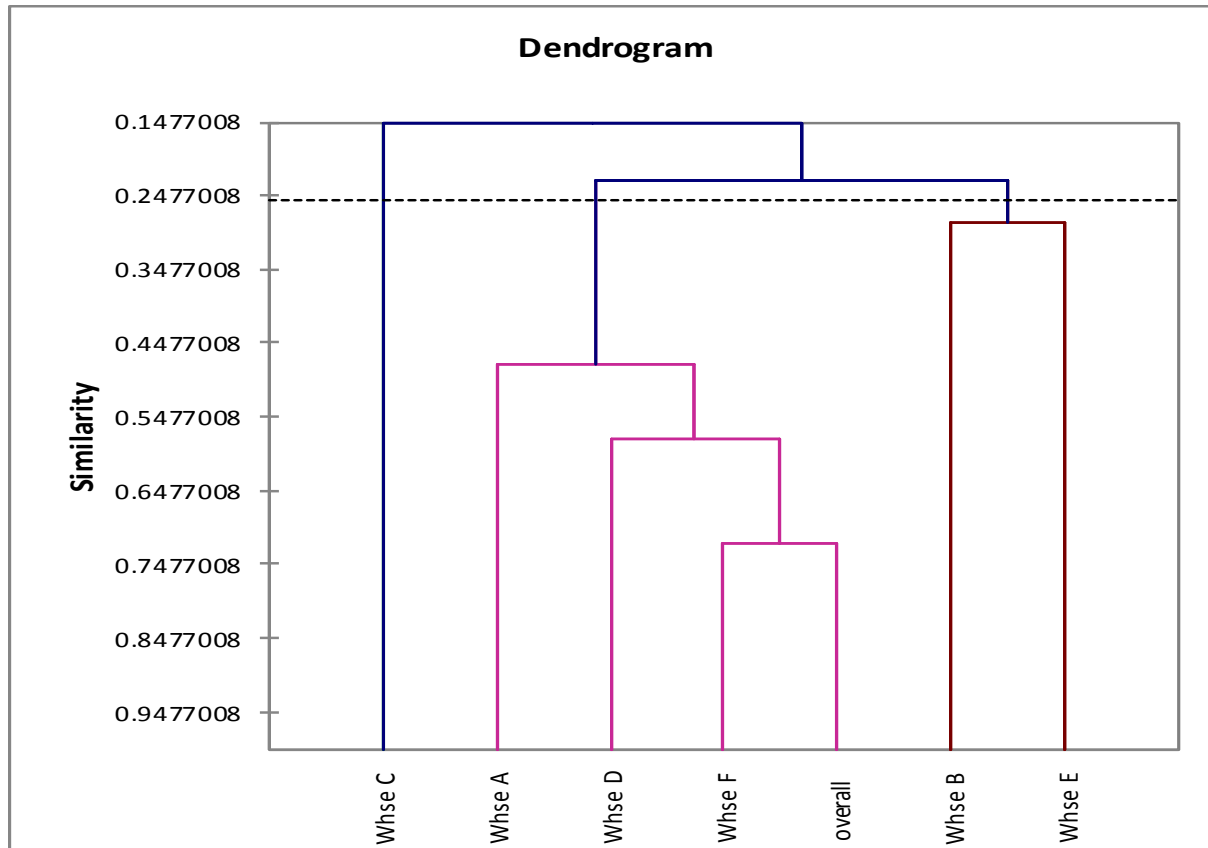


# Warehouses vs. Network Efficiency

- Compared the overall network efficiency in each period to individual warehouse efficiencies
  - Efficiency evaluations for 6 x 33 units
- Clustering approach to investigate similarities in terms of network and warehouse efficiencies
- Helps focus on improvement strategies and resource allocations



# Dendrogram based on CCR Scores



- Similarity: Spearman Correlation Coefficient; Agglomeration: Unweighted Pair-Group Average
- Cluster 1- A, D, F, Overall; Cluster 2- B, E; Cluster 3- C
- Initial focus is on improving the efficiencies of F, D, and A



# Tukey's Multiple Comparisons: Warehouses

Transportation Cost (Low to High)

WH/Group	1	2	3	4
C	X			
E	X			
A	X	X		
F		X	X	
D			X	X
B				X

Inventory (Low to High)

WH/Group	1	2	3	4
B	X			
C	X			
E		X		
A			X	
D				X
F				X

Customer Service (High to Low)

WH/Group	1	2	3
C	X		
B	X	X	
F		X	
E		X	X
A		X	X
D			X

Throughput (High to Low)

WH/Group	1	2	3	4	5
F	X				
D		X			
A			X		
E				X	
B					X
C					X

- Warehouse F facing high inventory and transportation costs with lower customer service levels but high throughput rates (**p-value < 0.01**)



## Limitations with CCR and BCC Models

- Unrestricted weight flexibility
- A unit can emphasize on few input and output factors in achieving high efficiency scores
- Cross-efficiencies can appease this issue



# Cross-Efficiency Evaluations

- Cross efficiency in DEA allows for effective discrimination between niche performers and good overall performers
- Cross efficiency score of a unit represents how well the unit is performing with respect to the optimal weights of another unit
- A unit that achieves high cross efficiency scores is a good overall performer



# Cross-Efficiency Matrix

DMU	1	2	3	N
1	$\theta_{11}$	$\theta_{12}$	$\theta_{13}$	$\theta_{1N}$
2	$\theta_{21}$	$\theta_{22}$	$\theta_{23}$	$\theta_{2N}$
3	$\theta_{31}$	$\theta_{32}$	$\theta_{33}$	$\theta_{3N}$
N	$\theta_{N1}$	$\theta_{N2}$	$\theta_{N3}$	$\theta_{NN}$

Efficiency score of **DMU 2** when evaluated  
with the optimal weights of **DMU 1**





# Cross-Efficiency Evaluations

- Weights obtained from the CCR model may not be unique, which undermines the usefulness of the cross-efficiency matrix
- We utilize game models to obtain a robust set of weights for cross efficiency evaluations
- Set of weights that not only maximizes the efficiency of a unit but in some sense minimizes the efficiency of all other units



# Cross-Efficiency Models – Blanket Formulations

Aggressive

$$\min \sum_{k=1}^s \left( v_k \sum_{i \neq p} y_{ki} \right)$$

$$s.t. \sum_{j=1}^m \left( u_j \sum_{i \neq p} x_{ji} \right) = 1$$

$$\sum_{k=1}^s v_k y_{ki} - \sum_{j=1}^m u_j x_{ji} \leq 0, \quad \forall i \neq p$$

$$\sum_{k=1}^s v_k y_{kp} - \theta_p \sum_{j=1}^m u_j x_{jp} = 0$$

$$v_k, u_j \geq 0 \quad \forall k, j$$

Benevolent

$$\max \sum_{k=1}^s \left( v_k \sum_{i \neq p} y_{ki} \right)$$

$$s.t. \sum_{j=1}^m \left( u_j \sum_{i \neq p} x_{ji} \right) = 1$$

$$\sum_{k=1}^s v_k y_{ki} - \sum_{j=1}^m u_j x_{ji} \leq 0, \quad \forall i \neq p$$

$$\sum_{k=1}^s v_k y_{kp} - \theta_p \sum_{j=1}^m u_j x_{jp} = 0$$

$$v_k, u_j \geq 0 \quad \forall k, j$$

Where  $\theta_p$  is the relative efficiency score of DMU p obtained from the CCR model



## X-bar Chart

- $UCL, LCL = \bar{\bar{x}} \pm 3 \frac{\bar{R}}{d_2 \sqrt{n}}$
- where  $\bar{\bar{x}}$  is the average of all the cross-efficiency scores;  $d_2$  is the table value obtained from standard quality control tables;  $\bar{R}$  is the mean sample range, which is calculated as:
- $\bar{R} = \left( \frac{\sum_{i=1}^m R_i}{m} \right)$ , where  $R_i$  is the difference between the largest and smallest cross efficiency scores

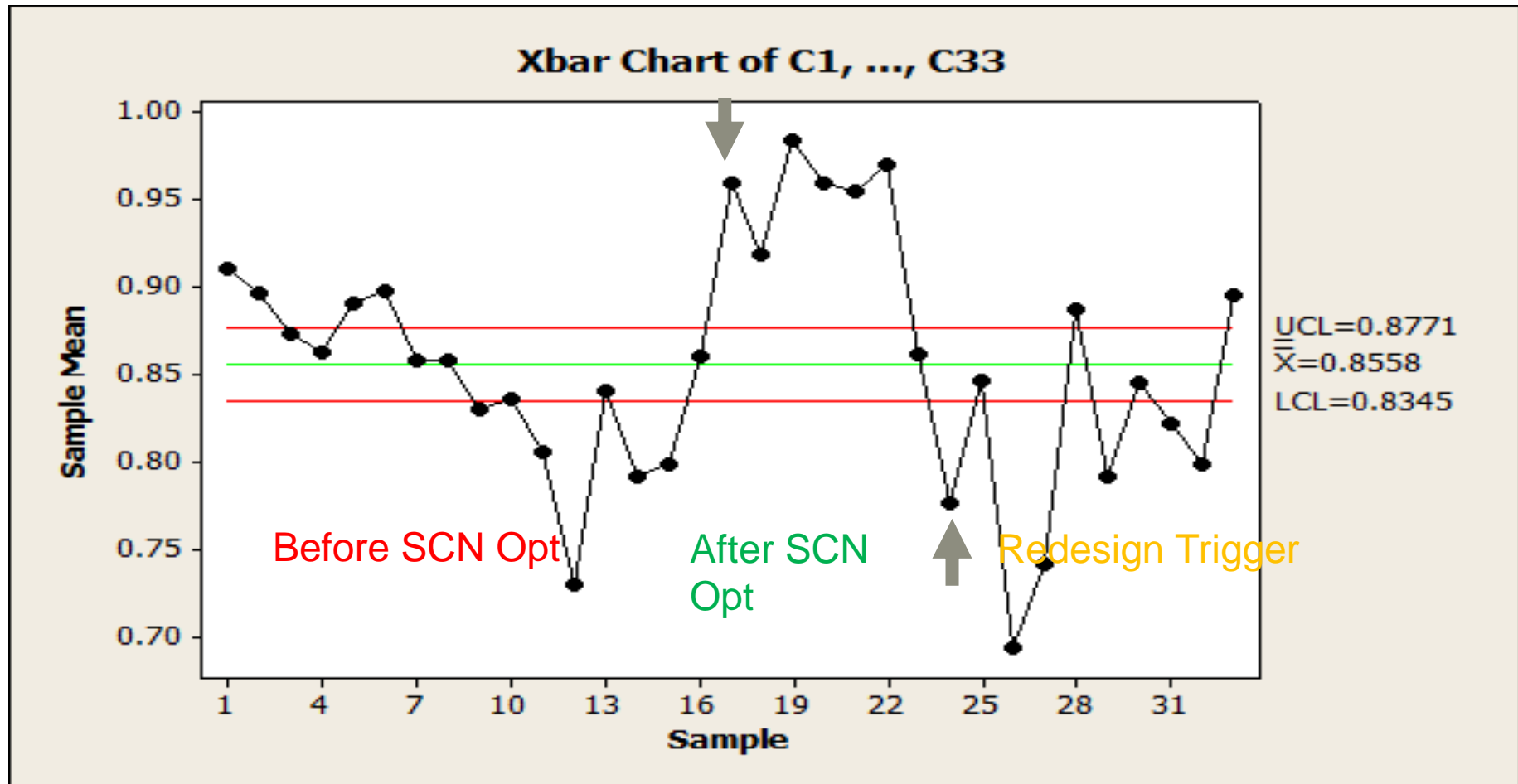


## R Chart

- The control limits for the range R chart are defined by:
- $UCL = D_4 \bar{R}$
- $LCL = D_3 \bar{R}$
- Where,  $D_4$  and  $D_3$  are table values obtained from standard quality control tables.

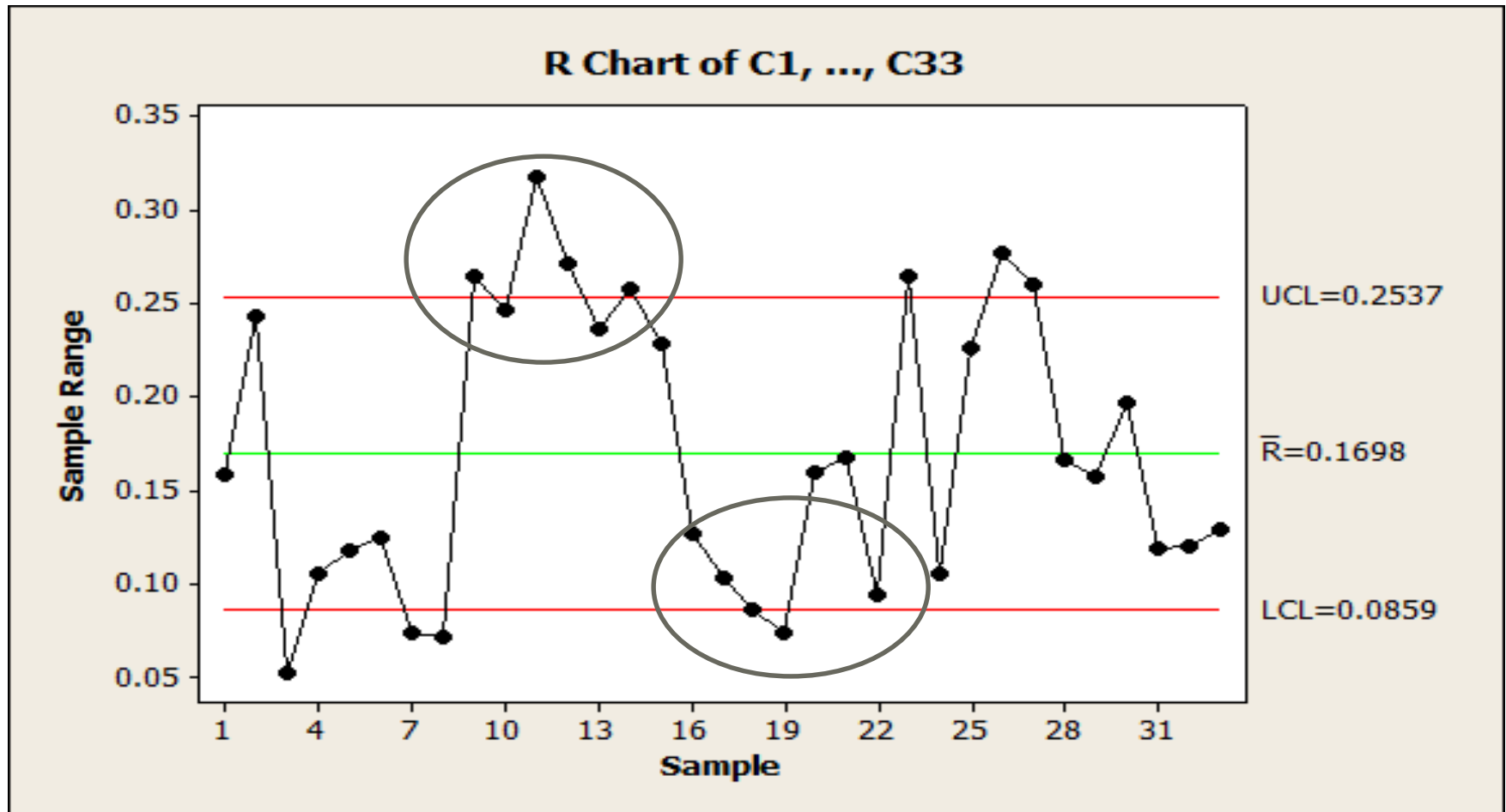


# Supply Chain Network Cross Efficiency Results: $\bar{X}$ Chart





# Supply Chain Network Cross Efficiency Results: R-Chart





## Conclusions and Next Steps

- Case Company is using our approach as a dashboard system to monitor network efficiency
- Make the network assessment more comprehensive
  - Plant level data
  - Upstream data (suppliers)
  - Efficacy of Network DEA models
  - Big data and interactions between various supply chain partners