Procurement in the Twenty First Century: New Approaches to Old Problems

Awi Federgruen

Joint work with Daniel Guetta and Garud Iyengar
**Motivation**

- **Distribution systems** are becoming **increasingly complex**.

- The days of a **single retailer** selling a **small number of products** at a **single location** – if they ever existed – are **long gone**.
  - Amazon.
  - “Stores within stores”.
  - Using **brick and mortar** stores as “**distribution centers**”.
  - Many products, leading to an **inability to stock everything**.

- In the past, operational excellence was often **less of a priority**.

- In an **increasingly competitive** market, this is **no longer the case**.
Motivation

- Over 100 fulfilment centers
- 11 global marketplaces
- Buying customers in 180 countries
- More than 30 listing categories globally, competing for storage space
Motivation

- Over 11,000 stores worldwide, operating under 59 different names
- Just under 17 million SKUs
- Transforming some of its stores to distribution centers as it strengthens its online operations
- Recent acquisition of Jet.com is also part of this move
Our Model

- Two echelons
- Multiple retailers
- Inventories at the depot
- Arbitrary demand distributions
- Arbitrary cost parameters
- Capacitated retailers
- Multiple items
- Inter-item dependencies
Brief Literature Review
Clark & Scarf (1960)

- Two echelons
- Multiple retailers
- Inventories at the depot
- Arbitrary demands
- Arbitrary costs
- Capacitated retailers
- Multiple items
- Inter-item dependencies
Clark & Scarf (1960)

- Two echelons
  - Multiple retailers
  - Inventories at the depot
  - Arbitrary demands
  - Arbitrary costs
  - Capacitated retailers
  - Multiple items
  - Inter-item dependencies
Federgruen & Zipkin (1984a, b, c)

- Two echelons
- Multiple retailers
- Inventories at the depot
- Arbitrary demands
- Arbitrary costs
- Capacitated retailers
- Multiple items
- Inter-item dependencies
Federgruen & Zipkin (1984a, b, c)

- Two echelons
- Multiple retailers
  - Inventories at the depot
  - Arbitrary demands
  - Arbitrary costs
  - Capacitated retailers
  - Multiple items
  - Inter-item dependencies

Procurement in the Twenty First Century
Kunnumkal & Topaloglu (2008)

- Two echelons
- Multiple retailers
  - Inventories at the depot
  - Arbitrary demands
  - Arbitrary costs
  - Capacitated retailers
  - Multiple items
  - Inter-item dependencies
Kunnumkal & Topaloglu (2008)

- Two echelons
- Multiple retailers
- Inventories at the depot
- Arbitrary demands
- Arbitrary costs
  - Capacitated retailers
  - Multiple items
  - Inter-item dependencies

Procurement in the Twenty First Century
Approximation strategy

- Easy
  - Cost of heuristic policy
- Hard
  - Optimal cost
- Easy
  - Optimal cost of a different problem obtained by relaxing our current problem
A Dynamic Programming Formulation
A Dynamic Programming Formulation
Modeling the Capacity Constraints

• Conservatively
  \[
  \text{Shipment} + \text{Pipeline} + \text{Inventory} \leq \text{Capacity}
  \]

• Ideally
  \[
  \text{Shipment} + \text{Pipeline} + \text{Inventory} - \text{Interim Demand} \leq \text{Capacity}
  \]

• Instead, use the following robust constraint
  \[
  P\left(\text{Shipment} + \text{Pipeline} + \text{Inventory} - \text{Interim Demand} \geq \text{Capacity}\right) \leq \alpha
  \]
Modeling the Capacity Constraints

\[ P\left( \text{Shipment + Pipeline + Inventory} \right. \quad - \quad \text{Interim Demand} \quad \geq \quad \text{Capacity} ) \leq \alpha \]

- In the single-product case...
  \[ \text{Shipment + Pipeline + Inventory} \quad - \quad \alpha\text{-fracticle-demand} \quad \leq \quad \text{Capacity} \]

- Multi-product case
  \[ \sum_{\text{items}} \max( \text{Shipment + Pipeline + Inventory} \quad - \quad \alpha\text{-demand}, 0) \quad \leq \quad \text{Capacity} \]

Backorder is not free capacity
The state space...
Obtaining a Lower Bound
The state space...
First Relaxation

Adelman and Mersereau (2008)
The state space...
Second Relaxation

Lagrangian Relaxation of non-negativity constraints on shipments

Optimal \((s, S)\) policy
A Heuristic Strategy
An upper bound

Three steps to a heuristic
1. Ordering strategy
2. Withdrawal strategy
3. Allocation strategy

Order using the \((S, s)\) policy from the lower bound

Ship using a heuristic withdrawal and allocation policy
Procurement in the Twenty First Century

Federgruen & Zipkin (1984a, b)

- No inventories at the depot means no withdrawal policy is necessary.
- Whenever an order arrives, an allocation policy is needed.
- F&Z use a myopic allocation policy. Minimizes expected costs in the first period in which shipment arrives.
The Perils of a Myopic Policy

Big order arrives (enough for many periods)

Equal Demands

- Low Holding Cost
- High Holding Cost
- High Holding Cost
• **No inventories at the depot** means **no withdrawal policy** is necessary.

• Whenever an order arrives, an **allocation policy** is needed.

• Instead of minimizing costs in the first period in which shipments arrive, target an **arbitrary period** $k$ within the replenishment cycle.

• For example, set $k$ to be the **period in which inventory is next likely to run out**.
Our Heuristic Policy

• **Withdrawal policy** is necessary.

• Decisions now potentially need to be made in **every period of the replenishment cycle**.

• Minimize **total expected costs** over **every period** in this (expected) replenishment cycle with respect to **every shipment decision** in this (expected) replenishment cycle
  → **Large-scale multiperiod** convex optimization problem

• **Re-solve this problem** on a **rolling horizon basis** in light of new information revealed in each period
Computational details

- For Each Product
  - Solve single-product lower bound DP with given multipliers $\lambda$
  - Find subgradients with respect to $\lambda$
    - Optimize Over Multipliers $\lambda$
      - Find $(s, S)$ policy optimal for each item given optimal multipliers $\lambda$
      - Solve the Heuristic withdrawal and allocation policy
      - Simulate Heuristic Policy
Testing the Heuristic Strategy’s Performance
### Results (Multi-Product Case)

**$T = 20$, 8 retailers, 7 products**

<table>
<thead>
<tr>
<th><strong>Ratio of Holding:Backorder Costs at the Retailers</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Kept either constant or random across retailers. Calibrated to average 4 or 10</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Holding Costs at the Depot</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Set to either the <em>maximum</em> holding cost at any retailer, or ( \frac{1}{2} ) that maximum holding cost</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Fixed Order Costs</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibrated to target a replenishment cycle of 3 periods or 7 periods</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Lead times</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>• Supplier → Depot: 3 or 4</td>
<td></td>
</tr>
<tr>
<td>• Depot → Retailers: 2 or 3</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Demand Distributions</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal distributions, approximated by a discrete distribution.</td>
<td></td>
</tr>
<tr>
<td>Means picked uniformly in ([80, 120])</td>
<td></td>
</tr>
<tr>
<td>CVs either constant or random.</td>
<td></td>
</tr>
<tr>
<td>Calibrated to average 0.15, 0.3 or 0.4</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Retailer Capacities</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Set to mean demand plus ({-1, 5, 1000}) SD of demand</td>
<td></td>
</tr>
</tbody>
</table>
### Results (Multi-Product Case)

<table>
<thead>
<tr>
<th>Structural parameters</th>
<th>T = 20, 8 retailers, 7 products</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Holding &amp; backorder costs at retailers</strong></td>
<td>Kept either constant or random across retailers. Calibrated to average 4 or 10</td>
</tr>
<tr>
<td><strong>Holding cost at the depot</strong></td>
<td>Set to either the maximum holding cost at any retailer, or ( \frac{1}{2} ) that maximum holding cost</td>
</tr>
<tr>
<td><strong>Fixed order costs</strong></td>
<td>Calibrated using the EOQ model to target a replenishment epoch of 3 or periods 7 periods</td>
</tr>
</tbody>
</table>
| **Lead times** | Supplier → Depot: 3 or 4  
Depot → Retailers: 2 or 3 |
| **Demand distributions** | Normal distributions, approximated by a 49-point discrete distribution.  
Means picked uniformly in [80, 120]  
CVs either constant or random. Calibrated to average 0.15, 0.3 or 0.4 |
| **Retailer capacities** | Set to mean demand plus \{-1, 5, 1000\} SD of demand |
### Results (Multi-Product Case)

<table>
<thead>
<tr>
<th></th>
<th>CV\text{Base} = 0.15</th>
<th></th>
<th>CV\text{Base} = 0.3</th>
<th></th>
<th>CV\text{Base} = 0.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>overPenalty $\rightarrow$ 0.5</td>
<td>0.5</td>
<td>1</td>
<td>0.5</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>chiBase $= -1$</td>
<td>Const. CV</td>
<td>0.18</td>
<td>3.02</td>
<td>0.19</td>
<td>3.1</td>
</tr>
<tr>
<td></td>
<td>Rand. CV</td>
<td>0.08</td>
<td>4.49</td>
<td>0.1</td>
<td>4.65</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>chiBase $= 5$</td>
<td>Const. CV</td>
<td>0.18</td>
<td>2.05</td>
<td>0.19</td>
<td>2.87</td>
</tr>
<tr>
<td></td>
<td>Rand. CV</td>
<td>0.08</td>
<td>3.72</td>
<td>0.1</td>
<td>3.48</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>chiBase $= 1000$</td>
<td>Const. CV</td>
<td>0.18</td>
<td>0.65</td>
<td>0.19</td>
<td>0.65</td>
</tr>
<tr>
<td></td>
<td>Rand. CV</td>
<td>0.08</td>
<td>0.63</td>
<td>0.1</td>
<td>0.63</td>
</tr>
</tbody>
</table>

Table 3.2: 100 \cdot (\text{UB} - \text{LB})/\text{LB} results for $L = 4$, $\ell = 3$, $\text{targetEpochs} = 7$, and $\text{baseCostRatio} = 10$. 

Procurement in the Twenty First Century
Results (Multi-Product Case)

\[
\text{Metric} = 100 \cdot \frac{UB - LB}{LB}
\]

• Across all instances, the maximum percentage difference was 8%. The mean percentage difference was 1.27%, and the median was 0.86%.
• 82% of all instances had gaps smaller than 2%.
• Running a naïve linear regression on the results, it appears that high depot costs is the stronger predictor of a larger gap, adding 1.49 percentage points on average.
• Predictably, a longer replenishment cycle also seems to increase the gap.
Strategic Insights
Capacity Considerations

• The larger the capacity at the retailers, the cheaper the operational costs.

• How much cheaper exactly?

• Increasing the capacity at retailers can also be costly.

• Given the cost of endowing retailers with given capacities, what is the optimal capacity level to use?

• We carried out a simulation study for a system comprising 8 retailers and 8 products.
Capacity Considerations

The graph shows the cost premium over the maximum capacity case as a function of capacity. The cost premium decreases as capacity increases, indicating economies of scale in procurement. The x-axis represents capacity, while the y-axis represents the cost premium over the maximum capacity case (%).
Value of Increasing Capacity

![Graph showing the value of increasing capacity against cost per unit capacity. The curve indicates that as the cost per unit capacity increases, the optimal capacity decreases.]
Jiang, Jerath, and Srinivasan (2011) consider Amazon.com, which stocks some items, and outsources most others to third-party sellers.

<table>
<thead>
<tr>
<th>Category/subcategory</th>
<th>Total no. of products</th>
<th>% sold by Amazon</th>
<th>% sold by Amazon among top 100 best sellers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>2,024,750</td>
<td>7.0</td>
<td>64</td>
</tr>
<tr>
<td>Accessories &amp; Supplies</td>
<td>407,149</td>
<td>10.5</td>
<td>62</td>
</tr>
<tr>
<td>Camera &amp; Photo</td>
<td>410,312</td>
<td>10.1</td>
<td>76</td>
</tr>
<tr>
<td>Car electronics</td>
<td>16,731</td>
<td>23.3</td>
<td>90</td>
</tr>
<tr>
<td>Computers &amp; Accessories</td>
<td>997,543</td>
<td>4.9</td>
<td>73</td>
</tr>
<tr>
<td>GPS &amp; Navigation</td>
<td>8,453</td>
<td>21.9</td>
<td>89</td>
</tr>
<tr>
<td>Home audio &amp; Theater</td>
<td>10,433</td>
<td>24.2</td>
<td>71</td>
</tr>
<tr>
<td>Marine electronics</td>
<td>593</td>
<td>41.1</td>
<td>83</td>
</tr>
<tr>
<td>Office electronics</td>
<td>39,214</td>
<td>6.7</td>
<td>77</td>
</tr>
<tr>
<td>Portable audio &amp; Video</td>
<td>48,678</td>
<td>15.1</td>
<td>47</td>
</tr>
<tr>
<td>Security &amp; Surveillance</td>
<td>11,320</td>
<td>15.9</td>
<td>66</td>
</tr>
<tr>
<td>Televisions &amp; Video</td>
<td>14,753</td>
<td>6.4</td>
<td>75</td>
</tr>
<tr>
<td>Tools &amp; Home improvement</td>
<td>2,460,108</td>
<td>5.8</td>
<td>88</td>
</tr>
<tr>
<td>Sports &amp; Outdoors</td>
<td>3,695,634</td>
<td>3.1</td>
<td>76</td>
</tr>
<tr>
<td>Jewelry</td>
<td>1,287,098</td>
<td>3.2</td>
<td>34</td>
</tr>
<tr>
<td>Toys &amp; Games</td>
<td>798,977</td>
<td>5.9</td>
<td>66</td>
</tr>
<tr>
<td>Shoes</td>
<td>344,710</td>
<td>16.7</td>
<td>72</td>
</tr>
</tbody>
</table>
Jiang, Jerath, and Srinivasan (2011) consider Amazon.com, which stocks some items, and outsources others to third-party sellers.

JJ&S do not directly consider the problem of picking the optimal assortment of items.

Instead, they focus on the incentive third party sellers have to underperform, and formulate this phenomenon as a game.

They assume each party’s operational costs are quadratic in some service level $e$. 

Suppose we have a “menu” of 8 heterogeneous items we can choose to stock.

- **Question 1**: suppose we need to stock a **subset of these items**. Which is the **cheapest subset** to stock from an **operational perspective**?

- **Question 2**: what is the **optimal assortment size**?
### Operational Impact of Assortments

<table>
<thead>
<tr>
<th>Low Mean Demand ($\mu = 50$)</th>
<th>High Mean Demand ($\mu = 100$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Uncertainty ($CV = 0.15$)</td>
<td></td>
</tr>
<tr>
<td><img src="image1" alt="Seasonal demand" /> <img src="image2" alt="Regular demand" /></td>
<td></td>
</tr>
<tr>
<td><img src="image3" alt="Seasonal demand" /> <img src="image4" alt="Regular demand" /></td>
<td></td>
</tr>
<tr>
<td>High Uncertainty ($CV = 0.3$)</td>
<td></td>
</tr>
</tbody>
</table>

Performance measure: expected operational cost to expected revenue ratio
Q1: suppose we need to stock a **subset of these items**. Which is the **cheapest subset** to stock from an **operational perspective**?

- $n = 8$
- $n = 7$
- $n = 6$ (High demand)
- $n = 5$
- $n = 4$ (High coefficients of variation)
Q2: what is the **optimal assortment size**?
Single-Location Supply Chain Management with Dynamic Demand Updates
Problem formulation
Problem formulation

\[
\begin{array}{c|c}
F_1 & D_1 \\
F_2 & D_2 \\
F_3 & D_3 \\
F_4 & D_4 \\
F_5 & D_5 \\
F_6 & D_6 \\
F_7 & D_7 \\
\end{array}
\]
Problem formulation

\[ f_1 d_1 \]
\[ f_2 d_2 \]
\[ f_3 d_3 \]
\[ f_4 D_4 \]
\[ F_5 D_5 \]
\[ F_6 D_6 \]
\[ F_7 D_7 \]
Problem formulation

\[ \begin{align*}
    f_1 & \quad d_1 \\
    f_2 & \quad d_2 \\
    f_3 & \quad d_3 \\
    f_4 & \quad D_4 \sim (D_4 \mid F_4 = f_4) \\
    F_5 & \quad D_5 \sim (D_5 \mid F_4 = f_4) \\
    F_6 & \quad D_6 \sim (D_6 \mid F_4 = f_4) \\
    F_7 & \quad D_7 \sim (D_7 \mid F_4 = f_4)
\end{align*} \]
Decisions

\[ W_t \in \mathcal{W}_t \]

\[ L \]
We incur standard fixed and variable orderings costs

\[ c_t W_t + K_t \mathbb{I}_{\{W_t > 0\}} \]

We also incur inventory costs

\[ Q_t (x_t + W_t \mid f_t) \]

Pipeline inventory at the start of period \( t \)
The full DP

\[ V_t(x_t, f_t) = \min_{W_t \in \mathcal{W}_t} \left\{ K_t \mathbb{I}_{\{W_t > 0\}} + c_t W_t + Q_t(x_t + W_t | f_t) \right. \\
\left. + \mathbb{E}_{D_t, F_{t+1} \mid F_t = f_t} \left[ V_{t+1}(x_t + W_t - D_t, F_{t+1}) \right] \right\} \]

- Iida and Zipkin (2006), Sethi and Cheng (1997), Gallego and Özer (2001), etc...
- Shaoxiang and Lambrecht (1996)
- Levi and Shi (2013), Shi et. al. (2014), Truong (2014), etc...
The Information Relaxation

Brown, Smith, and Sun (2010)

\[
V_t(x_t, f_t) = \min_{W_t \in \mathcal{W}_t} \left\{ K_t \mathbb{I}_{\{W_t > 0\}} + c_t W_t + Q_t(x_t + W_t \mid f_t) + \mathbb{E}_{D_t,F_{t+1} \mid f_t} \left[ V_{t+1}(x_t + W_t - D_t, F_{t+1}) \right] \right\}
\]

Consider a specific realization of demands and information sets

\[
f = \left\{ f_1, \cdots, f_T \right\} \quad \text{and} \quad d = \left\{ d_1, \cdots, d_T \right\}
\]

We can then find the optimal policy over this sample path

\[
u_t^{f,d}(x_t) = \min_{W_t \in \mathcal{W}_t} \left\{ K_t \mathbb{I}_{\{W_t > 0\}} + c_t W_t + Q_t(x_t + W_t \mid f_t) + v_{t+1}^{f,d}(x_t + W_t - d_t) \right\}
\]

And then average over all such paths

\[
\nu_t(x_t, f_t) = \mathbb{E}_{F,D \mid f_t} \left[ v_t^{F,D}(x_t) \right]
\]
Penalizing the Relaxation

\[
v_{t}^{f,d}(x_{t}) = \min_{W_t \in \mathcal{W}_t} \left\{ K_t \mathbb{I}_{\{W_t > 0\}} + c_t W_t + Q_t(x_t + W_t \mid f_t) + v_{t+1}^{f,d}(x_t + W_t - d_t) \right\}
\]
Penalizing the Relaxation

\[ \tilde{v}^{f,d}(x_t) = \min_{W_t \in \mathcal{W}_t} \left\{ K_t \mathbb{I}_{\{W_t > 0\}} + c_t W_t + Q_t(x_t + W_t \mid f_t) + \tilde{v}^{f,d}_{t+1}(x_t + W_t - d_t) + \text{Penalty}^G(f, d, x_t, W_t) \right\} \]

\[ \tilde{v}_t(x_t, f_t) = \mathbb{E}_{F, D \mid F_t = f_t} \left[ \tilde{v}^{F,D}_t(x_t) \right] \]

Theorem (Strong Duality): There exists a penalty such that

\[ \tilde{v}^{f,d}_t(x_t) = V_t(x_t, f_t) \]

Theorem (Weak Duality): Regardless of the choice of \( G \), \( \tilde{v}_t \) is always a lower bound on \( V_t \).

Theorem (Concavity): For any value of \( x_t \) and \( f_t \), \( \tilde{v}_t(x_t, f_t) \) is a concave function of \( G \).
Penalizing the Relaxation

\[ \tilde{\nu}_{t}^{f,d}(x_t) = \min_{W_t \in \mathcal{W}} \left\{ K_t \mathbb{I}_{\{W_t > 0\}} + c_t W_t + Q_t(x_t + W_t \mid f_t) + \tilde{\nu}_{t+1}^{f,d}(x_t + W_t - d_t) \right. \]
\[ + \mathbb{E}_{D_t, F_{t+1} \mid F_t = f_t} \left[ \tilde{V}_{t+1} (x_t + W_t - D_t, F_{t+1}) \right] \]
\[ - \tilde{V}_{t+1} (x_t + W_t - d_t, f_{t+1}) \right\} \]
\[ \tilde{\nu}_t (x_t, f_t) = \mathbb{E}_{F, D \mid F_t = f_t} \left[ \tilde{\nu}_t^{F,D} (x_t) \right] \]

Theorem (Strong Duality): Suppose we pick \( \tilde{\nu}_t = V_t \) for all \( t \). Then
\[ \tilde{\nu}_t^{f,d}(x_t) = V_t (x_t, f_t). \]

Theorem (Weak Duality): Regardless of the choice of \( \tilde{\nu}_t \), \( \tilde{\nu}_t \) is always a lower bound on \( V_t \).
Quadratic Penalties

\[ \tilde{V}_t(x_t, f_t) = \left( x_t \quad (f_t)^\top \right) \left[ \begin{array}{cc} a_{t-1} & \frac{1}{2} (b_{t-1})^\top \\ \frac{1}{2} b_{t-1} & G_{t-1} \end{array} \right] \left( x_t \quad f_t \right) \]

Theorem (Concavity): For any value of \( x_t \) and \( f_t \), \( \tilde{V}_t(x_t, f_t) \) is a concave function of the parameters above.
• We test our lower bound approach on the advanced demand information model of Gallego and Özer (2001).

• Demands in each period $t$ are revealed over the previous $N$ periods. In each period, therefore, we observe information that will affect our belief about future demands.
Numerical Study

- We consider the following combination of parameters:
  - Leadtimes to the depot: \( L \) in \{0, 1, 2, 3, 4\}
  - Advance demand periods: \( N \) in \{\( L + 2 \), \( L + 3 \}\}
  - Fixed ordering costs: \( K \) in \{0, 10, 50\}
  - Backorder costs: \( p \) in \{1, 10, 50\}
  - Maximum order size allowed: \( C = \{3, 12, \infty\}\)
- We also vary the advance demand information mechanism.
- For each of these cases, we find the true optimal cost by solving the full high-dimensional DP, and compare it to our lower bound.
Results

In all cases, our lower bound never differed from the true optimal solution by more than 8%, and often much less.
Ongoing Research
Ongoing research

- Further **strategic insights**. For example
  - How should the system be structured? Is there value in **reducing leadtimes to the retailers** at the cost of **increasing the leadtime to the depot**?
  - If a choice can be made to **combine a number of retailers** (at the cost of **decreased demand** due to the resulting inconvenience to consumers), should that tradeoff be made?

- Finding **structure** in the heuristic policy, and developing **visualization** techniques for these kinds of systems.

- Tackling **other difficult features** of supply chains encountered in industry. For example, **realistic demand forecasting**.
Myopic upper bound

For all $i$: $D_i \sim N(1, 0.3^2)$ \quad $\chi_i = 10$ \quad $p_i = 10h_i$
Non-myopic upper bound

For all $i$: $D_i \sim N(1, 0.3^2)$ \quad $\chi_i = 10$ \quad $p_i = 10h_i$

Systemwide

(69,109)
LB: 37.03
UB: 41.02

h = 0.82  h = 0.82  h = 0.88  h = 0.98  h = 1.01

h = 1.06  h = 1.08  h = 1.08  h = 1.11  h = 10