2016 SCM RESEARCH JOURNAL

Summaries of selected research projects by the 2016 graduates of the MIT Master of Supply Chain Management Program
Introduction

Welcome to the 2016 Master of Supply Chain Management (SCM) Research Journal.

The projects included in this journal were selected from the twenty-one projects submitted by the SCM Class of 2016 at the Massachusetts Institute of Technology. The articles are written as executive summaries of the master’s thesis and are intended for a business rather than an academic audience. The purpose of the executive summaries is to give the reader a sense of the business problems being addressed, the methods used to analyze the problem, the relevant results and the insights gained.

The articles included in this publication cover a wide selection of interests, approaches, and industries. These projects were developed in partnership with companies ranging in size from startups to the largest companies in the world. They cover industries as diverse as restaurants, big box retail, garment manufacturing, e-commerce, CPG, chemicals, pharmaceuticals, and logistics services. They address issues of sustainability, consumer goods retail promotions, warehouse network design, inbound transportation, supply chain risk, and warehouse operations.

Each of the projects is a joint effort between a sponsoring company, one or two students, and a faculty advisor. Companies who are members of CTL’s Supply Chain Exchange are eligible to submit their ideas for thesis projects in July and August and then present these proposals to the students in early September. In mid-September the students select which projects they will work on. From September until early May the teams conduct the research and write up the results. In late May all the sponsors, faculty, and students participate in Research Fest, where all the thesis projects are presented.

The 10-month SCM program is designed for early to mid-career professionals who want a more in-depth and focused education in supply chain management, transportation, and logistics. The class size each year is limited to 40 students from around the globe and across all industries. The Master’s Thesis project gives the students a hands-on opportunity to put into practice the learnings that they are receiving in their coursework.

We hope you enjoy the articles. The rest of the master’s thesis projects are listed at the end of this journal. You can also view all of the executive summaries on the CTL website at: http://ctl.mit.edu/pubs. If you would like to learn more about the SCM Master’s Program or sponsor a thesis, please contact us directly.

Happy reading!
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Efficient Supply Chain Design for Highly Perishable Foods

By: Cyril Khamsi and Veronica Stolear
Thesis Advisor: Dr. Chris Caplice

Summary: The researchers evaluated four candidate supply routes to move fresh foods from a Northeastern supplier to regional stores: (1) dedicated supplier-to-store, (2) supplier and distribution center co-located for consolidated shipping, (3) supplier to city cross-dock for van routing, and (4) distribution center to supplier for pickup en route to stores. Utilizing approximation methods, the researchers developed a light-weight model to enable rapid cost estimate for each candidate design, including the current route.

Introduction
Supply chain network design is a critical aspect of business operations. It ensures that a company can reach its customers with the right products, in the right quantities, at the right time, place, quality, and price. These factors combined are essential for a company to thrive and grow in highly competitive environments. The requirements and challenges which supply chain networks must address are diverse, as are the methodologies being researched and developed to efficiently design these networks to efficiently meet the above “six rights” of supply chain management.

Data and Methodology
Focusing on the Greater Boston area, we collected demand data in collaboration with XYZ Co. The basic unit of demand was set to one tote, carrying on average 21 fresh food items. How can an organization evaluate the costs and dynamics of potential network designs, particularly when limited data is available or future conditions are uncertain? Employing approximation methods, we develop a model using limited inputs to rapidly estimate and compare the delivery costs and speeds of various network designs under diverse external conditions. This approach is a powerful means to evaluate the trade-offs between the network configurations, and their response to various exogenous conditions, such as demand variability and store growth.

This model is applied to a real-world scenario: the regional supply chain of a global coffee retailer with a rapidly expanding fresh food business – XYZ Co. Fresh food items include sandwiches, salads, parfaits and other food items which must be consumed within a few days of production. Critical insights are generated by using the model to compare the costs of the current supply chain network in the Greater Boston region with a set of alternative configurations and varied exogenous conditions. These insights provide direction as to which network designs are most robust as demand for highly perishable foods increases.

KEY INSIGHTS
1. Among network designs examined, co-locating fresh food production with distribution centers offers significant and immediate delivery cost savings for XYZ Co – a food and beverage retailer.
2. Dedicated fresh food networks can greatly improve lead times and product freshness, if combined with shifts in production schedules and product shelf-life.
3. Increases in tote fill-rates and demand have a significant impact on vehicle utilization, yielding dramatic cost savings.
An annual base tote demand of 85,000 units was determined, compared to non-fresh food demand of 1M totes. With demand established, the existing Greater Boston network design was mapped, as shown in Figure 1.

An independent supplier delivers the items to a XYZ Co distribution center. The distribution center acts as a cross-docking and consolidation facility, where fresh food items are consolidated into trucks with non-fresh food goods destined for stores that evening. The fresh food products are placed for sale the next morning and kept on store shelves for a maximum of two days.

Translating the network into a model, the supply process from supplier loading to store drop-off was divided into a set of three broad steps: (1) one-to-one “trunk” delivery (i.e. supplier facility to DC); (2) cross-docking (i.e. handling at the DC), and (3) one-to-many “branch” delivery (i.e. distribution center to stores). For each step, time and distance estimates were approximated and combined with general vehicle and wage inputs to calculate activity costs, classified into four categories: maintenance, fuel, wages, and leasing.

Fleet size was estimated based on two factors: (1) the volume capacity of a given vehicle compared to demand volumes and (2) drive time compared to legislative time limitations. Continuous approximation was used to calculate the required fleet size to meet the daily demand volumes, as well as the total hours required for the traveling salesman route and stops. The larger of the two determined the minimum vehicles required.

Once the baseline network was modeled, alternative network designs for comparison and testing were chosen in discussion with XYZ Co. These include:

1. Current (Supplier -> DC -> Stores): Current supply network as described above;
2. D2Store (Supplier -> Stores): Supplier delivers fresh food straight to the store, bypassing any DC or cross-docking;
3. Pick-up (DC-> Supplier -> Stores): The distributor trucks stop at the supplier’s current facility to pick up fresh food items while en-route to the city;
4. Zone Skip (Supplier -> City -> Stores): Supplier delivers a dedicated fresh food load to a city cross-dock within the city, where products are transferred to smaller vehicles for local tours;
5. Co-Location (Supplier/DC -> Stores): Supplier is co-located with the DC, and fresh foods are directly consolidated with other goods on trucks bound for stores.

The model structure allows for rapid iterations, enabling sensitivity testing of network costs and speeds to any set of inputs. With the above network designs mapped to the model, sensitivities were run on most inputs to understand the impact on costs and delivery times. After the initial, broad testing the following five areas became the focus of the analysis: fresh food demand growth, equipment selection, production schedules, store delivery intervals (how often a store receives a shipment), and tote fill-rates.
Results

Fresh Food Demand: XYZ Co expects demand to grow as much as 5x over the next several years, complemented by more tempered non-fresh food growth and new store locations. Figure 2 illustrates how the change in volumes can be expected to influence delivery cost in each network design.

Under current demand, delivery costs range from $1.75 to $7.03 per tote depending on the network design; the current network is estimated to cost $3.15 tote. As demand increases to 5x current levels (the high-end of XYZ Co’s multi-year growth expectations), costs drop and the range narrows to $1.62 to $2.68. This is primarily because economies of scale allow for higher utilization, in larger equipment.

Co-location is consistently the least costly option. An immediate shift from the current network design would create savings on tote delivery of $120k per year; this increases to $360k per year as demand increases. Aside from co-location, the current design remains the most cost-effective until 3.8x demand levels, when it is matched by the Zone Skip and D2Store scenarios.

Equipment Selection: Transportation activities are a primary cost driver for each network design, making equipment selection critical. The impact of equipment choice (i.e., vans, ‘26 truck, ‘36 truck, ‘48’ truck or ‘53 truck) on both cost and delivery times was evaluated.

Selecting equipment to minimize costs yields a cost per tote of $2.23 for transport activities, 15% below the average cost and 34% below the most expensive selections. It’s noteworthy that the least expensive options may be slower. Significant time savings of six hours delivery can be achieved when selecting vehicles for speed under the Co-Location, Pick-up, and Current networks design. However, any potential benefits of product freshness to customer are lost since current production policies do not allow fresh foods to arrive before evening, and they are not consumed until the next morning. As an example, whether the product is delivered at 5pm or 11pm, neither will be available for sale until 6am the next day.

Production Schedule: Shifts to the production schedule and shelf life policies were tested to estimate potential speed gains for the network designs and the impact on delivery costs. We found that by combining faster deliveries (via equipment selection) with shifts in the production policy, foods can be ready for purchase 24 hours sooner. The additional delivery cost is $0.01-$0.02 per item. XYZ Co can evaluate whether the additional freshness is worth this incremental cost.

Delivery Intervals: Such a change also enables XYZ Co to shift the delivery interval per store from 2 to 3 days with a 12-hour shelf-life extension. At 3x current demand, the higher vehicle utilization achieved by less frequent shipping saves $.42 per tote, offsetting the cost of more rapid deliveries.

Tote Utilization: XYZ Co’s totes hold an average of 21 fresh food items – a 53% fill rate. The cost implications of increasing the fill rate through better packing practices or reducing tote size yielded dramatic cost savings. At 3x current demand, the expected savings of increasing tote fill to 35 units (89% utilization) across network designs ranges from 17% to 43%, or $0.50 to $0.70 per tote. With currently low tote demand per store (2.7 units), high underutilization is inevitable; an alternate approach to ship less “air” would be to reduce the tote sizes.
Conclusions
By applying approximation methods in a light-weight, total cost model, important insights were generated as XYZ Co considers the supply chain for its rapidly growing fresh food business:

- Co-Location saves. Across models, co-locating fresh food production with distribution centers offers significant delivery cost savings.
- Demand must increase before dedicated fresh food networks are viable due to the lack of economies of scale with shipping fresh food as a stand-alone product.
- Tote fill-rates significantly impact costs and can drive savings ranging from 17% to 43% across network designs.
- Vehicle selection is an important driver of cost and delivery time, allowing for savings of 15%-34%, or yielding savings of six hours for most network designs.
- Production policies influence freshness. A 12-hour shift in production policy will accelerate delivery to customers by 24 hours at a minor cost of $0.01-$0.02 per item.
- Delivery interval shifts from 2 days to 3 with a maximum 12-hour shelf-life extension, offers cost savings to offset the premium of more rapid deliveries.

These insights allow XYZ Co to understand key cost drivers for fresh food delivery and hone in on network designs that can be implemented as demand increases. While focused on the Greater Boston area, this model can be used in any sub region. Moreover, the approach can be applied by other organizations attempting to evaluate supply network designs for highly perishable fresh foods.
Retailers often face demand uncertainty due to seasonality and consumer shopping behaviors, so supply chain robustness is critical to ensure sufficient product availability. A common strategy to combat demand uncertainty is the use of safety stock, but this also increases the risk of excess stock, obsolescence, and higher carrying costs. We propose an alternative solution that does not increase the level of inventory. Our research focused on restructuring the inbound transportation process to ensure the right inventory was moved at the right time as opposed to ordering more.

Our research partner, ShopCo, places weekly orders for various types of merchandise throughout the United States, but its ordering can exceed the inbound capacity of committed carriers. Historically, ShopCo relied on its suppliers and carriers to determine the order in which loads were picked up — each load may consist of one or more purchase orders (PO’s). Unfortunately, these suppliers and carriers would use logic that may not have matched the needs of ShopCo. ShopCo has taken over the inbound process but is still looking for a solution to improve product availability at the store level. Currently, it uses an internally developed load optimization tool to assign PO’s to loads, but the model’s objective function is largely based on reducing costs rather than improving product availability.

Thus, ShopCo was looking for a mechanism to prioritize loads to determine which loads are picked up when there is a carrier capacity constraint (i.e. the number of trucks available is less than number of loads needing to be picked up on a given day). The challenge was overcoming the difficulty in comparing loads with different characteristics. Further, the stakeholders involved had conflicting perspectives on priority, so these differences had to be amicably aligned.
Analytic Hierarchy Process

This research focused on improving ShopCo’s decision-making process when capacity is constrained, so we developed a prioritization mechanism to assign a numerical priority score to each load. Equipped with these priority scores, ShopCo will be able to prioritize its inbound loads and make informed decisions regarding which loads are shipped.

We utilized the Analytic Hierarchy Process (AHP) to develop the prioritization logic, because this method facilitates decision-making when multiple dimensions and factors are involved. Following the AHP, we prioritized loads in four key steps: developed key decision criteria, performed pairwise comparisons, synthesized results and performed consistency checks, and calculated load priority scores.

1. Developed key decision criteria
   First, we conducted multiple interviews with ShopCo’s transportation strategy team to determine a load’s key factors. From these interviews, a hierarchical framework was developed to break down these key factors into sub-factors. For example, the Load Type factor has two sub-factors: Truckload and Less-than-Truckload. Each factor and sub-factor had to be mutually exclusive to ensure a fair weighting.

2. Performed pairwise comparisons
   Next, we developed pairwise comparison matrices based on the factors and sub-factors defined in the hierarchical framework and had a group of key stakeholders perform pairwise comparisons. To align cross-functional judgments, we included a diverse group of stakeholders covering a range of roles, including transportation strategy, transportation operations, replenishment strategy, supply chain strategy and data visibility strategy. We asked each stakeholder to provide judgments on the relative importance of each factor and sub-factor relative to one another in a specific category. The scoring for the judgments was based on The Fundamental Scale for Pairwise Comparisons.

3. Synthesized the results and performed consistency checks
   Then, each pairwise comparison matrix was synthesized to convert the relative values into priority values. There are different methods to perform this synthesis, but we chose the row geometric mean method (RGMM), as it is insensitive to an inversion of the scale and less susceptible to rank reversal. An inversion of the scale occurs when the reciprocal of each pairwise comparison is taken. Logically, the ranking of an inverted scale should be the exact reverse of a non-inverted scale, but ranking differences have been found when using other synthesis methods.

   A key advantage of the AHP is that it allows the user to measure the consistency of the pairwise comparison judgments, so we used the Geometric Consistency Index (GCI) as the consistency measure for the RGMM. If the GCI for a matrix was less than the predefined thresholds, the matrix was considered consistent. If not, the pairwise comparison judgments were reevaluated. After each matrix was consistent, the final PO priority weights were determined by multiplying the factor and respective sub-factor priority values (Figure 1).

![Figure 1. Sub-Factor Priority Values](image)
4. Calculated load priority scores

Lastly, we used the PO priority values to calculate the PO priority scores. First, we converted raw transactional data to normalized, categorical data for each PO so that the categories matched the AHP sub-factors. Then, the categories were matched with the AHP decision tree to fetch priority values for each sub-factor the respective PO had. The summation of the PO sub-factor values determined the final load priority score for loads with only one PO. For loads with more than one PO, each PO’s priority score was weighted by its case quantity – the summation of the case-weighted PO priority scores was divided by the total case quantity for all of the PO’s in the load, resulting in a case-weighted, load priority score.

The load priority scores equip ShopCo with a decision-making mechanism when capacity is constrained: loads with higher priority scores receive priority. Further, since the priority scores are ratio-scaled, ShopCo is able to determine the relative difference in priority of each load, thus allowing ShopCo to determine when a lower priority load should be delayed or expedited.

Sensitivity Analysis

The impact of holding a load on a load’s priority was a key concern for ShopCo, because ShopCo wanted to ensure that the AHP added additional priority to a load not being shipped. Theoretically, a load’s priority would increase if the load were continually skipped for shipment, because its (1) Lead-time Status would worsen and (2) Inventory Position would deteriorate, thus increasing the priority weight for each of those factors. Further, a load with the highest possible Lead-time Status and Inventory Position weights would have a load score \( \geq 0.3908 \), which was greater than all of the load scores from the sample data.

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<th>Load</th>
<th>Initial Priority</th>
<th>Initial Percentile</th>
<th>1-Day Hold</th>
<th>1-Day Hold Percentile</th>
<th>2-Day Hold</th>
<th>2-Day Hold Percentile</th>
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<td>0.1172</td>
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<td>No Change</td>
<td>54.94%</td>
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<tr>
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<tr>
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<td>49.59%</td>
</tr>
</tbody>
</table>

Table 1: The Impact of Holding a Load

To test the impact of holding a load for 1 and 2 days, we took a random sample of 5 loads and adjusted the Lead-time Status priority weights accordingly, assuming that all else remained equal (Table 1). Except for Load 4, which already had a load priority score above the 98 percentile, the rest of the sample loads increased in percentile by at least 21.8 percentage points within 1 to 2 days. It is important to note that these improvements in percentile are conservative, because this test shows the effect on only the Lead-time Status but not Inventory Position.

The Inventory Position impact could not be determined without dynamic demand and/or forecast data, but as a load is held, the Inventory Position would deteriorate, resulting in a higher Inventory Position weight for that load. Thus, the loads in Table 1 may increase to an even greater priority percentile with dynamic data. For example, if Load 5’s Inventory Position went from “Strong” to “Moderate” after a 2-day hold, its priority would increase from 0.1444 to 0.1970, resulting in a new percentile of 69.17%. If the Inventory Position deteriorated even more drastically from “Strong” to “Critical” after a 2-day hold, the load’s priority would increase to 0.3670, resulting in a new percentile of 99.68%.

Knapsack Optimization – Mixed Integer Linear Programming

With the AHP prioritization logic, ShopCo is able to determine the priority of each load and maximize the total priority scores that are shipped with existing carrier capacity, thus improving service levels without incurring additional costs. As mentioned, ShopCo uses a load allocation tool to assign PO’s to loads. We hypothesized that we could increase the total priority scores shipped by reshuffling the PO’s by solving a Knapsack optimization model. Our objective was to maximize the total load priority score being shipped as well as to minimize the number of trucks utilized. Since linear programming allows only one objective function, we set a large penalty point for each utilized truck so that the optimizer would minimize the number of trucks while maximizing the total load priority score.

The optimization model had four key constraints:

1. The total volume of all the PO’s within a load needed to be less than or equal to the maximum volume capacity of a truck;
2. The total weight of all the PO’s within a load needed to be less than or equal to the maximum weight capacity of a truck;
3. Each PO needed to be assigned to one load or was assigned to the dummy truck (we created a dummy truck that was not subject to the volume and weight constraints so that we could track the PO’s that were not assigned to the available trucks);
4. The total number of loads needed to be less than or equal to the number of trucks available.

Based on the optimization test runs we performed, we observed priority score improvements by up to 8.3% as compared to the current assignment (Figure 2). We found that the load priority scores were very close between the Knapsack optimization results and current load assignments. The existing load allocation tool ShopCo uses appears to be sufficiently optimizing the loads; therefore, although the key objective of the existing load allocation tool is to minimize costs, it may also consider service level factors as well, producing close-to-optimal results.
Conclusion

The AHP provides ShopCo a tool to prioritize inbound loads awaiting shipment by assigning priority scores to each load based on factors defined by ShopCo.

ShopCo will be able to identify the relative priority of the loads and determine which loads should receive priority when carrier capacity is constrained, facilitating improved service levels without incurring additional costs. Further, the Knapsack optimization model found opportunities to improve the load priority shipped by up to 8.3% as compared to the current load assignment.

We believe this research will benefit not only ShopCo but also other companies and industries managing their inbound transportation with carrier capacity constraints by applying this framework. Although the factors and sub-factors used may differ, this underlying framework can align load priority with company objectives.
Quantifying and Visualizing Risk in the Garment Manufacturing Supply Chain

By: Jason Braud and Siqi Gong
Thesis Advisor: Dr. Bruce C. Arntzen

Summary: This project involved working with a company in the garment manufacturing industry to map risk in their supply chain for a few representative products. While previous studies have quantified and visualized risk in companies’ supply chains, our research sought to combine different categories of risk in order to give a more comprehensive picture of the risk at each supply chain node. We looked at disruption risks due to natural disasters, supplier bankruptcy, and political instability and equated the different risk values with annual probabilities of loss for each supply chain node. We were then able to calculate a value-at-risk at each node.

KEY INSIGHTS
1. A comprehensive method to quantify significant supply chain risks is necessary to focus risk mitigation resources.
2. A multitude of different risks can potentially affect a company’s supply chain.
3. Different categories of risks can be combined to present a comprehensive picture of relevant risk throughout a company’s supply chain network.
4. By quantifying and visualizing the values-at-risk across the supply chain, an effective risk mitigation tool can be built.

Introduction
In pursuing low-cost manufacturing, many companies have moved production farther away from their customers. When manufacturing is outsourced to low-cost areas, a number of factors combine to increase companies’ supply chain risk.

In addition to the increased lead time to transport finished goods to market, the low-cost countries generally have less robust infrastructure to protect against and recover from natural disasters.

They are also exposed to increased geopolitical risks from regional conflicts, criminal violence, and corruption.

Companies must be able to quantify and visualize the risk in their supply chain in order to effectively manage it. Efforts have been made in the past to quantify the value-at-risk in supply chains due to the effects of natural disasters. We built a model which considers some of the additional factors that pose risks to companies’ supply chains. By combining the risks from natural disasters, suppliers financial stability, and political events, we planned to gain insight into value-at-risk at nodes in our sponsor company’s supply chain. When companies are presented with a clear map of their supply chain overlaid with relative values-at-risk at each node, their risk management decision-making is simplified.

Methodology
Two main inputs were required in order to map the value-at-risk at different nodes in our sponsor company’s supply chain: a visualization of their supply chain and a value-at-risk for each node in their supply chain.

Visualization
Our sponsor company manages a large number of stock keeping units (SKU). We focused on a sub-set of these products which had elevated importance to the company. In order to map the supply chain for these products, we collected information from our sponsor company.
A bill of materials for the products we mapped along with supplier locations were the most critical inputs for the visualization.

**Value-at-Risk**
A unique value-at-risk exists at each node in the supply chain. Value-at-risk is the product of the risk exposure index and the annual probability of loss for the node.

**Risk Exposure Index**
The risk exposure index seeks to quantify how much revenue would be lost if a node in the supply chain were disrupted. It takes into account the inventory days of supply of the component, the recovery days for the node, and the forecast revenue for products which rely on the component sourced at the node.

**Annual Probability of Loss**
For each node, we calculated an annual probability of loss. To determine these values, we considered three different categories of risks: natural disasters, financial stability, and geopolitical risks.

For natural disasters, we used indices from AIR Worldwide, a company which provides catastrophe risk modeling solutions. AIR provided us with location-based building damage data for storms of varying frequencies. We selected a building damage threshold that would equate to the loss of a supply chain node. When a storm breached this building damage threshold, we took its corresponding frequency and converted it to an annual probability. Figure 1 details this process for one of the supply chain nodes with multiple natural disasters breaching our selected damage threshold. It shows that an earthquake at this location would be expected to cause 1% building damage once every 25 years. A 25-year event has a 4% annual probability of occurrence. For a cyclone at this location, the annual probability for an event that breaches the 1% building damage threshold is 2.5%. We assumed these two natural disasters were independent events, which gave us a 6.4% combined probability that either of the events would occur in a given year.

For financial stability, we calculated the annual probability of bankruptcy for our sponsor company’s suppliers. We used the Altman Z-Score as an input. The Z-Score uses multiple corporate income and balance sheet values to measure the financial health of a company. The information required to calculate a Z-Score is not publicly available for private companies. Our sponsor company was able to obtain Z-Scores from the majority of their private suppliers. The Z-Scores were converted to annual probabilities of loss using the normal density distribution function.

For geopolitical risks, we relied on indices from Verisk Maplecroft, a global risk analytics, research, and strategic forecasting company.

![Building Damage Due to Natural Disasters](Image)

*Figure 1: Multiple Natural Disasters Causing > 1% Building Damage at a Supply Chain Node.*
Verisk Maplecroft provided us with five indices for each supplier location: Political Risk, International Terrorism, Corruption, Criminal Violence, and Regional Conflict. We obtained information from Verisk Maplecroft on what exactly each index quantified as well as the qualitative or quantitative nature of the inputs used to create each index. With this knowledge, we worked with our sponsor company to develop annual probability of loss curves for each of the indices. We assumed that suppliers were exponentially more likely to be lost as an index’s values approached 0. Due to this assumption, we relied on the exponential decay function as the basis for the annual probability of loss curves. Working with our sponsor company, we adjusted the curves’ maximum values and gradients in order to more accurately represent each individual index’s disruptive probability.

Once the annual probability of loss curves (Figure 2) were established for the indices, we converted the index values to annual probabilities of loss at each location. By assuming independence between the disruptive conditions modeled by each of the different indices, we were able to combine the five annual probabilities of loss at each location into an overall annual probability of loss due to geopolitical risks.

Once probabilities of loss were calculated for the three categories of risks, we combined them by assuming independence between the natural disasters, financial stability, and geopolitical risks.

### Analysis

The probabilities of loss used to determine the value-at-risk at each supply chain node were a factor of the three categories of risks. For each node, we calculated the contribution of each of the three risk categories to the overall probability of loss we used for the individual supply chain nodes. The average contributions across all nodes were 46%, 18%, and 36% for financial, natural disaster, and geopolitical risks respectively.

As explained in the Methodology section, the probability of loss values are combined with other factors at each supply chain node in order to arrive at values-at-risk. The values ranged from $0-$4.37 M with a standard deviation of $1.03 M. Because of the assumptions made in the calculations, the actual dollar values of the values-at-risk should be treated with suspicion; however, their relative values can point to the riskier nodes in the supply chain.

To visualize the risk in our sponsor company’s supply chain, we utilized SourceMap to overlay the value-at-risk for each node in the supply chain on a geographic depiction of their supply chain. Figure 3 shows SourceMap’s value-at-risk output. The visual depiction makes it easy to identify the riskier locations in the supply chain. Once identified, risk mitigation efforts can be focused on these nodes in the larger supply chain network.

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**Figure 2: Annual Probability of Loss Curves for AIR Worldwide Risk Indices**
Conclusions
Supply chains are exposed to a variety of risks as they become more complex and geographically diverse. Disruptions due to these risks can be costly. Companies cannot hope to mitigate all of their supply chain risks. In order to focus risk management resources on locations in the supply chain with the most risk, companies need a comprehensive method to quantify all of their significant supply chain risks.

A multitude of different risks can potentially affect a company’s supply chain. While it may not be feasible to model the effects of all these risks, companies can make a determination as to which risks most concern them. In our case, these risks to supply chain disruption were natural disasters, geopolitical events, and supplier bankruptcy. Our thesis showed that different categories of risks can be combined to present a comprehensive picture of relevant risk throughout a company’s supply chain network.

By quantifying and visualizing the values-at-risk across the supply chain, an effective risk mitigation tool can be built. Our results showed that specific high risk nodes in a company’s supply chain can be easily identified with this risk mitigation tool.

Once they are identified, mitigation measures such as dual sourcing, increased safety stock, and reduced recovery time can significantly reduce the value-at-risk. While the tool we built is specific to our sponsor company, companies in other industries could apply a similar approach to build an organizational risk management tool.

Further Research
Our research assumed all events were independent since we did not have enough information on the correlation between disruptive events. Future studies could seek to identify conditional probabilities for different types of disruptive events.

The bankruptcy forecasts from the Altman Z-Score have various accuracy levels depending on the number of years into the future one is attempting to predict bankruptcy. Further research could be done to incorporate the accuracy percentage of the model into the probability of loss values.

The conversion of the geopolitical event index values to probabilities of loss was based on discussion with our sponsor company and Maplecroft. Further research could explore the relationship between the likelihood of disruptions and the risk factors quantified by each index.

Figure 3: Value-at-Risk ($M)
**E-Commerce Drop-Shipping: Building a CPG Supply Chain**

By: Christopher Alan Creyts and Nora Weisskopf  
Thesis Advisor: Jarrod Goentzel  

**Summary:** Should a large CPG manufacturer fulfill orders directly from its distribution centers to the customer on behalf of an online retailer? We first consider how providing drop shipping would impact a manufacturer’s DC facility’s capacity and costs. We built a model to show how costs will shift between the retailer and manufacturer under the drop shipping model. We also consider potential revenue benefits to the manufacturer by using a higher fill rate to capture sales currently lost by the e-commerce retailer. Lost sales rates were estimated using Web Extraction System data. Lastly, we assess the impact on delivery times to customers. We conclude that in our case, drop shipping only seems beneficial if the potential for capturing lost sales were significantly higher and/or the retailer would compensate the manufacturer for the service.

Prior to MIT, Christopher Creyts received his Bachelor of Arts in Economics at the University of Michigan. He then went on to work for industrial supply company Grainger for 3 years.

Prior to MIT, Nora Weisskopf received her Master of Arts in International Business from the University of Edinburgh. She went on to work at UBM Aviation, the UN and the World Bank for five years.

**KEY INSIGHTS**

1. Drop shipping fulfillment costs slightly more but results in a significant shift in cost from the retailer to the manufacturer.
2. Drop shipping frees up significant working capital at the retailer and considerably lowers overall channel working capital.
3. Data from a Web Extraction System can reveal stock-outs and help estimate lost sales in e-commerce.
4. Drop shipping can prove beneficial for a CPG manufacturer when the potential to capture lost sales is high or when the manufacturer has the ability to sell drop shipping as a supply chain service.

An approach that is often explored is drop shipping - where the manufacturer takes on the responsibility of shipping directly to the consumer. Retailers are interested in this model as it shifts their inventory responsibility upstream and frees up working capital. Manufacturers are intrigued with the prospect of drop shipping as a way to capture lost sales due to stockouts at the retailers. They believe that their retailers might be providing lower-than-optimal service levels on certain high-value product categories that experience intense seasonality, leading to lost revenue opportunities for the manufacturer. Without having any true methods to investigate their retailer’s inventory availability due to information asymmetry, they have a difficult time assessing these prospects.

In partnership with a CPG manufacturer, we built a framework that can be used to assess the important aspects of setting up a drop shipping model. We aim to show manufacturers and retailers how to assess the changes in distribution costs and working capital in the supply chain as well as how to bridge information gaps to gauge potential lost sales impacts.

**Introduction**

E-commerce has significantly shaped the supply chains of retailers and manufacturers today. A frequent debate is who should hold inventory and fulfill orders in this new system. In the traditional model, a retailer uses its own distribution network to fulfill customer orders. A manufacturer’s role is simply to ship the products to the retailer’s distribution network. However, businesses are increasingly questioning whether there are alternative ways to fulfill customer orders.
the CPG’s existing direct-to-consumer facility.

**Variable fulfillment cost**

To assess the cost associated with drop shipping, we utilize Activity-Based Costing (ABC). ABC is a common method used to allocate indirect costs based on distinct cost drivers for individual processes or activities.

Using data from the existing direct-to-consumer shipping operation and historic POS data, we built a model that calculated the costs for drop shipping all orders of the two personal appliance categories. The model only considered the variable cost per order incurred rather than any fixed cost associated with the operation. The activities considered in the model include: (i) Receiving and putaway (ii) replenishment (from the co-located inventory storage area to a picking area with racks) (iii) each pick (iv) audit and manifest of package content; and (v) packing of parcel. We also included the cost of material (cardboard box and tape) in the model. In order to understand the cost implications of drop shipping, we compared this projected cost with the existing fulfillment cost. Currently, the only activities conducted by the manufacturer in fulfilling e-Commerce orders are inbound and outbound processing.

To test the impact of our underlying assumptions in the model, we conducted a number of sensitivity analyses. First we tested how varying the lines per order would change cost. This may be particularly interesting when looking at promotions (e.g. “buy one, get one half price”). Box sizes are adjusted depending on the number of line items processed. Secondly, we tested for potential capacity constraints at the current facility. For this we added different levels of incremental sales expected from capturing lost sales (‘Holiday Factor’). Lastly, we tested the model’s susceptibility to constraints in hiring policies. The model assumed that labor could be hired instantaneously in any amount. We tested two different scenarios where labor could only be hired in increments of either 20 or 30 hours per week. This could be expected to be the case in companies where high levels of unionization prevail.

**Channel cost and cost allocation**

To understand changes in overall channel cost and how these would be allocated, we compared the costs per unit in the current and the drop ship model. This demonstrated how the total channel distribution costs changed, and how each channel partner’s costs changed in relation to each other.

In addition to comparing the distribution cost for the different models, we also looked at how these changes would affect the manufacturer’s and retailer’s balance sheets in terms of working capital. Working capital was estimated based on the average daily inventory that would be held by each party in the system.

Sensitivity analysis were completed showing how changes in parcel transportation and retailer DC labor cost would affect the model’s outcome.

**Lost sales estimation**

The ability to capture lost sales has the potential to be a considerable revenue driver for a manufacturer and could provide a strong justification to move towards drop shipping. To attempt to measure lost sales, we used an external Web Extraction System that was purchased by the CPG manufacturer. The objective in using this data was to identify the magnitude of the impact of lost sales, and to discover whether we needed to account for extra unit volume in the drop shipping projections. For this purpose, we paired daily POS information with daily website availability information for each product across the peak holiday period.

**Delivery Time**

To estimate approximate customer delivery times with the new drop ship service, we used a time-in-transit table calculator from UPS. We coupled this information with population density data to understand where the majority of orders would come from and to obtain a weighted average delivery time for the whole network. This gave us an indication of how quickly the CPG manufacturer could fulfill orders out of its only facility.

**Results**

**Variable fulfillment cost**

Base model. The ABC analysis showed that in the base model, shipping a unit out of the existing facility within the given parameters resulted in a variable cost of $2.66 per unit. This cost is largely driven by the high packaging materials cost (almost $0.80 per unit). This is followed by putaway/receiving cost and audit and manifesting activities, which are $0.55 and $0.56 respectively (see Figure 1).

![Figure 1: Variable cost break-down (per unit shipped)](image-url)
Sensitivity analysis. The sensitivity analysis for lines per order showed that when doubling lines per order from 1 to 2 the variable cost is 30% lower. Our analysis on volume changes showed that under the current circumstances, the manufacturer will not exceed their current facility’s capacity and will require minimal changes to their existing operations. Only at an increase of 38% over the existing December volume, would the facility exceed its capacity. When restricting labor flexibility to hiring at a minimum of 20h per week total, labor cost increases by 4% and the variable cost per unit increases from $2.66 to $2.73. For a limitation of 30h per week, there is a 10% increase in total labor cost and a variable cost increase from $2.66 to $2.85.

Channel cost and cost allocation

Base model. In the base model channel costs increase by 1.2% in a drop shipping setup (relative to the current model). Although the drop shipping model does succeed in eliminating several costs, including two separate transportation steps en route to the retailer’s e-Commerce DC, and labor at two separate retailer facilities, it still is a more expensive channel model overall. The high labor costs at the manufacturer’s DC along with the single facility model (which drives up transportation costs) outweigh the savings from all of the removed steps in the supply chain.

The model also breaks down the cost allocation between manufacturer and retailer. In the existing fulfillment model, the CPG manufacturer is paying for 14% of the total supply chain costs, but in the drop shipping model, they assume responsibility for 37% of the total supply chain costs, which themselves have increased from $9.82 to $9.92. With the drop shipping model, the CPG manufacturer will incur $2.26 per/unit in incremental costs relative to the existing distribution model. This is in contrast to the retailer, who actually will save $2.14 in supply chain costs per unit. The detailed cost comparison can be seen in Table 1.

### Table 1: Cost comparison existing and drop ship model

<table>
<thead>
<tr>
<th></th>
<th>Existing Model</th>
<th>Drop Ship Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPG DC Labor</td>
<td>$0.79</td>
<td>$2.66</td>
</tr>
<tr>
<td>Transport to Retailer</td>
<td>$0.20</td>
<td>-</td>
</tr>
<tr>
<td>CPG Holding Cost</td>
<td>$0.39</td>
<td>$0.98</td>
</tr>
<tr>
<td>Retailer DC Labor</td>
<td>$0.80</td>
<td>-</td>
</tr>
<tr>
<td>Transport to E-Com DC</td>
<td>$0.11</td>
<td>-</td>
</tr>
<tr>
<td>Retailer e-Commerce DC Labor</td>
<td>$1.00</td>
<td>-</td>
</tr>
<tr>
<td>Parcel Shipment to Customer</td>
<td>$5.00</td>
<td>$6.30</td>
</tr>
<tr>
<td>Retailer Holding Cost</td>
<td>$1.53</td>
<td>-</td>
</tr>
<tr>
<td>Model Total Cost</td>
<td>$9.82</td>
<td>$9.94</td>
</tr>
</tbody>
</table>

Sensitivity analyses. The sensitivity analyses show that the model is highly susceptible to changes in parcel transportation cost. When lowering parcel rates by 10%, the drop shipping cost decreases by $0.63 and the drop shipping channel cost becomes $0.51 cheaper per unit than the per unit cost in the current distribution model.

This signifies that, if negotiated well, lower parcel cost can easily outweigh incremental labor, material and capital cost. We also tested the case in which the e-Commerce DC labor is 50% more expensive ($1.50 per unit as opposed to $1 in the base case) but still significantly less than the $2.66/unit that the CPG company would pay in the drop ship model. When increasing retailer DC labor cost from the base model, the drop ship model actually becomes less expensive than the current model.

Working Capital. The analysis shows that by drop shipping items from the manufacturer and not tying up capital in inventory, the retailer gains around $3.28 million in working capital. However, on the other side, the manufacturer now needs to carry inventory to serve the customer orders and their working capital will increase by $1.19 million. Overall, with the switch to drop shipping, the total working capital in the system will be reduced from $4.05 million to approximately $1.97 million, an overall decrease of $2.08 million. The largest portion of the decrease in working capital is due to the difference in manufacturer COGS and wholesale price. In addition, the available data displayed poor inventory planning at the retailer. We found that the retailer is holding excessive amounts of inventory on very slow moving SKUs. This significantly increases their working capital requirements, working capital that the manufacturer would presumably be able to remove by carrying lower stock.

Lost sales estimation

Our analysis on the potential of lost sales using Web Extraction System data showed that availability was actually very high for the SKUs considered (see example in Figure 2).
The retailer appeared to be carrying sufficient inventory (and in some cases, too much inventory) to handle the extremely volatile holiday demand. This finding may provide evidence as to why a retailer would prefer the manufacturer to drop ship. Drop shipping would allow the retailer to shed the high working capital cost required to fulfill these SKUs to customers.

**Delivery time**

Our analysis of impacts on delivery time showed that for the retailer’s distribution network under the current model, the average parcel time in transit is 1.51 days. When we simulated the drop shipping model out of the manufacturer’s single DC, we calculated an estimated weighted lead time of 2.67 days -- over a full day increase for each customer. Also, under the retailer shipping model, 99% of the country can be reached in 3 days or less, whereas in the drop shipping model, it takes 4 days to delivery to a significant portion of the Western United States.

**Conclusion**

Based on the results of our framework, we offer a few insights into the feasibility of drop-shipping from a manufacturer’s perspective.

**Capacity, cost and cost allocation.** We found that the manufacturer would be able to set up drop shipping capabilities in an existing facility without exceeding its capacity. We also found that the drop shipping model would increase the total fulfillment cost for the manufacturer from $1.38 per unit to $3.64. The transfer of the distribution, labor and inventory holding cost from the retailer to the manufacturer drives these cost shifts. However, it is important to note that the overall channel costs only increase by $0.12 per unit, as there are large savings by removing two stages of transportation and DC labor from the supply chain.

We found that the model is sensitive to changes in cost assumptions, particularly parcel rates, which make up the largest portion of the cost equation. We also showed that the retailer would be able to free up $3.28 million in working capital. In shifting models, the manufacturer would only need to take on $2.0 million in inventory. This may provide an opportunity for contractual negotiations that are mutually beneficial.

**Lost sales estimation.** Data from a Web Extraction System, when combined with POS and outbound inventory data, can prove useful to gain more insight into retailer availability, which is often very difficult to access and analyze. Using these techniques, we found that availability was actually very high for the SKUs considered. The retailer seemed to carry sufficient, if not excessive inventory in all cases.

**Lead time.** For domestic deliveries, the shift from multiple DC’s to a single centralized facility increases the average delivery time by one day. In our context, this was not particularly significant, as the majority of product sales seemed to occur well before the actual holiday.

Overall we believe that, in the case of this manufacturer, a shift to this new model would only seem beneficial if the potential for lost sales were significantly higher and/or the retailer would compensate the manufacturer for the service. Another consideration that may drive the implementation of drop shipping is the competitive landscape. If other manufacturers were to agree to this, it may lead to them getting preferential treatment from retailers.

Further research could focus on the development of Web Extraction Systems specifically for inventory level estimations under data constraints. There is also value in understanding the benefits that manufacturers can gain from closer interaction with their customers.
Gaining an Operational Edge: Piece-Picking Process Optimization

By: Stephanie Hsuan-Chia Chen and Eunji Han
Thesis Advisor: Dr. Bruce Arntzen

Summary: In this thesis, we evaluated a piece-picking improvement scheme proposed by our sponsor company, a large US retailer. Simulating the scheme’s implementation revealed that the scheme would reduce picks and increase picking efficiency. However, it would also shift some inventory from the retailer’s distribution center to stores and might, in some situations, increase overall company inventory. SKU segmentation was performed to determine which SKUs could eliminate the most picks with the least influence on inventories. Results support scheme implementation on those segments of SKUs.

Prior to MIT, Stephanie completed a master’s degree in Regional Studies-East Asia at Harvard and worked in the sales of eco-friendly synthetic leather. She became interested in supply chain management there, bringing her to MIT. She will be joining The Hershey Company after MIT.

Prior to MIT, Eunji worked on the TMS for LG Electronics and Hanjin Shipping for 6 years. Her experience shaped her interest in supply chain management, bringing her to MIT. Eunji holds a BA in computer science from Ewha Womans University, and after MIT, she will be joining The Hershey Company.

KEY INSIGHTS
1. Piece-picking SKUs in twos by rounding up odd-number orders can increase picking efficiency and lower picking cost.
2. For a retailer, such rounding up will preposition SKU units from the distribution center to the stores as an inventory shift that may increase the stores’ and possibly the company’s inventory.
3. SKU segmentation can determine which SKUs will yield larger savings given a set amount of inventory impact so that the company and store inventories encounter minimal change.

Operational Context
Currently, during the replenishment cycle for each of the retailer’s stores, the DC serving the store generates a pick list for the store based on demand forecast. Pickers in the DC then travel to storage bins, each containing an SKU that has been ordered, and pick the number of pieces forecast for delivery to store. Each bin trip is thus equivalent to one pick and one shipment of the SKU. The company uses a “shelf-pack” of 1 for piece-picking, where pickers must pick each SKU by a quantity that is a multiple of the shelf-pack value, in this case in eaches. Each SKU has one unified shelf-pack value across the DC regardless of the store it is shipped to.

The company proposed changing some SKUs’ shelf-pack from 1 to 2, rounding up each odd-number forecast and order quantity by 1 to an even quantity. This would increase the units per pick for each of these SKUs. However, the proposed scheme needed to borrow 1 unit of that SKU from a future week in which the unit would have originally been picked. In this way, the scheme would preposition an inventory unit to the store and increase store inventory. The scheme would be applied only to those SKUs where such prepositioning should not deplete DC inventory to a level that triggered replenishment from suppliers. Thus, the scheme’s impact would mainly be a shift of inventory from DC to store. However, if it did deplete DC inventory and trigger a replenishment, the DC would be reordering earlier.

Introduction
Order-picking is integral to the daily operations of a warehouse (WH) or distribution center (DC). However, it is also the most labor-intensive operation in manual picking and a very capital-intensive operation in automated picking. It takes up 50%–65% of the operating expenses of a WH or DC. Our thesis sponsor, a large US retailer, uses manual piece-picking in their DCs to replenish their stores. To improve picking efficiency, they asked us to evaluate an improvement scheme they were proposing.
than originally planned.

This could increase the company inventory for the SKUs ordered. Thus, to evaluate the scheme, we examined its savings and inventory impact. We also aimed to determine the SKUs suitable for the scheme, defined as SKUs that generated large savings relative to the increase in store inventory. Limiting the scheme to these SKUs should maximize the savings and minimize the prepositioning of inventory from DC to store.

Method, Data, and Preliminary Findings

Our sponsor provided us with 74 weeks of weekly shipment quantities for every SKU in five stores served by a DC. Each week’s shipment for all the SKUs for one store constituted one pick list. We simulated the shipment quantities that should result from the shelf-pack change and examined the results to find suitable SKUs.

When a SKU unit was prepositioned from a future pick, the store carried 1 extra unit of inventory for the weeks between the future and current picks. For example, in Table 1, a unit was prepositioned across two weeks from week 3 to 1. Therefore, the store inventory increased by one unit for these two weeks. The result was 2 unit*week’s of extra inventory in the store.

<table>
<thead>
<tr>
<th>Table 1: Extra Inventory in Store and Picks Saved due to Shelf-Pack Change for 1 SKU</th>
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</thead>
<tbody>
<tr>
<td>Delivery Week</td>
</tr>
<tr>
<td>Pre-Simulation Store Inventory: Shelf-Pack 1</td>
</tr>
<tr>
<td>Forecasted Sales (Units)</td>
</tr>
<tr>
<td>Inventory at Beginning of Week</td>
</tr>
<tr>
<td>Picked &amp; Delivered Quantity</td>
</tr>
<tr>
<td>Inventory After Delivery</td>
</tr>
<tr>
<td>Units Sold (Forecasted)</td>
</tr>
<tr>
<td>Inventory at End of Week</td>
</tr>
<tr>
<td>Post-Simulation Store Inventory: Shelf-Pack of 2</td>
</tr>
<tr>
<td>Forecasted Sales (Units)</td>
</tr>
<tr>
<td>Inventory at Beginning of Week</td>
</tr>
<tr>
<td>Picked &amp; Delivered Quantity</td>
</tr>
<tr>
<td>Inventory After Delivery</td>
</tr>
<tr>
<td>Units Sold (Forecasted)</td>
</tr>
<tr>
<td>Inventory at End of Week</td>
</tr>
</tbody>
</table>

Pink highlights indicate where the inventory increased after change. Green highlights indicate where a 1-unit pick was saved.

Essentially, three trends emerged:

1. The more 1-unit shipments an SKU has, the more 1-unit picks can be prepositioned, and more future 1-unit picks can be saved.
2. SKUs with a history of larger inter-shipment gaps are likelier to have many weeks in between current and future picks, increasing the store inventory by many unit*weeks.
3. If an SKU’s unit cost is higher, the inventory increase in the store will be higher in dollar value.

We observed that an SKU could have many 1-unit shipments for pick reduction that made it suitable for the scheme but a high unit cost that made it unsuitable. Therefore, to determine which SKUs were suitable, we segmented them according to their number of 1-unit shipments per year, unit cost, and shipment frequency. We used shipment frequency as a proxy for inter-shipment gaps, assuming that more frequent shipments would lead to smaller gaps. Depending on whether their number of 1-unit shipments, unit cost, and shipment frequency were high, medium or low, we assigned SKUs into 27 segments. For instance, an SKU with many 1-unit shipments, high unit cost, and high shipment frequency would be in a different segment from an SKU with many 1-unit shipments, high unit cost, but low shipment frequency. Then, we calculated two ratios for each SKU:

- Picks saved per inventory unit increase in the store.
- Picking cost saved over dollar value of inventory increase.

For each ratio, a higher value indicated more savings per inventory impact, signifying greater suitability.

Results

Segments with SKUs of high and medium SKU cost had very low ratios. Segments containing SKUs with a high and medium number of 1-unit shipments had high ratios. This occurred regardless of the SKUs’ shipment frequency. Thus, segments with low SKU cost and high or medium number of 1-unit shipments were the most suitable for the scheme.

Scheme simulation on all SKUs reduced approximately 20% of each store’s picks and increased the picking efficiency of the SKUs by an average of 0.67 units/line across the stores. Inventory prepositioning by the scheme began shifting SKU units into each store as the simulation began, creating an increase in store inventory plateauing beyond the data’s 74th week (Figure 1). The extrapolated plateau, the final net increase, was greater than 7,600 units per store. If the scheme were applied to all of the stores in the DC simultaneously, DC inventory could be depleted depending on the level of safety stock typically carried, triggering a DC replenishment...
that would increase the company’s inventory as well. Next, a unified shelf-pack change across the DC on SKUs in the suitable segments generated fewer pick reductions since fewer SKUs were changed. Picks were reduced by 11%~13% per store. The picking efficiency for the SKUs to which the scheme was applied increased on average by 0.61 units/line across the stores. The increase in store inventory plateaued within the 74 weeks, at only around 2,700 units (Figure 1). Since such an increase is smaller than in universal scheme implementation, DC replenishment is less likely to be triggered to increase company inventory.

We also simulated the situation where the company system could change to allow for store-specific shelf-packs. Instead of uniformly changing the shelf-pack across the DC for each SKU in the good segments, we changed each of these SKUs’ shelf-packs for some stores but not others depending on their store-specific scheme suitability. For the SKUs changed, the picking efficiency improved on average by 0.71 units/line across the stores. Picks were reduced by 9%~11% per store. Each store’s inventory increased by only around 1,400 units (Figure 1). Since such an increase is even smaller than the DC-wide good-segment scheme above, DC replenishment is unlikely to be triggered to increase company inventory.

Clearly, the store-specific scheme yields the best results. As illustrated in Figure 2, from no shelf-pack change, to change on SKUs specific to store, to DC-wide change on SKUs in good segments, and to change on all SKUs, the slope of picks reduced over increase in store inventory is turning less negative for each store. In this order, the picks saved for each store is diminishing per inventory impact. In other words, store-specific shelf-pack change generates the largest savings given the same amount of inventory impact from the scheme, followed by the DC-wide good-segment scheme, then finally the all-SKU implementation. As such, SKU segmentation has indeed eliminated SKUs that create a greater increase in store inventory given the same amount of picks saved.

Conclusions

While a universal shelf-pack change will likely lead to excessive increase in store and company inventory, the proposed selective change can generate savings in picks and increase picking efficiency with minimal increase in store inventory and DC replenishment. SKU segmentation performed according to a few SKU characteristics can determine the SKUs suitable for the change. The savings per inventory impact will be even larger if shelf-pack change can be targeted more specifically by store for each SKU. However, currently, the DC-wide unified improvement policy should suffice.
Water: Pricing the Priceless
By: Rishi Gohil and Maria Carolina Mendez Vives
Thesis Advisors: Dr. Alexis Bateman

Summary: Water scarcity and quality have the potential to significantly disrupt the manufacturing operations of Unilever, a major multinational CPG. This issue is further compounded as water’s true value across the world is not reflected in its pricing. In this research, we develop a framework to appraise water, considering the effect of location specific water scarcity and water quality on company operations. This will enable Unilever to more accurately account for water’s true value and build resiliency into its operations.

Introduction
Water scarcity is a growing concern within businesses worldwide. Unilever has sites worldwide that are experiencing increasing water stress or depleting water quality, thereby increasing the risk of production disruption.

In many instances, the price of water does not reflect market dynamics insofar as water is cheaper where there is low availability and vice versa.

Business continuity costs due to poor water quality or water shortages can far outweigh the direct costs Unilever incurs in purchasing water. Therefore, in order to optimize water use and build resilience within its manufacturing operations, the objective of this research is to create a framework that calculates the true value of water incorporating the financial value of business disruptions at any manufacturing site around the world. Unilever could employ this value in its business decision-making to incentivize water efficiency and catchment-based water stewardship initiatives where they are needed most.

Our project was performed in a phased manner – first, by capturing the various risks associated with water scarcity and water quality, among other risks – then by translating those factors into a monetary value.

Methodology
We began with a site visit to a Unilever manufacturing facility to better understand water’s contextual opportunities and challenges. Next, we performed interviews with relevant stakeholders to gain insights that would support our water-pricing framework. Then, we examined current tools employed in the industry to learn from established techniques used to capture the value of water.

Rishi Gohil received his bachelor’s degree in Chemical Engineering from The University of Texas at Austin. Prior to the SCM program, he worked as a risk engineer in the oil and gas sector and as a social entrepreneur. Upon graduation, he joined Amazon.com as a Pathways Operations Manager in Austin, Texas.

Before coming to MIT, Maria Carolina Mendez Vives graduated in Mechanical Engineering from Universidad de los Andes, Bogotá (Colombia). She then worked at several companies, including General Motors and Vale, for more than five years.

KEY INSIGHTS
1. Water prices across the world typically do not reflect water’s true value even in areas of scarcity. This causes business continuity costs to far outweigh the artificially low price paid to acquire water.
2. Existing water pricing tools often fail to assess the high costs associated with business disruption. Such tools generally rely on incomplete, old, or non-water data sets and yield inconsistent results.
3. Our framework monetizes three types of risks associated with water: physical, reputation and regulation. In the absence of historical data, our framework relies on operational experience.
Results
As we progressed towards creating the framework, we used our findings from interviews, insights from the current practices review, and key points noted in our literature review.

Findings from Interviews
1. Unilever Personnel
   • Regionally, water shortages have begun affecting operations in South America more so than in Africa.
   • Unilever’s sustainable finance team has explored carbon pricing but has not yet similarly developed water-pricing schemes.
2. External Experts
   • Reputational and regulation risk are difficult to estimate in terms of likelihood.
   • We were advised to evaluate reputational and regulation risk as qualitative measures separate from the model rather than to incorporate them as quantitative parameters.
   • In order to promote stakeholder and end-user engagement, we were recommended to aim towards creating a practicable, user-friendly and simple framework with a defensible basis.

Review of current industry practices
A common theme among the tools reviewed was the use of location as the primary input and the use of qualitative color scales as the output format. We chose to review the four most popular methods publicly available reported through 2014 CDP industry water surveys. The review showed that the general trend in industry water valuations is to reflect overall water risk through weighted averages created using a combination of different indicators. However, the use of weighted averages introduces subjectivity into the model. Also, we found that these tools generally rely on incomplete, old, or non-related to water datasets.

Components of our Framework
In developing a framework to comprehensively and accurately monetize the value of water we decided to employ the Total Cost equation used in Inventory Management, as shown in Equation 1.

\[ TC(Q) = cD + c_t \left( \frac{Q}{Q_0} \right) + c_e \left( \frac{Q}{Q_0} \right) + c_s E[\text{Units Short}] \]  

(1)

Each constituent of this equation was mapped to a corresponding water-related cost component, as depicted in Figure 1.

We identified and developed the three core components of our framework: purchase price, processing and handling cost and business disruption cost.

Figure 1: Comparison of components of Water Valuation Framework and Total

The “Purchase price” offers a baseline value supplemented by value additives such as the “Processing and Handling cost” and the “Business Disruption cost”.

1. “Purchase price” is the price paid in order to acquire water at the given location. As the valuation exercise is expected to be performed on an annual basis, we suggest using the total water acquisition cost from the previous year’s site pricing data, which is readily available centrally, as the basis for estimating the Purchase price.

2. “Processing and Handling costs” include all costs associated with having water in the condition required for operation – these costs include water handling and processing costs incurred in activities such as per-treatment and wastewater treatment. The Processing and Handling cost is estimated by aggregating operational and maintenance costs associated with water treatment and handling processes. Based on our sponsor’s recommendation, this was accomplished by using the Beverage Industry Environmental Roundtable (BIER) tool, which is a publicly available tool from the True Cost of Water toolkit. The BIER tool performs a comprehensive, spreadsheet-based calculation of the Processing and Handling cost based on a set of process related inputs.

3. “Business Disruption cost” represent the value-at-risk resulting from water-related disruption events. As this is our main contribution, the factors used to calculate are detailed in the following section. Estimation of Business Disruption cost.

As mentioned previously, Business Disruption cost corresponds to the financial implications of operational disruptions resulting from events associated with location-specific water stress. The cost, also known as value-at-risk, is a function of the likelihood of the various undesirable water scenarios multiplied by the corresponding financial costs incurred by Unilever, as shown in Equation 2.
\[ \text{Business Disruption Cost} = \sum_{k=1}^{n} \sum_{i=1}^{m} \frac{f_k (c_{ik} + \cdots + c_{mk})}{W} \]  

\( n \) - number of scenarios

\( m \) - number of cost types

\( f_k \) - frequency of scenario \( k \) (per year)

\( c_{ik} \) – financial cost type \( i \) for scenario \( k \)

\( W \) – water abstracted (per year)

1. Mitigation options

The financial cost is directly influenced by the availability of mitigation measures, such as additional capacity in terms of on-site water storage or inventory safety stock. Mitigation options represent the site’s flexibility in responding to water shortage events. We assume that the following mitigation options can be available at a site:

- **On-site water storage**, which includes tanks or other storage infrastructure that enable a site to temporarily continue operations in case of supply disruptions.

- **Inventory of finished goods** available on site, which we refer to as the Average Days of Inventory (DI) - it is expressed in terms of days of production.

- **Alternative sources of water** available for on-site use were included based on client input. These sources include: municipal or piped water, groundwater, surface water, brackish or saline water, tanker to site, and other sources, in case a different water source is available.

2. Scenario analysis

We use scenario analysis as a means to calculate the total value-at-risk cost. Recognizing that the best available site-specific operational information resided with operational experts on the ground, in monetizing water risks, we decided to initially rely primarily on the best judgment of operations personnel, with support from the corporate sustainability group. Using disclosures reported by companies operating in the same industry as Unilever (Consumer Staples) on CDP Water Reports for the years of 2013, 2014 and 2015, we incorporated a pre-populated compilation of historical water-loss scenarios within our framework.

The list of scenarios included within the framework represents a general list of commonly experienced water-related events that have been historically experienced by companies around the world. However, the list of scenarios is not exhaustive. We designed this framework to enable the seamless addition of site-specific scenarios.

a. Likelihood

Although we were able to generate a baseline water stress rating using Aqueduct for locations where Unilever operates, a direct connection to the probability of the scenarios identified was not discernible due to the lack of historical data. Consequently, at each location, Unilever operations personnel would be surveyed using the data-gathering template we generated to determine the frequency of the scenarios outlined.

Upon gathering a representative set of site data regarding the frequency of water shortage events, we suggest building several scenario likelihood profiles to correlate event frequencies with an objective risk indicator, such as the risk rating provided by Aqueduct and aligned with climate models. Established scenario likelihood profiles can then be applied universally based on location-specific Aqueduct risk ratings.

b. Financial Consequences

Broadly speaking, financial consequences were divided into the following categories:

- Lost production and revenue
- Additional cost of alternative sources
- Infrastructure investment and increased operational expenditures
- Other costs

We used decision trees to estimate the lost production and revenue and the additional cost of alternative sources. To illustrate these, the diagram used to estimated cost of lost of production is presented in Figure 2.

![Figure 2: Estimated cost of lost of production and revenue](image)
**Case Review**

We calculated the true value of water in four different cases to demonstrate the functionality of our framework and how it yields different results with varying inputs. Given factors in place during this research project, we used our best judgment in testing the framework.

The four test cases are:

- **Case 1**: high level of production and one mitigation option (inventory)
- **Case 2**: high water stress and no mitigation option and purchase price of €0/m³
- **Case 3**: Two mitigation options and lower water stress
- **Case 4**: one mitigation option and lower water stress

From this exercise, we can infer that the addition of the Business Disruption cost, which captures both water risks and existing mitigation options at the site, provides a better representation of the true value of water than just the current purchase price alone. However, we advise model users to be circumspect in performing the exercise. In particular, the appropriate days of inventory and the frequency and impact of scenarios should be carefully deliberated and selected to ensure model accuracy.

**Recommendations**

We offered several recommendations for future research in order to improve performance and functionality of the model once data is available.

The current revision of the framework excludes numerous factors that could impact the price of water at a given location, for a number of reasons including lack of available data, an absence of objective quantifiable approaches or a preference on the part of our sponsor. These factors can be built-in at a later date with greater understanding.
Warehouse Network Design for a Commodity Chemicals Manufacturer

By: Dangfun Pornnoparat
Thesis Advisor: James B. Rice, Jr.

Summary: This research uses mixed-integer programming optimization model to determine drivers of costs and the optimal warehouse network configuration to minimize transportation and warehousing costs for a petrochemicals manufacturer. A simple model with transportation costs was developed to assess the benefits of each warehouse location. Then, a model which incorporated warehousing costs and capacity constraints was optimized under different scenarios. Inventory turns and storage capacity constraints are found to be the key drivers of inefficiencies. The optimal solution suggests that the company should retain fewer warehouses and expand capacities at these locations.

Prior to MIT, Dangfun Pornnoparat worked as a supply chain analyst in a large industrial conglomerate in Thailand, and a consultant, focusing in ERP implementation. Dangfun holds a BS in Information Technology from Thammasat University and a MS in Management Science from Stanford University.

KEY INSIGHTS
1. When warehouses in the network are located very close together, it is more cost effective to ship from each warehouse directly to customers.
2. Under limited capacities, different inventory turns lead to different warehouses being selected to minimize total costs.
3. The optimal warehouse configuration for the case at hand is to expand existing plant-attached warehouses and close two standalone warehouses.

Introduction
The choice of the location and number of warehouses is a strategic-level decision that can have a long-lasting impact on a firm’s performance.

Warehouse locations and their capacities determine how products flow within a firm’s supply chain, which directly influences a firm’s performance in terms of cost and service level. As a firm grows, facilities such as warehouse and production plants are often added incrementally to its supply chain network to support its growth. Over time, the firm may find that this incremental design of its supply chain network leads to overall operational inefficiencies. In this situation, firms often want to reassess their supply chain to determine the best number and location of their facilities and how products should flow between them.

This research applies a mixed integer linear programming method to evaluate factors that drive existing inefficiencies in a warehouse network belonging ChemCo¹, a Thai commodity chemicals manufacturer. The objective is to determine an optimal warehouse network configuration that minimizes the firm’s total transportation and warehousing cost.

Data and Methodology
A mixed-integer programming model was developed to model our problem of interest. Specifically, the model was intended to address the following questions:
1. What is the total cost of the ChemCo’s current warehouse network?
2. Which warehouses should be retained, expanded, and eliminated so that the total cost is minimized?
3. Which customers should be served by which warehouses?

A simplified logical diagram of the model is shown in Figure 1. The optimization model incorporated five data inputs: product data, annual customer demand by location, production plant data, transportation costs, and warehousing costs and capacities.

¹ Name changed for confidentiality
All ChemCo’s products were grouped into one product with base units being tons. Annual customer demands were aggregated into four groups based on delivery zones. Production volume was based on ChemCo’s historical data. The model assumed that the choice of production site to satisfy the demand of a specific customer group can be per-determined.

Transportation costs were separated into inbound and outbound costs. The inbound transport cost is the cost to move one unit of product from a production plant to a warehouse. The outbound transport cost is the cost to move one unit of product from a warehouse to a customer. Average cost was used for each lane since products are always moved in full truck loads.

Warehousing costs consisted of fixed and variable costs. Warehouse capacities were separated into throughput capacity and storage capacity. Storage capacity at 80% utilization was used, since this is the maximum utilization at which a warehouse can operate efficiently. In order to incorporate storage capacity constraint into the model, it was converted into the amount of flow that a given storage capacity can support using the equation: Flow = Inventory turns x Storage capacity. To account for the variability of inventory turns across months, three numbers were calculated to represent minimum, mean, and maximum inventory turns at each warehouse.

The model was validated using actual data. Validation results were then compared to actual costs incurred by ChemCo.

A simple model considering only transportation cost was first optimized to understand implications of different warehouse locations in the network. Then, a model which incorporated warehousing cost and capacities was optimized to assess total cost and capacities under different scenarios. Finally, a sensitivity analysis was performed to assess the robustness of the proposed solution.

**Results**

**Model Validation**

Results from the validation were about 2% lower than the actual costs. This difference was primarily driven by underestimated internal transfer and warehousing handling costs. The model only considers costs associated with movements that generate sales volume, while ChemCo’s accounting data contains both costs associated with movements that generate sales volume and those that do not. It is not possible to distinguish between the two costs using the Company’s accounting data.

**Optimized Model with Transportation Costs Only**

For this model, five scenarios were tested. In each, a different number of warehouses is allowed to be opened. Optimization results showed that having warehouses in two locations (WL and W7) gave ChemCo the largest incremental savings in transportation costs of about 25.6 million Baht (MBht), as shown in Figure 2. The incremental savings greatly diminished after the third warehouse was added, showing that existing locations were too close together to offer benefits of transportation cost savings. Warehouse W10 was never selected.

**Optimized Model with Warehousing Costs and Capacities**

Seven scenarios were optimized on the existing network. Then, capacity constraints were removed to allow the model to expand the existing warehouses. Results showed that ChemCo can still operate with its existing warehouse network. However, all warehouses would have to remain open and operate at or near capacity. This is due to storage capacity constraints in the existing warehouses, especially at warehouse W1.
Using the existing network, internal transfer would still account for 17% of total transportation costs even under the optimized scenarios. Therefore, the optimal configuration for the Company is to expand three plant-attached warehouses—W1, W3, and W7—and close two standalone warehouses, W10 and WL. In this configuration, all customer orders would be shipped from each warehouse directly to the customers; hence, internal transfer cost is zero.

As shown in Figure 3, the difference in total cost between the optimal scenario with expansion and the optimized baseline scenario of the existing network is approximately 30 MBht. The difference represents a threshold for the investment required to expand capacities at warehouses W1, W3, and W7.

**Sensitivity Analysis**

The fixed cost of warehouse W3 can increase as much as 50% for it to remain selected. Warehouses W1 and W7 have a much higher threshold at 170% and 260%, respectively. The fixed cost of warehouse WL must reduce by at least 98% for it to be selected. Warehouse W10 remains unselected despite any change to its fixed cost.

Once the inbound transportation cost decreases by 51%, W3 is no longer selected and product volume originally routed through this warehouse shifted to warehouse W7. As soon as the inbound transportation cost decreases more than 53%, product volume starts to shift more and more towards warehouse WL.

When the outbound transportation cost increases by more than 58%, the optimal solution changes. In this situation, warehouse W3 is closed, and warehouse WL is open to handle volume for export customer.

Overall, the optimal configuration is quite robust since costs must change by more than 50% for the solution to change.

**Conclusion**

Storage capacity and inventory turns are the main constraints driving the ChemCo’s total cost and warehouse choices. Existing warehouse locations are located too close together for the ChemCo to gain cost savings from multiple warehouse locations. As a result, going forward, ChemCo may want to consider new warehouse locations further away, especially in locations closer to the customers. The model can be further improved in a number of ways. Different inventory turns targets can be used for each warehouse. In addition, the inventory turns should be based on the target turns that the Company would like to achieve, rather than historical data. In order to determine such targets, the Company may want to perform an inventory analysis exercise to assess their inventory policy, and subsequently, the inventory turns. Additionally, further sensitivity analysis can be performed to assess the effect of any changes in volume shift.

**Suggested Customer to Warehouse Assignment**

The optimized baseline model suggests results similar to the policy that ChemCo is currently using, except for warehouse W10. The assignment rule suggested by the model is summarized as follows:

1. Assign domestic shipments to plant-attached warehouses. In case there is any remaining capacity, assign export shipments of products coming from their respective plants.
2. Assign export shipments to warehouse WL. In case there is any remaining capacity, assign domestic shipments.
3. Assign remaining shipments to warehouse W10 (if existing).
Additional 2016 SCM Theses

The Effect of Supply Chain Visibility Systems on Business Processes
By: Anna Stanchik
This research studied the effect of supply chain visibility solutions (SCVS) on key supply chain processes. A qualitative “with and without SCVS” framework revealed positive impacts on data management via automation, standardization, and better raw data. These in turn benefited key operational processes, such as shipment and inventory management, risk management, procurement, and partner collaboration.

A Framework to Evaluate Interoperable Data Exchange Models for Drug Supply Chain Security Act Compliance
By: Peter Chung and Tao Zhang
This research develops a data management strategy for pharmaceutical companies to comply with the Drug Supply Chain Security Act (DSCSA) by 2023. We use robust comparison to choose the most viable strategy from among numerous candidates proposed by experts. We concluded the research with our recommended strategy after examining the categorized models using an extensive set of criteria.

Inventory Strategy with Variable Supplier Service Levels
By: Vikash Chandra and Michael Tully
This research examines raw material inventory policy for a fast-moving consumer goods (FMCG) manufacturer and proposes a simulation tool for evaluation of various raw material inventory policies. Using this tool, company management can benchmark current performance and determine the impact of any future policy changes on chosen key performance indicators.

Planning for a “Sudden-Death” Inventory Loss Triggered by International Tax Competition
By: Abraham Zamcheck
This study addresses a medical device company’s need to relicense its products for export after declaring a new legal manufacturer. Approval results in the instantaneous obsolescence, or “sudden-death,” of inventory bound for export. As a result, the company needs to re-align its supply chain strategy to avoid stock-outs or inventory obsolescence. This thesis develops a model that aids the organization in assessing the decisions and necessary information that can help navigate the transition.

Multi-Stop Trucking: Cost and Acceptance
By: Xiaojia (Amy) Chen and Shang lin (Peter) Tsai Yang
This research investigates multi-stop truckload (MSTL) pricing and tender acceptance, focusing on its differences from traditional point-to-point full truckload (TL). We modeled pricing and acceptance using a large dataset of past tenders. Results showed that the extra burden placed on carriers by MSTL is reflected implicitly in their price and acceptance decisions. These insights also reveal ways in which shippers can optimize their loads for better pricing and acceptance.

Forecasting and Inventory Planning
By: Mike Brocks and Renzo Trujillo
This thesis analyzes the potential of using machine data and predictive analytics in a company’s spare parts inventory forecasting and planning system(s). We compared two different methods for generating a spare parts forecast, one using traditional time-series historical demand data and the other using machine data with a binary classification matrix. We found that the improved forecast based on machine data could reduce spares inventory levels by 5% and improve customer service level by 1%.

Mobilizing Project-Driven Supply Chains in the Chemical Industry
By: Sze Xin Mok and Ruggero Moretto
This thesis proposes a mobilization template for setting up project-driven supply chains in the chemical industry. Such supply chains are unique, non-repeatable and established to support a single project. The adoption of the mobilization template is expected to drive a more efficient and effective mobilization of project-driven supply chains for companies within the chemical industry and beyond.

How to Assess Supplier Flexibility?
By: Remya Pushpangatha Kurup and Peng Bi
This research identifies the factors influencing flexibility of suppliers in the oil and gas industry through systematic literature review and interview research methodology. We designed a survey to validate the flexibility factors using statistical measures. Finally, we developed the first version of a self-administered auditable instrument using Microsoft Excel, which can be used by companies in volatile industries to assess the flexibility of their supply base.
Impact of Regulation on Trucking Prices and Capacity
By: Law Chan How
This thesis analyzes the impact on the trucking industry due to the introduction of an ELD mandate on prices and capacity. This mandate requires truck drivers to record their working hours in a specified electronic device instead of a pen and paper method. This thesis utilizes the change in average truck driver working hours, cost of ELD equipment and distance from origin to destination of truck loads to determine the potential impact on the trucking market.

Product Promotion Effectiveness: Root Causes Of Stock-Outs
By: Alankrita Nigam
The partner company is a CPG manufacturer, which has formed strategic partnerships with major retailers worldwide. Both the retailer and the CPG manufacturer incur lost sales due to frequent stock-outs during promotions. The research focuses on determining the root-causes of these stock-outs. We use the auditor's responses for zero on-shelf availability (OSA) to create a fault-tree diagram and used it to identify various qualitative and quantitative root-causes for stock-outs.

Parameters Driving Consumer Demand in Brazil
By: Krishna Rajendran
This thesis determines the statistically significant parameters driving sales for each of the 36 departments of Lojas Americanas, a large Brazilian retail chain. With this information, the company can modify its retail assortment policy to optimize sales. Various parameters related to store location and consumer socio-economic profile are analyzed. Furthermore, for the company's overall revenue, a set of 10 key parameters is identified.

Obsolescence Reduction through Product Segmentation
By: Ranjani Rajan and Ying Wang
One of the biggest challenges faced by the food industry is the obsolescence of products in the supply chain, before reaching the customer. Our team explored the company's shipping data to manage the SKU velocity and sales volume at distribution centers. We aimed to assess the shortcomings of the current picking strategy, explore the possibility of an alternate strategy or an appropriate product segmentation (clustering) technique, and identify the conditions under which it would be beneficial and reduce obsolesces.

Analyzing Trade-offs between Working Capital and Production Capacity for Multi-stage Manufacturing Processes
By: Karim Kamareddine and Yihong Yao
Large pharmaceutical companies struggle to reduce work-in-process inventory in their production facilities. We focus on the trade-off between inventory and production capacity through investing in new facilities and equipment. This trade-off depends on the company's objectives and what it is willing to give up in return for reducing inventory. We found that increasing manufacturing capacity to reduce work-in-process inventory is not always the most favorable approach in terms of net present value.

Driving the New York State Hop Industry to Meet Demand
By: Nathan Stempel
This thesis is a policy analysis of New York State's Farm Brewery Act of 2012. The law creates a tie between brewers and hop and barley farmers that mandates an in-state supply and demand relationship. Analysis was done using the Bass Diffusion Model to predict growth of the breweries required to source from within NYS and the hop production levels that will be needed to sustain that growth.

Decoding the Secret to Faster Drug Production through Simulation Modeling
By: Mimi Tsai
This research focused on improving the capacity and reducing turnaround time of the drug synthesis process at a cutting-edge biotechnology firm. The objective was to optimize product flow and improve the efficiency and utilization of both machinery and personnel. The researcher simulated three sets of models to understand the impacts the three potential changes would have on throughput and cycle time.

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