Strategic Optimization of Global Supply Chain Lead Times

A ROBUST NEWSVENDOR APPROACH

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I. Executive Summary

This project addresses the inherent volatility of global logistics lead times using a **Robust Newsvendor Model**. Traditional supply chain models often rely on mean delay values, which fail to account for the "Tail Risk" of stochastic shipping disruptions. By leveraging a Python-based optimization engine and SQL data engineering, this study analysed lead-time distributions across major global trade lanes.

The model identified significant cost-recovery opportunities by minimizing the "Maximum Regret" associated with inventory stockouts and holding costs. Key findings include a **Total Absolute Savings** of over $700 (across the top 20 cities) and an average **Risk Reduction of 55%**. These results demonstrate that transitioning from a Naive to a Robust optimization framework provides a measurable competitive advantage in global supply chain resilience.

II. Problem Statement

In global logistics, the "Naive" approach to inventory management assumes that lead times are relatively stable, optimizing for the mean delay. However, lead-time variance—driven by port congestion, customs delays, and carrier inefficiency—creates a "Volatility Gap." This gap leads to:

- **Excessive Holding Costs:** Over-stocking in low-risk lanes.
- **Stockout Penalties:** Under-stocking in high-variance lanes.
- **Inaccurate Costing:** Failure to quantify the financial "Regret" of being unprepared for lead-time noise.

III. Methodology

3.1 Data Acquisition & Engineering (SQL)

The foundational dataset was processed using SQL to create a high-fidelity risk profile for each trade lane.

- **Aggregation:** Data was grouped by City and Shipping Mode.
- **Metrics:** We calculated **Mean Delay (μ)**, **Volatility/Sigma (σ)**, and **Max Observed Delay** to identify extreme lead-time scenarios.
- **Filtering:** To ensure statistical significance, the analysis focused on trade lanes with a robust sample size (Shipments > 500).

3.2 Optimization Engine (Python)

Using a **Robust Newsvendor Framework**, we implemented a prescriptive model that minimizes **Maximum Regret**. Unlike traditional models, this logic treats lead time as a stochastic variable rather than a fixed average.

- **Naive Cost Baseline:** Calculates costs assuming standard mean-based distributions.
- **Robust Optimization:** Accounts for the standard deviation (σ) of delays to determine an optimal safety buffer that minimizes the worst-case financial impact.

IV. Analysis of Results

4.1 Optimization Impact

The transition from Naive to Robust modeling yielded immediate financial improvements across the global network.

Location	Absolute Savings (USD)	Risk Reduction %	Volatility (σ)
Mexico City	$44.54	60.4%	1.30
Estocolmo	$42.76	60.3%	1.15
London	$39.54	58.4%	1.22
Buenos Aires	$39.59	58.4%	1.25
Managua	$37.34	56.5%	1.35

Note: Data derived from the optimization_summary dataset.

4.2 Shipping Mode Volatility Insight

By examining the **Risk Data**, we observed that shipping modes are not created equal:

- **Second Class Shipping:** Consistently showed higher volatility (e.g., **Brisbane** at 1.37 and **Estambul** at 1.48).

- **First Class Shipping:** Generally exhibited lower standard deviation, requiring a smaller "Robust Buffer".
- **Correlation:** There is a direct positive correlation between **Volatility (σ)** and the **Absolute Savings** generated by the robust model.

V. Strategic Recommendations

1. **Deploy Variance-Aware Buffering:** Standardize the use of the Robust Model for trade lanes with a $\sigma > 1.0$, where the Naive model's error rate is highest.
2. **Mode-Specific Safety Stock:** Adjust safety stock factors specifically for **Second Class** routes, which currently represent the highest "Value at Risk."
3. **Continuous Monitoring:** Implement the Power BI dashboard as a live "Risk Watchlist" to flag cities where **Max Observed Delay** begins to deviate from historical sigmas.

VI. Conclusion

This project proves that **stochastic noise** in lead times is not just a logistical hurdle, but a quantifiable financial risk. By moving from reactive averages to proactive robust optimization, the organization can reduce its regret costs by an average of **55%**.

As a 3rd-year AI&DS student, this project demonstrates the scalability of prescriptive analytics in global supply chain management.