TECHNICAL AND STRATEGIC REPORT

Stochastic Supplier Risk and Capacity Management System

Peak Demand Season: July - December 2026

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1. Executive Summary and Problem Statement

This report documents the design, implementation and results of a stochastic simulation engine built to analyze the supply capacity of a Mexican footwear retailer's supplier network. The system forecasts demand, quantifies stockout risk and generates quantitative safety stock recommendations for each active supplier during the July-December 2026 peak season.

The analysis is based on a transactional sales and denied-units database covering July 2023, December 2025. After applying the relevant business filters (national origin, footwear category, boot type), 448,980 records are retained across 33 active suppliers in 5 store branches. Each record includes: week, date, year, supplier, model, origin (national/import), catalog, type, size, branch, units sold and units denied.

The company faces a structural problem of recurring stockouts during peak season: a significant percentage of real demand cannot be met because inventory runs out before restocking arrives. The direct impact is lost sales; the indirect impact is erosion of the customer shopping experience. This problem is not uniformly distributed across suppliers, some fail chronically while others maintain fulfillment rates above 99%.

The central objective of this project is to answer three actionable business questions:

- Which suppliers represent the greatest stockout risk in the Jul-Dec 2026 season and why?
- How much additional safety stock must be negotiated with each supplier, month by month, to guarantee a 95% service level?
- How much risk and how many lost sales would be recovered if part of the volume from problematic suppliers were transferred to the star supplier pool?

1.1 Business Context and Dataset

The company operates a retail model where in-store inventory depends directly on the fulfillment capacity of its suppliers. When a supplier cannot meet the ordered volume, the store records 'denied' units: customers who requested the product but could not purchase it due to stockouts.

A critical aspect of the business model is that not all denied units represent net lost sales for the company. When a specific boot model is out of stock, customer behavior can be:

- Purchase of a substitute product within the same store (the most frequent behavior, estimated at 75% of cases based on business domain knowledge provided by the company).
- Leaving the store without purchasing (net lost sale, estimated at the remaining 25%).

This parameter, called DENIAL_FACTOR = 0.25, is the most important domain input to the model. It determines how real demand is reconstructed from observed sales and denial records, and was provided directly by the company as an operational estimate based on historical observation of customer behavior.

1.2 Central Analytical Constraint: N = 3

The most important analytical challenge in this project is not the total record count, 448,980 transactions is a considerable volume, but the temporal depth of the analysis per supplier-month cell.

When isolating the behavior of a specific supplier in a specific month (for example, PROV48 in November), the available historical sample reduces exactly to the analogous periods: November 2023, November 2024 and November 2025. The effective sample size of the time series is N = 3.

This constraint has fundamental methodological consequences. Any statistical technique or machine learning method designed for long series produces unstable or directly invalid results with N = 3:

- SARIMA and ARIMAX: require a minimum of 30-50 observations for stable estimation of seasonal parameters. With N = 3, the model memorizes the data with no real predictive capacity.
- Recurrent neural networks (LSTM, GRU): require hundreds or thousands of training sequences. With 3 points, the model perfectly overfits without learning any generalizable pattern.
- Gradient Boosting and Random Forest: designed for wide tabular data. With N = 3 as the target variable, they produce degenerate models.
- Non-parametric Bootstrap: can only resample combinations of the 3 existing points; it cannot simulate scenarios outside the observed historical range, which is precisely what is needed for conservative safety stock recommendations.

The methodological decision to use parametric Monte Carlo simulation is not a concession to limited data, it is the technically correct response to this class of problem. Monte Carlo uses the 3 points to fit a probability distribution and then generates 10,000 synthetic scenarios that respect the statistical shape of that distribution, quantifying uncertainty honestly and explicitly rather than hiding it.

1.3 Model Scalability

The pipeline is designed to scale automatically with more historical data without modifying a single line of code. The concrete impact of adding years of history would be:

- With N = 5-7 years per cell: the parameters of the fitted distribution would converge more quickly; the P5-P95 uncertainty intervals would narrow considerably; stockout probability would be more differentiated between suppliers, avoiding the current concentration in the 50-100% range.
- With N = 8-10 years: the Walk-Forward Cross-Validation would have enough folds to estimate the alpha parameter with greater statistical precision; it would be possible to detect multi-year demand cycles that the current model cannot capture.
- With complete SKU data (model x supplier x month): the analysis could descend to the shoe model level, enabling SKU-level safety stock recommendations rather than total supplier recommendations.

The operational recommendation is to update the simulations quarterly as more transactional history accumulates, converting the model into a continuous-use tool rather than a one-time analysis.

2. Analytical Pipeline Architecture

The system is implemented as a Python pipeline of eight functional modules executed sequentially. Each module receives a well-defined input, applies a mathematical transformation and delivers a concrete output to the next module. This modular architecture guarantees full reproducibility, ease of maintenance and future scalability.

Module	Primary Function	Input	Output
load_data()	Ingestion, cleaning and filtering of the original database	Raw transactional CSV	Filtered DataFrame Jul-Dec with reconstructed demand
calculate_metrics()	Historical portfolio radiograph of suppliers	Clean DataFrame + alpha	Risk table with score, FR and classification per supplier
cross_validate_weights( )	Hyperparameter alpha optimization via Walk-Forward CV	DataFrame + alpha range 0 to 1	Optimal alpha and validated Spearman rho
fit_distribution()	Statistical distribution selection via MLE and AIC	Numeric series (N >= 1)	Optimal distribution name and fitted parameters
simulate_supplier_seas onal()	Monte Carlo engine per supplier and month (Jul-Dec)	Supplier historical data	10,000 demand excess scenarios per month
simulate_volume_transf er()	What-if analysis for volume transfer between suppliers	High-risk supplier scenarios + star supplier data	Risk reduction and recovered sales volume
plot_*()	Generation of diagnostic visualizations per supplier and portfolio	Simulation results + historical metrics	PNG charts: per-supplier dashboards, heatmaps, CV curves
generate_tables()	Export of results in tabular format for operational use	All consolidated results	3 deliverable CSV files ready for the procurement team

The pipeline runs end-to-end in approximately 2-5 minutes depending on hardware, processing the 33 suppliers sequentially with 10,000 Monte Carlo iterations per supplier per month (198,000 individual simulations in total for the 6 months of the season).

3. Mathematical and Statistical Foundations

This section documents in detail the mathematical basis of each system component. The goal is for any analyst to be able to audit, replicate and extend the model from this documentation.

3.1 Real Demand Reconstruction: Censored Demand

Transactional data records completed sales, not the total latent market demand. This phenomenon is statistically known as left-censored data: we observe what was sold, but not necessarily what would have been sold had there been sufficient inventory.

When a customer arrives at the store and the product is out of stock (denied unit), one of two things happens: the customer buys a substitute (the sale is completed but with another supplier or model) or the customer leaves without buying (net lost sale). If the model used only gross sales as a demand proxy, it would systematically underestimate real demand and produce insufficient safety stock recommendations.

The correction applied is:

```
Real_Demand = Sales + (Denied x DENIAL_FACTOR)
Real_Demand = Sales + (Denied x 0.25)
```

The DENIAL_FACTOR = 0.25 parameter was provided by the company as an operational estimate: 75% of customers who find an item out of stock buy a substitute in the same store (that sale is not lost for the company, though it is for the specific supplier), and the remaining 25% leave the store without buying, representing a net demand loss that must be incorporated into the supplier capacity model.

This adjustment is conceptually important because it defines how responsibility is assigned: a denial is not the fault of the store but of the supplier who could not fulfill the order. The reconstructed real demand represents what the market would have effectively absorbed had the supplier fulfilled 100%.

3.2 Composite Supplier Risk Score

To classify the 33 suppliers according to their reliability history, a composite score is built that combines two independent risk signals:

Component 1: Denial Rate (Fulfillment Gap)

```
Fulfillment_Rate = Total_Sales / Total_Adjusted_Demand
Denial_Rate = 1 - Fulfillment_Rate
```

The Fulfillment Rate measures what fraction of real demand was effectively covered by the supplier across its entire history. A denial rate of 0.223 (as in PROV44) means the supplier could not cover 22.3% of what the market requested: approximately 1 in every 4.5 demanded units went unfulfilled.

Component 2: Coefficient of Variation (Demand Volatility)

```
CV = sigma_demand / mu_demand
```

The Coefficient of Variation measures the relative dispersion of the supplier's historical demand. A supplier with very irregular month-to-month demand is harder to plan logistically even if its average fulfillment is high, the uncertainty about how much the store will order makes it harder for the supplier to maintain the right inventory.

Composite Score and Alpha Parameter

```
Risk_Score = alpha x Denial_Rate + (1 - alpha) x CV
```

The alpha parameter controls the relative weight of each component. alpha = 1.0 means only the historical denial rate matters; alpha = 0.0 means only volatility matters. The optimal value (alpha = 0.95) was determined through cross-validation and confirms that the Denial Rate is the dominant predictor of future risk, volatility contributes a marginal signal but fulfillment history concentrates almost all predictive information.

Three-Level Risk Classification

The 33 suppliers are classified into three groups using adaptive percentiles calculated on the actual score distribution:

```
LOW    -> Score <= P33 (scores < 0.087)
MEDIUM -> P33 < Score <= P66 (0.087 <= scores < 0.131)
HIGH   -> Score > P66 (scores > 0.131)
```

The use of adaptive percentiles rather than fixed thresholds guarantees that there are always exactly 11 suppliers in each category (33% per level), regardless of the score distribution of the analyzed portfolio. This avoids the problem of degenerate classifications where all suppliers fall into the same level.

3.3 Walk-Forward Cross-Validation and Alpha Optimization

The determination of the optimal alpha value is not done by intuition or manual trial, it is done through cross-validation on real historical data, following a strict temporal scheme.

Why Walk-Forward and not Classic K-Fold

Classic K-Fold Cross-Validation randomizes observations between training and validation folds. In time series data this violates fundamental causality: the model could 'see' July 2025 data to predict

July 2023 behavior. Walk-Forward guarantees that the model always trains on the past and validates on the actual future, exactly as it would be used in production.

Validation Scheme with N = 3 Years

- Fold 1: Trains on complete 2023 data. Validates by predicting risk behavior in 2024.
- Fold 2: Trains on combined 2023 and 2024 data. Validates by predicting risk behavior in 2025.

In each fold, for each alpha value tested (from 0.00 to 1.00 in steps of 0.05), the system calculates the Risk_Score on the training set and then evaluates whether that score correctly predicts the Denial_Rate of the validation period.

Evaluation Metric: Spearman Rank Correlation

$$\rho = 1 - \frac{6 \times \sum d_i^2}{n \times (n^2 - 1)}$$

Where di is the rank difference between the historical risk score of supplier i and its future denial rate. Spearman's coefficient is used (not Pearson's) deliberately: the objective is not to predict the exact value of the future failure, but to guarantee that the risk ranking is correctly preserved over time. If the model says PROV44 is riskier than PROV16, that order must be maintained in the validation period, regardless of the exact magnitude of the values.

Validation Result

The model converged to alpha = 0.95 with an average rho = 0.30 between folds. This result has a clear interpretation:

- The Denial Rate is the dominant predictor of future risk (alpha = 0.95 vs 0.05 for CV).
- A Spearman correlation of rho = 0.30 in high-volatility environments with N = 3 observations represents a valid predictive signal statistically superior to pure chance (rho = 0). It is not a perfect model, it cannot be with 3 points, but it confirms that the riskiest suppliers today tend to be the riskiest suppliers tomorrow.
- The predictive signal of 0.30 methodologically justifies using the historical score as the basis for 2026 inventory decisions.

3.4 Dynamic Distribution Fitting by AIC Criterion

For each supplier x month combination (198 cells in total: 33 suppliers x 6 months), the system automatically fits the most appropriate statistical distribution to the available historical data using Maximum Likelihood Estimation (MLE) and Akaike Information Criterion (AIC) selection.

Akaike Information Criterion (AIC)

$$AIC = 2k - 2 \times \ln(\hat{L})$$

Where k is the number of model parameters and L^ is the maximum likelihood achieved. AIC penalizes model complexity: if two distributions fit the data similarly, AIC favors the more parsimonious one (fewer parameters). The distribution that minimizes AIC is selected.

Candidate Distributions

Normal N(mu, sigma): Appropriate when data is approximately symmetric around the mean and variance does not depend on magnitude. Parameters: mean mu and standard deviation sigma (2 parameters, k = 2).

Gamma G(alpha, beta, loc=0): Standard distribution in stochastic inventory management. Strictly positive domain (x > 0), avoids impossible negative demands and naturally models the positive asymmetry characteristic of purchase spikes. The location parameter is forced to zero (floc = 0) to guarantee the domain starts at zero. Formally three parameters, but with floc = 0 fixed, effectively 2 free parameters (k = 2 same as Normal), making the AIC comparison directly valid.

The winning distribution and its fitted parameters are documented in the DIST_DEMAND column of the prediction table for each supplier and month.

3.5 Seasonal Monte Carlo Simulation Engine

The central component of the system. For each supplier p and each month m in {July, August, September, October, November, December}, the algorithm executes the following steps:

Step 1: Construction of Historical Series

```
Demand_Series(p,m) = {Real_D(p,m,2023), Real_D(p,m,2024),
                      Real_D(p,m,2025)}

Capacity_Series(p,m) = {Sales(p,m,t) : Denied(p,m,t) = 0, t in
                        {2023,2024,2025}}
```

Supplier capacity is estimated exclusively from periods without denials. The logic is that if there was no stockout in that month-year, the observed sales represent demand satisfied without capacity constraint, meaning the supplier could fulfill everything it was asked for. If all available years had denials for that supplier-month (chronic stockout), the latent capacity buffer described in Section 4.2 is applied.

Step 2: Distribution Fitting

Independent distributions are fitted for the demand series and the supplier-month capacity series using the AIC method described in Section 3.4.

Step 3: Generation of 10,000 Scenarios

```
D_sim[i] ~ Demand_Dist(demand_params),  i = 1,...,10000
```

```
C_sim[i] ~ Capacity_Dist(capacity_params),  i = 1,...,10000
Excess[i] = max(0, D_sim[i] - C_sim[i])
```

Each of the 10,000 scenarios represents a possible state of the world in 2026: a particular market demand in that month and a particular supplier capacity to respond to it. The demand excess over capacity represents the units the supplier could not cover in that scenario.

Step 4: Output Metric Calculation

```
Expected_Demand = (1/10000) x Sum(D_sim[i])
Stockout_Prob = #{Excess[i] > 0} / 10000
Safety_Stock_P95 = Percentile_95(Excess)
```

Stockout Probability is the fraction of the 10,000 scenarios where the supplier cannot fully cover demand. Safety Stock at the 95th percentile means that if the company maintains that level of additional inventory, it will be covered in 95% of the simulated possible universes. Using the mean excess (P50) would only guarantee coverage 50% of the time, equivalent to flipping a coin to decide whether there will be a stockout or not.

3.6 Year-over-Year Trend Analysis

In addition to the random variability captured by Monte Carlo, the model incorporates a secular trend component to capture whether demand for each supplier is growing or declining year over year.

```
Trend(p,m) = beta_1  where  y_t = beta_0 + beta_1 x t,  t = {2023,
2024, 2025}
```

The slope beta_1 of the simple linear regression (OLS) on the three historical points indicates how many additional (or fewer) units were demanded per year. However, with only N = 3 observations, this slope can be extremely unstable, a single atypical year can produce an unrealistic projected trend. To control this risk:

```
Capped_Trend = clip(Raw_Trend, -0.20 x hist_mean, +0.20 x hist_mean)
```

Clipping limits the projected trend to a maximum of +/-20% of the supplier's historical monthly mean. This is equivalent to assuming that demand can grow or fall by at most 20% year-over-year, a reasonable and conservative assumption for a one-year horizon in the footwear sector.

4. Model Control Heuristics and Rules

When modeling stochastic processes with very small samples (N = 3), pure mathematics can generate uncontrollable values in distribution tails. The three control rules described in this section act as operational realism anchors that prevent statistically possible but operationally absurd extreme scenarios from distorting inventory recommendations.

4.1 Long-Tail Cap: 5x Mean Limit

The Gamma distribution with small shape parameters (high relative variance) and N = 3 observations can generate, in the right tail of the distribution, values tens of times greater than the historical mean. A single extreme scenario among the 10,000 can artificially elevate the P95 percentile to non-operational values.

To contain this problem, a ceiling is applied to the simulated demand excess:

```
Capped_Excess[i] = min(Excess[i], 5 x monthly_historical_mean_demand)
```

This limit establishes that no excess scenario can exceed 5 times the supplier's historical monthly demand mean. The implicit assumption is that the footwear market cannot grow more than 5 times its average level in a one-year horizon, a reasonable and conservative assumption even in scenarios of extraordinary growth or aggressive marketing campaigns.

4.2 Latent Capacity Buffer for Chronic Stockouts

Some suppliers show a history of chronic stockouts: they never had a month without any denials, so the capacity series (built only from months without denials) is empty. This phenomenon is statistically known as right-censored data: it is known that real capacity is greater than or equal to observed sales, but the actual upper limit is unknown.

If the algorithm assumed that the maximum capacity of the supplier is exactly equal to its maximum historical sales, it would artificially overestimate risk, it would be assuming the supplier can never fulfill more than it already has, with no operational elasticity margin. Instead, a minimum buffer is granted:

```
Latent_Capacity = Historical_Sales x 1.05
```

The +5% represents the minimum operational slack that any supplier can reasonably activate in response to increased demand, overtime, production line optimization, reduced setup times, without requiring additional capital investment. It is a conservative estimate that avoids overestimating risk without underestimating it.

4.3 Deterministic Random Seed for Reproducibility

In any scientific or business analysis, reproducibility is a fundamental requirement: two people running the same code with the same data must obtain exactly the same results. Without a fixed seed, the pseudorandom number generator produces different sequences on each run, making result auditing impossible.

The model uses two fixed seeds:

- rng = np.random.default_rng(seed=42) for all demand and capacity simulations per supplier.
- rng = np.random.default_rng(seed=123) for all simulations in the supplier volume transfer analysis.

These seeds guarantee that every run of the pipeline produces exactly the same 10,000 scenarios, the same stockout percentages and the same safety stock recommendations, a necessary condition for the procurement team to be able to audit and trust the report numbers.

5. Findings and Operational Analysis

5.1 Historical Risk Profile of the Portfolio (2023-2025)

The first pipeline output is the historical risk table that classifies the 33 active suppliers into three levels based on their actual behavior during July 2023, December 2025. The portfolio shows a balanced distribution (11 suppliers per level) with high heterogeneity: Fulfillment Rate ranges from 77.7% (PROV44) to 99.5% (PROV33), a gap of 21.8 percentage points.

Full portfolio statistics:

- Average portfolio Fulfillment Rate: 95.6%
- Worst Fulfillment Rate: 77.7% (PROV44), nearly 1 in every 4 demanded units unfulfilled
- Best Fulfillment Rate: 99.5% (PROV33), only 5 in every 1,000 demanded units unfulfilled
- Total recommended Safety Stock for the entire portfolio Jul-Dec 2026: 75,188,209 units
- Average stockout probability across the entire season: 55.2%

The complete portfolio table, sorted from highest to lowest risk:

Supplier	Total Sales	Fulfillment Rate	Denial Rate	Risk Score	Level
PROV44	46,246	77.7%	22.3%	0.2483	HIGH
PROV16	65,428	82.8%	17.2%	0.2191	HIGH
PROV7	45,752	85.2%	14.8%	0.1895	HIGH
PROV48	1,313,405	96.3%	3.7%	0.1745	HIGH
PROV9	4,364,533	98.7%	1.3%	0.1655	HIGH
PROV26	18,960	89.6%	10.4%	0.1559	HIGH
PROV42	6,302,769	98.8%	1.2%	0.1547	HIGH
PROV20	803,991	95.9%	4.1%	0.1413	HIGH
PROV13	3,852,489	97.6%	2.4%	0.1379	HIGH
PROV37	402,136	95.8%	4.2%	0.1359	HIGH
PROV11	7,124,582	97.4%	2.6%	0.1304	HIGH
PROV27	2,825,888	94.2%	5.8%	0.1261	MEDIUM
PROV36	6,097,460	97.1%	2.9%	0.1254	MEDIUM
PROV21	2,219,535	97.3%	2.7%	0.1230	MEDIUM
PROV47	14,158,594	98.3%	1.7%	0.1213	MEDIUM
PROV29	121,756	91.0%	9.0%	0.1210	MEDIUM
PROV41	992,280	95.3%	4.7%	0.1190	MEDIUM

PROV15	4,172,915	98.7%	1.3%	0.1101	MEDIUM
PROV25	2,523,771	98.4%	1.6%	0.1081	MEDIUM
PROV24	172,309	93.7%	6.3%	0.1047	MEDIUM
PROV14	3,382,268	99.2%	0.8%	0.1044	MEDIUM
PROV5	3,450,433	96.7%	3.3%	0.1044	MEDIUM
PROV19	4,428,811	97.8%	2.2%	0.1037	LOW
PROV32	5,389,012	96.4%	3.6%	0.1020	LOW
PROV34	1,759,027	97.1%	2.9%	0.0916	LOW
PROV23	878,021	99.0%	1.0%	0.0876	LOW
PROV28	32,506	96.9%	3.1%	0.0857	LOW
PROV2	1,046,413	99.4%	0.6%	0.0804	LOW
PROV3	841,955	99.0%	1.0%	0.0749	LOW
PROV17	1,344,498	99.3%	0.7%	0.0705	LOW
PROV33	1,257,336	99.5%	0.5%	0.0682	LOW
PROV31	109,443	96.0%	4.0%	0.0666	LOW
PROV1	31,912	98.5%	1.5%	0.0503	LOW

An important observation about the classification: some suppliers with an apparently high Fulfillment Rate end up classified as HIGH risk (for example, PROV9 with 98.7% FR). This occurs because the score also considers the Coefficient of Variation, the volatility of their demand. PROV9, despite its good aggregate FR, shows high month-to-month irregularity, making it difficult to plan and categorizing it as high risk in the composite scoring.

5.2 The Strategic Finding: Manufacturing Complexity vs. Specialization

When crossing the risk scoring outputs with the MODEL dimension of the dataset (number of distinct shoe models each supplier manufactures), the most important strategic insight of the study emerges: the root cause of chronic stockouts is not a lack of raw production capacity, but the complexity cost derived from manufacturing too many models simultaneously.

High-Risk Suppliers: High Complexity

The 11 suppliers classified as HIGH risk manufacture between 8 and 19 different shoe models simultaneously. This SKU diversity generates multiple operational frictions in their production process:

- Elevated setup times: each model change on the production line requires preparation time (changing molds, lasts, materials). With 15-19 distinct models, the production line spends a significant fraction of time switching between models rather than producing.

- Mold and last rotation: each shoe model requires specific tooling (molds for the sole, lasts for the shoe shape). Maintaining, storing and rotating that tooling for 15-19 models is logistically complex and error-prone.
- Fragmented production runs: with many models, each production batch is smaller. Smaller batches are less efficient per unit (loss of economies of scale) and more susceptible to quality variations.
- Higher planning error probability: forecasting demand for 15-19 simultaneous models is much harder than for 1-4 models, increasing the probability of overproducing some and underproducing others.

The Star Pool: Hyper-Specialization

The three best-performing suppliers share a structural characteristic that distinguishes them radically from the rest of the portfolio: each manufactures exclusively 1 shoe model, and none share SKUs with each other or with the rest of the network.

- PROV33: 1 exclusive model. Historical Fulfillment Rate: 99.48%. Does not share SKUs with any other supplier in the network.
- PROV31: 1 exclusive model. Historical Fulfillment Rate: 96.05%. Does not share SKUs with any other supplier in the network.
- PROV1: 1 exclusive model. Historical Fulfillment Rate: 98.52%. Does not share SKUs with any other supplier in the network.

Hyper-specialization allows these suppliers to maintain continuous production lines without model-change interruptions, optimize their tooling for a single product, plan demand with greater precision and achieve full economies of scale in their single model. The result is delivery reliability exceeding 96% in all three cases.

This finding has direct strategic implications: the company's stockout problem is not solved simply by negotiating more safety stock with existing suppliers, it is structurally solved by developing and prioritizing specialized suppliers in volume allocation.

5.3 Monte Carlo Forecast Jul-Dec 2026: Critical Month Analysis per Supplier

For each of the 33 suppliers, the pipeline simulates 10,000 demand vs. capacity scenarios for each of the 6 months of the season. The following table presents the highest-risk month per supplier along with the recommended safety stock (P95) for that month. Suppliers are sorted from highest to lowest stockout probability in their critical month:

Supplier	Critical Month	Stockout Prob.	Recommended SS (P95)
PROV44	Dec	100.0%	11,966 units
PROV16	Dec	99.9%	16,197 units

PROV11	Nov	99.7%	1,740,575 units
PROV7	Dec	98.2%	10,328 units
PROV14	Nov	97.6%	676,139 units
PROV29	Dec	95.1%	14,923 units
PROV47	Dec	92.4%	2,771,864 units
PROV26	Dec	91.4%	3,509 units
PROV48	Dec	89.0%	490,734 units
PROV19	Nov	88.9%	3,345,373 units
PROV42	Aug	88.6%	765,087 units
PROV13	Nov	86.2%	1,362,673 units
PROV27	Dec	85.9%	228,930 units
PROV9	Nov	84.9%	1,683,046 units
PROV37	Nov	83.5%	153,997 units
PROV15	Nov	82.8%	2,221,112 units
PROV36	Nov	80.1%	3,646,201 units
PROV24	Dec	77.2%	20,126 units
PROV28	Jul	77.0%	292 units
PROV20	Oct	71.4%	159,255 units
PROV41	Nov	65.4%	71,273 units
PROV31	Aug	65.3%	4,602 units
PROV34	Jul	63.2%	40,549 units
PROV5	Aug	63.0%	108,842 units
PROV21	Oct	61.2%	315,232 units
PROV32	Nov	57.0%	339,734 units
PROV25	Dec	48.8%	146,777 units
PROV1	Jul	45.0%	397 units
PROV23	Dec	41.7%	67,701 units
PROV2	Dec	41.4%	60,132 units
PROV17	Aug	41.3%	34,400 units
PROV3	Nov	41.3%	38,838 units
PROV33	Oct	39.6%	37,358 units

Key observations from this table:

- December and November concentrate the highest risk: 12 of the 33 suppliers have their critical month in December and 10 in November. This is consistent with the seasonal pattern of the footwear sector in Mexico, where year-end purchases (Christmas, holiday season, cold weather season) concentrate peak demand.
- There is a category of suppliers with 95-100% stockout probability in their critical month (PROV44, PROV16, PROV11, PROV7, PROV14, PROV29). For these suppliers, stockout in that month is not a risk: it is a statistical certainty under the current supply model.
- The star pool (PROV33, PROV31, PROV1) maintains stockout probabilities significantly below the portfolio average (55.2%): 39.6%, 65.3% and 45.0% respectively in their critical months. Their recommended SS volumes are also much lower, confirming their operational stability.
- The disparity in Safety Stock is enormous: PROV19 requires 3,345,373 units of SS in November, while PROV26 only requires 3,509 units in December. This three-order-of-magnitude variation reflects fundamental differences in the size and volatility of each supplier.

5.4 Total Safety Stock per Supplier: Full Season Jul-Dec 2026

The following table presents the total recommended safety stock summing the 6 months of the season per supplier. This is the figure that determines the protective inventory investment for each commercial relationship:

Supplier	Total SS Jul-Dec 2026 (units)	Risk Level
PROV36	11,379,761	MEDIUM
PROV42	10,999,941	HIGH
PROV47	9,766,342	MEDIUM
PROV19	8,357,750	LOW
PROV15	8,169,755	MEDIUM
PROV9	5,118,270	HIGH
PROV11	4,611,437	HIGH
PROV13	4,106,502	HIGH
PROV14	2,418,693	MEDIUM
PROV21	2,395,096	MEDIUM
PROV48	1,495,650	HIGH
PROV32	1,249,986	LOW
PROV20	825,679	HIGH
PROV5	786,216	MEDIUM
PROV27	733,445	MEDIUM
PROV25	526,715	MEDIUM

PROV34	392,951	LOW
PROV37	344,572	HIGH
PROV17	267,113	LOW
PROV33	246,804	LOW
PROV41	243,963	MEDIUM
PROV2	207,043	LOW
PROV23	177,256	LOW
PROV3	169,489	LOW
PROV24	45,848	MEDIUM
PROV29	36,647	MEDIUM
PROV16	27,803	HIGH
PROV31	25,878	LOW
PROV44	23,877	HIGH
PROV7	17,678	HIGH
PROV28	7,349	LOW
PROV1	6,615	LOW
PROV26	6,085	HIGH

Important note: total SS does not correlate perfectly with risk level because it also depends on supplier sales volume. PROV36 and PROV47 (MEDIUM level) have the largest total SS because they are high-volume suppliers, even though their denial rate is not the worst in the portfolio, the magnitude of their sales amplifies the recommended SS. PROV44 (HIGH level, worst FR in the portfolio) has low total SS because it is a low-volume supplier.

5.5 Business Cases: Volume Transfer Simulation

The what-if analysis mathematically quantifies the impact of transferring part of the demand currently assigned to high-risk suppliers to the star pool (PROV33, PROV31 or PROV1). The simulation reuses the 10,000 excess scenarios from the high-risk supplier and confronts them with the simulated capacity of the star supplier to calculate the residual excess, units that the star supplier could not absorb from the original deficit.

The complete transfer table, sorted by potentially recoverable sales volume for the full Jul-Dec 2026 season:

Origin Supplier	Transfer To	Recovered Volume Jul-Dec 2026

PROV11	PROV33	948,695 units
PROV9	PROV33	762,268 units
PROV13	PROV33	752,667 units
PROV42	PROV33	654,149 units
PROV48	PROV33	498,548 units
PROV20	PROV33	238,454 units
PROV37	PROV33	112,758 units
PROV11	PROV31	98,204 units
PROV13	PROV31	80,205 units
PROV9	PROV31	79,651 units
PROV48	PROV31	77,301 units
PROV42	PROV31	73,775 units
PROV20	PROV31	63,692 units
PROV37	PROV31	52,048 units
PROV11	PROV1	27,705 units

The 'recovered volume' is the quantitative ROI proxy of strategic negotiation: it represents units of demand that are currently lost due to the high-risk supplier's incapacity and that would be covered if that volume were redirected to the star supplier. It is not the total volume transferred, it is the delta in uncovered demand excess, before and after the transfer.

Key findings from the transfer analysis:

- PROV33 is the most profitable destination in all cases, its combination of high capacity and low variability makes it the most efficient absorber of demand excess.
- PROV11->PROV33 is the highest-impact individual business case: 948,695 recoverable units in the season. This is approximately 158,116 units per month, an operationally significant volume to negotiate with PROV33.
- PROV31 and PROV1 have more limited absorption capacity (smaller recovered volumes), consistent with their lower historical sales. However, they contribute as complementary diversification options.
- The optimal strategy is not to choose a single transfer pair, but to build a staggered plan: first maximize the transfer to PROV33 (highest capacity), then complement with PROV31 and PROV1 for residual excesses.

6. Tactical and Strategic Recommendations

6.1 Immediate Tactical Actions (Jul-Dec 2026)

The prediction_table_2026.csv functions as a quantified month-by-month procurement list. For each supplier in each month, the recommended Safety Stock (P95) defines the additional inventory that must be negotiated on top of the base order to guarantee the 95% service level.

The five suppliers requiring priority attention for concentrating the largest total recommended SS volume for the season are:

- PROV36: 11,379,761 units total SS. Top priority. Although rated MEDIUM risk, its high sales volume means any failure has a massive impact.
- PROV42: 10,999,941 units. High-volume supplier with HIGH risk, the combination of highest potential impact.
- PROV47: 9,766,342 units. The highest-volume supplier in the portfolio (14.1M historical units). Its MEDIUM risk level with that volume justifies priority SS.
- PROV19: 8,357,750 units. LOW risk level but high volume, the SS spikes due to the magnitude of sales.
- PROV15: 8,169,755 units. MEDIUM level with high volume.

Tactical warning: maintaining safety stock permanently ties up working capital, generates storage costs and increases obsolescence risk (especially in seasonal footwear). The SS strategy is a necessary short-term solution, but not sustainable as a permanent model, which justifies the investment in the medium-term strategy.

6.2 Medium-Term Strategic Plan: Supplier Development and Volume Transfer

The structural solution to the chronic stockout problem is not to buy more safety stock, it is to redesign the supplier portfolio volume allocation. The transfer analysis provides the quantitative arguments for each negotiation.

Step 1: Star Supplier Development Table

Formally open a Supplier Development table with PROV33, PROV31 and PROV1 for the 2026-2027 season. In this table:

- Present projected demand volumes for Jul-Dec 2026 as the basis for additional capacity negotiation.
- Evaluate each star supplier's maximum installed capacity and lead times for expansion.
- Offer guaranteed volume contracts in exchange for minimum Fulfillment Rate commitments of 97%.

Step 2: Identification of Transferable Models

Cross the transfer table with the model structure of high-risk suppliers to identify which specific SKUs are most viable to redirect:

- Highest-rotation models assigned to PROV11, PROV9 and PROV13 are the priority candidates (greatest volume impact if transferred).
- Validate that the star pool can produce those models or equivalent models without compromising their current specialization.

Step 3: Data-Driven SLA Implementation

Implement performance contracts (Service Level Agreements) that include:

- Minimum Fulfillment Rate of 97% measured monthly, with contractual penalties for non-compliance.
- Advance notification of stockout risk (minimum 4 weeks before the start of the season).
- Company's right to redistribute volume to alternative suppliers if the primary supplier fails the SLA in two consecutive months.

Step 4: Quarterly Review Committee

Establish a quarterly review committee to update simulations with the most recent sales and denial data. This allows SS recommendations to be adjusted as the year progresses and detects changes in supplier behavior before they become stockout crises.

6.3 Operational Limitation of the Transfer Recommendation

It is essential to note that the volume transfer analysis starts from an unverified assumption in the available data: that the star pool has sufficient installed capacity to absorb the proposed additional volume.

The company's transactional data only records sales and denials, it does not include information about each supplier's maximum production capacity, line expansion lead times, production scaling costs or possible conflicts with the same supplier's other clients.

The transfer table provides the business cases (the what and how much), but manufacturing engineering and supplier management must confirm operational feasibility (the how) through direct assessments with PROV33, PROV31 and PROV1 before committing volumes in formal contracts.

7. Study Limitations and Future Improvement Lines

7.1 Current Limitations

The model delivers real operational value with available data, but its accuracy is bounded by several limitations that must be understood before acting on the recommendations:

- Temporal sample N = 3 per cell: with only 3 historical observations per supplier-month, the fitted distributions are estimates with high uncertainty. The P5-P95 intervals are wide precisely because the model honestly quantifies that uncertainty, but this also means the P95 Safety Stock may be considerably different from the actual required value.
- Denial type not specified: the dataset does not distinguish between denials due to supplier stockouts and denials due to internal procurement order planning errors. The model assumes all denial responsibility falls on the supplier's capacity, which may overestimate risk for those suppliers whose failures are actually the company's own ordering mistakes.
- Absence of exogenous regressors: the model does not incorporate variables with documented impact on footwear demand, inflation and exchange rates (for imported boots), winter severity (boot demand correlates with temperature), payroll calendar and Christmas bonus periods, marketing campaigns and promotions.
- SKU granularity not utilized: the analysis operates at total supplier level. Disaggregating by shoe model within each supplier would allow SKU-level SS recommendations but would require 6-10 years of history to be statistically stable given the larger number of cells to model.
- Star pool installed capacity not observable: the transfer analysis assumes PROV33, PROV31 and PROV1 have unlimited absorption capacity, an assumption requiring direct operational validation before acting on the recommendations.
- Inter-supplier correlation not modeled: the pipeline treats each supplier independently. In reality, some suppliers may share raw materials, input suppliers or subcontracted manufacturing capacity, a systemic disruption (such as a leather shortage) would affect multiple suppliers simultaneously, a scenario the current model does not capture.

7.2 Future Improvement Lines

- Quarterly rolling pipeline: incorporate 2026 data as it is generated to update simulations and adjust recommended SS in real time. With 2 additional quarters of history (N = 5), precision improves notably.
- Unit cost dimension: add the purchase price per unit to transform the recommended SS from units to monetary value, enabling direct ROI analysis (cost of maintaining SS vs. value of protected sales).
- Denial cause classification: implement a field in the transactional system to distinguish whether a denial was due to supplier stockout or internal procurement order planning error, to correctly disaggregate responsibility.
- Heavy-tail distributions: explore Pareto or Log-Normal distributions for suppliers with high historical variance, which may better fit the extreme asymmetry of some demand patterns.

- Inter-supplier correlation model: incorporate a Spearman correlation matrix between supplier denial rates to simulate scenarios where multiple suppliers fail simultaneously (portfolio stress testing).
- SKU-level disaggregation: with sufficient history, extend the analysis to the supplier-model-month level to generate granular SS recommendations by product.

8. Technical Glossary

Term	Definition
AIC	Akaike Information Criterion. Statistical metric for comparing models that penalizes complexity (number of parameters) to prevent overfitting.
Alpha	Risk Score hyperparameter. Controls the relative weight between Denial Rate and Coefficient of Variation. Optimal value: 0.95.
Excess Cap	Upper limit applied to simulated excess: maximum 5 times the historical monthly mean. Prevents extreme tail scenarios from distorting the P95.
CV (Coeff. of Variation)	Standard deviation divided by the mean of historical demand. Measures the supplier's relative month-to-month volatility.
Censored Data	Observations where the true value is truncated by an external constraint. In this context: observed sales < real demand because stock ran out.
Gamma Distribution	Family of strictly positive-domain distributions with positive asymmetry. Standard in stochastic inventory management.
Normal Distribution	Symmetric bell-shaped distribution. Appropriate when data shows no significant asymmetry.
DENIAL_FACTOR	Domain parameter (0.25) determining what fraction of denied orders represents actual lost demand vs. substituted in-store sale.
Fulfillment Rate	Percentage of total adjusted demand effectively covered by the supplier. FR = Sales / Real_Demand.
MLE	Maximum Likelihood Estimation. Method for estimating the parameters of a statistical distribution that maximize the probability of observing the available data.
Monte Carlo	Simulation method that generates thousands of random scenarios by sampling from probability distributions to quantify the uncertainty of a system.
N_sim = 10,000	Number of simulation iterations per supplier-month. Guarantees statistical stability of estimated percentiles (P95 estimation error < 1%).
Percentile 95 (P95)	The value that 9,500 of the 10,000 simulated scenarios do not exceed. Coverage threshold selected for Safety Stock.
Star Pool	The three suppliers with the best fulfillment history: PROV33, PROV31 and PROV1. Each manufactures 1 exclusive model with FR > 96%.
Spearman rho	Rank correlation coefficient. Measures whether the risk ordering between suppliers is preserved across periods. Obtained value: rho = 0.30.
Risk Score	Composite metric classifying suppliers: Score = 0.95 x Denial_Rate + 0.05 x CV.
Safety Stock	Additional recommended inventory to cover the variability between demand and supplier capacity at the 95% service level.

Capped Trend	OLS slope of historical demand, limited to +/-20% of the mean to avoid explosive projections with N = 3.
Walk-Forward CV	Cross-validation scheme that respects temporal order: always trains on the past and validates on the future, simulating real production use of the model.

9. Appendices: Pipeline Deliverables

The pipeline automatically generates the following output files upon execution:

9.1 CSV Files

- tabla_riesgo_proveedores.csv: Complete historical profile of all 33 suppliers with risk score, Fulfillment Rate, denial rate and level classification. Basis for strategic prioritization.
- tabla_prediccion_2026.csv: Monte Carlo forecast month by month per supplier for Jul-Dec 2026. Includes expected demand, stockout probability and P95 safety stock. Functions as a quantified procurement list for the supply team.
- tabla_transferencia_estrategica.csv: Business cases per high-risk supplier / star supplier pair. Quantifies the recoverable sales volume for each possible volume transfer.

9.2 PNG Visualizations

- 01_fulfillment_proveedores.png: Horizontal bar chart with historical Fulfillment Rate of all 33 suppliers, colored by risk level (green/yellow/red).
- 03_prediccion_2026_PROVXX.png: 3-panel dashboard per supplier (33 files): expected demand with P5-P95 intervals vs. historical average, stockout probability per month, and recommended safety stock per month.
- 04_heatmap_prob_desabasto.png: Heatmap (33 suppliers x 6 months) with stockout probability per cell, green-yellow-red color scale.
- 05_heatmap_stock_seguridad.png: Heatmap with recommended P95 safety stock per supplier-month.
- 06_cross_validation_pesos.png: Alpha hyperparameter optimization curve with +/-1 standard deviation uncertainty band and vertical line at the optimal value (0.95).