Summary Report for Montgomery Realty Insurance Analysis

Objective
The primary goal of this analysis was to evaluate Montgomery Realty's exposure to catastrophic risks—specifically Fire, Named Windstorm (NWS), and Earthquake (EQ)—and to assess the performance of three proposed insurance programs. This report addresses Tasks 1 and 2, documenting our findings from loss simulations and justifying recommendations for selecting the most suitable insurance program.

Overview
We conducted Monte Carlo simulations to estimate annual aggregate losses for the Fire, NWS, and EQ perils. These simulations, based on historical data and inputs from catastrophe (CAT) modeling for NWS and EQ, were designed to generate a robust understanding of Montgomery Realty's loss profile.

Common distributions used to model claim severity include:

- **Lognormal Distribution:** Often used because many types of claim amounts are multiplicative in nature and tend to be right-skewed.
- **Gamma Distribution:** Useful for modeling positively skewed data, especially when shape and scale parameters allow flexibility in tail behavior.
- **Pareto Distribution:** Commonly used for modeling heavy-tailed phenomena where extreme losses occur with non-negligible probability, especially in catastrophe or large loss modeling.

Other potential distributions include Weibull or Generalized Pareto, but the three listed above are among the most frequently used.

When considering the inclusion of an external $150M fire loss from the competitor, several factors need to be evaluated:

- **Relevance and Similarity:** In this case, the $150M loss appears to be an extreme outlier that does not fit with the historical data on fire losses for Montgomery's portfolio. Our

Excel data on catastrophe type and trended ultimate loss suggests that such a loss is not typical for our exposure.

- **Impact on Severity Modeling:** Including an extreme outlier like a $150M loss could significantly distort the tail of the severity distribution. For our analysis, incorporating this data would not enhance the model but rather hinder it, as it does not represent the typical risk profile or the data we have on fires.
- **Model Stability and Data Consistency:** Given that the competitor's loss is not similar or relevant to our portfolio and historical data, using it would introduce noise and potential bias. It would complicate the fitting process and skew the severity distribution away from what our data supports.

Decision:
After careful consideration, we decided not to incorporate the competitor's $150M fire loss into our severity modeling. This event is an outlier and does not represent a similar risk profile to Montgomery's assets. Including it would pose a major hindrance to our current models and information without providing meaningful insight. Instead, we focus on the relevant historical data that best represents Montgomery's annual aggregate Fire loss, ensuring our models remain robust and reflective of actual exposure.

Perform a severity fit and justify severity distribution(s) best representative of Montgomery's annual aggregate Fire loss.

Fitting Statistics:

- **Akaike Information Criterion (AIC):** Measures the relative quality of statistical models for a given dataset, penalizing for model complexity.
- **Bayesian Information Criterion (BIC):** Similar to AIC but with a higher penalty for models with more parameters, encouraging simpler models.
- **Kolmogorov-Smirnov (KS) Test Statistic:** Evaluates the maximum difference between the empirical distribution and the fitted theoretical distribution.

Severity Fit and Justification: Using historical trended fire loss data, we fitted several candidate distributions, including Lognormal, Gamma, and Pareto. By comparing AIC, BIC, and KS test results across these distributions:

- The Lognormal distribution provided the lowest AIC/BIC values and passed the KS test with acceptable results, suggesting it closely represents the data without overcomplicating the model.

- AIC = 6850.71
- BIC = 6857.66
- KS test:
    - D = 0.055
    - p-value = 0.466
- Graphical assessments (such as QQ-plots and density overlays) supported the Lognormal as best fitting for Montgomery's annual aggregate Fire loss.

Thus, the Lognormal distribution was selected as the severity model for Fire losses, as it balances model fit and simplicity, and aligns well with observed data.

Simulation Approach:

- **Frequency Modeling:** We assumed annual Fire claims follow a Poisson distribution with $\lambda = 15$, based on historical claim frequency.
- **Severity Modeling:** Using the fitted Lognormal distribution parameters from historical data, individual claim severities were simulated.
- **Aggregate Loss Calculation:** For each simulated year, we generated a random number of claims, then summed their severities to obtain an annual aggregate Fire loss. This process was repeated over many simulated years (e.g., 10,000, 1,000) to capture variability.

Exhibit Creation: The simulation produced a distribution of annual aggregate Fire losses. To visualize volatility:

- **Boxplots:** Show the spread, median, interquartile range, and extreme values of annual losses.
- **Histograms/Density Plots:** Illustrate the frequency and shape of the loss distribution, highlighting the tail behavior.
- **Summary Statistics:** Calculated mean, standard deviation, and percentiles (such as the 99th percentile) to quantify volatility.

Example Visualization: A boxplot of annual Fire losses reveals a wide spread, indicating high volatility with potential for extreme losses. Histograms and density plots confirm a right-skewed distribution, consistent with heavy-tail characteristics, which are critical for risk assessment and stress testing.

Assumptions Stated:

- **Annual Fire Losses** are modeled with a Poisson(15) frequency distribution and a Lognormal severity distribution with parameters fitted to historical data.

- **Named Windstorm** Frequency: 40% chance of 2 claims, 20% chance of 3 claims, 20% chance of 4 claims, 20% chance of 5 claims Severity Pareto with mean = $794K and CV = 3.7
- **Earthquake** Frequency: 60% chance of no claims, 20% chance of 1 claim, 10% chance of 2 claims, 10% chance of 3 claims Severity Pareto with mean = $10.67M and CV = 34.5
- **The Model Simulation** assumes independence of claims and that the future loss experience will reflect historical patterns adjusted for trends.

By running this Monte Carlo simulation and generating these exhibits, we capture the inherent uncertainty and volatility in Montgomery's Fire loss profile, providing valuable insights for risk management and decision making.

Inputs and Methodology

- **Fire Losses**
  - Modeled using a Log-Normal distribution fitted to historical data.
  - Parameters:
    - Meanlog (μ): Derived from historical trends.
    - Sdlog (σ): Represents variability in fire losses.
  - Frequency: Average of 15 fire events per year.
- **NWS Losses**
  - **Frequency:** 40% chance of 2 claims; 20% chance each of 3, 4, and 5 claims.
  - **Severity:** Modeled using a Pareto distribution (mean = $794,000; CV = 3.7).
- **EQ Losses**
  - **Frequency:** 60% chance of no claims; 20% chance of 1 claim; 10% chance each of 2 and 3 claims.
  - **Severity:** Modeled using a Pareto distribution (mean = $10.67M; CV = 34.5).

Findings

- **Aggregate Losses:**

Simulated total annual losses over 10,000 years displayed a highly right-skewed distribution driven by the heavy-tailed nature of NWS and EQ risks.

Statistic	Fire Losses	NWS Losses	EQ Losses	Total Losses
Mean	$11.1 MM	$1.25 MM	$3.8 MM	$16.1 MM
Median	$9.58 MM	$795 K	$0	$12.9 MM

Std. Deviation	$7.10 MM	$1.7 MM	$17.2 MM	$19.1 MM
99th Percentile	$34 MM	$7.4 MM	$41.7 MM	$61.1 MM

- **Key Observations:**
  - Fire losses exhibited moderate variability within expected ranges.
  - NWS and EQ losses displayed extreme volatility due to heavy tails, with rare but significant outliers.
  - Combined losses frequently exceeded $50M in extreme years.

Justification for Using CAT Models

Reliance on external CAT models for NWS and EQ was necessary due to their specialization in low-frequency, high-severity events, access to high-quality data, and alignment with industry best practices and regulatory standards. These models enhance the accuracy of our risk assessment for catastrophic events.

Prepared by:
Ariel Farzan, Atharva Raut, Grant Berkey