

Axis Brokerage LLC

Executive Summary

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Overview

The objective is to assist Montgomery Realty in choosing the optimal commercial property insurance program for their real estate portfolio that faces risks from Named Windstorms (NWS), Earthquakes (EQ), and Fires. Using historical loss data from 2010 to 2024, we modeled fire losses with severity distributions and conducted Monte Carlo simulations to assess annual aggregate losses for all three events.

Methodology and Data

To evaluate Montgomery's annual aggregate Fire losses, we analyzed 15 years of historical fire loss data to fit appropriate severity distributions. Using these distributions, we conducted Monte Carlo simulations, as explained in the Monte Carlo and Volatility section of the report, to predict annual losses and assess their volatility under different scenarios.

In terms of external data, the Risk Manager raised a consideration about a competitor's recent \$150M fire loss to an asset. While incorporating external data can provide more perspective, we chose not to include this specific data point in our analysis due to several factors. Firstly, the information is vague, as we lack sufficient details about the competitor's asset profile, location, and exposure. Without this information, the data cannot be directly compared to Montgomery's assets or the risks they face. Secondly, Montgomery's assets may differ significantly from the competitor's in terms of value, location, and vulnerability to fire risks. If the competitor's assets were of much higher value or situated in a higher-risk area, their loss might be disproportionately high in comparison to Montgomery's usual exposures. Therefore, the competitor's loss could be an outlier and may not accurately reflect Montgomery's risk profile. In addition, the \$150M fire loss is significantly higher than the historical fire losses recorded by Montgomery over the past 15 years. If we include such an extreme data point, it could distort the loss distribution, which could potentially skew the model and make it less accurate for predicting future fire risks. However, we did consider the possibility of this extreme loss being useful by testing how well the model performs under rare but high-severity scenarios. This could help identify weaknesses and help Montgomery prepare for extreme events, which may require adjustments in risk management and reserves.

Ultimately, after careful consideration, we decided not to incorporate the competitor's \$150M fire loss into our modeling. We believe that focusing on Montgomery's historical data and risk profile will give us a more reliable and accurate assessment of potential fire losses.

CAT Modeling

The widespread use of catastrophe (CAT) models has arisen to address the shortcomings of relying solely on historical data to project property losses for low-frequency, high-severity perils such as hurricanes and earthquakes. As a result, it has become a market expectation to consult CAT models when assessing risk for insurance purposes. When incorporating external CAT models into an actuarial report, it is important to adhere to the existing framework to ensure proper conclusions are drawn from the data. By following ASOP guidelines No. 38 and 39, actuaries can effectively integrate the findings of external CAT models to sharpen their own conclusions when assessing at-risk areas such as Tampa Bay, Florida, where Montgomery holds assets. When used correctly, external CAT models provide robust, highly specialized insights due to their development by domain experts. These models offer actuaries comprehensive data sources and advanced statistical analyses, enabling accurate and informed decision-making.

Severity Fit

An important aspect of modeling risk and loss is identifying what distribution fits the given severity curve. There are many distributions commonly used to model loss with three of them being Pareto, Lognormal, and Gamma. As we were given the distributions modeling the loss for EQ and NWS from the CAT modeling team, we were responsible for finding a distribution that best fit Montgomery's annual aggregate Fire loss.

For the severity fit, we decided to fit six different distributions to the data and used five metrics to determine which one was the best¹. When it comes to the metrics, we used two p-value-based statistics and three comparative ones to measure how well each distribution fits the data.

Addressing the p-value-based tests first, we used Kolmogorov-Smirnov (KS) and Cramér-von Mises (CVM). These tests produced the same result of Pareto, Gamma, and Weibull being poor fits to our data. This left Lognormal, Generalized Pareto, and Burr being the remaining potential distributions that best fit the data. When looking at the actual statistics generated by these tests, we saw that Lognormal consistently had the smallest value among the remaining three distributions. This suggests that Lognormal was the best distribution, but to further confirm that we also used comparative measures like log-likelihood, root mean square error, and AIC and BIC. These additional metrics further supported that Lognormal was the distribution that best fit the data.

Monte Carlo and Volatility

A common method to simulate uncertain events is through Monte Carlo simulations. There are two essential parts of the simulation: the frequency distribution of the number of claims per year and the severity distribution of the loss per claim. Combining the frequency and the severity distribution, we are able to simulate a projected total loss per year. We will address the results of the annual aggregate Fire losses, annual aggregate NWS losses, annual aggregate EQ losses, and annual aggregate Total losses. After running the simulations, we have created a boxplot exhibit

to display the volatility of each scenario. Additionally, we have created a table to compare other important statistics: count of outliers, interquartile range (IQR), and standard deviation (SD).

Fire

For annual aggregate Fire losses, we assumed a frequency distribution with Poisson($\lambda = 15$) claims per renewal period and a severity distribution with Lognormal($\mu = 12.60$, $\sigma^2 = 1.82$) through the Severity Fitting. In reference to the boxplot⁴, we see that the whiskers of the plot are the longest between the three individual perils. Moreover, the IQR suggests the same. Due to the spread of the majority of the data, not including the outliers, we see that fire may be one of the more volatile perils. However, fire has the smallest number of outliers², which could mean the variation does not create as many extreme losses.

NWS

For annual aggregate NWS losses, we assumed frequency distribution as outlined by the CAT Model and a severity distribution with Pareto($\alpha = 2.16$, $\theta = 919134.40$), also derived from the CAT model. Of the volatility measures, NWS has the lowest values for IQR and SD². Thus, NWS is likely the least volatile of the perils. It has a higher number of outliers than fire, suggesting higher extreme losses.

EQ

For annual aggregate EQ losses, we assumed the CAT Model's frequency distribution and a Pareto($\alpha = 2.00$, $\theta = 10687925.60$) severity distribution from the CAT Model. EQ has the highest standard deviation and outliers, both by a significant amount². Thus, it may be the most volatile peril. Not only does it heavily deviate from its mean, it also has a high probability for extreme values.

Total

For the annual aggregate Total losses, we combined each peril to get a simulation of a year that includes all three. Notably, we see that the IQR³ and the whiskers⁴ are the greatest in comparison to the individual perils. This could be because the combination of three volatile datasets spreads out the quartiles, leading to a larger IQR. However, the outliers do not increase because of the spread of the annual aggregate Total losses. It allows for less data points to be considered extreme, so we see that the outliers have not increased from the highest number of outliers as seen in EQ.

Appendix:

Figure 1:

	KS Statistic	KS p-value	CVM Statistic	CVM p-value	Log-Likelihood	RMSE	AIC	BIC
Distribution								
Pareto	0.292841	9.939137e-19	7.015034	2.017878e-10	-3545.037150	2.629853	7096.074301	7106.516218
Lognormal	0.055820	4.276823e-01	0.125419	4.742740e-01	-3436.806227	0.365378	6879.612453	6890.054370
Genpareto	0.061543	3.105189e-01	0.186199	2.960026e-01	-3445.347683	0.432512	6896.695365	6907.137282
Burr	0.065377	2.456328e-01	0.144731	4.062671e-01	-3443.029811	0.366884	6894.059622	6907.982178
Weibull	0.114925	3.226653e-03	0.711766	1.185821e-02	-3459.157501	0.854754	6924.315001	6934.756918

Figure 2:

	Num Outliers	SD	IQR
Claim Type			
Fire	4380	7084381	7101818
NWS	6425	5296280	2237166
EQ	14228	38468940	5984701

Figure 3:

	Num Outliers	SD	IQR
Claim Type			
Total	7205	39546187	13962049

Figure 4:

