6D.3 UNDERSTANDING DAMAGE FROM LANDFALLING TROPICAL CYCLONES

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Power-Law distributions have shown to be useful tools for describing rare, high impact “black swan” events (Hernandez 2014). The Pareto distribution (e.g., Hardy 2010) describes the tail of the distribution of historical hurricane losses. A separate Power-Law distribution, the Zipf distribution (Newman 2005), fits the tail of the size distribution of populated places. The sizes of the largest populated places are inversely proportional to their rank so that the Zipf distribution is effectively a Pareto distribution with unit exponent. Hernandez (2014) uses an idealized hurricane catastrophe model (e.g., Grossi and Kunreuther 2005), Z-CAT, to simulate damage on a Zipf distributed coastal population. Z-CAT demonstrates that the tail of the distribution (representing the largest impacts) inherits its shape from the distribution of assets along the coast. These losses account for approximately 2/3 of historical losses but only ~10% of damaging events.

Statistical analysis of damage shows that nationally aggregated US hurricane losses normalized for inflation, population and individual wealth has been constant since 1900 (Pielke et al. 2008). Detrended nominal damage increases at approximately the same rate as the US Gross Domestic Product; ~ 6% increase. Yet, normalized and detrended US damage are approximately log-normal with logarithmic standard deviations equivalent to factors of 10 to 12 about their geometric means. Z-CAT cannot reproduce this large variability.

One way to look into the entire distribution of damage, as opposed to just the tail, is to use exceedance probabilities, the probability that damage will exceed certain value. Exceedance curves for both normalized and detrended nominal damage distributions show that both are lognormal and leptokurtic. Figure 1a shows the exceedance probability for normalized hurricane damage per season. The standard deviation is .94 with a skewness of -.02457 and a kurtosis of 2.2481 making it leptokurtic. Figure 1b shows the exceedance probability for detrended nominal hurricane damage by season. Here, the standard deviation is .89 with a skewness of -.1093 and a kurtosis of 2.07. Both distributions are lognormal and leptokurtic with slightly negative skewness.

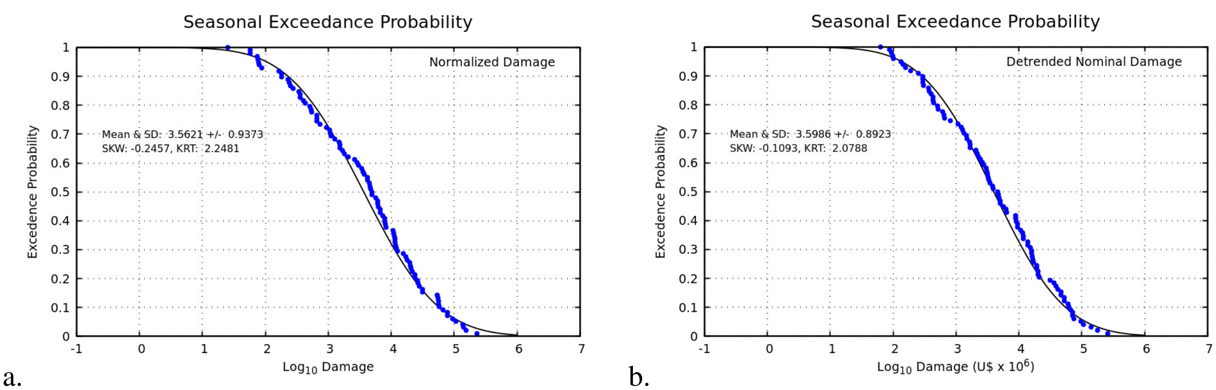

Figure 1. Exceedance Probability curves for (a) normalized Damage and (b) detrended nominal damage. Points indicate actual damage and the solid curve is the compliment of the error function with the same logarithmic mean and standard deviation.

Z-CAT is an idealized hurricane catastrophe model developed at FIU. It focuses not upon detailed physical representation of Tropical Cyclone (TC) hazards, but rather on gaining fundamental insight into how the hazard characteristics translate into

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impacts. Commercial catastrophe models are used to assess risks due to geophysical hazards. Hurricane catastrophe models represent details of inventory, peril, vulnerability and cost. The inventory module is a digital list of insured property. The peril module represents the tropical cyclone's physical attributes including size, intensity, and translation speed. Vulnerability is calculated using an S shaped function that returns percent damage as a function wind speed. The cost or total damage is then calculated from percent damage and repair or replacement prices (Grossi Kunreuther 2005). Through the use of a modified Z-CAT, we aim to understand what factors affect the shape of this exceedance probability curve. What causes the curve to deviate from being completely lognormal? What factors make the curve more leptokurtic about the mean damage?
Current population size distributions show log-normality much like the distribution of losses but

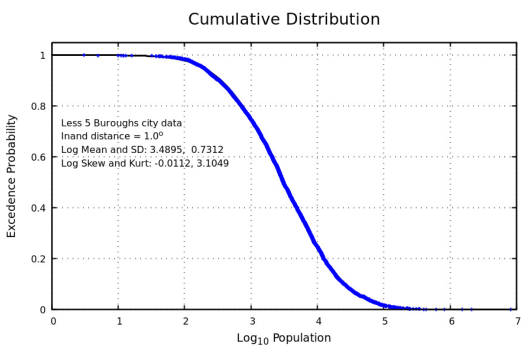

Figure 2. Exceedance probability of coastal city populations.

with a smaller variance. Here we reassess US aggregated loss under the hypothesis that the log normal distribution of losses is inherited from a log-normal distribution of assets proportional to population rather than from a Zipf distribution. Population is platykurtic and less skewed than damage (Figure 2). The standard deviation is .73 with a skewness of -.0112 and a kurtosis of 3.1049, although this value is very close to the threshold of 3. The distribution of population on the United Stated coast could be a driver for lognormal distribution of assets. To test this, we will begin with the actual distribution of coastal population and perhaps to scale it for per capita wealth as a function of population.

Another factor that is likely to shape the statistical distribution of damage is the geographic variability of risk along the coast. While, the former version of Z-CAT did not take this effect into consideration, into the distribution of frequency of landfalls can be applied to the model.

Climactic variability can also play a large role in the distribution of damage. The teleconnections associated with ENSO have shown to suppress tropical cyclone activity when ENSO is in its warm phase (Maue 2011) and enhance them in the cool phase. Similarly cool and warm phases of the AMO have also led to a suppression and enhancement of Atlantic tropical cyclone activity. (Trenberth and Shea 2006)(Lewis et al. 2001) We hypothesize that the phase of ENSO and AMO should decrease mean damage, increase variance, and cause negative skewness. The HURDAT climatology will support development of another function to account for the effects of ENSO and AMO.

A final and perhaps overwhelmingly important factor is flooding. The previous version of Z-CAT simulates only windstorm losses. Simulating inland flooding on an idealized model can be done by applying Kraft's "rule of thumb" (Kidder et al. 2005). It approximates storm total rainfall in inches as 100 divided by the translational speed of the storm in knots. The HURDAT climatology provides information to develop a function for translational speed of storms at landfall. Moreover, storm surge damage contributes significantly to losses as well. The areas at risk within each population center are mapped out and subjected to estimated surge based upon the size and speed of the storm.

The application of a hurricane catastrophe model that uses the actual distribution of coastal cities as well as geographic, inter-seasonal, multi-decadal or secular variations of landfall intensity and frequency will aid in understanding the peril. A salient result from the previous study was that damage would need to double on a century timescale to attain significance using standard nonparametric tests. Yet, increasing hazards may become financially significant before they become statistically significant. An example is the impact of Hurricane Maria on Puerto Rico. How would using log normally distributed assets change this? How rapidly would hurricanes characteristics need to change to produce significant trends in losses? How does the intensity and frequency of the peril affect the damage trend? If more threatening perils become more frequent, how would building standards have to improve to compensate? How would insurers, regulators, and policy holders address the conflict between the actual changes in peril that may or may not be masked by long term natural variability such as ENSO and AMO.

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