Mitigating Flood Risk with CAT bonds: A New Orleans Case Study

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Abstract

Floods cause billions of dollars in losses each year and involve different natural disasters like hurricanes, mudslides, and prolonged rainfall. Data from the Federal Emergency Management Agency (FEMA) indicates that flood losses in the U.S. have increased in severity and frequency over the years, stemming from climate change and a greater number of extreme weather events. This paper presents a case study of how catastrophe (CAT) bonds can be used to manage the financial risk of flooding in Orleans Parish, an area with high exposure to flooding, according to data retrieved from FEMA.

We present a multi-period model for the valuation of a CAT bond with an indemnity trigger, that aims to provide coverage for extreme flood losses. This valuation method incorporates Extreme Value Theory to model flood losses. The price of the CAT bond is obtained through Monte Carlo simulations with stochastic rates. Different assumptions are then tested, to show the sensitivity of the CAT bond's price to the coverage provided and the model parameters.

1 Introduction

Catastrophe bonds (CAT bonds) are financial instruments that can help mitigate extreme losses from natural disasters such as floods, earthquakes, and others. In this sense, CAT bonds represent an alternative to traditional reinsurance, as catastrophic losses may pose a severe financial stress to reinsurance companies, due to the unpredictability of these extreme events (Ma & Ma (2013)). This is due to the nature of how CAT bonds are financed, as risks are securitized and ceded to financial markets.

Investors in financial markets can purchase CAT bonds and receive regular coupon payments, usually quarterly, for a maturity that normally ranges from three to five years (Edesess (2014)). The key difference between CAT bonds and other securities is the existence of a "trigger" in the bond contract related to (re)insurance risk. If the trigger is activated before the bond's maturity, part or all of the principal paid by the investor may not be returned, in order to cover the issuer's losses. Issuers of CAT bonds can be reinsurance companies, governments, corporations, and other organizations.

These triggers thus represent a crucial element in the pricing of CAT bonds and depend on the type of extreme event that the bond looks to mitigate. This paper will focus on mitigating flood losses for the New Orleans Parish, a coastal county in the U.S. which is especially vulnerable to extreme weather events (see Grossi & Muir-Wood (2016), for example). Using data from the U.S. Federal Emergency Management Agency (FEMA), a multi-period CAT bond pricing model will be presented which applies Extreme Value Theory (EVT) and Monte Carlo simulations. The order of this paper is as follows.

A literature review of CAT bonds, their applications for extreme weather events, and EVT will be presented in Section 2. A general overview of the main FEMA data from the Orleans Parish is included in Section 3. The definitions of the CAT bond pricing model will be included in Section 4. Lastly, the results obtained for the model are shown in Section 5, followed by some conclusions.

2 Literature Review

Catastrophe bonds provide entities like reinsurance companies and governments with the opportunity to mitigate their risk exposure to extreme weather events, which may result in large economic and social losses. According to Nicholls et al. (2012), there is evidence since the 1950s of changes in climate extremes, which may lead to these sorts of catastrophic events. Specifically, the authors state that there have been statistically significant increases in the number of heavy precipitation events (e.g. the 95th percentile), in more regions than there have been statistically significant decreases.

This could explain, for example, the increasing number of extreme flooding events in the Orleans Parish, which will be shown in the next section. For a general study on the effects of climate change on heavy precipitation and flooding see Trenberth (2006). Meanwhile, a regional analysis of changes in extreme precipitation intensity and flood intensity by changes in global warming is presented in Tabari (2020). For a more specialized case study of changes in flood events in the eastern coast of Spain, see Cortes et al. (2019).

In order to model these extreme weather events, models from Extreme Value Theory are usually applied under the umbrella of catastrophe modelling. Grossi et al. (2006) provide an introduction to catastrophe modelling, including the history of these models, structure, and uses in risk management. Additionally, a formal framework of extreme value analysis applied to natural hazards is presented by Haigh & Wahl (2019). The authors compile the findings of studies of catastrophe modelling of various natural disasters. For arguably the seminal text on modelling extremes see Embrechts et al. (1999).

For the specific case of modelling extreme flooding events, Wright (2015) includes different techniques to analyze flood hazards. One such technique is the use of a General Extreme Value distribution to model river discharge, a model which will be used in section 4. Sampsom et al. (2014) meanwhile, construct a catastrophe risk model for flooding in Dublin, Ireland. The authors' model includes a financial component, which uses a traditional aggregate loss framework to estimate the annual exceedence probability of floods for this region. An alternative approach to model flood risk can be found in Thistlethwaite et al. (2019), where the authors use a proprietary G-CAT risk model to generate different scenarios for flood losses in Nova Scotia, Canada. The issue with these types of proprietary models however, is a lack of transparency in the assumptions used.

While this is not meant to be an exhaustive review of catastrophe modelling, the literature mentioned above illustrates the different sorts of techniques that may be applied to model catastrophic weather events such as extreme flooding. In terms of financial risk mitigation, reinsurance has traditionally only offered partial coverage to these low-probability, high-cost events (see Froot (1999), for example). Furthermore, although floods are considered as high frequency/low severity perils, they are less modelled and prevalent in CAT bond markets due to the relative small size of the flood insurance market.

In this sense, CAT bonds can more easily accommodate losses from extremely large events than reinsurance, per Xu et al. (2022). This is due to the fact that CAT bonds are primarily funded by investors in financial markets, with supplemental insurance premiums paid by the entity obtaining the risk protection. CAT bonds were created in the mid-1990s after Hurricane Andrew, the costliest hurricane in U.S. history up to that point, which caused sufficient damage to bankrupt several insurance companies (Edesess (2014)). For a thorough history of the CAT bond market and its development, see Polacek (2018) and Cummins (2008).

In terms of their structure, according to Difiore et al. (2021), CAT bonds belong to the insurance-linked securities (ILS) market. These securities are fixed income instruments typically structured as floating-rate, principal-at-risk notes. Figure 1 illustrates the parties involved in a CAT Bond deal.

Figure 1: CAT Bond deal structure from Difiore et al. (2021)

Sponsors are the cedants of the risk, such as reinsurance companies and governments, and pay insurance premiums which are deposited in the Special Purpose Reinsurance Vehicle collateral account (SPRV). This account is independent of both investors and sponsors, protecting them from counter-party risk. Investors meanwhile, pay cash on issue of the CAT bond and this amount is deposited in the SPRV. In return, investors receive coupons on a floating rate (for example, U.S. money market funds) and their principal, contingent on the activation of the bond's catastrophe trigger.

If the CAT bond is triggered, investors may receive part or none of their principal at maturity, depending on the bond's structure. If this occurs, the sponsor receives an amount to cover for their losses. Triggers for natural disasters can be parametric (such as the occurrence of category 5 hurricane), indemnity (actual losses incurred by the sponsor), industry (total estimated industry losses on the insured event), and modelled (estimated on projected claims by an independent modelling company), per Edesess (2014).

Both premiums and note proceeds are invested by the SPRV in liquid instruments like government-backed debt, until the CAT bond's maturity or a triggering event takes place. For an overview of how premiums can be modelled in an incomplete market see Galeotti et al. (2009) and Stupfler & Yang (2018). For this paper, we will not estimate the risk premium and instead apply the findings from Ciumaş & Coca (2007). The authors presented the risk premium used to model the CAT bonds that account losses incurred from the 2005 Hurricane Katrina, which affected New Orleans severely, as will be discussed in the next section.

For CAT bond pricing models, the focus of this paper, Ma & Ma (2013) perform a mixed approximation method using a compound non-homogeneous Poisson process to price a general natural disaster CAT bond. We based our pricing structure on the multi-period model presented by Zimbidis et al. (2015), which relied on Monte Carlo simulations and stochastic interest rates to value earthquake CAT bonds. Our contribution is a CAT bond model which takes into account flood risk, and tries to mitigate extreme losses for Orleans Parish, a singularly vulnerable area to this type of natural disaster.

3 New Orleans Case Study

On August 23, 2005, the Category 3 Hurricane Katrina made landfall in the southern state of Louisiana, where the city of New Orleans is located. According to Johnson (2006), the devastation left after hurricane was immense in New Orleans, with levee breaches resulting in floods covering around 80% of the city. The direct loss of human life from the hurricane was estimated at 1833 people, in spite of widespread prior evacuations, and 275,000 homes were damaged or destroyed.

In economic terms, Hurricane Katrina remains the costliest hurricane in U.S. history. A publication from Swiss Re by Pourrabbani (2020), estimates the total economic damage from Hurricane Katrina at 160 billion, adjusted in 2020 USD. The same study estimates that private insurance companies paid USD 54 billion (2020 USD) on 1.7 million claims, for residential, commercial and automotive damage. Public losses from the Federal Emergency Management Agency's National Flood Insurance Program (FEMA NFIP), were estimated at 21.5 billion (2020 USD).

For this paper, we will use public data from the NFIP to model the flood losses from New Orleans[1]. To provide some context, the NFIP is a public program

[1]The link to the full dataset is here: `https://www.fema.gov/about/openfema/data-sets`

created in the U.S. in 1968, to provide homeowners from qualifying communities with access to flood insurance (Mathewson et al. (2011)). A fact-sheet from FEMA (2021) states there are over 5.1 million NFIP policies in place, providing $1.7 trillion USD in coverage for building and content flood losses. For an overview of the history of the NFIP and its eligibility requirements, see Altmaier et al. (2017) and FEMA (2016), respectively.

The subset taken from the NFIP includes over 2.5 million claims from 1976 to 2020. Claims include the date reported for the loss, county code, state code, among other identifiers. The two key variables for this study are the amounts paid on building and contents claim losses. These losses were summed up to generate the total losses paid by the NFIP per claim. We chose to censor at 2020, since there may still be open claims for more recent years. Figure 2 illustrates the distribution of these total losses, once missing values were removed from the dataset and values were adjusted for inflation.

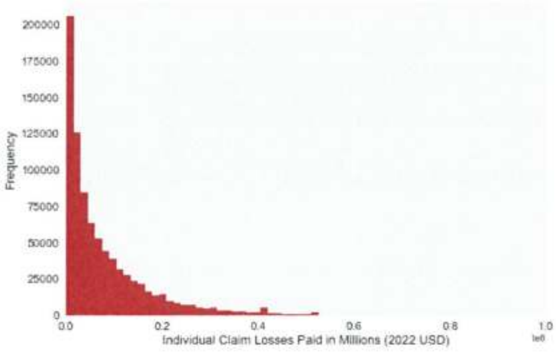


Figure 2: Histogram of individual claim losses paid by the NFIP

The distribution of these claim losses is clearly heavy-tailed, as shown in Figure 2. For reference, the largest total loss recorded for this subset was approximately 14 million USD, and the graph had to be censored for display purposes. Additionally, FEMA also provides a dataset with the NFIP claim policies. This dataset is not directly compatible with the claims reported, as there are discrepancies in the effective policy dates for example, and the claim IDs are adjusted to protect policyholders.

Still, these claim policies can serve as an approximation for the exposure of the NFIP program on a spatial dimension. For example, Figure 3 highlights the U.S. counties with claim exposures above the 90th percentile, which are counties with over 530000 policies in the most recent version of the policies dataset (as of 14/2/2023). The map also estimates the ratio of claim losses to exposure, displaying those with the highest ratios in the darker colors. Note that all losses were adjusted to 2022 USD price levels.

Figure 3: Spatial distribution of NFIP Losses/Exposure by U.S. county

From Figure 3 we can see most of these counties are located in the East coast of the U.S., particularly the South East where New Orleans is located. In fact, by performing a zoom in Figure 4 we can confirm that Orleans Parish and neighboring St. Bernard Parish have some of the highest claim losses/exposure ratios in the dataset. In fact, both counties are in the top 5 for highest total losses and also losses/exposure.

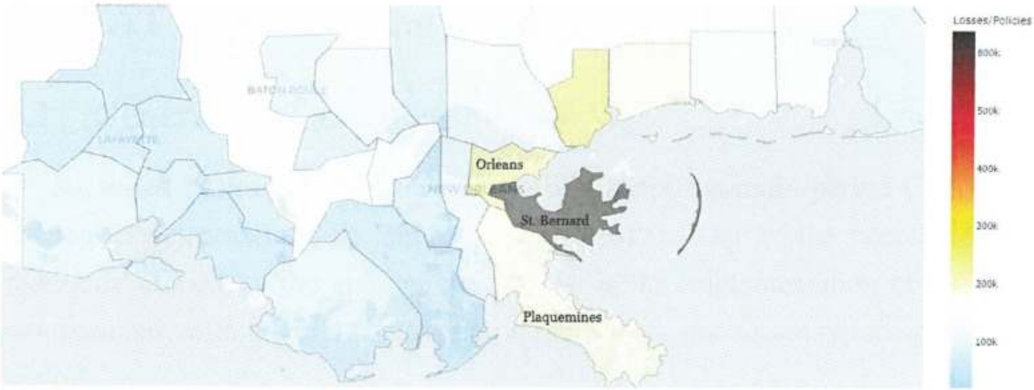


Figure 4: Losses/Exposure for vulnerable Louisiana Parishes

This illustrates the vulnerability of New Orleans to flooding, as it is surrounded by large lakes, the Mississippi river, and the Gulf of Mexico. The aggregated quarterly total losses for Orleans Parish are shown in Figure 5. The single peak represents the quarterly losses from Hurricane Katrina, which were above 7 billion USD just for this county, when adjusted to 2022 USD. This is the extreme we will model in the next section.

Figure 5: Aggregated quarterly losses for Orleans Parish (2022 USD)

4 CAT Bond Pricing Model Definitions

4.1 General CAT bond cashflows

As stated in the literature review, we will adapt the multi-period CAT bond pricing model presented by Zimbidis et al. (2015). One of the benefits of the model developed by the authors cited above is the implementation of different risk tranches, with payoffs contingent on the catastrophe losses reported for each period.

For this paper, we will estimate the "fair price" of a 3 year New Orleans CAT bond with quarterly coupon payments, though this model can be used with other maturities. We say this is the "fair" price since CAT bonds are traded in over the counter markets, using pricing models which are not publicly available. Furthermore, the valuation of CAT Bonds is done under an incomplete market framework, as payoffs in this case are contingent on flood losses, and there are no other traded securities like stocks or traditional bonds with similar payoffs.

First, we will suppose the face amount (F) for this bond is 100. The coupon rate is a spread (s) on a floating rate (r_t), in this case we will use 3-month U.S. Treasuries. The coupons (c_t) for quarter t are thus given by:

$$c_t = 100 \times (s + r_t) \tag{1}$$

Meanwhile, the repayment of principal or redemption amount ($\hat{C}$) depends on the occurrence of a triggering event (M) before the bond reaches maturity. We will denote L_t the quarterly flood losses for Orleans Parish. In our initial model, we will only evaluate the maximum quarterly flood loss recorded ($\max(L_t)$) for the duration of the bond. This is only a simplification, as there may be multiple qualifying events before the bond reaches maturity. Future research could incorporate aggregate loss models, for example, which contemplate multiple occurrences of extreme events, in this case floods.

$$\hat{C} = \begin{cases} 100 + c_{12}, & \text{if } \max(L_t) \in [0, 0.5M] \\ \frac{2}{3}100 + c_{12}, & \text{if } max(L_t) \in [0.5M, 0.75M] \\ \frac{1}{3}100 + c_{12}, & \text{if } max(L_t) \in [0.75M, M] \\ c_{12} & \text{if } max(L_t) \in [M, \infty] \end{cases} \tag{2}$$

This payoff structure for the redemption value implies investors will receive their entire principal if the maximum loss incurred is less than $0.5M$. Investors will receive only part of their principal at maturity if the maximum loss is $0.5M \leq \max(L_t) < M$. Lastly, if there is a catastrophic loss greater than or equal to M, investors will lose their principal and receive only a coupon. If this happens, the amount investors lose would be sent to the sponsors of the CAT bond in New Orleans to cover for their losses. We can summarize the contingent cashflows of the bond as follows:

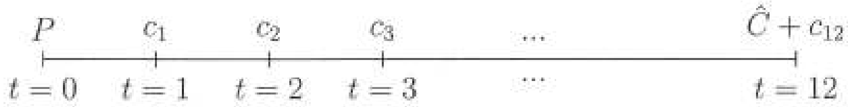


Figure 6: Timeline for contingent CAT bond cashflows

Since we do not know the future flood losses at the time the bond is issued, used to determine $\hat{C}$, we can only model the price dynamics through Monte Carlo simulations. This also includes a stochastic model for the r_t used in the coupon payments. In the next subsection we will outline some assumptions needed to find the price (P) of this bond.

4.2 Model assumptions

The CAT bond pricing model relies on Monte Carlo simulations that involve stochastic rate processes and heavy-tailed loss distributions. First, we will establish the discount factor used when discounting the coupon payments with rate r_t.

We will add a risk premium for the flood losses j and denote our discount factor as v_t, which will be calculated as:

$$v_t = e^{-(j+r_t)t} \tag{3}$$

Note that j will remain fixed at 5% for all simulations, as used in Zimbidis et al. (2015). Additionally, we will model r_t using the Vacicek model for interest rates, which has been used to model short-term securities like U.S. Treasuries in Khramov (2013), for example. This stochastic model, in the case of r_t, is given by:

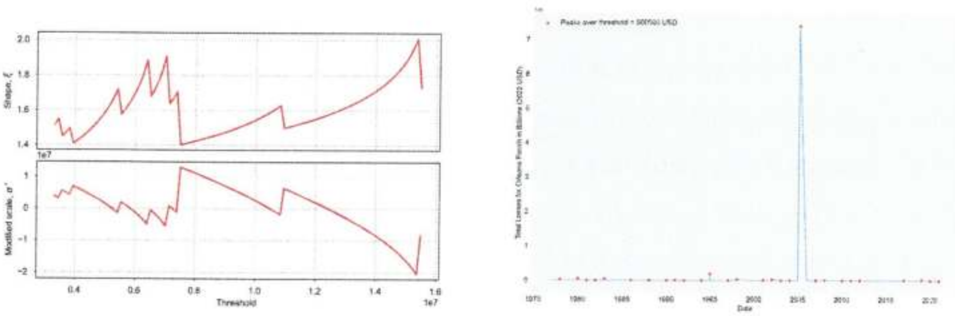
$$dr_t = \kappa(\theta - r_t)dt + \sigma dW \tag{4}$$

where κ is the mean reversion strength, θ is the long-run mean, and σ is the volatility of r_t. These parameters were estimated using Maximum Likelihood, and the simulated rate trajectories were performed in Python.[2]

The total flood losses for New Orleans were modelled using a Peaks Over Threshold (POT) model. This approach is based on the Picklands-Balkema-De Haan theorem, which states that as the threshold or truncation point (u) selected increases for a random variable, its excess distribution converges to a Generalized Pareto Distribution (GPD). For a complete deduction of this theorem and the POT approach, see Makarov (2007) .

In the case of the quarterly flood losses for Orleans Parish, we set $u = 500000$. To determine u, we used the stability of parameters plot shown in Figure 7a. As we can see, there is not much stability for most threshold ranges, probably due to the small sample size in qualifying events. The POT plot using $u = 500000$ is shown in Figure 7.b, where each orange dot represents losses which exceed u.

[2]For the code used to implement the model see Howard's (2017) repository `https://clinthoward.github.io/portfolio/2017/08/19/Rates-Simulations/`, while further details can be found in Appendix 1



(a) Stability of parameters plot

(b) POT plot with $u = 500000$

Figure 7: Extreme Value Analysis for Orleans Parish quarterly losses

Theses peaks were then sampled to generate a series of extremes, which were initially modelled using a Generalized Pareto Distribution (GPD) through the SciPy library, developed by Virtanen et al. (2020). Two additional distributions were also tested, the Exponentiated Weibull and Johnson SU distribution. Figure 8 shows how the GPD seems to overestimate the right tail for the highest quantiles, in comparison to the empirical distribution. Thus, we will use the Exponentiated Weibull for our baseline simulation of $\hat{L}_t$ [3].

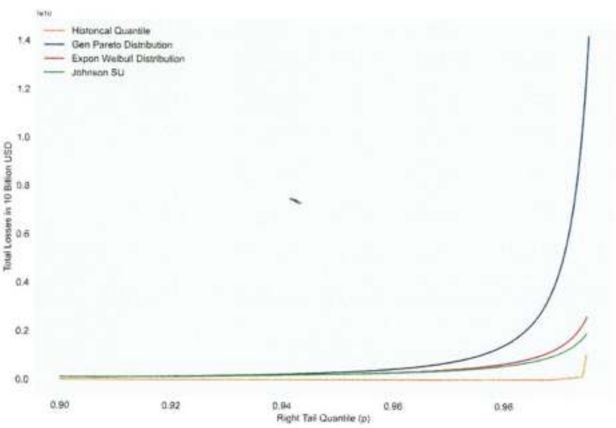


Figure 8: Tail behavior for different distributions used to model flood losses

[3] see Appendix 2 for more details on the parameters and tests performed for these distributions

4.3 Simulation framework

We will showcase the results from one iteration of the Monte Carlo simulation in order to illustrate the different procedures performed. In our baseline scenario we will set $M = 7$billion, which is the NFIP loss for Hurricane Katrina in Orleans Parish when adjusted for inflation. Table 1 shows 12 total losses simulated from the Exponentiated Weibull as a proportion of M. Recall from equation 4.1 that investors receive only part or none of their principal ($\hat{C}$), if $0.5 \leq \max L_t/M$.

For this specific iteration, we can see none of the simulated $\hat{L}_t/M$ exceed 0.5, i.e. no catastrophic flood losses took place, so investors receive their full principal (100) at maturity. The simulated rates are shown as $\hat{r}_t$, along with the discount factor $\hat{v}_t$ taken from 4.2. The price of the bond at $t = 0$ is the sum of the discounted cashflows (DCF_t), which for this iteration equals \$117.44.

Quarter (t)	$\hat{L}_t/M$	$\hat{c}_t$	$\hat{C}$	$\hat{r}_t$	$\hat{v}_t$	DCF_t
1	0.00	12.28	0	0.04	0.91	11.19
2	0.01	12.38	0	0.04	0.83	10.26
3	0.01	12.53	0	0.05	0.75	9.42
4	0.00	12.92	0	0.05	0.67	8.69
5	0.00	13.42	0	0.05	0.59	7.97
6	0.00	12.87	0	0.05	0.55	7.12
7	0.12	13.28	0	0.05	0.49	6.47
8	0.00	13.63	0	0.06	0.43	5.82
9	0.00	13.41	0	0.05	0.39	5.25
10	0.00	12.85	0	0.05	0.37	4.80
11	0.13	13.05	0	0.05	0.33	4.32
12	0.00	12.46	100	0.04	0.32	36.13

Table 1: Sample iteration from baseline simulation

For this sample iteration no catastrophic loss, as we have defined it, occurred. Investors would receive all of their principal (100) and a final coupon of 12.46. This bond is being sold at a premium, which may be due to the high spread that we used for the coupons (8%).

5 Model Results

After performing 10,000 simulations, with $M = 7B$, the average "fair price" of the New Orleans flood CAT bond is 118.53. Thus, for a face value of 100, the bond would be sold at a premium. To visualize the results for this baseline simulation, we can perform a heat-map that explores the relationships between the average return rates used in each iteration, the max value of $\hat{L}_t/M$, with the price of the CAT bond:

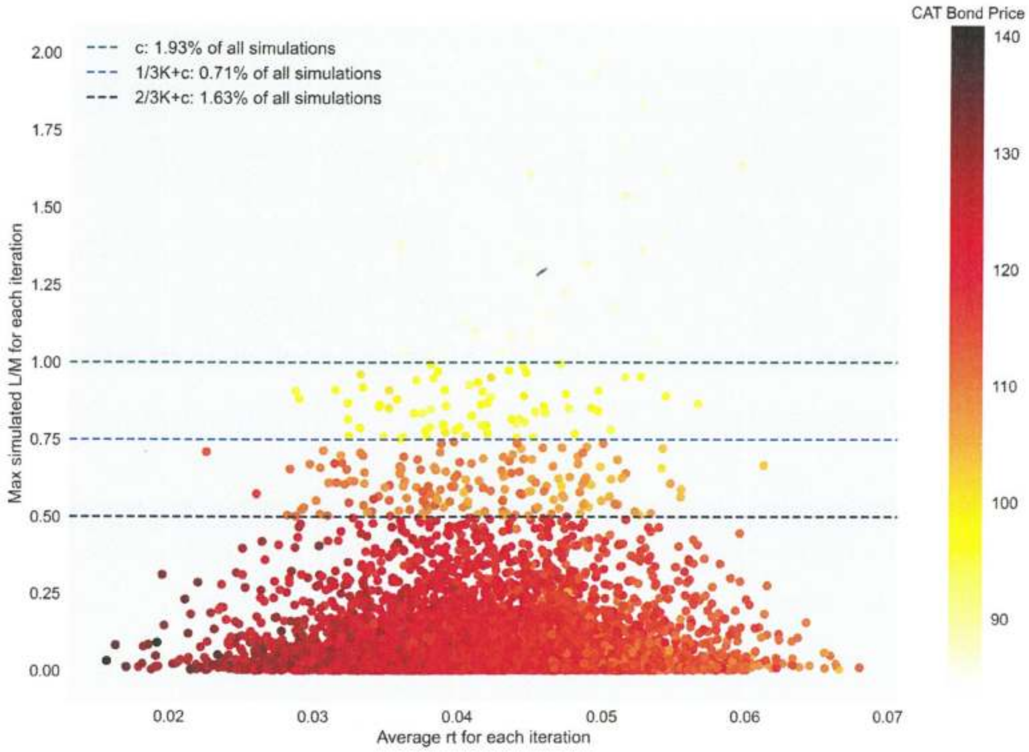
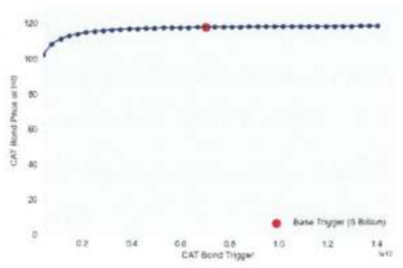


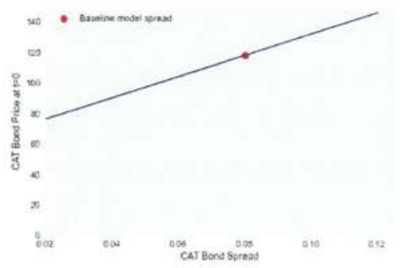
Figure 9: Relationship between rate dynamics and CAT Bond prices

Each dot in Figure 9 represents the price of a CAT bond for a single iteration. The darker dots are those with the highest price, which occurs when r_t is lowest and losses are below $0.5M$. The horizontal lines on the plot represent the payoffs for the different tranches. For example, looking at the top tranche, investors lost their principal in 1.93% of the simulations. Meanwhile, at the bottom tranche, investors would receive 2/3 of their principal with a probability of 1.63%.

Now we will perform some sensitivity analysis for our CAT bond pricing model. Figure 10a shows how the price of this CAT bond price decreases as we set lower triggers M, as the probability of a triggering event would increase. Meanwhile, Figure 10b shows how the price changes as we alter the spread. Here the change is much more significant, as the bond would be sold at a discount ($P < 100$) for spreads lower than 5.5%.



(a) Bond price with different triggers M



(b) Bond price with different spreads s

Figure 10: Sensitivity analysis for CAT bond pricing model

We can also verify how the bond prices would change with different loss distributions in Figure 11. The GPD, which had a heavier tail as shown in Figure 8, does lead to lower CAT bond prices by M, though not significantly so.

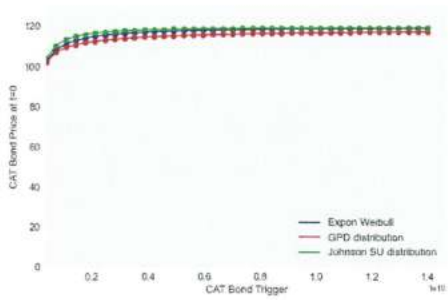


Figure 11: Bond prices with different triggers and loss distributions

6 Conclusions and future research

In this paper we have found the "fair price" for a CAT Bond to cover extreme flood losses for Orleans Parish, an area vulnerable to extreme weather events like the 2005 Hurricane Katrina. Local authorities could use a bond such as this one to cover for extreme losses, which go beyond the coverage of traditional reinsurance. Our model was tested using different triggers, spreads and loss distributions, with fairly consistent results.

Interestingly, the variable which has the highest impact on the CAT bond prices for our model were the spreads. This is a finding which could be looked at more profoundly in future research. We could also consider a more complex way to simulate the flood losses, by taking into account claim arrivals, via a Compound Poisson process, for example. Although, since our triggers were quite high, it is also realistic to expect only qualifying event or catastrophe for this New Orleans CAT bond.

Lastly, an interesting finding from Section 3 was the spatial concentration of the losses. Future research could attempt pricing for different coastal areas in the U.S., for example, to see how geography also impacts the pricing of these instruments. Additionally, the incorporation of weather and hydrological data could also be modelled, to see if this analysis could be replicated in countries which do not have publicly available data for flood losses.

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Appendix 1 - Vacicek Model for Rates

As stated in Section 4, the Vacicek model was used to model the floating rates used in the CAT Bond valuation. Recall that the floating rate selected was the rate for 3-month U.S. Treasuries. Figure 11 plots the historical sample for the daily Treasuries (DTB3), taken from the U.S. Federal Reserve:

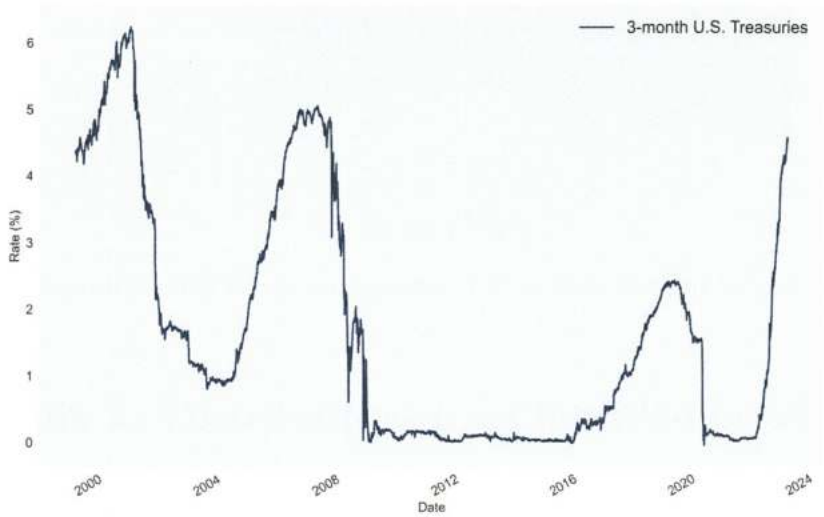

Figure 12: DTB3 data sample used in Vacicek model

Recall the Vacicek model is given by the equation:

$$dr_t = \kappa(\theta - r_t)dt + \sigma dW \tag{5}$$

For DTB3, the estimated parameters of the Vacicek model were: $\hat{\kappa} = 0.074$; $\hat{\theta} = 0.017$, $\hat{\sigma} = 0.007$, $r_0 = 0.045$. The simulated return trajectories for the DTB3 are shown in Figure 13. In this case, the 3-month Treasuries are currently at a 10-year max, so there is a large difference between r_0 and θ. This explains why most return paths in three years do not revert back to the long-run mean for these rates.

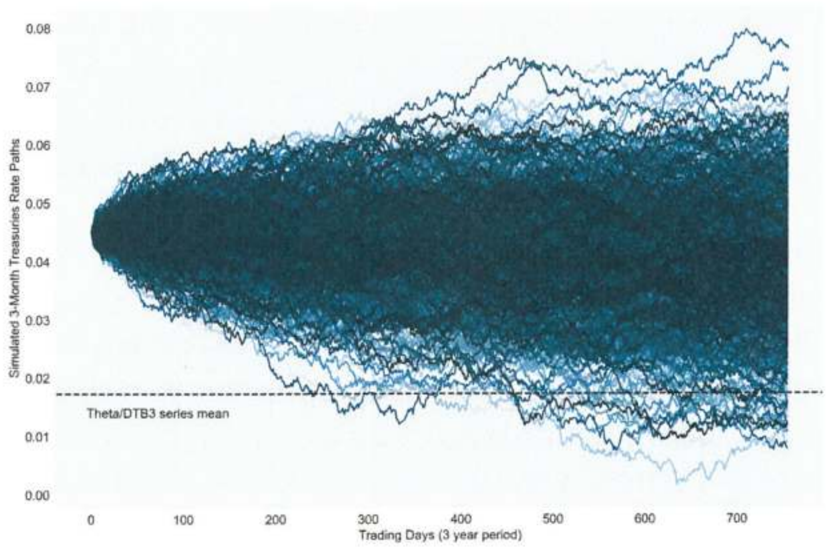

Figure 13: DTB3 simulated trajectories with Vacicek model

Appendix 2 - Distributions used for flood losses

This appendix will provide more detail on the three distributions used to model the total quarterly flood losses from the NFIP program in Orleans Parish. First we will define these distributions using the notation from SciPy and the present the results from the Kolmogorov-Smirnov test used to measure the goodness of fit.

1. Generalized Pareto distribution:

$$f(x;c) = (1+cx)^{1-1/c} \tag{6}$$

defined for $x \geq 0$ if $c \geq 0$ and for $0 \geq x \geq -1/c$ if $c < 0$; and $f(x,c,l,s)$ is equal to $f(y;c)/s$ with $y = \frac{(x-l)}{s}$

The parameters for the extremes found using POT were estimated with Maximum Likelihood and are as follows: $c = 1.647$, $l = 500000$, $s = 3800621$. The results from the Kolmogorov-Smirnov test gave $KS = 0.097; p = 0.929$. We do not reject the null and the Gen Pareto can be considered a good fit for these extremes.

2. Exponentiated Weibull distribution:

$$f(x; a, c,) = ac[1 - \exp(-x^c)]^{a-1} \exp(-x^c) x^{c-1} \tag{7}$$

for $x, a, c > 0$; and $f(x, a, c, l, s)$ is equal to $f(y, a, c)/s$ with $y = \frac{(x-l)}{s}$

The parameters for the extremes found using POT were estimated with Maximum Likelihood and are: $a = 60.99$, $c = 0.119$, $l = 500000$, $s = 17.974$. The results from the Kolmogorov-Smirnov test gave $KS = 0.084; p = 0.977$. We do not reject the null and the Exponentiated Weibull can also be considered a good fit for these extremes.

3. Johnson SU distribution:

$$f(x; a, b) = \frac{b}{\sqrt{x^2 - 1}} \phi(a + b \log(x + \sqrt{x^2 + 1})) \tag{8}$$

where x, a, and b are real scalars, a and b are shape parameters, $b > 0$, ϕ is the standard normal, and $f(x, a, b, l, s)$ is equal to $f(y, a, b)/s$ with $y = \frac{(x-l)}{s}$

The parameters for the extremes found using POT were estimated with Maximum Likelihood and are: $a = -3.992$, $b = 0.445$, $l = 500000$, $s = 1509.388$. The results from the Kolmogorov-Smirnov test gave $KS = 0.092; p = 0.953$. We do not reject the null and the Johnson SU can also be considered a good fit for these extremes.