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Executive Summary

The most fundamental activity for an insurance company is managing risk - risk assumed from the policies they underwrite. If there is one law that all insurance companies seek to enforce, it is the *law of large numbers*. It is much easier to estimate the future damage for a portfolio of 500,000 cars than to estimate the future damage for one car. Thus, insurance companies estimate expected losses for policies related to auto, home and life with much greater accuracy and confidence than they do for infrequent events such as natural catastrophes.

Losses from future catastrophe events are much more difficult to estimate for two primary reasons (Lamparelli 2015):

- A single event can affect thousands of policyholders simultaneously, and
- There are relatively few historical catastrophe events to predict future occurrences with confidence

This uncertainty leads to greater risk exposure for a single insurance company to shoulder on its own. To shield this exposure from their balance sheets, insurance companies have two primary avenues to transfer risk: 1.) reinsurance market or 2.) catastrophe bond market. The latter will be the focus of our paper.

Catastrophe bonds are comprised of various characteristics (e.g. covered perils and regions, when claims qualify for reimbursement, modeled expected loss, etc.) and sold through a securitized investment vehicle to buyers who are willing to assume the risk in exchange for a risk premium (reward). There are two primary elements that comprise the price of a bond: 1.) floating risk-free rate and 2.) credit spread. The credit spread can be further divided into the expected loss and risk premium.

Historically, the catastrophe bond market has operated with considerable opaqueness. Insurance companies do not fully understand the criteria that an investor uses to ascertain a "fair" premium for assuming risk. Further, investors do not fully understand which bond characteristics should be considered and how to optimize the weights for each against the risk premium. Therefore, there is tremendous value in systematically defining credit spread by disaggregating it into measurable features.

In this paper, we attempt to predict the credit spread of a catastrophe bond given its specific attributes (explicitly stated and derived) and market conditions. If successful, this work will be significantly relevant for two reasons:

- It allows an insurance company to estimate the most likely price an investor will pay for a given bond. With this information, the insurance company can determine the most profitable risk profile to sell to their policyholders.
- It provides the investor with a consistent pricing method to accurately assess the risk profile of a given bond and obtain a "buy/no buy" signal. This reduces the arbitrage in the market and potential losses for the investor.

Acknowledgements

We would like to thank Professor Kathleen Derose for sharing her excellent knowledge of the financial markets and leading us down the straight and narrow path for this project. She saved us numerous hours from climbing down many unproductive rabbit holes and helping us develop a robust framework for our hypothesis and final paper. Also, a big shout-out to Professors Mike Pinedo and Anindya Ghose for providing feedback on this paper. We discovered the healthy tension in writing technical content in a way that can be readily understood by a broader audience.

Section 1
Introduction

Respected veterans in the catastrophe bond (cat bond) industry such as (Lane and Mahul 2008), (Bodoff and Gan 2009) and (Braun 2016) have created statistical models to explain the variation in credit spread of cat bonds relative to their associated features. Of these features, expected loss is an aggregated statistic derived from a distribution of simulated losses. This feature explains the largest amount of variation in the credit spread of cat bonds. We hypothesize that the spread can be further explained by disaggregating the expected loss and other attributes of the bond (e.g., peril, region, seasonality, historical lagged prices, etc.), while controlling for a time-variant, cost of capital proxy through the use of corporate bond spreads and market cycles due to historical losses.

Using the CRISP-DM methodology, our work has allowed us to replicate prior research, engineer meaningful features, embed time series, create multiple variants of regressions to predict credit spread and test for robustness of our predictions. We desire to openly share our work and provide access to the modeling framework with participants in the cat bond market. As a result, we developed a web-based modeling tool for a business user that can deliver an accurate prediction of the cat bond spread using one or more Machine Learning (ML) models and provide the ability to compare this spread with other data and predictions that have been made over time.

To accomplish our objectives, we set the following high-level activities:

- Study prior published research related to cat bond credit spread behavior and its interaction with features that define risk
- Study prior finance literature on price elasticity (supply and demand) to help us understand how the credit spread is impacted by market cycles observed in the cat bond market (i.e. subsequent to a natural catastrophe or event in the financial markets)
- Undertake data acquisition, data preparation and detailed exploratory data analysis to develop our business and domain understanding
- Investigate a variety of regression based ML techniques to create a suite of robust models in both R and Python using hyperparameter optimization, cross-validation and regularization.
- Deploy these model(s) and provide a RESTful API using SWAGGER, so we can serve predictions and analytics to a user experience (UX)
- Build a web-based UX for a business user (i.e. prospective analyst and investor) employing R and Shiny which can collect data, invoke and track predictions, provide comparative analytics and serve interactive data visualizations

Section 2
Business Understanding

2.1 A Backdrop for Catastrophe Bonds

Insurance companies optimize their profits by effectively managing risks. This is best accomplished by identifying the likelihood of a future event in which an insurance company is obligated to reimburse a policyholder for covered damages. Predicting the likelihood of an event requires historical data of similar events, and hopefully, lots of it. For frequently occurring events such as those covered by auto, home and life insurance policies, data scientists can accurately predict the aggregate amount of claims that an insurance company will be expected to cover over a given time period. Armed with this information, insurance companies can profitably establish premiums based upon the probability of an expected loss for which a given policyholder will be reimbursed.

Over the past 25 years, insurance demand has increased for events which occur infrequently. Catastrophic events, such as earthquakes and hurricanes, rarely occur, but can cause significant damage. Due to the sparse frequency of these events, it is considerably more difficult to predict their timing, and equally important, their associated severity. Because a catastrophic event can impact a large population within a single moment, the timing of qualifying claims submitted by policyholders no longer follows a log-normal distribution. The simultaneity of claims creates tremendous financial stress on a single insurance company, which can result in bankruptcy. Insurance companies seek to solve this problem by transferring catastrophe risk from their balance sheet to third parties.

Entities such as reinsurers and investors may add a fraction of the total catastrophe risk to their balance sheets and investment portfolios dependent upon the expected loss (amount of risk) and financial reward. Because the large risk, which was once on the insurance company's balance sheet, has now been distributed in fractional "shares" to third parties, it reduces the financial impact on any single investor and increases the chances that all qualifying claims by policyholders will be reimbursed.

The remainder of this paper is devoted to the fractional shares of risk which are sold to investors in the form of cat bonds.

2.2 Catastrophe Events and Their Impacts

In 1992, Hurricane Andrew killed 65 people and caused nearly $27B USD of losses in Florida (Lenihan 2017). Andrew's financial impact on the industry was significant as it doubled the modeled loss estimates which forced several insurance companies into bankruptcy and depleted the remaining reinsurance risk capacity.

Areas have become more densely populated leading to greater property loss for residents and businesses when an event occurs. Table 2.1 (Amadeo 2019) lists catastrophe losses (inflation-adjusted USD) over the past 20 years due to U.S. hurricanes.

Table 2.1: Insured and Economic Losses

Year	Hurricanes	Insured Losses	Economic Losses
2004	Ivan, Charlie, Francis and Jeanne	$40B	$71B
2005	Katrina, Wilma and Rita	$118B	$208B
2007	Ike and Gustav	$25B	$42B
2012	Sandy	$31B	$70B
2017	Maria, Irma and Harvey	$92B	$217B

Even national, regional and local governments are at risk of increasingly large losses due to catastrophe events. In particular, developing economies, which are largely uninsured from catastrophe events, risk losing years of economic progress from a single large-scale event. The United Nations and the International Monetary Fund are currently discussing the use of different industry investment structures (see appendix A.1) to preserve economic progress from catastrophic events. Figure 2.1 shows the total economic and insured losses worldwide from catastrophe events ("Munich RE - NatCatSERVICE Analysis Tool. Munich RE" 2019). Of great concern, is the increasing trend in economic losses and the spikes of uninsured losses.

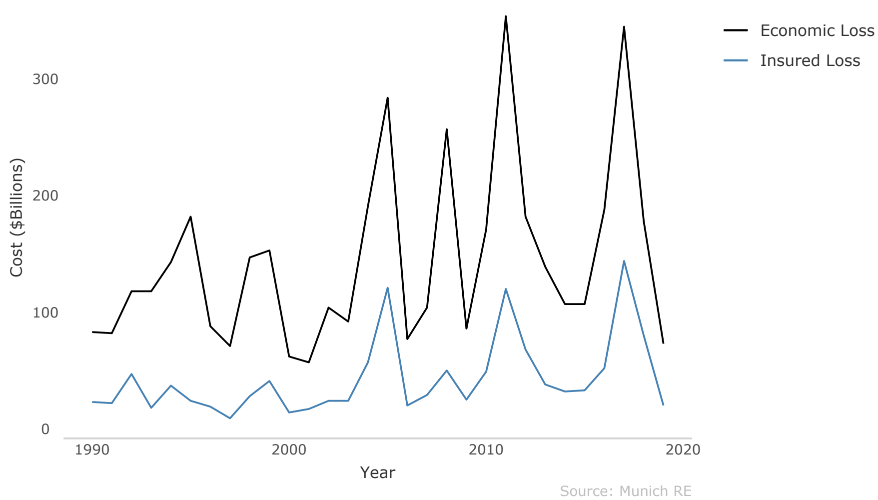


Figure 2.1: Cost of worldwide natural disasters from 1990 - 2019

2.3 Structure of Catastrophe Bonds

2.3.1 Special Purpose Vehicle

Sponsors of cat bonds create a Special Purpose Vehicle (SPV). SPVs are limited partnerships or company entities established for the purpose of transferring debt from the sponsor's balance sheet to this temporary entity ("Special Purpose Vehicle (SPV). Practical Law" 2020). The SPV receives premiums from the sponsor in exchange for providing coverage via issued securities. Additionally, the SPV receives principal amounts from investors, and in return issues securities to them. As a result of industry changes resulting from the Lehman Brother's bankruptcy in

2008, the SPV invests the principal into a collateralized account, typically invested in near risk-free assets (LIBOR/U.S. T-bills) to generate low-risk returns.

The investor's coupon or interest payments are comprised of interest from the collateralized capital and a contribution from the sponsor's premiums. Hence, the cat bond pays the investor a substantial spread over money market returns at a pre-agreed coupon, as shown in Figure 2.2.

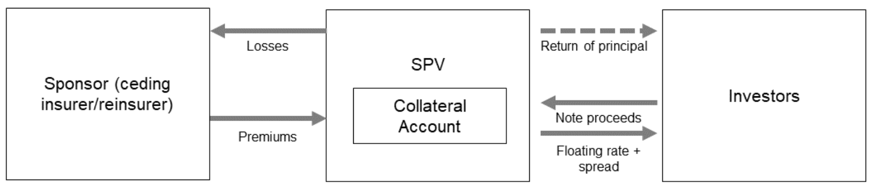


Figure 2.2: Structure of a cat bond transaction

If qualifying losses are not incurred, the collateral is liquidated at the maturity of the bond, typically three years. In this case, the investor receives the accumulation of quarterly coupons plus their initial principal. If a qualifying event occurs, all or part of the principal is transferred to the insurance company. In this situation, the investor's quarterly coupon payments cease or are reduced, and at maturity, the investor may receive only a portion of their initial principal or none at all.

2.3.2 Triggers

Most cat bonds are structured to cover losses when a specific set of criteria (triggers) have been met as a result of one or more catastrophe events. When the cat bond is triggered, the SPV liquidates the required collateral to cover the qualifying losses and reimburses the insurance company according to the terms of the catastrophe bond transaction.

There are two primary triggers (Alvarez 2017):

- Indemnity – covers total losses incurred by the sponsor above a certain threshold for a specific event. For example, if the indemnity threshold is set at $100M and the total losses from a qualifying event are $300M, then $200M of the bond's corpus is used to cover the losses.
- Index (non-indemnity) – the bond is triggered when the losses exceed a specified limit on a given index not directly tied to the sponsor. There are three non-indemnity triggers: modeled, industry and parametric.
  - Modeled Index – parameters from an event are inputted into a catastrophe model and losses are calculated. If modeled losses exceed a certain threshold, then the bond covers losses.
  - Industry Index – the cat bond specifies an agency which will calculate the total industry losses incurred from a specific event. If the total loss exceeds a predetermined amount, the bond will cover losses.

  - Parametric Index – specific parameters of an event such as wind speed in a hurricane or strength of ground movement during an earthquake will be reported by third parties. If the parameters exceed predetermined thresholds, then losses from the event will be covered by the bond.

The various types of triggers have advantages and disadvantages to both the investor and the sponsor as seen in Figure 2.3 ("Cat Bonds Demystified - RMS Guide to the Asset Class" 2012).

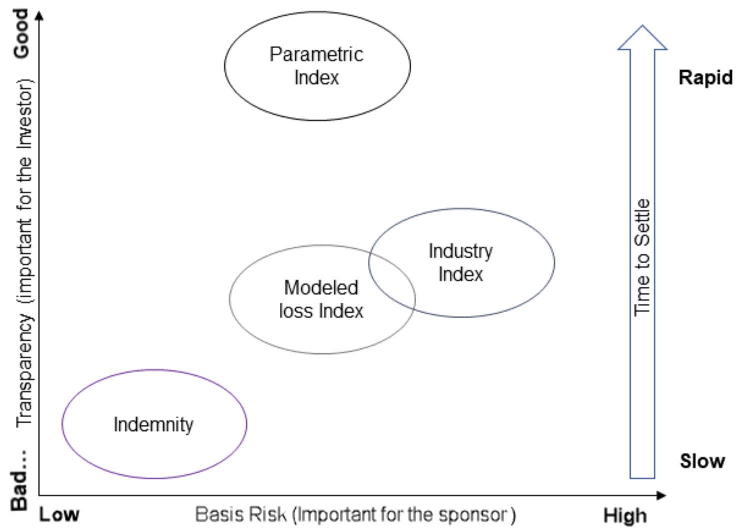


Figure 2.3: Characteristics of Trigger Types

Indemnity triggers require extensive legal definitions of the key terms, such as the book of business, recognition of loss and what constitutes a catastrophe event. They have a benefit to the sponsor, since the sponsor's specific loss experience is used as the trigger. The funds recovered from the catastrophe bond will match the underlying claims very closely, minimizing the sponsor's basis risk. From the investor's perspective, indemnity triggers are the least desirable for two main reasons: 1.) it can take years to determine the total principal loss from a single event and 2.) moral hazard is increased due to less incentive to vigilantly settle claims and write less risky coverage.

2.3.3 Market Dynamics

Shocks in the market can cause cycles to shift (see appendix A.2). Since 2002, there have been three primary types of shocks that have contracted (i.e. hard market) or expanded (i.e. soft market) the flow of capital to the cat bond market:

- Substantial Financial Shocks. During the Great Recession of 2007 - 2008, the financial markets declined approximately 40% which caused a material number of investors to liquidate portions of their portfolios to meet cash demands of distressed assets. Due to the strength of cat bonds, during that time, distressed investors began liquidating their cat bonds at substantial discounts to cover other asset calls. This resulted in increased cat bond yields, because available capital was reduced in the cat bond market.

- Significant Catastrophe Events. Increased yields are driven by large losses in the insurance market due to major catastrophe events (e.g., Hurricane Katrina, California Wildfires, etc.). These events remove liquidity from the cat bond market due to an increase in perceived risk, thereby creating a hard market.

- Structural Changes. Insurance policies directly linked to a given cat bond must be fully covered by capital secured in collateralized financial instruments. In 2008, Lehman Brothers was aggressively investing this collateral in high-risk, mortgage-backed derivatives. When the financial markets collapsed, Lehman Brothers was unable to cover these capital losses along with other significant financial commitments, and they filed for bankruptcy which directly impacted several large, on-risk cat bond issues. As a result of this failure, changes were made to invest collateral in low-risk securities (e.g., U.S. T-bills) and provide the investor with greater transparency of the investment vehicles. These changes ensured less exposure and correlation to the broader financial markets, while removing complexity and uncertainty from the cat bond credit spread.

2.3.4 Pricing Dynamics

The price paid on any given cat bond can be broken down into two primary components (Price and Credit Spread):

$$\text{Price} = \text{Risk-free rate of return} + \text{Credit Spread}$$
$$\text{Credit Spread} = \text{Expected Loss} + \text{Risk Premium}$$

Figure 2.4 demonstrates how the cat bond price can be disaggregated.

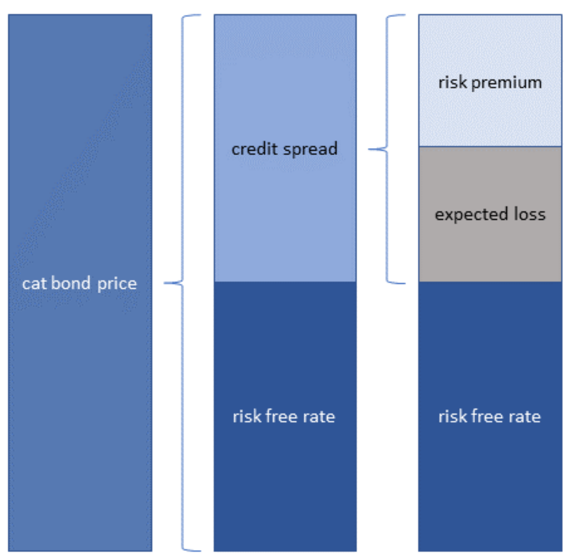


Figure 2.4: Primary components of the cat bond price

The risk-free rate of return is based on floating rate securities (e.g., U.S. short-term money market securities/index). Cat bonds reset periodically to match these rates. Due to the use of floating-rate securities, cat bonds are much less sensitive to duration and interest rate changes. For the purposes of this research, we will not examine the risk-free rate of return as a component of price, but rather, we will solely focus on examining credit spread.

The credit spread reflects the expected loss of the underlying insurance risk (based on experience and stochastic modeling) plus the amount of risk premium the investor wants for the basis risk in the event that the modeled losses do not match the actual probability of loss. The investor's view of risk may also change over time due to frequency and severity of catastrophe events (i.e. 2005 experienced three hurricanes [Katrina, Wilma and Rita]). Also, investors demand an additional premium for higher levels of expected loss and for cat bond structures that are complex (see appendix A.3 for investment benefits of cat bonds). The risk premium is directly tied to the market's dynamics and can vary materially for bonds with the same risk profile. The industry interchangeably uses multiple terms when referring to credit spread, such as "spread over LIBOR", "risk premium" or simply "spread". For the remainder of this paper, we will use the term "spread" to mean credit spread.

2.4 Evolving Catastrophe Bond Spread

Evidence in the market is pointing to a decrease in spread resulting from the *law of one price* theory. Simply stated, when sufficient competition and transparency are present in a free-market, arbitrage will eventually be eliminated through efficient and uninhibited exchanges. In the case of cat bonds, we believe that market factors, such as significant increases in cat bond issues and capital inflows, more sophisticated risk assessment technology and increases in market participants and investors, are beginning to introduce greater information and accuracy into the prediction of catastrophe spreads and the quantification of the underlying risk. This is ultimately creating a more efficient market.

(Adam Alvarez 2014) states, "The perception of ILS has changed from an exotic asset class to something much more mainstream and this explains much of the decline in yields." He further explains that in 2002, cat bonds were mainly owned by reinsurance companies and hedge funds, but today, institutional asset managers are driving the market.

With the advent of auction marketplaces and increasing amounts of disintermediation in the value chain for catastrophe risk placement, this market will continue to see increased efficiencies. This means continued compression of spreads and reduction in the cost of capital to finance these transactions. But, how much of the variation in the spread can be explained by greater efficiencies in the market versus improvements in probabilistic catastrophe event models? We will explore this question and how the components of spread interact.

The Banker's model provides a broadly accepted definition of spread as follows (Bodoff and Gan 2009):

$$\text{Spread \%} = \text{Constant \%} + \text{Loss Multiplier} \cdot \text{Expected Loss \%}$$

The constant in the above equation accounts for the various price intercepts as a function of the type of expected loss (e.g., peril, region, etc). Further, it interacts a loss multiplier (i.e. a risk premium an investor demands) with expected loss. Our supposition is that the constant is a correlated component of expected loss, while the loss multiplier is uncorrelated.

Section 3
Data Understanding

We have compiled a variety of data (see appendix C.2) from public and private sources. Our data is divided into two datasets. While both datasets are multidimensional, the second dataset changes over time.

The two datasets are as follows:

- The first dataset provides the data for the issuance price of a cat bond. It serves as the basis of our exploratory phase, where we use this data to replicate the prior research by (Bodoff and Gan 2009). It describes key characteristics about a cat bond such as: 1.) the cat bond's peril which is a combination of region(s) and nature of the catastrophe event(s) (section 3.3.1.1), 2.) type of trigger (section 2.3.2) and 3.) information from prior market cycles (appendix A.2).
- The second dataset provides longitudinal data that impacts the price of a cat bond over time, such as: 1.) cross-sectional unit of time in seven cross-sections at the time the cat bond is issued, then respectively at 4, 8, 12, 28, 28 and 102 weeks prior to the issue date of the bond, 2.) binary variable in the case of a catastrophe event(s) occurrence covered by the cat bond, 3.) mark-to-market prices observed at each point in time, 4.) periodic structural resets of the cat bond, 5.) impairments to the principal amount, due to catastrophic losses, in the occurrence of a catastrophe event and 6.) other time-based features.

3.1 Data Summary

The following provides context to the observations we use in our modeling. The time-series datasets for this market are available on a weekly basis; and therefore, we have used this frequency when gathering other data from broader financial markets.

Table 3.1: Summary of datasets used in our analysis

Dataset	Source	# Observations	Frequency
Cat bonds	Artemis	414 cat bonds issued, 246 resets (660)	Issue Date
Cat bond prices	Swiss Re	323,002 mark to market prices	Weekly
Cat events	Munich Re	97	Event Date
Stochastic Model	AIR Worldwide	10,000 simulated years per cat bond with breakdown of losses by region/peril/day of year	N/A
Seasonality Model	AIR Worldwide	365 per cat bond, then disaggregated by region/peril	N/A

Dataset	Source	# Observations	Frequency
Lane Indices	Lane Financial	52 observations per year	Weekly
S&P Indices	Yahoo Finance	52 observations per year	Weekly
Return Indices	Lane Financial	52 observations per year	Weekly
ROL Index	Guy Carpenter	1 observation per year	Annually

We commence our analysis with data from January 2002. This date coincides with the inception of published cat bond indices made available by Swiss Re. The following chart shows the rate of issuance since 2002.

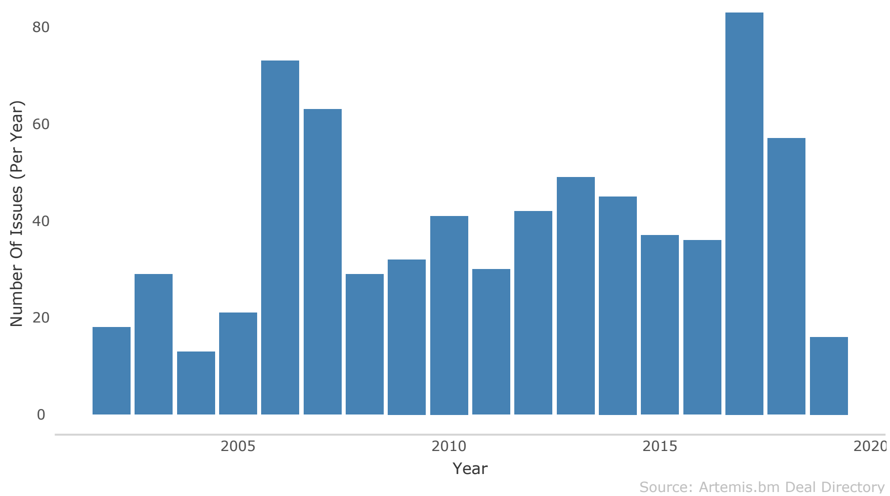


Figure 3.1: Historical Cat Bond Issuance (based on data) since 2002

Therefore, our two datasets comprise of:

- 714 cat bonds (and any subsequent resets)
- 714 cat bonds (subjects) for the unbalanced panel with the following metrics:

Metric	# Observations
Total Count	109,745
Min (bond)	22
Max (bond)	368
Mean (bond)	155

3.1.1 Outliers

The outliers fall into two distinct categories: 1.) structural and 2.) data quality. These cases abnormally impact the Ordinary Least Squares (OLS) coefficients:

- Structural - Four cat bonds that defaulted in 2008 while Lehman was acting as the Total Return Swap (TRS) counterparty have been removed from our study. We are primarily interested in instruments that default due to natural catastrophe. This deficit in contract structure has since been rectified by the use of the SPV with funds held in a collateral account, whereby the sponsor is the beneficiary of the funds.
- Data Quality - Eleven cat bonds had significantly higher expected loss multiples and were heavily influential relative to the other observations in our dataset when performing an OLS regression and calculating Cook's distance. Eight of these cat bonds belong to the Swiss Re successor issuance, and all eleven bonds were removed from our study.

For other data quality issues, we devoted time to understanding and rectifying those cases. We found bonds with incorrect duration, expected loss, etc. For example, when analyzing expected loss, we noticed a grouping of bonds that had an expected loss of .5% (an extremely low expected loss value). Upon further inspection, it was obvious that the decimal conversions for this group of bonds were miscalculated (i.e. divided by 100 rather than 10). These bonds were corrected and retained for our study.

3.2 Unresolved challenges with the data

The sources for the data in our project are fragmented, proprietary and do not use standard nomenclature or feature/time granularity. We have spent considerable time collating and organizing our data feeds and reviewing the information collected across numerous sources. This appears to be a common thread throughout the prior research we studied. This makes it difficult to compare results across research authors as there is no common baseline dataset from which one can commence their work. Lack of data standardization and sharing is systematic in the industry and creates inefficiencies. For the cat bond market to work more efficiently, these barriers must be significantly reduced, if not eliminated.

3.3 Key Findings and Observations

Within our business and data understanding, we studied key characteristics, trends and cycles that play a critical role in determining the spread of a cat bond. It is important to derive a feature set that addresses each of these key findings and observations, and thus, provides our suite of models with the ability to make sensible and robust predictions.

Spread is made of two components: 1.) expected loss and 2.) risk premium.

3.3.1 Expected Loss

Unique to (Bodoff and Gan 2009), when published, they argued that various perils (e.g., earthquake, wind, etc.) have their own inherent price slope per unit of risk. Their study was solely limited to bonds with a single peril/region, which is a small portion of issued cat bonds. Additionally, they demonstrated that various perils and geographic locations (i.e. peak, non-peak or diversifying) have their own price constant (intercept), meaning that they don't all have the same assumed spread when the expected loss is equal to zero.

We hypothesize that a more robust model can be built to predict spread by disaggregating the expected loss into the following components:

3.3.1.1 Perils and Regions

Different from Bodoff and Gan, we include single- *and* multi-peril/region bonds in our analysis. To account for the different price slopes and intercepts, we add numerical values of expected loss by peril/region in addition to the bond's assigned, aggregated expected loss. This disaggregation is unique to our model.

3.3.1.2 Statistics of Expected Loss Distribution

The shape of the expected loss distribution is important. For example, assume two bonds have the same modeled expected loss of 5%. The expected loss for one bond is derived from a single event, whereas the other bond's expected loss is an accumulation of multiple events. Although both bonds share the same expected loss value (5%), their distributions are significantly different, and may explain variance in the spread. A distribution with a longer (versus shorter) left tail, represents greater exposure to loss, which demands a greater spread. We use TVAR, derived from a distribution of losses created by a Monte Carlo simulation, to assign each bond continuous values representing the shape and characteristics of its distribution. This feature is unique to our work.

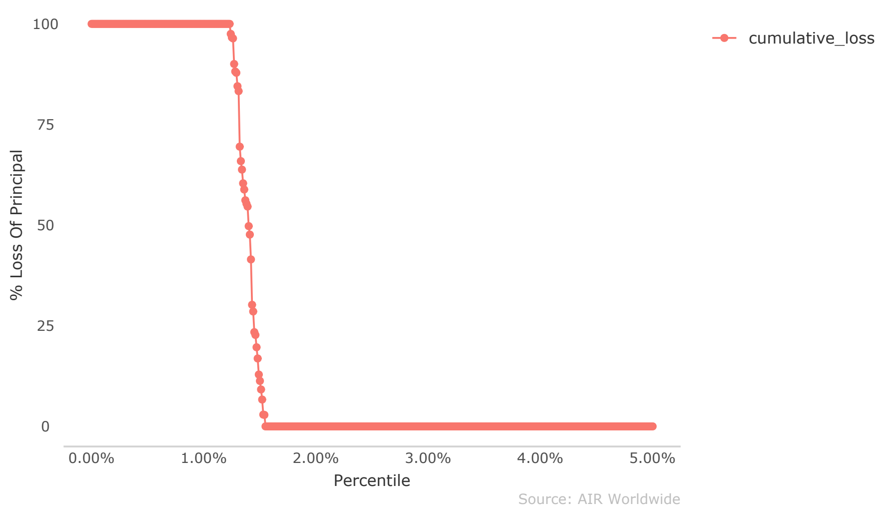


Figure 3.2: Cat bond exceedance curve (U.S. Hurricane)

The Exceedance Probability curve visualizes the probability that the cat bond will make a payout based on the simulated events and subsequent losses. In the example above, the cat bond begins to erode the principal at the 9850 percentile and is estimated to make a 100% payout at the 9877 percentile. This means the probability of attachment is 1.5% and the probability of exhaust is 0.27% (i.e. a full payment of the principal to the cat bond issuer).

3.3.1.3 Seasonality

The likelihood of default changes over time due to seasonal variations based on the covered region and peril. For example, U.S. wind coverage experiences the greatest risk of loss from July through September, when hurricanes are most likely to occur. Periodic pricing of U.S. wind cat bonds (in the secondary market) during these months increases. In a benign season and after September, these bond spreads begin to fall as the risk diminishes. We will explore these interesting traits in greater detail as we develop our research with time-series.

Figure 3.3 shows how hurricane risk is accumulated over the summer months and impacts expected loss of the cat bond.

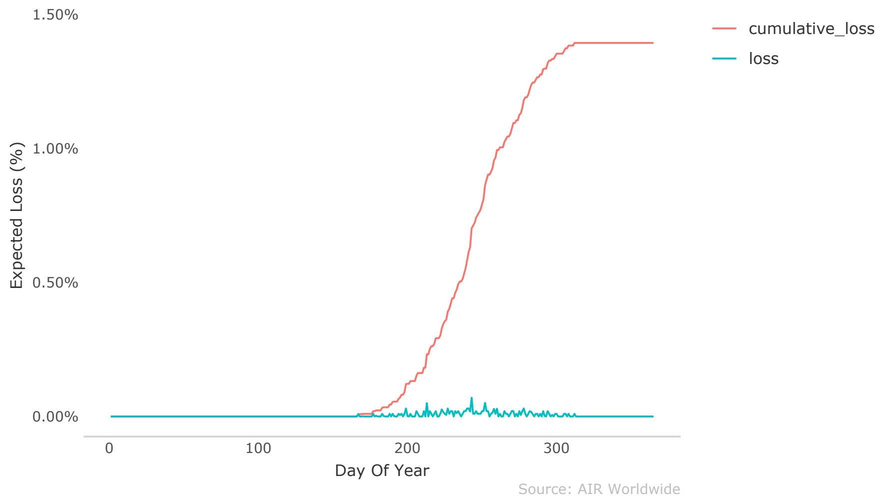


Figure 3.3: Cat bond seasonality (U.S. Hurricane)

3.3.2 Risk Premium

3.3.2.1 Type of Trigger

Indemnity triggers transfer the majority of the basis risk to the investor, whereas non-indemnity triggers transfer the majority of the basis risk to the issuer. In the former case, the insurer has less incentive to write less risky coverage. Due to higher risk exposure, the investor will demand additional spread for an indemnity triggered bond. We created a categorical dummy variable to account for this bond characteristic.

3.3.2.2 Hard and Soft Markets (dynamics of supply and demand)

The cat bond market, like other financial markets, is subject to supply and demand dynamics which is observed in the dataset. We will explore this cyclical dynamic with the use of three proxy types attached to each bond:

- A single binary dummy variable representing a hard/soft market at the date of issue.
- 16 binary dummy variables assigned to each year (2003 - 2018) indicating whether that particular year was a hard/soft market. We surmise that the coefficients will vary, even for years that share the same hard/soft market binary indicator.
- It is likely that the previous two proxies will experience some level of data leakage as the market cycle indicator is not known until the end of the year. Further, we want to explore the possibility of explaining additional variation by using a continuous versus binary market cycle indicator. For this proxy, we are using a lagged numeric measurement

(mark-to-market pricing as a percent change to the par of the market) sponsored by Lane Financial (See Figure 3.4) (Lane and Beckwith 2019).

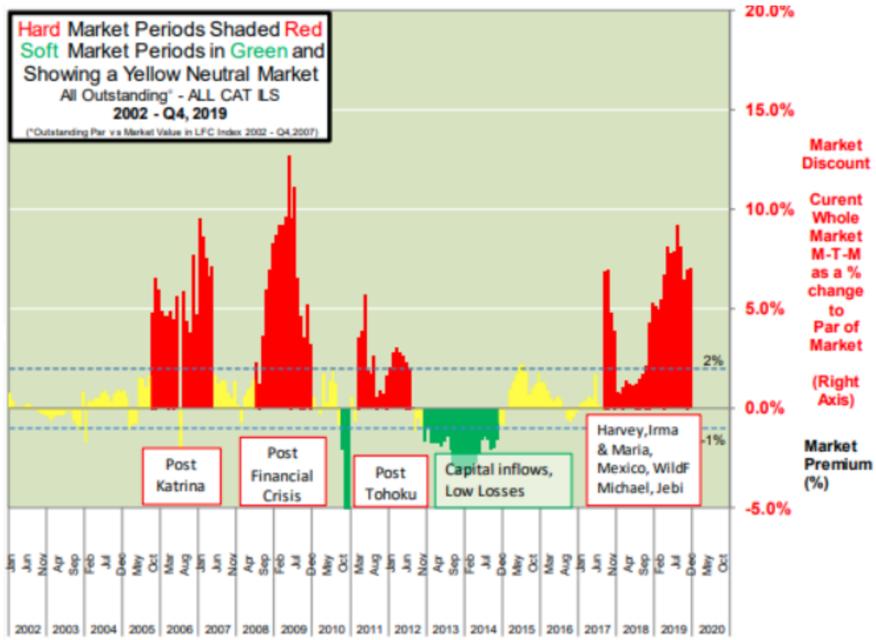


Figure 3.4: Hard and Soft Markets

3.3.2.3 Bond Ratings

Typically, a corporate bond rating is a proxy for the probability of default by the custodian of the capital - the issuer. With cat bonds, the capital is collateralized with low-risk investments (e.g., U.S. T-bills). As such, the rating of a cat bond does not represent the financial condition and imputed risk of the issuer, but rather the probability of capital loss due to a catastrophe event. The expected loss is determined using models that embed assumptions regarding the severity, frequency and probability of an event(s). Thus, we surmise that the bond rating is collinear with expected loss, trigger type and other attributes related to modeled risk (e.g., peril, region, probability of loss, data quality, past performance of the issuer, etc.), and may add no additional predictive power.

3.3.2.4 Multiple to Expected Loss

In the *Banker's Model* used by (Bodoff and Gan 2009), the unadjusted risk multiple for catastrophe bonds has been steadily decaying over time (see Figure 3.5).

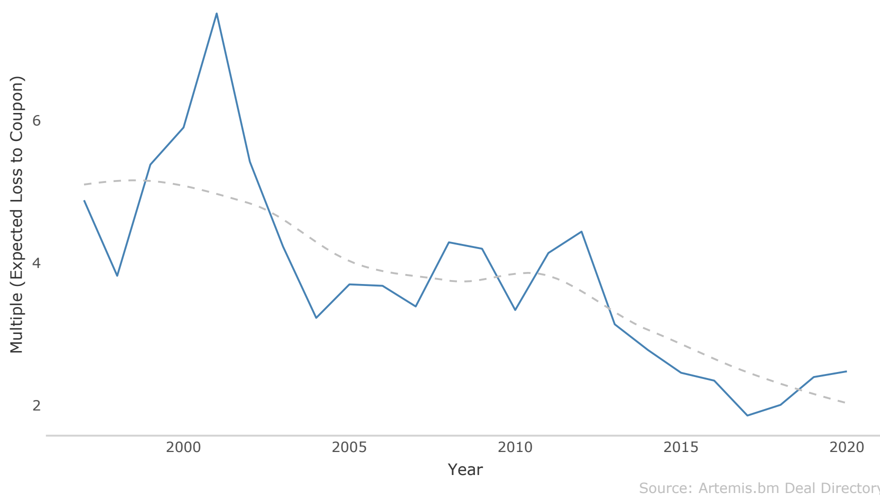


Figure 3.5: Historical Multiples

Through our data exploration, we discovered that bonds with a higher expected loss experience an accelerated decay in the multiple compared with bonds of lower expected loss.

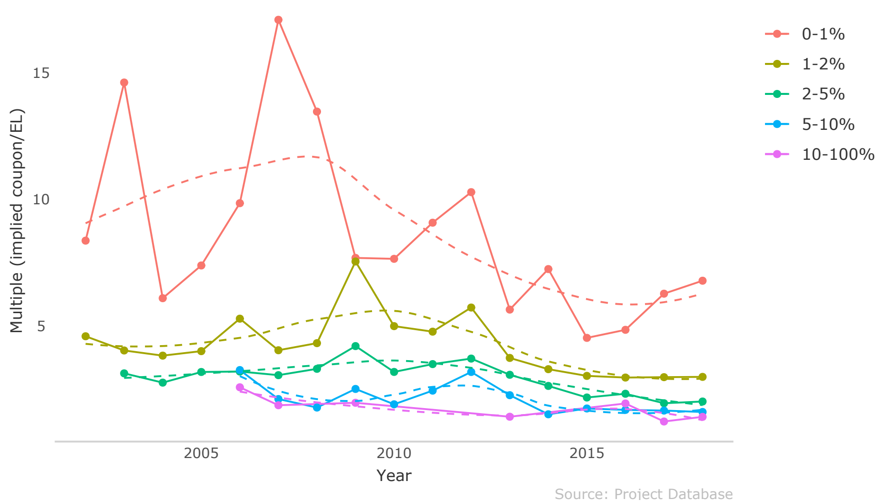


Figure 3.6: Multiple By Year And Expected Loss

Figure 3.6 disaggregates the multiple by expected loss. Although multiples overall are in decline, multiples for lower levels of risk are higher. This is a counterintuitive phenomenon that may be explained by opaqueness or lack of information in the market. In any event, the market is rewarding those investors in low-risk bonds more so than in the high-risk bonds.

There are several observed factors that correlate with the declining risk multiple, such as the growth of the market (i.e. risk capital and the number of participants). Whether these are root causes of decay in risk multiple is a topic for future research. With that said, we are hopeful to explain a portion of this decay by controlling for the total size of issuance in the market at the time each bond is issued.

Lastly, when an event occurs, the shock to the multiple is non-linear and differs by region and peril. In the 1990's, a major catastrophe event in one part of the world would have a rippling effect on the spread of cat bonds in all parts of the world. By 2005, this trend began to shift (see Figure 3.7), and shocks mostly affected bonds in the geographic region of the event rather than having a global impact. Nick Frankland, CEO of EMEA Operations at Guy Carpenter explained about the market, "…it used to respond as a market to major catastrophe events, sharing the burden and benefiting across the industry from the payback…essentially, what you've got now is a market that responds locally and regionally." (Artemis.bm 2015) We see this increasing localization of event shocks demonstrated in our data.

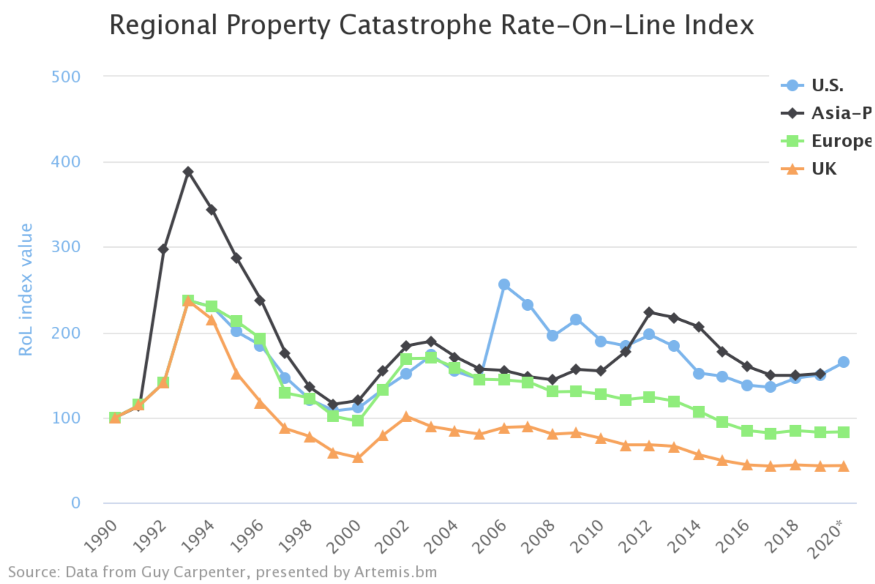


Figure 3.7: Rate-on-Line Index

Section 4
Modeling

4.1 Approach

Our modeling approach identifies features that best explain the variance in the cat bond's spread over the risk-free rate. The expected loss of contracts will vary over time for the same unit of risk as year-over-year models are adjusted to capture new knowledge based on observed natural catastrophe events. However, this will not account for changes in spread based on investors' sentiment towards risk and other market dynamics. Further, we have observed from the time-series analysis in the prior section (see figure 3.7) that historical events over time impact the spread, thus these features are examined in our approach.

Initially, we replicated the work by (Bodoff and Gan 2009) to create a baseline understanding of the intrinsic relationships that exist in the data. We adapted their work and accretively leveraged historical time-series, features derived from the contracts and cross-validation. Time-series cross-validation ("Cross-Validation for Time Series Rob J Hyndman" 2020) was chosen to avoid data leakage due to time-related dependencies (e.g., historical catastrophe losses and market dynamics) that may be introduced by using k-fold cross-validation and sampling.

4.2 Dependent variable

The spread of the cat bond is the dependent variable, which is a continuous numerical value. Further, regression techniques are used to predict its value.

4.3 Methodology

Our analysis uses features related to the bond and market dynamics that are known at the time each cat bond is issued. The dataset is parsed to perform in-sample and out-of-sample testing using a split ratio of 90% (training/cross-validating) and 10% (out-of-sample testing). Because our model is temporal, time-series cross-validation ("Cross-Validation for Time Series Rob J Hyndman" 2020) is implemented by the Caret package in R.

In the first iteration, OLS is used with robust standard errors (Bodoff and Gan 2009) and stepwise linear regression (James et al. 2014, P. Bruce and Bruce 2017) to provide a baseline for our predictions.

We chose Coefficient of Determination (R^2), Adjusted Coefficient of Determination ($AdjR^2$), Mean Absolute Error (MAE) and Root Mean Standard Error ($RMSE$) as our metrics to measure model performance. The $AdjR^2$ is used, because the feature space is highly dimensional, and we want to avoid the curse of dimensionality (Bellman, Corporation, and Collection 1957). Also, we use the Akaike Information Criterion (AIC) (Akaike 1973) to assess the parsimony of the best model when using OLS.

4.3.1 Ordinary Least Squares (OLS) Regression

We create an initial model using OLS regression with robust standard errors and a limited set of features. This allows us to quickly iterate on the data, explore the key features and begin testing our hypothesis. In the OLS, features are included from the bond's offering circular, which is distributed to investors at the time the bond is issued. This includes among other features, the region(s), peril(s), tenor and year the bond is issued. We hypothesize that this regression will capture the relationship between the bond's expected loss and spread. Further, we expect the model will assign various weights to each year where the basic risk/reward relationship has deviated due to time-dependent characteristics (e.g., market dynamics).

An OLS and stepwise regression are run with the following formulae to obtain the most parsimonious model:

$$\begin{aligned}\text{spread} = C &+ \beta_1 \cdot \text{tenor} + \beta_2 \cdot \text{peril}_{\text{wind}} + \beta_3 \cdot \text{peril}_{\text{quake}} + \beta_4 \cdot \text{peril}_{\text{all}} + \beta_5 \cdot \text{peril}_{\text{multi}} + \beta_6 \cdot \text{peril}_{\text{pandemic}} + \\ &+ \beta_7 \cdot \text{region}_{\text{us}} + \beta_8 \cdot \text{region}_{\text{jp}} + \beta_9 \cdot \text{region}_{\text{eu}} + \beta_{10} \cdot \text{region}_{\text{ww}} \\ &+ \beta_{11} \cdot \text{zone}_{\text{peak}} + \beta_{12} \cdot \text{zone}_{\text{non peak}} + \beta_{11} \cdot \text{zone}_{\text{diversifying}} \\ &+ \beta_{14} \cdot \text{expected loss} + \sum_{year=2002}^{2019} C_{year} + \sum_{year=2002}^{2019} \beta_{year} \cdot \text{expected loss}\end{aligned} \tag{4.1}$$

Equation 4.1: Regression Definition

Regressing the features in Equation (4.1), the model obtains an $AdjR^2$ = 0.8243253. See the regression results in the Modeling Appendix table **??**. The coefficients for expected_loss, tenor_days, zone_peak (USA region), perils (wind/quake/multi) are all statistically significant with a p-value of < 0.01. This is somewhat expected as the USA is considered a peak zone in terms of spread paid vs. expected loss.

When year proxy is combined with expected loss through an interaction term, the coefficients are all statistically significant. The interaction term varies, indicating different pricing levels within a given range of expected loss across years. This observation confirms our earlier finding that multiples of expected loss to spread are decaying over time.

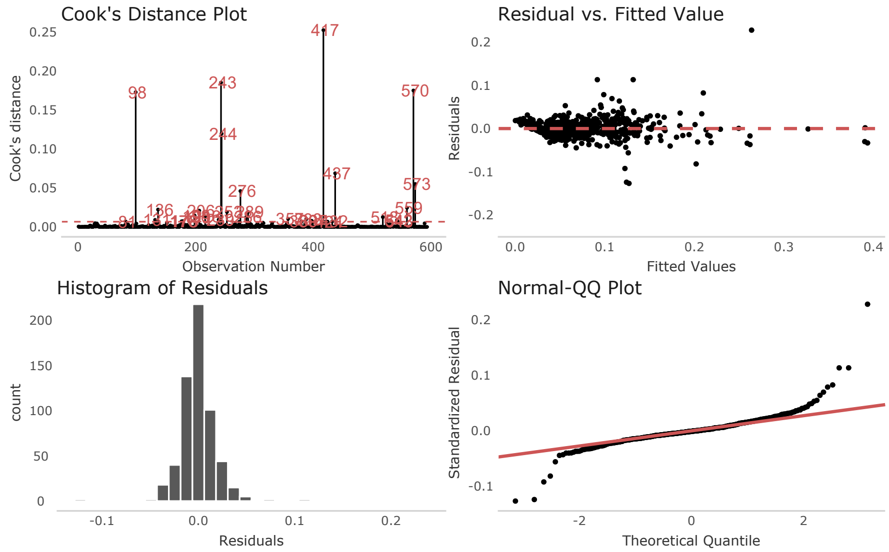


Figure 4.1: OLS regression - Diagnostics

When analyzing the above diagnostic plots of the linear regression, the distribution of the residuals looks normally distributed, but there are large tails of residuals on both sides of this distribution (see Histogram of Residuals).

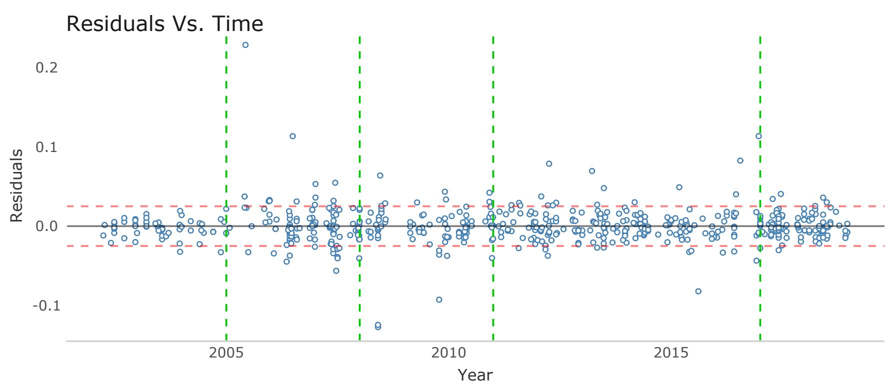


Figure 4.2: OLS regression - Residuals vs. Year

In Figure 4.2, two red bounding lines have been added at +/- 0.25 on the Residuals axis to serve as a reference for the allowable range of residual error. On the Year axis, green vertical lines have been added to indicate years of large natural catastrophic loss. Years following these events have increased levels of residuals. We presume this is related to significant price deviation from the model definition due to features and interactions not being observed within the model. Additionally, these outliers appear in the above Cook's distance plot. We investigated each of these outlying bonds and noticed that they tend to be priced in years following a natural catastrophe, which supports our presupposition.

4.3.2 Gradient Boosted Regression Tree (GBRT)

While the OLS model provides an initial baseline for our work, it requires significant iteration to determine if any interactions are at play between the various features of the dataset. This is important as we hypothesize that when regions and perils are combined, the coefficients may change. Also, as observed in the prior section (see Figure 3.5), the multiple of expected loss to spread decays over time for differing levels of risk, and this appears to be non-linear.

With this in mind, we use a gradient boosted regression tree (GBRT). This technique automatically teases out interactions between features and beneficially provides ensembles of trees created through boosting.

We employ two important techniques for this model. First, parameter tuning is used to find the optimal set of hyperparameters. Second, cross-validation is used in a sliding window based on 36 historical (chronological order) observations while predicting the subsequent 12 chronological observations. The size of the window is fixed. As it slides across the dataset (to the right), it retains the ratio of train/test while it preserves the chronological order of the observations.

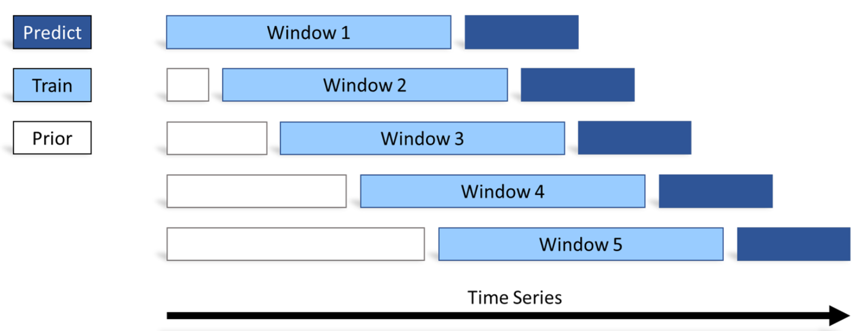


Figure 4.3: Sliding Window Time Series Cross Validation

Once the optimal set of hyperparameters have been identified, we proceed to define the values for each. We have chosen to vary the depth of the tree, the minimum number of observations per node, and the number of trees in the ensemble. A seed is set on the random number generator, so that the results can be replicated.

Variations in the performance of the GBRT from the hyperparameter tuning are assessed by analyzing the RMSE.

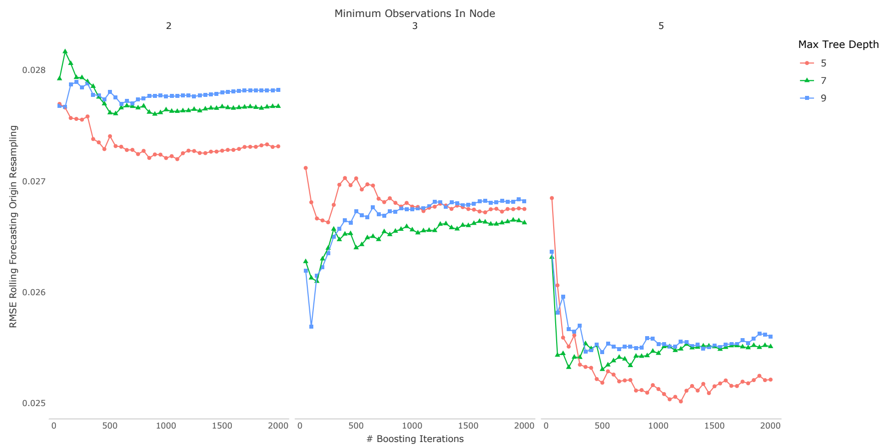


Figure 4.4: GBRT - Iterations from hyperparameter search

Figure 4.4 shows the best model fit of RMSE across all variants. The best fit results in an interaction depth of seven and a minimum of nine observations in a given node. Our final GBRT model is defined as follows:

Table 4.1: GBRT - Final model parameters

shrinkage	interaction.depth	n.minobsinnode	n.trees
0.1	7	9	50

Table 4.2: GBRT - Final statistics

RMSE	Rsquared	MAE	RMSESD	RsquaredSD	MAESD
0.0251419	0.7041503	0.0183332	0.0027576	0.0704523	0.0027475

Statistics are calculated based upon the in-sample data, and the $R^2 = 0.7042$ and the $RMSE = 0.02514$.

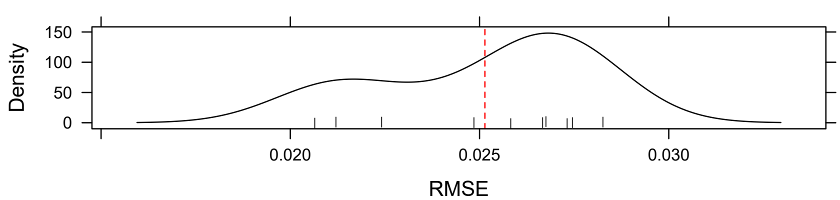


Figure 4.5: GBRT - Density plot of RMSE

Figure 4.5 shows the location of the best model selected in relation to the other training iterations. We take note of the best model and this will be used to perform a deeper evaluation of the model (see Section 5).

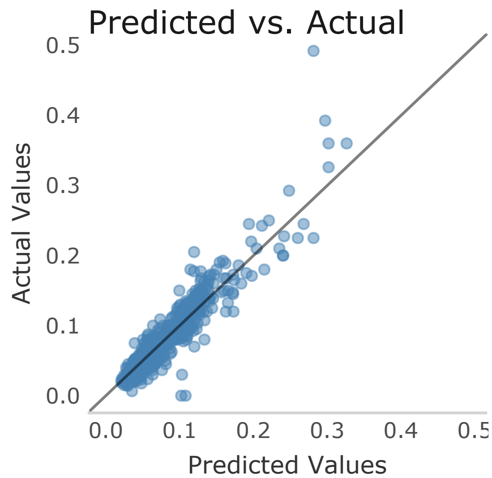


Figure 4.6: GBRT - Actuals vs. Predicted

Figure 4.6 shows that the model performs well versus the training data. However, the caveat to this outcome is the amount of time it takes to train the model using a grid search while identifying the appropriate hyperparameters.

As we incorporate more complexity into the model by introducing time-series for historical events, we have elected to use the XGBoost technique. While both models use gradient boosting, XGBoost uses regularized models to give improved performance and control of overfitting.

4.3.3 Xtreme Gradient Boosted Regression Tree (XGBRT)

We transition from the GBRT model to a new regression model (XGBRT) with an enhanced feature set. We seek to prove that the year-over-year variation experienced in the prior model can be predicted based on historical events. We believe that the variance in market behavior is underpinned by investors changing their perception of risk. This can occur when the severity and frequency of events seem to be misaligned with the model's probability and severity distribution. This may be due to model error or the specific sample drawn from the distribution. When the perception of risk changes, investors will demand to be paid a different multiple for the same amount of risk than they previously demanded.

To explore this hypothesis, we enhanced the dataset to introduce time-series features from historical events, exposure (i.e. peril and region) and other market dynamics as observed on a weekly basis. This weekly data is joined to each cat bond using a date key derived from the issue date of the bond. Additionally, the dataset has been augmented with other features to capture the traits of the cat bond per the offering circular and any specific conditions.

Exponential moving averages (see equation (4.2)) are used for insured and economic losses as well as various market signals. The exponential moving averages will place greater weight and significance on more recent observations in the historical dataset, but still allow some residual impact in future periods to events and observations that have happened up to 24 months in the past.

$$\text{Exponential Loss}_t = \text{Loss}_t \cdot \frac{\alpha}{1+\text{lag}} + \text{Exponential Loss}_{t-1} \cdot \left(1 - \frac{\alpha}{1+\text{lag}}\right) \tag{4.2}$$

$$\alpha = \text{smoothing coefficient}$$
$$\text{lag} = \text{number of periods to include in exponential moving average}$$

Next we outline our revised regression model:

$$\begin{aligned}
\text{implied} = {} & C + \beta_1 \cdot \text{tenor} + \beta_2 \cdot \text{issue_size} + \beta_3 \cdot \text{is_indemnity} + \beta_4 \cdot \text{is_reset} + \beta_5 \cdot \text{is_single_peril} \\
& + \beta_6 \cdot \text{zone}_{\text{peak}} + \beta_6 \cdot \text{zone}_{\text{non peak}} + \beta_8 \cdot \text{zone}_{\text{diversifying}} \\
& + \sum_{m=1}^{40} \beta_m \cdot \text{expected_loss}_m \cdot \text{seasonality}_{m,p} \\
& + \sum_{i=1}^{6} \sum_{l=1}^{3} \left(\text{market_index}_{i,t} \cdot \frac{\alpha}{1+\text{lag}_l} + \text{market_index}_{i,t-1} \left(1 - \frac{\alpha}{1+\text{lag}_l}\right)\right) \\
& + \sum_{l=1}^{6} \sum_{p=1}^{1197} \sum_{m=1}^{40} \beta_{m,t} \cdot \text{exposure}_m \left(\text{insured_loss}_{t,m} \cdot \frac{\alpha}{1+\text{lag}_l} + \text{insured_loss}_{m,t-1} \left(1 - \frac{\alpha}{1+\text{lag}_l}\right)\right) \\
& + \sum_{\text{l}=1}^{6} \sum_{t=1}^{1197} \sum_{\text{m}=1}^{40} \beta_{\text{m,t}} \cdot \text{exposure}_m \left(\text{economic_loss}_{m,t} \cdot \frac{\alpha}{1+\text{lag}_l} + \text{economic_loss}_{m,t-1} \left(1 - \frac{\alpha}{1+\text{lag}_l}\right)\right)
\end{aligned}$$

$$\begin{aligned}
m &= \text{metarisk index where } m = 1, .., 10 \text{ region/peril zones} \\
t &= \text{time period index where } t = 1, ..., 1197 \text{ week periods observed} \\
i &= \text{market index} \\
y &= \text{year index} \\
l &= \text{lag index} \\
p &= \text{seasonality period}
\end{aligned} \tag{4.3}$$

Equation 4.3: Regression for Time-Series

Various datasets are brought together to create the training data, where each row in the dataset comprises of one observation per week for each bond.

Table 4.3: Summary of features

Feature	Description
tenor	The duration of the cat bond in days
issue size	The size in USD $000's of the bond issue
is indemnity	Is the trigger on the cat bond of type indemnity? if so the investor carries basis risk
is reset	Is the observation a periodic reset of coupon and contract terms?
is single peril	Does the cat bond only cover a single peril?

Feature	Description
zone	What region/peril zone is covered by the cat bond i.e. USWind
expected loss	The aggregate expected rate of loss
exposure	Vector of indicator variables representing if a bond is exposed to a specific peril / region
metarisk	Vector representing list of regions/perils covering the world
market indices	Matrix representing market indices (standardized) that have been observed over time
insured losses	Matrix representing insured losses (000's) that have been observed over time by peril / region
economic losses	Matrix representing economic losses (000's) that have been observed over time by peril / region
seasonality index	Matrix representing by zone the seasonality index (0-1) of the losses, i.e. summer months have % Hurricane risks
α	Smoothing coefficient of exponential moving averages, value set to 2
lag	Vector of lags used [4,8,12,24,48,102] to coincide with the number of weeks

Using the new time series dataset, an XGBoost regression tree model is created. This is motivated due to the large increase of parameters. Also, adaptive hyperparameter tuning using futility analysis (Kuhn 2014) is deployed to find the optimal set of hyperparameters for this model rather than performing a brute force grid search within the hyperparameter space. The Bradly-Terry Resampling method (Bradley and Terry 1952) is used, running fifty iterations with ten repeats of each iteration. An eviction rate with a p-value of 0.05 or greater is used to eliminate features that are found to be insignificant. Early stopping is set to five rounds and each hyperparameter must be resampled at least 15 times to ensure careful examination of the distribution of possible values for each hyperparameter. Once a set of hyperparameters was found, we subsequently used time series cross validation and performed a reduced grid search for our final set of hyper-parameters parameters.

We assess the final model performance using both R^2 and $RMSE$. Once again, a seed is set on the random number generator, so that our results can be replicated.

Our final model was selected using XGBoost with the following hyperparameters:

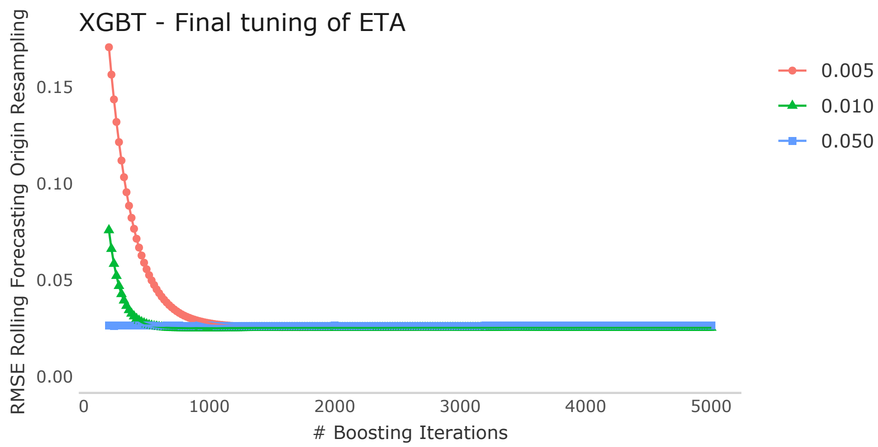
Table 4.4: XGBRT - Final model parameters

eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds
0.01	4	0	0.4	2	0.5	1060

Table 4.5: XGBRT - Final statistics

RMSE	Rsquared	MAE	RMSESD	RsquaredSD	MAESD
0.0249671	0.7815927	0.0200916	0.0035581	0.0568346	0.0031982

In our final iteration of training, we obtain our best statistics for $RMSE$ and $R2$ on the training dataset using at ETA of 0.01, this was achieved after 1060 boosting iterations.



We calculate the statistics based on the in-sample data and the $R^2 = 0.9619$ and the $RMSE = 0.009792$.

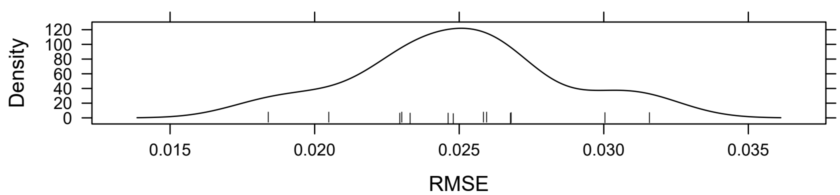


Figure 4.7: XGBRT - Density plot of RMSE

Figure 4.7 confirms our selection of the optimal model and associated hyperparameters.

When analyzing features associated with terms of economic and insured losses, we have noticed that the duration of the moving averages appear important and supports our hypothesis that the market has a residual effect from past events up to 24 months (104 weeks) and possibly longer. Also, the model has identified that the years which have experienced the most traumatic losses have been in US Wind, Asia xJapan and Australia/New Zealand. These features appear to effectively predict the spread of bonds, subject to the occurrence of catastrophic events. It is important to caveat this statement by ensuring that these predictions are limited to the price prior to a bond being impaired. Once a bond is impaired, its pricing behavior will depend solely on the size of the loss and other key characteristics specific to that bond and the associated catastrophe event.

The feature importance chart is helpful in identifying those features that should be used in a more parsimonious model. However, the artifacts and metrics do not provide understanding with regards to the feature's positive or negative contribution to the overall prediction. This will be investigated further in Section 5 using techniques as outlined by (Molnar 2020) and (Ribeiro, Singh, and Guestrin 2016b).

Plot actuals vs. predicted (in-sample dataset)

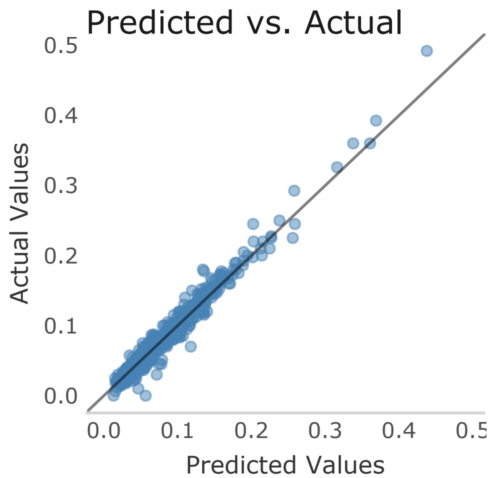


Figure 4.8: XGBRT - Actuals vs. Predicted

We observe in figure 4.7 that the model predictions are correlated positively to the actual data with some level of residual error. The model appears to perform well even at higher levels of expected loss > 20%.

4.4 Overall Results for In-Sample

Table 4.6: Overall metrics (in-sample)

Method	$RMSE$	R^2
Ordinary Least Squares	0.0221897	0.8358984
Gradient Boosted Regression Trees	0.0251419	0.7041503
XGBoost Regression Trees	0.0097918	0.9619247

Based on table 4.6 we can see all models perform better than chance and the XGBoost model is the highest performer. Even though we have used cross validation and early stopping, the results raise some concerns about how well the XGBoost model will perform against the out-of-sample data and will if generalize well to unobserved data. NOTE: The in-sample data includes bond issued prior to 2019; whereas the out-of-sample data includes bonds which were issued during 2019.

4.5 Overall Results for Out-of-Sample

Examining Figure 4.9, the XGBRT model predicts spreads with a narrower band of error except in the expected loss band of 10-12%. We need to investigate why this is happening in this narrow band of the model. This behavior is present in the other models as well, although the XGBRT seems to accentuate this error. We should reconsider reviewing our original dataset to see what bonds are within this area of the feature space.

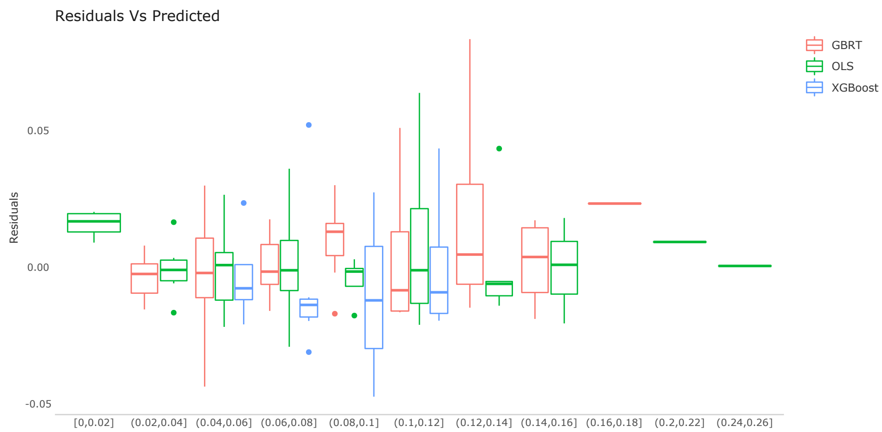


Figure 4.9: Out of sample residuals

The following table shows the metrics derived for each of the models.

Table 4.7: Overall metrics (out-of-sample)

Method	$RMSE$	R^2
Ordinary Least Squares	0.0164387	0.8812536
Gradient Boosted Regression Trees	0.018391	0.8499289
XGBoost Regression Trees	0.0252642	0.4293801

In the out-of-sample model, the XGBRT model underperforms the other models whereas in prior stages it outperformed.

4.6 Conclusion

We used three different modeling techniques: OLS, GBRT and XGBRT. We tested the models using two different datasets: 1.) "in-sample data" and 2.) "out-of-sample data". We concluded the best performing model providing improved prediction accuracy by using two metrics - R2 and RMSE. We observe that in the "out-of-sample data", the XGBRT model underperforms the other two models when compared to its previous overperformance using in-sample-data. Hence, we will review if the XGBRT model has overfitted the data previously, even though we have used cross-validation. We introduced an early stopping against an interim dataset, using a train, test and validation approach. We are encouraged that the models appear to have strong predictive power, especially when the "year" feature was removed. Our new features based on historical, time-series features shows that the model can identify the contributing drivers of our dependent variable – spread. The improved accuracy in prediction and unveiling of the XGBRT "black box" will be discussed in Section 5.

Section 5 Evaluation

When evaluating our model and its performance, or when explaining its predictive outcomes, we are faced with a challenge using "black box" modeling techniques (Ribeiro, Singh, and Guestrin 2016a) such as Gradient Boosted Regression Trees (GBRT) and XGBoost Regression Trees (XGBRT). Our solution needs to balance interpretability and accuracy. While the feature importance charts are helpful in understanding how features are used by our selected algorithm, this technique falls short of what is truly required to obtain insights into the model's predictions.

Additionally, when positioning our model and solution to business stakeholders, interpretability is ranked much more favorably over accuracy, and hence in this section of our report, we focus on evaluating the performance of our model and providing a mechanism for interpretation and understanding. This does not mean accuracy is not important, clearly it is, but not at the sacrifice of interpretability.

Based on (Ribeiro, Singh, and Guestrin 2016a) the desirable aspects of a model-agnostic explanation system are, as follows:

- Model flexibility: The interpretation method can work with any machine learning model, such as random forests and deep neural networks.
- Explanation flexibility: one is not limited to a certain form of explanation. In some cases, it might be useful to have a linear formula, in other cases a graphic with feature importances.
- Representation flexibility: The explanation system should be able to use a different feature representation as the model.

Therefore, we seek to satisfy our need to interpret each model agnostically and inform our stakeholders by using SHapley Additive exPlanations (SHAP) (Lundberg and Lee 2017), feature effects and feature interations.

5.1 Feature importance

For this regression task we choose to measure the loss in performance with the mean absolute error ("mae"). The measure removes each feature in turn and measures how much the performance drops.

In Figure 5.1, the GBRT assigns the highest feature importance to expected_loss which aligns with the results from the OLS regression. The tenor (duration_days) of the contract plays an important role as a longer contract term exposes the bondholder (i.e. investor) to a greater probability of experiencing some loss. The third most important feature, region_us, indicates that the spread is driven by cat bonds exposed to catastrophe events in the U.S. The U.S. is considered a peak zone comprising a large portion of the premium generated globally, followed by Europe and then Japan (considered non-peak zones). Within peak zones, quakes, multi perils, all perils and wind account for the majority of risk. We surmise that these years have been identified as there was relatively low catastrophe event activity during this time. These year variables are used to counteract the influence of expected loss in the later periods, but they rank low versus the other features discussed.

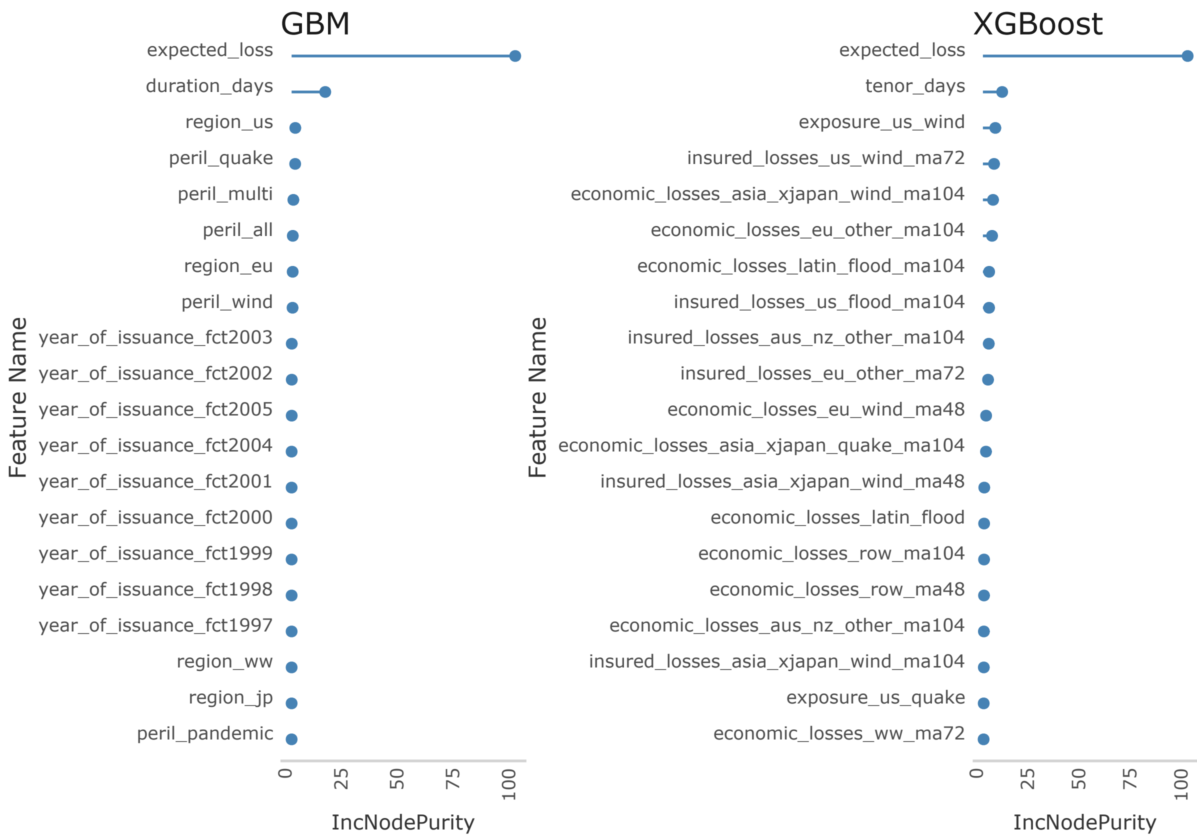


Figure 5.1: Feature Importance

When examining the figure for XGBRT there are now large differences as a result of changing the regression to exclude specific year variables and include the extended time series features. Expected_loss remains our primary feature, which is to be expected. Interestingly, the U.S. Wind feature (exposure_us_wind) appears to be important in predicting the price of those bonds that include this risk. Single peril bonds tend to price more accurately than those bonds with multiple perils, as these contracts are favored by investors due to their specificity.

When analyzing features associated with terms of economic and insured losses, we have noticed that the duration of the moving averages appear important and supports our hypothesis that the market has a residual effect from past events up to 24 months (104 weeks) and possibly longer. Also, the model has identified that the years which have experienced the most traumatic losses have been in U.S. Wind, Asia xJapan and Australia/New Zealand. These features appear to effectively predict the spread of bonds, subject to the occurrence of catastrophic events. It is important to caveat this statement by ensuring that these predictions are limited to the price prior to a bond being impaired. Once a bond is impaired, its pricing behavior will depend solely on the size of the loss and other key characteristics specific to that bond and the associated catastrophe event.

The feature importance chart is helpful in identifying those features that should be used in a more parsimonious model. However, the artifacts and metrics do not provide understanding with regards to the feature's positive or negative contribution to the overall prediction. This will be investigated further using techniques as outlined by (Molnar 2020) and (Ribeiro, Singh, and Guestrin 2016b).

5.2 Accumulated Local Effects

(Molnar 2020) stated that "Besides knowing which features were important, we are interested in how the features influence the predicted outcome".

The following plot shows the accumulated local effects (ALE) for the feature "expected_loss". ALE shows how the prediction changes locally, when the feature is varied. The x-axis shows the distribution of the "expected_loss" feature. The axis also shows us a density mark that allows to to determine how relevant a region is during our interpretation. When there are areas of the chart with few observations we should carefully assess any interpretations made.

The Figure 5.2 demonstrates that as the expected loss increases the relationship to spread is near linear and then the multiple appears to decline after approxmately 8%. After 10%, the number of data points is reduced and this is demonstrated by the almost straight line fit. In the second figure, we observe that as the tenor (length) of a contract increases the contribution to expected loss initially rapidly declines. This decline occurs in the first 12 months, subsequently after this point the impact is still negative but minor. We believe this is happening because short term contracts are typically issued post natural catastrophes to provide short term cover to counterparties in distress and thus this may explain why the multiple of contribution to expected loss is so high. We also again need to be aware of the low number of observations in this part of the distribution of the observations.

In Figure 5.3 we examine several of the features dervied from insured and economic losses. We can see that as the log10 value of the 104 week moving average increases for insured losses in Asia xJapan for earthquake that there is a nominal reduction in the impact the expected loss. Then we examine the second figure for economic losses in the same region for the same peril, we observe the opposite effect.

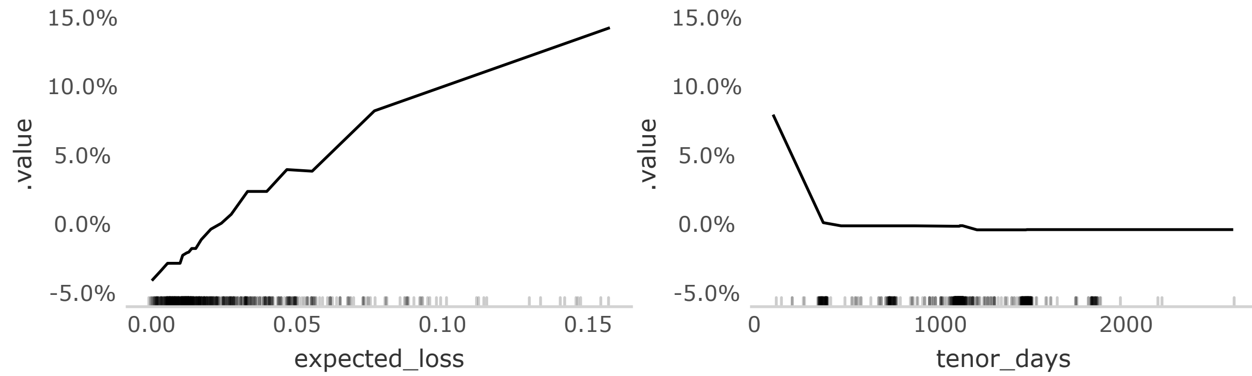


Figure 5.2: ALE charts - Expected Loss and Tenor (days)

We surmise that this occurs because these two features would be somewhat colinear. We would expect when there are large economic losses then there would also be insured losses. Therefore when there is a large quake event that causes disruption in the market, this causes the expected spread for a unit of Japan quake risk to increase more than the effect on the insured feature. Overall the impact will result in a positive increase spread.

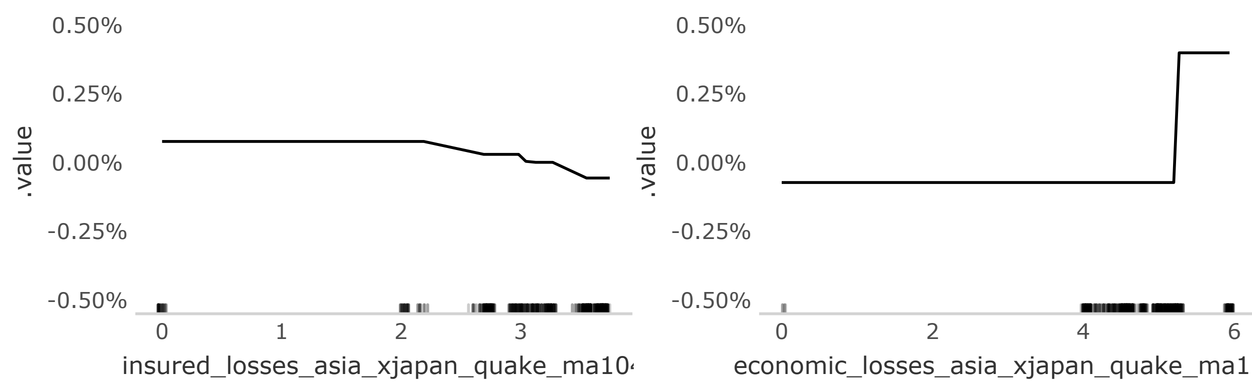


Figure 5.3: ALE charts - Japan Quake Losses

Overall these charts provide useful insights into the relationship between each feature and the dependant variable, which is not inherently apparent from the model natively. These charts are also comparable across each of our models, allowing us to compare them in a meaningful approach.

5.3 Measure interactions

(Molnar 2020) stated that “we can also measure how strongly features interact with each other. The interaction measure regards how much of the variance of f(x) is explained by the interaction. The measure is between 0 (no interaction) and 1 (= 100% of variance of f(x) due to interactions)”. So, for each feature, we measure how much it interacts with each of the other features and rank each feature. The Figure below 5.4 illustrates that the interation strength of US wind losses explains ~6% of the variance of the predicted spread. This then reduces to zero for many of the variables. This makes a lot of sense as natural catastrophe events are inherently independant and therefore a US hurricane bond would have little impact on the pricing of a European wind / quake bond in most scenarios other than a incredibly large loss causing a shock in the market.

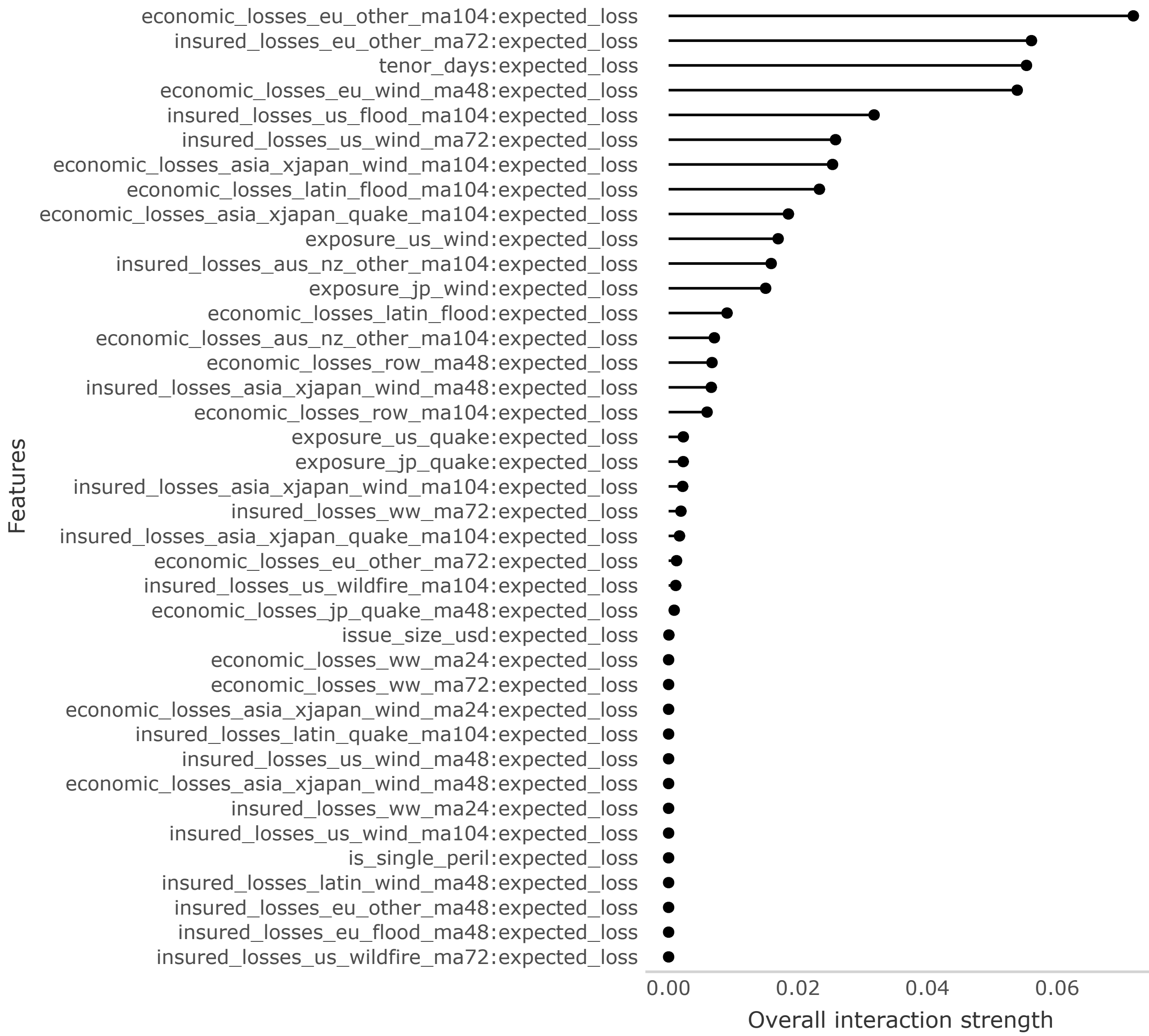


Figure 5.4: Feature Interactions

5.4 SHapley Additive exPlanations (SHAP)

SHAP was introduced by (Lundberg and Lee 2017) in "A Unified Approach to Interpreting Model Predictions NIPS paper". They outline that "SHAP is a game theory approach to explain the output of any machine learning model. SHAP takes each prediction and determines the feature importance for that local prediction over the ensemble of trees within the XGBoost model. SHAP can be applied to a range of black box machine learning techniques, in a similiar approach to that we outlined herein. An alternative for explaining individual predictions is a method from coalitional game theory named Shapley value. Assume that for one data point, the feature values play a game together, in which they get the prediction as a payout. The Shapley value tells us how to fairly distribute the payout among the feature values". To calculate the Shapley values we use the R library *ShapForXGBoost* developed by (Liu 2020).

Initially we calculate the shap values for the final model using the in-sample training data. Then we determine the breakout of the contribution of each feature for each observation in the dataset. The result comprises of an intercept term and then the contribution of each feature to the final predicted value (yhat). The contribution may be positive or negative, which adds a level of interpretability up and beyond that of the feature importance calculation.

Next we examine two particular bonds and compare their SHAP contributions.

5.4.1 Example 1 - Laetere Re Ltd. Series 2016-1 Class A

This cat bond incepted in June 2016, and expires on May 31st, 2017. It was issued with $30m principal and a annual yield coupon of 2.28% above the risk free rate. The bond covered risks in US hurricane and US earthquake. It has an indemnity trigger and a tenor of 365 days.

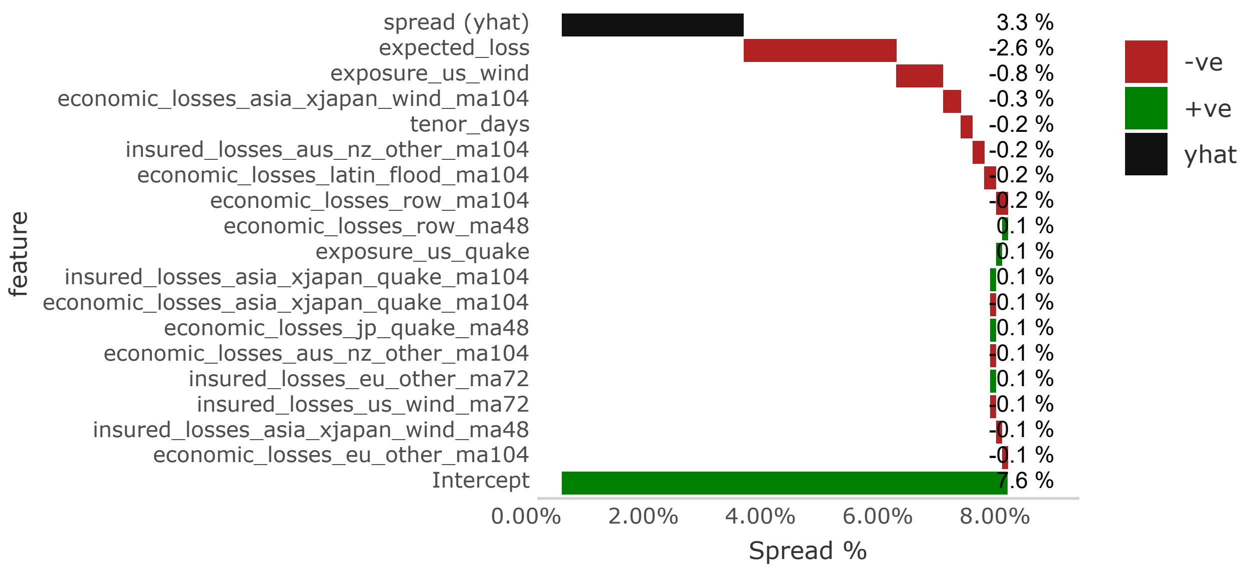


Figure 5.5: SHAP Plot - Laetere Re Ltd.

The Figure 5.5 gives us a detailed breakdown of the features and their contribution to the predicted spread of 3.3% vs. actual spread of 2.28%. We can see that the intercept of the model is 7.6% and a variety of features make nominal differences to the predicted spread. The largest drivers of the predicted spread are expected loss and exposure to us wind.

5.4.2 Example 2 - Buffalo Re Ltd Series 2017-1 Class A

This cat bond incepted in April 2017, and expires on March 31st, 2010. It was issued with $150m principal and a annual yield coupon of 3.48% above the risk free rate. The bond covered risks in US hurricane and US earthquake. It has an indemnity trigger and a tenor of 1095 days.

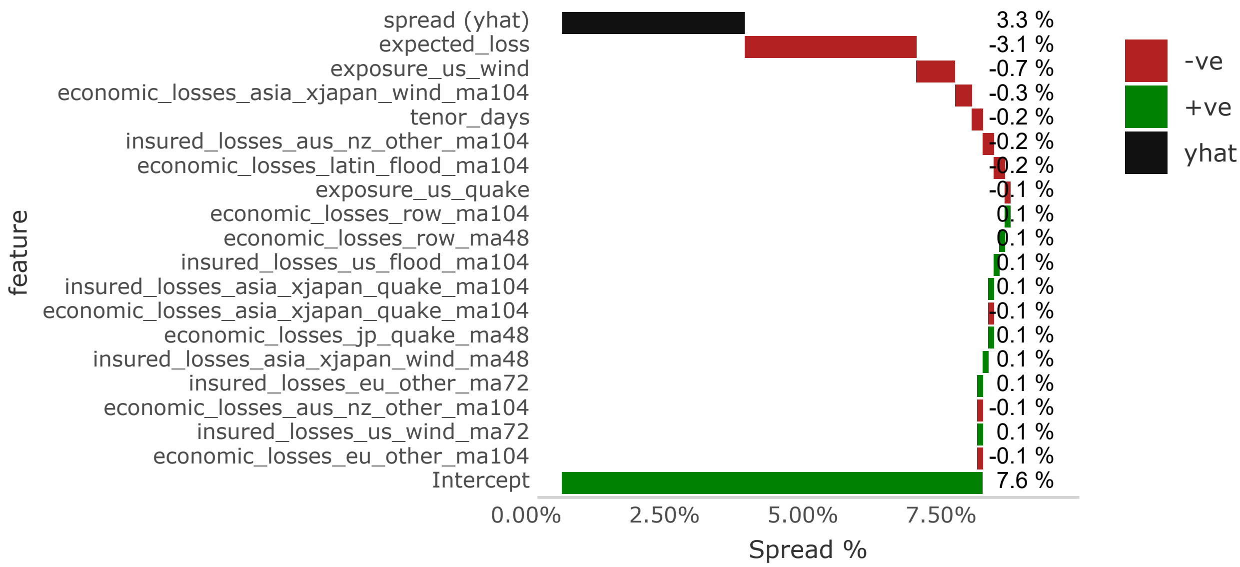


Figure 5.6: SHAP Plot - Buffalo Re Ltd.

The Figure 5.6 gives us a detailed breakdown of the features and their contribution to the predicted spread of 3.3% vs. actual spread of 3.48%. We can see that the intercept of the model again is 7.6% and a variety of features make nominal differences to the predicted spread. The largest drivers of the predicted spread are expected loss, exposure to us wind and the tenor of the contract. We also see US quake is a relevant feature of the model.

In both cases these models have a low coupon and hence why the model adjusts the prediction down from the intercept term of 7.6%

Finally we plot the distribution of feature contributions to the model output. In this example, we plot the SHAP values of each of our features for every bond spread observation. Each dot is an observation (cat bond issue/reset or mark-to-market pricing event) on the chart. The points in purple are influencing the final outcom and those in yellow have less influence. We can see in in Figure 5.7 how the each of the features contributes to the overall model output and where the observations are clustered on the distribution of feature values.

5.5 Conclusions

We have used a variety of techniques include Shapley additive explanations to all us to interpret the results from our black box XGBoost model. This provides valuable insights both for the modeller and stakeholders alike when using these techniques. We will investigating how to improve our out-of-smaple results for our XGBoost model. We will be incorporating this model and the evaluation features discussed above into our UX as a means of adding further visibility and interpretability into the behaviour and predictions made by our model. The modeling conducted uses a limited dataset; however, it has already proven to be strongly predictive of the spread. As data are not readily available this continues to be the largest limitation for academic research in this area.

Figure 5.7: SHAP Summary

Section 6
Conclusion

In this work, we create a predictive model by disaggregating components of a cat bond's spread – namely expected loss and risk premium. Expected loss of a catastrophe event explains a significant portion of a cat bond's spread. Risk premium is further divided into features of either the bond characteristics or market dynamics for which the bond has exposure. These additional features (e.g., tenor of contract, regions and perils exposed and issue size) have the ability to further explain the variation in spread. To explore the impact of market dynamics over time on cat bonds, corporate bond spreads and economic loss from catastrophe events are used as proxies.

As more capital enters the market, the multiples in the upper expected loss bands are decaying whereas in the lower expected loss bands the multiples appear stagnant. Counterintuitively, this means that there is greater investor reward per unit of risk in the lower expected loss bands. The model has demonstrated that it has predictive power to explain a portion of the spread associated with historical economic losses occurring due to catastrophe events.

In future work, we recommend that additional time be invested in data collection. Specifically, bond pricing data collected from cat bond brokers and reinsurance product pricing collected from the reinsurance brokers may provide better information granularity for the model to consume. Also, more time can be devoted to disaggregating expected loss with greater granularity across perils and regions.

Our resulting model provides accretive value to the cat bond industry. The model provides greater transparency for the investor to understand the underlying features of the bond and how these features contribute to the bond's assigned spread value. With this information, they can determine if the aggregate risk has been fairly priced. For the bond issuer, the model identifies proposed characteristics of the bond and their negative or positive contribution to spread. This information will allow issuers to structure bonds with characteristics that have broader investor appeal; and therefore, more available capital to underwrite the proposed bond issue. All-in-all, the model provides greater knowledge for cat bond participants to capture pricing advantage.

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Section A
Business Understanding Appendix

A.1 Structure of the Industry

A.1.1 Insurance Companies

Insurance companies are the direct-to-consumer channel for providing coverage from potential losses. Normally, an insurance company writes policies for loss events that happen frequently with relatively small losses (e.g. home fires, auto accidents, etc.). This creates a more efficient market through the *law of large numbers*, whereby the actual loss converges on the expected loss. Conversely, catastrophe insurance covers losses from events which occur infrequently, but can have high severity/loss. This creates two potential problems for an insurance company: 1.) the actual loss compared to the expected loss can be significantly different and 2.) widespread loss from a catastrophe event could devastate a single insurance company's balance sheet. As a result, insurance companies have sought to diversify these risks from their balance sheet through the reinsurance and insurance-linked securities markets.

A.1.2 Reinsurance Companies

(Alvarez 2017) states that, "A reinsurance company insures insurance companies." Meaning, a reinsurance company sells contracts to an insurance company to reduce capital requirements and risk from the insurance company's balance sheet. The contract is specifically related to property catastrophe from infrequent and high-severity events. These contracts are normally held on the reinsurer's balance sheet rather than distributed to the broader market, thus making these contracts illiquid. The reinsurance company manages the risks associated with the contract by diversifying the portfolio or receding risks to other reinsurance companies or insurance-linked securities participants. Reinsurers supplement their profits by investing premiums into the financial markets (Banks 2013).

A.1.3 Insurance-Linked Securities

Insurance-Linked Securities (ILS) are "…tradable, high-yielding debt instruments that are used by companies (usually insurance and reinsurance companies) to transfer insurance risk to the capital markets" (Alvarez 2017). ILS raise substantially more capital than the reinsurance markets (Lakshmanan 2013).

Cat bonds, which makeup a significant portion of the ILS market, are high-yield debt instruments that provide protection to the insurer's balance sheet and provide them with the ability to settle claims with their policyholders for covered losses incurred from predefined catastrophes (natural or manmade). Cat bonds are collateral account with highly-secured investments (e.g. government treasuries). The first cat bond was issued for $85M in 1994 by Hannover Re and in recent years, the market has grown to $40B of outstanding issuance (See Figure A.1) (Artemis.bm 2020b). A growing secondary market has matured allowing cat bonds to be sold anytime between issuance and maturity. This liquidity feature is an attractive advantage of cat bonds over their reinsurance counterparts.

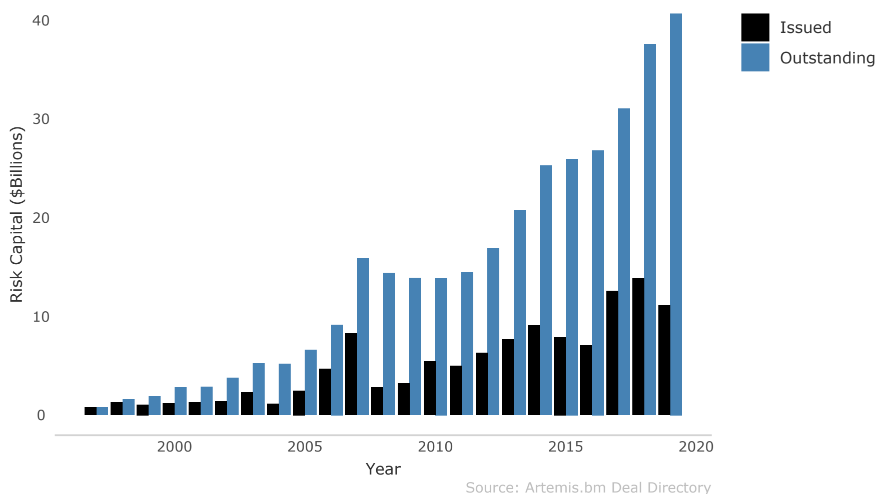

Figure A.1: Size of the cat bond market 1997 - 2019

The importance of the cat bond market was proven in 2017 when three of the five costliest hurricanes in U.S. history caused $92B of insured losses and $217B in economic losses.

A.2 Market Dynamics

The cat bond market, like other financial markets, is subject to supply and demand dynamics. (Banks 2013) demonstrates these dynamics in the following sequence.

Neutral Market

In a market without financial or catastrophe event shocks, the investor risk capacity Q1 (Figure A.2) will be in equilibrium with the demand for insurance coverage, creating a market price of P1.

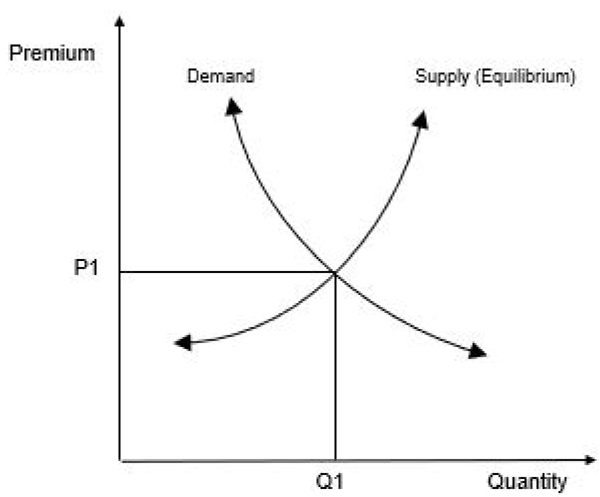

Figure A.2: Neutral market demand curve

Hard Market (Supply Decrease)

When a catastrophe event takes place, it creates two shocks in the cat bond market. One shock impacts the risk capacity investors are willing to supply to the market. Due to the increased perception of risk as a result of a catastrophe, investors remove money from the cat bond market, thereby decreasing risk capacity from Q1 to Q2 (Figure A.3). Due to less supply of risk capacity on the same demand curve, the price increases from P1 to P2.

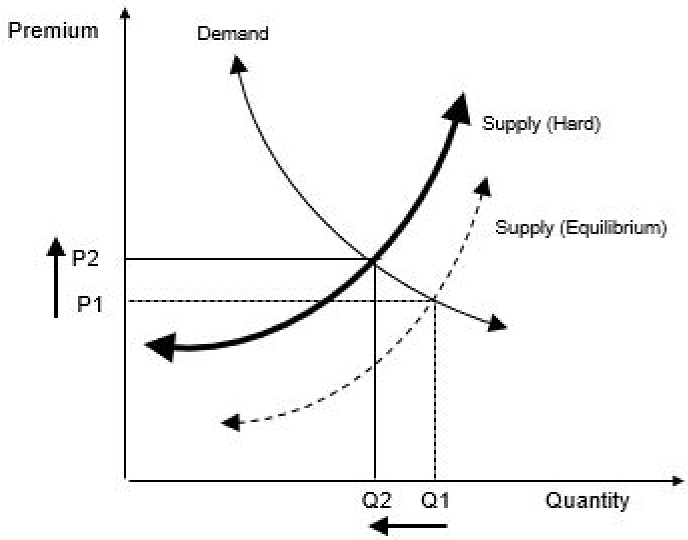

Figure A.3: Hard market due to reduced risk capacity

Hard Market (Demand Increase)

A second shock that takes place after a catastrophe event is an increase in consumer demand for insurance coverage. This moves the demand curve to the right from "ex ante" to "ex post" (Figure A.4). To satisfy this increased demand along the same supply curve (moving risk capacity from Q2 to Q1), the price of coverage increases from P2 to P3.

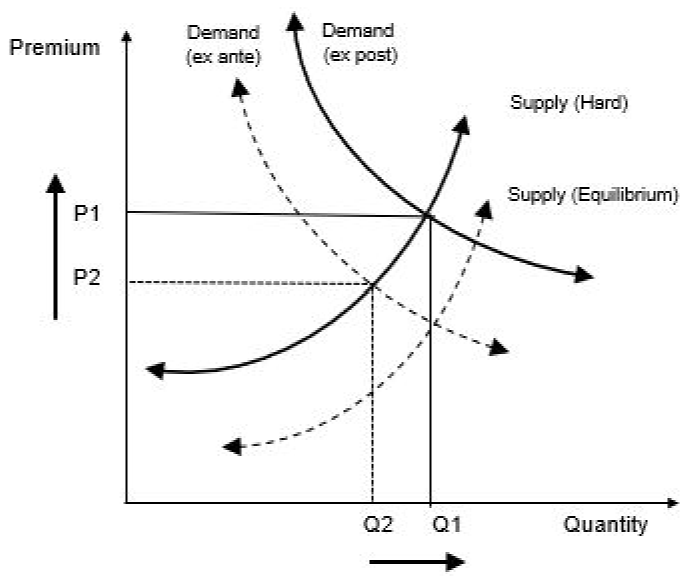

Figure A.4: Hard market due to increased demand

Soft Market

Conversely, when a neutral market (Figure A.2) experiences a prolonged absence of catastrophe events, investors' perception of risk is decreased and an oversupply of risk capacity enters the cat bond market. This shifts the supply curve to the right (moving from Q1 to Q2) on the same demand curve, which reduces the price of coverage from P1 to P2 (Figure A.5).

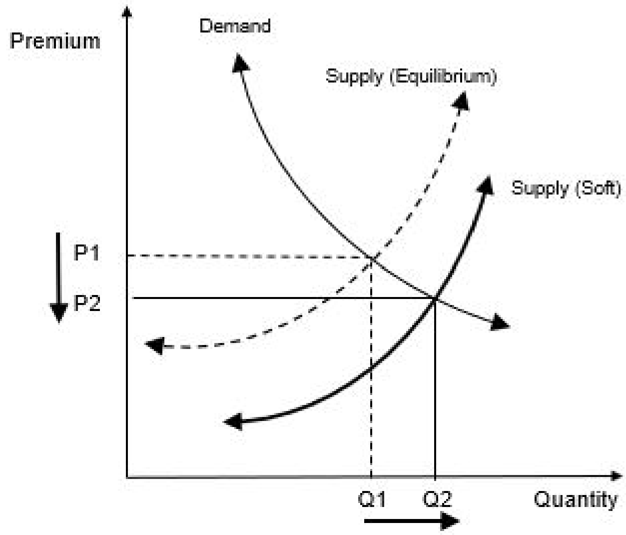

Figure A.5: Soft market due to increased risk capacity

A.3 Catastrophe Bonds as an Investment

A.3.1 Catastrophe Bonds Uncorrelated with the Financial Markets

Cat bond yields are uncorrelated with the broader stock market. Figure A.6 analyzes this relationship by comparing the log of prices for cat bonds and S&P (Patel 2015). Following are a few highlights:

- During the fallout from the bankruptcy of WorldCom in 2002, the financial markets declined; yet the cat bond market was not impacted.
- In the aftermath of Hurricane Katrina (August 2005) resulting in an economic loss of $118B, the cat bond market declined, and the financial markets were unscathed.
- In 2017, the California fires and the Indonesia earthquake caused a significant pullback in the cat bond market, and during this same period, the financial markets rallied.

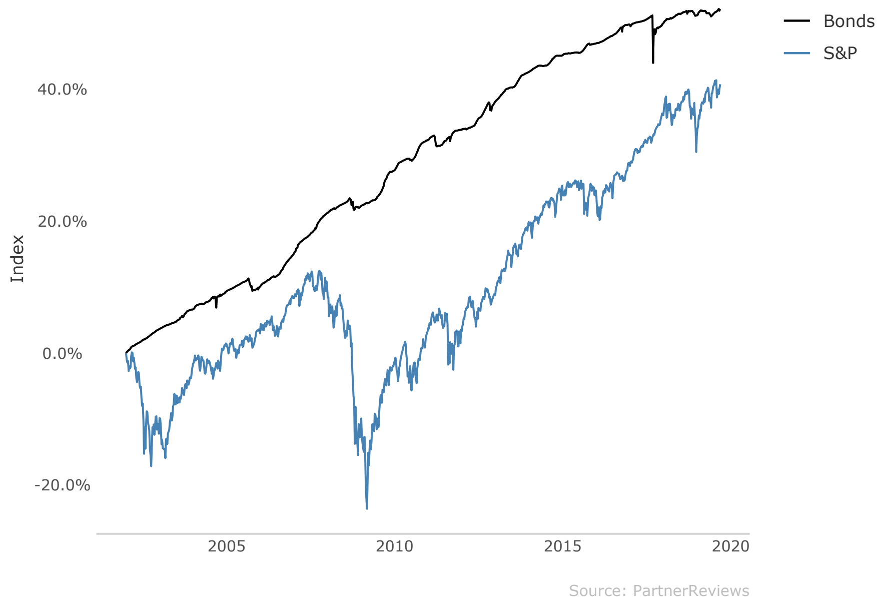

Figure A.6: Cat Bond Index vs. S&P Index

There are times when a correlation between the broader financial and cat bond markets can be observed. We hypothesize that this correlation is due to the lack of liquidity. For example, a financial bear market may increase the demand for liquidity, thus impacting the cat bond market. In such cases, an investor may liquidate a portion of their cat bond portfolio in order to meet cash demands of other distressed assets. This was particularly evident in 2008 during the Great Recession, when Lehman Brothers filed for bankruptcy and created a domino effect, whereby financial institutions began calling loans and other securities. Due to the strength of cat bonds during that time, distressed investors began liquidating their cat bond investments at substantial discounts. This drawdown in risk capacity increased cat bond yields.

A.3.2 Catastrophe Bonds versus Corporate Bonds

There are three main investment advantages that cat bonds have over their counterparts in the corporate bond market: 1.) less interest rate sensitivity 2.) higher average returns and 3.) low correlation to the broader financial markets (near-zero-beta).

Cat bonds are floating-rate securities, which means their index resets periodically to match the prevailing short-term interest rates; therefore, they have less sensitivity to changes in interest rates over the term of the bond. Conversely, corporate bonds are mostly fixed-rate securities, whereby the coupon yield is fixed at issuance (Patel 2015).

Historically, the total return of cat bonds outperformed similar rated corporate bonds. In Figure A.7, B-rated cat bonds outperformed their corporate bond counterpart from 2015 - 2019.

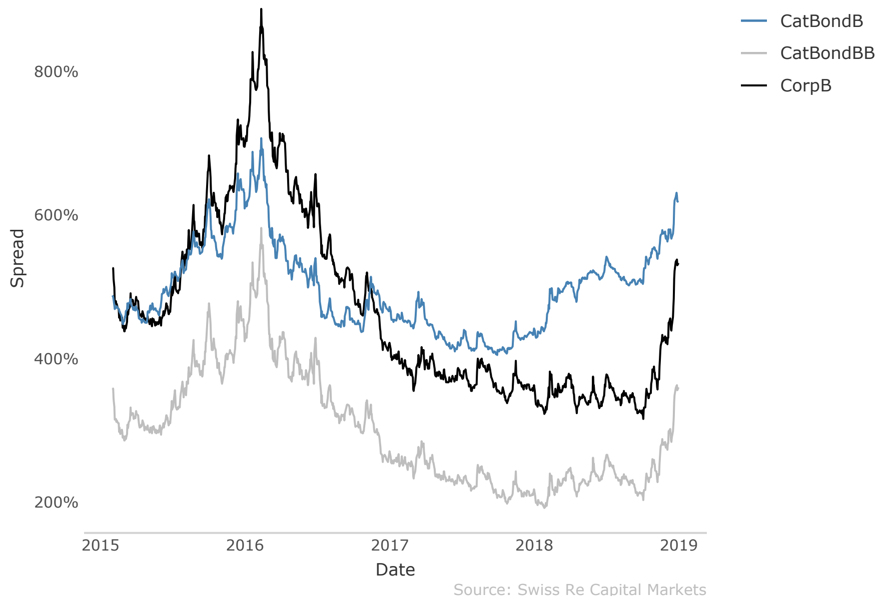

Figure A.7: Comparative adjusted catastrophe bond and high-yield corporate bond spreads

A.3.3 Performance of Catastrophe Bonds versus the S&P

Referring to the previous Figure A.6, a zero baseline is established for both markets at the beginning of 2002. (We use this date as the Swiss Re cat bond index was incepted at this time.) Over the next 17 years, cat bonds have a higher total return than the S&P.

Section B
Modeling Appendix

Table B.1: OLS regression results with robust standard errors

	Dependent variable:
	implied
tenor_days	-0.00001^{***} (0.00000)
peril_wind	-0.019^{***} (0.004)
peril_quake	-0.027^{***} (0.003)
peril_multi	-0.013^{**} (0.006)
zone_peak	0.024^{***} (0.003)
zone_diversifying	0.009^{*} (0.005)
expected_loss	4.434^{***} (0.420)
year_of_issuance_fct2003	0.017^{***} (0.006)
year_of_issuance_fct2005	0.025^{***} (0.007)
year_of_issuance_fct2006	0.029^{***} (0.006)
year_of_issuance_fct2007	0.015^{***} (0.006)
year_of_issuance_fct2008	0.029^{***} (0.010)
year_of_issuance_fct2009	0.064^{***} (0.009)
year_of_issuance_fct2010	0.035^{***} (0.007)
year_of_issuance_fct2011	0.033^{***} (0.006)
year_of_issuance_fct2012	0.040^{***} (0.008)
year_of_issuance_fct2013	0.014^{**} (0.006)
year_of_issuance_fct2014	0.014^{***} (0.005)
year_of_issuance_fct2015	0.012^{**} (0.006)
expected_loss:year_of_issuance_fct2003	-1.873^{***} (0.428)
expected_loss:year_of_issuance_fct2004	-2.137^{***} (0.423)
expected_loss:year_of_issuance_fct2005	-2.408^{***} (0.485)
expected_loss:year_of_issuance_fct2006	-2.069^{***} (0.429)
expected_loss:year_of_issuance_fct2007	-2.660^{***} (0.437)
expected_loss:year_of_issuance_fct2008	-2.822^{***} (0.704)
expected_loss:year_of_issuance_fct2009	-3.078^{***} (0.460)
expected_loss:year_of_issuance_fct2010	-3.226^{***} (0.549)
expected_loss:year_of_issuance_fct2011	-2.685^{***} (0.460)
expected_loss:year_of_issuance_fct2012	-2.609^{***} (0.521)
expected_loss:year_of_issuance_fct2013	-3.025^{***} (0.470)
expected_loss:year_of_issuance_fct2014	-3.268^{***} (0.427)
expected_loss:year_of_issuance_fct2015	-3.169^{***} (0.428)
expected_loss:year_of_issuance_fct2016	-2.836^{***} (0.520)
expected_loss:year_of_issuance_fct2017	-3.328^{***} (0.440)
expected_loss:year_of_issuance_fct2018	-3.182^{***} (0.432)
Constant	0.024^{***} (0.007)
Observations	593
R^2	0.836
Adjusted R^2	0.824
Residual Std. Error	0.023 (df = 553)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Section C
Data Appendix

C.1 Data Dictionary

Name of the Variable	Rationale	Data Type	Reference
Trigger Type (indemnity, index)	reflects ….	categorical / nominal	(Zhao, Chuang, and Yu 2018), (Jovaisa and Petkova 2010)
Total cat-bonds issued in the market	reflects demand correlated with cat bond investments	numeric / continuous (Patel 2012)	
Spread at the issue	reflects the risk of the cat bond	numeric / continuous	(Laura Gomez Cordano, 2014)
Expected loss	factor explicitly associated with risk of the bond	numeric / continuous (Laura Gomez Cordano, 2014)	
Credit rating	reflects standardized definition of risk of default	categorical / ordinal	(Laura Gomez Cordano, 2014)
Time to maturity	reflects the time to maturity each bond	numeric / discrete	(Laura Gomez Cordano, 2014)
BB-bonds index	reflects standardized definition of risk	numeric / continuous	(Laura Gomez Cordano, 2014)
Interest rates	reflects direct impact on coupons of floating rate securities	numeric / continuous	(Laura Gomez Cordano, 2014)
Swiss Re Cat Bond Total Return Index (SCATTRR) reflects performance of catbond price in secondary markets	numeric / continuous	(Laura Gomez Cordano, 2014)	

C.2 Datasets

The following data sets were sourced for use in our project:

- Artemis Insurance Linked Securities dataset (Artemis.bm 2020a)
- Stochastic risk modeling data for each catastrophe bond

- Seasonal earnings curve(s) for each catastrophe bond
- FINRA Bond TRACE Data ("Trade Reporting and Compliance Engine (TRACE) FINRA.org" 2020)
- Swiss Re cat bond indices covering global, BBB+ rated and U.S. Wind ("Swiss Re Cat Bond Indices Methodology Swiss Re" 2020)
- Swiss Re cat bond weekly mark-to-market prices ("Swiss Re Cat Bond Indices Methodology Swiss Re" 2020)
- Guy Carpenter global, U.S. and regional property catastrophe rate-on-line index ("Home Guy Carpenter" 2020)
- ICE BofAML US High Yield BB Option-Adjusted Spread (ICE Benchmark Administration Limited (IBA) 1996)
- ICE BofAML US High Yield B Option-Adjusted Spread (ICE Benchmark Administration Limited (IBA) 1996)
- 3-Month London Interbank Offered Rate (LIBOR)("USD LIBOR - Current Rate, Historical Data, Dynamic Chart. IBORate" 2020)
- CBOE Volatility Index (VIX) ("Cboe Index Home" 2020)
- Lane Financial Long Term Index Of Catastrophe Reinsurance Prices ("Lane Financial - Home" 2020)
- Lane Financial Mark to Market as % change to Par of market ("Lane Financial - Home" 2020)
- Historical record of catastrophic events
- AON Benfield Insurance Linked Securities dataset ("Risk - Reinsurance - Retirement - Health - Data & Analytics Aon" 2020)
- S&P Index ("S&P 500 (^GSPC) Charts, Data & News - Yahoo Finance" 2020)

C.2.1 Artemis Insurance Linked Securities dataset

Artemis via its web site provides an insurance linked securities data set that details all natural catastrophe bonds and resets issued from 1998 to 2019, including details such as issuance, rating, tenor, inception & expiry, issue price, coupon and any losses/defaults.

Source: https://www.artemis.bm/deal-directory/

C.2.2 Stochastic risk modeling data for each catastrophe bond

The stochastic risk modeling data is extracted from running a catastrophic risk model over the contract terms of the cat bond. These models encapsulate assuptions about the following components: region, peril, line of business, event severity, frequency, vunerability and hazard. The output of each analysis is a data set that illustrates how a cat bond would respond to a simulated set of natural catastrophes. These results comprise of the modeled occurrence expected loss, aggregate expected loss, distribution of losses over a simulated calendar year. Each monte-carlo simulation is run producing 10,000 simulated outcomes.

Source: AIR Worldwide

C.2.3 Seasonal earnings curve(s) for each catastrophe bond

The seasonal earning curve captures the patterns of when a cat bond is subject to increased levels of risk by region and peril. These patterns coincide with the seasonal component describing the natural cycles in nature for Hurricane, Tornado, Typhoon, Winterstorm and Flood risk.

Source: AIR Worldwide

C.2.4 FINRA 144A TRACE Data

FINRA provides historical transaction-level data to academic institutions. Our dataset focuses on the listed 144A listed securities for catastrophe bonds.

C.2.5 Swiss Re cat bond performance indices covering global, BBB+ rated and U.S. Wind

We have used the following three indices

- Global Cat Bond Performance Index Total Return
- US Wind Cat Bond Total Return Index
- BB Rated Cat Bond Total Return Index

These indices are produced by Swiss Re published by S&P and track the aggregate performance of cat bonds offered under Rule 144A. The index captures all rated and unrated cat bonds and they provide coupon, price and total return variants of each index. The indices are published weekly and commence in 2002.

- Swiss Re Global Cat Bond Performance Index Total Return

Ticker: SRGLTRR Index

This index tracks the aggregate performance of all catastrophe bonds issued Rule 144A. The index captures bonds denominated in any currency, all rated and unrated cat bonds, outstanding perils, and triggers. The Global index is not exposed to currency risk from non-USD denominated cat bonds. Currency risk associated with non-USD denominated cat bonds is hedged at the inception of the bond.

- Swiss Re BB Rated Cat Bond Total Return Index

Ticker: SRBBTRR Index

This index tracks the aggregate performance of USD denominated, BB rated catastrophe bonds rated by Moody's (Ba1, Ba2, Ba3) and S&P (BB, BB+ or BB-). The bonds in this index tend to have lower modeled expected losses than the other indices.

- Swiss Re US Wind Cat Bond Total Return Index

Ticker: SRUSWTRR Index

This index tracks the aggregate performance of USD denominated cat bonds exposed exclusively to US Atlantic hurricane. The USD Wind Index does not include bonds exposed to hurricanes affecting countries other than the US.

Source: Swiss Re / Bloomberg

C.2.6 Swiss Re cat bond weekly secondary market price indications

Each week Swiss Re (and other brokers) publish secondary market price indications. These prices are indicative only and may not represent actual bids or offers on any of the underlying cat bonds by Swiss Re or any of its affiliates. These indicative prices may also vary significantly from actual trade prices and from indicative prices provided by other counterparties.

Source: Swiss Re

C.2.7 Guy Carpenter global, U.S. and regional property catastrophe rate-on-line index

This is the proprietary index of global property catastrophe reinsurance Rate-on-Line (ROL) movements on brokered excess of loss placements that has been maintained by Guy Carpenter since 1990. The index covers all major global catastrophe reinsurance markets. It is updated following January 1st renewals each year by calculating the change in ROL year-on-year across the same renewal base.

https://www.gccapitalideas.com/2019/02/12/chart-global-property-catastrophe-rol-index-5

C.2.8 ICE BofAML US High Yield BB Option-Adjusted Spread

Ticker: BAMLH0A1HYBB

This data represents the Option-Adjusted Spread (OAS) of the ICE BofAML US Corporate BB Index. This is a subset of the ICE BofAML US High Yield Master II Index tracking the performance of US dollar denominated below investment grade rated corporate debt publicly issued in the US domestic market. This subset includes all securities with a given investment grade rating BB. The ICE BofAML OASs are the calculated spreads between a computed OAS index of all bonds in a given rating category and a spot Treasury curve. An OAS index is constructed using each constituent bond, OAS, weighted by market capitalization. When the last calendar day of the month takes place on the weekend, weekend observations will occur as a result of month ending accrued interest adjustments.

Source: https://fred.stlouisfed.org/series/BAMLH0A1HYBB/

C.2.9 ICE BofAML US High Yield B Option-Adjusted Spread

Ticker: BAMLH0A2HYB

This data represents the Option-Adjusted Spread (OAS) of the ICE BofAML US Corporate B Index, a subset of the ICE BofAML US High Yield Master II Index tracking the performance of US dollar denominated below investment grade rated corporate debt publicly issued in the US domestic market. This subset includes all securities with a given investment grade rating B. The ICE BofAML OASs are the calculated spreads between a computed OAS index of all bonds in a given rating category and a spot Treasury curve. An OAS index is constructed using each constituent bond, OAS, weighted by market capitalization. When the last calendar day of the month takes place on the weekend, weekend observations will occur as a result of month ending accrued interest adjustments.

Source: https://fred.stlouisfed.org/series/BAMLH0A2HYB

C.2.10 3-Month London Interbank Offered Rate (LIBOR)

Ticker: USD3MTD156N

London Interbank Offered Rate is the average interest rate at which leading banks borrow funds of a sizeable amount from other banks in the London market. Libor is the most widely used "benchmark" or reference rate for short term interest rates.

Source: https://fred.stlouisfed.org/series/USD3MTD156N

C.2.11 CBOE Volatility Index

Ticker: VIX

This index is used to represent the volatility implied by the S&P Index. This represents the market's expectation of 30-day forward-looking volatility and is used to provide a measure of market risk and investors' sentiment.

Source: Bloomberg

C.2.12 Lane Financial Indexes

We use a variety of indexes and data from Lane Financial LLc.

- Market Value of outstanding ILS
- Par Value of outstanding ILS
- Hard/Soft market indicator dervied as "Mark to market as a percentage change to Par of Market"
- Synthetic rate on line index
- Arithmetic Average Secondary Market Yield Spreads

Methodology: http://www.lanefinancialllc.com/images/stories/Publications/2007-08-15_Developing%20LFC%20Return.pdf Index Source: http://www.lanefinancialllc.com/images/stories/Publications/2019-12-31%20Quarterly%20Review.pdf

C.2.13 Historical record of catastrophic events

MunichRe provides a public web service from which we could extract historical events, their characteristics and the insured/non-insured losses adjusted for inflation.

Source: http://natcatservice.munichre.com

C.2.14 Insurance Linked Securities dataset

In the published AON Benfield Insurance Linked Securities Update 2018, they provided a detailed catalog of all catastrophe bonds issued and their key characteristics. We have used this to supplement the information available from Artemis to increase our coverage of the market and key characteristics.

Source: http://thoughtleadership.aonbenfield.com/Documents/20180905-securities-ils-annual-report.pdf

C.2.15 S&P Index

Ticker: INDEXSP

The S&P 500 Index is a stock market index that measures the stock performance of 500 large companies listed on stock exchanges in the United States. It is one of the most commonly followed equity indices, and many consider it to be one of the best representations of the U.S. stock market.

Source: Bloomberg

Section D
Deployment Appendix

We will deliver a web-based application that deploys predictive and descriptive models to provide users real-time analysis and price predictions on future cat bond investments.

D.1 Architecture

The backend architecture will utilize a combination of services on Google Cloud Platform to support storage, database, ETL, and computational capacity.

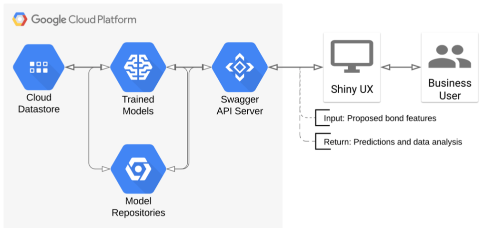

Figure D.1: Back-end architecture

D.2 Wireframe

The UX will allow users to input details of a bond. The application will return a price prediction, evaluate feature importance and provide a list and comparable bonds in the market. With this application, we strive to provide business users greater transparency into the price of cat bonds and determine the potential value of bond offerings to investors.

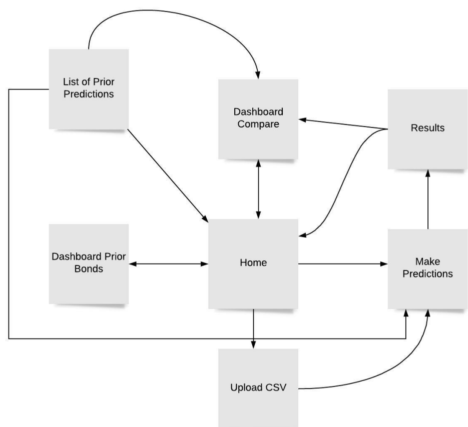

Figure D.2: Navigation

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