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Abstract

The COVID pandemic has highlighted the importance of hedging against catastrophic events, for which the catastrophe bond market plays a critical role. Our paper develops a two-level modelling and uses a unique, hand-collected dataset, which is one of the largest and most detailed datasets to date containing: 101 different issuers, 794 different bonds, spanning 1997-2020. We identify issuer effects robustly, isolating them from bond specific pricing effects, therefore providing more credible pricing factor results. We find that bond pricing and volatility are heavily impacted by the issuer, causing 26% of total price variation. We also identify specific issuer characteristics that significantly impact bond pricing and volatility, such as the issuer's line of business accounting for upto 36% of total price variation. We further find that issuer effects are significant over different market cycles and time periods, causing substantial price variation. The size and content of our data also enables us to identify the counter-intuitive relation between bond premiums and maturity, and bond premiums and hybrid bond triggers.

JEL classification: G12; G14; G22; C32
Keywords: Catastrophe risk bonds; primary market; multilevel modelling; issuer effect; hedging.

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1 Introduction

The Covid-19 pandemic has been a catastrophic event for most economies around the world. Previously a global pandemic of this scale was never truly considered in most firms; the rarity of such events and their high insurance costs imply that in most cases such high cost disasters go uninsured (e.g., Froot, 2001; Froot and O'Connell, 2008).[1] Yet the financial impact of such extreme events has demonstrated the importance of being able to hedge and/or insure against extreme events (also known as "perils"), such as the use of *catastrophe* (CAT) risk bonds (e.g., Cummins et al., 2002; Niehaus, 2002; Hagendorff et al., 2014).[2] Consequently, the importance of the efficient pricing of CAT bonds for such extreme events cannot be overstated and is now more important than ever before. In addition, the Covid-19 pandemic has further attracted new issuers to the CAT bond market, looking to benefit from both the protection and diversification potential offered by such *insurance linked securities* (ILS) instruments. Thus, investors would be interested in understanding the specific risks faced by newer entrants before formally participating in the CAT market. Furthermore, new types of ILS investments that the market seems keen on introducing[3] can only be successful if the necessary issuer screening and market efficiency analysis is conducted to determine suitability.

The CAT bond market developed as a result of the reduction in reinsurance capacity observed after Hurricane Andrew in 1992, and reinsurance companies being overwhelmed by increasing losses from catastrophic events (Swiss Re, 2012). The market is still in its expansion stage (only having been formally in existence for the last

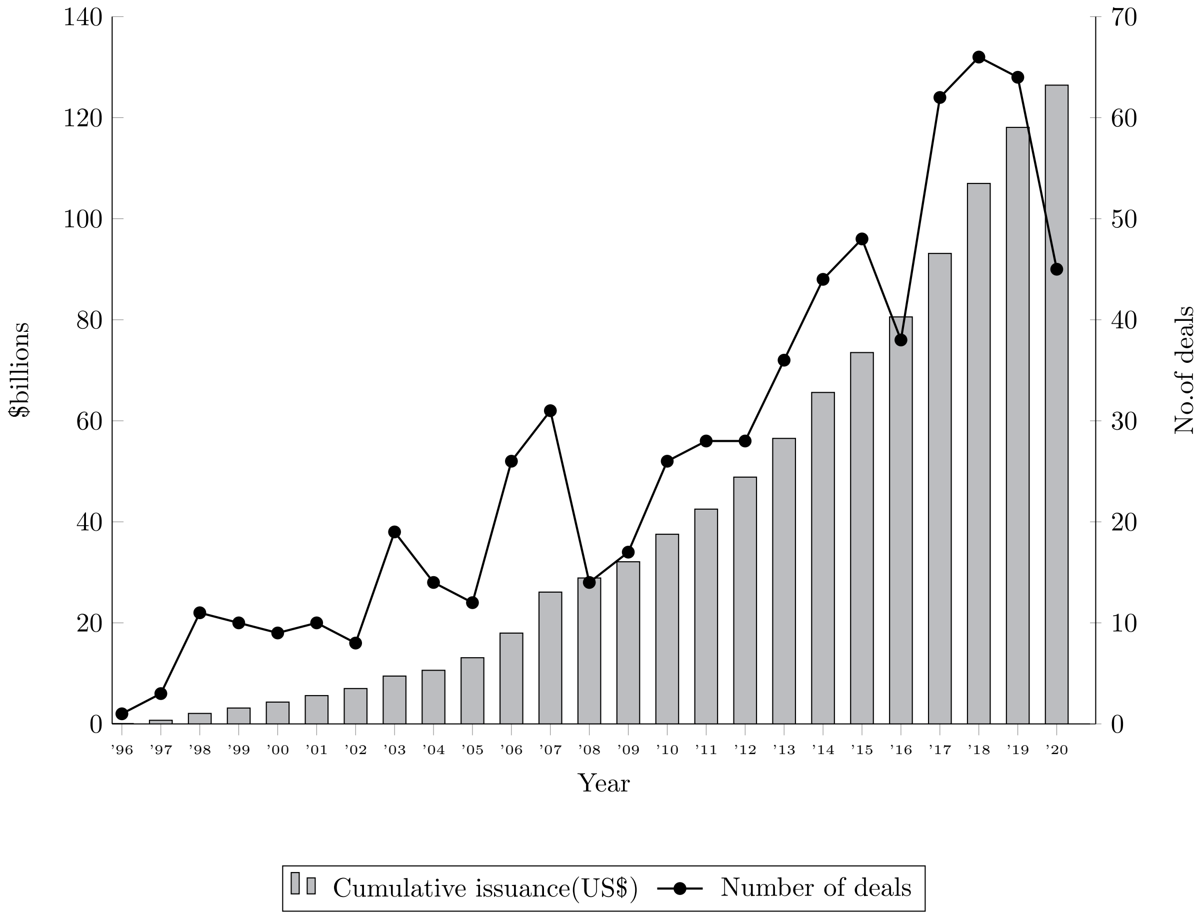
[1] Although some previous events have been insured, e.g., the Wimbledon tennis tournament which had been insured against the SARS outbreak since 2003, causing the organisation's policy to pay out US$142 million to cover the cost of cancelling the 2020 tennis tournament, these types of coverage are not always guaranteed in each year. In the Wimbledon case, the coverage was not renewed in 2021 due to an increase in premiums.

[2] The CAT bonds pay regular coupons and the principal value at maturity, similar to other bonds, and is a high-yield debt instrument. The CAT bonds provide cover against catastrophes by structuring the bond to provide payments contingent on such catastrophic events: the principal (and in some cases the coupons) is repaid conditional on a specified catastrophe not occurring. If the catastrophe occurs, investors lose either part or all of the principal, and possibly the coupons too (e.g. Cox and Pedersen, 2000; Zimbidis et al., 2007; Lai et al., 2014).

[3] https://www.artemis.bm/news/cat-bond-market-can-grow-to-50bn-pandemic-risk-esg-are-drivers-swiss-re/ (Retrieved on 28th August 2021)

25 years), and to date over $123 billion worth of CAT bonds have been issued. Since the CAT market is essentially a hybrid of the insurance and financial markets, it is potentially subject to inefficiencies and risks from both these markets, most of which stem from behavioural or structural elements (Kunreuther, 2012).

Figure 1: Catastrophe Bond Issuance by Year



Note: The figure above shows the development of CAT bond issues over time since the inception of the CAT bond market in 1996. To date (22nd June 2020), over US$123 billion worth of these bonds have been issued. The bar graph displays the total cumulative issuance while the line graph displays the number of CAT bond issues within the respective year. This data was retrieved from the Insurance Linked Securities' website Artemis.bm (Retrieved 22nd June 2020).

Furthermore, the primary CAT bond market represents an interesting market to investigate because the CAT bonds on identical perils should be identically priced (assuming all other characteristics are identical). This is because (theoretically) there would be no difference in risk between such CAT bonds, whereas for other bond markets identical pricing never occurs on bonds because bonds fundamentally differ on risk. In most bonds (including high-yield or junk bonds), the bond's price arises from the issuer's credit risk, for a CAT bond, however, bond pricing arises from the risk of a peril (such as an earthquake, e.g., Zimbidis et al., 2007; Shao et al., 2015). As the risk of a peril is identical for many bonds (and independent of the issuer), therefore the bonds should be identically priced. In addition, collateralization guarantees receipt of payments at the end of the contract period or on bond payment trigger, ensuring counterparty risk is virtually eliminated.

In CAT bonds, a *Special Purpose Vehicle* (SPV)[4] is created that ensures bankruptcy remoteness (Pearce II and Lipin, 2011), effectively separating the risks faced by the issuing company from those of the CAT bond.[5] Given all the contingencies in place for CAT bond payments, bond prices in the primary CAT market should essentially converge for the same catastrophe trigger event (if all other bond characteristics are similar). This should be even more the case given that the primary CAT market is dominated by informed traders (e.g., pension funds, hedge funds) hence we expect asset pricing to be efficient, and not subject to speculative or behavioural effects.

Whilst the literature on CAT bonds has identified bond specific characteristics (such as the bond's maturity, expected loss) that impact bond pricing, as one would rationally expect, the research on issuer characteristics (such as the line of business of the issuing firm) on bond pricing has been limited (see, Major and Kreps, 2002; Braun, 2016; Goetze and Gürtler, 2020). Despite the fact that issuers should not affect CAT bond premiums, this is not always the case in practice, for instance frequent issuers may receive better pricing over time than infrequent issuers, due to the relationships developed with investors (Spry, 2009). Additionally, the incentive to accurately es-

[4]The SPV is a company created for the express purpose of providing reinsurance to the issuer if a catastrophe occurs (e.g., Cox and Pedersen, 2000; Zimbidis et al., 2007; Pearce II and Lipin, 2011)

[5]SPV takes up the responsibility for ensuring full and timely cash flow payments are provided to investors.

timate the expected loss (EL) is also not strong due to the added costs incurred of underestimating EL. This could cause investors to price in underestimation risks into issues, especially for newer, or less frequent, issuers.

The lack of research on issuer effects on CAT bonds can be attributed to two key factors: firstly prior methodologies do not take into account the nested data structure of CAT bonds by issuers, hence ignoring issuer specific effects in pricing. Secondly, prior datasets contained limited information on issuers which impeded issuer related analysis.

Whilst in theory the issuer should not have any impact on bond pricing, if there exists an impact of issuers on pricing this means that an issuer issuing multiple identical bonds in a given year, or over many years, this will lead to grouping in bond price data. This is because a low risk issuer can typically issue multiple bonds with a very low yield, whereas a high risk issuer typically issues fewer bonds and with higher yields (since yields are proportional to risk). Hence two groups of price data will form (with each group associated for a given issuer) even for CAT bonds with identical characteristics (e.g., maturity, peril). A critical consequence of recognising grouping in CAT data is that standard (or multiple) linear regression methods will not be able to detect issuer effects in bond pricing correctly. Instead, we may have CAT bond pricing factors attributed to bond characteristics and completely ignoring the influence of the issuer. Such models can lead to under-estimation of standard errors and over-estimation of the significance of explanatory variables, and thus, to incorrect inferences. Additionally, in ignoring issuer grouping in data then one will not be able to correctly separate out bond specific and issuer specific factors in bond pricing. Consequently, papers that examine CAT bond data may not provide correct analyses on bond pricing factors, and/or incorrectly attribute bond pricing factors to other factors, and/or wrongly assign issuer effects to inappropriate regression results.

Secondly, current papers on CAT bond analysis have utilised datasets where there is a significant limitation of data. In fact many studies use small sample sizes for their analysis with a limited number of issuers in the data. Furthermore some studies have utilised dated datasets that are unrepresentative of the current CAT bond market, since the market has significantly developed in the past 10 years. Consequently such data can lead to biased results in the analysis, this is particularly the case for the analysis of extreme events, where larger samples are required to capture such rare events.[6] In order to address the aforementioned points, we require a method to take into account the fundamental nested data structure in the CAT bond market, so that we can correctly detect bond and issuer pricing effects separately. We also require a large enough dataset that is sufficiently rich enough in issuer data, to provide sufficiently unbiased and reliable results. Additionally, the dataset ought to contain information on a number of issuer factors so that we can analyse a number of issuer effects on bond pricing.

In this paper, we investigate the impact of issuer and bond characteristics on CAT bond premiums, using the multilevel or two-level modelling (TLM) methodology with hand-collected CAT bond data on the primary market. The application of TLM to issuer effects is a new method to the CAT bond pricing literature. It is well known in statistical modelling literature that data that exhibits grouping should be examined in terms of TLMs in order to obtain correct regression results; in fact Major (2019) proposes that a method ought to be used to take into account the nested data structure in CAT bonds. A TLM is also recommended in Raudenbush and Bryk (2010). TLM takes into account the nested data structure and therefore enables us to detect various issuer (or equivalently grouping) effects in data. Our paper finds that, even after controlling for all the other factors that affect CAT bond prices, premiums still vary based on the sponsor or issuer of the bond. Multilevel analysis allows us to separate the effects of the issuer from those of the other explanatory variables believed to impact premiums. Additionally we are able to quantify the level of variation in premiums

[6] A key data issue in most CAT bond papers is that the datasets tend to be limited in issuer content. Firstly the number of different issuers that tend to be present in most data samples is insignificant. Whilst some studies assume that issuers do not affect CAT bond pricing, assuming issuer effects exist implies such studies will be heavily be biased towards the issuers represented in the data. Secondly, many studies lack any information on issuers themselves in the data (e.g. years active in the CAT bond market, lines of business). A consequence of using such issuer limited data is that prior studies have not been able to discern significant issuer related factors in bond pricing.

between issuers arising as a result of their inherent differences.

In this paper, we use a large sample of hand-collected primary market CAT bond data compared to competing studies, which also enables testing a range of issuer effects. To the best of our knowledge, our paper is the first paper to make use of a hand-collected datasets on CAT bonds, which contains a large and extensive CAT bond dataset that includes current data. Our dataset contains all CAT bonds issued in the primary market between June 1997 and March 2020, containing a large number of different issuer (101 issuers), and a large number of different bonds (749 in total). This enables us to draw statistically significant conclusions that are also not biased by data arising from a handful of issuers.

A key value of our hand-collected data is that it contains a number of issuer related characteristics (e.g., issue size and line of business) and this is typically not available in most datasets; to the best of our knowledge, our dataset provides the first systematic catalogue of such issuer characteristics. Consequently, we are able to undertake regression analysis on a wide range of issuer related effects on bond pricing. We are able to investigate stylised factors relating to the market, the time period and their relation to variability in the CAT bond premiums, e.g., total CAT bond issue size since inception, the issuer's line of business, the state of the market cycle at bond issue, and timing effects of the issue.

In most CAT bond studies they are focussed on the secondary OTC (over-the-counter) market, see, for example, Goetze and Gürtler (2020), this poses a problem for analysing bond pricing for a number of reasons. Firstly, bond markets are notoriously illiquid; even in highly traded bond markets (e.g., corporate bond market) it is well known bond prices suffer from liquidity issues affecting bond prices. This is because OTC traded markets have trading activity that is extremely limited, leading to price distortions. In the case of CAT bond markets liquidity is even more scarce, since substantially fewer traders exist in the market, hence secondary market prices will be heavily influenced by trading liquidity. Secondly, the secondary market is subject to greater counterparty risk than in the primary market: in OTC markets there is no central exchange to cover defaults, consequently, counterparty risk may distort bond prices. Hence in studying primary market bond prices we exclude all these problems and so obtain a better understanding of issuer effects.

The contribution of this research paper is as follows. Firstly, we apply a new methodology to CAT bond data modelling of issuer effects. TLM enables us to take into account the nested data structure of CAT bonds (unlike prior studies), so that we can identify issuer effects, and separately identify bond specific pricing factors that are not due to issuer specific characteristics.

Secondly, using our hand-collected dataset, we analyse the largest sample size of CATs to date, and determine the effect of issuers on premiums through a TLM model. We quantify the magnitude of this issuer effect to better establish the amount of volatility introduced by the differences between issuers. The magnitude of the bond specific effects (or other major explanatory variables) is also investigated. The large dataset size enables us to identify that, counter-intuitively, CAT bond premiums decrease with bond maturity (unlike in standard corporate bonds) and that hybrid triggers increase bond premiums.

Thirdly, we extend the issuer analysis to identify the specific characteristics of the issuer that most impact CAT bond pricing and volatility. We find that CAT bond pricing and volatility are affected by the issuer's line of business, years active in the CAT bond market and the issue size. We also show that different stages of the market cycle and different time periods also influence the impact of the bond specific and issuer specific characteristics on bond pricing and volatility.

In aggregate, by testing for the existence of the issuer effect and the main characteristics determining the magnitude of CAT bond pricing, we effectively determine the extent to which the primary CAT bond market exhibits mispricing. As an important impact, these mispricings considered here can be exploited by future first-time issuers, who can use them to pick the optimal avenue through which to issue new bonds. The results can also provide better one step ahead understanding of the factors to consider before introducing a new product, especially when conducting issuer screenings. This will further lead to increased participation and growth of the ILS markets.

The rest of this paper is structured as follows: the next section reviews the current literature in this area of CAT bond pricing. In Section 3 we introduce the hypotheses to be investigated in determining the factors that affect CAT bond pricing. In Section 4 we describe the data and sample selection, in Section 5 we give the methodology, which is followed by analysis in Section 6. In Section 7 we conclude the paper.

2 Related Literature

In Braun (2016), a multiple linear regression model is implemented to model CAT bond spreads which are modelled with standard explanatory factors such as expected loss, maturity, and the type of event trigger. Essentially the bond spreads are modelled by bond specific factors and they find expected loss is the most important pricing factor, however issuer specific factors are not substantially investigated. Similarly, in Carayannopoulos et al. (2022) a multiple linear regression model investigates CAT bonds and finds that expected losses and risk aversions affect CAT bond premiums. We note that alternative approaches can be applied to insurance linked securities, for example in Zheng (2015) such securities are analysed. In Zheng (2015), an analytical solution is derived on insurance linked securities, where the successful conditions for issuance are analysed.

In Lane and Mahul (2008), the relation between CAT bond pricing and liquidity is investigated, they find that liquidity premium can affect approximately 9% of the average CAT bond pricing. The bond pricing is investigated using 250 CAT bonds, and a multiple regression model whereby the bond's price is determined by standard bond specific factors such as expected loss, event trigger etc. . Whilst they find over the long term that the market-based catastrophe risk price is approximately 2.69 times the expected loss, no issuer specific factors are investigated.

In Chang et al. (2020), CAT bond spreads are modelled using multiple regression, but employ Poisson and negative binomial regression models. They investigate the empirical relationship between catastrophe frequency and CAT bond spreads. They also employ standard bond specific characteristics in modelling bond spreads such as expected loss, however they also include one issuer specific explanatory variable: classifying the bond as a Swiss Re issue or non-Swiss Re. This issuer variable is modelled as a dummy variable and so this model does not investigate significant issuer specific properties.

In Galeotti et al. (2013) a fixed effect multiple regression model is applied to CAT bond pricing, enabling incorporation of time dependent factors on pricing. Market factors, such as macroeconomic variables, and bond specific factors, such as maturity, are investigated, and a range of models are tested using out-of-sample analysis. They conclude that a relationship between the CAT bond premium and the expected loss exists, and find that the Wang transform improves modelling.

A common theme in the existing papers (and all the previously surveyed literature) is that issuer related factors are not investigated in depth, in the regression models for bond pricing. In some papers, the issuer is included as a dummy variable as in Chang et al. (2020) and Braun (2016), representing 1 if the issuer is Swiss Re and 0 otherwise. However, this does not properly investigate the different aspects of the issuer (such as the issue size), nor does it robustly isolate out issuer effects from bond specific effects. Furthermore, a dummy variable is limited in its ability to analyse a high number of issuers in the data (e.g., over 100) and so will not be a suitable modelling method for datasets containing a large number of issuers (such as our dataset). In other papers the issuer specific information is not included at all. This is because issuer specific data is generally not available in a convenient database. Additionally, it is normally assumed that (theoretically) issuers have no impact on CAT bond pricing, since the CAT bond payouts depend on the event trigger itself and not the issuer (unlike in other traded bonds).

In the current pricing literature, few of the CAT bond studies apply a TLM to investigate issuer effects, even though in Major (2019) it is suggested that the CAT bond's nested data structure should be taken into account through TLM. One paper that applies TLM is Gürtler et al. (2016): the secondary market bond pricing is investigated, they find that investors use bond ratings information for investment decisions. They also report that as the rating declines then premiums increase and this result is similar to those of Galeotti et al. (2013) and Braun (2016). However, the TLM is used for event analysis, for the impact of specific events (such as the Global Financial Crisis) upon bond pricing; issuer effects are not investigated. Hence TLM is not applied to isolate issuer effects from bond specific effects in bond pricing.

With respect to current CAT bond pricing research literature, in general, typically the datasets that are used in experiments are limited, with little or no detailed information on the issuers. For example in Braun (2016), CAT bond tranche data consists of data from 1997-2012 only, in Chang et al. (2020), 450 CAT bond tranches are used in the dataset from June 1997 to March 2013. The lack of a rich dataset may lead to bias or contrary results.

The closest paper to our work is Goetze and Gürtler (2020) which investigates the secondary CAT bond market. They investigate CAT bond premium using a random and fixed effect regression model, to investigate the time of pricing. They report that bond pricing varies with market conditions, such as hard and soft markets. A hard market is a period whereby one observes above average losses, typically following major catastrophic events, and is characterised by higher-than-expected premiums. Soft markets, on the other hand, represent periods of low losses, and are characterised by lower-than-expected premiums; neutral markets are characterised by premiums close to their expected values.

Whilst Goetze and Gürtler (2020) investigate CAT bond premium their paper focuses on different areas to our paper. Firstly, whilst Goetze and Gürtler (2020) investigate issuer related factors on bond premiums, we focus on investigating the impact of the issuer *itself* on bond premiums. This is an important distinction because our study investigates a more significant market inefficiency, in that CAT bond prices can differ purely on the issuer itself. Although issuer related characteristics offer interesting insights into pricing, they can be explained by rational investors with respect to risk and reward; for example an issuer with greater time in the market may command lower risk premia because it implies lower operational risk as well as other risks. However, a rational investor cannot explain pricing two identical bonds differently due to the issuer's name, hence our paper investigates a more significant pricing anomaly.

Secondly, unlike in Goetze and Gürtler (2020), we are able to more effectively isolate the impact of the issuer itself from other independent variables in our regression model. This is because our TLM and extensive (hand collected) dataset enables us to more robustly model the issuer's impact on pricing, compared to the work in Goetze and Gürtler (2020). Consequently, it is not clear whether the results drawn in Goetze and Gürtler (2020) on issuer related effects on bond premium are due to the issuer related factors, or the issuer itself.

Finally, Goetze and Gürtler (2020) investigate bond prices in the secondary market, whereas our paper is focussed on the primary market only. The advantage of focussing on primary markets is that we can obtain more reliable and robust results relating to bond premiums, issuer and issuer related factors. The secondary market for bonds (and, in particular, for CAT bonds) is more subject to pricing distortions and irrational pricing than the primary market, hence studies related to the secondary market are more likely to be unreliable. The secondary bond markets are notoriously illiquid; even in highly traded bond markets (e.g., corporate bond market), leading to price distortions and in the case of CAT bond markets secondary market prices will be far more heavily influenced by trading liquidity.

The secondary market is subject to greater counterparty risk than in the primary market, leading to counterparty risk distorting bond prices. Furthermore, the secondary market is subject to more speculative trading (e.g., bubbles) and price distortion is even more accentuated when dealing with high risk events such as catastrophic events. There is extensive literature demonstrating that risk premiums can vary significantly, and these variations increase with extreme events. Hence in studying the primary market bond prices we exclude all these problems and so obtain a better understanding of the issuer effects.

3 Hypotheses

In this section, we state the hypotheses that we will investigate. The first hypothesis examines issuer specific factors and so is separated into four distinct hypotheses.

Hypothesis 1a: *CAT premiums differ depending upon the bond issuer, after controlling for all other independent variables.*

Hypothesis 1b: *Issuers with a higher total issue volume will have a lower volatility in bond premiums compared to those with a lower total issue volume.*

Hypothesis 1c: *The duration of the issuer's participation in the primary CAT market reduces the premium's volatility.*

Hypothesis 1d: *Issuers in the insurance line of business only will have higher bond premium volatility than issuers in other lines of business (e.g., multi-line).*

As mentioned previously, there is theoretical and empirical evidence that issuer effects exists in CAT bond pricing. Firstly, the grouped data structure of CAT bonds, which is observable in our own dataset (see Table 1[7]) and mentioned in Major (2019), imply a dependency exists between pricing and issuers. Secondly, the issuer potentially represents a source of perceived idiosyncratic risk to investors; this could arise from operational risk, legal risk or any other firm specific risk. Consequently it is important to investigate the potential impact of issuers on pricing.

A potential source of idiosyncratic risk is the issuer's key sector or line of business. An issuer whose main line of business is insurance is less likely to have a stable level of cash and assets compared to other lines of business. This is because insurers are subject to large losses when claims are made, unlike other businesses such as multi-line businesses. By a similar principle, we would expect issuers with larger issue volumes to have lower volatility because larger issues must command more confidence in the

[7]The Table 1 lists the CAT bonds issued by the well established issuer USAA from 1997-2020; this represents an extensive time period. As one can observe in Table 1, we can firstly notice in the 'No.' column that multiple identical issues can occur in a given year, for many years. Secondly, we also notice that many bonds that are issued have very similar characteristics (e.g., similar perils, similar size bonds etc.). This issue has been identified in Major (2019): CAT bond issues are frequently issued by the same issuer every year, or even multiple times within the year, and with similar characteristics (the new bonds replace or 'renew' the expiring bonds).

Table 1: USAA CAT Bond Issues

Year	No.	Size($m)	Term	Month	S&P Global Rating	Peril
1997	2	477	1	June	AAA, BB	US Hurricane
1998	1	450	1	June	BB	US Hurricane
1999	1	200	1	June	BB	US Hurricane
2000	1	200	1	May	BB+	US Hurricane
2001	1	150	3	May	BB+	US Hurricane
2002	1	125	3	May	BB+	US Hurricane
2003	1	160	3	May	BB+	US Hurricane; Earthquake
2004	2	227.5	3	May	BB,B	US Hurricane; Earthquake
2005	2	176	3	May	BB,B	US Hurricane; Earthquake
2006	2	122.5	3	June	B,BB+	US Hurricane; Earthquake
2007	5	600	3	June	BB,B,B,BB+,BB+	US Hurricane; Earthquake
2008	3	350	3	May	BB,B,BB+	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2009	2	250	3	May	BB-,B-,BB-	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2010-1	4	405	3	May	BB,B+,B-,NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2010-2	3	300	2.5	Dec	BB,NR,NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2011-1	3	250	4	May	B+,B-,B	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2011-2	2	150	4	Nov	NR,NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2012-1	3	200	4	May	BB-,BB,NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2012-2	4	400	4	Nov	BB+,BB,NR,NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2013-1	2	300	4	May	B-,NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2013-2	2	150	4	Dec	NR,BB-	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire
2014-1	2	130	4	May	NR,NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite
2014-2	1	100	4	Dec	NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite
2015-1	2	150	4	May	NR,NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite
2015-2	1	125	4	Dec	B-,NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite
2016-0	1	50	4.5	March	NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite; ONP
2016-1	3	250	4	May	NR,NR,BB-	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite; ONP
2016-2	3	400	1,4,4	Nov	NR,B-,B-	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite; ONP
2017-1	3	425	1,4,4	May	NR,NR,BB-	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite; ONP
2017-2	3	295	1,4,4	Nov	NR,NR,B-	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite; ONP
2018-1	2	350	1,4	May	NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite; ONP
2018-2	2	200	1,4	Nov	NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite; ONP
2019-1	2	135	4	May	NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite; ONP
2019-2	2	160	1,4	Nov	NR	US Hurricane; Earthquake; Thunderstorm; Winter storm; Wildfire; Volcanic and Meteorite; ONP

Note: This table lists the USAA's CAT bond issues over time. Changes in the number of bond issues per year (No.), the issue sizes (in $m), the terms of the issued bonds (in years), the issue month, the rating expressed in the S&P scale at issue and the covered peril can be deduced from the respective columns of the table. The rating abbreviation NR represents bonds that were Non-Rated, while the peril abbreviation ONP represents Other Natural Perils identified as catastrophes by reporting agency PCS.

market to have more money invested in its bond, hence they are perceived as lower risk. Consequently, we investigate the impact of the issuer's line of business and issue volume upon bond premiums and volatility.

It was previously discussed that there is evidence to support CAT bond premiums are dependent on participation in the CAT bond market, since frequent issuers may receive better pricing over time than infrequent issuers. This is potentially due to issuers developing relationships with their investors (Spry, 2009); this is similar to the clientele effect in stocks. Additionally, newer issuers may be more likely to underestimate risks, causing investors to price in such a risk, hence bond prices would differ depending on the issuer. A consequence of these factors is that pricing and volatility are impacted by issuer participation in the CAT bond market.

In the hypotheses, we investigate the impact of an issuer effect upon the bond premium's volatility, because volatility is a widely used measure of risk, in industry and research. As the issuer effects typically lead to a change in risk of the CAT bond, we should therefore be able to observe its effect in terms of the premium volatility. Hence we investigate the relation between premium volatility and changes in (issuer) risk in our hypotheses.

Using our TLM, we are able to isolate issuer and bond specific pricing factors more robustly. Consequently, we now state the hypotheses that test for bond specific factors, to determine the impact on bond pricing (with factors more robustly isolated from issuer effects).

Hypothesis 2: *Bonds classed as peak or multiperil will have higher bond premiums than bonds classed as non-peak or diversifying peril.*

Following Cummins and Mahul (2009), peril types are classed into four major categories based on geographic region and event: *peak* are hurricanes and earthquakes in the US region; *non-peak* are European wind storms and Japanese earthquakes; *diversifying* are Mexican earthquakes, Australian earthquakes and hurricanes, Japanese typhoons, and European earthquakes; *multi-perils* combine peak and non-peak perils in the same transaction.

It is assumed that peak CAT bonds will normally have higher premiums than non-peak bonds (Cummins, 2008), because the peak regions are more prone to natural disasters such as hurricanes, typhoons, earthquakes, tornadoes (Zimbidis et al., 2007; Shao et al., 2015; Karagiannis et al., 2016). In addition, peak bonds do not offer as much diversification benefit as non-peak bonds. Multi-peril bonds are also assumed to have higher premiums due to the greater opportunity for a catastrophic event triggering a CAT bond (Gürtler et al., 2016).

Hypothesis 3: *Bonds with hybrid (that is multiple) triggers have higher premiums than bonds with a single trigger.*

There are five major trigger types in the CAT bond market: *indemnity*, *parametric*, *industry loss*, *modelled loss* and a *hybrid trigger* (a combination of any of the other four triggers). Consequently, we expect hybrid trigger bonds to have higher premiums because such bonds have greater opportunity to be triggered by a single catastrophic event.

Hypothesis 4: *Bonds with a higher credit rating will have a lower premium.*

A CAT bond's credit rating gives investors an indication of the bonds risk of default and helps companies reduce their cost of capital (White, 2013). Whilst we may expect credit ratings to influence CAT bond premiums (as in standard bonds), CAT bonds investors in general do not rely on bond ratings (Krutov, 2010), in fact Cummins (2008) states that the modelling of the bond is a more important driver of price than ratings. This hypothesis is particularly interesting to investigate, given that we can apply TLM to isolate issuer effects from influencing credit rating.

Hypothesis 5: *Longer-maturity bonds have higher premiums than shorter-maturity bonds.*

In standard (corporate) bonds, we expect premiums to increase with term maturity due to the maturity premium effect (Bodie et al., 2014). This is because longer-term bonds have higher risk due to their increased price sensitivity to fluctuations in interest rates. Consequently, we should therefore expect CAT bonds with longer maturities to have higher premiums than shorter maturity bonds. On average, CAT bonds have a maturity period of about three years, but maturity has been observed to be as short as five months and as long as six years.

Hypothesis 6: *CAT bond premiums increase proportionally with the cyclic index, controlling for all other independent variables.*

The CAT bond market has been shown to follow reinsurance cycles (Lane and Mahul, 2008), with rising premiums during hard markets and lower premiums during soft markets. There can be hard, soft and neutral markets representing respectively increasing, decreasing and stable prices. This is because the insurance market faces cycles; prices have been observed to increase after significant catastrophic events, and they decrease during periods of stability (see, Cummins and Weiss, 2009; Swiss Re, 2019).

If the bond is issued in a hard, soft or neutral market then it will affect its observed spreads due to the overall market's conditions and investor sentiment at the time of issue. Bonds issued in hard markets tend to have higher premiums than comparable bonds issued in soft markets due to a higher cost of coverage and changes in risk perception. Again, it is important to test this factor, independent of issuer effects, which is possible with our dataset and TLM approach.

Hypothesis 7: *CAT bond premiums increase proportionally to the spreads in similar high-yield corporate bonds.*

As CAT bonds are similar to high yield bonds in terms of risk and reward, with an equal rating (Cox and Pedersen, 2000), investors can choose between investing in either the corporate or the CAT bonds; hence both markets are in competition. Consequently, we expect CAT bond premiums to track high yield corporate bonds, otherwise investors can always switch investing to the more attractive investment.

4 Data

One of the key contributions of this paper is the collection and usage of our hand-collected dataset. Firstly, the dataset was obtained by collating and compiling data from various CAT bond sources; the majority of the data is acquired from Lane Financial LLCs trade notes.[8] As this initial dataset contained significant omissions in datapoint values, especially for bonds issued in the earlier years of the CAT market (approximately 1997-2000), this is amalgamated with data from other respected sources; some of these sources include data from the ILS portal Artemis.bm, Aons Annual ILS Reports, Swiss Res ILS Market Updates, Munich Re and Guy Carpenter reports, the Institute and Faculty of Actuaries' publications and Froot (1999). This collation and compilation of data from additional sources follows the same method taken in Braun (2016) and Goetze and Gürtler (2020).

After the initial dataset is collated and compiled into a dataset amenable to standard econometric software, we obtain data on 101 CAT bond issuers. The dataset contains two issuer specific characteristics: total issue size and the number of years the issuer is participating in the CAT bond market. In terms of the issuer specific characteristic on the issuer's line of business, no database currently exists on CAT bond issuers that systematically categorises their lines of business. As a result, the issuer's line of business(es) had to be determined for the 101 issuers by hand-collecting information on the issuer's official financial and company reports. We categorise the issuer's line of business as: 'insurer', 'reinsurer' or 'multiline/other' as these capture the key issuer businesses in the CAT bond market. An issuer is categorised as 'multiline/other' if the issuer is not purely an insurer or reinsurer, for example Munich Re's main subsidiaries consist of insurance, reinsurance as well as an investment or trading.

The resultant (raw) hand-collected data is a panel dataset consisting of 749 bonds, issued in the primary CAT bond market, between June 1997 and March 2020. This panel data therefore represents a new and valuable data source that has not been compiled before, providing useful insights on the issuer characteristics (such as line of business). Consequently, this data source provides an opportunity to investigate a number of empirical relationships and hypotheses that would not have been previously available on other datasets.

[8]see http://www.lanefinancialllc.com/

The (raw) dataset is then cleaned, as it is found on closer examination that some CAT bonds exhibit unusual payment structures compared to typical CAT bonds, or some bonds had missing values on key variables. Furthermore, we exclude all bonds covering life and health risks (such as mortality and diseases) as they have different underlying variables that determine their pricing compared to the majority of our dataset, which covers natural disasters (such as hurricanes and earthquakes). If one includes all the aforementioned bonds in our final dataset this would lead to biases in our results, consequently such CAT bonds are removed.

After data cleansing, we remove 25 CAT bonds from our 749 CAT bond dataset, resulting in a final dataset of 724 CAT bonds. For each bond, we collect information on the issuer, underwriters, size of issue (in millions of US dollars), issue rating[9], term, issue and maturity month, spread per annum, expected loss, peril and geographical location, trigger, probability of first loss and the conditional expected loss. The dataset also contains 101 individual issuers: Swiss Re (11.22%), USAA (8.46%), Hannover Re (5.25%), Everest Re (4.34%) and Munich Re (4.18%) are the top five issuers by size of issues. Hence we have a broad and diversified dataset of issuers; this is an advantage compared to other papers where studies are restricted to a small number of issuers (due to lack of data availability) and therefore leads to biases in results.

The key data for every issuer data is given in Table 2, for example one can find information on the premium and expected loss for a given issuer. As the entire collected dataset is large we are not able to reproduce all the data collected for every issuer in the paper, however we provide an example of the type of information collected for a given issuer in Table 1. In Table 1, we provide key details on the CAT bonds issued by USAA, from 1997-2019, providing information on the perils covered, the credit ratings and month of issue.

[9]For bonds with multiple ratings, we pick the lowest rating.

Table 2: Catastrophe bonds by issuer

Issuer	Size ($m)	% Size	Obs. (No)	% Obs.	Premium (%)	EL (%)	P/EL	EER (%)	Term
Achmea Re	54.70	0.06%	1	0.14%	3.30%	1.29%	2.56	2.01%	36.00
AGF	129.00	0.13%	2	0.28%	4.29%	0.69%	8.56	3.60%	60.00
AIG	1,325.00	1.37%	8	1.10%	6.53%	1.72%	4.03	4.81%	29.25
Aioi Nissay Dowa Insurance	167.90	0.17%	2	0.28%	3.00%	0.83%	4.00	2.17%	41.50
Allianz SE	1,755.00	1.81%	16	2.21%	10.36%	3.24%	4.80	7.12%	37.50
Allstate Insurance Company	2,725.00	2.81%	12	1.66%	5.30%	1.04%	5.06	4.27%	46.58
Am Family Mutual	200.00	0.21%	2	0.28%	7.48%	2.72%	3.04	4.76%	37.50
Am Re	176.80	0.18%	2	0.28%	4.24%	0.40%	13.14	3.84%	17.00
American Coastal Insurance	383.00	0.40%	2	0.28%	4.19%	0.46%	9.29	3.73%	21.00
American Modern Insurance	75.00	0.08%	1	0.14%	3.55%	0.57%	6.23	2.98%	36.00
American Re	116.40	0.12%	1	0.14%	5.58%	0.75%	7.44	4.83%	12.00
American Strategic Insurance	600.00	0.62%	4	0.55%	5.07%	1.85%	2.98	3.22%	38.25
Amlin AG	500.00	0.52%	3	0.41%	10.06%	3.63%	2.91	6.42%	44.00
AmTrust Financial Services	100.00	0.10%	1	0.14%	3.80%	1.19%	3.19	2.61%	47.00
Argo Re	372.00	0.38%	5	0.69%	13.44%	5.25%	2.82	8.19%	39.60
Arrow Re	162.80	0.17%	3	0.41%	3.95%	0.59%	34.68	3.37%	12.00
Arrow Re/St Farm	52.20	0.05%	1	0.14%	4.62%	0.63%	7.33	3.99%	12.00
Aspen Insurance Holdings	325.00	0.34%	2	0.28%	5.83%	2.29%	2.64	3.54%	30.00
Assicurazioni Generali	486.60	0.50%	2	0.28%	2.66%	1.66%	1.73	1.00%	42.00
Assurant	605.00	0.62%	9	1.24%	8.82%	2.06%	4.78	6.76%	36.00
Avatar P&C	100.00	0.10%	3	0.41%	8.45%	4.68%	2.66	3.77%	35.00
AXA Global Re	1,105.30	1.14%	4	0.55%	3.32%	1.28%	2.68	2.04%	41.75
AXIS Re	915.00	0.94%	4	0.55%	7.53%	3.73%	2.22	3.80%	41.25
Balboa Insurance Company.	50.00	0.05%	1	0.14%	3.04%	0.82%	3.71	2.22%	36.00
Bayview Opp Fd	225.00	0.23%	2	0.28%	4.57%	1.75%	3.16	2.82%	35.00
Brit Insurance Holdings plc	140.00	0.14%	2	0.28%	4.57%	0.78%	12.60	3.79%	36.00

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Table 2 – continued from previous page

Issuer	Size ($m)	% Size	Obs.	% Obs.	Premium (%)	EL (%)	P/EL	EER (%)	Term
California Earthquake Authority (CEA)	3,725.00	3.85%	13	1.80%	5.14%	2.09%	2.80	3.05%	37.85
California State Compensation Insurance Fund	660.00	0.68%	3	0.41%	2.75%	0.25%	11.90	2.51%	45.33
Castle Key Insurance & Indemnity	700.00	0.72%	2	0.28%	4.44%	0.78%	5.89	3.67%	41.50
Catlin Group	1,041.80	1.08%	6	0.83%	7.48%	2.42%	6.91	5.06%	36.50
Central Re Corp	100.00	0.10%	1	0.14%	4.11%	0.73%	5.63	3.38%	34.00
Centre Solutions (Bermuda) Ltd (Zurich Group)	113.15	0.12%	2	0.28%	3.75%	0.80%	4.69	2.95%	12.00
Chubb Group	1,745.00	1.80%	12	1.66%	7.60%	1.78%	4.90	5.81%	44.00
Citizen's Property Insurance	3,350.00	3.46%	6	0.83%	8.48%	2.47%	3.33	6.00%	33.67
Converium	100.00	0.10%	1	0.14%	5.48%	1.07%	5.12	4.41%	60.00
Dominion Resources	50.00	0.05%	1	0.14%	20.78%	1.54%	13.49	19.24%	7.00
Electricite de France	232.50	0.24%	2	0.28%	2.74%	0.28%	41.66	2.46%	60.00
Endurance Specialty Holdings	125.00	0.13%	1	0.14%	8.11%	1.13%	7.18	6.98%	18.00
Equator Re Ltd	250.00	0.26%	1	0.14%	3.80%	1.34%	2.84	2.46%	36.00
Everest Re	4,200.00	4.34%	19	2.62%	8.58%	4.78%	1.99	3.80%	52.32
First Mutual Transportation Assurance (MTA)	325.00	0.34%	2	0.28%	4.16%	2.07%	2.12	2.09%	35.50
Flagstone Re	489.00	0.50%	7	0.97%	12.07%	3.37%	4.74	8.69%	36.00
FM Global	300.00	0.31%	1	0.14%	3.17%	0.71%	4.46	2.45%	36.00
FONDEN, Mexico	315.00	0.33%	3	0.41%	7.86%	3.71%	2.23	4.15%	38.00
Frontline	350.00	0.36%	2	0.28%	9.51%	5.77%	1.70	3.74%	47.00
Gerling	180.00	0.19%	2	0.28%	4.41%	0.60%	7.77	3.81%	48.00
Glacier Re	255.00	0.26%	4	0.55%	10.05%	2.80%	3.87	7.25%	36.00
Great American Insurance Co.	285.00	0.29%	3	0.41%	4.99%	1.67%	3.24	3.32%	39.00
Groupama	292.00	0.30%	1	0.14%	3.65%	0.89%	4.10	2.76%	36.00
Gulfstream Ins.(for Vivendi)	175.00	0.18%	2	0.28%	6.64%	1.18%	6.35	5.46%	43.00
Hannover Re	5,081.20	5.25%	26	3.59%	7.51%	3.11%	3.03	4.40%	40.81
Hartford Fire Insurance	915.00	0.94%	7	0.97%	5.88%	0.93%	6.99	4.95%	45.00
Heritage P&C	852.50	0.88%	8	1.10%	6.56%	3.22%	2.38	3.34%	42.00

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Table 2 – continued from previous page

Issuer	Size ($m)	% Size	Obs.	% Obs.	Premium (%)	EL (%)	P/EL	EER (%)	Term
Hiscox Syndicate	33.00	0.03%	1	0.14%	6.84%	1.14%	6.00	5.70%	36.00
IBRD - Chile	500.00	0.52%	1	0.14%	2.53%	0.86%	2.94	1.67%	36.00
IBRD - Colombia	400.00	0.41%	1	0.14%	3.04%	1.56%	1.95	1.48%	36.00
IBRD - Mexico	1,105.00	1.14%	9	1.24%	6.70%	4.11%	1.98	2.58%	36.44
IBRD - Peru	200.00	0.21%	1	0.14%	6.08%	5.00%	1.22	1.08%	36.00
IBRD - Philippines	225.00	0.23%	2	0.28%	5.66%	2.97%	1.90	2.69%	36.00
ICAT Syndicate 4242	164.50	0.17%	2	0.28%	5.07%	2.89%	2.03	2.19%	37.00
Kemper	80.00	0.08%	1	0.14%	3.74%	0.50%	7.48	3.24%	37.00
Lehman Re	499.50	0.52%	3	0.41%	4.39%	0.49%	10.20	3.83%	18.67
Liberty Mutual	1,175.00	1.21%	7	0.97%	9.46%	1.53%	7.04	7.93%	34.29
Louisiana Citizens	565.00	0.58%	5	0.69%	6.13%	2.23%	2.62	3.90%	38.40
Markel Bermuda	100.00	0.10%	1	0.14%	2.79%	0.14%	19.93	2.65%	37.00
Mitsui Sumitomo	640.00	0.66%	5	0.69%	2.69%	0.97%	2.81	1.72%	52.80
MMM IARD SA+	239.22	0.25%	3	0.41%	6.64%	5.31%	1.28	1.33%	48.33
Montpelier Re	150.00	0.15%	2	0.28%	13.31%	3.51%	3.80	9.80%	36.00
Munich Re	4,051.40	4.18%	30	4.14%	7.12%	1.99%	4.26	5.14%	39.50
National Union Fire Insurance	1,850.00	1.91%	8	1.10%	9.19%	1.86%	5.38	7.33%	34.50
Nationwide Mutual	2,640.00	2.73%	18	2.49%	6.58%	2.40%	3.34	4.18%	38.78
Natixis SA	214.60	0.22%	2	0.28%	7.36%	3.56%	2.09	3.80%	57.00
NC Insurance Underwriting Association	550.00	0.57%	2	0.28%	5.58%	2.02%	2.79	3.56%	35.00
Nephila Capital Ltd.	240.00	0.25%	3	0.41%	3.85%	0.65%	29.30	3.21%	32.00
Oak Tree Assurance	400.00	0.41%	1	0.14%	2.79%	0.80%	3.49	1.99%	39.00
OCIL (Oil Casualty Insurance Ltd.)	405.00	0.42%	3	0.41%	4.55%	0.89%	16.17	3.66%	36.00
Oriental Land	100.00	0.10%	1	0.14%	3.14%	0.42%	7.48	2.72%	60.00
Palomar Specialty Ins.	166.00	0.17%	3	0.41%	4.39%	2.49%	1.92	1.90%	36.00
Passenger Railroad Ins.	275.00	0.28%	1	0.14%	4.56%	1.99%	2.29	2.57%	38.00
Platinum	200.00	0.21%	1	0.14%	4.82%	0.56%	8.61	4.26%	36.00

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Table 2 – continued from previous page

Issuer	Size ($m)	% Size	Obs.	% Obs.	Premium (%)	EL (%)	P/EL	EER (%)	Term
PXRE	550.00	0.57%	4	0.55%	7.10%	1.18%	7.33	5.92%	48.00
Renaissance Re	550.00	0.57%	3	0.41%	7.70%	2.95%	2.73	4.75%	39.33
Safepoint Insurance	435.00	0.45%	7	0.97%	7.71%	3.68%	3.08	4.04%	35.86
SCOR	2,716.60	2.80%	21	2.90%	9.00%	2.47%	8.15	6.53%	39.43
Sempra En, SD G&E, S C	125.00	0.13%	1	0.14%	4.06%	0.21%	19.33	3.85%	36.00
Sompo Japan Nipponkoa	878.00	0.91%	4	0.55%	2.53%	0.88%	3.02	1.65%	48.25
Sorema	34.00	0.04%	2	0.28%	5.07%	0.43%	16.30	4.66%	24.00
State Farm	3,158.60	3.26%	10	1.38%	2.37%	0.28%	51.80	2.09%	35.90
Swiss Re	10,868.00	11.22%	173	23.90%	9.51%	2.96%	8.07	6.56%	29.56
Texas Windstorm Insurance Association (TWIA)	600.00	0.62%	2	0.28%	3.93%	1.89%	2.07	2.04%	36.00
Tokio Marine	985.00	1.02%	6	0.83%	2.53%	0.62%	6.95	1.91%	49.67
Tokio Millenium Re	630.00	0.65%	3	0.41%	5.66%	1.47%	4.94	4.19%	43.33
Transatlantic Re	500.00	0.52%	3	0.41%	6.00%	2.49%	2.59	3.51%	47.00
Travellers Group	2,350.00	2.43%	7	0.97%	4.72%	1.01%	5.03	3.70%	39.29
Turkish Cat Ins Pool	500.00	0.52%	2	0.28%	2.92%	1.23%	2.40	1.69%	36.00
UnipolSai Assicurazioni	276.11	0.29%	2	0.28%	3.37%	0.38%	8.58	2.99%	39.50
United P&C & affiliates	300.00	0.31%	5	0.69%	8.60%	5.02%	2.22	3.58%	19.40
US Fidelity and Guaranty	65.30	0.07%	3	0.41%	6.88%	2.00%	5.22	4.88%	12.00
USAA	8,199.18	8.46%	74	10.22%	9.24%	3.62%	4.69	5.61%	38.30
Validus Re	400.00	0.41%	3	0.41%	9.21%	5.01%	1.85	4.20%	48.00
Vesta Fire Ins.	41.50	0.04%	1	0.14%	4.16%	0.70%	5.94	3.46%	36.00
XL Insurance (Bermuda)	2,200.00	2.27%	18	2.49%	9.09%	4.97%	2.11	4.12%	41.50
Zenkyoren (Japan)	3,445.00	3.56%	15	2.07%	2.68%	0.69%	4.93	1.99%	56.13
Zurich Insurance Group	842.00	0.87%	5	0.69%	6.70%	1.33%	5.33	5.38%	34.40
Grand Total	96,871.36	100.00%	724	100.00%	7.64%	2.60%	6.35	5.04%	37.02

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Table 2 – continued from previous page

Issuer	Size ($m)	% Size	Obs.	% Obs.	Premium (%)	EL (%)	P/EL	EER (%)	Term

Note: This table shows the aggregate characteristics of CAT bonds issued by all the issuers in the CAT bond market since inception. The table displays the total issue size (in millions of US dollars), total number of issues (Obs), the average premium, average expected loss (EL), the average multiple of the premium with respect to the expected loss (P/EL), the expected excess return (EER) and the average bond term in months for each issuer. In addition, the total issue size and number of observations for each issuer are displayed as a percentage of the total. These characteristics are given for CAT bonds issued between June 1997 and March 2020 in the primary market.

In Table 3, we present summary statistics of the 724 CAT bond dataset over the observation period, where the data is summarised in terms of key bond specific characteristics: peril type, trigger type and rating category. We provide details on the issue quarter (Q1-Q4) as this will be examined in our analysis. In Table 3, *P/EL* is a ratio or *multiple* that gives the number of times the premium is higher than the expected loss; this is normally higher during hard markets. Also, *EER* is the *expected excess return*, which is given by the premium minus the expected loss, consequently it is a measure of investor compensation required for taking on a given level of risk (measured in terms of expected loss).

Table 3: Summary data characteristics

	Size ($m)	Obs. (No)	P(%)	EL (%)	P/EL	EER (%)	Term
Peril							
Peak	65,718.53	460	7.89	2.60	6.54	5.29	36.00
Multiperil	12,927.30	127	9.65	3.41	7.80	6.24	36.53
Non-Peak	12,111.42	91	4.85	1.54	5.24	3.31	42.59
Diversifying	6,114.11	46	5.13	2.45	2.69	2.69	37.67
Trigger							
Hybrid	2,145.50	33	13.96	5.21	3.33	8.75	33.33
Indemnity	47,801.66	307	6.71	2.37	8.11	4.34	38.19
Industry loss	29,545.90	200	8.98	3.08	4.07	5.89	37.43
Modelled loss	3,951.10	40	7.18	1.62	6.36	5.57	36.20
Parametric	13,427.20	144	6.46	2.10	6.45	4.36	35.06
Rating							
High yield	49,571.41	396	7.47	1.86	5.04	5.60	35.34
Investment grade	3,199.60	33	2.34	0.15	49.46	2.19	35.76
Not Rated	44,100.35	295	8.47	3.87	3.29	4.60	39.43
Issue Quarter							
Quarter 1	20,443.26	149	7.22	2.40	7.76	4.81	38.30
Quarter 2	41,865.46	304	7.38	2.42	6.43	4.96	36.78
Quarter 3	8,678.50	63	7.33	2.24	7.58	5.09	35.73
Quarter 4	25,884.14	208	8.42	3.12	4.85	5.30	36.86
Grand Total	96,871.36	724	7.64	2.60	6.35	5.04	37.02

Note: This table summarises the main characteristics of the key variables included in our sample. These include the bond peril, the bond trigger, the bond rating at issue, and the issue quarter. For each of these variables, the size of issue (in millions of US dollars), the number of bonds/observations (Obs.No), the expected loss (EL), the premium (P), the multiple of the premium given the expected loss (P/EL), the expected excess return (EER), and the bond term (in months) are given. These values are calculated for the full dataset of 724 CAT bonds issued in the primary market between June 1997 and March 2020.

In Table 4, we present summary statistics of the 724 CAT bond dataset over the observation period, where the data is summarised in terms of the bond's credit rating. We provide details on the size, premium, expected loss, and other pertinent characteristics. As can be observed from Table 4, the investment-grade bonds have lower premiums P, due to their low expected loss values EL, whereas non-rated and high credit risk bonds have higher premiums.

Table 4: Catastrophe bond ratings

Lowest Rating	Size ($m)	Obs. (No)	P(%)	EL (%)	P/EL	EER (%)	Term
AA	256.00	1	0.66	0.01	66.00	0.65	36.00
A+	26.50	1	1.01	0.01	144.29	1.00	36.00
A	647.60	1	1.77	0.01	177.00	1.76	36.00
A-	225.50	4	2.03	0.04	64.58	2.00	29.00
BBB+	509.50	5	2.45	0.08	119.51	2.37	43.20
BBB	225.00	2	2.77	0.07	82.20	2.70	36.00
BBB-	1,599.50	20	2.49	0.22	11.77	2.28	35.80
BB+	13,145.28	81	4.73	0.82	6.51	3.90	39.73
BB	12,038.68	77	5.96	1.06	6.26	4.89	33.45
BB-	9,244.05	103	6.67	1.43	4.98	5.25	36.01
B+	5,226.00	35	9.01	2.22	4.18	6.79	35.14
B	6,906.00	60	10.57	3.44	3.28	7.14	30.97
B-	2,721.40	39	12.23	4.07	3.04	8.16	34.72
NR	44,100.35	295	8.47	3.87	3.29	4.60	39.43
Grand Total	96,871.36	724	7.64	2.60	6.35	5.04	37.02

Note: This table summarises the CAT bond ratings (at issue) for the bonds included in the sample. The ratings are standardised to the Standard & Poors (S&P) scale, and can be split into three main groups. These are the investment-grade bonds (those with a BBB- rating and above); high-yield bonds (those with a B- rating and above, up to BB+); and the non-rated (NR) bonds. For each of the ratings displayed, the size of issue (in millions of US dollars), the number of bonds/observations (Obs.No), the expected loss (EL), the premium (P), the multiple of the premium given the expected loss (P/EL), the expected excess return (EER), and the bond term (in months) are given. These values are calculated for the full dataset of 724 CAT bonds issued in the primary market between June 1997 and March 2020.

In Table 5, we provide a summary of key statistical metrics (specifically the mean, median, standard deviation, minimum and maximum values) on key metrics, that is premium, term, expected loss, size and expected excess return.

Table 5: Summary descriptive statistics

Variable	Mean	Median	Std.Dev.	Minimum	Maximum
Size ($m)	133.800	100.000	117.371	1.800	1500.000
EER (%)	5.000	4.100	3.500	0.650	41.100
EL (%)	2.600	1.600	2.600	0.007	17.400
Premium(%)	7.600	6.100	5.100	0.660	49.900
Term (months)	37.025	36.000	12.067	5.000	69.000

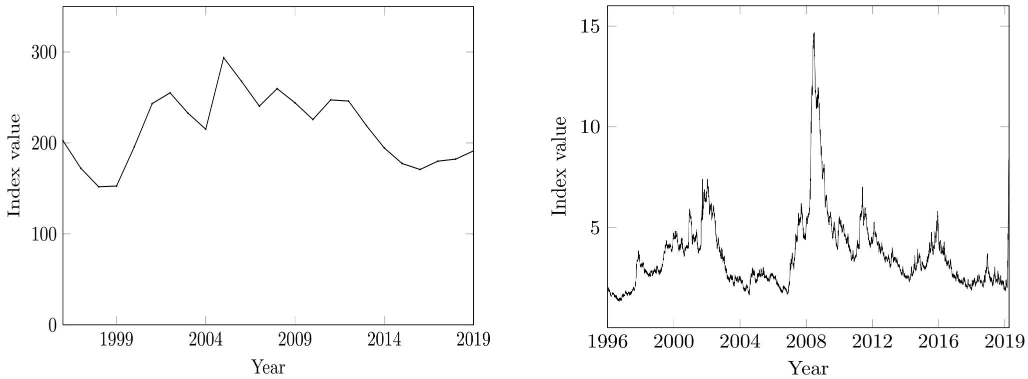
Note: This table summarises descriptive statistics of the key variables in our sample, excluding the reinsurance cycle and the competing financial environment, which are separately displayed. These variables include the bond issue size (in millions of US dollars), the expected loss (EL), the bond premium (P), the expected excess return (EER) (calculated as the difference between the premium and the expected loss), and the bond term (in months). The mean, median, standard deviation, and minimum and maximum values are displayed for each variable, for the full dataset of 724 CAT bonds issued in the primary market between June 1997 and March 2020.

In order to test the relation to the reinsurance cycle the Guy Carpenter[10] Global Property Catastrophe Rate on Line Index (GC Rol Index) is used as an indicator of the reinsurance cycle. This index is similarly applied in Gürtler et al. (2016), and is an index of global property catastrophe reinsurance rate-on-line movements, covering all major global catastrophe reinsurance markets. As our dataset covers CAT bonds with property-linked risks, this index is therefore a good representative of the state of the property reinsurance market.

Moreover, to test the relation to spreads in similar high-yield corporate bonds, we use the ICE Bank of America Merrill Lynch BB US High Yield Option-Adjusted Spread Index (denoted as variable BB Spread Index in our regression model). This index tracks the performance of US-dollar-denominated BB-rated corporate debt, publicly issued in the US domestic market. As the majority of the rated CAT bonds are assigned a BB rating, this index therefore contains securities that compete with the CAT bond market for investment. We provide graphs of the GC Rol Index and the Corporate BB Spread Index, respectively, in Figure 2.

[10]The Catastrophe Bond Market at Year-End: The Market Goes Mainstream (Retrieved 11 September 2020) https://www.gccapitalideas.com/2008/02/28/the-catastrophe-bond-market-at-year-end-the-market-goes-mainstream/

Figure 2: Graphs of the reinsurance cycle and the financial market



(a) GC Rate-on-Line Index (b) BB Spread Index

Note: The line graphs above display developments in the reinsurance cycle and the competing financial environment over the period of analysis. The reinsurance cycle is represented by the Guy Carpenter Global Property Catastrophe Rate on Line Index (GC Rate-on-Line Index), and is given annually for the period beginning January 1997 (for 1996) and ending January 2020 (for 2019). The competing financial environment is represented by the ICE Bank of America Merrill Lynch BB US High-Yield Option Adjusted Spread Index (BB Spread Index), and is given daily for the period beginning 31st December 1996 and ending 31st March 2020.

5 Methodology

5.1 Two-level Model

As discussed previously, CAT bonds have a nested data structure and therefore the TLM is most appropriate for regression analysis (see, for instance, Kreft and de Leeuw, 1998; Raudenbush and Bryk, 2010). From the CAT bond data used here, we observe the data is grouped by issuers and so the TLM is most suited to examining issuer effects, with each group associated with an issuer. Overall, TLMs are an extension of generalised linear models (Gelman and Hill, 2007), but are used to assess the extent of grouping in a sample. In particular, we will be applying the random intercept model from TLM. The random intercept TLM is given by Raudenbush and Bryk (2010)

$$Y_{ij} = \tilde{\beta}_{0j} + \sum_{k=1}^{p} \beta_k X_{ijk} + \varepsilon_{ij}, \tag{1}$$

where equation 1 is commonly referred to as the 'level 1' equation, and the 'level 2' equation is

$$\tilde{\beta}_{0j} = \beta_0 + u_{0j},$$

where Y_{ij} is the dependent variable for datapoint i in group j (in our application j represents a specific issuer), $\tilde{\beta}_{0j}$ is the random intercept for group j, with $k = 1, 2, ..., p$ independent variables in $X_{(.)}$, with associated coefficients β_k. The coefficients β_k are also known as 'fixed effects', whereas the random intercept $\tilde{\beta}_{0j}$ is also known as the 'random effect'. We assume the error terms $\varepsilon_{ij} \sim N(0, \sigma^2{}_e)$ and $u_{0j} \sim N(0, \sigma^2{}_u)$ are random and uncorrelated (Tolmie et al., 2011), with $N(.,.)$ denoting the Normal distribution function; u_{0j} is also known as the explained variation and ε_{ij} as the unexplained variation ε_{ij}. Furthermore, we notice that the intercept $\tilde{\beta}_{0j}$ varies for the issuer j. In pricing terms, if Y_{ij} represents the CAT bond premium, the model implies that the minimum premium charged for each CAT bond changes with each issuer.

A significant methodological advantage of TLM over other regression methods is that it does not require independent observations. As has been mentioned previously, issuers that issue frequently are able to gain better pricing terms than those issuers who issue less frequently (Spry, 2009) (presumably because investors trust more frequent issuers). By definition this implies a serial correlation in issue prices, and so we cannot assume observations are independent. Consequently other regression methods may result in misleading conclusions, whereas TLM will give more robust results.

It can be easily seen that the level 2 equation can be substituted into the level 1 equation, and so we have:

$$Y_{ij} = \beta_0 + u_{0j} + \sum_{k=1}^{p} \beta_k X_{ijk} + \varepsilon_{ij}. \tag{2}$$

We will be using this version of the random intercept TLM equation for ease of reference. Using equation (2), our proposed model for bond premium is given by (with

$p = 7$)

$$P_{ij} = \beta_0 + \beta_1 EL_{ij} + \beta_2 PeakMultiperil_{ij} + \beta_3 GCIndex_{ij} + \beta_4 BBSpread_{ij} + \\ \beta_5 Term_{ij} + \beta_6 IG_{ij} + \beta_7 Hybrid_{ij} + u_{0j} + \varepsilon_{ij}, \tag{3}$$

where P_{ij} is the bond premium for observation i in issuer (or group) j, *EL* represents the expected loss, *PeakMultiperil* represents all peak and multiperil bonds with dummy variable definition

$$PeakMultiPeril = \begin{cases} 1, & \text{if peak or multiperil.} \\ 0, & \text{if non-peak or diversifying,} \end{cases} \tag{4}$$

Term represents the bond term in months, *IG* represents an investment-grade rating with dummy variable definition

$$IG = \begin{cases} 1, & \text{if investment grade bond.} \\ 0, & \text{if not investment grade bond,} \end{cases} \tag{5}$$

Hybrid represents the trigger with dummy variable definition

$$Trigger = \begin{cases} 1, & \text{if hybrid.} \\ 0, & \text{otherwise,} \end{cases} \tag{6}$$

BBSpread is the high yield corporate bond index and *GCIndex* represents the reinsurance cycle index.

In the TLM, the regression coefficients $\beta_{(.)}$ represent sensitivities that affect premiums P, hence we can determine the importance of each independent variable upon P. The issuer effect is captured by the term u_{0j}; as the issuer changes this term changes and leads to different premiums P. Hence we are able to isolate the issuer effect from other parts of the regression model.

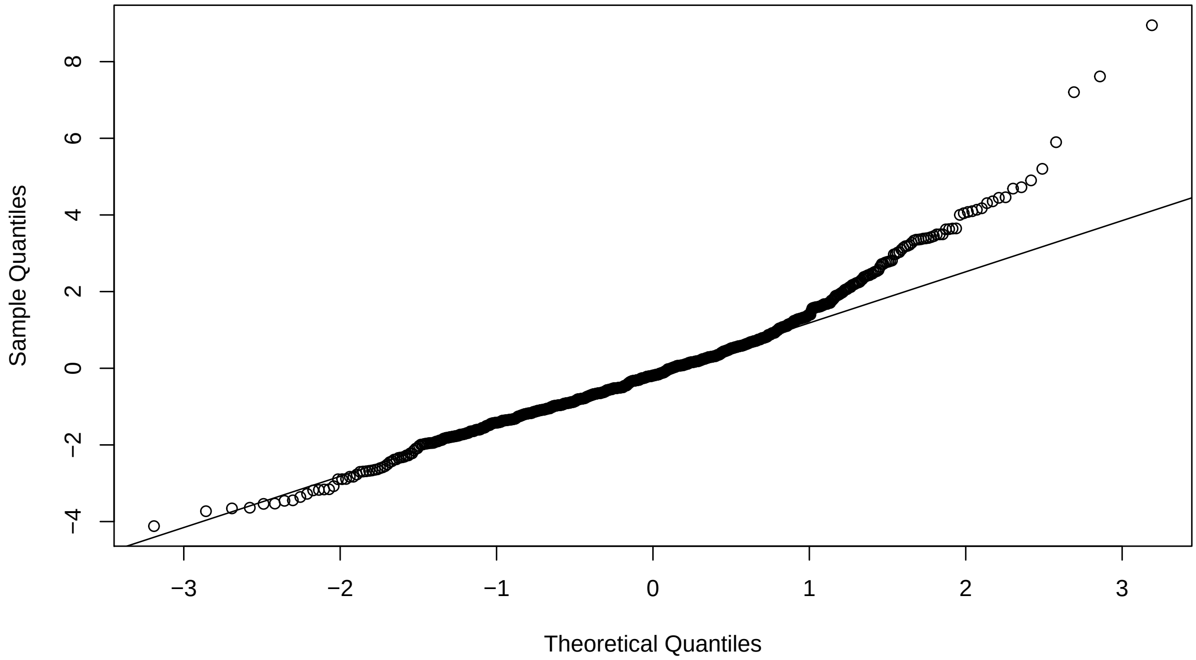
5.2 Method

In order to conduct our regression analysis, we exclude outliers from our final sample, which are identified using studentised deleted residual plots and Cook (1977)'s distance. To generate studentised deleted residuals, the observations are deleted one at a time, and the regression model is fitted to the remaining $n-1$ observations. The observed response values are then compared to the values from the refitted model to generate the deleted residuals. Thereafter, these deleted residuals are standardised to generate studentised residuals (Aguinis et al., 2013). Cook (1977)'s distance follows a similar process, and considers both residuals and leverage, i.e., both the independent and dependent variables.

Consequently, we exclude bonds that are identified as outliers by both the studentized residual plots and Cook (1977)'s distance, hence 20 bonds are excluded from the original sample of 724, leaving 704 bonds in the dataset. The excluded bonds typically involved unique underlying structures or covered unique properties, for example the Swiss Re Successor Series are priced at extremely high premiums and are different from any other bond ever issued. Consequently six bonds from the Swiss Re Successor Series are excluded.

In order to estimate the TLM parameters, we require a parameter estimation method. Whilst the standard estimation method is maximum likelihood estimation, we apply the *restricted maximum likelihood* (REML) estimation as REML has been shown to yield more accurate results for datasets where the normality assumption on standard errors do not hold (Forman, 2019). If we apply standard maximum likelihood we require a large sample size and that standard errors are normally distributed (Wang et al., 2011). Our dataset is sufficiently large enough given that our sample size consists of 704 CAT bonds and 101 issuers, giving a broad and diversified range of issuers; our sample size for TLM is also large enough based on recommendations in Maas and Hox (2005). In order to test for normality in standard errors, we generate a QQ plot of residuals (see Figure 3).

Figure 3: QQ-Plot of Residuals



Note: The figure above displays the distribution of residuals (sample quantiles) against theoretical normal residuals for our sample. For the normality of residuals assumption to hold, the plotted residuals should lie close to the diagonal line.

The majority of the data points should lie close to the straight line in the QQ plot for the normality assumption to hold. Although most of our data points lie on the straight line, they are still skewed to the right, hence maximum likelihood estimation would result in standard errors and other variance components that would be biased downward (e.g., Busing, 1993; van der Leeden et al., 2008). Consequently we apply the REML estimation method to obtain more robust results.

Furthermore, to test the relation between our model and issue specific factors (specifically the number of years for which the issuer has issued bonds in the primary CAT bond market, the issuer's total issue size since the inception of the CAT bond market, and the issuer's lines of businesses), the full dataset of 704 CAT bonds from 101 issuers is split it into sub-samples according to the specific factor of interest. For testing the relation between issue size and our model, the data is classified based on the total size of the bond issues in the CAT bond market since inception, for each issuer. The issuer data is then split into three equal sub-samples, each with approximately one-third of the total issuer population. Similarly, to estimate the effect of the issuer's line of business on our model, the data is split into three sets of observations based on each specific issuer's main line of business. A similar approach with data was also taken for the number of years the issuer has been active in the primary market.

6 Empirical Analysis

6.1 General Results

In our dataset, we observe in Table 3 that Q2 is the most dominant issue period by number of bonds issued, with 42% of all the bonds issued in this quarter, followed by Q4 at 29%, the first quarter (Q1) at 20%, and the third quarter (Q3) has the least number of issues at approximately 9%. This seasonal pattern of issuing can be explained by the fact that the hurricane season typically occurs in Q3 and so there is aversion to issuing new bonds at the most riskiest time. In Q2 we have maximum issues as it is just before the hurricane season and so greatest demand exists then for hedging catastrophic risks; this is also consistent with the conclusions in (Braun, 2016).

Furthermore, we observe in Tables 3 and 4 that non-rated bonds dominate the market, comprising 41% of our sample by number of bonds issued, with rated bonds making up the remaining 59%. In recent years, the number of rated bonds fell significantly, while non-rated bonds increased and this number is expected to increase for future issues. We also observe in Table 4 that high-yield bonds contribute to 55% of the 59% of rated bonds, whereas the investment-grade bonds contribute to 4% of the 59% of rated bonds. This suggests that there is significant demand for high risk CAT bonds, rather than low risk CAT bonds.

In Figure 2, we see the GC RoI Index graph exhibits spikes: after the 9/11 attacks in 2001, Hurricane Katrina in 2005, during the financial crisis, and after the 2017

Atlantic hurricane season that saw Hurricanes Irma, Harvey and Maria (among others) causing widespread losses. According to Swiss Re (2018), global insured losses from catastrophes in 2017 were estimated at US$136bn. As the GC RoI Index is an indication of the premium charged, Figure 2 implies that premiums increase following major catastrophes and/or extreme economic events. The BB Spread chart in Figure 2 further reinforces this point, with notable spikes in the index after 9/11 and during the financial crisis. One can also note that natural catastrophes do not seem to affect corporate spreads as much as they did for the GC RoI Index.

In Table 5, we observe in our dataset that the average premium in the CAT bond market is 7.6% whilst the median spread is 6.1% , implying that outliers might exist in the dataset and may significantly impact mean premium values. In Table 5, we observe that the mean expected loss is 2.6%, which implies the low expected loss of most catastrophic events. Finally, in Table 5, one can observe that the mean term of CAT bonds is 37 months (effectively three years) and a mean size of $133.8M, suggesting that most CAT bonds are issued as medium term investments and with very high monetary value.

In Table 6, we undertake some correlation analysis of our dataset in terms of key factors. In our dataset, we observe that CAT bond premium is significantly positively correlated with expected loss (0.7792), and at the 99% confidence interval. This is consistent with conclusions in the literature, whereby expected loss is a main determinant of CAT bond premiums. Secondly, we notice that GCIndex and bond premiums have a weak positive correlation at the 99% significant level (0.2585), this is not unexpected as we would expect the reinsurance cycle to have some impact on premiums.

Table 6: Correlation matrix of key variables

Variable	Premium	EL	GCIndex	BBSpread	Term	Size
Premium	1.0000					
EL	0.7792***	1.0000				
GCIndex	0.2585***	-0.0822**	1.0000			
BBSpread	0.1387***	0.0770**	0.2477***	1.0000		
Term	-0.2563***	-0.1361***	-0.2123***	0.0494	1.0000	
Size	-0.2454***	-0.1968***	-0.2329***	-0.1299***	0.1746***	1.0000

Note: This table displays the pairwise correlations of the key variables included in our sample. These include the CAT bond premium, the expected loss (EL), the reinsurance cycle (represented by the Guy Carpenter Index, GCIndex), the competing financial environment (represented by the BB Corporate Bond Index, BBSpread), the bond term (in months) and the bond size (in millions of US dollars). The significance of each of these values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

In Table 6, we observe that premiums are negatively correlated with bond size (-0.2454) and term maturity (-0.2563) at the 99% significance level. Whilst in standard (corporate) bonds we would expect premiums to increase with term maturity (due to the maturity premium) and size (due to liquidity preferences) such relations do not occur in the CAT bond market, as can be observed in our dataset in Table 6. This is because the most trusted or lower risk issuers tend to also issue larger size and term CAT bonds, whereas higher risk issuers tend to be able to issue only smaller size and shorter term CAT bonds. This is because higher risk issuers are less likely to be trusted with larger sums of money or effectively insure larger sums, as well as effectively insure over longer periods. Consequently, larger size and term CAT bonds have lower premiums as the (issuer) risks are considered lower. Finally, we notice that expected loss, GC Index, BBSpread, Term and Size are all generally weakly correlated, implying that such variables act independently in influencing bond premiums. This is consistent with expectations with bond premiums.

In conclusion, the Table 6 results are reassuring because they are consistent with the current literature on CAT bond premiums, hence this implies that we have a representative dataset for CAT bonds. Furthermore, the premium correlations with Term and Size imply that issuer risks are an important factor in influencing bond premiums rather than other factors. Hence, these empirical results also provide the motivation for TLM and examining the issuer effect in bond premiums.

6.2 Bond Specific Characteristics (Fixed Effects Analysis)

We now discuss the results relating to bond specific characteristics (or fixed effects) by examining Table 7. In Table 7, we present the results of our TLM intercept and regression coefficients ($\beta_0 - \beta_7$) with their associated significance levels, their standard errors, and their effect sizes. As we can observe from Table 7, all the fixed effects $\beta_0 - \beta_7$ are significant, with most of them at the 99% significance level.

Table 7: Fixed effect estimates

	Estimate	Standard error	Effect size
Fixed effects			
Intercept	-0.5907*	0.3440	
Expected Loss	1.3986***	0.0314	3.0141
PeakandMultiperil	2.2520***	0.1932	0.1984
GCIndex	0.0377***	0.0023	0.3845
BBSpread	0.4613***	0.0471	0.1283
Term	-0.0239***	0.0064	0.0166
IG	-2.6742***	0.3312	0.0994
Hybrid	0.7057**	0.3415	0.0035
Issuers	101		
Observations	704		

Note: This table provides estimates of the relationship between CAT bond premiums and factors affecting those premiums, excluding the effect of the bond issuer. The factors include the expected loss, the underlying peril, the reinsurance cycle (represented by the Guy Carpenter Index), the competing financial market environment (represented by the BB Spread Index), the bond term, the bond rating (Investment-Grade), and the bond trigger (Hybrid). The data covers all CAT bonds issued in the primary market between June 1997 and March 2020, and consists of 704 CAT bonds issued by 101 issuers after excluding outliers. Estimates are annualised percentage changes in premiums given a unit change in the covariates, and the effect size measure is derived through the Cohen's f^2 measure. The significance of each of these values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

The results in Table 7 support Hypothesis 2 (peril hypothesis). The results in

Table 7 show that, on average, premiums on peak and multi-peril bonds are approximately 2.25% higher than non-peak or diversifying bonds. This result is consistent with expectations because because peak and multiperil bonds tend to be higher risk than non-peak or diversiying bonds, hence higher risk is reflected by higher premiums.

The results in Table 7 support Hypothesis 3, that is hybrid triggered bonds require 0.71% more in premiums (at the 95% significance level) than non-hybrid bonds. This is a significant result given no prior research study has investigated hybrid triggers in premium pricing. This has probably not been investigated in prior research because it is likely that previously smaller sample sizes only existed for hybrid triggered bonds, hence an analysis on such bonds would have been infeasible. However, using our dataset we have a long and extensive set of data on hybrid triggered bonds and so enables us to investigate issues such as hybrid triggers. Therefore hybrid triggered bonds result in more expensive returns for issuers, and so issuers may not wish to provide such bonds if they can hedge out their risks with individual triggers.

In Table 7, we observe that the bond rating hypothesis (Hypothesis 4) is confirmed: highly rated bonds receive lower premiums when compared to either lower or non-rated bonds, with a difference of 2.67% on average. This is a significant impact on bond premium, with bond rating having the highest value regression coefficient in Table 7. This is consistent with expectations, given that credit rating is always a major factor in all bonds, and that the credit rating relates to the main risk of the bond, that is default.

In Table 7, we observe that the bond maturity has a minor impact on premium (Term's regression coefficient is -0.0239), although it is statistically significant at the 99% significance level. The results in Table 7 imply that increasing the bond term by one more month leads to a 0.02% decrease in premiums on average. Therefore maturity is negatively related to bond premiums and so we reject Hypothesis 5.

The negative relation between bond premium and maturity is a significant result for a number of reasons: firstly, it is a counter-intuitive result because bond premiums typically increase with maturity (due to the maturity premium effect) to compensate the investor for various risks, such as liquidity risk. Secondly, it is a result that has not been reported in previous studies, this is because prior studies used smaller sample sizes and less uptodate datasets. Our dataset is more extensive, enabling us to detect such factors more significantly (in statistical terms), moreover, the CAT bond market has significantly developed in the recent years with longer maturity bonds. Consequently, such maturity effects would only be detected using more recent data.

A potential explanation for a negative relation between bond maturity and premium is related to the issuer. The more trustworthy CAT bond issuers, who are less likely to withhold agreed payments, are also able to issue bonds with longer maturities. However, less trusted issuers can only issue shorter maturity bonds because there is less confidence in their ability to pay significant amounts of money over a longer period. As shorter maturity bonds tend to be associated with riskier issuers, this also means higher premiums tends to be associated with shorter maturities.

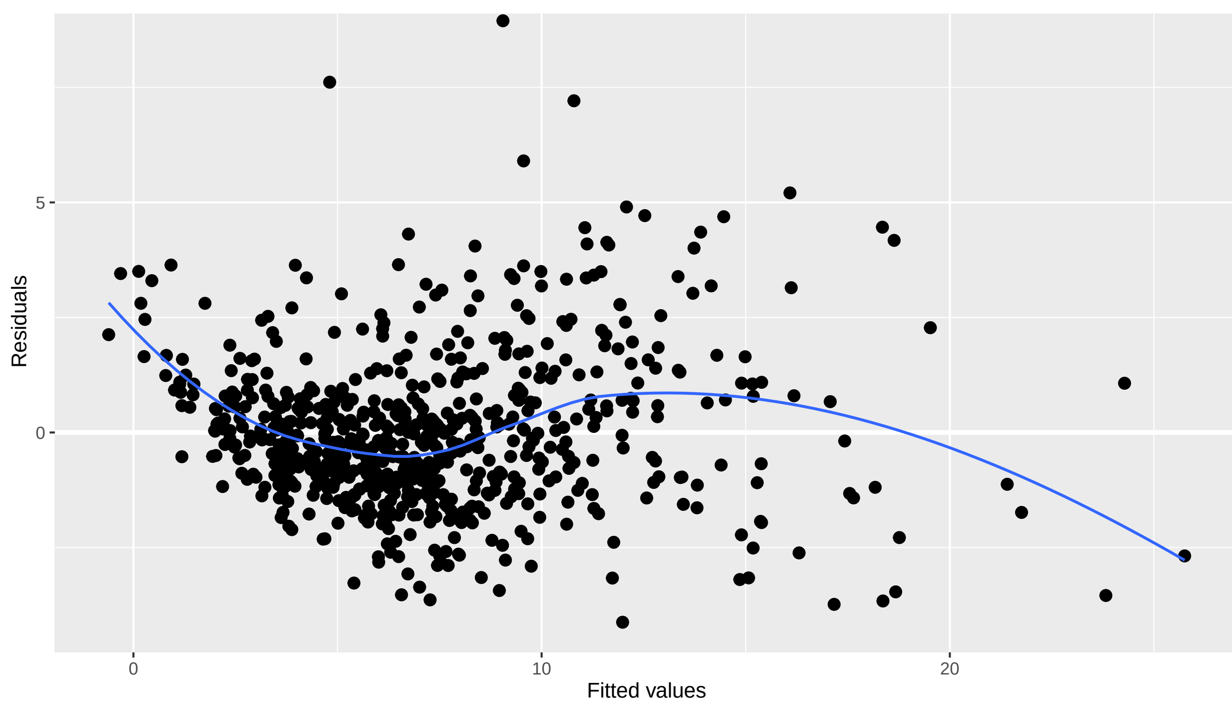
Finally, in Table 7, we can see both the reinsurance cycle (Hypothesis 6) and the state of the competing financial market (see Hypothesis 7) have an effect on premiums. Therefore, our results confirm our hypotheses and are consistent with previous studies (e.g., Gürtler et al., 2016; Lane, 2018). We expect reinsurance cycles to impact CAT bond pricing, since it has been empirically observed bond prices follow cyclical behaviour over time. Similarly, we expect a relation between the competing financial market and the CAT bond market, since both are bond investments and are affected by similar factors, e.g., riskless rate fluctuations.

The effect size is a measure of the magnitude of the effect of each independent variable on the variation in the dependent variable: according to Cohen (1992), the effect size is considered large at 0.35, medium at 0.15 and small at 0.02. To analyse effect size, we use a variation of the Cohen (1992)'s f^2 included in Selya et al. (2012). The effect size column in Table 7 implies that expected loss, peril type and the reinsurance cycle have the greatest effect on the variation in the CAT bond premiums; such factors are also identified in studies by Lane and Mahul (2008) as key factors that determine premiums. As one can see in Table 7, the effect size of the expected loss is exceedingly large (3.0141), implying it is by far the most important factor influencing variations in premiums than any other factors. This is consistent with theoretical relations between expected loss and CAT bond premiums (e.g., Lane, 2018).

6.3 Robustness Tests

Our first robustness test is that we need to test for linearity (Galeotti et al., 2013) and homogeneity of the variance for individual observations. On inspection of the figure below we may assume linearity and homogeneity hold, however for robustness we conduct an Analysis of Variance (ANOVA) test.

Figure 4: Homogeneity of variance



Note: The figure above displays the distribution of level 1 residual variance. For the homoscedasticity assumption to hold, the plotted residuals should be distributed equally above and below the blue line.

From the ANOVA results, we confirm linearity and homogeneity of variance. Furthermore, we undertook collinearity diagnostics for the fixed effects to test for non-collinearity. We calculated the variance inflation factors (VIF) and found we have a low variance inflation factors (VIF < 1.1) for all fixed effects, thus we can conclude that there is no-collinearity.

Our next set of robustness tests involved investigating alternative TLM models and comparing them to our final model. Firstly, we considered replacing the explanatory variable *Hybrid* with *Indemnity* to our model, which denotes indemnity triggers. Indemnity triggers provide an issuer's perfect hedge, as pay-outs are set equal to an issuer's actual losses, whereas non-indemnity triggers are not set equal an issuer's actual loss. Hence a non-indemnity trigger leads to imperfect hedges.

Our model therefore becomes

$$\begin{aligned} P_{ij} = \beta_0 + \beta_1 EL_{ij} + \beta_2 PeakMultiperil_{ij} + \beta_3 GCIndex_{ij} + \beta_4 BBSpread_{ij} \\ + \beta_5 Term_{ij} + \beta_6 IG_{ij} + \beta_7 Indemnity_{ij} + u_{0j} + \varepsilon_{ij}. \end{aligned} \tag{7}$$

Indemnity-triggered bonds would be expected to have higher premiums than non-indemnity triggered bonds because there is increased moral hazard risk to the investor (Doherty and Richter, 2002). There are also increased transaction costs because more due diligence is required compared to non-indemnity bonds (Cummins and Weiss, 2009).

Another model we consider is replacing explanatory variable *IG* with *Non-Rated*, which denotes the impact of a lack of credit rating on the CAT bond. The model therefore becomes

$$\begin{aligned} P_{ij} = \beta_0 + \beta_1 EL_{ij} + \beta_2 PeakMultiperil_{ij} + \beta_3 GCIndex_{ij} + \beta_4 BBSpread_{ij} \\ + \beta_5 Term_{ij} + \beta_6 Non-Rated_{ij} + \beta_7 Hybrid_{ij} + u_{0j} + \varepsilon_{ij} \end{aligned} \tag{8}$$

The majority of CAT bonds issued within the past eight years do not have a rating, consequently, investors price bonds by conducting their own due diligence on such bonds rather than relying on credit ratings. The variable *Non-Rated* therefore determines whether credit ratings influence pricing decisions, or that investors are more influenced by their own due diligence.

The third model we consider is adding the explanatory variable of seasonality *Quarter*, which denotes the CAT bond was issued in the second quarter (Q2). Our model therefore becomes

$$\begin{aligned} P_{ij} = \beta_0 + &\beta_1 EL_{ij} + \beta_2 PeakMultiperil_{ij} + \beta_3 GCIndex_{ij} + \beta_4 BBSpread_{ij} \\ &+ \beta_5 Term_{ij} + \beta_6 IG_{ij} + \beta_7 Hybrid_{ij} + \beta_8 Quarter_{ij} + u_{0j} + \varepsilon_{ij} \end{aligned} \tag{9}$$

The CAT bond issues mostly occur in the second (Q2) or fourth (Q4) quarter, where Q2 precedes the hurricane season. Therefore, it is assumed that there will be higher spreads allocated to this period compared to the other quarters, due to an increase in perceived risk.

The indemnity trigger *Indemnity* and Q2 *Quarter* variables are incorporated as dummy variables in the alternative regression models. For example, for *Quarter* we have

$$Quarter = \begin{cases} 1, & \text{if issued in the second quarter.} \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

We test the alternative models by conducting the goodness-of-fit tests based on the log-likelihood ratio (LLR) and the Akaike Information Criterion (AIC) (Akaike, 1974). The Likelihood Ratio Test (LRT) provides a way to compare models based on their likelihoods; in our case we compare the final model against the alternative models. The AIC, on the other hand, gives a measure of the information lost as the model's complexity increases by considering the estimated residual variance and the complexity of the model as additive terms (Chen and Li, 2017). The AIC equation is given below (Akaike, 1974):

$$AIC = -2 * ln(L) + 2k,$$

where L represents the maximum likelihood and k represents the number of estimated model parameters. A lower AIC value implies a better model fit.

In Table 8, we calculate the AIC for each of the alternative models and our final model. As can be seen in Table 8 all the alternative models result in higher AIC values than the final model (2837.5), implying the alternative models provide a worse fit to the data. Hence on an AIC basis our final model is superior and the alternative models do not improve our modelling. Whilst we see the LRT results are significant at the 99% confidence level for all models, as well as generally comparable to the final model's LRT (12.71), the final model has the lowest AIC, hence we conclude that the final model is the best model.

In Table 8, we report the conditional and marginal R-squared values (which are calculated based on Nakagawa and Schielzeth (2012)); they represent the amount of variation explained by the total of the fixed and random effects, and the variation explained by the fixed effects only, respectively. As can be observed in Table 8, in each case the conditional R-squared is greater than the marginal R-squared, implying that the amount of variation is better explained by the inclusion of the random effects than without it. Hence we conclude that modelling with random effects (which is incorporated in TLM) improves our model compared to fixed effects only models.

In Table 8, we calculate the intra-class correlation coefficient (ICC), which gives the variation explained by the random effects only. As can be seen in Table 8, the "indemnity trigger" and Issue Quarter models give higher ICC compared to our final model, however both models also have higher AIC. Consequently, these models do not provide a better fit and so we do not use these models.

Table 8: Model factor specification

	Final model	Indemnity	Not Rated	Issue Quarter 2
Marginal R^2	0.8172	0.8135	0.8040	0.817
Conditional R^2	0.8369	0.8377	0.8182	0.8368
ICC	0.1078	0.1297	0.0725	0.1082
AIC	2837.5	2840.9	2899.1	2841.5
LRT	12.71***	14.58***	7.90***	12.75***

Note: This table summarises the explanatory and fit properties of the final model in comparison to other models. The conditional and marginal R-squared values are calculated based on Nakagawa and Schielzeth (2012), with the conditional R-squared representing the amount of variation explained by the total of the fixed and random effects, and the marginal R-squared representing the variation explained only by the fixed effects. The intra-class correlation coefficient (ICC) gives the variation explained only by the random effects. In addition, the AIC and the likelihood ratio test (LRT) statistic are given. The significance of each of these values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively. These values are calculated for the full dataset of 704 CAT bonds (after exclusion of outliers) issued in the primary market between June 1997 and March 2020.

Finally, an additional robustness test that we may consider is to test the suitability between fixed and random effect models; the assumption of exogeneity in our model in that our level 2 errors are uncorrelated with independent variables. The Hausman Test (Hausman, 1978) is a possible method for standard applications in econometrics, however, for our dataset and model in particular, the test has some deficiencies. Firstly the test cannot distinguish effectively between small non-zero and zero correlations. This can lead to incorrect conclusions in model selection (see, for instance Dieleman and Templin, 2014), in fact in Clark and Linzer (2015), it is reported that the Hausman Test is neither a necessary nor sufficient statistic in choosing between fixed and random effect models. Secondly, the test is not informative for clustered data (see, Talloen et al., 2019, for a discussion), since class related factors can affect the test's results. As the CAT bond data consists of many clusters (related to 101 issuers), this poses a problem in the reliability of the Hausman Test for specific model.

In order to determine suitability between fixed and random effect models (or endogeneity in our model), we follow the methodology in Maddala (1971) and Castellano et al. (2014). The factor of endogeneity is typically an issue for small samples ($n < 30$), however for large samples one can assume regression estimates of random and fixed effects models converge.[11] In particular for our study, the CAT bond dataset contains over 704 observations and 101 issuers, we can therefore conclude that we have a large sample dataset and so can assume that endogeneity is not a significant factor in our study.

In addition to relying on the large sample assumption on regression estimates of random and fixed effects models converging (Castellano et al., 2014), we also regress both types of models in our experiments. We report that the regression coefficient values have an absolute difference with mean of 0.02 and median 0.007. We report that both models have similar regression coefficients, as one would expect under the large sample property, and so can assume regression coefficients of the random and fixed effects models converge. Therefore, based on our large sample dataset and our regression results, we conclude that the random effects model is an acceptable model.

6.4 Issuer Effects (Random Effects)

In this section, we investigate issuer effects: the impact of the issuing firm itself upon CAT bond pricing. This would be an unexpected effect in pricing on two key reasons: firstly the default risk of CAT bonds arises from the underlying catastrophe and is independent of the issuer's credit risk (Cummins, 2008). Secondly, the CAT bonds are issued by a bankruptcy-remote SPV, which implies that the credit risk of the SPV are independent of the issuer. Consequently, in theory, we should not expect any relation between issuers, CAT bond pricing and volatility.

Our first investigation involves comparing our TLM (with the random effect modelled) against a single level model (where there is no random effect term modelled), and determining whether the two are significantly different. In modelling terms, the inclusion of a random effect term implies that the issuer itself has an effect on the pricing, whereas no random effect in the model implies issuer effects are not important. We

[11] The reader is referred to Maddala (1971) and Castellano et al. (2014) for more information.

will test whether the two are significantly different by conducting the goodness-of-fit tests based on the LLR and the AIC.

In Tables 9 and 10, we report the LRT results: this is 12.7100 and is also significant at the 99.9% confidence level. Hence we can conclude that the model with random effects (i.e., our TLM) is a better fit for the data than a single level model (without the random effects). We note in passing that the two level model is a 10 parameter model, whereas the single level model is a 9 parameter model.

Table 9: ANOVA-like Table for Random Effects : Single term deletions

Deleted Variable	Parameters (No.)	logLik	AIC	LRT	Dof	Pr(>Chisq)
None	10	-1408.7	2837.5			
Random effect (issuer)	9	-1415.1	2848.2	12.71	1	0.0004***

Note: This table displays the goodness-of-fit test results for our two-level model when compared to a single-level model for our data. The random effect term (the issuer effect) is removed in the second model, and the two models then compared to determine which of the two provides the best fit for the distribution of the data. The model with a superior fit will have a lower Akaike information criterion (AIC) and a significant likelihood ratio test (LRT) statistic. The table also displays the number of parameters in each model (Parameters (No.)), the log-likelihood ratio (logLik) for each of the models, the degrees of freedom for the likelihood ratio test, i.e. the difference in the number of parameters between the two models, and the p-value based on the Chi-square distribution (Pr(>Chisq))Kuznetsova et al. (2017). The significance of the LRT is also indicated. The significance of each of these values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

Table 10: Hypothesis 1a: Random (issuer) effect estimates

	Estimate	Standard error
Random effects		
σ_u	0.5922**	0.1593
σ_e	1.7042***	0.1663
LRT	12.7100***	
ICC	0.1087	
Issuers	101	
Observations	704	

Note: This table summarises the effect of issuer variability on CAT bond premiums for all 101 issuers. The σ_u estimate gives the volatility introduced due to differences in pricing between issuers, while the σ_e term represents the level of unexplained volatility (σ_u accounts for 26% of total volatility). To determine whether the multi-level model provides a better fit for the data than a single-level model, we use the likelihood ratio test (LRT). A significant LRT would indicate that the multi-level model was indeed better than the single-level model. The intra-class correlation (ICC) indicates the proportion of the total variability in the premiums that arises due to issuer pricing differences (around 11% in this case). The significance of each of these values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

In Table 10, the size of the issuer effect can be determined from the ICC statistic, which can be interpreted as the amount of variation arising from random effects as a proportion of the total variation in the model (Lorah, 2018). The ICC indicates that around 11% of the variation in the regression model can be explained by issuer differences, hence the issuer effect on pricing is substantial.

In Table 10, we present results on σ_u, which represents the volatility in pricing between issuers, and σ_e which represents the volatility in the noise term ϵ. As can be seen in Table 10 σ_u is significant at the 95% confidence level and is a significant value (0.5922), also σ_e is 1.7 at the 99% confidence interval. As the total model volatility is given by the sum of σ_u and σ_e therefore significant volatility (or premium variation) is caused by σ_u: there is significant variation between premiums based on issuers alone. This implies that an issuer effect exists and so confirms Hypothesis 1a: bond premiums differ on similar bonds if we have different issuers.

We now examine total issue size effect (Hypothesis 1b). We investigate total issue size by splitting the CAT bond data into 3 categories: smaller medium and larger issues. The issue size is aggregated for all the bonds sold by the respective issuer, this determines the issuer's size group. The data is then split equally over the three groups to ensure each sub-sample contains an equal number of issuers. Hence the larger issue size represent the top one-third of all issuers, while the smaller issue size represent the bottom one-third of all issuers based on total issue size. All other issuers are included in the medium sub-sample. We then estimate the regression coefficients of our explanatory variables (fixed effects) and the random effect values, for each set of data; the results are presented in Table 11.

Table 11: Hypothesis 1b: Random effects by total issue size

	Larger issuers		Medium issuers		Smaller issuers	
	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error
Fixed effects						
Intercept	-1.3757***	0.4447	-1.8549**	0.8143	2.2975**	0.9146
Expected loss	1.4175***	0.0352	1.3171***	0.0861	1.2636***	0.0617
PeakandMultiperil	2.5655***	0.2277	1.8337***	0.4001	1.2350*	0.6079
GCIndex	0.0428***	0.0029	0.0310***	0.0049	0.0135**	0.0048
BBSpread	0.4211***	0.0508	1.1445***	0.1847	0.3892*	0.1868
Term	-0.0151**	0.0075	0.0043	0.0180	-0.0378*	0.0179
IG	-2.8340***	0.3952	-1.9867***	0.7303	-2.8524***	0.4926
Hybrid	0.6058	0.4010	1.7397***	0.6234	-0.3627	1.5218
Random effects						
σ_u	0.6200**	0.1914	0.0000†	0.4115	1.3408***	0.5374
σ_e	1.7440***	0.1896	1.4799***	0.5058	0.5803***	0.1140
ICC	0.1122		0.0000		0.8423	
Issuers	34		33		34	
Observations	558		92		54	

† In this instance, the variation associated with the issuer effect is so small compared to the background noise that this volatility is assumed to be zero.

Note: This table displays estimates of the factors affecting CAT bond premiums for different total issue sizes. The bond issue size is aggregated for all the bonds sold by the respective issuer to determine the issuer's sub-group. The data are then split equally over the three main sub-samples to ensure each sub-sample contains an equal number of issuers. Larger issuers represent the top one-third of all issuers, while the smaller issuers represent the bottom one-third of all issuers based on total issue size. All other issuers are included in the medium sub-sample. Finally, estimates and standard errors are calculated for both fixed and random effects. The significance of each of these values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

As can be observed from Table 11, for the explanatory variables (fixed effects) we notice that most values are significant at the 90-99% confidence level, furthermore, there is a general trend of increasing values as one progresses from smaller issue size to larger issue size. If we examine Expected loss, PeakandMultiperil and GCIndex we find that their values increase with issue size, implying that an issuer effect exists in terms of size.

If we examine the random effects in Table 11, we see that σ_u is a significant proportion of the total volatility in the model, and this appears to increase as issue size decreases. This is consistent with expectations: as issue size decreases there is likely to be a greater range of riskier issuers, since riskier issuers tend to be smaller issuers rather than large issuers. Consequently, we expect σ_u to increase, in fact σ_u=1.3408 for smaller issuers, which is almost twice σ_e. In conclusion our results in Table 11 confirm Hypothesis 1b, that is issuers with a higher total issue volume will have lower volatility in premiums compared to those with a lower total issue volume.

We now examine the impact that the number of years the issuer has participated in the primary CAT bond market impacts bond premium and volatility (Hypothesis 1c). The number of years for which the issuer has been issuing bonds in the primary CAT market effectively acts as a proxy for the issuer's reputation in the market, since less reputable issuers would exit the market through the market forces of competition. This assumption is consistent with Spry (2009), and results in issuers with better pricing terms.

We examine the number of years of the issuer participation in the primary CAT bond market in Table 12. This was achieved by grouping issuers into 3 categories: issuers who have only issued bonds in one year fall within the first class (one year), those who have been issuing for two or three years fall into the second class (two to three years), and those who have been issuing bonds for four years or more fall into the third class (four or more years). The time splits are chosen to ensure that each sample includes an adequate number of issuer observations. We then calculated estimates and standard errors for the fixed and random effects in each sub-group.

Table 12: Hypothesis 1c: Random effects by years in primary CAT market (reputation)

	One year		Two to three Years		Four years or more	
	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error
Fixed effects						
Intercept	1.0147	0.7524	0.0741	0.7033	-1.4230***	0.4893
Expected Loss	1.2545***	0.0671	1.3221***	0.0705	1.4303***	0.0377
PeakandMultiperil	1.4077***	0.4615	2.1600***	0.4992	2.4751***	0.2448
GCIndex	0.0200***	0.0048	0.0450***	0.0074	0.0431***	0.0030
BBSpread	0.2167	0.1898	0.2616*	0.1549	0.4542***	0.0534
Term	-0.0093	0.0155	-0.0309**	0.0141	-0.0155*	0.0081
IG	-2.1645***	0.4203	-4.6744***	1.0843	-2.7844***	0.4069
Hybrid	-0.4610	1.3704	0.3734	0.6783	0.5959	0.4121
Random effects						
σ_u	1.0964***	0.3836	1.0150*	0.5393	0.6139*	0.0140
σ_e	0.7387***	0.1527	1.3154***	0.2801	1.7906***	0.2086
ICC	0.6878		0.3732		0.1052	
Issuers	44		30		27	
Observations	72		121		511	

Note: This table provides estimates of the relationship between CAT bond premiums and factors believed to affect these premiums based on the issuer's longevity in the CAT bond market. The number of years for which the respective issuer has been issuing bonds in the primary CAT bond market is aggregated and each issuer allocated according to this length of time. Issuers who have only issued bonds in one year fall within the first class, those who have been issuing for two or three years fall into the second class, and those who have been issuing bonds for four years or more fall into the third class. The time splits are chosen to ensure that each sample includes an adequate number of issuer observations (level two variables) to aid analysis. Estimates and standard errors are then calculated for both fixed and random effects in each sub-group. The significance of each of these values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

As can be observed in Table 12, there exists trends between CAT bond participation and bond pricing. In the fixed effect variables in Table 12 we observe Expected Loss, PeakandMultiperil, GCIndex and BBSpread tend to increase in value as the number of years increases. As issuers with shorter participation periods tend to be perceived as riskier issuers (as they have a shorter trading history) their bond pricing may be less influenced by fundamental factors (such as Expected Loss and PeakandMultiperil) and more affected by their perceived risk. This supports the idea that the issuer itself has an impact on CAT bond pricing.

In Table 12, we examine the random effects variables. As can be observed from Table 12 we see that σ_u increases and becomes a greater proportion of total volatility as participation in the CAT bond market increases. Therefore bond pricing variation increases as participation history decreases. This is consistent with the idea that issuers with shorter trading histories are perceived as riskier, leading to a greater variation in bond premium. This impact is the smallest for those companies that have been issuing bonds over a longer time period, having a trusted investor base. As the company issues more and more bonds therefore, its terms of issue should also improve, and the effects of issuer characteristics on pricing should diminish. This is also evidenced by the decreasing ICC value in Table 12. In conclusion, our results in Table 12 confirm Hypothesis 1c, that is the longer the issuer participates in the primary CAT bond market, the lower the premium volatility.

We now examine the impact that the issuer's industry will have upon bond premiums and volatility than issuers in other industries (e.g., multi-line lines of business); this relates to Hypothesis 1d. We investigate this issuer effect by splitting our data into the following categories: we class data into 'Insurers' as those issuers whose businesses that primarily conduct insurance business; 'Reinsurers' include those issuers whose businesses primarily conduct reinsurance business or are syndicates of reinsurance; 'Multiline/Others' includes all other business activities, including those businesses that conduct both insurance and reinsurance business, investment managers, or insurance agents. We also include companies not operating in the financial services sector within

‘Multiline/Others’, including supranational organisations and utility companies.

In Table 13, we can see some significant patterns exist between insurer and non-insurer businesses in bond pricing and volatility. If we first examine the fixed effect variables, we see that Expected Loss, PeakandMultiperil, GCIndex, IG and Hybrid tend to have less of an impact on bond pricing for insurers than non-insurers. Additionally, if we examine the random effects variables, we see σ_u is highest for insurers than non-insurers, as well as a higher proportion of total volatility. Consequently, we see that insurers tend to be perceived as higher risk issuers compared to non-insurers. This might be a consequence of the sizes of the companies that fall into each of these classifications, with reinsurers and multi-line companies being significantly larger in size than most insurers, especially since they need to be able to take on insurer losses. This ability can afford such companies a lower risk rating than smaller insurance companies. In conclusion, we therefore confirm Hypothesis 1d, that is issuers in the insurance industry will have higher volatility than issuers in other lines of business.

We now wish to examine the impact of market cycles on issuer specific effects. We investigate market effects by splitting our data according to the state of the cycle prevailing at the time of the issue. We therefore create two sub-samples of data, one representing hard market issues (where premiums ought to be higher) and the other group representing soft or neutral market issues (where premiums ought to be lower or stable, respectively). The fixed and the random effects, with their respective estimates and standard errors, are reported in Table 14.

In Table 14, the results show that random effects are significant only in the soft or neutral market periods, but not in the hard market. This could be because other factors, particularly the fixed effects, have a larger impact on premium variability in hard market periods than the issuer, evidenced by higher estimates for the fixed effects in hard markets. The proportion of variability based on the ICC is therefore higher in soft or neutral markets due to the higher impact of issuer differences and lower impact of fixed effects on premiums.

Finally, we wish to examine the impact on the time period on issuer effects, over

Table 13: Hypothesis 1d: Random effects by issuer's line of business

	Insurers		Reinsurers		Multiline/Others	
	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error
Fixed effects						
Intercept	0.2833	0.7799	-0.4213	0.7526	1.3377**	0.4616
Expected Loss	1.3330***	0.0747	1.3549***	0.0619	1.4195***	0.0427
PeakandMultiperil	1.3725***	0.4660	2.5580***	0.4546	2.6479***	0.2332
GCIndex	0.0258***	0.0041	0.0377***	0.0049	0.0408***	0.0031
BBSpread	0.5643***	0.0890	0.6000***	0.1023	0.3638***	0.0662
Term	-0.0209	0.0146	-0.0316**	0.0151	-0.0137*	0.0079
IG	-1.4306**	0.6087	-1.9646***	0.7060	-3.4174***	0.4575
Hybrid	0.2551	1.6248	0.8084	0.7004	0.4566	0.4100
Random effects						
σ_u	0.7892**	0.2538	0.6116	0.3981	0.0000†	0.0293
σ_e	1.3947***	0.2243	1.5628***	0.3371	1.8432***	0.2253
ICC	0.2425		0.1328		0.0000	
Issuers	47		27		27	
Observations	194		144		366	

† In this instance, the variation associated with the issuer effect is so small compared to the background noise that this volatility is assumed to be zero.

Note: This table displays estimates of the factors affecting CAT bond premiums based on the issuer's main line of business. 'Insurers' include those businesses that primarily conduct insurance business; 'Reinsurers' include those businesses that primarily conduct reinsurance business or are syndicates; and 'Multiline/Others' includes all other companies, including those that conduct both insurance and reinsurance business, investment managers, or insurance agents. Companies not operating in the financial services sector are also included within this classification, including supranational organisations and utility companies. Each issuer is then allocated into their respective sub-groups and estimates and standard errors calculated for both fixed and random effects. We note that σ_u accounts for 36% of total volatility in Insurers. The significance of each of the values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

Table 14: Robustness by state of market cycle at issue

	Hard market		Soft or neutral market	
	Estimate	Standard error	Estimate	Standard error
Fixed effects				
Intercept	-0.2640	0.4936	-1.5230***	0.4011
Expected Loss	1.4192***	0.0506	1.3858***	0.0314
PeakandMultiperil	2.7479***	0.2793	1.9092***	0.2126
GCIndex	0.0337***	0.0032	0.0395***	0.0027
BBSpread	0.5808***	0.0604	0.3760***	0.0725
Term	-0.0297***	0.0097	0.0034	0.0069
IG	-2.2472***	0.5815	-2.7234***	0.3213
Hybrid	0.7559	0.5834	0.7356**	0.3392
Random effects				
σ_u	0.4780	0.2797	0.5751**	0.1439
σ_e	1.8942***	0.3268	1.2406***	0.1235
ICC	0.0603		0.1769	
Issuers	78		65	
Observations	329		375	

Note: This table provides estimates of the extent to which the chosen independent variables impact CAT bond premiums over the state of the market cycle. The data are split according to the state of the cycle prevailing at issue. This results in two sub-samples, one representing hard market issues where premiums are assumed to be higher than expected and the other representing soft or neutral market issues where premiums are assumed to be lower or stable respectively. Both the fixed effects and the random effects are displayed, with their respective estimates and standard errors. The significance of each of these values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

Table 15: Robustness by time period

	1997-2010		2011-2020	
	Estimate	Standard error	Estimate	Standard error
Fixed effects				
Intercept	0.9287**	0.4548	-1.9594***	0.4514
Expected Loss	1.8603***	0.0581	1.3127***	0.0329
PeakandMultiperil	2.1222***	0.2409	2.2988***	0.2560
GCIndex	0.0156***	0.0032	0.0530***	0.0037
BBSpread	0.3416***	0.0522	0.3727***	0.0941
Term	-0.0125	0.0084	-0.0003	0.0089
IG	-2.1723***	0.3434	-2.0310	1.4696
Hybrid	-0.1225	0.3991	-0.1759	0.5796
Random effects				
σ_u	0.5822*	0.1969	0.5281*	0.1469
σ_e	1.6237***	0.2206	1.4415***	0.1672
ICC	0.1139		0.1183	
Issuers	53		72	
Observations	323		381	

Note: This table provides estimates of the extent to which the chosen independent variables impact CAT bond premiums over two (almost) equal time periods. The data are divided into two sub-samples: one representing the early CAT bond issues (1997-2010), and the other representing more recent CAT bond issues (2011-2020). The data is split almost exactly in half to ensure the retention of a sufficient number of issuers (the level two variable) in each sample to aid comparison. Both the fixed effects and the random effects are displayed, with their respective estimates and standard errors. The significance of each of these values is also indicated. Significance at 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

two (almost) equal time periods: one representing the early CAT bond issues (1997-2010), and the other representing more recent CAT bond issues (2011-2020). The data is split almost exactly in half to ensure the retention of a sufficient number of issuers in each sample. Both the fixed effects and the random effects are calculated in Table 15, along with their respective estimates and standard errors.

In Table 15, we see that in both samples the random effects and most of the fixed effects are significant, at least at a 90% confidence level. Random effects are significant at 90% confidence, with around 12% of the total variation in premiums being explained by issuer differences. Fixed effects including the expected loss, the underlying bond peril, the reinsurance cycle and the competing financial environment are significant at a 99% confidence level in both time periods, while the term and trigger variables are insignificant. The rating variable, representing investment-grade bonds, is significant only in the pre-2010 sample (1997-2010), and insignificant in the post-2010 sample (2011-2020). This can be explained by the fact that most bonds issued after 2010 do not have a rating, and those that do are mainly non-investment grade bonds. The effect of the investment-grade rating is therefore mainly observed in the first sub-sample.

7 Conclusion

This study investigates the bond specific and the issuer specific pricing factors in the primary catastrophe (CAT) bond market. This paper is the first to apply the two-level model (TLM) analysis technique, utilising the random intercept model, to CAT bond data. The TLM is able to produce more reliable and robust results for CAT bond data because TLM enables modelling of data with a grouped data structure, unlike other regression modelling methods that are currently used in CAT bond analysis. Consequently, we can also isolate out issuer-specific variable factors from bond specific pricing factors more robustly.

Our TLM model and empirical results support deductions that, all else constant, differences in premiums exist between issuers. The differences are attributable to issuer's duration of activity in the market (which is a proxy for reputation), issuer characteristics and total size of issues. In fact, issuers with smaller total issue sizes and a shorter activity period in the primary market tend to exhibit more variability, with stability in pricing increasing as the issuer's duration within the CAT bond market increases. Also, issuers conducting mainly insurance business experience higher volatility in premiums than those in reinsurance or multi-line businesses. In addition to issuer specific variables, we investigated key bond specific explanatory variables, similar to those identified in previous studies (e.g., Braun, 2016; Gürtler et al., 2016; Lane, 2018). We also investigate explanatory variables: expected loss, peril, term, trigger, rating, reinsurance cycle and state of the competing financial environment.

In our study, we produce a hand-collected, large and extensive dataset on CAT bonds, which is the largest CAT bond dataset to the best of our knowledge. The large dataset size enabled us to identify that, counter-intuitively, CAT bond premiums decrease with bond maturity (unlike in standard corporate bonds) and that hybrid triggers increase bond premiums. The dataset also contains issuer specific information and enables to determine issuer specific factors that affect CAT bond pricing.

In terms of future research, one could investigate additional pricing factors in CAT bonds, such as issuer specific and market specific factors. Secondly, one could investigate further factors, tests and relationships by collating and creating additional hand-collected data sources for CAT bonds. In addition, other techniques that do not rely on the assumptions of maximum likelihood estimation, e.g., non-parametric bootstrap techniques, could be used to further test for these relationships. Finally, one could investigate alternative methods of catastrophe hedging and analyse their relation to catastrophe bonds, such as risk and return relationships.

References

H. Aguinis, R. K. Gottfredson, and H. Joo. Best-practice recommendations for defining, identifying, and handling outliers. *Organizational Research Methods*, 16(2):270–301, 2013.

H. Akaike. A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6):716–723, 1974.

Z. Bodie, A. Kane, and A. J. Marcus. *Investments*. The McGraw-Hill/Irwin series in finance, insurance and real estate. Mc-Graw-Hill Education, New York, NY, 10th edition, 2014.

A. Braun. Pricing in the primary market for Cat bonds: New empirical evidence. *Journal of Risk and Insurance*, 83(4):811–847, 2016.

F. M. T. A. Busing. Distribution characteristics of variance estimates in two-level models: A monte carlo study. *Leiden Psychological Reports: Psychometrics and Research Methodology*, 4, 1993.

P. Carayannopoulos, O. Kanj, and M F. Perez. Pricing dynamics in the market for catastrophe bonds. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 47:172–202, 2022.

K. E. Castellano, S. Rabe-Hesketh, and A. Skrondal. Composition, context, and endogeneity in school and teacher comparisons. *Journal of Educational and Behavioral Statistics*, 39(5):333–367, oct 2014.

C. W. Chang, Y.-J. Wang, and M.-T. Yu. Catastrophe bond spread and hurricane arrival frequency. *The North American Journal of Economics and Finance*, 54: 100906, 2020.

B-S. Chen and C-W. Li. *Big Mechanisms in Systems Biology*. Elsevier, 2017.

T. S. Clark and D. A. Linzer. Should i use fixed or random effects? *Political Science Research and Methods*, 3(2):399–408, 2015.

J. Cohen. Statistical power analysis. *Current Directions in Psychological Science*, 1 (3):98–101, 1992.

R. D. Cook. Detection of influential observation in linear regression. *Technometrics*, 19(1):15–18, 1977.

S. H. Cox and H. W. Pedersen. Catastrophe risk bonds. *North American Actuarial Journal*, 4(4):56–82, 2000.

J. D. Cummins. Cat bonds and other risk-linked securities: State of the market and recent developments. *Risk Management & Insurance Review*, 11(1):23–47, 2008.

J. D. Cummins and O. Mahul. *Catastrophe Risk Financing in Developing Countries : Principles for Public Intevrvention*. The World Bank, Washington, D.C, 2009.

J. D. Cummins and M. A. Weiss. Convergence of insurance and financial markets: Hybrid and securitized risk-transfer solutions. *Journal of Risk and Insurance*, 76(3): 493–545, 2009.

J. D. Cummins, N. Doherty, and A. Lo. Can insurers pay for the big one? measuring the capacity of the insurance market to respond to catastrophic losses. *Journal of Banking & Finance*, 26(2-3):557–583, 2002.

J. L. Dieleman and T. Templin. Random-effects, fixed-effects and the within-between specification for clustered data in observational health studies: a simulation study. *PloS ONE*, 9(10):e110257, 2014.

N. A. Doherty and A. Richter. Moral hazard, basis risk, and gap insurance. *Journal of Risk & Insurance*, 69(1):9–24, 2002. ISSN 0022-4367.

J. Forman. Introduction to linear mixed models for repeated measurements data: Analysis of single group studies with sas proc mixed. Section of Biostatistics, University of Copenhagen, November 2019.

K. A. Froot. The evolving market for catastrophic event risk. *Risk Management & Insurance Review*, 2(3):1–28, 1999.

K. A. Froot. The market for catastrophe risk: a clinical examination. *Journal of Financial Economics*, 60(2-3):529–571, 2001.

K. A. Froot and P.G.J. O'Connell. On the pricing of intermediated risks: Theory and application to catastrophe reinsurance. *Journal of Banking & Finance*, 32(1):69–85, 2008.

M. Galeotti, M. Gürtler, and C. Winkelvos. Accuracy of premium calculation models for CAT bonds-an empirical analysis. *Journal of Risk and Insurance*, 80(2):401–421, 2013.

A. Gelman and J. Hill. *Data Analysis Using Regression and Multilevel / Hierarchical Models: Analytical Methods for Social Research*. Cambridge University Press, 2007.

T. Goetze and M. Gürtler. Hard markets, hard times: On the inefficiency of the CAT bond market. *Journal of Corporate Finance*, 62:101553, 2020.

M. Gürtler, M. Hibbeln, and C. Winkelvos. The impact of the financial crisis and natural catastrophes on CAT bonds. *Journal of Risk and Insurance*, 83(3):579–612, 2016.

B. Hagendorff, J. Hagendorff, K. Keasey, and A. Gonzalez. The risk implications of insurance securitization: The case of catastrophe bonds. *Journal of Corporate Finance*, 25:387–402, 2014.

J. A. Hausman. Specification tests in econometrics. *Econometrica*, 46(6):1251–1271, 1978.

N. Karagiannis, H. Assa, A.A. Pantelous, and C.G. Turvey. Modelling and pricing of catastrophe risk bonds with a temperature-based agricultural application. *Quantitative Finance*, 16(12):1949–1959, 2016.

I. Kreft and J. de Leeuw. *Introducing Multilevel Modeling*. SAGE Publications, Ltd, United Kingdom, 1998.

A. Krutov. *Investing in Insurance Risk: Insurance-Linked Securities: a Practitioner's Perspective*. Risk Books, London, 2010.

H. Kunreuther. *Insurance and Behavioral Economics: Improving Decisions in the Most Misunderstood Industry*. Cambridge University Press, Cambridge, 2012.

A. Kuznetsova, P.B. Brockhoff, and R.H.B. Christensen. lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software*, 82(13), 2017.

V.S. Lai, M. Parcollet, and B.F. Lamond. The valuation of catastrophe bonds with exposure to currency exchange risk. *International Review of Financial Analysis*, 33: 243–252, 2014.

M. Lane and O. Mahul. Catastrophe risk pricing: An empirical analysis. *Policy Research Working Papers*, 2008. doi: 10.1596/1813-9450-4765.

M. N. Lane. Pricing cat bonds: Regressions and machine learning: Some observations, some lessons, 2018.

J. Lorah. Effect size measures for multilevel models: Definition, interpretation, and TIMSS example. *Large-scale Assessments in Education*, 6(8), jul 2018.

C. J. M. Maas and J. J. Hox. Sufficient sample sizes for multilevel modeling. *Methodology*, 1(3):86–92, 2005.

G. S. Maddala. The use of variance components models in pooling cross section and time series data. *Econometrica*, 39(2):341–358, 1971.

J. A. Major. Methodological considerations in the statistical modeling of catastrophe bond prices. *Risk Management & Insurance Review*, 22(1):39–56, 2019.

J. A. Major and R. E. Kreps. Catastrophe risk pricing in the traditional market. In *Alternative Risk Strategies*, pages 201–220. Risk Waters Group, 2002.

S. Nakagawa and H. Schielzeth. A general and simple method for Obtaining R2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution*, 4(2): 133–142, 2012.

G. Niehaus. The allocation of catastrophe risk. *Journal of Banking & Finance*, 26 (2-3):585–596, 2002.

J. A. Pearce II and I. A. Lipin. Special purpose vehicles in bankruptcy litigation. *Hofstra Law Review*, 40(1), 2011.

S. W. Raudenbush and A. S. Bryk. *Hierarchical Linear Models: Applications and Data Analysis Methods*, volume 1 of *Advanced quantitative techniques in the social sciences*. SAGE Publications LTD, 2nd edition, 2010.

A. S. Selya, J. S. Rose, L. C. Dierker, D. Hedeker, and R. J. Mermelstein. A practical guide to calculating cohen's f2, a measure of local effect size, from PROC MIXED. *Frontiers in Psychology*, 3, 2012.

J. Shao, A. Pantelous, and A. D. Papaioannou. Catastrophe risk bonds with applications to earthquakes. *European Actuarial Journal*, 5(1):113–138, 2015.

J. Spry. Non-life insurance securitization: Market overview, background and evolution. In *Handbook of Insurance Linked Securities*, pages 7–18. John Wiley and Sons Ltd., 2009.

Swiss Re. What are insurance–linked securities (ils), and why should they be considered?, September 2012. URL `https://www.casact.org/community/affiliates/CANE/0912/Cat-Bond.pdf`.

Swiss Re. Ils market update : September 2019, 2019. URL `https://www.swissre.com/our-business/alternative-capital-partners/ils-market-update-sept-2019.html`.

W. Talloen, T. Loeys, and B. Moerkerke. A bootstrap version of the hausman test to assess the impact of cluster-level endogeneity beyond the random intercept model. *Multivariate Behavioral Research*, 54(1):1–14, 2019.

A. Tolmie, D. Muijs, and E. McAteer. *Quantitative Methods in Educational and Social Research Using SPSS*. Open University Press, 2011.

R. van der Leeden, E. Meijer, and F. M.T.A Busing. *Handbook of Multilevel Analysis*, chapter 11, pages 401–433. Springer, New York, NY., 2008.

J. Wang, H. Xie, and J. Fisher. *Multilevel Models: Applications using SAS*. Walter de Gruyter, 2011.

L. J. White. Credit rating agencies: An overview. *Annual Review of Financial Economics*, 5(1):93–122, 2013.

M. Zheng. Heterogeneous expectations and speculative behavior in insurance-linked securities. *Discrete Dynamics in Nature and Society*, 2015, 2015.

A. A. Zimbidis, N. E. Frangos, and A. A. Pantelous. Modeling earthquake risk via extreme value theory and pricing the respective catastrophe bonds. *ASTIN Bulletin: The Journal of the IAA*, 37(1):163–183, 2007.