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PRICING IN THE PRIMARY MARKET FOR CAT BONDS: NEW EMPIRICAL EVIDENCE

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Pricing in the Primary Market for Cat Bonds: New Empirical Evidence

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Abstract

We present empirical evidence from the primary market for cat bonds, which provides new insights concerning the prevailing pricing practice of these instruments. For this purpose, transactional information from a multitude of sources has been collected and cross-checked in order to compile a data set comprising virtually all cat bond tranches that were launched between June 1997 and December 2012. In order to identify the main determinants of the cat bond spread at issuance, a series of OLS regressions with heteroskedasticity and autocorrelation consistent standard errors is run. Our results confirm the expected loss as the most important factor. Apart from that, covered territory, sponsor, reinsurance cycle, and the spreads on comparably rated corporate bonds exhibit a major impact. Based on these findings, we then propose an econometric pricing model for cat bonds in the primary market that is applicable across territories, perils, and trigger types. It exhibits a robust fit across different calibration subsamples and achieves a higher in-sample and out-of-sample accuracy than several competing specifications that have been introduced in earlier work.

Key Words: Cat Bonds, Newey-West Estimator, Econometric Pricing Model, Out-of-Sample Analysis

JEL Classification: G10; G12; G19; G22

1 Introduction

Throughout the last decade, the market for catastrophe (cat) bonds has witnessed substantial growth rates. Cat bonds are securities that pay regular coupons to investors unless a predetermined event occurs, leading to full or partial loss of capital. The principal is held by a special purpose vehicle (SPV) in the form of highly rated collateral and paid out to the hedging (re)insurer to cover its losses if the trigger condition, as defined in the bond indenture, has been met (see, e.g., Braun, 2011). The success of this type of insurance-linked security (ILS) is based on its popularity as an alternative risk transfer technique for (re)insurance companies and on its reputation for exhibiting an appealing risk-return profile as well as low correlations with traditional asset classes. Particularly institutional fixed-income investors are increasingly attracted by the instrument, since it is fully collateralized and offers an almost pure exposure to natural disaster risk in a familiar bond format (see Swiss Re, 2006). Although the cat bond asset class has withstood the major dislocations during the recent financial crisis fairly well, issuance volumes

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declined sharply in 2008. In the meantime, however, the size of the primary market has returned to pre-crisis levels. Unlike other securitizations, such as asset-backed securities (ABS), cat bonds still represent a niche segment of the global capital markets, but are starting to reach a critical scale relative to property-catastrophe reinsurance (see Cummins, 2008). Thus, it is safe to state that these instruments have firmly established themselves as a permanent alternative in the risk transfer domain. In addition, due to the securitization of new risk types, an increasingly liquid secondary market, and an ever expanding investor base, the future perspectives look bright (see, e.g., Cummins and Weiss, 2009; Deutsche Bank, 2010).

Despite their growing importance, a relatively limited amount of scholarly research has been devoted to the valuation of cat bonds so far. Most extant work in this regard is concerned with contingent claims (see, e.g., Lee and Yu, 2002 Wu and Chung, 2010 Jarrow, 2010) or equilibrium models (see, e.g., Cox and Pedersen, 2000 Egami and Young, 2008 Zhu, 2011). In contrast, pure econometric approaches, which are commonly employed in the empirical asset pricing literature, have not been firmly established yet. Although the latter may seem scientifically less satisfying at first glance, if their specification is chosen carefully based on economic theory, they can be a powerful means for the identification of major pricing determinants. Consequently, a factor pricing model with a sufficient degree of stability and accuracy, as proven by a battery of cross-sample and out-of-sample checks, may provide a valuable foundation for more intricate theoretical models.

The persisting lack of applied research on cat bond prices is mainly attributable to the scarcity of publicly available data. One of the earliest empirical studies is authored by Lane (2000), who fits a power function with two parameters, the probability of first loss and the conditional expected loss, to a small cat bond sample from 1999. Lei et al. (2008), in contrast, rely on a linear model and extend their analysis by the probability of exhaustion as well as transaction-specific characteristics such as maturity, issue size, trigger type, and rating. Their data set comprises 177 primary market deals, covering the period from 1997 to 2007. Similarly, Lane and Mahul (2008) examine about 250 tranches that have been issued between 1997 and early 2008, illustrating the impact of the underlying peril and the reinsurance cycle. Subsequently, they reestimate their model with small cross sections of secondary market prices at two different points in time. Dieckmann (2009) considers secondary market data for a cross section of 61 cat bonds before and after the occurrence of Hurricane Katrina in August 2005 to reveal significant spread drivers as well as the effect of mega-events on the pricing relation. The impact of the 2005 hurricane season is also examined by Ahrens et al. (2009), who draw on a Bayesian estimation technique to test the model of Lane (2000) based on 199 observations between 2003 and 2008. Furthermore, Gatumel and Guégan (2009) aggregate market maker quotes for a few cat bond tranches into an index time series, which they then employ to study the behavior of secondary market spreads from 2004 to 2009. Another analysis of the primary market is provided by Papachristou (2009), who explores factors that affect the cat risk premium by applying a generalized additive model to 192 bonds launched between 2003 and 2008. Bodoff and Gan (2009) rely on a sample of 115 transactions issued before 2008 to devise a pricing approach, incorporating expected loss, covered territory, and reference peril. Moreover, Jaeger et al. (2010) and Galeotti et al. (2012) compare the fit of different models that have been brought forward in the literature. In doing so, the former adopt both indicative cat bond and industry loss warranty (ILW) prices as of August 31, 2009, while the latter use primary market spreads for 176 issues between 1999 and 2009. Finally, the most sophisticated secondary market study to date has been conducted by Guertler et al. (2014), who assess the impact of financial market turmoil and large natural disasters on cat bond spreads by means of panel data methodology.

Owing to these prior efforts, much is already known about the role of the expected loss in cat bond pricing as well as the suitability of different functional forms for premium calculation models. Nevertheless, further determinants of the primary market spread are still not sufficiently well understood. Apart from that, some of the earlier analyses appear to suffer from drawbacks such as small sample sizes, inconsistent standard errors, and selection bias. The paper at hand is intended to address these issues by providing new empirical evidence from the primary market. Our contributions are threefold. First, we have compiled the most comprehensive cat bond data set considered in the literature to date, comprising 466 tranches that were issued between June 1997 and December 2012. Hence, our analysis is going to account for every important stage since the inception of this market in the 1990s such as its takeoff period, the hard market following Hurricane Katrina in 2005, and the global financial crisis of 2008. Second, we identify the main drivers of the cat bond spread at issuance by running a series of ordinary least squares (OLS) regressions with heteroskedasticity and autocorrelation consistent (HAC) standard errors. Third, based on the respective findings, we introduce an econometric pricing model for cat bonds in the primary market and assess its in-sample and out-of-sample accuracy relative to other, rather actuarially-oriented specifications that have been suggested in the literature.

The remainder of this paper is organized as follows. In Section 2, we review the typical characteristics of cat bond transactions such as the structure, the trigger types, and the underlying perils, and derive a range of testable hypotheses. The empirical analysis is conducted in Section 3. Here, we describe our data set, document a number of facts about the primary market for cat bonds, provide a multitude of descriptive statistics, and test the significance of various potential spread determinants. In Section 4, we then propose the econometric pricing model and evaluate its performance. Finally, in Section 5, we summarize our main results and draw our conclusion.

2 Background and Development of Hypotheses

2.1 Catastrophe Bonds

Cat bonds have been developed by insurers and reinsurers as a means to transfer natural disaster risks to the capital markets. As depicted in Figure 1, at the heart of a typical transaction is an SPV that sells protection against catastrophe losses to the ceding entity called sponsor via a reinsurance contract (or a cat swap).[1] To fund the risk incurred thereby, the SPV issues securities to investors and uses the proceeds to purchase collateral, which are then held in a trust account. In case a catastrophic event occurs

[1] For a comprehensive discussion of cat swap contracts refer to Braun (2011).

before maturity (or during a predefined risk period) and triggers the embedded reinsurance contract, the collateral is liquidated to reimburse the sponsor, and investors lose all or part of their principal.[2] For bearing this risk they are compensated with regular coupons, consisting of a variable interest rate (e.g., LIBOR) plus a spread that will be denoted S^{CAT}throughout the course of this paper. This S^{CAT} governs the price of a cat bond and includes the expected loss of the tranche plus a risk premium.[3]

Until late 2008, it was common to protect the collateral against interest rate risk and impairment through a total return swap (TRS). In exchange for (fixed) coupons and value gains of the trust account assets, the swap counterparty provided a floating rate payment minus the TRS spread and covered potential value losses. However, the default of the investment bank Lehman Brothers, which acted as swap counterparty in four cat bond deals, revealed that the combination of TRS and inadequate collateral, in terms of both quality and maturity, is associated with a nonnegligible degree of credit risk (see, e.g., Cummins and Weiss, 2009).[4] Hence, the typical post-crisis structure shown in Figure 1 refrains from utilizing a TRS altogether (see, e.g., Towers Watson, 2010). Instead it relies on much tighter collateral arrangements, including strict criteria for permissible investments, intensified monitoring and mark-to-market requirements, as well as regular investor reports. Today's trust accounts are almost exclusively composed of money market funds that invest in short-term sovereign debt (discount notes), such as US T-Bills, on a rolling basis. Those are extremely secure, highly liquid, have easily observable prices, and minimize interest rate risk. Intransparent structured finance securities, in contrast, are no longer accepted. Another relatively recent development in the cat bond market is the increasing usage of shelf-offerings such as the Swiss Re Successor Series (see, e.g., Guy Carpenter, 2008). These programs enable sponsors, within a certain time span and up to a maximum volume, to repeatedly issue additional classes of notes (referred to as "takedowns") out of the same SPV and based on a single offering circular that covers the general characteristics of the securities. In doing so, it is possible to access risk bearing capacity as needed and achieve a substantial reduction in transaction costs. Moreover, shelf offering programs tend to be welcomed by investors since they indicate the experience of a sponsor as well as its willingness to provide a steady deal flow in the future (see, e.g., Spry, 2009).

In order to ascertain whether a payout to the cat bond sponsor is due, different types of triggers can be applied.[5] Each of these mechanisms is based on a preset threshold value that needs to be breached by an underlying variable. The choice of trigger typically involves a trade-off between transparency and basis risk (see, e.g., Swiss Re, 2009). Indemnity triggers are associated with asymmetric information between the transaction partners, since they directly reference the losses incurred by the sponsor. Consequently, they give rise to a moral hazard problem. More specifically, due to the acquired protection, the sponsor of an indemnity-based cat bond has the incentive to relax its underwriting and claims handling standards to the detriment of the investors. Furthermore, the payout of deals with indemnity triggers needs to be preceded by a rather lengthy loss verification process, implying that a quick settlement after the occur-

[2] Note that both binary and proportional payouts to the sponsor are possible (see, e.g., Cummins and Weiss, 2009).
[3] This is the same composition as for corporate bond spreads (see, e.g., Elton et al., 2001).
[4] The affected transactions were Ajax Re, Carillon Ltd. A-1, Newton Re 2008 A-1, and Willow Re B.
[5] See Hagedorn et al. (2009) for a more detailed discussion of the choice of trigger types.

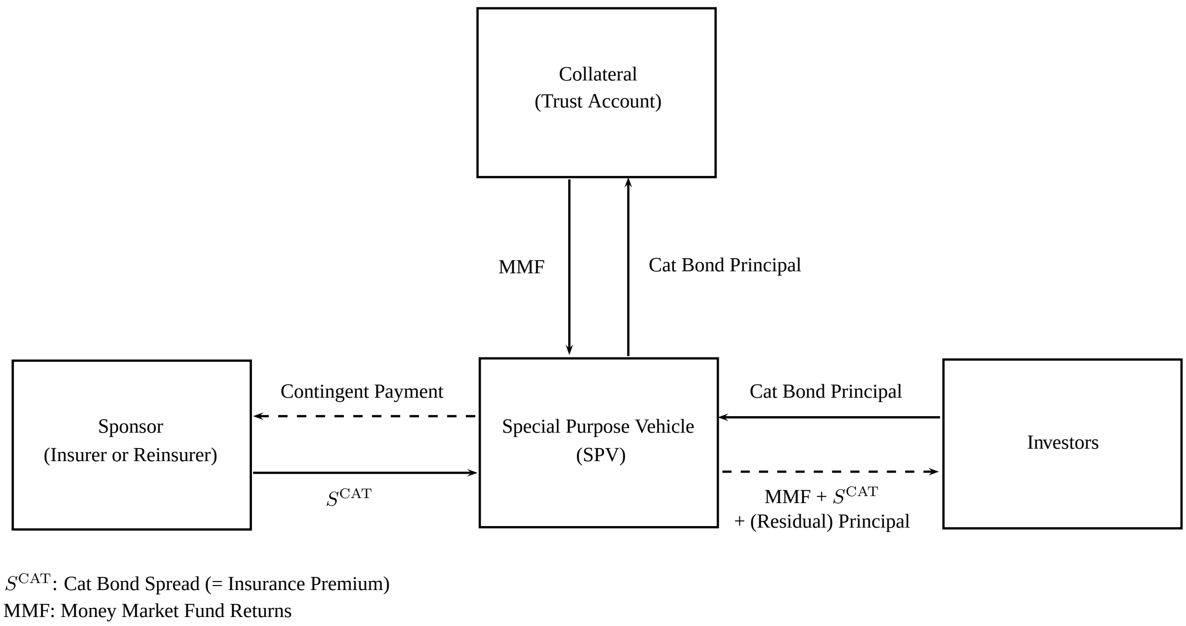


Figure 1: Typical Post-Crisis Structure of a Cat Bond Transaction (see, e.g., Swiss Re, 2009)

rence of a qualifying event is not possible. While non-indemnity triggers can be employed to tackle these issues, they expose the sponsor to basis risk since the actual losses in its portfolio of insurance contracts are, in general, not perfectly correlated with the variable referenced by the trigger. A prominent representative of this class is the industry index trigger, which is based on the losses of the whole insurance sector. The respective claims data is collected and aggregated by third-party service providers such as Property Claims Services (PCS). Furthermore, modeled loss triggers require the physical parameters of the disaster to be entered into an escrow model that serves to estimate the relevant losses. In contrast to that, pure parametric triggers focus on the physically measured severity of the catastrophe instead of claim sizes.[6] Besides, there is a refined version of the pure parametric trigger called parametric index trigger. Here, readings from different measurement stations are weighted and aggregated into an index, the value of which then determines whether the sponsor receives a payment. Finally, cat bonds can also feature a combination of multiple trigger types.

The natural hazard risk securitized by cat bonds is specified by a combination of covered territory and reference peril (see, e.g., Jaeger et al., 2010).[7] The covered territory represents the geographic area in which a catastrophic event has to occur in order to be relevant under the bond indenture and is commonly defined in terms of countries (e.g., United States), regions (e.g., Gulf Coast), or states (e.g., California). Reference peril, in contrast, means the underlying type of disaster such as windstorms (e.g., hurricanes, tornadoes, typhoons) or earthquakes. Today, the most widespread combinations of territory and peril are

[6] One commonly draws on the moment magnitude scale for earthquakes and the Saffir-Simpson Scale for hurricanes.
[7] Note that, in practice, the term "peril" is frequently used to refer to the actual combination of geographic zone and natural hazard (see, e.g., Bodoff and Gan, 2009). Hence, the terminology in this regard is not entirely precise.

U.S. Wind, U.S. Earthquake, Europe Wind, and Japan Earthquake (see, e.g., AON Benfield, 2011). In addition, transactions including multiple territories and multiple perils have become quite common (see, e.g., Swiss Re, 2009).[8]

These stringent definitions are necessary to ensure that the occurrence of a qualifying event can be determined objectively. In addition, they are a crucial input for analytics firms, such as RMS, AIR, and EQECAT, which assume a central role in the quantification of the catastrophe risk.[9] For this purpose, they maintain complex scientific models to simulate stochastic event sets, i.e., large numbers of disaster scenarios that are characterized by key physical parameters, such as wind speeds or tremor magnitudes, as well as the corresponding occurrence probabilities. These scenarios are then superimposed on large databases containing all properties that, due to their locations, are exposed to the respective catastrophe risk.[10] Together with information about the susceptibility of each structure, as determined by the main construction materials, the age, the size, etc., it is thus possible to estimate the physical damage taken by buildings and household belongings in every scenario. Finally, based on the property values as well as the terms of active insurance policies, the physical damage is translated into financial losses and aggregated on the portfolio level. In combination with the trigger configuration of a cat bond issue, the data output generated by this analysis enables the modeling firms to derive a loss distribution for each tranche. This distribution underlies the derivation of key risk metrics, such as the expected loss, the probability of first loss, as well as the probability of exhaustion, and is therefore central to the risk assessment of cat bonds. It is also one of the main aspects that drive the rating of a transaction.[11]

2.2 Testable Hypotheses

Due to the similarities of ILS with traditional reinsurance contracts, the expected loss has emerged as the main measure for the riskiness of such transactions. Consequently, it is also considered to be the single most important driver of the cat bond spread. Since empirical evidence for this notion has already been provided in several earlier studies (see, e.g., Lane and Mahul, 2008; Dieckmann, 2009; Galeotti et al., 2012), we do not see the necessity of formulating an explicit hypothesis in this regard.[12] Instead, our attention is focused on other potential spread determinants that could help to improve the explanatory power of an econometric pricing model.

First of all, we consider the bond-specific characteristics issue size, term, and trigger type. In line with Dieckmann (2009), we base our presumption concerning the first of these three variables on the

[8] Lane (2004) establishes a relationship between multiperil and singleperil cat bonds based on no-arbitrage considerations.
[9] A detailed description of the catastrophe modeling process can be found in Brookes (2009).
[10] The identification of relevant structures is supported by the process of geocoding, which serves to convert address information into geographic coordinates, consisting of latitude and longitude (see, e.g., Brookes, 2009).
[11] Apart from the likelihood of losses caused by disasters, rating agencies also consider the default risk of the sponsor, the collateral assets, and a potential swap counterparty (see, e.g., Heath, 2009). Further information with regard to the rating methodology for cat bonds can be found in Standard & Poor's (2009), Moody's (2006), and Fitch Ratings (2011).
[12] Note that the combination of probability of first loss (PFL) and conditional expected loss (CEL), which is sometimes employed for pricing purposes as well, essentially conveys the same information as the expected loss (EL), since the following relationship holds: EL = PFL · CEL (see, e.g., Lane, 2000).

findings of Edwards et al. (2007) for the corporate debt market, who show that larger issue volumes are associated with lower transaction costs. This, in turn, should lead to a higher fungibility and ultimately lower required yields to maturity. Moreover, if the liquidity preference or the market segmentation hypothesis holds, the cat bond spread should increase with the term of the security.[13] Finally, due to the longer post-event loss verification process and the possibility of moral hazard by the sponsor, it is likely that investors demand to be compensated with higher spreads in case a cat bond exhibits an indemnity trigger (see, e.g., Cummins and Weiss, 2009). Taking these considerations into account, we formulate the following three hypotheses:

H_1*(a): The spread of a cat bond issue decreases with its size.*

H_1*(b): Cat bond spreads increase with the term of the security.*

H_1*(c): A pure indemnity trigger is associated with a markup in the cat bond spread.*

Second, we turn to the covered territory and the reference peril, which characterize the underlying catastrophe risk of a transaction. An effect of these factors has already been documented by Lei et al. (2008), Bodoff and Gan (2009) as well as Papachristou (2009), and was subsequently controlled for in later studies (see, e.g., Galeotti et al., 2012).[14] Beyond the aforementioned literature, it has been confirmed by industry sources that cat bonds covering the U.S. carry larger spreads than transactions exposing investors to similar natural hazards in the rest of the world (see, e.g., AON Benfield, 2011, 2012). This phenomenon is attributed to the fact that the vast majority of risk capital in the cat bond market relates to events on U.S. soil, thus characterizing the country as a peak territory. Transactions covering nonpeak zones, such as Europe, Japan, or other parts of the world, in contrast, should exhibit lower risk premiums because they are a sought-after means for the diversification of ILS portfolios. A similar effect can be expected with regard to peak perils (e.g., windstorms). Furthermore, peril-specific markups might arise due to differences in scientific models for the main types of disasters and the associated uncertainty of the estimated loss distributions. Hence, in our analysis, we will provide for a strict differentiation between the geographic scope and the type of disaster. Apart from separate effects, however, there might also be a combined impact of territory and peril, since, in practice, these two factors are commonly considered together. Based on these thoughts, we postulate:

H_2*(a): Cat bond spreads for peak territories are larger than for nonpeak territories.*

H_2*(b): Cat bond spreads for peak perils are larger than for nonpeak perils.*

H_2*(c): Interaction effects between peak territories and perils increase the cat bond spread.*

A third batch of potential explanatory factors over and above the expected loss relates to reinsurance pricing and the investors' perception of credit risk inherent in cat bond structures. Spry (2009) notes

[13]These strands of thought underpin common theories of the term structure of interest rates (see, e.g., Cox et al., 1985).
[14]Lane and Mahul (2008) examine the relationship between peril-specific expected losses and the spread of multiperil bonds.

that, when deciding on their required spreads, experienced cat bond investors also assess the specifics of the sponsor. Therefore, repeat issuers with a strong track record can expect to be rewarded with tighter execution pricing (see, e.g., Guy Carpenter, 2008). To our knowledge, the impact of the sponsor has not been considered in the empirical literature before. In addition, Lane and Mahul (2008) were the first to point out the relevance of the underwriting cycle with regard to cat bond pricing. Researchers and industry experts agree that the reinsurance business is subject to periods of soft markets with plenty of coverage and rather low premiums as well as hard markets with restricted risk-bearing capacities and higher premiums (see, e.g., Cummins and Weiss, 2009). Thus, being a direct substitute for traditional reinsurance contracts, cat bonds should, by no-arbitrage reasoning, follow relatively similar pricing patterns over time. Moreover, it is a matter of common knowledge that yields for corporate and government bonds vary across rating classes (see, e.g., Elton et al., 2001). A similar link can be suspected between the spread of a cat bond and its rating. Finally, since many fixed-income investors perceive securities with the same rating to carry identical risks, there could be contagion effects that give rise to a dependence of cat bond on corporate bond spreads (see, e.g., Guertler et al., 2014). The fact that, through the collateral, the sponsor, and a potential TRS counterparty, cat bond structures still hide a residual degree of credit risk further contributes to this view. In a nutshell, we state our final hypotheses as follows:

H_3(a): Long-standing and well-respected sponsors can afford to pay lower cat bond spreads.

H_3(b): Cat bond spreads fluctuate in line with the reinsurance underwriting cycle.

H_3(c): The higher the rating class of a cat bond, the lower its spread.

H_3(d): Corporate bond spreads exert a positive influence on cat bond spreads.

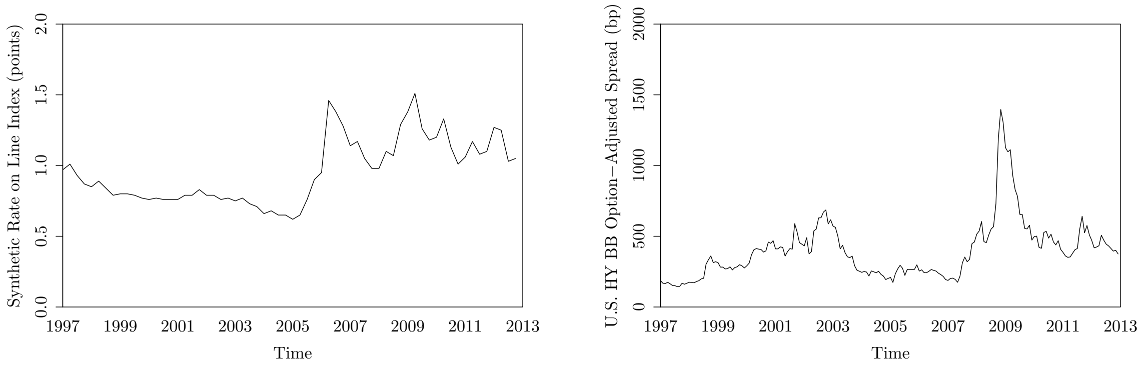
3 Empirical Analysis

3.1 Data and Sample Selection

The biggest obstacle for empirical work on cat bonds is the scarcity of publicly available transaction data. To tackle this problem, we have combined and cross-checked information from a multitude of different sources, including the Thomson Reuters Insurance Linked Securities Community, trade notes by Lane Financial LLC, the Artemis Deal Directory, rating agency reports, as well as market research of Swiss Re, Munich Re, Aon Benfield, and Guy Carpenter. The resulting data set comprises a total of 466 cat bond tranches issued between June 1997 and December 2012, for which we have the per annum spread, expected loss, probability of first loss, and conditional expected loss.[15] In addition, we were able to acquire information about the issue date, size (in USD), term, trigger type, covered territory, reference peril, sponsor, and rating of almost every transaction.[16] After removing 29 of the 466 original cases due to missing fields, we are left with a sample of 437 observations. To test the hypotheses for

[15] Due to differences in the natural catastrophe risk models of RMS, AIR, and EQECAT (see Section 2), these figures are not perfectly comparable across different bond issues. Without access to these firms' proprietary software, we have to accept that this may cause slight inaccuracies in our results.

[16] Further details, such as modeling firm, lead underwriters, and TRS counterparty, were only sporadically available.



(a) Synthetic Rate on Line Index

(b) U.S. High Yield BB Option-Adjusted Spread

Figure 2: Potential Cyclical Drivers of the Cat Bond Spread
Historical development of the Lane Financial LLC Synthetic Rate on Line Index (measured in points) and the Bank of America Merrill Lynch U.S. High Yield BB Option-Adjusted Spread (measured in basis points).

the environmental factors "underwriting cycle" and "corporate bond spreads", further sources of data are required. The general level of reinsurance premiums will be proxied by means of the Lane Financial LLC Synthetic Rate on Line Index (henceforth RoL index or rate on line index), which is published by the Thomson Reuters Insurance Linked Securities Community on a quarterly basis. Since pricing information for traditional reinsurance contracts is rather opaque and difficult to obtain, this index draws on secondary market quotes for all outstanding ILS as well as ILW premiums to measure shifts in catastrophe risk prices.[17] Values above one indicate a hard market. Due to the fact that the vast majority of cat bonds exhibit a BB rating, we decide to capture the influence of the corporate bond markets via the Bank of America Merrill Lynch U.S. High Yield BB Option-Adjusted Spread (henceforth BB spread or BB corporate bond spread), which is calculated as the difference between a yield index for the BB rating category and the Treasury spot curve. It tracks the performance of publicly issued BB-rated U.S. corporate debt and is available on a monthly basis. Figure 2 shows the development of these potential cyclical drivers of the cat bond spread from January 1997 until December 2012.

3.2 The Primary Market for Cat Bonds

We begin the empirical analysis by drawing on our data to document a number of facts about the primary market for cat bonds. Due to its comparatively high yields and its low correlation with traditional investments, this asset class has successively attracted institutional investors from outside the insurance industry (see, e.g., Cummins and Trainar, 2009). As of 2012, the cat bond investor base was estimated

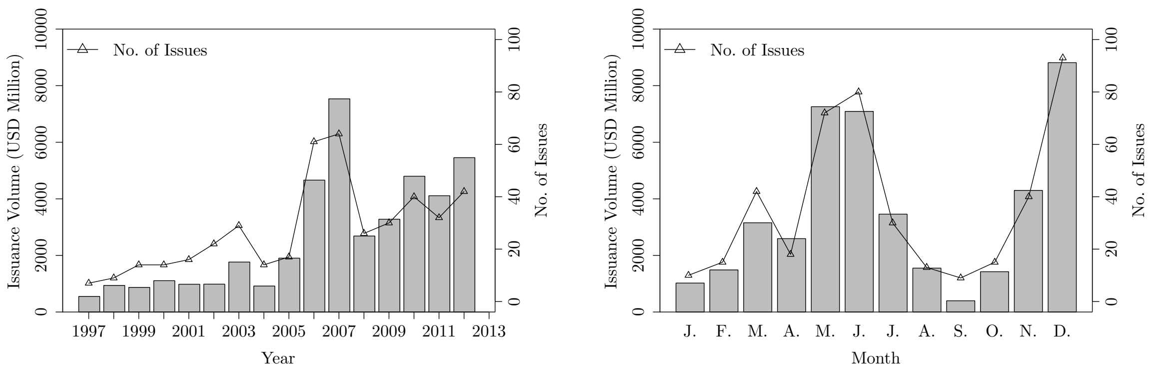
[17] Please refer to the Thomson Reuters Insurance Linked Securities Community for additional information about this index, including the current calculation methodology. Since the time series available online does not date back to before 2002, we have combined it with earlier data of the long-term index of catastrophe reinsurance prices, which is based on the same principles and has been published in an appendix to Lane and Mahul (2008). The adequacy of this approach is underlined by the fact that both indices are highly correlated during the time period between the first quarters of 2002 and 2008, in which they overlap. The resulting time series starts with a value of one in the fourth quarter of 1996.

to consist of 61 percent dedicated funds, 17 percent money managers, 14 percent pension funds, 4 percent insurers, 3 percent hedge funds, and 1 percent reinsurers (see, e.g., Swiss Re, 2013). The instrument's growing popularity has led to a continuous inflow of new capital into the market, particularly between 2005 and 2007. This is illustrated by Figure 3(a), which displays the size of the primary market for cat bonds and the number of new transactions per year. From 1997 up until 2007, we estimate a compound annual growth rate (CAGR) in issuance volumes of 29.91 percent. In 2008, however, the financial crisis caused a huge decline. The rapid disengagement from risky asset classes is known to be a typical aspect of investor behavior in such flight-to-quality periods (see, e.g., Caballero and Krishnamurthy, 2008). Yet, in this particular case, it was even aggravated by the fact that the investors of four cat bonds suffered substantial losses due to the default of the TRS counterparty Lehman Brothers (see Section 2). Returning investor confidence and the removal of structural weaknesses then led to a rebound in 2009 and 2010, with estimated growth rates of 22.04 percent and 46.36 percent, respectively. After a slight setback in 2011, the market is now approaching its precrisis size again.

Figure 3(b) shows the total issuance volume and the number of new transactions per calendar month. Upon the examination of this chart, we notice that the primary market for cat bonds is most active in the second and fourth quarters of the year, while the first and third quarters are rather quiet. It seems that this phenomenon and potential reasons for its occurrence have not yet been discussed in the literature. Our intuition suggests that, during the second quarter, market participants anticipate the Atlantic hurricane season from June to November, leading to an increased demand for coverage. Since, to date, U.S. Wind is the most frequent combination of territory and peril (see Section 2), this should have a substantial effect on the overall market activity. Similarly, the surge in issuance volumes towards the end of the calendar year could occur due to the fact that sponsors draw on securitization to rebalance their firm-wide risk situation before the preparation of their financial statements.

Further insights that can be derived from our data are related to the evolution of the catastrophe risk premium over time. Figure 4(a) illustrates the development of expected losses and cat bond spreads in the primary market between June 1997 and December 2012. The plotted time series represent the averages of the respective figures across all tranches in our sample that were issued in the same quarter.[18] For comparison purposes, we have added the corresponding levels of the BB corporate bond spread. Three prominent peaks in the average quarterly cat bond spread can be observed. The first one occurred in the wake of the Indian Ocean (Sumatra-Andaman) earthquake in December 2004 and the second one after Hurricane Katrina in August 2005. Instead of a major natural disaster, the third spike followed the default of Lehman Brothers in September 2008. Accordingly, it was accompanied by a massive surge in corporate bond spreads, while expected losses remained largely stable. This indicates a certain impact of credit-related issues on the primary market for cat bonds, which will be further examined in Section 3.4. Moreover, the means of the quarterly time series equal 727.10 basis points (bp) for the cat bond spread, 175.15 bp for the expected loss, and 400.66 bp for the BB corporate bond spread. Hence, in the time

[18]There are a total of four quarters in which no bonds have been issued. In these cases the figures for the previous quarters have been retained.



(a) Per Year

(b) Per Calendar Month

Figure 3: Historical Cat Bond Issuance Activity

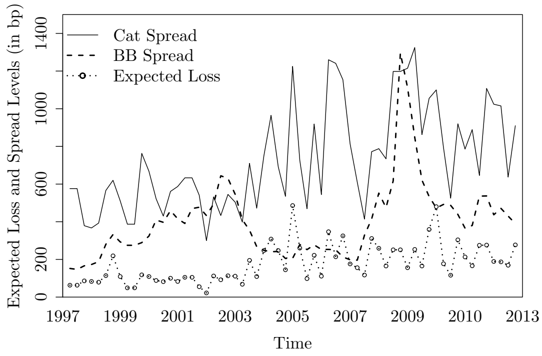
Historical cat bond issuance activity as implied by our data. Figure 3(a) shows the yearly number of transactions and their aggregated issuance volumes in millions of US dollars from June 1997 until December 2012. Similarly, in Figure 3(b) the corresponding information has been provided by calendar month.

period under consideration, cat bond investors were, on average, compensated with a risk premium of 551.95 bp above the expected loss and an excess spread of 326.44 bp compared to similarly rated corporate debt. This is an even larger figure than the historical difference of 100 to 200 bp between the two asset classes mentioned in a study by Guy Carpenter (2008). The corresponding multiple of 1.81, in contrast, is slightly smaller than one would expect based on the secondary market results of Dieckmann (2009) for the year 2005, who found the average cat bond spread to be roughly twice as large as the spread of a comparable corporate bond. Overall, it seems that the spreads in the cat bond market still remain higher than those in the corporate bond market. Potential explanations for this phenomenon that have been brought forward in the literature include the relatively lower liquidity and higher perceived complexity of cat bonds as well as a markup for the nontraditional nature of the risk (see, e.g., Swiss Re, 2006).[19]

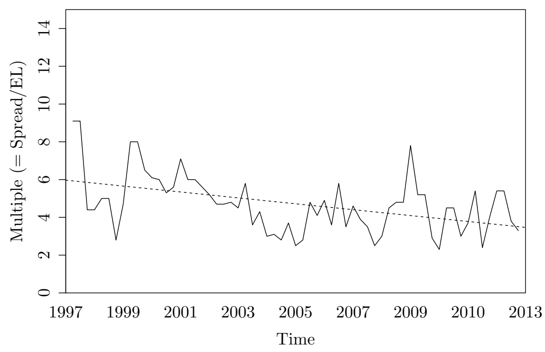
The evolution of the ratio of cat bond spread to expected loss, corresponding to Figure 4(a), is presented in Figure 4(b).[20] We notice a downward trend paired with a substantial degree of volatility. The fact that the general level of these multiples declined since the inception of the market is also described by Cummins (2008). Apart from that, our multiple time series starts with a value of 9.14 in 1997. This is very close to the average ratio of spread to expected loss of 9.09 derived by Cummins et al. (2004) based on a set of 32 transactions from the late 1990s. Furthermore, Cummins and Weiss (2009) report multiples of around 6.00 for 2001, between 2.00 and 3.00 for early 2005, and between 2.50 and 3.00 for 2007. Similarly, Dieckmann (2009) estimates that, between March 2005 and March 2006, the average ratio of spread to expected loss amounted to 4.30. All of these results are in line with Figure 4(b). Finally,

[19]This markup is sometimes referred to as a "novelty premium" (see, e.g., Bantwal and Kunreuther, 2000). However, since ILS in general and cat bonds in particular have been around for one and a half decades now, we deem this to be a rather unlikely reason for excess spreads observed today.

[20]The values for Q4/2001 and Q1/2002 have been linearly interpolated between Q3/2001 and Q2/2002 to avoid distortions due to a very small number of cat bond issues and extraordinarily high multiples on two of the relevant transactions.



(a) Average Cat Bond Spread and Expected Loss



(b) Multiple of Spread over Expected Loss

Figure 4: Evolution of the Catastrophe Risk Premium

Figure 4(a) illustrates the development of expected losses and cat bond spreads in the primary market between June 1997 and December 2012. The time series have been generated by averaging the respective figures across all cat bond tranches in the sample that were issued in the same quarter. For comparison purposes, the corresponding levels of the BB corporate bond spread have been included as well. Figure 4(b) displays the evolution of the multiple of spread divided by expected loss as implied by the time series shown in Figure 4(a). A trend line has been added to facilitate the interpretation.

the mean of our quarterly time series of multiples equals 4.73 and reduces to 3.97 if only the more recent observations in 2010, 2011, and 2012 are taken into account. Compared to that, Cummins and Weiss (2009) indicate that historical multiples of premium to expected loss for the upper layers of coverage in the reinsurance market tend to lie between 3.00 and 5.00. Therefore, cat bonds now seem to be priced competitively relative to traditional contracts.

3.3 Descriptive Statistics

In this section, we provide a variety of descriptive statistics with regard to our sample. Table 1 contains the mean, median, and standard deviation, as well as maximum and minimum values for the key characteristics of the full cross section of 437 bonds. The mean spread amounts to 818.07 bp and the mean expected loss equals 208.12 bp. Consequently, we observe a risk premium of, on average, 609.95 bp per bond. In addition, the spread varies considerably across all bonds in the sample, which is indicated by the respective standard deviation as well as the minimum and maximum values. It can, for example, be as low as 65 bp or as high as 49.20 percent. Expected losses, in contrast, range between 0.50 bp and 14.75 percent. Furthermore, the average size of the cat bond tranches in the sample is USD 97.34 million, while issues as small as USD 1.80 million and as large as USD 750.60 million have been observed.[21] Finally, the sample comprises transactions with terms from a minimum of 5 months up to a maximum of 10 years, and the average cat bond matured after 33.97 months (2.83 years).

[21]Note that transactions with very small volumes are usually part of shelf offering programs.

Variable	Mean	Median	S.D.	Max	Min
Spread (bp)	818.07	675.00	559.57	4'920.00	65.00
Expected Loss (bp)	208.12	129.00	211.64	1'475.00	0.50
Risk Premium (bp)	609.95	528.00	391.01	4'039.00	64.00
Multiple	10.21	4.82	31.66	450.00	1.58
Size (USD mn)	97.34	75.00	86.96	750.00	1.80
Term (months)	33.97	36.00	13.13	120.00	5.00

Table 1: Descriptive Statistics for the 437 Cat Bonds in the Sample

This table shows the mean, median, and standard deviation (S.D.), as well as the maximum and minimum values for the spread, expected loss, risk premium, multiple of spread to expected loss, size, and term of the full cross section of 437 cat bonds.

	No.	Percent	⊘ Spread (in bp)	⊘ EL (in bp)	⊘ RP	⊘ Multiple (in bp)	⊘ Size (USD mn)	⊘ Term (months)
Territory								
U.S.	252	57.67	838.22	182.95	655.28	9.91	106.03	31.61
Europe	46	10.53	662.54	204.93	457.61	5.26	94.87	37.87
Japan	25	5.72	442.24	119.56	322.68	4.93	100.48	50.76
Other	16	3.66	614.53	233.88	380.66	5.15	90.63	34.75
Multiterritory	98	22.43	968.35	292.74	675.61	15.46	76.47	33.92
	437	100.00						
Peril								
Wind	152	34.78	861.58	219.07	642.51	5.35	104.86	33.89
Earthquake	92	21.05	526.06	128.95	397.11	5.79	92.54	33.37
Multiperil	193	44.16	922.99	237.24	685.76	16.14	93.71	34.38
	437	100.00						
Trigger								
Indemnity	121	27.69	731.66	148.25	583.40	18.16	124.10	33.75
Industry Loss	120	27.46	949.10	228.61	720.49	5.65	112.22	32.45
Pure Parametric	28	6.41	527.73	151.25	376.48	7.35	84.91	44.42
Parametric Index	100	22.88	701.56	207.33	494.23	7.16	65.77	34.49
Modeled Loss	41	9.38	744.88	158.66	586.22	6.25	80.00	33.20
Multiple Trigger	27	6.18	1466.67	522.38	944.29	15.04	67.48	30.56
	437	100.00						
Sponsor								
Swiss Re	154	35.24	956.53	304.54	651.99	5.58	54.15	28.84
Other	283	64.76	742.72	155.65	587.07	12.72	120.85	36.80
	437	100.00						
Rating								
High Yield	398	91.08	876.21	226.82	649.38	6.60	97.33	33.83
Investment Grade	39	8.92	224.76	17.27	207.49	47.05	97.42	35.69
	437	100.00						

Table 2: Descriptive Statistics for Different Categories of Cat Bonds in the Sample

Classification of the cat bonds in the sample according to covered territory, reference peril, trigger type, sponsor, and rating class. For each category the number and percentage of tranches as well as their average spread, expected loss, risk premium, multiple, size, and term are provided.

Further descriptive statistics for different categories of cat bonds in the sample can be found in Table 2. When focusing on the geographic classification, we observe that the vast majority of issues (57.67 percent) cover the United States. The second-largest fraction is represented by multiterritory bonds (22.43 percent). Due to their relative abundance in the market, transactions in these two categories exhibit the highest average spreads, risk premiums, and multiples. In contrast, deals referencing a single territory other than the U.S. or Europe are very rare. "Japan" and "Other" represent a mere 5.72 percent and 3.66 percent of the sample, respectively. These bonds offer the lowest risk premiums and multiples over expected loss, probably owing to their scarcity and valuable diversification properties. Moreover, the average issue size of U.S. (multiterritory) bonds is larger (smaller) than that of their counterparts covering Europe, Japan, or other areas. Finally, the average term of transactions on Japanese perils is substantially longer than for the remaining territories.

Turning to the peril-specific figures, we notice that the sample comprises 34.78 percent wind, 21.05 percent earthquake, and 44.16 percent multiperil bonds. The average spreads and expected losses, but also the risk premiums, are considerably lower for earthquake than for wind and multiperil bonds. This suggests that investors in the latter two categories tend to bear more risk, for which they receive an additional compensation. The prevailing risk-return trade-off seems to be particularly attractive for multiperil transactions, since they offer by far the largest average multiple of spread to expected loss. Furthermore, wind bonds exhibit a larger average issue size than earthquake and multiperil bonds. The differences in the average term for all three categories are negligible.

With regard to trigger types, indemnity (27.69 percent), industry loss (27.46 percent), and parametric index (22.88 percent) clearly dominate the sample. The highest average spread, expected loss, and risk premium are associated with bonds that contain more than one trigger mechanism. In contrast to that, cat bonds with indemnity triggers offer the third-lowest average spread and risk premium, although they supposedly compensate investors for moral hazard of the issuer. Their average multiple, however, is high. Furthermore, transactions with indemnity and industry loss triggers are associated with the largest, and parametric index triggers with the smallest average issue volumes. Finally, cat bonds featuring pure parametric triggers exhibit a much longer average term than the other trigger categories.

In terms of sponsors, we simply differentiate between Swiss Re and all other institutions. Since the Zurich-based reinsurer is the undisputed leader in terms of cat bond issuance and has pioneered many important developments in this market, it is not surprising that more than a third (35.24 percent) of the transactions in our sample have been launched by it. Although the respective deals exhibit a higher average spread and expected loss compared to the other bonds, the corresponding average multiple is much smaller. In addition, we notice that Swiss Re sponsored cat bonds tend to be less than half the size of those of other sponsors. A likely explanation for this observation is the firm's increasing usage of shelf offering programs. Since these allow new transactions to be executed quickly whenever required, the volumes of the individual securities tend to be much smaller than those of regular cat bond issues.

Finally, we see that only 8.92 percent of the cat bonds in our sample carry an investment-grade rating.[22] On average, these tranches pay a considerably lower spread and risk premium than high-yield cat bonds. At the same time, however, due to their very low expected loss figures, the average multiple of spread to expected loss is extraordinarily large. Consequently, investors of highly rated cat bonds receive a tremendous compensation per unit of expected loss.

3.4 Determinants of the Cat Bond Spread at Issuance

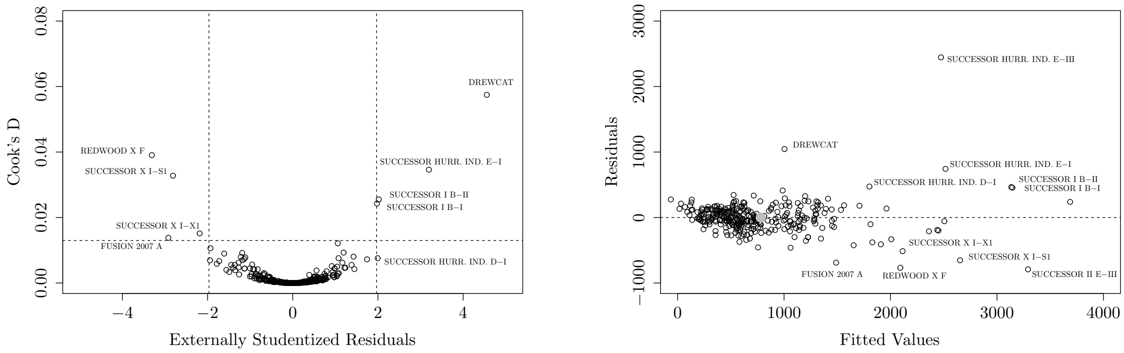
Earlier research has documented that a linear relationship is well-suited to explain primary market cat bond spreads (see, e.g., Galeotti et al., 2012). Thus, our inference statistical analysis will rely on OLS regression methodology. Beforehand, however, we split the full sample of 437 transactions into two parts. The first part consists of 323 tranches that have been issued between June 1997 and December 2009 and will be employed for the testing of our hypotheses as well as the assessment of the in-sample performance of the econometric pricing model that we introduce below. In contrast to that, the remaining 114 observations will be reserved for the out-of-sample analysis in the last section. To prepare the in-sample analysis, we want to identify outliers, i.e., cases with an abnormally large impact on the least squares coefficients. For this purpose, we estimate a full model including all considered predictors and then compute the externally (jackknifed) studentized residuals as well as Cook's D.[23] By means of the visual representation of these statistics together with their critical values in Figure 5(a), we are able to reveal the 11 cases outside the box in the bottom center as heavily influential.[24] This finding can be confirmed with the scatter plot of residuals against fitted values shown in Figure 5(b), since the previously identified transactions exhibit large distances to the centroid, i.e., the spot marked by a gray circle around which all other cases cluster. When considering the outliers in detail, we notice that eight of them belong to the Swiss Re successor series. Hence, this particular shelf offering program seems to adhere to somewhat different pricing rules than the other cat bonds in the sample. After the outliers have been removed, we are left with 312 transactions.

As discussed in Section 2, the expected loss of a cat bond is undoubtedly the most important driver of its spread. However, the descriptive statistics presented in Table 2 indicate that there are other factors that play a significant role in the pricing of these financial instruments. The category "U.S.", for example, exhibits a higher average spread than the category "Other", despite its lower average expected loss. Similarly, the average spread of transactions with indemnity triggers is substantially larger than that of deals with pure parametric triggers, although the average expected loss of both groups is virtually the same. Such outcomes are at odds with models that rely on the expected loss as its sole input parameter. Hence, we run a series of cross-sectional regressions in order to reveal additional determinants of the cat bond spread. Based on the results of these analyses, we will then select the factors for our econometric pricing model.

[22] All rating classes from BBB– upwards by Standard & Poor's and Fitch (or the Moody's equivalent Baa3) are termed investment grade (see, e.g., www.standardandpoors.com).

[23] The definitions for these measures can be found in the Appendix. Equation (1) without interaction effects for perils and territories is a formal representation of the full model that has been employed for the identification of outliers.

[24] Note: Successor II Class E-III and Successor Hurricane Ind. Class E-III lie beyond the outer bounds of Figure 5(a).



(a) Cook's D vs. Externally Studentized Residuals

(b) Residuals vs. Fitted Values

Figure 5: Identification of Outliers

These diagrams serve to identify outliers in the data set. In Figure 5(a), Cook's D has been plotted against the externally studentized residuals for each case. The critical values for both measures are represented by dotted lines, which form a box in the bottom center. Observations outside this box are considered as outliers. The selected cases exhibit a large distance from the centroid (gray dot) in the scatterplot of residuals against fitted values shown in Figure 5(b).

The top part of Table 3 contains the coefficient estimates (both unstandardized and standardized) and corresponding significance levels for the considered model specifications. In the bottom part, we have included the adjusted R^2 and the standard error of the estimate (denoted SEE) as measures for explained variance and goodness of fit. Furthermore, White's test and the Breusch-Pagan test have been employed as heteroskedasticity diagnostics. To ensure robust inferences, all standard errors and p-values are based on the Newey-West HAC covariance matrix.[25] Let S_i^{CAT} denote the spread of cat bond i measured in bp. We begin with model 1, which includes all regressors and can be formally described as follows:

$$\begin{aligned} S_i^{\text{CAT}} &= \alpha + \beta_{\text{EL}}\text{EL}_i + \beta_{\text{SIZE}}\text{SIZE}_i + \beta_{\text{TERM}}\text{TERM}_i + \beta_{\text{INDEM}}\text{INDEM}_i \\ &\quad + \beta_{\text{WIND}}\text{WIND}_i + \beta_{\text{EQ}}\text{EQ}_i + \beta_{\text{MT}}\text{MT}_i + \beta_{\text{US}}\text{US}_i + \beta_{\text{EU}}\text{EU}_i + \beta_{\text{JP}}\text{JP}_i \\ &\quad + \beta_{\text{USW}}\text{US}_i \times \text{WIND}_i + \beta_{\text{USEQ}}\text{US}_i \times \text{EQ}_i + \beta_{\text{EUW}}\text{EU}_i \times \text{WIND}_i + \beta_{\text{JPEQ}}\text{JP}_i \times \text{EQ}_i \\ &\quad + \beta_{\text{SR}}\text{SR}_i + \beta_{\text{ROLX}}\text{ROLX}_i + \beta_{\text{IG}}\text{IG}_i + \beta_{\text{BBSPR}}\text{BBSPR}_i + \epsilon_i, \end{aligned} \tag{1}$$

where α denotes the intercept and EL_i, SIZE_i, TERM_i, as well as INDEM_i represent the expected loss (in percentage points), the issue volume (in million USD), the term (in months), and the trigger type of cat bond tranche i, respectively. More specifically, INDEM_i is a dummy variable that equals one if transaction i relies on an indemnity trigger, and zero otherwise. In addition, the dummy variable WIND_i

[25] Although our sample essentially represents a cross section of cat bonds, each individual transaction has been launched at a different point in time. This suggests that some of the observations may not be entirely independent, since, as shown in Figure 3(b), cat bond issuance activity tends to cluster around specific dates. An irregular spacing in the time dimension can be a problem for standard autocorrelation diagnostics and remedies. However, recent work by econometricians has revealed that the well-known HAC covariance matrix of Newey and West (1987) is asymptotically consistent and exhibits preferable finite sample properties under very general conditions when applied in the sense of an "equal spacing estimator", i.e., by treating the series as equidistant, irrespective its actual spacing in time (see Datta and Du, 2012). Even before its formal justification, this method had already been widely applied in high-class credit risk research (see, e.g., Acharya and Johnson, 2007, Jorion and Zhang, 2007, Pan and Singleton, 2008, Zhang et al., 2009).

	Model 1				Model 2				Model 3			
	coeff.	stand.	p-val.	sig.	coeff.	stand.	p-val.	sig.	coeff.	stand.	p-val.	sig.
Intercept	–50.84	–	0.6600		–38.86	–	0.5504		–124.93	–	0.0881	*
Expected Loss	215.31	0.83	0.0000	***	214.92	0.83	0.0000	***	219.80	0.85	0.0000	***
Size	–0.27	–0.05	0.0292	**	–0.27	–0.05	0.0214	**				
Term	0.70	0.02	0.2008									
Indemnity	–70.37	–0.07	0.0023	***	–68.13	–0.06	0.0079	***				
Wind	–70.44	–0.04	0.4327									
Earthquake	–166.29	–0.10	0.0703	*	–64.54	–0.06	0.0062	***				
Multiterritory	168.07	0.17	0.0884	*	190.62	0.17	0.0000	***	206.76	0.18	0.0000	***
U.S.	212.71	0.26	0.0452	**	208.55	0.22	0.0000	***	195.50	0.21	0.0000	***
Europe	–57.89	0.00	0.5649									
Japan	–31.85	0.00	0.7576									
U.S.×Wind	25.91	–0.01	0.7949									
U.S.×Earthquake	75.00	0.02	0.4565									
Europe×Wind	107.39	0.02	0.3438									
Japan×Earthquake	138.70	0.03	0.2249									
Swiss Re	–101.02	–0.10	0.0009	***	–111.28	–0.12	0.0001	***	–90.21	–0.09	0.0006	***
RoL Index	254.08	0.14	0.0000	***	235.10	0.13	0.0000	***	239.46	0.13	0.0000	***
Investment Grade	–150.17	–0.11	0.0000	***	–143.69	–0.10	0.0000	***	–150.43	–0.11	0.0000	***
BB Spread	26.08	0.10	0.0004	***	28.60	0.11	0.0002	***	31.67	0.12	0.0003	***
df	293.00				301.00				304.00			
SEE	149.90				150.00				154.00			
Adjusted R^2	0.90				0.90				0.89			
White's Test	32.44		0.0000	***	32.21		0.0000	***	27.39		0.0000	***
BP Test	46.34		0.0003	***	37.93		0.0000	***	33.35		0.0000	***

Table 3: Determinants of the Primary Market Cat Bond Spread

Least squares estimates of unstandardized (coeff.) and standardized (stand.) regression coefficients, p-values, significance levels (sig.), and degrees of freedom (df) for five different model specifications. All standard errors and p-values have been computed based on the Newey-West HAC covariance matrix. The adjusted R^2 and the standard error of the estimate (SEE) measure explained variance and goodness of fit for each model. White's test and the Breusch-Pagan (BP) test have been conducted as heteroskedasticity diagnostics.

assumes a value of one, if windstorms, such as hurricanes or tornadoes, are referenced and EQ_i equals one for earthquake bonds. If both of these variables are zero, transaction i represents a multiperil bond. The binary covariates for the covered territory are differentiated into multiterritory (MT_i), United States (US_i), Europe (EU_i), and Japan (JP_i).[26] If none of these variables equals one, then the bond relates to another geographic area (e.g., Mexico). We also consider interaction effects for the most common combinations of territory and peril, i.e., U.S. Wind, U.S. Earthquake, Europe Wind, and Japan Earthquake. Furthermore, SR_i is a dummy variable that equals one if cat bond i is sponsored by Swiss Re, and zero otherwise. Similarly, IG_i assumes a value of one for investment-grade and zero for high-yield ratings. The remaining two variables capture the cyclical spread drivers: ROLX_i denotes the rate on line index (in points) and BBSPR_i represents the BB corporate bond spread (in percentage points). For both of these factors, the values at the time of issuance of cat bond i enter the regression analysis.

The results for model 1 are shown in columns two to five of Table 3. Unsurprisingly, the coefficient for the expected loss is highly significant. Apart from that, we find evidence for an impact of the suspected liquidity advantage of larger cat bond issues on their pricing, thus being able to confirm hypothesis 1(a). Hypothesis 1(b), in contrast, has to be rejected, implying that the term structure of cat bond spreads in the primary market is flat. With regard to the coefficient for the trigger type, we make a quite intriguing observation. Investors are not or at least no longer compensated for the moral hazard associated with indemnity trigger deals. In fact, the latter seem to command lower instead of higher spreads, which contradicts the corresponding results by Papachristou (2009), Dieckmann (2009), and Galeotti et al. (2012). Upon closer inspection, however, recent practitioner studies offer a plausible explanation for this phenomenon. Swiss Re (2009), for example, reports an increasing acceptance of indemnity triggers among market participants. Similarly, Spry (2009) claims that the rejection of transactions solely on grounds of moral hazard has become obsolete. As he stresses, particularly the main group of long-standing cat bond investors has grown relatively comfortable with indemnity triggers and instead focuses on a detailed assessment of the ceding entity.[27] Another potential reason is the dissemination of incentive provisions under which issuer and investors share the risk above the trigger threshold according to preset ratio (see Cummins and Weiss, 2009).

We now turn to hypotheses 2(a), (b), and (c). When examining the respective results in Table 3 we notice that, unlike wind bonds, earthquake bonds exhibit significantly lower spreads compared to multiperil securities. Due to the way we report the peril-related dummy variables, however, model 1 does not allow us to carry out a direct comparison between earthquake and wind risk. Hence, we assessed this effect by means of a separate analysis with "Earthquake" as the base category. The results, which can be made available upon request, indicate that wind bonds command higher spreads. It follows that windstorms and multiple disasters are peak, whereas earthquakes are nonpeak perils. Moreover, Table 3 shows that the geographic specifications "Multiterritory" and "U.S." are associated with markups relative to transactions that cover other parts of the world. A further complementary analysis with "Multiterritory"

[26] The dummy variable "EU" refers to the continent of Europe in a geographical sense. It does not mean European Union.
[27] In line with this notion, we document a significant link between the sponsor and the spread, confirming hypothesis 3(a).

serving as the base category revealed that it is indistinguishable from "U.S.". These two variables thus form the group of peak territories. Similarly, the are no significant spread differences between "Europe", "Japan", and "Other", implying that those categories may be lumped together as nonpeak territories. Finally, we do not find any signs of significant interaction effects between the peril and territory variables. To sum up, hypotheses 2(a) and (b) can be confirmed, but hypothesis 2(c) needs to be rejected. As postulated, it seems that risks which occur in larger numbers are indeed perceived to be less valuable for the diversification of cat bond portfolios and thus require higher spreads. Owing to our explicit separation of peril and zone, we are able to distinguish these effects more precisely than Papachristou (2009) and Galeotti et al. (2012).[28] In future applications one may now recode the categorical variables for territory and peril into simple binary variables that identify peak and nonpeak risks.

Finally, we consider the results for hypotheses 3(a), (b), (c), and (d), i.e., the effects of the ceding entity, the reinsurance cycle, the rating class, and the BB corporate bond spread. Not only do we find all of the tested variables to be significant spread drivers beside the expected loss, but the observed effects are also consistent with the direction suggested by our hypotheses. Thus, due to its solid reputation among investors, Swiss Re as the market leader in structuring ILS indeed seems to be able to achieve better conditions than other sponsors. Furthermore, the general level of reinsurance premiums has a strong positive influence on cat bond spreads at the time of issuance, investment-grade offer lower spreads than speculative-grade transactions, and there is evidence for a cross-link with the corporate bond markets.

4 Econometric Pricing Model

4.1 Model Specification

Based on the aforementioned insights, it is possible to derive an econometric pricing model for cat bonds. To this end, we first of all eliminate all statistically insignificant factors from the regression equation and accordingly estimate the following specification (model 2):

$$\begin{aligned} S_i^{\mathrm{CAT}} &= \alpha + \beta_{\mathrm{EL}}\mathrm{EL}_i + \beta_{\mathrm{SIZE}}\mathrm{SIZE}_i + \beta_{\mathrm{INDEM}}\mathrm{INDEM}_i \\ &\quad + \beta_{\mathrm{EQ}}\mathrm{EQ}_i + \beta_{\mathrm{MT}}\mathrm{MT}_i + \beta_{\mathrm{US}}\mathrm{US}_i \\ &\quad + \beta_{\mathrm{SR}}\mathrm{SR}_i + \beta_{\mathrm{ROLX}}\mathrm{ROLX}_i + \beta_{\mathrm{IG}}\mathrm{IG}_i + \beta_{\mathrm{BBSPR}}\mathrm{BBSPR}_i + \epsilon_i. \end{aligned} \tag{2}$$

The respective results are displayed in columns six to nine of Table 3. Both the previously reported significances and fit statistics remain virtually unchanged. We proceed in line with the principle of parsimony and consider the substantive (economic) significance of the independent variables as indicated by their standardized regression coefficients. In doing so, we notice that the three statistically significant factors SIZE_i, INDEM_i, and EQ_i are by far the least influential. More specifically, their beta coefficients of –0.05, –0.06, and –0.06 imply that the cat bond spread declines by less than one-tenth of a standard

[28]In contrast to evidence provided by Bodoff and Gan (2009), further unreported results showed no signs of interactions between the peril variables and the expected loss. The corresponding estimates are available upon request.

deviation, if any of these independent variables increases by one standard deviation. Consequently, we may remove them without a notable sacrifice of explanatory power. This can be seen by examining the last four columns of Table 3, which contain the results for model 3 that exclusively relies on both statistically and economically significant spread drivers:[29]

$$\begin{aligned} S_i^{\mathrm{CAT}} &= \alpha + \beta_{\mathrm{EL}}\mathrm{EL}_i + \beta_{\mathrm{MT}}\mathrm{MT}_i + \beta_{\mathrm{US}}\mathrm{US}_i + \beta_{\mathrm{SR}}\mathrm{SR}_i \\ &\quad + \beta_{\mathrm{ROLX}}\mathrm{ROLX}_i + \beta_{\mathrm{IG}}\mathrm{IG}_i + \beta_{\mathrm{BBSPR}}\mathrm{BBSPR}_i + \epsilon_i. \end{aligned} \tag{3}$$

Before we continue with an assessment of robustness and out-of-sample properties, we decide to drop the intercept term. The reasons for this step are twofold. Firstly, in all three previous regressions, it turned out to be either insignificant or only weakly significant. Secondly, economic intuition suggests that in the hypothetical case where all of the risk drivers take up a value of zero, there should be no spread on the cat bond.[30] Apart from that, all transactions covering the U.S. or multiple geographic areas will now be grouped together as peak territories, represented by the binary variable PEAK_i. Thus, we ultimately suggest the following econometric pricing model for cat bonds in the primary market:

$$\begin{aligned} S_i^{\mathrm{CAT}} &= \beta_{\mathrm{EL}}\mathrm{EL}_i + \beta_{\mathrm{PEAK}}\mathrm{PEAK}_i + \beta_{\mathrm{SR}}\mathrm{SR}_i \\ &\quad + \beta_{\mathrm{ROLX}}\mathrm{ROLX}_i + \beta_{\mathrm{IG}}\mathrm{IG}_i + \beta_{\mathrm{BBSPR}}\mathrm{BBSPR}_i + \epsilon_i. \end{aligned} \tag{4}$$

The corresponding estimation results can be found in the first four columns of Table 4. All six explanatory variables exhibit highly significant regression betas. Again, the corresponding signs match our expectations as expressed in Section 2. Taking a closer look at the estimated effect magnitudes, we find that the cat bond spread widens by 221.04 bp per percentage point of expected loss. Moreover, if the transaction under consideration refers to a peak territory, the spread rises by 175.08 bp. Swiss Re sponsored deals, in contrast, receive a spread reduction of 103.58 bp compared to the transactions of other ceding entities. In addition, the spread widens by 161.85 bp per point of the rate on line index, declines by 159.76 bp if the cat bond exhibits an investment-grade rating, and increases by 26.57 bp for each percentage point of the BB corporate bond spread. With an adjusted R^2 of 0.89 and an SEE of 155.50, this model exhibits virtually the same in-sample fit as the full model (see Table 3), although it uses only a third of its predictors.[31] Unreported collinearity diagnostics indicate that the regressors are only minimally correlated with each other. Therefore, we are confident that the model is not overfitted and will offer a solid degree of statistical robustness.

4.2 Robustness

A reliable factor pricing approach needs to build upon strong economic relationships such that its overall fit remains stable across different samples drawn from the same population. Hence, we reestimate the

[29] Note that, as a corollary, the exclusion of EQ_i enables a calibration of the model with peril-specific cat bond samples.
[30] The same reasoning is regularly applied for empirical tests of asset-pricing models (see, e.g., Fama and French, 1993).
[31] It is important to note that we continue to report the centered adjusted R^2, although the regression line now runs through the origin. Considering the uncentered R^2 would restrict comparability, since it is frequently much larger than the centered R^2 (see Wooldridge, 2008).

	Full Time Period			06/1997–12/2003			01/2004–05/2007			06/2007–12/2009		
	coeff.	p-val.	sig.	coeff.	p-val.	sig.	coeff.	p-val.	sig.	coeff.	p-val.	sig.
Expected Loss	221.04	0.0000	***	244.55	0.0000	***	226.24	0.0000	***	194.67	0.0000	***
Peak Territory	175.08	0.0000	***	134.98	0.0000	***	267.59	0.0000	***	134.29	0.0039	***
Swiss Re	–103.58	0.0003	***	–76.45	0.0029	***	–59.82	0.1019		–177.33	0.0006	***
RoL Index	161.85	0.0000	***	196.37	0.0005	***	211.92	0.0003	***	66.75	0.2259	
Investment Grade	–159.76	0.0000	***	–108.00	0.0001	***	–183.10	0.0022	***	–171.24	0.0004	***
BB Spread	26.57	0.0074	***	19.40	0.0280	**	-30.68	0.3419		59.52	0.0000	***
df	306.00			105.00			104.00			85.00		
SEE	155.50			105.80			139.70			180.30		
Adjusted R^2	0.89			0.86			0.94			0.88		
White's Test	36.29	0.0000	***	3.78	0.1508		0.04	0.9787		3.55	0.1693	
BP Test	49.51	0.0000	***	9.52	0.1466		3.51	0.7432		6.80	0.3396	

Table 4: Robustness with Regard to Subsamples for Different Time Periods

Least squares coefficients (coeff.), p-values, significance levels (sig.), and degrees of freedom (df) for the proposed cat bond pricing model estimated on the full sample (06/1997–12/2009) and three similarly sized subsamples (111, 110, and 91 bonds) for different time periods. All standard errors and p-values have been computed based on the Newey-West HAC covariance matrix. The (centered) adjusted R^2 and the standard error of the estimate (SEE) measure explained variance and goodness of fit for each model. White's test and the Breusch-Pagan (BP) test have been provided as heteroskedasticity diagnostics.

model on three similarly sized subsamples for different time periods, each of which represents a specific market environment. The first one (06/1997–12/2003) reflects the takeoff phase of the cat bond asset class, the second one (01/2004–05/2007) includes the Sumatra-Andaman earthquake and Hurricane Katrina, and the third one (06/2007–12/2009) covers the recent financial crisis. In addition, we consider three peril-specific subsamples, exclusively comprising wind, earthquake, or multiperil bonds. The results for these robustness checks are shown in Tables 4 and 5.[32] Adjusted R^2 and SEE indicate that the fit remains strong across all six subsamples. However, we do notice some variation in the regression coefficients and, in a few cases, certain factors do not seem to be priced at all. Thus, as a further confirmation of the model's soundness, we will briefly explore reasonable explanations for these observations.

Consider, for example, the "peak territory" coefficients as shown in the second row of Table 4. In the first and the last time period, these equal 134.98 and 134.29 bp, respectively. For the subsample of cat bonds issued between January 2004 and May 2007, however, we notice a sharp increase to 267.59 bp. A potential reason for this phenomenon is the occurrence of hurricanes Katrina, Rita, and Wilma in 2005. Due to these mega-events, market participants may have become much more alert with regard to U.S. hazards.[33] Similarly, the discount associated with investment-grade ratings is higher than in the first subsample, whereas the coefficients for the sponsor and the BB spread turned out insignificant. Together, these effects indicate that catastrophe risk instead of credit-related issues formed the dominant concern in the market. Furthermore, between June 2007 and December 2009, we estimate a considerably larger negative coefficient for the sponsor-related dummy variable "Swiss Re" than in the first two periods. This suggests that the uncertainty during the global financial crisis induced cat bond investors

[32] We have also estimated the full model on the three peril-specific subsamples in order to provide insights concerning the relevance of further covariates. The respective results can be found in the Appendix.

[33] Based on their analysis of the 2005 hurricane season, Ahrens et al. (2009) also suspect such a shift in investor perceptions.

	All Natural Perils			Wind			Earthquake			Multiperil		
	coeff.	p-val.	sig.	coeff.	p-val.	sig.	coeff.	p-val.	sig.	coeff.	p-val.	sig.
Expected Loss	221.04	0.0000	***	214.99	0.0000	***	202.25	0.0000	***	217.09	0.0000	***
Peak Territory	175.08	0.0000	***	175.58	0.0000	***	214.46	0.0000	***	104.50	0.0543	*
Swiss Re	–103.58	0.0003	***	–58.31	0.2473		–97.94	0.0004	***	–82.49	0.1170	
RoL Index	161.85	0.0000	***	215.41	0.0000	***	145.86	0.0011	***	194.79	0.0105	**
Investment Grade	–159.76	0.0000	***	–35.74	0.1850		–126.00	0.0002	***	–192.48	0.0000	***
BB Spread	26.57	0.0074	***	11.27	0.4131		15.28	0.0542	*	41.33	0.0001	***
df	306.00			96.00			77.00			121.00		
SEE	155.50			161.80			117.80			161.60		
Adjusted R^2	0.89			0.88			0.79			0.91		
White's Test	36.29	0.0000	***	5.65	0.0594	*	4.42	0.1095		21.96	0.0000	***
BP Test	49.51	0.0000	***	13.15	0.0408	**	9.32	0.1566		27.84	0.0001	***

Table 5: Robustness with Regard to Peril-Specific Subsamples

Least squares coefficients (coeff.), p-values, significance levels (sig.), and degrees of freedom (df) for the proposed cat bond pricing model estimated on the full sample (all natural perils) and three peril-specific subsamples (wind, earthquake, and multiperil bonds). All standard errors and p-values have been computed based on the Newey-West HAC covariance matrix. The (centered) adjusted R^2 and the standard error of the estimate (SEE) measure explained variance and goodness of fit for each model. White's test and the Breusch-Pagan (BP) test have been provided as heteroskedasticity diagnostics.

to attach an even greater importance to the ceding entity of the transaction. On the other hand, we do not find a significant effect for the rate on line index, although it is clearly one of the key spread drivers in the first two periods. We attribute this to the default of Lehman Brothers, due to which four transactions lost their TRS counterparty and ended up in distress. As a result, the market's focus shifted from reinsurance prices towards the credit risk inherent in cat bonds. This notion is supported by the elevated coefficient for the BB spread, implying a contagion from the markets for high-yield corporate debt.

The first important observation with regard to the results for the peril-specific subsamples in Table 5 is that we are unable to document a significant impact of three of the model's independent variables on the spread of wind bonds. It turns out that for the factor "investment grade", this is a statistical artifact rather than a substantive issue, since our subsample of wind bonds comprises only one transaction with an investment-grade rating. Thus, the observed variation is simply too low to yield significant estimates. The variables "Swiss Re" and "BB spread", however, do indeed not seem to play a central role in the pricing of wind bonds. Moreover, the coefficient estimates for earthquake bonds appear to be roughly in line with our findings for the full sample. Finally, just as for wind bonds, the binary regressor "Swiss Re" is also insignificant in the multiperil subsample. In contrast to singleperil transactions, this type of cat bond offers a certain inherent diversification of natural disaster risk. Therefore, its investors may be less focused on the sponsor and his underwriting and structuring abilities. The same reasoning applies to the comparatively lower markup for peak territories that we find for multiperil bonds.

The aforementioned deviations in the coefficients of certain regressors point to potential structural breaks between the subsamples. Those have been confirmed by unreported results of a Chow test which are available from the author upon request.[34] Hence, the primary market for cat bonds adheres to varying regimes across time, causing the effect strengths of the main spread drivers to change. Analogously, each type of natural peril is associated with a somewhat different weighting of the pricing factors. Potential consequences of this diagnosis with regard to our model's out-of-sample performance will be evaluated in the following section. In any case, to ensure that the pricing is consistent with the prevailing economic environment, one should aim for a regular recalibration of the model, including data for the most recent transactions. Similarly, the model could be estimated and applied separately for each peril.[35]

4.3 Comparison with Alternative Model Specifications

In-Sample Model Fit

Having established the properties of our econometric pricing model across different subsamples, below we will compare its fit with five actuarially-oriented alternatives that have been proposed in the literature.[36] Although some specifications require straightforward logarithmic transformations first, all of them can be calibrated by means of OLS. Hence, we directly provide the expressions for the fitted models, indicating estimated parameters as follows: $\hat{\alpha}$, $\hat{\beta}$, $\hat{\gamma}$, $\hat{\lambda}$.

- The most trivial alternative treats the spread as a simple linear function of EL_i:

$$\hat{S}_i^{\mathrm{CAT}} = \hat{\alpha} + \hat{\beta}\mathrm{EL}_i. \tag{5}$$

- Furthermore, in the second model the spread is polynomial in the natural logarithm of EL_i:

$$\hat{S}_i^{\mathrm{CAT}} = \hat{\alpha} + \hat{\beta}\ln(\mathrm{EL}_i) + \hat{\gamma}\ln(\mathrm{EL}_i)^2. \tag{6}$$

- Lane (2000) relies on the probability of first loss PFL_i and the conditional expected loss CEL_i:

$$\hat{S}_i^{\mathrm{CAT}} = \mathrm{EL}_i + \hat{\alpha}\mathrm{PFL}_i^{\hat{\beta}}\mathrm{CEL}_i^{\hat{\gamma}}. \tag{7}$$

- Similarly, Major and Kreps (2002) assume the spread to be a power function of EL_i:

$$\hat{S}_i^{\mathrm{CAT}} = \hat{\alpha}\mathrm{EL}_i^{\hat{\beta}}. \tag{8}$$

- Finally, the following specification has been developed by the ILS fund Fermat Capital:

$$\hat{S}_i^{\mathrm{CAT}} = \mathrm{EL}_i + \hat{\lambda}\sqrt{\mathrm{EL}_i(1-\mathrm{EL}_i)/\xi_i}, \tag{9}$$

[34] Although the Chow statistic generally requires homoskedasticity, Ghilagaber (2004) has shown that it is well behaved as long as the tested samples are equal in size and display a similar form of heteroskedasticity.

[35] Yet another remedy would be to modify the original model by means of interaction effects for those variables that exhibit particularly large fluctuations across perils.

[36] An overview can be found in Jaeger et al. (2010). It is important to note that the model of Lane and Mahul (2008), which relies on the expected loss and the rate on line index as predictors, is nested in our more general specification. In addition, there is no need for a separate evaluation of the framework by Bodoff and Gan (2009), since we have already rejected peril-specific intercepts and potential interaction effects with the expected loss in Section 3.

where λ equals the "ILS Sharpe Ratio" to be estimated and ξ_i is the "peril rank" (or catastrophe risk weight) of issue i (see Gatumel and Guégan, 2009). According to Jaeger et al. (2010), this parameter is normally set to 1 for U.S. Wind, 2 for U.S. Earthquake, 3 for Europe Wind, and 4 for Japan Earthquake transactions. Due to their comparable abundance, we assign U.S. Multiperil bonds to the same category as U.S. Wind bonds. All other transactions receive a ξ-value of 5.

All estimations are carried out on the full sample of 312 cat bonds issued between June 1997 and December 2009. Figure 6 is a graphical illustration of the aforementioned approaches together with our suggested specification, which will hereafter be referred to as "Multifactor (2014)". The corresponding parameter values can be found in Table 6. Interestingly, with an SEE of 208.10, the simple linear model exhibits the best fit among the five alternatives, followed by the approach of Lane (2000). Moreover, it explains the largest amount of variance in the cat bond spreads (adjusted R^2 of 0.80). When comparing these figures with the results for our econometric pricing model as shown in the first columns of Tables 4 and 5 (adjusted R^2: 0.89, SEE: 155.50), however, we notice that the latter provides a substantially better in-sample fit.

Out-of-Sample Performance

The larger the number of explanatory variables, the more susceptible an econometric model is to overfitting, which may result in a good in-sample accuracy but a poor out-of-sample pricing performance. Therefore, as a final step in our analysis, we also conduct an out-of-sample test of our model in comparison with the previously considered alternatives. A typical procedure in this regard is to estimate the parameters of the model on one part of the data (calibration sample) and then use it to price the remaining transactions (test sample). Thereby one emulates the actual practical problem of not knowing the future values of the dependent variable. The following common out-of-sample performance measures will be applied (see, e.g., Xu and Taylor, 1995; Campbell and Thompson, 2008):

- Mean error (ME):

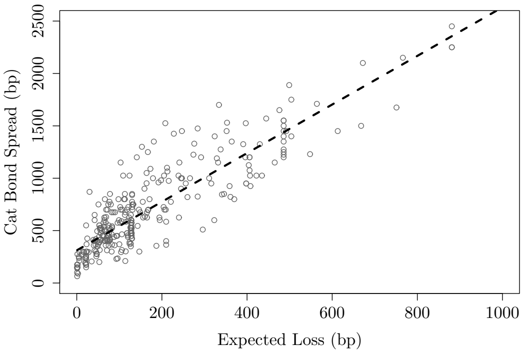
$$\text{ME} = \frac{1}{N'} \sum_{i=1}^{N'} \left(S_i^{\text{CAT}} - \hat{S}_i^{\text{CAT}} \right). \tag{10}$$

- Mean absolute error (MAE):

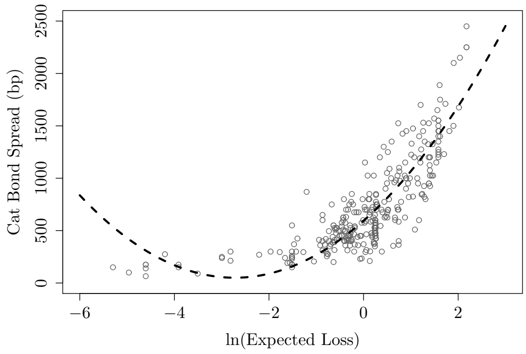
$$\text{MAE} = \frac{1}{N'} \sum_{i=1}^{N'} \left| S_i^{\text{CAT}} - \hat{S}_i^{\text{CAT}} \right|. \tag{11}$$

- Root mean square error (RMSE):

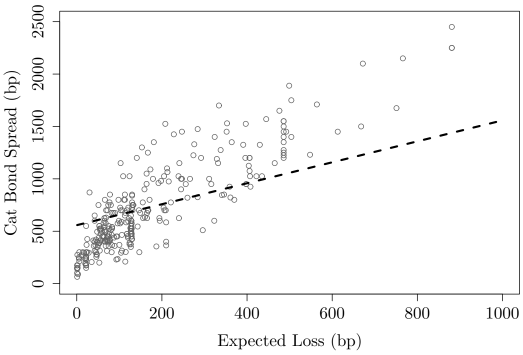
$$\text{RMSE} = \sqrt{\frac{1}{N'} \sum_{i=1}^{N'} \left(S_i^{\text{CAT}} - \hat{S}_i^{\text{CAT}} \right)^2}. \tag{12}$$



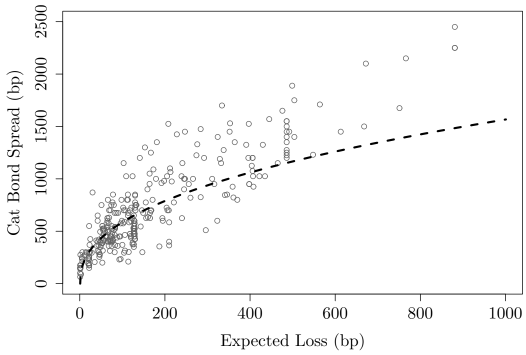
(a) Linear in Expected Loss



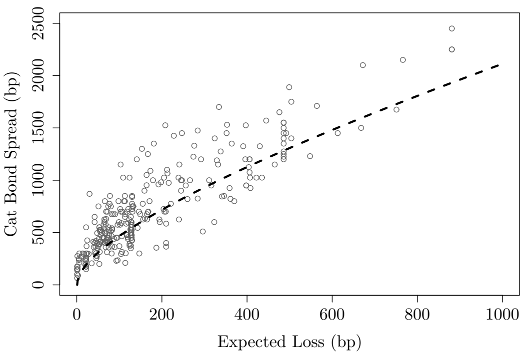
(b) Polynomial in Ln(Expected Loss)



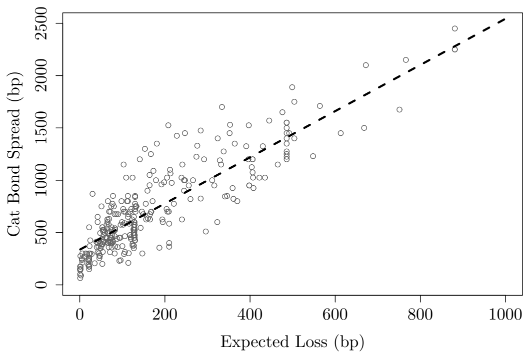
(c) Lane (2000)



(d) Major and Kreps (2002)



(e) Fermat Capital



(f) Multifactor (2014)

Figure 6: Graphical Illustration of the Fitted Models

Each model has been estimated by means of OLS on the sample of 312 cat bonds issued between June 1997 and December 2009. The dashed lines represent the predicted values of the spread for different magnitudes of the expected loss. To enable a presentation of the multifactor models "Lane (2000)" and "Multifactor (2014)" in this two-dimensional space, all further independent variables apart from the expected loss have been set to their sample mean. Similarly, the peril rank in the model of Fermat Capital has been set to 2.5, i.e., the center of the range of possible values.

	Linear in EL			Polynomial in Ln(EL)			Lane (2000)			Major/Kreps (2002)			Fermat Capital		
	coeff.	p-val.	sig.	coeff.	p-val.	sig.	coeff.	p-val.	sig.	coeff.	p-val.	sig.	coeff.	p-val.	sig.
$\hat{\alpha}$	313.70	0.0000	***	594.58	0.0000	***	415.74	0.0000	***	588.54	0.0000	***			
$\hat{\beta}$	232.02	0.0000	***	399.49	0.0000	***	0.37	0.0000	***	0.43	0.0000	***			
$\hat{\gamma}$				73.32	0.0000	***	0.08	0.1159							
$\hat{\lambda}$													58.71	0.0000	***
df	310.00			309.00			309.00			310.00			311.00		
SEE	208.10			242.60			221.15			266.84			241.70		
Adjusted R^2	0.80			0.73			0.54			0.71			0.50		
White's Test	7.10	0.0287	**	29.75	0.0000	***	0.28	0.8703		16.87	0.0002	***	15.04	0.0005	***
BP Test	7.10	0.0077	***	34.24	0.0000	***	1.14	0.5650		16.87	0.0000	***	15.04	0.0001	***

Table 6: In-Sample Fit of the Five Alternative Model Specifications

Least squares coefficients (coeff.), p-values, significance levels (sig.), and degrees of freedom (df) for five cat bond pricing models proposed in the extant literature. All standard errors and p-values have been computed based on the Newey-West HAC covariance matrix. The (centered) adjusted R^2 and the standard error of the estimate (SEE) measure explained variance and goodness of fit for each model. White's test and the Breusch-Pagan (BP) test have been provided as heteroskedasticity diagnostics.

	Multifactor (2014)	Linear in EL	Polynomial in Ln(EL)	Lane (2000)	Major and Kreps (2002)	Fermat Capital
Panel A: Calibration Sample: 06/1997–12/2009 (N = 312); Test Sample: 01/2010–12/2012 (N' = 114)						
ME	–34.14	57.49	13.29	105.05	123.14	49.27
MAE	180.34	203.96	191.52	202.34	209.59	193.93
RMSE	241.81	270.97	254.35	266.66	283.88	261.32
R^2_{OS}	0.70	0.62	0.67	0.29	0.59	0.31
Panel B: Calibration Sample: 06/1997–12/2010 (N = 352); Test Sample: 01/2011–12/2012 (N' = 74)						
ME	59.17	124.21	66.07	156.45	161.05	103.84
MAE	192.46	236.46	226.40	250.54	253.44	213.24
RMSE	258.56	304.47	292.76	316.27	331.59	287.94
R^2_{OS}	0.68	0.55	0.59	0.22	0.47	0.35
Panel C: Calibration Sample: 06/1997–12/2011 (N = 384); Test Sample: 01/2012–12/2012 (N' = 42)						
ME	94.19	148.91	102.59	183.39	184.22	135.25
MAE	203.84	249.77	249.37	271.95	277.74	222.84
RMSE	280.91	332.32	323.47	347.28	361.83	286.47
R^2_{OS}	0.65	0.51	0.54	0.17	0.42	0.43

Table 7: Out-of-Sample Pricing Performance of the Models

Out-of-sample performance measures for the suggested econometric pricing model and five alternative specifications. All models have been estimated on the subsample of N bonds issued during the indicated calibration period and then applied to price the remaining N' transactions in the test period. The tabulated numbers are the mean errors (ME), mean absolute errors (MAE) and root mean square errors (RMSE) and the out-of-sample R-squared (R^2_{OS}).

- Out-of-sample R-squared (R^2_{OS}):

$$R^2_{\mathrm{OS}} = 1 - \frac{\sum_{i=1}^{N'} \left(S_i^{\mathrm{CAT}} - \hat{S}_i^{\mathrm{CAT}} \right)}{\sum_{i=1}^{N'} \left(S_i^{\mathrm{CAT}} - \bar{S}_i^{\mathrm{CAT}} \right)}, \tag{13}$$

where N' denotes the number of transactions in the test sample, S_i^{CAT} is the observed spread of transaction i, $\hat{S}_i^{\mathrm{CAT}}$ represents the spread generated by the pricing model, and $\bar{S}_i^{\mathrm{CAT}} = \bar{S}^{\mathrm{CAT}}$ equals the historical average spread in the calibration sample.

Table 7 contains the results for three different calibration and test periods. The figures in Panel A, for example, have been obtained as follows: first of all, we fitted each model to the subsample of 312 cat bonds sold in the primary market between June 1997 and December 2009. Subsequently, the resulting parameter vectors were applied to calculate the predicted spreads for the remaining 114 transactions with issue dates between January 2010 and December 2012 that we had reserved for the out-of-sample analysis (see Section 3). The predicted spreads were then combined with the observed spreads of the test sample to determine ME, MAE, RMSE, and R^2_{OS} according to Equations (10) through (13). The same procedure applies to the analyses summarized in Panels B and C, which, however, rely on larger calibration samples.

Examining Table 7, we notice that the multifactor pricing approach produces the smallest MAE and RMSE as well as the highest R^2_{OS} in all three out-of-sample analyses. Similarly, in Panels B and C, the model's ME suggests a superior accuracy than those of the alternatives. Only the polynomial model in Panel A achieves a lower ME in absolute terms. Furthermore, while the out-of-sample accuracy generally deteriorates for the more recent test samples that include fewer observations, this trend is less pronounced for the multifactor specification. Thus, a simple econometric model, which adds a few key explanatory variables to the expected loss, seems to be a quite reliable tool for the pricing of cat bonds in the primary market.

5 Summary and Conclusion

Based on a large data set, encompassing one and a half decades of issuance activity, we identify the main determinants of the primary market cat bond spread. For this purpose, a series of OLS regressions with HAC standard errors is run. In addition, we propose an econometric pricing model, assess its robustness across different subsamples, and compare it with several competing specifications that have been introduced in earlier work. Our findings indicate that the expected loss, the covered territory, the sponsor, the reinsurance cycle, and the BB corporate bond spread are major drivers of the cat bond spread. In contrast to that, issue volume, trigger type, as well as reference peril are much less influential and the term of the security does not seem to be priced at all. The pricing model that we derive from these insights exhibits a stable fit across different calibration subsamples and achieves a higher in-sample and out-of-sample accuracy than the considered alternative approaches.

Due to the scarcity of applied work in this area, the aforementioned insights should be relevant to investors and sponsors alike. Despite our comprehensive analysis, however, a number of open questions remain. First and foremost, our model is specifically designed to price newly issued transactions, meaning that some of the incorporated determinants are not suitable for a recurring valuation of cat bond portfolios over time. Hence, in future research, one could aim to develop a similarly accurate approach for the secondary market, relying on time series instead of cross-sectional data. Second, it could be insightful to attempt a comparison of actuarial and econometric models with some of the contingent claims or utility-based pricing approaches that have been brought forward in the ILS literature. Further empirical evidence will undoubtedly contribute to a broader understanding of the cat bond asset class and help to promote the growth of this still relatively small segment of the capital markets.

6 Appendix

6.1 OLS Estimator, Jackknifed Residuals, and Cook's D

The standard linear regression model for N cross-sectional data points and k independent variables (including an intercept) can be described as

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}, \tag{14}$$

where $\mathbf{y} = (y_1, ..., y_N)'$ denotes the $N \times 1$ vector of values of the dependent variable, $\mathbf{X} = (\mathbf{x}'_1, ..., \mathbf{x}'_N)'$ is an $N \times k$ matrix whose column vectors include the values for the explanatory variables (regressors), $\boldsymbol{\beta} = (\beta_1, ..., \beta_k)'$ represents the $k \times 1$ vector of unknown regression coefficients, and $\boldsymbol{\epsilon} = (\epsilon_1, ..., \epsilon_N)'$ stands for the $N \times 1$ random vector of independent and identically distributed (iid) errors (disturbances), which captures all effects on $\mathbf{y}$ that are not caused by the $\mathbf{X}$. The OLS estimator of $\boldsymbol{\beta}$ is defined as follows (see, e.g., White, 1980):

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}. \tag{15}$$

It minimizes the sum of squared residuals implied by the model and can be computed from a random sample $\{(y_i, x_{i1}, ..., x_{ik}) : i = 1, ..., N\}$ of N observations for the dependent variable and the regressors (see, e.g., Wooldridge, 2008). The corresponding fitted residuals are given by

$$\mathbf{e} = \mathbf{y} - \hat{\mathbf{y}} = \mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}, \tag{16}$$

with $\mathbf{e} = (e_1, ..., e_N)'$. Moreover, $\hat{\mathbf{y}} = \mathbf{X}\hat{\boldsymbol{\beta}} = (\hat{y}_1, ..., \hat{y}_N)'$ are the fitted values, i.e., the model's predictions for the dependent variable based on the observed values for $\mathbf{X}$.

For the identification of outliers, we estimate a model including all regressors and save the fitted residuals e_i ($i = 1, ..., N$). Subsequently, we compute the (internally) studentized residuals, e_i^s, which are defined as[37]

$$e_i^s = \frac{e_i}{\text{SEE}\sqrt{1 - h_{ii}}}, \quad i = 1, ..., N, \tag{17}$$

where $\text{SEE} = \sqrt{\mathbf{e}'\mathbf{e}/(N-k)}$ is the standard error of the estimate and h_{ii} equals the distance of case i from the centroid in a scatter plot of the e_i against the $\hat{y}_i$. The h_{ii} can be found on the main diagonal of the $N \times N$ matrix $\mathbf{H} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$. Moreover, using the e_i^s, we obtain the externally studentized residuals, t_i, as follows:

$$t_i = \frac{e_i}{\text{SEE}_{-i}\sqrt{1 - h_{ii}}} = e_i^s\sqrt{\frac{N-k-1}{N-k-(e_i^s)^2}}, \quad i = 1, ..., N, \tag{18}$$

with SEE_{-i} being the standard error of the estimate when the i-th case has been removed from the sample. Hence, in order to obtain the SEE_{-i} and, in turn, the t_i, one could simply reestimate the model

[37] The following definitions and formulae can, e.g., be found in Kianifard and Swallow (1996).

repeatedly, excluding one of the N cases in each step. An equivalent but less computationally intensive way to arrive at the same result is given by the right-hand side of Equation (18). Furthermore, the e_i^s and h_{ii} can also be employed to calculate Cook's D (distance), D_i, another commonly used measure for the influence of an observation on the OLS estimators that is given by

$$D_i = \frac{(e_i^s)^2}{k} \frac{h_{ii}}{1 - h_{ii}}. \tag{19}$$

Since the externally studentized residuals are t-distributed with $N - k = 308$ degrees of freedom, we are able to derive a critical value of ± 1.97 for the five percent significance level.[38] Each t_i in excess of this threshold indicates an outlier. Similarly, cases that display a Cook's D in excess of $4/(N - k) = 0.0130$ are considered as unusual.

6.2 Further Estimation Results for the Peril-Specific Subsamples

	All Natural Perils			**Wind**			**Earthquake**			**Multiperil**		
	coeff.	p-val.	sig.	coeff.	p-val.	sig.	coeff.	p-val.	sig.	coeff.	p-val.	sig.
Intercept	–50.84	0.6600		–43.89	0.7565		85.63	0.4286		–122.97	0.3630	
Expected Loss	215.31	0.0000	***	203.80	0.0000	***	193.74	0.0000	***	219.64	0.0000	***
Size	–0.27	0.0292	**	–0.46	0.0581	*	–0.15	0.3864		–0.38	0.0411	**
Term	0.70	0.2008		–0.80	0.5015		–0.35	0.5965		2.30	0.0871	*
Indemnity	–70.37	0.0023	***	–99.53	0.0357	**	0.13	0.9984		–35.56	0.3621	
Wind	–70.44	0.4327										
Earthquake	–166.29	0.0703	*									
Multiterritory	168.07	0.0884	*	318.69	0.0000	***	479.98	0.0000	***	137.81	0.2170	
U.S.	212.71	0.0452	**	186.40	0.0143	**	268.98	0.0005	***	175.97	0.1323	
Europe	–57.89	0.5649		–0.67	0.9931		–101.63	0.1526		–73.76	0.6112	
Japan	–31.85	0.7576		–162.98	0.1515		132.41	0.0674	*	96.31	0.4297	
U.S.×Wind	25.91	0.7949										
U.S.×Earthquake	75.00	0.4565										
Europe×Wind	107.39	0.3438										
Japan×Earthquake	138.70	0.2249										
Swiss Re	–101.02	0.0009	***	–124.06	0.0202	**	–98.42	0.0019	***	–95.55	0.0313	**
RoL Index	254.08	0.0000	***	350.18	0.0001	***	82.83	0.1219		251.24	0.0028	***
Investment Grade	–150.17	0.0000	***	8.59	0.8622		–142.49	0.0000	***	–175.14	0.0000	***
BB Spread	26.08	0.0004	***	19.18	0.1826		1.42	0.8438		37.17	0.0000	***
df	293.00			89.00			70.00			114.00		
SEE	149.90			149.50			108.90			160.50		
Adjusted R^2	0.90			0.89			0.81			0.91		

Table 8: Robustness with Regard to Peril-Specific Subsamples

Least squares coefficients (coeff.), p-values, significance levels (sig.), and degrees of freedom (df) for the model including all considered predictor variables estimated on the full sample (all natural perils) and three peril-specific subsamples (wind, earthquake, and multiperil bonds). All standard errors and p-values have been computed based on the Newey-West HAC covariance matrix. The adjusted R^2 and the standard error of the estimate (SEE) measure explained variance and goodness of fit for each model. Note that coefficients for WIND_i and EQ_i as well as the corresponding interaction effects cannot be tested, since the subsamples do not exhibit variation across these dummy variables.

[38] Recall that 29 of the original 466 bonds have already been eliminated due to missing data. From the remaining 437 transactions, 323 fall into our estimation period from June 1997 to December 2009. Hence, our N for this analysis equals 323, from which we subtract a total of 14 regressors plus the intercept.

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