The Secondary Market of Catastrophe Bonds: Seasonality, Trading and Returns

Von der Mercator School of Management, Fakultät für Betriebswirtschaftslehre, der

Universität Duisburg-Essen

zur Erlangung des akademischen Grades

eines Doktors der Wirtschaftswissenschaft (Dr. rer. oec.)

genehmigte Dissertation

von

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aus

Frechen

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Tag der mündlichen Prüfung: 28. September 2021

Acknowledgement

First and foremost I want to thank my two co-authors Prof. Dr. Martin Hibbeln and Prof. Dr. Alexander Braun for their support. I am especially grateful to Martin as my supervisor for his continuous guidance throughout the time I spend writing this dissertation. In addition, I want to thank the whole team at the chair of Finance at the University of Duisburg-Essen for their support, comments and suggestions: Werner Osterkamp, Raphael Kopp, Ralf Metzler, Noah Urban, Courtney Schuh, Felix Kochhan and Ines Fricke-Groenewold.

I also want to thank all my friends and family who have supported me over the past five years. I thank my sister Claudia and my parents Andrea and Richard. In addition, I want thank the Rudel in Münster: Christoph, Julia, Jan, Bibi, Marlena, Sven, Judith, Theresa, Stella, Martin and Ina for all the fun times we have had over the past five years. I especially want to thank Martin and Christoph for our fruitful discussions on research and teaching. More thanks goes out to my University of Münster business school gang: Pascal, Manuel, Michael, Markus and Martin. I also want to thank Johanna, Anne and Kristiane.

Last but not least I want to thank my girlfriend Saskia for her unwavering support, love and good spirit.

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1. Introduction

1.1 Relevance and problem

Insurers turn to reinsurers for large loss event coverage. Reinsurance companies are able to cover large risks because they offer a broad within industry diversification, which is unavailable to individual insurers. However, reinsurers' ability for within industry diversification has limits, especially for perils with extreme loss potential such as earthquakes, wildfires or hurricanes. With increasing frequency, the (re-)insurance industry draws on the financial markets for additional diversification, when within industry diversification is exhausted or becomes too expensive. (Re-)insurers often use catastrophe bonds (”cat bonds”) to perform this task. Not only (re-)insurance companies but also government institutions can sponsor cat bonds. In 2019, the World Bank has issued cat bonds with a nominal value of US$ 1685 million to cover emergency payments and rescue efforts of emerging economies such as Mexico, Chile, Columbia and Peru for earthquakes but also for the Philippines, which are heavily affected by reoccurring typhoons. Overall, natural catastrophe damages are expected to rise substantially in the wake of climate change (e.g., Munich Re 2020, Swiss Re 2020). For some perils, such as hurricanes, insurability will depend on the insurance industry's ability to diversify.

If a (re-)insurance company (“sponsor”) wants to issue a cat bond, it sets up the following structure: A special purpose vehicle (SPV) engages in a reinsurance contract with the sponsor, selling reinsurance coverage to the sponsor. To cover potential losses from the reinsurance contract, the SPV issues bonds that contain a default trigger that mirrors the reinsurance contract's payment clauses. This reinsurance contract can cover a certain layer of the sponsor's actual losses for a given time period for a specified peril type (or for multiple perils). Alternatively, the SPV and the sponsoring (re-)insurer can agree upon specified catastrophe parameters such as wind speed or an earthquake severity on the Richter scale that trigger the default of the cat bond. The underwriting risk in the reinsurance contract is fully collateralized through the issued bonds. The collateral is kept in a trust account, usually invested in short term treasuries or assets of similar quality and liquidity. Thus, credit risk from the sponsor is excluded in a cat bond transaction. Cat bonds are floating rate notes that pay the investors a fixed coupon over the flexible interest from the trust account. This fixed coupon is fully covered by premium payments, which the sponsor pays to the SPV in exchange for the catastrophe coverage. These fixed payments reimburse the investors for the cat bond's inherent underwriting risk.

When pricing this type of risk transfer, the empirical cat bond literature has focused on the explanation of yield spreads through default risk and other components such as financial market conditions or cat bond specific properties such as peril types or trigger types. Similar to corporate bonds, the individual cat bond's default risk is the primary driver of yield spreads (e.g., Major/Kreps 2002, Lane/Mahul 2008, Braun 2016, Gürtler et al. 2016). Although its tradability is a cat bond's most important advantage over traditional reinsurance contracts, the secondary market of cat bonds is almost completely unexplored. Dieckmann (2010) uses limited secondary market data to investigate the change in reinsurance rates for existing bonds after hurricane Katrina. Gürtler et al. (2016) use secondary market data to investigate the impact of hurricane Katrina and the default of Lehman Brothers. Braun et al. (2019) indirectly rely on secondary Insurance-Linked Security (ILS) data by determining common risk factors in ILS fund returns. However, none of these articles (1) model the strong seasonal fluctuations of the secondary cat bond market, (2) investigate its trading and the associated liquidity premium and (3) explain its realized returns.

For cat bonds, the default risk consists of its inherent underwriting risk. Specialized risk modelling firms determine a cat bond's inherent underwriting risk through sophisticated earthquake and weather models (e.g., for hurricanes, wildfires and hail storms). Their efforts culminate in a risk report that contains a detailed probability distribution of loss potential. The expected loss (EL) as the first moment of this distribution is typically used to account for default risk in empirical cat bond research. However, to the best of my knowledge, these risk reports and the attached loss distribution are only issued once prior to the issue of a cat bond. This means, they do not guide an investor through a cat bond's life cycle. This is especially important in the context of the seasonal nature of the cat bond market: hurricanes only occur in the second half of a calendar year. The hurricane season generally peaks in September. Essentially, a single-peril cat bond is a riskless investment outside of the hurricane season. This translates into substantial changes with respect to the cat bond's risk exposure throughout the calendar year. These substantial changes should be reflected in secondary cat bond market trading and pricing. Since this seasonal event risk is the most important driver of cat bond spreads, it is important to carefully model these seasonal swings in order to open up an avenue to investigate the secondary cat bond market, for example, with respect to its liquidity and realized returns.

The illiquid nature of cat bonds (e.g., Lane 2016) indicates a substantial illiquidity premium in addition to the default risk premium. However, cat bond liquidity has not been investigated as a yield spread determinant beyond rudimentary liquidity measures such as issued volume and remaining maturity. Braun (2016) finds a negative relationship of issued volume and yield spread while Gürtler et al. (2016) find the opposite effect, and none of these studies finds a significant effect for the remaining maturity. In addition, actual trading remains unexplored.

Although yield spreads are very important to investors for pricing and investment decisions, realized returns are more important. To the best of my knowledge, no article in the relevant literature has yet explained the realized returns of cat bonds. Instead, three articles have attempted to use higher-level approaches in investigating cat bond returns. Trottier et al. (2019) analyze the risk-return profile of the Swiss Re Cat Bond Performance Indices. Drobetz et al. (2020) explore the role of cat bonds as a diversifier in multi-asset portfolios. Braun et al. (2019) investigate Insurance Linked Securities funds returns as a proxy for returns of the cat bond market. Thus, the cat bond literature lacks a factor model to explain cat bond returns.

1.2 Aims and research questions

As mentioned above, cat bonds can be an important cornerstone in risk transfer and risk coverage efforts, especially in the wake of climate change where catastrophe losses of adverse weather events continue to rise. Since tradability of cat bonds is their most important advantage over regular reinsurance contracts, it is important to explore the secondary market of these securities. Contrary to its importance, only little is known in the literature about the secondary market for cat bonds. This means, little is known about how the seasonal nature of some catastrophes move the market, little is known about how cat bonds are actually traded and how its liquidity impacts yield spreads and little is known about the returns on bond level and how risk factors might explain them. Ultimately, the expanded knowledge of the secondary cat bond market could lower its market entry barriers and attract more investors improving extreme event protection for the insurance industry and their policyholders. This dissertation answers the following research questions in three essays:

<u>Seasonality in catastrophe bonds and market-implied catastrophe arrival frequencies (Essay 1)</u>

- Do the yield spreads of cat bonds fluctuate with the within year distribution of U.S. hurricanes and European winter storms?
- Can we develop a conceptual framework to model the within year likelihood of a cat bond being triggered?
- Can we also develop a method to extract the investors' opinion on the within year distribution on these perils from the observable seasonal fluctuations in yield spreads?

Trading and liquidity in the catastrophe bond market (Essay 2)

- How are cat bonds traded on the secondary market?
- How can we measure and explain the associated liquidity?
- Is there a liquidity premium on the cat bond market and can it be quantified?

Common risk factors in the cross section of catastrophe bond returns (Essay 3)

- What are the realized returns on the cat bond market?
- What factors can explain the cross-section of cat bond returns?
- Can we propose a comprehensible cat bond factor pricing model?

1.3 Summary of essays

Essay 1 – Seasonality in catastrophe bonds and market-implied catastrophe arrival frequencies

with Martin Hibbeln

This article has been presented at the 4th World Risk and Insurance Economics Congress (WRIEC), 2020; 26th Annual Meeting of the German Finance Association (DGF), 2019; 46th Annual Seminar of the European Group of Risk & Insurance Economists (EGRIE), 2019; Doctoral Brown Bag Seminar in Economics, Mercator School of Management (MSM), 2019; Annual Congress of the German Insurance Science Association (DVfVW), 2019; 12th Ruhr Graduate School in Economics Doctoral Conference (RGS), 2019; 53rd Annual Meeting of the Western Risk and Insurance Association (WRIA), 2019; Frankfurt Insurance Research Workshop (FIRW), 2018. This project received financial support from the German Insurance Science Association (DVfVW). On 10th January 2021, this article has been published in: *Journal of Risk and Insurance*, 88(3): 785-818. CC BY-NC-ND 4.0, https://doi.org/10.1111/jori.12335

Whereas for the vast majority of traditional corporate bonds there is no clear seasonality of default risk, the default risk of cat bonds fluctuates with the likelihood of qualifying events, e.g., U.S. hurricanes mostly occur in summer or fall and do not occur in spring. Although seasonality clearly has an impact on cat bonds, the link between the seasonal nature of catastrophic events and cat bond spreads is unexplored in the empirical literature. At the same time, these current secondary market spreads are of utmost importance to investors and issuers alike: Investors purchase additional cat bonds if spreads are high enough to satisfy their risk appetite, whereas they may refrain from the purchase of new cat bonds on the primary markets if they do not offer the same or better rates as cat bonds on the secondary markets. Issuers sell additional cat bonds if spreads on the secondary market for similar risk are lower than rates for traditional reinsurance contracts.

We develop a conceptual framework to model the seasonality in the probability of trigger events in catastrophe bonds. This conceptual framework has two elements: a hazard rate model and a modeled seasonality measure. 1) Based on the hazard rate model, we illustrate the theoretical implications for cat bond spreads stemming from seasonal fluctuations in the probability of a cat bond being triggered. 2) We derive a comprehensible measure to model the seasonal fluctuations in spreads. This measure transforms seasonally fluctuating arrival frequencies – i.e., the distribution of the likelihood of peril events occurring across one year – into the time-varying expected loss of each individual cat bond. We support this theoretical framework by analyzing fluctuations of secondary market cat bond spreads with fixed effect regressions. To this end, we use a data set that includes 386 seasonality-affected cat bonds issued between 2002 and 2017. We have three main results: First, we document how seasonality affects cat bond spreads. We find that spreads peak right before the risk season starts and reach their lowest point right after risk season ends; the amplitude of seasonal fluctuation increases as a bond nears maturity; in absolute terms, bonds with EL loss fluctuate more strongly than bonds with low EL; single-peril bonds fluctuate more strongly than multi-peril bonds. Second, the proposed "seasonality-adjusted EL" measure, which is based on the developed conceptual framework, captures seasonal fluctuations on cat bond spreads. It explains up to 47% of all secondary market fluctuations among cat bonds that are affected by seasonality (measured by adjusted within R^2). The results on the seasonality measure are strongly supported by the robustness check with TRACE data. Third, we are able to estimate the market-implied distributions of arrival frequencies from secondary market data. These market-implied distributions explain secondary market fluctuations as good as modeled distributions of arrival frequencies.

Essay 2 – Trading and liquidity in the catastrophe bond market

with Martin Hibbeln

This article has been presented at the Annual Congress of the German Insurance Science Association (DVfVW), 2021; 55th Annual Meeting of the Western Risk and Insurance Association (WRIA), 2021; 53rd Annual Meeting of the Southern Risk and Insurance Association (SRIA), 2020; 4th World Risk and Insurance Economics Congress (WRIEC), 2020; Doctoral Brown Bag Seminar in Economics, Mercator School of Management (MSM), 2020. This project received financial support from the German Insurance Science Association (DVfVW). This article has won the 2020 Harris Schlesinger Memorial Doctoral Research Award of the Southern Risk and Insurance Association (SRIA). This article is currently under review (2nd round revise and resubmit "Major Revision") at the Journal of Risk and Insurance (VHB JQ3: A).

To control for the substantial seasonal fluctuations in cat bond yield spreads enables us to further explore the secondary cat bond market. For corporate bonds it is known that liquidity is another important driver of yield spreads, second only to default risk. Chordia et al. (2004) define liquidity as the ability to buy and sell large quantities of an asset quickly and at a low cost. Investors are willing to pay a premium on a liquid asset compared to a less liquid asset of similar default risk. Although the illiquid nature of cat bonds indicates a substantial liquidity premium in the cat bond market, there is only very limited knowledge on actual trading, liquidity determinants, and the liquidity premium for cat bonds. Instead, Braun et al. (2019) state that the separation of the liquidity premium from other yield spread components is currently not possible for ILS due to these limitations in ILS data. On the contrary, we are now able to separate the liquidity premium from other yield spread components through the increasing availability of ILS data in the Trade Reporting and Compliance Engine (TRACE) where we observe bid-ask spreads on individual secondary market trades on the over-the-counter (OTC) market. Bid-ask spreads are frequently used as liquidity measures in the empirical corporate bond pricing literature (e.g., Chen et al. 2007, Acharya et al. 2013, Schuster/Uhrig-Homburg 2015).

We acquire a TRACE data set from January 2015 to March 2019. During this period, we observe the bid-ask spread of 3341 trade pairs from 229 cat bonds. We employ pooled ordinary least squares (OLS) and fixed effects regression models. For corporate bonds, estimating the liquidity premium is notoriously difficult, because default risk and liquidity are endogenously linked. Chen et al. (2018) theorize a spiral of deteriorating default risk and liquidity: Default risk is negatively correlated with liquidity when firms have difficulty to roll over debt. A low liquidity makes rolling over debt more costly which makes a default more likely. At the same time, an increase in default risk can increase inventory costs for dealers which in turn reduces liquidity. Contrary to corporate bonds, the default event in cat bonds is strictly exogenous. Nevertheless, we support our results with simultaneous equations models. We are able to contribute to the empirical cat bond literature in three ways: First, we find that cat bonds are more strongly traded outside of the U.S. hurricane season. Trading is especially low August through September when the hurricane season reaches its peak. Additionally, trading increases as a bond nears its maturity. It appears that the secondary market of cat bonds is dominated by dealers who do not hold an inventory as indicated by the large share of round trip trades. Second, using bid-ask spreads as a liquidity measure, we identify the following major liquidity determinants: A bond's liquidity is low when its default risk is high, it is more expensive to execute trades of large volume, and liquidity is increasing when a bond approaches its maturity. Third, we find that a lower liquidity causes a substantially increasing yield spread: A 1 basis point (bp) increase in bid-ask spreads is associated with 10 bps increase in yield spread. On average, the liquidity component of a cat bond is 98 bps. Overall, 21% of the yield spread of cat bonds can be attributed to the liquidity premium. This liquidity premium is even larger for bonds with a high default risk, which is driven by a time-series and a cross-sectional determinant: Liquidity is low in time periods of high default risk, and liquidity is more strongly priced for risky cat bonds. We measure the latter effect by forming sub samples of different rating categories. In addition, we find evidence for a positive relationship between market liquidity – measured by the mean bid-ask spread of the current quarter – and yield spreads.

Essay 3 – Common risk factors in the cross-section of catastrophe bond returns

with Alexander Braun and Martin Hibbeln

This article has been presented at the Doctoral Brown Bag Seminar in Economics, Mercator School of Management (MSM), 2021; Annual Meeting of the American Risk and Insurance Association (ARIA), 2021. This project received financial support from the German Insurance Science Association (DVfVW).

Although a substantial literature has emerged that explains observable yield spreads, to the best of our knowledge only three papers to date have examined realized cat bond returns. Trottier et al. (2019) analyze the risk-return profile of the Swiss Re Cat Bond Performance Indices. Drobetz et al. (2020) explore the role of cat bonds as a diversifier in multi-asset portfolios. Braun et al. (2019) develop a new breed of factor models for the ILS asset class, which succeed at explaining the historical returns of dedicated ILS funds based on the returns of the cat bond market. However, these ILS-specific factor models do not reveal the fundamental drivers of risk premiums in the cat bond market itself. Historically, cat bonds have provided high single-digit average annual returns, paired with a low volatility and little correlation to other asset classes (Braun et al., 2019). This indicates surprisingly high abnormal returns compared to other classes of financial instruments such as corporate bonds. Thus, we investigate the returns of cat bonds to address this cat bond return puzzle (Bantwal/Kunreuther 2000).

Based on a novel data set, provided by a global reinsurance brokerage firm, we contribute the first analysis of expected excess returns in the cat bond market. Our data comprises monthly secondary market prices and coupon payments for virtually all cat bonds that existed in the twenty years from 2001 to 2020. This allows us to calculate realized excess returns on individual cat bonds and subsequently explore the cross-sectional determinants of cat bond risk premiums. First, we create a group of candidates of potential cat bond factors. These candidates are composed of seasonal event risk variables, a downside risk factor and the bond property factors indemnity, multi-peril, multilocation, hurricane and U.S. Second, we use independent univariate and bivariate portfolio sorts and Fama/MacBeth (1973) regressions to restrict this field of candidates to the candidates that are able to explain the cross-section of one-month ahead returns. Third, we create factor returns for the leftover event risk candidates by creating long-short portfolios for these factors. We find that two seasonal event risk factors explain the time-series of the cat bond market returns. Fourth, we add the corporate bond factors DEF and TERM from Fama/French (1993) to the preliminary two-factor cat bond model and find that they also explain a small proportion of the cat bond market returns. Finally, we propose a four-factor model for the cat bond asset class, consisting of the time-varying probability of first loss, a separate seasonality factor as well as the TERM and DEF factors. This four-factor model predicts 60% of the time series variation of the historical cat bond market returns, whereas the standard Fama-French three-factor model (see Fama/French 1993) with TERM and DEF and the Fama-French five-factor model (see Fama/French 2015) applied to the cat bond market only yield adjusted R-squares of 4% and 3%, respectively. Compared to the same Fama-French models, our four-factor model substantially reduces the observable alpha on the cat bond market from roughly 0.38% per month to 0.16% per month.

Seasonality in Catastrophe Bonds and Market-Implied Catastrophe Arrival Frequencies

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Abstract

We develop a conceptual framework to model the seasonality in the probability of catastrophe bonds being triggered. This seasonality causes strong seasonal fluctuations in spreads. For example, the spread on a hurricane bond is highest at the start of the hurricane season and declines as time goes by without a hurricane. The spread is lowest at the end of the hurricane season assuming the bond was not triggered, and then gradually increases as the next hurricane season approaches. The model also implies that the magnitude of the seasonality effect increases with the expected loss and the approaching maturity of the bond. The model is supported by an empirical analysis that indicates that up to 47% of market fluctuations in the yield spreads on single-peril hurricane bonds can be explained by seasonality. In addition, we provide a method to obtain market-implied distributions of arrival frequencies from secondary market spreads.

Keywords: alternative risk transfer, bond spreads, underwriting risk, seasonality, catastrophe arrival frequencies

JEL: G12, G22

On 10th January 2021, this article has been published in: *Journal of Risk and Insurance*, 88(3): 785-818. `https://doi.org/10.1111/jori.12335`

2. Essay 1 – Seasonality in catastrophe bonds and market-implied catastrophe arrival frequencies

2.1 Introduction

Catastrophe bonds ("cat bonds") are vehicles to transfer underwriting risk from sponsors, which are mostly insurance or reinsurance companies but sometimes also corporates or sovereigns, to capital markets.[1] The development of the cat bond market mirrors the growing demand for major natural catastrophe protection. Climate change and growing properties in coastal areas may have contributed to this demand. Although the main characteristic of cat bonds is fungibility of catastrophe risk on the secondary market, the knowledge of the secondary market of cat bonds is sparse. We want to reduce this gap by providing insights into one of the most important drivers of secondary market spreads: seasonality. Whereas for the vast majority of traditional corporate bonds there is no clear seasonality of default risk, the default risk of cat bonds fluctuates with the likelihood of qualifying events, for example, U.S. hurricanes mostly occur in summer or fall and do not occur in spring. Although seasonality clearly has an impact on cat bonds, the link between the seasonal nature of catastrophic events and cat bond spreads is unexplored in the scientific empirical literature.

A typical cat bond pays a flexible coupon that consists of a floating interest rate such as the LIBOR or a money market rate plus a fixed additional coupon—the risk premium or spread. While the fixed coupon of a bond remains unchanged, its implicit spread may fluctuate throughout its lifetime depending on its price on secondary markets. These current secondary market spreads are of utmost importance to investors and issuers alike: Investors purchase additional cat bonds if spreads are high enough to satisfy their risk appetite whereas they may refrain from the purchase of new cat bonds on the primary markets if they do not offer the same or better rates as cat bonds on the secondary markets. Issuers sell additional cat bonds if spreads on the secondary market for similar risk are lower than rates for traditional reinsurance contracts.[2]

The empirical literature on cat bonds rarely investigates secondary market spreads. Braun

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[1] Cat bonds have importance beyond the insurance sector: For example, developing countries issue cat bonds to receive payments required for reconstruction and to support the population in case of the occurrence of natural catastrophes. In 2018 the International Bank for Reconstruction and Development launched a series of cat bonds that protect Latin American countries from earthquake damages for a total volume of US$ 1360 m. FIFA issued a US$ 262 m cat bond to protect itself against the possible cancellation of the 2006 World Cup in Germany.

[2] Braun (2016) provides a detailed description of the structure of a cat bond.

(2016) establishes an econometric pricing model to estimate cat bond spreads on primary markets. Lane/Mahul (2008) investigate the influence of the expected loss, peril type, and the reinsurance cycle on cat bond spreads. They use secondary market data in form of one additional observation after issuance for each bond. Dieckmann (2010) uses secondary market data to investigate the change in reinsurance rates for existing bonds after hurricane Katrina. However, he abstracts from seasonality in windstorms by assuming constant exogenous parameters, which can distort empirical results. Braun et al. (2019) indirectly rely on secondary ILS data by determining common risk factors in ILS fund returns. Gürtler et al. (2016) use secondary market data to investigate the impact of hurricane Katrina and the default of Lehman Brothers on spreads; moreover, they study the impact of bond-specific factors and macroeconomic variables on cat bond spreads. They acknowledge seasonality effects on secondary markets but eliminate it by dropping all observations where the time to maturity deviates from a multiple of a full year, thereby loosing up to 75% of their quarterly observations.

We develop a conceptual framework to model the seasonality in the probability of trigger events in catastrophe bonds. This conceptual framework has two elements: A hazard rate model and a modeled seasonality measure. (1) Based on the hazard rate model, we illustrate the theoretical implications for cat bond spreads stemming from seasonal fluctuations in the probability of a cat bond being triggered. From this hazard rate model, we derive a set of hypotheses describing the seasonality on the cat bond market, for example, the general pattern and its increasing amplitude with respect to maturity and riskiness. (2) We derive a comprehensible measure to model the seasonal fluctuations in spreads. This measure transforms seasonally fluctuating arrival frequencies—that is, the distribution of the likelihood of peril events occurring across 1 year—into the time-varying expected loss of each individual cat bond.

We support this theoretical framework by analyzing fluctuations of secondary market cat bond spreads based on a data set that includes 386 seasonality-affected cat bonds issued between 2002 and 2017. This data set includes almost the entire cat bond universe. We acquire these spreads from yearly market reports from Lane Financials LLC. Spreads supplied in these market reports are quotes surveyed from dealers. These quotes from different dealers are then averaged across dealers do acquire spreads for individual bonds (Gürtler et al. 2016).[3] In addition, we show seasonality effects for spreads drawn from actual trading data as reported in the Trade Reporting and Compliance Engine (TRACE). To the best of our knowledge, we are the first to

[3] Yearly market reports from Lane Financials LLC are available at www.lanefinancialllc.com.

use TRACE data on cat bonds in a scientific paper; however, our main analyses rely on dealer quotes because the available time frame for the TRACE data started only in 2015 and, given the low trading frequency for cat bonds, the number of observations is much smaller than in the quarterly Lane Financials LLC data set. To explain fluctuations on secondary markets, we use linear fixed effects regression models, thereby explaining the changes in spreads within each individual bond's observations. We use the relative distributions of arrival frequencies for hurricanes and European winter storms modeled by Applied Insurance Research (AIR) on a monthly basis. To obtain these distributions, we were in touch with a representative from AIR and used information provided in Poliquin/Lalonde (2012). Additionally, we provide a method to extract market-implied arrival frequencies from secondary market spreads, thereby offering an opportunity to access the additional information that investors possess.

We have three main results: First, we document how seasonality affects cat bond spreads. We find that spreads peak right before the risk season starts and reach their lowest point right after risk season ends; the amplitude of seasonal fluctuation increases as a bond nears maturity; in absolute terms, bonds with high expected loss (EL)[4] fluctuate more strongly than bonds with low EL; single-peril bonds fluctuate more strongly than multi-peril bonds. Second, the proposed "seasonality-adjusted EL" measure, which is based on the developed conceptual framework, captures seasonal fluctuations on cat bond spreads. It explains up to 47% of all secondary market fluctuations among cat bonds that are affected by seasonality (measured by adjusted within R^2). The results on the seasonality measure are strongly supported by the robustness check with TRACE data. Third, we are able to estimate the market-implied distributions of arrival frequencies from secondary market data. These market-implied distributions explain secondary market fluctuations as good as modeled distributions of arrival frequencies.

The remainder of this article is as follows: Section 2.2 provides an overview of related literature. In Section 2.3, we develop a conceptual framework to model the seasonality in the probability of catastrophe bonds being triggered and establish hypotheses on seasonality. Section 2.4 describes the data set. The econometric models are presented in Section 2.5. Section 2.6 contains results on the hypotheses, the proposed seasonality measure, and a robustness check. Section 2.7 presents the methodology for the market-implied distribution and its empirical results. Section 2.8 concludes.

[4]The yearly EL can be taken from the cat bond prospectus. Our data source for the EL are yearly market reports from Lane Financials LLC.

2.2 Literature

2.2.1 Seasonality on financial markets

Seasonality effects on the general financial markets have been investigated thoroughly in the empirical literature. For stocks, Keim (1983) and Lakonishok/Smidt (1984) find depressed returns on Mondays and week-of-the-month patterns, while others (e.g., De Bondt/Thaler 1987, Gultekin/Gultekin 1983, Rozeff/Kinney 1976) find abnormal returns for certain months of the year most prominently defining the "January effect." Jordan/Jordan (1991) and Schneeweis/Woolridge (1979) find that corporate bonds exhibit January, turn-of-the-year, and week-of-the-month effects. More recent literature relates the January effect to systematic risk and fluctuating risk aversion (Sun/Tong 2010), to the returns of the momentum strategy (Yao 2012) and to the returns of mutual funds (Vidal-García/Vidal 2014). Overall, the established empirical literature on seasonality in bond or stock returns has not found strong evidence for the existence of abnormal returns of certain days of the week or certain months of the year. Generally, the magnitude of seasonality for stocks and bonds is small and unpronounced. Additionally, Zhang/Jacobsen (2013) find different monthly effects with reversing directions depending on selected sub samples from a 300-year long data set of UK stock returns. They conclude that monthly return patterns are due to selection bias, noise and data snooping but are no real effect.

For agricultural commodities, Black (1976) states that prices follow a seasonal pattern: Prices are high before harvest and low after harvest. The success of a harvest is closely related to external conditions such as sunshine, wind, and rainfall. Consequently, the price of these assets is related to climate and weather. For futures of concentrated orange juice, Roll (1984a) finds clear empirical evidence for a seasonal pattern in relation to extreme weather events. Orange trees die during prolonged periods of below freezing temperature. In Florida, where most U.S. orange juice is produced, these extreme temperatures can only occur in the winter. Hence, the likelihood of below freezing temperature is an important risk factor in the pricing of orange juice futures during this time: Prices are high in autumn reflecting the probability of freezing temperatures during the winter season."Each day thereafter that passes without a freeze should be accompanied by a slight price decline, a relief that winter is one day closer to being over" (Roll 1984a). For orange juice and other agricultural products, seasonal prices are supply-driven. For prices of other commodities, such as natural gas, which is typically used to heat houses during the winter, prices are instead demand-driven (see Gorton et al. 2013). The magnitude of seasonal fluctuations in commodities is alleviated by costs of storage (see Fama/French 1987).

For the property and casualty insurance industry, Ammar (2020) identifies seasonal changes in the implied volatility smile of insurance stock options. Generally, the slope of the implied volatility smile is much steeper for insurance stock options than for the whole economy. However, outside of the hurricane season, the smile for insurance stock options becomes flatter than during the hurricane season. Ammar (2020) indicates that markets might demand more in-the-money and at-the-money options outside of the hurricane season because large drops in insurance stock prices are less likely.

2.2.2 Seasonality on cat bond markets

As previous research has indicated, the EL is the primary driver of cat bond spreads (e.g., Braun 2016, Galeotti et al. 2013, Gürtler et al. 2016, Lane/Mahul 2008). As discussed by Lane (2000), the EL is the product of the probability of first loss (PFL) and the conditional expected loss (CEL).[5] The PFL in turn is some function of the arrival frequency λ_t of qualifying events. The EL is measured on a per-year basis.

$$EL_t = PFL(\lambda_t) \cdot CEL \tag{1}$$

Consider a bond, which triggers a default when certain predetermined parameters of a catastrophe are fulfilled. This can be an earthquake of a certain level on the Richter scale or a hurricane whose wind speed exceeds a certain threshold. This type of trigger is referred to as a parametric trigger.[6] The likelihood of qualifying events depends on two conditions: (a) an event needs to take place and (b) this event has to be of a magnitude large enough to set off the parametric trigger. For some perils, such as earthquakes, likelihood and severity of events are independent and identically distributed (i.i.d.). Within a calendar year, these events do not have seasons. Other events that depend on weather conditions are unevenly distributed; namely, European winter storms, North-American hurricanes, and Japanese cyclones.[7] For example, the

[5] In a credit risk context, different terms are used for the elements of the EL. The PFL is equivalent to the probability of default (PD), the CEL is equivalent to the loss given default (LGD).

[6] The trigger types that are employed more frequently are "Indemnity" and "Index" triggers. The EL of these bonds depends on the likelihood of events and their severity in a similar fashion as bonds with parametric triggers. Please refer to Finken/Laux (2009) for a discussion on the benefits of index and parametric triggers and Braun (2016) for further discussion on indemnity triggers.

[7] There are only seven single-peril cyclone bonds in our data. This number is too low to separately model the Japanese cyclone season with panel data regression models. Hence, we abstract from modeling this seasonality. Nevertheless, the suggested methodology can be applied to Japanese cyclone bonds if more of these bonds are issued in the future. Additional events, whose likelihood and severity are not independent and identically distributed across a calendar year, are tornados, thunderstorms and hail. However, since cat bonds are usually created to cover extreme risk, we focus our model on large-scale seasonal perils: hurricanes and European winter storms.

likelihood of a hurricane is high between June and November while it is almost zero between December and May. In consequence, the EL of a cat bond can fluctuate substantially throughout a calendar year. This fluctuation is not represented in coupons: Cat bonds typically pay a fixed coupon above LIBOR or some other money market rate that does not adjust according to changes in underlying EL. This means contrary to the empirical asset literature on stocks and bonds, cat bond spreads are strongly affected by seasonality, but no existing study explicitly analyzes their seasonal patterns.[8] Overall, the seasonality of cat bonds follows a clear rationale: the uneven distribution of default risk.[9] As a consequence of seasonality, cat bond spreads are partially predictable. However, seasonal fluctuation in spreads stem from fluctuations in the EL, which means that spreads react to the seasonality of the underlying risk. Thus, fluctuations of cat bond spreads do not automatically allow for the creation of alpha, and they are not necessarily a violation of the efficient market hypothesis (see Fama 1970).

Table 1: Modeled distribution of arrival frequencies.

	U.S. hurricanes	EU winter storms
January	0.0%	26.0%
February	0.0%	16.5%
March	0.0%	11.5%
April	0.0%	0.0%
May	0.2%	0.0%
June	3.6%	0.0%
July	12.5%	0.0%
August	28.7%	0.0%
September	34.6%	0.0%
October	18.3%	11.0%
November	2.0%	14.0%
December	0.1%	21.0%

Note: Distributions of arrival frequencies for U.S. hurricanes and EU winter storms as modeled by AIR. These numbers describe the relative share of arrival frequencies throughout a calendar year.

Hainaut (2012) models seasonality in tornados through a double stochastic Poisson process whose arrival frequency fluctuates across a year following an Ornstein-Uhlenbeck process fitted to empirical data. We implement a variable that instead relies on the modelled arrival frequencies of

[8]Only a few other financial securities, like industry loss warranties (ILWs), weather derivatives and some commodities, are also known for having such strong seasonal fluctuations. For a discussion on contract features and pricing of ILWs please refer to Gatzert/Schmeiser (2011); for a discussion on the pricing of weather derivatives please refer to Alaton et al. (2002) and Campbell et al. (2005). It appears plausible that ILWs and weather derivatives exposed to seasonal perils fluctuate in similar fashion as cat bonds. Hence, it may be worthwhile to apply the proposed methodology to model seasonality in ILWs, too.

[9]Seasonal fluctuations on cat bonds can occur in the absence of new information in the market. In other words, such seasonality is already contained in the current information set. On the contrary, announcements of loss events and hurricane forecasts bring new information to the cat bond market, which is conceptually related to ad-hoc profit warnings in the context of other financial securities.

AIR, which is one of the leading risk modeling firms. They use weather models and simulation methods to derive arrival frequencies for U.S. hurricanes and European winter storms from empirical data. We have data on the relative distribution of arrival frequencies of European winter storms and U.S. hurricanes on a monthly basis. Since we lack data on the severity, we assume the severity of a peril event (hurricane or European winter storm) to be i.i.d. for each time period within a year.

Table 1 illustrates the distributions of arrival frequencies for North American hurricanes and European winter storms as provided by AIR. Using these data, we assume that the distribution of arrival frequencies is constant between years.[10] The American hurricane season begins in June and ends in November, and most hurricanes occur in August and September. The European winter storm season begins in October and ends in March, and most winter storms occur in December and January. In months where the arrival frequency is zero, it is virtually impossible that a respective event can occur.

2.2.3 Other drivers of cat bond spreads

The cat bond literature considers additional factors that influence cat bond spreads.[11] We separate these factors into two groups: (a) time-invariant factors and (b) time-variant factors. While the factors of group (a) are very important for explaining cat bond spreads, we do not include them in our empirical analysis due to their time-invariant nature. Instead, we explain within-bond secondary market fluctuations through within transformations, thereby controlling for any observable and unobservable constant variables on bond level (see Section 2.5). On the contrary, we include variables of group (b) as control variables in our following empirical analyses. Nevertheless, we briefly describe the influencing factors of both groups (a) and (b) to provide a more complete picture of factors that influence cat bond spreads.

Group (a) includes bond specific properties like trigger type, peril types and locations, peril numbers, issue volume, rating, and sponsor. Bonds with indemnity trigger could exhibit higher spreads due to possible moral hazard (Cummins/Weiss 2009), but there is no clear empirical

[10] If the seasonal pattern changed over time, time-varying arrival frequencies would be required to capture these changes. However, we have no information regarding such time-varying arrival frequencies. Moreover, it should be noticed that neither a general trend toward an increasing likelihood of natural catastrophes, nor cyclical event prob-abilities between years (e.g., due to El Niño), as discussed in Goldenberg et al. (2001), imply that the within-year distribution is time-varying, too.

[11] Please refer to Braun (2016) and Gürtler et al. (2016) for a thorough empirical investigation of many of these factors. While most of the empirical cat bond literature employs ordinary least square (OLS) or panel data regression models, Beer/Braun (2021) use Poisson intensities from a reduced form model to explain spreads.

evidence (Braun 2016). Peril types and locations have been investigated thoroughly in the literature (e.g., Braun 2016, Lane/Mahul 2008, Papachristou 2011). Cat bonds with more than one peril type[12] or peril location exhibit a spread premium due to increased complexity (Gürtler et al. 2016). Additionally, spreads are higher for peak peril types (hurricane) and locations (U.S.). For cat bonds with a large issue volume, spreads could be lower due to higher liquidity (Dieckmann 2010), but empirical results are inconclusive (Braun 2016, Gürtler et al. 2016). Cat bonds with better ratings have lower spreads (Braun 2016, Gürtler et al. 2016). Spreads are lower for bonds sponsored by Swiss RE, which can be attributed to high sponsor reputation (Braun 2016).

The time-variant variables of group (b) include variables that are bond specific like time to maturity, but mostly refer to conditions on the financial market, like corporate bond spreads, equity returns, and reinsurance prices. Concerning time to maturity, there is no empirical evidence that declining time to maturity leads to declining spreads due to increasing liquidity (Braun 2016, Dieckmann 2010, Gürtler et al. 2016). Cat bond spreads are positively related to corporate bond spreads and equity returns (Braun 2016, Gürtler et al. 2016). Furthermore, while cat bonds are often considered zero-beta bonds, they have exposure to general financial market conditions through possible flight-to-quality effects in downturn scenarios (Gürtler et al. 2016). As a substitute for reinsurance, cat bond spreads increase during a hard re-insurance market (Braun 2016, Gürtler et al. 2016, Lane/Mahul 2008).

2.3 Conceptual framework, modeled seasonality, and hypotheses

2.3.1 Conceptual framework

We develop a conceptual framework to model the seasonality in the probability of catastrophe bonds being triggered based on a hazard rate model, and we suggest one comprehensible measure of a seasonality-adjusted EL to model the seasonal fluctuations in secondary market cat bond spreads.

To keep it simple, we value a cat bond that does not pay any coupons, that is, a zero-coupon bond, which is repaid at time of maturity T. In case of a default, there is no repayment, that is, its CEL is 100%. Investors are risk neutral, the riskless interest rate is 0%, and there are no transaction costs. Under these assumptions the valuation of *nonseasonal* cat bond at time t is simple. The value equals the probability to survive until maturity multiplied by its face value.

[12] For a discussion on the pricing of multi-peril bonds relative to single-peril bonds please refer to Lane (2004).

We model the survival probability through a hazard rate model that follows a Poisson process. The bond survives if the number of defaults until maturity $N(T)$ is zero:

$$P[N(T) = 0] = exp(-\lambda_h(T - t)) \tag{2}$$

where λ_h denotes the (homogeneous) hazard rate. The value of the non defaulted zero-couponbond at time t equals:

$$V_t = FV \cdot P[N(T) = 0] = FV \cdot exp(-\lambda_h(T - t)) \tag{3}$$

where FV denotes the face value of the bond. The economic intuition behind this valuation formula is the following: To a risk-neutral investor with a riskless interest rate of zero, a cat bond is worth its face value that is, paid out in case of survival multiplied by the probability the bond survives until maturity. The longer the maturity of the bond (T–t) and the higher the hazard rate, the lower is the probability of its survival. For a nonseasonal peril, the hazard rate λ_h is constant throughout its maturity. The relation between the value and the spread s_t of a zero-coupon bond with continuous discounting is[13]

$$V_t = \frac{FV}{e^{(s_t(T-t)}} \Leftrightarrow s_t = \frac{ln(\frac{FV}{V_t})}{T - t} \tag{4}$$

We can insert Equation (3) into Equation (4) to obtain a formula for the spread of a non-seasonal cat bond based on the hazard rate model:

$$s_t = \lambda_h \tag{5}$$

Now, we assume the zero-coupon cat bond is not exposed to a nonseasonal peril such as earthquakes but is exposed to a *seasonal* peril, that is, the hazard rate λ_h fluctuates seasonally. More precisely, we use an inhomogeneous Poisson process where the intensity function $\lambda_h(t)$ fluctuates within the year. We can determine the value of such a seasonal cat bond at time t, which is non defaulted at that time, based on the survival probability from t to T of an inhomogeneous Poisson process as follows:

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[13]More generally, the spread can be defined as the difference between the yield to maturity and the risk-free rate, but in our model we assumed a risk-free rate of zero.

$$V_t = FV \cdot exp\left(-\int_t^T \lambda_h(\tau)d\tau\right) \tag{6}$$

We can now insert Equation (6) into Equation (4) and solve for s_t to acquire the corresponding fluctuating spread:

$$s_t = \frac{\int_t^T \lambda_h(\tau)d\tau}{T-t} \tag{7}$$

With λ_0 as the total hazard rate for one calendar year $\int_0^1 \lambda_h(\tau)d\tau =: \lambda_0$ we can define the ratio $\lambda_h(t)/\lambda_0 =: \lambda(t)$ as the density function of arrival frequencies. This results in:

$$s_t = \frac{\int_t^T \lambda_h(\tau)d\tau}{T-t} = \frac{\lambda_0 \cdot \int_t^T \lambda(\tau)d\tau}{T-t} \tag{8}$$

For illustration purposes, we provide an example where we model a seasonal zero-coupon cat bond whose $\lambda_h(t)$ follows a cosine function that peaks in the middle of the year and is zero at the turn of the year:

$$\lambda_h(t) = \lambda_0 \cdot (1 - cos(2\pi t)), \tag{9}$$

where λ_0 is the total hazard rate for one calendar year: $\int_0^1 \lambda_h(\tau)d\tau = \lambda_0$. The value of such a cat bond is:

$$\begin{aligned} V_t &= FV \cdot exp\left(-\lambda_0 \cdot \int_t^T \lambda_h(\tau)d\tau\right) \\ &= FV \cdot exp\left(-\lambda_0 \cdot \left(T - t - \frac{1}{2\pi}(sin(2\pi T) - sin(2\pi t))\right)\right) \end{aligned} \tag{10}$$

and the spread equals:

$$s_t = \frac{\lambda_0 \cdot \left(T - t - \frac{1}{2\pi}(sin(2\pi T) - sin(2\pi t))\right)}{T-t} \tag{11}$$

Figure 1 illustrates values and spreads of a hypothetical nonseasonal and a seasonal zero-coupon cat bond. They have a maturity of 3 years, a hazard rate λ_h (and λ_0, respectively) of 8% and a CEL of 100%. We use Equations (3) and (5) to determine the value and spread of the nonseasonal cat bond and Equations (10) and (11) accordingly for the seasonal cat bond.

The value of the nonseasonal cat bond in Figure 1 increases almost linearly in the case without default. In the case of default, the value would immediately jump to zero and remain at this value as we assumed a CEL of 100%. The value of the seasonal cat bond also increases over time, but it fluctuates depending on the seasonal state. At the turn of the year the value of the seasonal cat bond increases only slowly because the hazard rate is low, which means the probability that the bond survives until maturity increases relatively slowly. In the middle of a calendar year, the value of a seasonal cat bond increases strongly in the case without default because the hazard rate is high, so that the probability the bond survives until maturity increases relatively quickly.

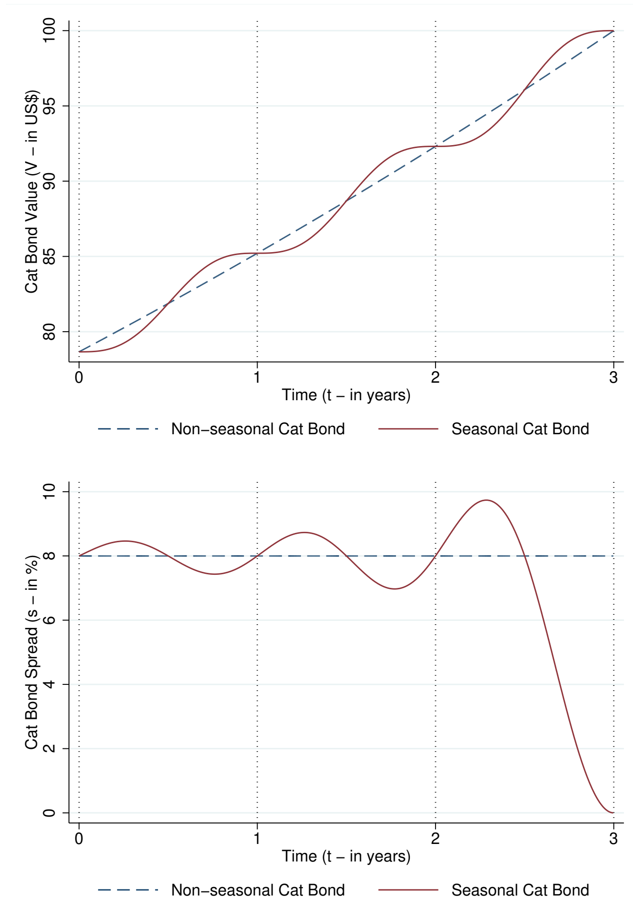
The spread of a nonseasonal cat bond in Figure 1 is constant throughout its maturity, while the spread of a seasonal cat bond fluctuates strongly. At maturity, the spread approaches zero because the season ends on the same day as the bond matures. We can derive two main observations from this figure: A general seasonal pattern and an increasing amplitude as a bond nears its maturity. First, regarding the seasonal pattern, spreads peak a couple of months before the season reaches its peak in the middle of the year. They reach their bottom a couple of months before the season fades out at the end of the year. Second, the amplitude between seasonal peaks and bottoms increases as a bond approaches its maturity. From the first to the second year, the amplitude between the maximum and minimum in spreads increases from 1.12% points to 1.90% points, and increases further in the ultimate year.[14] The reason for the increasing seasonal amplitude of spreads when approaching maturity is as follows: While the amplitude of the seasonal value fluctuation remains almost constant throughout the cat bond's maturity, its remaining time to maturity decreases. However, the bond's spread is more sensitive to changes in prices the closer it is to maturity.

2.3.2 Modeled seasonality measure

We now establish a new seasonality measure utilizing the EL as the most important variable to explain cat bond spreads. In the hazard rate model, Equation (8) illustrates the seasonal fluctuation in spreads. We translate this formula into a new seasonality measure EL_t. The intuition behind this translation is as follows: The EL is related to the hazard rate λ_h and should fluctuate seasonally, accordingly. This "true" EL—the loss that investors expect at time t—thus, fluctuates with seasonal arrival frequencies. On the secondary market, investors do not price a cat bond according to the constant, yearly $EL_{initial}$ provided by the risk modeler, which can betaken from the offering circular, but rather evaluate the amount of remaining risk

[14]In the last year spreads approach zero as the bond approaches its maturity and its last season fades out.

Figure 1: Value and spread of hypothetical cat bonds.



Note: Value and spread of hypothetical zero-coupon cat bonds with a hazard rate $\lambda_h = 8\%$ and a conditional expected loss CEL $= 100\%$ in the case without default. The cat bonds have a maturity of 3 years. The investors are risk-neutral and riskless interest rates are 0%. The nonseasonal cat bond has a hazard rate λ that is evenly distributed across a calendar year. The seasonal hazard rate $\lambda_h(t)$ for the seasonal cat bond follows a cosine function. This hazard rate $\lambda_h(t)$ for a seasonal bond is highest in the middle of the year and lowest at the end of the year.

against the background of its remaining time to maturity. Considering that the EL is effectively the absolute amount of expected losses divided by the remaining time to maturity and the face value, we define EL_t as the relative expected loss on an annual basis which fluctuates depending on changes in the absolute amount of expected losses remaining and the decreasing time to maturity. Thus, we propose the following formula to create a seasonality-adjusted expected loss measure EL_t:

$$EL_t = \frac{Remaining\ risk_t}{Remaining\ time_t} = \frac{EL_{initial} \cdot \int_t^T \lambda(\tau)d\tau}{T-t} \tag{12}$$

where t stands for the time of risk evaluation, T is the time of maturity and $\lambda(\tau)$ is the density function of arrival frequencies, which varies depending on the point in time τ. This seasonality-adjusted EL measure incorporates actual arrival frequencies. Since our data on spread is on quarterly basis, we generally aggregate monthly arrival frequencies to quarterly arrival frequencies, but the proposed formula can be used for arbitrary frequencies.

We obtain the modeled distributions of arrival frequencies λ for hurricanes and European winter storms from AIR. These distributions are on a monthly basis and exogenous to our model. As previously discussed, we do not have an exogenous distribution on the severity of peril events but instead we assume the severity of a peril event to be i.i.d. for each time period within a year. This could limit the accuracy of the proposed seasonality measure if the severity of peril events varies during different parts of the season. However, the proposed methodology could also be applied to severity if an exogenous distribution of severity is available. Such a model could either have two separate or a single seasonality measure for a combined distribution of arrival frequency and severity.

2.3.3 Hypotheses

The theoretical model in Sections 2.3 and 2.3.2 implies that the spread of a seasonal cat bond fluctuates strongly. As illustrated in Figure 1, spreads peak a couple of months before the season reaches its peak, and reach their bottom when the season fades out at the end of the year. We expect a similar pattern for the real-world distribution of hurricanes and European winter storms and hypothesize the following:

H1: *Seasonality pattern: Cat bonds follow a seasonal pattern that expresses its highest spreads before risk season begins and its lowest spreads after risk season ends.*

Second, we can observe that the amplitude between seasonal peaks and bottoms increases as a bond approaches its maturity. The reason for the increasing seasonal amplitude of spreads when approaching maturity is as follows: While the amplitude of the seasonal value fluctuation remains almost constant throughout the cat bond's maturity (see e.g., Figure 1), its remaining time to maturity decreases. However, the bond's spread is more sensitive to changes in prices the closer it is to maturity. Hence, we hypothesize the following:

H2a: *Seasonality amplitude – maturity: The seasonal fluctuation of cat bonds increases with decreasing time to maturity.*

The theoretical model indicates that the amplitude of the seasonal fluctuation scales with the total hazard rate of one calendar year (see Equations 8 and 12). This total hazard rate λ_h translates into the yearly EL of a Cat Bond. This EL is typically reported in the offering circular. Cat bonds have different yearly ELs. Some are very risky and have a high yearly EL of 15% while others have an EL below 1%. This could have an impact on the amplitude of seasonal fluctuation: Although the *relative* fluctuation of EL in seasonal cat bonds might be the same, the *absolute* fluctuation of EL might be larger for cat bonds that have a high yearly EL. Hence, in absolute terms, the spreads of cat bonds with a high yearly EL should fluctuate more strongly than the spreads of cat bonds with a low EL.

H2b: *Seasonality amplitude – EL: The absolute seasonal fluctuation of cat bonds with a high EL is larger than the seasonal fluctuation of cat bonds with a low EL.*

While our modeled seasonality measure from Section 2.3.2 simultaneously captures the three effects expressed in hypotheses H1, H2a, and H2b, we hypothesize two additional effects that influence the amplitude of seasonal fluctuations in cat bond spreads: Many cat bonds protect against more than one peril. Typically, these multi-peril bonds also protect against earthquakes that are not affected by seasonality; the arrival frequency of an earthquake is evenly distributed across a calendar year. These multi-peril bonds should express less pronounced seasonal fluctuation. The remaining fluctuation should be proportional to the distribution of its risk exposure between seasonal (e.g., wind or hurricane) and unseasonal perils (e.g., earthquake). Consider a simple cat bond pricing model, where the spread (s_t) is the sum of some function $h(\cdot)$ of a bond's exposure to hurricane risk and some function $q(\cdot)$ of the same bond's exposure to earthquake risk. The weight ($w \in [0, 1]$) determines how the bond's overall risk exposure is divided between hurricane and earthquake.

$$s_t = w \cdot h(EL_t) + (1 - w) \cdot q(EL_{initial}), \tag{13}$$

with $EL_t = EL_{initial} \cdot a_t$. EL_{inital} is the constant yearly EL modelled by a risk modelling firm, which can be taken from the offering circular. The parameter a_t is a random variable that fluctuates with the U.S. hurricane season and is defined in such a way that $E(a_t) = 1$. As the model suggests, earthquakes are not exposed to seasonality. Therefore, the second summand does not contain a seasonally fluctuating EL. In this model, the bond's seasonal change in spread is proportional to the bonds weight w in hurricane exposure. If w is close to one, the spread fluctuates strongly with the U.S. hurricane season. When w is close to zero, the spread fluctuates only weakly with the U.S. hurricane season. From our data, we do not know a bond's specific weight w. However, we know that $0 < w < 1$ for any multi-peril bond. Therefore, a multi-peril bond exposed to some form of seasonality should fluctuate less than a single-peril bond that is affected by the same peril (in this case, U.S. hurricanes).

H2c: *Seasonality amplitude – multi-peril bonds: The seasonal fluctuation of multi-peril bonds is lower than the seasonal fluctuation of single-peril bonds.*

Similar to multi-peril and single-peril bonds, there may also be differences between peril types. U.S. hurricane bonds have very clear seasons: The arrival frequency of a hurricane is zero through the first half of a calendar year and varies throughout the second half. European wind bonds do not have a clear aggregate season: While the arrival frequencies for European winter storms fluctuates with a similar magnitude as hurricanes, European wind bonds often also protect against hail and thunderstorms that also occur outside of the winter storm season. In consequence, the arrival frequency of European wind perils is more evenly distributed across a calendar year. Hence, seasonality effects for European wind bonds should be less pronounced than seasonality effects for U.S. hurricane bonds.

H2d: *Seasonality amplitude – peril type: The seasonal fluctuation of North American hurricane bonds is higher than the seasonal fluctuation of European wind bonds.*

2.4 Data

Our initial data set consists of 587 cat bonds from 1996 to 2017. These bonds represent nearly the whole cat bond universe. We collected data from Artemis (hand-collected information on location and type) and Lane Financial LLC (EL, coupon, volume, maturity, and spread).[15] In additional robustness checks, we consider cat bonds pricing information from actual cat bond trades reported in TRACE. Our theoretical considerations and empirical analysis are based on (currently) non-defaulted bonds, which could default at any time in the future. Accordingly,

[15]Used information from Artemis can be acquired through the deal directory on www.artemis.bm. Used information from Lane Financial LLC can be acquired from annual reviews of the ILS markets, authored by Morton Lane and Roger Beckwith, provided on www.lanefinancialllc.com.

we drop all bonds that were "distressed", which can mean a cat bond incurred a permanent loss after a trigger event or experienced a substantial temporary markdown.[16] We only mark a bond as "distressed" if it is reported as distressed in the Trade Notes of Lane Financials or part of the "Cat Bond Losses and Bonds At Risk" list on artemis.bm. Additionally, we dropped the following bonds: mortality risk bonds, bonds lacking crucial information such as EL, coupon, type or location and bonds lacking spreads—Lane Financial provides quarterly spreads from 2002 onwards. Furthermore, we drop all bonds whose perils are not affected by U.S. hurricanes or European winter storms. Ultimately, our final sample includes 386 bonds and 3947 quarterly observations from 2002 to 2017. The specific dates of the quarterly observations refer to 31st March for Q1, 30th June for Q2, 30th September for Q3, and 31st December for Q4.

Table 2: Cat bond specific information on 386 cat bonds.

Variable		No. of bonds	Percentage
Region			
	North America	342	88.60%
	Europe	121	31.35%
	Japan	41	10.62%
	Other	3	0.78%
Peril			
	Hurricane	238	61.66%
	Wind	230	59.59%
	Earthquake	210	54.40%
Peril number			
	Single-peril	161	41.71%
	Multi-peril	225	58.29%
Peril Location			
	Single-location	302	78.24%
	Multilocation	84	21.76%
Peril Number and peril location			
	Single-peril and single-location	158	40.93%
	Multi-peril and/or multilocation	228	59.07%
Rating			
	AA	4	1.04%
	A	4	1.04%
	BBB	8	2.07%
	BB	162	41.97%
	B	101	26.17%
	NR	107	27.72%

Note: For region and peril, the percentages of the categories exceed 100% because multi-peril and multilocation bonds have multiple peril types and locations, respectively. All other categories add up to 100%.

Table 2 provides summary statistics on important variables. Eighty-nine percent of these

[16] A temporary markdown occurs when a historic natural disaster threatens to trigger a bond, but the affected bond is ultimately cleared from a loss.

cat bonds have exposure in North America, with Europe and Japan following at 31% and 11%, respectively. Concerning perils, hurricane is the most prominent whereas wind and earthquake have similar shares.[17] This means that the U.S. hurricane season is the most important season. Region and Peril add up to more than 100% because multi-peril and multilocation bonds are included. Overall, more than half of the bonds are multi-peril bonds while less than a quarter are multilocation bonds. Table 3 provides summary statistics on the continuous variables $EL_{initial}$, the proposed seasonality measure EL_t for the hurricane season and the European winter storm season, spread as well as control variables. For each cat bond deal, an external risk modeling company provides a report of the underlying risk. It contains a distribution of modeled losses on a yearly basis. Hence, the mean of the loss distribution is the EL over one calendar year. During a cat bond's maturity, this $EL_{initial}$ stays constant over time.[18] While the $EL_{initial}$ can reach almost 15%, the median and the mean of $EL_{initial}$ are 1.67% and 2.63%, respectively EL_t fluctuates between 0% and 29%. It is 0% when the bond has gone through all of its risk seasons but still has some time remaining until maturity. The maximum of 29% is roughly twice as large as the maximum for $EL_{initial}$. Quarterly spreads are taken from yearly market reports provided by Lane Financial LLC. For individual cat bonds, spreads can reach almost 44%. However, the median spread is 5.99% and the average spread is 7.38%.

Table 3: Summary statistics for $EL_{initial}$, spread and control variables.

	Obs.	Mean	Std. Dev.	Min.	q25	q50	q75	Max.
$\mathrm{EL}_{\mathrm{inital}}$ (in %)	386	2.63	2.45	0	1.12	1.67	3.41	14.75
EL_t-US modeled (in %)	3431	2.25	2.71	0	0.71	1.38	2.87	28.58
EL_t-EU modeled (in %)	1248	2.53	3.03	0	0.74	1.45	3.62	28.73
Spread (in %)	3947	7.38	4.95	0.64	4.13	5.99	9.23	43.69
Reins. index (in points)	16	233	32	170	215	241	251	293
Corp. bond spreads (in %)	60	4.53	2.59	1.22	1.77	4	5.48	14.79
Equity return 90 days (in %)	60	1.9	7.7	-18.3	-1.1	2.1	6.3	18.5
Remaining maturity (in months)	3947	20.4	13.24	0	9	20	30	98

Note: Summary statistics for the continuous variables expected loss at issue (EL_{inital}) on bond level and spread on observation level. $EL_{initial}$, as provided by risk modelers, is constant over time. Control variables are on a yearly basis (*Reinsurance Index*), quarterly basis (*Corporate bond spreads* and *Equity return 90 days*) and observation level (*Remaining maturity*).

In the empirical analyses, we also include time-variant control variables, namely re-insurance

[17] Earthquake bonds in our sample stem from seasonality-affected multi-peril bonds that have some exposure to earthquakes.

[18] For an example on risk modeling and the resulting loss distribution please refer to Lane (2012). For bonds, which employ an indemnity trigger, the EL could change if the ceding insurance company, for example, underwrites more business. However, such cat bonds usually contain reset clauses that reset attachment and exhaustion points at regular time intervals to keep the EL constant in case the business of the insurance company has changed.

prices, corporate bond spreads, equity returns, and remaining time to maturity.[19] As a measure of reinsurance prices, we use the Guy Carpenter Global Property Rate-on-Line Index, which is on a yearly basis.[20] As corporate bond spreads, we use the Bank of America Merrill Lynch Option-Adjusted Spread indices of various rating classes, which are on a daily basis; concretely, we assign the corporate bond spread index with the same rating to the corresponding cat bonds. If a cat bond is not rated, we assign the BB corporate bond spread index because BB is the most common cat bond rating. For equity returns, we use the S&P500 performance index, which is on a daily basis.

2.5 Econometric model

We are interested in explaining how secondary market spreads of each individual bond change due to seasonality after they were issued on primary markets. Therefore, we explain the variance of spreads within a group of observations on bond level. To do so, we use fixed effects regressions. A side effect is that we do not need any control variables that stay constant over time.[21] We use the following model for the spread s_{it}:

$$s_{it} = \beta' X_{it} + \eta' C_{it} + \alpha_i + \varepsilon_{it}, \tag{14}$$

where i stands for the individual cat bond at time t; in our case, these are separate quarters. The vector X_{it} includes variables that fluctuate over time and are different on bond level. These variables are the seasonality measure from Section 2.3.2 or seasonal dummy variables defined in the subsequent section. The vector C_{it} contains all control variables that change over time. These time-variant variables are the remaining maturity, corporate bond spreads, equity returns and reinsurance prices. The error term is denoted by ε_{it}. The variable α_i is a bond-specific intercept that contains all variables of bond i that are constant over time. This variable disappears when within transformation is applied, that is, subtracting the mean of each variable from the respective variable in the model (e.g., $\ddot{s}_{it} = s_{it} - \bar{s}_i$):

$$\ddot{s}_{it} = \beta' \ddot{X}_{it} + \eta' \ddot{C}_{it} + \ddot{\varepsilon}_{it}, \tag{15}$$

---

[19] For a detailed discussion of the underlying effects of these time-variant controls please refer to Section 2.2.3.

[20] Gürtler et al. (2016) use the Guy Carpenter Global Property Rate-on-Line Index. Braun (2016) uses the Lane Financial LLC Synthetic Rate-on-Line Index.

[21] Examples for such controls include the number of perils, the number of locations, peril type, peril location, trigger type, rating, volume or the constant yearly $EL_{initial}$.

Through the resulting fixed effect model, we estimate the coefficients in such a way that they capture differences to their bond-specific means. This way the model estimates the change of spreads within bonds across time while abstracting from differences between bonds. We measure the explanatory power based on the adjusted within R^2, which measures how much of the fluctuation of secondary market spreads around the individual mean can be explained by the seasonality variables.

2.6 Empirical results

2.6.1 Results for the hypotheses

We illustrate the seasonal fluctuation in spreads in two steps: In the first step, we create three different sets of seasonal dummy variables to test our hypotheses from Section 2.3.3. We use dummy variables because these effects would otherwise be hidden in the new seasonality measure. We employ: (a) interaction terms between the seasonal dummy variables with a cat bond's years to maturity, (b) interaction terms between the seasonal dummy variables with EL, and (c) separate dummy variables for European and North American seasons. In the second step, we use the new seasonality measure to capture these effects simultaneously and explain a large proportion of the secondary market fluctuation in cat bond spreads.

Table 4: Definition of seasonal dummy variables.

Quarter	North American hurricanes	European winter storms
Q1	No season US	After season EU
Q2	Pre season US	No season EU
Q3	High season US	Pre season EU
Q4	After season US	High season EU

Note: Seasonal dummy variables are on continental level. The seasonal dummy variables equal one in the corresponding quarter and zero otherwise. If a cat bond is unaffected by the U.S. or EU season, the respective dummy variables are zero.

Data on spreads are available on a quarterly basis. The specific dates of our quarterly observations refer to 31st March for Q1, 30th June for Q2, 30th September for Q3 and 31st December for Q4. Consequently, we define seasonal variables on this quarterly basis reflecting the respective seasonal states of these quarters. Our four seasonal variables are: *Pre season*, *High season*, *After season*, and *No season*.

Table 4 defines the set of seasonal dummy variables. U.S. seasonal dummies take the value "1" if they have some exposure to US hurricane or U.S. wind perils; EU seasonal dummies take the value "1" if they have some EU wind exposure. For both, U.S. and EU seasonal dummies, this includes multi-peril and multilocation bonds.

Table 5: Impact of seasonality on spreads – test of hypotheses.

Dependent variable:	Spread					
Test of hypothesis:	H1	H2a	H2b	H2c	H2c	H2d
Sample:	US HU/Wind: full sample	US HU/Wind: full sample	US HU/Wind: full sample	US HU/Wind: single-peril	US HU/Wind: multi-peril	EU Wind: single-peril
	(1)	(2)	(3)	(4)	(5)	(6)
High season US	-1.846***	-0.979***	-1.291***	-2.665***	-1.835***	
	(-20.01)	(-14.28)	(-9.15)	(-10.96)	(-17.12)	
After season US	-2.311***	-1.170***	-1.200***	-3.648***	-1.980***	
	(-17.92)	(-12.31)	(-6.83)	(-11.09)	(-12.65)	
No season US	-1.457***	-0.449***	-0.477**	-2.293***	-1.063***	
	(-14.51)	(-5.64)	(-2.67)	(-9.65)	(-9.68)	
Penultimate year		0.448**				
		(2.72)				
Ultimate year		1.976***				
		(6.49)				
High season US # Penultimate year		-0.394***				
		(-4.57)				
High season US # Ultimate year		-2.356***				
		(-11.67)				
After season US # Penultimate year		-0.450***				
		(-3.44)				
After season US # Ultimate year		-3.035***				
		(-11.52)				
No season US # Penultimate year		-0.208*				
		(-2.00)				
No season US # Ultimate year		-2.899***				
		(-12.11)				
High season # EL			-0.230***			
			(-3.55)			
After season # EL			-0.457***			
			(-5.57)			
No season # EL			-0.404***			
			(-4.59)			
High season EU						0.014
						(0.14)
After season EU						-0.851***
						(-5.00)
No season EU						-0.085
						(-0.45)
Reins. index	0.018***	0.019***	0.018***	0.013+	0.015**	0.013*
	(5.70)	(6.18)	(5.81)	(1.95)	(2.63)	(2.27)
Corp. bond spreads	0.486***	0.476***	0.482***	0.441***	0.541***	0.385***
	(17.31)	(17.91)	(17.47)	(10.81)	(13.42)	(5.28)
Equity price index	0.033***	0.031***	0.033***	0.038***	0.022**	0.041***
	(6.70)	(6.47)	(7.12)	(4.20)	(3.10)	(3.98)
Rem. maturity	0.054***	0.049***	0.055***	0.040**	0.072***	0.002
	(8.13)	(4.21)	(8.23)	(3.12)	(6.72)	(0.32)
Constant	1.613*	0.791	1.614*	3.736*	1.042	0.335
	(2.32)	(0.99)	(2.33)	(2.55)	(0.82)	(0.25)
Observations	3411	3411	3411	871	1421	483
Number of bonds	342	342	342	84	128	40
Within R^2	0.355	0.415	0.388	0.376	0.457	0.237
Adj. within R^2	0.354	0.413	0.386	0.370	0.455	0.225

Note: This table uses fixed effects regression models to determine the effect of seasonal factors on spreads (in %). All models, except for model (6), are limited to bonds that have exposure to U.S. storms (i.e. U.S. hurricane or U.S. wind bonds). *Pre season* is the base category for seasonal dummy variables. Models (1), (2) and (3) use all bonds with exposure to U.S. hurricanes. Model (4) uses single-peril/single-location U.S. hurricane bonds. Model (5) uses multi-peril bonds with some exposure to U.S. hurricanes; these bonds have exposure to U.S. hurricanes and other perils but do not cover other regions except North America. Model (6) uses single-peril/single-location EU wind bonds. t-values are shown in parentheses and heteroscedasticity robust standard errors are clustered at bond level. The symbols *, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 5 shows a set of models with fixed effects estimation, which employ the seasonal dummy variables. The sample is limited to bonds that are affected by seasonality. Standard errors are clustered on bond level and robust to heteroscedasticity. *Pre season* is always the base category where spreads are expected to be highest. We test the seasonality pattern (H1) with model (1). We test for different seasonality amplitudes w.r.t. remaining maturity (H2a) and EL (H2b) based on models (2) and (3), respectively. With models (4), (5), and (6), we test the differences between multi-peril and single-peril bonds (H2c) as well as differences between U.S. and EU bonds (H2d).

To investigate the general pattern of seasonality (H1), we look at the seasonal dummies in model (1). Spreads are, on average, 1.85% points lower during *High season* than during *Pre season*. *After season*, spreads drop further to 2.31% points below *Pre season*. From *After season* to *No season*, spreads increase by 0.85% points, which is 1.46% points below *Pre season*. All differences from *Pre season* are statistically significant at the 0.1% level. The order of the seasons is in line with indicated theoretical arguments, lending support to H1.[22] Lane/Beckwith (2017) indicate the seasonal pattern can be reversed in large loss years to some extent. Normally, spreads decline during the season when no losses or only very few losses materialize. On the contrary, in large loss years with multiple distressed bonds, realized losses can cause drops in prices leading to jumps in spreads. However, this effect should not be pronounced in our analysis because we drop all distressed bonds.

To investigate the influence of a bond's approaching maturity (H2a), we use model (2). Again, *Pre season* serves as the base category. The interaction terms between *Ultimate year* and the seasonal dummies as well as *Penultimate year* and the seasonal dummies indicate whether the amplitude of seasonal fluctuation increases in the last 2 years of maturity. For these time variables, the time before the last 2 years of maturity serves as the base category.[23] All six interaction terms indicate increasing seasonal fluctuation as cat bonds near their maturity. Five of these interaction terms are significant at the 0.1% level, while the interaction term between *No season* and *Penultimate year* is significant at the 5% level. We exemplify the interpretation of the corresponding coefficients for *After season*: The coefficient of the interaction term between the *Penultimate year* and *After season* indicates that the amplitude of seasonal spread fluctuation increases by 0.45% points when a bond enters its penultimate year of maturity. In total, the amplitude between *Pre season* and *After season* is 1.62% points during this time. This effect is further amplified in the ultimate year of a bond's maturity: The coefficient of the interaction term between *Ultimate year* and *After season* indicates that the amplitude increases by 3.04% points as compared to the years before the penultimate year. In total, the amplitude

[22] We have also applied the seasonality dummies for the U.S. and European seasons to a different sample of single-peril earthquake bonds. These bonds should not exhibit a seasonal fluctuation. We find small quarterly fluctuations, but this fluctuation appears negligible in size and of little explanatory power (R^2 = 2%). This is substantially different, for example, from single-peril hurricane bonds, where seasonality can explain up to 47% of the spread variation (without considering additional control variables). Detailed results are available upon request.

[23] Most cat bonds have a maturity of 3 years. For these bonds, the base category is the first year. For all other bonds with a maturity of more than 3 years, the base category is a combination of all years before the ultimate and penultimate years.

reaches 4.21% points.[24] Overall, this indicates the seasonal amplitude has increased in the penultimate year but even more strongly in the ultimate year of maturity. The coefficients of the remaining interaction terms between *High season* and *No season* how the same effect with a similar magnitude. The results from model (2) strongly support hypothesis H2a that the seasonal fluctuation of cat bonds increases as their time to maturity decreases.

To investigate the influence of a bond's EL on amplitude (H2b), in model (3) we interact the seasonal dummy variables with the individual yearly EL of each bond. The coefficient of the interaction term between *After season* and EL of -0.46 indicates that the absolute difference in spreads between *Pre season* and *After season* increases by 0.46% points for each 1% point increase in EL. The coefficient is statistically significant at the 0.1% level. These results support hypothesis H2b that the absolute amplitude increases with the EL of a cat bond.[25]

We use models (4) and (5) to compare single-peril and multi-peril bonds (H2c). Model (4) is limited to single-peril U.S. hurricane bonds whereas model (5) is limited to multi-peril U.S. hurricane bonds whose other perils are exclusively located in North America. For single-peril bonds, the *After season* coefficient is much higher than for multi-peril bonds. In model (4), a single-peril bond has, on average, a 3.65% points higher spread right after risk season compared to right before risk season. In model (5) for a multi-peril bond, this difference is only 1.98% points. This means that single-peril bonds fluctuate more strongly with seasonality variables than multi-peril bonds, which supports hypothesis H2c.

To investigate differences between North American and European seasons (H2d), model (6) contains the seasonal dummies for the European season. Its sample contains single-peril wind bonds exclusively located in Europe. Generally, the coefficients for the North American season in model (4) are larger than the coefficients for the European season in model (6). Additionally, the European season is less clear: We see a difference between *Pre season* and *After season* as

[24] Modell (2) also includes dummy variables for the Penultimate year and Ultimate year. These coefficients are large and statistically significant. However, these coefficients must not be interpreted in such a way that the mean spread of a cat bond changes as it approaches its maturity. If one is to determine the mean change in spreads for a cat bond as it moves to its Penultimate year or Ultimate year implied by the dummy variables, he needs to include the mean coefficient of the respective interaction terms between the year dummies and seasonal dummies including a hypothetical coefficient of zero for the base category and add the year dummy. For the Penultimate year, this indicates an average shift in spreads of (–0.394–0.450–0.208–0)/4 + 0.448 = 0.185% points change in mean spreads. For the Ultimate year, this indicates an average shift in spreads of (–2.356–3.035–2.899–0)/4 + 1.976 =–0.097% points. Both of these shifts are close to zero.

[25] Please note that the seasonal dummy variables must not be interpreted individually in model (3): The coefficient for *After season* is now smaller (in absolute terms) than the coefficient for *High season*. However, this does not mean that spreads are smallest during *High season*. The average EL in the sample is 2.3%, which results in –1.291%–0.230 * 2.3% =–1.820% for *High season* and–1.200%–0.457 * 2.3% =–2.251% for *After season*.

expected but spreads in *High season* and *No season* are almost on the same level as *Pre season*. The likely reason is that most North American bonds contribute capacity towards hurricanes while European wind bonds are not only triggered by European winter storms but also by other wind perils such as hail or thunderstorms.[26] In consequence, European wind bonds are less susceptible to the European winter storm season. Overall, the results indicate that the amplitude of U.S. hurricane bonds is larger than the amplitude of European wind bonds, which supports hypothesis H2d.

In summary, all hypotheses from Section 2.3.3 are supported by our results. A model that uses the complete set of dummy variables to combine the effects illustrated in Table 5 on a sample of all seasonality-affected cat bonds yields an adj. within R_2 of 0.301 without control variables and 0.447 when controls are included.[27] This means that 30% of all secondary market within fluctuation in spreads can be explained by seasonal dummy variables and the additional interaction terms between EL and respective year dummies until maturity.

2.6.2 Results for the modeled seasonality measure

Table 6 illustrates the effect of the new seasonality measure, the seasonality-adjusted expectedloss (EL_t), on secondary market spreads utilizing the exogenous arrival frequencies from AIR.[28] The spread compensates the investor for the EL (corresponding to the actuarially fair premium) and, additionally, for uncertainty in payoffs. Hence, the estimated EL coefficient, the EL multiple, is usually >1 in the empirical cat bond literature. If the coefficient is much larger than 1, investors demand a higher compensation for each unit of EL. In model (1), the coefficient of 1.135 for the U.S. hurricane EL_t indicates that a one-percentage point change

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[26] In Section 2.7 we determine the implied distribution for the observable seasonal fluctuation of European wind bonds. In this implied distribution, we observe substantial amounts of arrival frequencies in July, August, and September.

[27] Detailed results are available upon request.

[28] Although data from Lane Financial LLC are quarterly, we also utilize the within-quarter variation of arrival frequencies from AIR through within quarter issue and maturity dates. However, the use of this within-quarter distribution remains limited. We fully exploit the monthly distribution of exogenous arrival frequencies from AIR in the robustness check based on TRACE data where we have the specific dates of real trades and interpolate between months to obtain a daily distribution of arrival frequencies.

in EL_t leads to more than a one-percentage point change in spreads of the same sign.[29] The coefficient is highly significant at the 0.1% level. Concerning differences between U.S. hurricane and EU wind bonds, the coefficient for the European winter storm season is less than half the size of the coefficient for the hurricane season. The smaller coefficient for the European winter storm season lends further support to hypothesis H2d that U.S. hurricane bonds fluctuate more strongly than European wind bonds. Overall, the seasonality measure EL_t explains a large part of the fluctuation on secondary markets: The adjusted within R^2 of 0.326 shows that almost a third of all secondary market fluctuation of seasonality-affected bonds can be explained by the proposed seasonality measure. For comparison, a model that combines seasonal dummy variables and interaction terms to reflect maturity effects and the EL (H2a and H2b) only yields an adjusted within R^2 of 0.301.[30] This means that the proposed seasonality measure captures the different seasonality effects mentioned above and leads to a better model fit.[31]

Models (2) and (3) split the sample from model (1) into two separate subsamples: Model (2) contains single-peril bonds, while model (3) contains multi-peril bonds. For single-peril bonds, the coefficients for both seasons are larger than the coefficients for multi-peril bonds, lending further support to hypothesis H2c, which suggests that single-peril cat bonds are more strongly affected by seasonality than multi-peril bonds. The adjusted within R^2 of 0.466 in model (2) indicates that almost half of all secondary market fluctuation in single-peril bonds

[29] Galeotti et al. (2013) investigate different functional relationships between the spread and the EL and find a linear relationship to be most appropriate, which confirms that the risk premium can be described as a (constant) multiple of the EL. On primary markets, Braun (2016) reports a multiplier between the expected loss and spread of 2.210 (between estimation), which is double the amount we see on the secondary market (within estimation). The difference between the coefficient of the seasonality measure EL_t and the established coefficient in the literature is likely due to two effects: First, the multiple of spread and EL had a tendency to decrease since the inception of the cat bond market so that the multiplier could have declined over time; our sample ends 2017 while the sample of Braun (2016) ends 2009. A univariate OLS regression of spread on EL at issuance for our data set reveals a multiplier of 1.884 (between), confirming that the multiplier has indeed declined; results are available upon request. Second, the sample includes multi-peril bonds that contain risk, which are either not seasonality-affected (like earthquakes) or other wind perils whose seasonality we do not model (such as tornados or severe thunderstorms). For example, a cat bond that insures against earthquakes and hurricanes in equal shares fluctuates at the same pro-rata share with the hurricane season. To account for this effect, we repeat model (1) for the subsample of single-peril and single-location bonds in model (2). This analysis reveals a coefficient of 1.734 (within estimation). Ultimately, we acquire two coefficients that align quite well after we accounted for these two effects (1.884 between vs. 1.734 within).

[30] The model combines the interaction terms between EL and seasonal dummy variables, as well as the ultimate and penultimate years of maturity from models (2) and (3) in Table 5 using the full sample. Detailed results for this model are available upon request.

[31] We compare these two models using the Bayesian information criterion (BIC). For the model with the new seasonality measures, we acquire a BIC value of 15837 whereas the model with the set of dummy variables has a BIC value of 16182. The difference in BIC values clearly exceeds 10, which is strong evidence for a better model fit based on the new seasonality measure (see Raftery 1995).

can be accredited to seasonality. With an adjusted within R^2 of 0.282 in model (3), this share is much lower for multi-peril bonds due to exposure to other nonseasonal perils. Overall, results hold for both single-peril and multi-peril bonds.

Table 6: Impact of seasonality on spreads – seasonality-adjusted EL using the modeled seasonality measure.

Dependent variable:	Spread					
Sample:	Full sample	Single-peril	Multi-peril	Full sample	Single-peril	Multi-peril
	(1)	(2)	(3)	(4)	(5)	(6)
EL_t-US modeled	1.135***	1.734***	0.931***	1.093***	1.731***	0.858***
	(15.25)	(13.36)	(12.75)	(15.30)	(13.91)	(13.27)
EL_t-EU modeled	0.461***	0.736**	0.419***	0.445***	0.777***	0.390***
	(5.79)	(2.77)	(5.32)	(5.83)	(3.42)	(5.12)
Reins. index				0.020***	0.017***	0.022***
				(7.47)	(4.78)	(6.06)
Corp. bond spreads				0.413***	0.342***	0.473***
				(20.59)	(12.08)	(18.02)
Equity returns				0.024***	0.022***	0.024***
				(5.63)	(3.54)	(4.38)
Rem. maturity				0.030***	0.014*	0.044***
				(5.66)	(2.24)	(6.12)
Constant	4.795***	4.795***	3.559***	5.463***	3.559***	5.463***
	(30.03)	(30.03)	(15.30)	(28.84)	(15.30)	(28.84)
Observations	3947	1573	2374	3947	1573	2374
Number of bonds	386	154	232	386	154	232
Within R^2	0.326	0.466	0.282	0.494	0.576	0.509
Adj. within R^2	0.326	0.466	0.282	0.494	0.574	0.508

Note: This table uses fixed effects regression models to determine the effect of seasonal factors on spreads (in %) using modeled arrival frequencies from AIR. The sample is limited to bonds that are affected by seasonality. Model (1) introduces the seasonality-adjusted EL for the full seasonality sample. Models (2) and (3) use only single-peril or multi-peril seasonality bonds, respectively. Models (4)–(6) include control variables. t-values are shown in parentheses and heteroscedasticity robust standard errors are clustered at bond level. The symbols *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Throughout Table 6 the coefficients for the European winter storm season are below 1. However, this does not mean the seasonal fluctuations in European winter storms are not sufficiently reflected in spreads. Similar to the dampening effect of earthquake exposure in multi-peril bonds, the coefficient for the European wind bonds can also drop below 1 if wind bonds have a relatively strong exposure to other wind perils that occur outside of the European winter storm season. These other wind perils can be thunderstorms or hail which typically occur in the summer and not during the winter storm season. Section 2.7 shows that a large proportion of risk from July to September is implied in the trading activity of European wind bonds lifting the coefficient for single-peril European wind bonds to above 1.

Models (4)–(6) additionally include time-variant control variables. We find that the coefficients for the seasonality measures remain almost unchanged after the inclusion of controls.

The estimated coefficients of these controls are consistent with the empirical cat bond literature (see Gürtler et al. 2016 and Braun 2016), and almost all of them are significant at the 0.1% level.[32] Comparing the explanatory power of Models (1) and (4), an additional 17% of changes in spreads can be explained through corporate bond spread, equity returns, and reinsurance rates.[33]

2.6.3 Robustness check: TRACE data

In this robustness check we repeat the analyses from Table 6 with a separate daily data set from the Trade Reporting and Compliance Engine (TRACE). The results for the TRACE data set strongly support the previous results on seasonality. Instead of only relying on dealer quotes, we also use real trading data from TRACE. In general, TRACE contains the specific trading dates, the traded volume, and real prices net of accrued interest for over-the-counter trades. From January 2015 to March 2017, we acquired a data set that includes 134 bonds with 1537 daily prices. We drop all distressed bonds and use only seasonality-affected bonds to analyze seasonality effects, resulting in a TRACE data set with 1069 daily observations of 61 seasonality-affected bonds.

TRACE provides clean bond prices but no spreads. However, the TRACE prices allow us to determine spreads if we know each cat bond's individual cash flow: Cat bonds are Floating Rate Notes and usually pay a fixed coupon over a riskless interest rate. For the riskless interest rate, we use the United States Treasury yield curve. Following Fabozzi (2005), we use the forward rates determined from the United States Treasury yield curve to proxy unknown future spot rates. We have acquired the fixed coupons over the riskless interest rate from the Lane Financial data set and cross-checked them with data from Thomson Reuters DataStream. Compared to regular floating rate notes, cat bonds have a unique property: The fixed coupon above the riskless rate does not necessarily stay fixed throughout a cat bond's maturity. A catbond's maturity is usually a bit longer than the length of the underlying reinsurance contract between

[32] The coefficient of *Reinsurance index* indicates that a 1-point change in the Guy-Carpenter Rate-on-Line index is associated with a 0.02% point change in spreads, which confirms the results of Gürtler et al. (2016). A 1% point changein *Corp. bond spreads* is associated with a 0.41% point change in cat bond spreads; this effect is twice as large as Gürtler et al. (2016) and 1.5 times as large as in Braun (2016). A 1% point change in *Equity returns* is associated with 0.02% points change in cat bond spreads, which is slightly larger than in Gürtler et al. (2016). Finally, a 1-month decrease in remaining maturity is associated with a 0.03% point decline in cat bond spreads, which is in line with Gürtler et al.(2016). When comparing our coefficient of *Rem. maturity* to the coefficient of *TTM* in Gürtler et al. (2016), please note that *Rem. Maturity* is formatted in months while *TTM* is formatted in years.

[33] Estimated seasonality coefficients are also robust to unknown covariates expressed by quarter fixed effects, year fixed effects and year-quarter fixed effects. Detailed results are available upon request.

the sponsor and the special purpose vehicle (e.g., a 3-year cat bond usually has a maturity of 3 years and a few extra days or months). The time, when this reinsurance contract is in effect, is often referred to as the "risk period"of a cat bond. Outside of the risk period, a cat bond does not have exposure to the underlying insurance risk. During this time, a cat bond usually pays a much smaller fixed spread above the riskless rate to reflect the lower default risk. The specific end date of the risk period and the reduced spread above the riskless rate are unavailable to us. However, we believe the risk season should mimic reinsurance contracts and end on the last day of a month close to the cat bond's maturity date. Therefore, we assume the risk period to end on the last day of the month before its maturity. We assume a cat bond to pay a reduced spread above the riskless rate of 0.5% from the first day of the cat bond's month of maturity up to its day of maturity.[34] Consequently, this period of reduced coupons cannot be longer than 31 days.

To determine the necessary seasonality variable, we have used the methodology from Section 2.3.2. This time we have 365 steps per year corresponding to calendar days, accounting for the daily nature of the TRACE data set. We again employ the monthly distributions of U.S. hurricanes and European winter storms from AIR. We turn this monthly distribution into a daily distribution by interpolating between the midpoints of each month in a linear fashion. Hence, we gain a seasonality variable in a daily frequency.

Table 7 contains results on seasonality for the complete seasonality-affected TRACE sample as well as single-peril and multi-peril subsamples. For the complete TRACE sample in model (1), the coefficient for the U.S. season is highly statistically significant at the 0.1% level, while the coefficient for the European winter storm season is not statistically significant. Generally, only few European wind bonds were issued in the given period. Additionally, European bonds are often not included in TRACE. Thus, the coefficients for the European season remain insignificant due to the limited sample size. For the complete sample, 53% of the secondary market fluctuation can be explained through the seasonality measure. For the single-peril subsample in model (2), explanatory power increases to almost 62%. The coefficient for the U.S. season is larger than in model (1) and highly statistically significant at the 0.1% level. The coefficient for the European winter storm season is omitted because no single-peril European wind bond trades were reported in TRACE from January 2015 to March 2017. For multi-peril bonds in model

[34] The risk period of Cranberry Re 2017-1, for example, ends June 30, 2020, while the bond is repaid on July 13, 2020. Between June 30, 2020 and July 13, 2020, this bond pays a coupon of 0.5% above the riskless rate.

Table 7: Robustness check – impact of seasonality on spreads based on TRACE data.

Dependent variable:	Spread					
Sample:	Full sample	Single-peril	Multi-peril	Full sample	Single-peril	Multi-peril
	(1)	(2)	(3)	(4)	(5)	(6)
EL_t-US modeled	1.588***	2.013***	1.232***	1.341***	1.633***	1.136***
	(7.65)	(6.05)	(7.93)	(7.54)	(5.06)	(6.63)
EL_t-EU modeled	0.320		0.031	0.424		0.223
	(0.92)		(0.08)	(1.55)		(0.77)
Reins. index				0.031***	0.029	0.034***
				(3.46)	(1.50)	(4.56)
Corp. bond spreads				0.196*	0.126	0.190*
				(2.59)	(1.26)	(2.30)
Equity price index				-0.015	-0.011	-0.022*
				(-1.50)	(-0.53)	(-2.65)
Rem. maturity				0.036*	0.037	0.026*
				(2.52)	(1.29)	(2.14)
Constant	1.890***	1.219**	2.651***	-4.958**	-4.923	-4.774***
	(5.60)	(2.89)	(8.42)	(-2.99)	(-1.54)	(-3.53)
Observations	1069	454	615	1069	454	615
Number of bonds	91	30	61	91	30	61
Within R^2	0.529	0.618	0.472	0.643	0.696	0.600
Adj. within R^2	0.528	0.617	0.471	0.641	0.693	0.596

Note: Similar to Table 6, this table uses fixed effects regression models to determine the effect of seasonal factors on spreads (in %) using modeled arrival frequencies from AIR, but based on TRACE prices from FINRA. Model (1) introduces the seasonality-adjusted EL for the full seasonality sample. Models (2) and (3) use only single-peril or multi-peril seasonality bonds, respectively. Models (4)–(6) include control variables. t-values are shown in parentheses and heteroscedasticity robust standard errors are clustered at bond level. The symbols *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

(3), the explanatory power declines to 47%. The coefficient for the U.S. season remains highly statistically significant at the 0.1% level while its size has declined to a bit more than half its previous level. As compared to results for the Lane Financials data set in Table 6, coefficients and explanatory power have mostly increased. The increases in coefficients and explanatory power could be attributed to the different timeframes of both data sets as well as a more detailed modelling of seasonality through daily data. Although the seasonal coefficients slightly decrease, results hold after the inclusion of controls in Models (4)–(6). Overall, the results on the TRACE data set strongly support the results from earlier sections and highlight their reliability. Statistical significance remains high and explanatory power increases. In addition to results from the quarterly Lane Financials data, the daily TRACE data exemplifies the methodology's flexibility towards changes in data frequency.

2.7 Market-implied seasonality

2.7.1 Methodology for the market-implied seasonality measure

To create the seasonality measure described in Section 2.3.2, we employed a modeled distribution of arrival frequency shares provided by AIR, which were exogenous to our model. However, it is also possible to deduct a market-implied distribution of arrival frequency shares from secondary market data. Through this channel, the investors' opinion on seasonality and their distribution of arrival frequencies can be extracted from the data. Investors may have additional information, which the risk modelers have not provided. For the remainder of the paper, the externally modelled distribution of arrival frequencies from AIR is named modeled arrival frequency as opposed to the market-implied arrival frequency derived from secondary market trading. Again, severity is assumed to be i.i.d. for each period across a year.

To estimate the distribution of market-implied arrival frequencies, we create an econometric model that estimates arrival frequencies in such a way that it explains observed secondary market spreads as accurately as possible. To derive such a model, we utilize the seasonality measure from Section 2.3.2 to "reverse-engineer" the market-implied distribution of arrival frequencies. Thus, $\lambda_{im,\tau}$ denotes the estimates for the *implied* distribution of arrival frequencies:

$$EL_{it} = \frac{EL_{inital,i}}{T_i - t} \sum_{\tau=t}^{T_i} \lambda_{im,\tau}, \tag{16}$$

where we have used a discretized version of Equation (12). We define $H_{it} := EL_{initial,i}/(T_i - t)$ to simplify Equation (16):

$$EL_{it} = H_{it} \sum_{\tau=t}^{T_i} \lambda_{im,\tau}, \tag{17}$$

Consider a regression model that relates the spreads of bond i at time t to the fluctuating EL of bond i at time t, the vector of time-variate controls C_{it} and constant bond properties α_i:

$$\begin{aligned} s_{it} &= \beta_1 EL_{it} + \eta' C_{it} + \alpha_i + \varepsilon_{it} \\ &= \beta_1 H_{it}(\lambda_{im,t} + \lambda_{im,t+1} + \lambda_{im,t+2} + ... + \lambda_{im,T_i}) + \eta' C_{it} + \alpha_i + \varepsilon_{it}. \end{aligned} \tag{18}$$

A straightforward approach is to estimate every separate λ_{im} simultaneously. However, this approach appears infeasible because the number of separate λ_{im} increases linearly with the length of the data set. Consider the given data that ranges from 2002 to 2017 containing 15 years of spreads. In case of monthly estimation this results in estimating 180 separate parameters λ.

Instead, it is possible to simplify the finite series by assuming a static seasonal pattern, that is, seasons do not change from one year to the next year:

$$\lambda_{im,\tau} \equiv \lambda_{im,\tau+\kappa}, \tag{19}$$

where κ corresponds to the number of periods reflecting 1 year. Thus, different λ_{im} take on repeated values in cycles of 1 full year. Therefore, we define the following variables as the static shares of arrival frequencies of the yearlong season: $\gamma_1, \gamma_2, ..., \gamma_\tau$. These variables are the distribution of the arrival frequencies that we estimate from secondary market data. Since seasons repeat on a yearly basis, each $\lambda_{im,\tau}$ can be matched with a single γ that refers to the same seasonal period within each year. Consider the case of monthly arrival frequencies as explicitly provided in Table 1. For monthly data, the number of yearly steps is $\kappa = 12$. Then, γ_2 refers to the arrival frequency in January, γ_2 refers to the arrival frequency in February and soon. In consequence, γ_1 is equal to all λ_{im} that reflect January data. Therefore, the finite series from Equation (18) can be shortened to κ summands:

$$s_{it} = \beta_1 H_{it}(\gamma_1 m_{1,it} + \gamma_2 m_{2,it} + ... + \gamma_\kappa m_{\kappa,it}) + \eta' C_{it} + \alpha_i + \varepsilon_{it}, \tag{20}$$

where m_{it} describes how many times each arrival frequency γ is included in the remaining maturity of bond i at time t. To obtain a model equation that we can estimate, we define

$$\delta_j := \gamma_j \beta_1 \text{ and } d_{j,it} := m_{j,it} H_{it}, \tag{21}$$

which simplifies 20 to

$$s_{it} = \delta_1 d_{1,it} + \delta_2 d_{2,it} + ... + \delta_\kappa d_{\kappa,it} + \eta' C_{it} + \alpha_i + \varepsilon_{it}. \tag{22}$$

In principle, we can estimate the unknown parameters γ with standard OLS regression. The required values d_j can be determined with Formula (21). However, since the estimated arrival frequencies represent shares of peril events occurring for specific parts of a calendar year (e.g., days, months, or quarters), we apply two natural constraints to the parameters γ. First, it is impossible that less than 0% or more than 100% of all peril events occur at a specific day, month, or quarter. Thus, all parameters γ have to be larger than 0% and smaller than 100%. Second, the sum of all parameters γ has to equal 100%. Therefore, we formalize the following constraints:

$$\delta_1, ..., \delta_\kappa \geq 0 \; and \; \sum_{j=1}^{\kappa} \delta_j = 1. \tag{23}$$

To implement these constraints, we use a nonlinear model following Gould et al. (2010). For this purpose, we replace the parameters δ in Equation (22) with the following terms:

$$\delta_1 = \frac{1}{q}, \delta_2 = \frac{exp(\vartheta_2)}{q}, ..., \delta_\kappa = \frac{exp(\vartheta_\kappa)}{q}, \tag{24}$$

with $q = 1 + exp(\vartheta_2) + exp(\vartheta_3) + ... + exp(\vartheta_\kappa)$. Applying Equation (24) to Equation (22) and applying fixed-effects transformations yields the following model:

$$\ddot{s}_{it} = \frac{1}{q}\ddot{d}_{1,it} + \frac{exp(\vartheta_2)}{q}\ddot{d}_{2,it} + ... + \frac{exp(\vartheta_\kappa)}{q}\ddot{d}_{\kappa,it} + \eta'\ddot{C}_{it} + \varepsilon_{it}. \tag{25}$$

We estimate the nonlinear model and its parameters ϑ and η with maximum-likelihood estimation. After we have estimated the parameters ϑ, we reapply Formula (24) to obtain the estimates for the market-implied distribution of arrival frequency shares δ under the proposed constraints.

2.7.2 Results for the market-implied seasonality measure

In the previous section, we have established a methodology to estimate market-implied arrival frequencies from secondary market spreads. While the proposed methodology allows for different lengths of time steps (e.g., days, months, quarters), the specific length of a possible time step is limited by the frequency of available data. We have obtained quarterly spreads; however, it is possible to estimate a monthly distribution of arrival frequencies from quarterly data exploiting the specific dates of maturity. The estimation of each specific month is only possible if a sufficient number of bonds mature during this month. For example, U.S. hurricane bonds are typically tailored in such a way that they cover an entire hurricane season. Therefore, the estimation of monthly arrival frequencies within the hurricane season is difficult.

To estimate the market-implied distribution of arrival frequencies of U.S. hurricanes and European winter storms, we use single-peril/single-location subsamples of U.S. hurricane and European wind bonds, respectively. Additionally, we estimate the implied distribution of arrival frequencies of the aggregate cat bond market with a subsample of all seasonality-affected cat bonds that also contains multi-peril bonds. Table 8 contains the number of bonds that mature in the specific calendar months for the subsamples. The data confirm that no U.S. hurricane bonds mature in August through October. For EU wind bonds we observe that no bonds ma-

Table 8: Months of maturity for seasonality-affected cat bonds.

	Single-peril U.S. hurricane	Single-peril EU wind	Single-peril and multi-peril
January	9	8	78
February	4	0	12
March	3	3	21
April	3	8	39
May	21	3	52
June	18	12	102
July	5	1	16
August	0	0	2
September	0	1	2
October	0	0	2
November	3	0	6
December	18	4	54
Total	84	40	386

Note: Number of single-peril U.S. hurricane bonds and single-peril EU wind bonds that mature in the respective months of a calendar year. The third column reports the same numbers for all seasonality-affected bonds; in addition to single-peril hurricane and wind bonds, these bonds also include multi-peril bonds.

ture in February, August, October, and November, and for the aggregate seasonality-affected cat bond market, only few bonds mature August through October. To cope with these shortcomings, we combine these months with other months that offer a higher availability of data. For example, in U.S. hurricane bonds, we use a single parameter for October and November to obtain an average across these 2 months. We apply this method to all months that have too little data available. When combining months, we follow three rules: (a) We combine months where only two bonds or fewer mature, (b) we only combine months adjacent to each other, and (c) we do not combine months across quarters. Following these rules, we combine the following months: For U.S. hurricanes, we combine July/August/September and October/November. For EU Wind bonds, we aggregate January/February/March, July/August/September, and October/November/December. For the complete seasonality-affected cat bond market, we combine July/August/September and October/November.

The estimated market-implied distribution of arrival frequencies and the corresponding 95% confidence intervals are shown in Table 9. These arrival frequencies were estimated with the same control variables as in the previous models. The arrival frequencies for U.S. hurricanes and European winter storms mostly reflect the general pattern of the modeled distribution of arrival frequencies of AIR (see Table 1). For U.S. hurricanes, July, August, and September are the peak months for the hurricane season where investor trading implies hurricane arrival frequencies of 25.7% for each month. The season fades out during October and November with 10.6% each. The investor trading indicates no more hurricanes in December. All of these coefficients are statistically significant at the 0.1% level. For EU winter storms, January, February, and March

Table 9: Market-implied distributions of arrival frequencies.

	US hurricanes		EU winter storms		Cat bond market	
	Estimate	CI [95%]	Estimate	CI [95%]	Estimate	CI [95%]
January	1.6%**	[0.6%; 2.6%]	11.5%***	[8.5%; 14.4%]	6.9%***	[5.5%; 8.2%]
February	0%		11.5%***	[8.5%; 14.4%]	0%	
March	0%		11.5%***	[8.5%; 14.4%]	0%	
April	0%		0%		0%	
May	0%		0%		0%	
June	0%		0%		0%	
July	25.7%***	[24.7%; 26.8%]	12.3%***	[8.7%; 15.8%]	22.4%***	[21.8%; 23.0%]
August	25.7%***	[24.7%; 26.8%]	12.3%***	[8.7%; 15.8%]	22.4%***	[21.8%; 23.0%]
September	25.7%***	[24.7%; 26.8%]	12.3%***	[8.7%; 15.8%]	22.4%***	[21.8%; 23.0%]
October	10.6%***	[9.1%; 12.1%]	9.6%***	[6.7%; 13.8%]	13.0%***	[12.2%; 13.7%]
November	10.6%***	[9.1%; 12.1%]	9.6%***	[6.7%; 13.8%]	13.0%***	[12.2%; 13.7%]
December	0%		9.6%***	[6.7%; 13.8%]	0%	
Total	100.0%		100.0%		100.0%	

Note: Market-implied arrival frequencies for U.S. hurricanes, EU winter storms and the seasonality-affected cat bond market as derived from secondary market data. The shares of arrival frequency were estimated taking the control variables used in previous tables into account, namely *Reinsurance index*, *Corporate bond spreads*, *Equity returns*, and *Rem. maturity.* The symbols *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

are peak months for the winter storm season where investor trading implies winter storm arrival frequencies of 11.5% for each of these months. The other large portion of the winter storm season is reflected in the market-implied shares of arrival frequencies for October, November, and December with 9.6% each. Surprisingly, in July, August, and September, the market-implied share of arrival frequency deviates from the modeled share of arrival frequencies from AIR. In these months the shares of arrival frequencies are 12.3% each. The likely reason is that many EU wind bonds do not only insure against winter storms but also against other perils such as hail or severe thunderstorms, which typically occur in the summer. Thus, the market-implied arrival frequencies in July, August, and September can probably be attributed to the hail and thunderstorm season. All coefficients are highly statistically significant at the 0.1% level.

For the complete cat bond market, which includes all single-peril and multi-peril bonds, the U.S. hurricane season is the predominant seasonality factor. Investor trading indicates that most seasonal peril events occur from July through November. This also indicates that multi-peril bonds, whose distribution of risk among peril types is unknown to us, are also predominantly affected by U.S. hurricanes. The shares of peril events in January indicate the presence of the winter storm seasons. The lack of market-implied arrival frequency in February can be attributed to a lack of single-peril EU wind bonds that mature in February. If the additional multi-peril bonds, which mature in February, do not contain a substantial amount of winter storm risk, the model estimates 0% for this month. All coefficients are highly statistically significant at the

0.1% level.

Table 10: Comparison of market-implied and modeled seasonality measures.

Dependent variable:	Spread				
Sample:	US hurricane: single-peril		EU wind: single-peril		Cat bond market
	(1)	(2)	(3)	(4)	(5)
EL_t-US market-implied	1.820***				
	(15.33)				
EL_t-US modeled		1.802***			
		(13.87)			
EL_t-EU market-implied			1.247*		
			(2.62)		
EL_t-EU modeled				0.767**	
				(3.26)	
EL_t-World market-implied					1.124***
					(15.32)
Reins. index	0.021***	0.022***	0.014*	0.014*	0.020***
	(4.14)	(4.00)	(2.51)	(2.64)	(7.36)
Corp. bond spreads	0.334***	0.329***	0.419***	0.404***	0.413***
	(12.20)	(11.72)	(5.80)	(5.75)	(19.13)
Equity returns	0.014*	0.013+	0.050***	0.043***	0.027***
	(2.03)	(1.81)	(5.20)	(3.75)	(5.98)
Rem. maturity	0.022+	0.022+	-0.007	0.003	0.032***
	(1.96)	(1.98)	(-1.06)	(0.49)	(5.71)
Constant	-3.364**	-3.549**	-2.050	-1.689	-2.234***
	(-2.89)	(-2.83)	(-1.11)	(-1.08)	(-3.58)
Observations	871	871	483	483	3947
Number of bonds	84	84	40	40	386
Within R^2	0.679	0.666	0.304	0.294	0.458
Adj. within R^2	0.677	0.664	0.297	0.287	0.457

Note: This table uses fixed effects regression models to determine the effect of seasonal factors on spreads (in %) using the market-implied distribution of arrival frequencies derived from secondary market data as well as our modelled seasonality measure. Models (1) and (2) use a subsample that is limited to single-peril/single-location hurricane bonds. Models (3) and (4) are limited to single-peril/single-location European wind bonds. Model (5) uses all single-peril and multi-peril cat bonds that are affected by U.S. hurricane or European wind perils. t-values are shown in parentheses and heteroscedasticity robust standard errors are clustered at bond level. The symbols *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

As previously mentioned, the market-implied distributions of arrival frequencies are in line with the modeled distributions, while also picking up parts of the European hail and thunderstorm season. The results presented in Table 10 indicate how well the market-implied distributions explain the data by comparing them to models that use the modeled distributions. The subsamples are the same samples that were used to estimate the market-implied arrival frequencies. For U.S. hurricane bonds in model (1), the seasonal variable that uses market-implied U.S. hurricane arrival frequencies and time-variate controls explain 68% of all secondary market fluctuation. Comparing models (1) and (2), the coefficient for the U.S. hurricane season is almost the same for market-implied and modeled distributions of arrival frequencies. In both models, the coefficient is large and highly statistically significant at the 0.1% level. For European wind bonds in model (3), the seasonal variable that uses the market-implied distribution of arrival frequencies and time-variate controls explain roughly 30% of secondary market fluctuation. This is likely a consequence of a less pronounced season, because generally, EU wind bonds also insure against other perils that are not exclusively European winter storms. The coefficient is significant at the 1% level. Comparing models (3) and (4), the distribution of market-implied arrival frequencies for European winter storms yields a higher explanatory power than the modeled distribution of arrival frequencies. Additionally, the coefficient for the market-implied distribution in model (3) is larger than the coefficient for the modeled distribution in model (4). As previously mentioned, we believe the market-implied shares of arrival frequencies for European winter storms in Table 9 partially contain the hail and thunderstorm season as indicated by the high arrival frequency in quarter 3; this separate sub-season is not reflected in the modeled distribution. On the contrary, the coefficients and the explanatory power for the U.S. hurricane season are almost the same for market-implied and modeled distributions. For the complete market in model (5), the seasonal variable that uses the market-implied distribution of arrival frequencies and time-variant controls explain 46% of secondary market fluctuation. The coefficient is significant at the 0.1% level.

Generally, the results for market-implied arrival frequencies for U.S. hurricanes and the EU winter storms are in line with previous results from Section 2.6. The results indicate that the market-implied distribution of arrival frequencies can be a valuable alternative to modeled arrival frequencies for modeling cat bond seasonality, particularly in the case that modeled arrival frequencies are unavailable. However, the distributions of arrival frequencies of specific perils depend on the availability of specific cat bond types. Single-peril hurricane bonds allow for the estimation of market-implied shares of hurricane arrival frequencies while European wind bonds mix European winter storms with thunderstorms and hail.

2.8 Conclusion

Seasonal fluctuations are a major driver of cat bond spreads on secondary markets. We investigate their patterns for U.S. hurricane and European winter storm bonds. We propose a conceptual framework to model seasonality. This framework includes a hazard rate model to illustrate theoretical implications of seasonality on cat bonds and a new seasonality measure. This measure integrates the distribution of peril arrival frequency in econometric cat bond pricing models capturing theoretical implications from the hazard rate model.

Empirically, the seasonal pattern in spreads reflects the seasonal pattern in arrival frequencies: Spreads peak before risk season starts, hit their bottom after risk season ends, and adjust in between. The spreads' amplitude in seasonal fluctuation increases as a cat bond nears its maturity. Additionally, risky bonds with a high EL express stronger seasonal fluctuation than bonds with a low EL. Single-peril bonds express a stronger seasonal fluctuation than multi-peril bonds that have only some exposure to seasonal perils. Similarly, cat bonds that have a clear season (e.g., U.S. hurricane bonds) fluctuate more strongly than cat bonds whose season is less pronounced (e.g., European wind bonds).

The new seasonality measure captures these effects and explains a large fraction of secondary market fluctuations in seasonality-affected cat bonds. In addition, we provide a comprehensive method to deduct the market-implied distribution of peril arrival frequencies from observable secondary market spreads. Seasonal variables that use the market-implied instead of the modeled distribution of arrival frequencies explain secondary market spreads even slightly better as modeled seasonal variables. Generating the market-implied distributions of arrival frequencies offers an alternative if modeled distributions of arrival frequencies are unavailable; additionally, this method can be used to deduct the aggregate opinion of investors on arrival frequencies. We model arrival frequency and assume severity to be i.i.d. for each peril event during a calendar year. However, the methodology can be easily expanded to include two separate seasonality measures for arrival frequency and severity or a combination of both if a distribution of severity is available. On the contrary, the market-implied measure does not require the i.i.d. assumption but solves for the time-varying EL-multiple that best fits the data. The results for both seasonality measures are similar, which indicates that our modelling assumption is rather unproblematic.

Our proposed seasonality measure provides a comprehensive method to academics, insurance companies, and investors to model seasonality and explain secondary market fluctuation. For academics, the proposed seasonality measure offers an opportunity to model and control for seasonality in future secondary market research, thereby avoiding a large loss of observations. The methodology for deducting the market-implied distribution of arrival frequencies from secondary market spreads offers an opportunity to extract information from market participants concerning these perils. For practitioners, the illustrated seasonality effects could improve market transparency. When insurance companies decide between a cat bond and a traditional reinsurance contract to transfer risk, they may turn to secondary cat bond markets to project possible spreads for a cat bond placement. In this context, seasonality is an important factor because it causes large fluctuations on the secondary markets. (Re-)insures should not over- or under-estimate spreads due to reasons of seasonality. As investors, specialized ILS funds must value their cat bond portfolio correctly at investor entry or exit;[35] however, trading is very infrequent creating extended periods without any market valuation. Modelling seasonal fluctuation could allow for a fair valuation of cat bonds when a proper market valuation is lacking. Overall, we provide new insights on the impact of seasonality on secondary market spreads of cat bonds that could advance the markets maturity and further facilitate its growth.

Predictable spread movements on secondary cat bond markets raise the question of a potential trading strategy exploiting these predictable seasonal fluctuations. Such a trading strategy would only offer abnormal returns if these seasonal, predictable price movements implied mispricing. However, we believe the seasonal fluctuations follow a risk related rationale. Mispricing would only occur when the seasonal fluctuation is too strong or not strong enough, that is, a unit of change in EL_t is not priced properly. However, if we use the primary market as an indicator for "correct" valuation of a unit of EL, we cannot identify such a mispricing: In Section 2.6 the coefficient for EL_t does not significantly deviate from the EL coefficient on the primary market. Additionally, to make a potential trading strategy profitable, the associated transaction costs need to be lower than the exploitable mispricing, so that these deviations would need to be rather large. Although analyzing a potential mispricing on the secondary cat bond market is beyond the scope of this paper, it would be a highly interesting topic for future research.

[35] Aon Securities (2019) reports that in 59% of all ILS volume outstanding was held by specialized catastrophe funds in 2019.

Trading and Liquidity in the Catastrophe Bond Market

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Abstract

We provide first insights into secondary market trading, liquidity determinants, and the liquidity premium of catastrophe bonds. Based on transaction data from TRACE, we find that cat bonds are traded less frequently during the hurricane season and more often close to maturity. Trading activity indicates that the market is dominated by brokers without a proprietary inventory. Liquidity is high in periods of high trading activity in the overall market and for bonds with low default risk or close to maturity, which results from lower order processing cost. Finally, using realized bid-ask spreads as a liquidity measure, we find that on average 21% of the observable yield spread on the cat bond market is attributable to the liquidity premium. A magnitude of up to 141 bps for high-risk bonds suggests that steps towards an improved market liquidity would be highly beneficial.

Keywords: catastrophe bonds, liquidity, yield spreads, alternative risk transfer

JEL: G12, G22, G32

3. Essay 2 – Trading and liquidity in the catastrophe bond market

3.1 Introduction

The link between yield spreads and default risk of catastrophe bonds ("cat bonds") has been extensively analyzed in the theoretical and empirical literature (e.g., in actuarial models such as Jarrow 2010 and Lee/Yu 2002, and in empirical models such as Galeotti et al. 2013, Braun 2016 and Gürtler et al. 2016). For corporate bonds it is known that liquidity is another important driver of yield spreads, second only to default risk. Chordia et al. (2004) defines liquidity as the ability to buy and sell large quantities of an asset quickly and at a low cost. Investors are willing to pay a premium on liquid assets compared to less liquid assets of similar default risk. Although cat bonds are much less liquid than corporate bonds (see for example Lane 2016), which indicates a potentially substantial liquidity premium in the cat bond market, there is only very limited knowledge on cat bond trading and liquidity. Braun (2016) and Gürtler et al. (2016) have implemented the issue volume and maturity as liquidity measures but results are inconclusive. Zhao/Yu (2019) attempt to proxy cat bond liquidity through issued amount, sponsor type, deal complexity, age, maturity, volatility and yield dispersion; however, due to the lack of observable trade characteristics, they are unable to compute established liquidity measures from the corporate bond literature which rely on trading volume and/or trading frequency.[36] Instead, Braun et al. (2019) state that the separation of the liquidity premium from other yield spread components is currently not possible for Insurance Linked Securities (ILS) due to these limitations in ILS data. On the contrary, we are now able to separate the liquidity premium from other yield spread components through the increasing availability of ILS data in the Trade Reporting and Compliance Engine (TRACE) where we observe bid-ask spreads on individual secondary market trades on the over-the-counter (OTC) market; such bid-ask spreads are frequently used as liquidity measures in the empirical corporate bond pricing literature (e.g., Chen et al. 2007, Acharya et al. 2013, Schuster/Uhrig-Homburg 2015). Hence, this paper is able to shed light on actual trading, liquidity determinants, and the liquidity premium in the secondary cat bond market.

For corporate bonds, estimating the liquidity premium is notoriously difficult, because default risk and liquidity are endogenously linked. Chen et al. (2018) theorize a spiral of deteriorating default risk and liquidity: Default risk is negatively correlated with liquidity when firms have

[36] Examples are the Amihud measure (Amihud 2002), Roll's daily measure (Roll 1984b), and the Zero Returns measure (Lesmond et al. 1999).

difficulty to roll over debt. A low liquidity makes rolling over debt more costly which makes a default more likely. At the same time, an increase in default risk can increase inventory costs for dealers which in turn reduces liquidity. Ericsson/Renault (2006) show that equity holders have an incentive to default sooner when debtholders have fewer opportunities to sell their bonds in an illiquid market. Previous empirical research has dealt with the problem of endogeneity by identifying pairs of assets that have the same default risk but different liquidity. The difference in yield spreads between these assets is generally interpreted as the non-default component. Examples of these pairs include CDS and corporate bonds (Longstaff et al. 2005), BUNDs and Pfandbriefe (Kempf et al. 2012) or BUNDs and KfW-Bonds (Schwarz 2019). Alternatives include the creation of baskets of different rating categories (Dick-Nielsen et al. 2012) or simultaneous equations models (Chen et al. 2007). However, most of these approaches are only as good as their underlying counterfactual which quantifies the default risk component. On the contrary, cat bonds default events (e.g., hurricanes or earthquakes) are strictly exogenous. A natural disaster is not more likely to occur nor is a natural disaster more severe if a cat bond is less liquid. Therefore, the spiral of deteriorating default risk and liquidity is broken. This allows for an accurate identification of the liquidity and default components in cat bond spreads.

The liquidity of cat bonds is important to issuers and investors alike. Issuers need to be informed about the potential illiquidity premium they pay to investors when they issue a new cat bond while investors, such as specialized cat bond funds, draw from the cat bond market as a source of liquidity when they readjust their investments.[37] These funds also invest in purely illiquid alternative tools of catastrophe risk transfer, such as sidecars and collateralized reinsurance, and they often sell cat bonds when faced with trapped capital after catastrophe events or redemptions (Aon 2019, Swiss Re 2019). This highlights the importance of the cat bond market's liquidity in downturn scenarios stemming from catastrophe events but also crash scenarios on the general financial markets. Post Covid-19, Aon expects even more emphasis on liquidity leading to more growth in liquid investment strategies (Aon 2020).

We acquire the TRACE dataset on cat bond trading from Refinitiv Eikon that contains dates, clean prices and a dealer buy/sell indicator for all trades from January 2015 to March 2019. During this period, we observe the bid-ask spread of 3341 trade pairs from 229 cat bonds. This information is supplemented by specific bond information from Refinitiv Eikon, Lane Financials, and artemis.bm. We employ pooled ordinary least squares and fixed effects

[37] In 2019, specialized cat funds held the lion's share of 59% of the cat bond market (Aon Securities 2019).

regression models; in addition to the exogeneity of default events, we support our results with simultaneous equations models to account for possible dealer yield spread interactions.[38] By using a dataset from TRACE we are able to contribute to the empirical cat bond literature in three ways: First, we are able to shed light on the actual trading on the secondary cat bond market by identifying trade patterns and dealer behavior. Second, using bid-ask spreads as a liquidity measure, we are able to identify the bond characteristics that influence the liquidity of cat bonds. Third, we are able to quantify the liquidity premium on bond level and on the aggregate market through observable bid-ask spreads.

First, concerning trading on the secondary market, we find that cat bonds are more strongly traded outside of the U.S. hurricane season. Trading is especially low August through September when the hurricane season reaches its peak.[39] Additionally, trading increases as a bond nears its maturity. It appears that the secondary market of cat bond is dominated by dealers who do not hold an inventory as indicated by the large share of roundtrip trades that are concluded within 60 minutes. Second, we identify the following major liquidity determinants: A bond's liquidity is low when its default risk is high, it is more expensive to execute trades of large volume, and liquidity is increasing when a bond approaches its maturity. Third, we find that a lower liquidity causes a substantially increasing yield spread: A 1 basis point (bp) increase in bid-ask spreads is associated with 10 bps increase in yield spread. On average, the liquidity component of a cat bond is 98 bps. Overall, 21% of the yield spread of cat bonds can be attributed to the liquidity premium. This liquidity premium is even larger for bonds with a high default risk, which is driven by a time-series and a cross-sectional determinant: Liquidity is low in time periods of high default risk, and liquidity is more strongly priced for risky cat bonds. We measure the latter effect by forming subsamples of different rating categories. In addition, we find evidence for a positive relationship between market liquidity – measured by the mean bid-ask spread of the current quarter – and yield spreads.

The findings on the liquidity premium of cat bonds and its relation to default risk are generally in line with results from the empirical literature on corporate bonds (e.g., Longstaff et al. 2005, Chen et al. 2007, Bao et al. 2011). Concerning the determinants of liquidity, the

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[38] We consider this model because a dealer could nevertheless set his bid-ask spread in relation to the observed yield spread rather than the other way around. For example, a dealer could observe increased yield spreads due to a change in cat bond investor sentiment and adjust his bid-ask spread without a change in exogenous default risk.

[39] For a detailed discussion on seasonal effects in the yield spreads of cat bonds, please refer to Herrmann/Hibbeln (2021).

finding that liquidity is higher when a cat bond is closer to maturity or when there is much trading on the market is in line with Amihud/Mendelson (1986) and Goyenko et al. (2011). Concerning the overall liquidity of the cat bond market, our finding that yield spreads are lower when the general liquidity of the market is high is supported by Lin et al. (2011).[40] While the corporate bond literature generally supports the effects we have quantified for cat bonds, our results also contribute to the corporate bond literature: Exploiting the exogenous default risk of cat bonds, we identify and quantify many liquidity related effects. This way we can verify previous findings for corporate bonds where default risk and liquidity are endogenously linked. Thus, while previous attempts have mainly dealt with these endogeneity concerns by means of the econometric design, we achieve similar findings based on a type of bonds with strictly exogenous default risk implied by strictly exogenous catastrophe events.[41]

The remainder of this paper is structured as follows: Section 3.2 provides further details on the (re-)insurance and the cat bond market and derives hypotheses. Section 3.3 illustrates the TRACE dataset and the econometric model. Section 3.4 contains empirical results and Section 3.5 concludes.

3.2 Institutional background and hypotheses

3.2.1 Institutional background

Usually, insurers turn to reinsurers for large loss event coverage. Reinsurance companies are able to cover large risks because they offer a broad within industry diversification, which is unavailable to individual insurers. However, reinsurers' ability for within industry diversification has limits, especially for perils with extreme loss potential such as earthquakes, wildfires or hurricanes. The latter two are even expected to worsen in the wake of climate change. With increasing frequency, the (re-)insurance industry draws from the financial markets for additional diversification, when within industry diversification is exhausted or becomes too expensive. This

[40] Aligned with the individual liquidity of a bond, the risk that the level of liquidity worsens ("liquidity risk") is priced in the corporate bond market (Acharya/Pedersen 2005, Lin et al. 2011). Due to limitations in the quantity of data, we are unable to quantify liquidity risk in the cat bond market.

[41] In the empirical finance literature, natural disasters are frequently used as exogenous treatments. For example, Cortès/Strahan (2017) look into credit supply in the aftermath of a multitude of different natural disasters. Schüwer et al. (2019) use hurricane Katrina to investigate how affected banks react to a local shock depending on their affiliation with a holding company. Koetter et al. (2020) find that banks in flood areas increase lending after floods to support recovery; this effect is especially pronounced when the bank is affiliated with another bank in an area that was not affected by the flood. Berg/Schrader (2012) find that demand for credit increases after volcanic eruptions in Ecuador but the access to credit is restricted; a preexisting borrower-bank relationship reduces this mismatch.

growing demand for additional diversification is reflected in the size and growth of the cat bond market. According to artemis.bm, it has reached a record size of US$ 51 billion in 2021 up from US$ 27 billion in 2016.

If a (re-)insurance company ("sponsor") wants to get extreme-event coverage in form of a cat bond, it sets up the following structure:[42] A special purpose vehicle (SPV) engages in a reinsurance contract with the sponsor, selling reinsurance coverage to the sponsor. To cover potential losses from the reinsurance contract, the SPV issues bonds that contain a default trigger that mirrors the reinsurance contract's payment clauses. This reinsurance contract can cover a certain layer of the sponsor's actual losses for a given time period for a specified peril type (or for multiple perils). Alternatively, the SPV and the sponsoring (re-)insurer can agree upon specified catastrophe parameters such as wind speed or an earthquake severity on the Richter scale that trigger the default of the cat bond. The underwriting risk in the reinsurance contract is fully collateralized through the issued bonds. The collateral is kept in a trust account, usually invested in short term treasuries or assets of similar quality and liquidity.[43] Thus, credit risk from the sponsor is excluded in a cat bond transaction.[44] Cat bonds are floating-rate notes that pay the investors a fixed coupon over the flexible interest from the trust account. This fixed coupon is fully covered by premium payments, which the sponsor pays to the SPV in exchange for the catastrophe coverage. These fixed payments reimburse the investors for the cat bond's inherent underwriting risk.

For example, if a (re-)insurance company demands coverage against extreme losses from hurricanes in Florida in the volume of US$ 150 million, it can set up the described structure and have its SPV issue cat bonds with this volume. If the specified hurricane losses in Florida do not manifest for the (re-)insurance company during the cat bond's duration, the collateral is liquidated and returned to the investors. If the (re-)insurer incurs losses from a hurricane in Florida that exceed specified attachment points, the collateral is not returned to the investors but instead used to cover the (re-)insurer's reimbursements; the cat bond defaults. A default can be complete or partial depending on the specified default trigger and the occurred loss event. The cat bond structure breaks down when the sponsoring (re-)insurance company becomes

[42] For an illustration and discussion on cat bond design, please refer to Braun (2016).

[43] The collateral is usually highly liquid and not traded during the duration of the cat bond. Hence, we abstract from modelling the liquidity of the collateral.

[44] Nevertheless, Götze/Gürtler (2020a) find that some sponsor characteristics can affect yield spreads in hard and neutral market phases.

insolvent or goes out of business. In this case the principal is returned to the investors; the bond is repaid at par value. The repayment at par value is possible because the principal is kept in a trust account that is legally and physically separate from the sponsor. Hence, a cat bond does not bear any credit risk from the sponsor. Instead, all default risk of a cat bond can be attributed to the inherent underwriting risk.

Not only (re-)insurance companies but also government institutions can sponsor cat bonds. In 2019, the World Bank has issued cat bonds with nominal value of US$ 1685 million to cover emergency payments and rescue efforts of emerging economies such as Mexico, Chile, Columbia and Peru for earthquakes but also for the Philippines, which are badly affected by reoccurring typhoons. Overall, natural catastrophe damages are expected to rise substantially in the wake of climate change. For some perils, such as hurricanes, insurability will depend on the insurance industry's ability to diversify. Hence, the efficiency of the cat bond market that covers extreme events could prove vital in the insurability of coastal areas. Additional knowledge about the liquidity premium on the cat bond market could, thus, supplement risk management efforts in climate change.

When pricing this type of risk transfer, the empirical cat bond literature has focused on the explanation of yield spreads through default risk and other components such as financial market conditions or cat bond specific properties such as peril types or trigger types. A bond's liquidity has not been one of these components beyond rudimentary liquidity measures such as issued volume and remaining maturity. Braun (2016) finds a negative relationship of issued volume and yield spread while Gürtler et al. (2016) find the opposite effect, and none of these studies finds a significant effect for the remaining maturity. Overall, these results are inconclusive. Similar to corporate bonds, the individual cat bond's default risk is the primary driver of yield spreads (e.g., Major/Kreps 2002, Lane/Mahul 2008, Braun 2016, Gürtler et al. 2016). For corporate bonds, default risk is typically determined by credit rating agencies. For cat bonds, a credit rating from one of the established rating agencies only plays a subordinated role in bond pricing.[45] Instead, specialized risk modelling firms determine a cat bond's inherent underwriting risk through sophisticated earthquake and weather models (e.g., for hurricanes, wildfires, and hailstorms). Their efforts culminate in a risk report that contains a detailed

[45] Many cat bond issues do not receive a rating. In our data set, only about 30% of all cat bond issues have received a rating from Standard & Poors or other rating agencies, with a decreasing share over time.

probability distribution of loss potential.[46] The expected loss (EL) as the first moment of this distribution is typically used to account for default risk in empirical cat bond research. Abstracting from model risk, the more granular nature of the EL allows for a more detailed quantification of default risk than the ordinal scale of rating categories. Empirical evidence indicates that a linear relationship between yield spread and EL is most appropriate (Galeotti et al. 2013).

While the default risk in cat bonds is well-understood in the empirical cat bond literature, it is important to first discuss cat bond trading and its participants before further investigating the cat bond market's liquidity. Cat bonds are exclusively held and traded by institutional investors. This investor audience includes reinsurers, hedge funds, mutual funds, specialized cat funds and other institutional investors. In 2019, specialized cat funds held the lion's share of 59% of the cat bond market (Aon Securities 2019); hence, we presume this investor type dominates cat bond trading. These funds do not only invest in cat bonds but also in industry loss warranties, collateralized reinsurance, and sidecars. Braun et al. (2019) introduce a factor model to explain the returns of these specialized cat bond funds shedding light on their investment decisions. For several reasons, the liquidity of the cat bond market is very important to these investors. Instead of following a simple buy-and-hold strategy, they heavily rely on the possibility to trade cat bonds on the secondary market. First, investors regularly readjust their portfolios: They often sell cat bonds on the secondary market to release capital and to invest into new issuances on the primary market (AON 2017). Second, investors utilize the liquidity of the secondary market during adverse events. The need for liquidity in the secondary market for cat bonds during this time can even stem from other ILS classes: Capital invested in collateralized reinsurance and sidecars can become trapped in these vehicles while losses from an adverse event are assessed. This process can take years to complete. In consequence, this capital is unavailable for reinvestment and investor redemption. For example, Swiss Re (2020) reports that liquidity was at a premium in the cat bond market of 2019 as capital was tied in collateralized reinsurance transactions. Instead, investors sell cat bonds to release capital when faced with redemptions (Aon 2019). Contrary to collateralized reinsurance, a distressed cat bond can often still be bought and sold on the secondary market, though at a discount; hence, its capital is not completely trapped

[46] Notable risk modelling firms are AIR, RMS and CoreLogic. In our sample, AIR has over 80% market share. For a discussion on risk modelling in ILS please refer to Poliquin/Lalonde (2012).

when its maturity was extended.[47] Similar effects can be observed during downward scenarios on the financial markets: During the crash associated with the Covid-19 pandemic in March 2020, several key investors moved away from sidecars towards more liquid instruments, such as cat bonds (Aon 2020). In line with this, Swiss Re (2021) reports a strong uptick in cat bond trading in March 2020. Post Covid-19, Aon expects more emphasis on liquidity leading to more growth in liquid investment strategies (Aon 2020). Although the liquidity of the cat bond market is very important to specialized cat funds and other ILS investors, the actual secondary market trading is almost completely unexplored. We fill this gap with insights from the actual trades reported in TRACE.

3.2.2 Liquidity on the OTC market

Liquidity forms through trading among market participants. However, little is known about the trading of cat bonds on the OTC market.[48] As opposed to exchange traded stocks, corporate bonds are usually traded directly between investors. Traders in these markets search for counterparties and then bargain for a price reflecting their need for liquidity and outside alternatives (Duffie et al. 2007). Often traders do not search for possible counterparties individually but employ the services of a broker or dealer to execute trades. A dealer often serves as a market maker with a proprietary inventory of securities. Market makers immediately sell or buy securities from traders before searching for a counterparty to offset the trade (Goldstein/Hotchkiss 2020). They rebalance their inventory sometime after the trade by offloading to or buying from other dealers or traders. Market makers can significantly improve a market's liquidity and efficiency (Eldor et al. 2006). For their services, dealers are compensated by the bid-ask spread of the trade. Usually, the costs that a dealer incurs has three elements: a) adverse selection costs, b) inventory cost, and c) order processing cost (Huang/Stoll 1997). Adverse selection costs occur when traders have an informational advantage over dealers and trade an asset to the dealers' disadvantage. Inventory costs stem from capital requirements for dealer inventory. Additionally, a dealer can incur losses through adverse price movements (Schultz 2017). Searching for counterparties and executing trades causes order processing costs. Dealers set bid-ask spreads according to these cost elements: Bid-ask spreads are usually high for risky bonds where

[47] Similar to collateralized reinsurance, the maturity of a cat bond can be extended for multiple years for loss assessment.

[48] For corporate bonds, Duffie et al. (2005) offers a wide variety of theoretical implications of OTC trading and the bid-ask spread.

informational asymmetry is large driving adverse selection costs. Bid-ask spreads are also high when trading is infrequent, driving up inventory costs. Finally, bid-ask spreads are high when matching buyers and sellers of an asset is difficult, making the execution of a trade expensive. However, not all three of these cost elements must be present in the bid-ask spread: Goldstein/Hotchkiss (2020) indicate that dealers forgo an inventory altogether when trading is so infrequent that inventory costs are prohibitive. They find that over half of all dealer trades are offset within the same day. In this case, an inventory was not involved; instead, dealers without inventories for infrequently traded bonds serve as brokers who only match sellers and buyers without taking a bond onto their own balance sheet. Goldstein/Hotchkiss (2020) find that the share of within-day trade pairs increases when a bond is generally more rarely traded. Dealers who act as brokers are not exposed to adverse selection costs and inventory costs. Although the lack of these cost elements is often associated with lower bid-ask spreads for brokered trades, this advantage comes at a price for traders: The bond price can change while the trader waits for the execution of the trade, or the trade can even fail if no counterparty can be found. For cat bonds, Risk Management Solutions (2012) reports that cat bond trades are usually made on a matched basis with no inventory involved. Willis Towers Watson (2017) states that dealers sometimes hold inventory.[49] We expect dealers to behave in such a way as Goldstein/Hotchkiss (2020) describe when trading is scarce: Dealers rarely hold an inventory of cat bonds because they are so infrequently traded. Instead, they mostly act as brokers who only match buy and sell orders. This has the disadvantage that cat bond traders are not guaranteed an immediate execution when they choose to submit an order but can experience long holding periods before a trade can be executed.[50]

3.2.3 Hypotheses

The bid-ask spread of a trade compensates the dealer for adverse selection costs, inventory costs, and order processing costs (Huang/Stoll 1997). However, as the trading of cat bonds is scarce, it is likely that cat bonds dealers mostly act as brokers. As such brokers are not exposed to adverse selection costs and inventory costs (Goldstein/Hotchkiss 2020), we expect that order processing cost, due to searching for counterparties and executing trades, are the main driver of bid-ask spreads of cat bonds. As the investor audience for bonds with low default risk is

[49] No market reports have provided any numbers of possible inventory involvement.

[50] Please refer to Section 3.3.2 for information on the trading on the cat bond market. We find that 86% of all trades are offset within the same day and do not involve an inventory.

generally higher, searching for counterparties and executing trades are less costly, which implies higher liquidity. Hence, we hypothesize that liquidity is lower for cat bonds with high default risk.

H1.1: *Liquidity determinants – default risk: Liquidity is low if default risk is high.*

Similarly, when an investor submits a large order, it is more difficult for the commissioned broker to find a counterparty. The broker may even have to involve multiple investors if he does not find a single counterparty willing to fill the order. This economic reasoning is in line with Huang/Stoll (1997) who find that search costs are disproportionally larger for large trades. Thus, we hypothesize that bid-ask spreads are larger for trades with a large trading volume.

H1.2: *Liquidity determinants – trade size: Liquidity is low if trading volume is high.*

The model of Amihud/Mendelson (1986) implies that bonds with a shorter time to maturity are more liquid. This results from a clientele effect where, in equilibrium, long-term investors invest into less liquid assets whereas short-term investors invest into more liquid assets. The underlying economic reason is that long-term investors trade less often so that higher trading costs do have a smaller effect on their returns. In line with this model, Edwards et al. (2007) find that corporate bonds with a shorter time to maturity have lower transaction costs, leading to higher liquidity. Similarly, various papers investigate the term structure of the liquidity premium and find increasing liquidity premia for longer maturities (see Goyenko et al. 2011, Kempf et al. 2012, or Schuster/Uhrig-Homburg 2018). Hence, we hypothesize that liquidity is higher if a cat bond nears its maturity.

H1.3: *Liquidity determinants – remaining maturity: Liquidity is low if time to maturity is high.*

The liquidity component in yield spreads on the corporate bond market has been thoroughly established in the empirical literature (e.g., Longstaff et al. 2005, Chen et al. 2007, Bao et al. 2011). Considering that trading of cat bonds is rather scarce, it is plausible that the yield spread of cat bonds also contain a significant liquidity component: Cat bonds with low liquidity should exhibit a high yield spread. Following the overwhelming empirical evidence for a liquidity premium on the corporate bond market, we formulate the following hypothesis:

H2.1: *Liquidity premium – general: Bonds with low liquidity are associated with high yield spreads.*

Additionally, it is often argued that the liquidity premium is larger for non-investment grade bonds than for investment grade bonds. For example, Chen et al. (2007) find a liquidity effect that is 8 to 10 times larger for non-investment grade bonds than for investment grade bonds. According to the corporate bond literature, the liquidity premium is more pronounced in downturn scenarios (Acharya et al. 2013), especially in times of a crisis (see Dick-Nielsen et al. 2012 and Friewald et al. 2012 for the financial crisis or Schwarz 2019 for the sovereign debt crisis). A flight-to-liquidity in downturn scenarios can have opposing effects for investment grade and speculative grade bonds. Prices for investment grade bonds can rise as they are considered safe havens, while prices on speculative grade bonds fall (Acharya et al. 2013). Hence, we hypothesize that bonds with a high default risk have a high liquidity premium.

H2.2: *Liquidity premium – default risk: Bonds with a high default risk have a high liquidity premium.*

The liquidity premium for an individual bond could also be related to the general liquidity of the cat bond market. In a theoretical framework, the Liquidity CAPM relates an asset's liquidity premium and return to the general market's liquidity (Acharya/Pedersen 2005). Empirical results for the general corporate bond market confirm such an effect (Lin et al. 2011). Hence, we hypothesize that cat bonds exhibit a high yield spread during times of low market liquidity.

H3: *Liquidity premium – market liquidity: During a less liquid bond market, bonds exhibit higher yield spreads.*

3.3 Data and econometric model

3.3.1 Data

In the cat bond literature, this article is the first to use TRACE data on a broad scale. Generally, there are two versions of TRACE data: "Standard TRACE" and "Enhanced TRACE". Refinitiv Eikon is our vendor for standard TRACE data. We use standard TRACE because enhanced TRACE data on SEC 144a issues are not yet contained in Refinitiv Eikon or WRDS.[51]

[51] The enhanced TRACE data set from WRDS, which we use to investigate corporate bonds in sections 3.4.1 and 3.4.2, does not contain any cat bonds. Therefore, we have no specific information on volume if the trade size is larger than US$ 1 million. But even if we could use enhanced TRACE data, we would lose 18 months of trading information because enhanced TRACE is only published with an 18-month lag. This would severely limit our dataset, which is currently 51 months long.

Beyond what is reported in standard TRACE, enhanced TRACE essentially only contains uncapped trading volume (Dick-Nielsen 2014). We use the following steps to construct the TRACE data set and obtain specific information from Refinitiv Eikon: First, we obtain a list of all cat bonds traded on the secondary market from January 2015 to March 2019 from Lane Financials LLC.[52] Second, we search for these names in Refinitiv Eikon;[53] after we have found a cat bond, we can access all of its important information such as specific issue and maturity dates and coupon payment dates as well as its CUSIP. Third, we obtain standard TRACE data for each of these bonds by entering the identified CUSIPs into the Trace Viewer from Refinitiv Eikon. From this source for standard TRACE data, we acquire clean prices, trading dates, and trading volumes, which are capped at US$ 1 million.[54] Dealer buy and dealer sell indicators allow for the computation of bid-ask spreads. Detailed intraday trading times allow for a reliable matching of dealer sells and buys. Spanning from January 2015 to March 2019, we have 51 months of secondary market trading, where we observe 8883 trades for 245 cat bonds.[55] The original list of cat bond names contained 297 entries. However, some of these cat bonds are not TRACE eligible;[56] hence, they are not part of our sample. We supplement this data with additional cat bond information: Lane Financial LLC also provides EL, sponsor, volume, and rating for all cat bonds in our dataset. From the deal directory on artemis.bm we obtain trigger types, peril types and peril locations. Matching is performed based on cat bond names. Additionally, we use the Treasury Yield Curve and the Bank of America Merill Lynch BB Yield Spread Index from the Federal Reserve Bank of St. Louis. We use the Guy Carpenter Global Property Catastrophe Rate-On-Line Index to proxy general reinsurance rates. We supplement this data with another enhanced TRACE data set from WRDS to investigate the trading in selected corporate bonds

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[52]Once a year Lane Financial LLC publishes a market report in its Trade Notes that contains information on all newly issued cat bonds and surveyed quoted spreads for all live cat bonds on a quarterly basis.

[53]If we cannot find a match, we obtain the CUSIPs through an online search, and search for these CUSIPs in Refinitiv Eikon.

[54]When dealing with standard TRACE data, a filter from Dick-Nielsen (2009) is often used to deal with corrections and cancelations in reported standard TRACE trades. These errors can be identified in WRDS data and original TRACE trade reports. However, we did not identify any of these errors in Refinitiv Eikon TRACE data. It appears plausible these errors have already been corrected in the data set.

[55]Cat bonds already became available in standard TRACE in July 2014 (Lane 2016). However, in Refinitv Eikon, we cannot observe TRACE data before January 2015.

[56]E.g., they were issued under European jurisdiction.

issued by selected cat bond sponsors.[57]

3.3.2 Liquidity measure

As a liquidity measure, we use the observable bid-ask spread obtained from standard TRACE. Apart from the bid-ask spread, the empirical literature offers a whole menu of liquidity measures.[58] Common additional liquidity measures include high-frequency measures such as Schultz's measure (Schultz 2001), Interquartile Range (Pu 2009 and Han/Zhou 2007), Roll's daily measure (Roll 1984) or the High-Low Spread Estimator by Corwin/Schultz (2012), but also extend to the less-demanding Zero Returns measure by Lesmond et al. (1999). Due to limitations in available data, these measures are currently not applicable for cat bonds. Since enhanced TRACE data is not yet available in sufficient quantity, we do not have complete information on traded volumes. Additionally, the cat bond market is very illiquid with some cat bonds going for months without a single trade taking place. Due to the lack of volume, we are also unable to compute the well-established Amihud measure from Amihud (2002). However, instead of any of these liquidity measures, we can directly rely on bid-ask spreads from observable transaction prices as reported in standard TRACE data. Many papers either directly rely on bid-ask spreads (e.g., Chen et al. 2007, Acharya et al. 2013, Schuster/Uhrig-Homburg 2015) or specifically design their liquidity measures to proxy unobserved bid-ask spreads. Examples for these bid-ask spread proxies include the Roll's daily measure, the Interquartile Range and the High-Low Spread Estimator. In Black et al. (2016) about 80% of the non-default component (as attributable to the liquidity dimensions trading cost, depth and resilience) in corporate bond premiums comes from the bid-ask spread, while order-flow shocks and the Amihud measure explain only the remaining 20%. Hence, relying on the bid-ask spread as liquidity measure appears to be no major limitation.

We define the relative bid-ask spread as follows:[59]

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[57] When dealing with enhanced TRACE data on corporate bonds, we use the filter from Dick-Nielsen (2014) to deal with corrections and cancelations in reported enhanced TRACE trades.

[58] Schestag et al. (2016) offer a comprehensive discussion on available liquidity measures.

[59] Schestag et al. (2016) and Black et al. (2016) use a similar bid-ask spread measure where the only difference is that they use the average ask price minus average bid price divided by average mid-price for each trading day. They both refer to Hong/Warga (2000) when they introduce their bid-ask spread measures. Schuster/Uhrig-Homburg (2015) use the ask price minus the bid divided by the mid-price; in that sense, they use the same measure as we do, albeit for quoted prices. Macchiavelli/Zhou (in press) calculate the realized bid ask-spread based on the daily volume-weighted buy and sell prices for each dealer-bond pair.

$$L_{it} = \frac{p_{a,it} - p_{b,it}}{(p_{a,it} + p_{b,it})/2} \ , \tag{26}$$

where $p_{a,it}$ and $p_{b,it}$ denote the ask and bid prices of bond i at time t. We obtain the necessary bid-ask spreads from trades recorded in standard TRACE. This standard TRACE data set contains a dealer sell/buy indicator, the specific volume if a trade was smaller than US$ 1 million and the specific time of the trade.[60] This information can be used to match dealer sells and buys. However, if trading is very frequent, buy and sell matching of individual trade pairs can be challenging. For corporate bonds, the bid-ask spread is often proxied from aggregate daily buy and sell activity. For example, Black et al. (2016) take the difference between the daily volume-weighted averages of the buy and sell prices while Dick-Nielsen et al. (2012) use the Imputed Roundtrip Measure from Feldhütter (2012) that match trades in close timely proximity as buy and sells when a buy/sell indicator is unavailable. Since our TRACE dataset does contain dealer buy and dealer sell indicators, we do not have to use a measure of imputed roundtrips. Instead, we generate a measure for actual roundtrips similar to Green et al. (2007). We use the following matching algorithm: We match two trades in the dataset as a buy/sell pair under the following conditions: a) They are for the same bond, b) one trade is a dealer buy while the other trade is a dealer sell, c) the volume of both is the same,[61] and d) the two trades occur within 60 min of each other. [62]

In the context of matching trades, the infrequent nature of cat bond trades plays into our hands: There is rarely more than one buy/sell trade pair per day and bond. Hence, matching buy and sell trades for an individual bond is simple.[63] In rare cases, a trade did not just involve two parties and a dealer (hence one buy and one sell trade) but multiple parties expressed by a

[60]Please refer to section 3.3.1 for a brief discussion on the differences between standard TRACE and enhanced TRACE.

[61]When trade size is below the US$ 1 million cap, we can perform a very precise matching. If the volume of a trade is above the US$ 1 million cap, we continue matching with the above US$ 1 million label.

[62]Feldhütter (2012) matches trades within 15 minutes. However, his dataset lacks dealer buy and dealer sell indicators, so that close timely proximity is more important to reduce the risk of matching buys with buys and sells with sells. We choose 60 minutes because buy and sell indicators greatly improve matching precision.

[63]Our data set does not contain dealer identifiers. So, in theory it is possible that we match dealer buys and dealer sells from different dealers. However, we believe this scenario is very unlikely: In total we have 3884 bond-days in the data set where at least one trade took place. In 2640 of these bond-days we only observed two trades. If these two trades occur within 60 min and have one dealer buy and one dealer sell indicator, it seems highly unlikely they are from different dealers. For another 696 of bond-days, we observe only three or four trades, for which it is very unlikely, too, that the matching algorithm matches trades from different dealers. Only 167 bond-days have five trades or more, whereas 134 bond-days have only one trade.

multitude of buy and sell orders. If these multi-party trades could be identified by close timely proximity and a matching aggregate volume of buy and sell trades, we have matched these trades by hand. For multi-party trades, we calculated the means of buy and sell orders to determine bid-ask spreads.

In January 2015, TRACE reporting rules of OTC trades expanded to SEC 144a rule bonds. Overall, we observe a total of 245 bonds with 8883 trades from January 2015 to March 2019.[64] For four of these cat bonds we do not observe any matches; these four bonds in total only have eight trades observable in TRACE.[65] Hence, we observe bid-ask spreads for almost all cat bonds in the data set. We drop bonds with missing information such as EL and maturity dates (one bond is perpetual). Additionally, we drop trades from 180 days before a bond became distressed.[66] To not artificially inflate bid-ask spread information, we collapse the data set to the matched bid/sell trade pair level. Through this step, we keep roughly half of all remaining observations. We use the midpoint between buy and sell prices as bond prices. In total, we acquire a dataset of 229 cat bonds with 3341 trade pairs.

Table 11: Months of maturity for seasonality-affected cat bonds.

	Matched trades	Unmatched trades
Number of trades	7610	1273
Buys/sells	3798/3812	381/892
Mean trade size	US$ 785,000	US$ 761,000
Share of capped trades	62.9%	56.2%
Mean bond size	US$ 270 million	US$ 272 million
Mean EL	2.1%	2.2%
Mean coupon	5.5%	5.2%

Note: Comparison of matched and unmatched trades regarding Number of Trades, Buys/Sells, Mean Trade Size (Trade Size capped at US$ 1 million), Mean EL and Mean Coupon. Buy and sell trades were matched if they were from the same bond, had the same volume and occurred within 60 min of each other. The share of capped trades is the number of trades larger than US$ 1 million divided by the number of total trades.

Table 11 compares matched trades to unmatched trades for the initial dataset to identify possible biases from the trade matching procedure since we only use paired trades for the remainder of our empirical analysis. Additionally, the detailed examination of matched and

[64] Although TRACE reporting began in 2015, we observe six additional cat bonds in 2011 and 2012. However, we omit these six additional bonds because it is likely they were issued under different disclosure rules.

[65] The low number of trades for the four bonds which lack matches indicates that these bonds are not preferred by dealers. Thus, there is no indication that dealers hold inventory for them.

[66] Distressed means there was a complete or partial loss of principal. Additionally, a bond can be marked as distressed in anticipation of partial or complete loss of principal. Information on distressed bonds is acquired from Lane Financials and artemis.bm

unmatched trades allows us to gain some insights into cat bond trading activity. The results for both subsamples indicate that matched and unmatched trades are similar: Mean trade size, share of capped trades, mean size of the traded bond, mean EL and mean coupon are almost identical for matched and unmatched trades. This indicates that trade matching does not bias our sample.[67] Overall, we are able to match 85.7% of all trades to pairs of dealer buys and dealer sells within a 60 min timeframe. If we assume that these bonds were not kept on a dealer's balance sheet, because the sell and buy trades were executed in close timely proximity, this means that no inventory was involved for the vast majority of trades. In line with Goldstein/Hotchkiss (2020) we deduce that the market for cat bonds is dominated by brokers who focus on matching buy and sell transactions without inventory involvement. Hence, the bid-ask spreads in our empirical models mainly represent search costs for matching and executing trades and not inventory costs or costs from adverse selection.

3.3.3 Yield spread and EL

We apply basic theory on floating-rate notes from Fabozzi et al. (2000) to determine yield spreads from clean prices. The typical method to price a corporate bond is simple: An investor looks for the yield spread of another corporate bond with a similar risk profile and maturity. He then uses this yield spread to discount the future cash flow of the bond at hand to obtain its price. To this end, he needs to identify a similar corporate bond to obtain a yield spread and he needs to know the complete future cashflow of the bond at hand. We can apply the same method from corporate bonds to price a cat bond. In our case, we already have the clean price from TRACE and can determine the future cash flow from the cat bond data set. The only difference is that we do not determine the price using the yield spread from another cat bond but instead use the clean price from TRACE to determine the yield spread of the cat bond at hand. To this end, we determine the remaining cash flow for every price observation of every cat bond. First, we obtain the specific payment dates. From Refinitiv Eikon we obtain the

[67] We also consider a potential selection bias on bond-level: Dealers might choose which bonds to trade through and which bonds to trade into inventories (e.g., depending on liquidity and its premium). If a bond is always traded with inventory involvement, the corresponding bond would not be included in our analyses because the trades would not be matched by our algorithm. However, this potential selection bias would only be relevant if a substantial number of bonds was without matches. In the raw standard TRACE data set, we observe 245 cat bonds, and for the vast majority of them we observe bid-ask spreads: For 46 of these bonds, we were able to match all trades obtaining bid- ask spreads, and for another 195 bonds, we could match at least a part of the trades. Only the remaining four bonds, which have no matched trades at all, are not part of the main regressions because of lacking bid-ask spreads. These four bonds only have eight – in this case unmatched – trades. Thus, we conclude that potential selection effects should not have a relevant impact on our results.

first and last coupon payment dates. Using the coupon frequency, we can then determine the specific payment dates between the first and last coupon payments.[68] Second, we determine every expected coupon payment for each payment date: Cat bonds pay a fixed coupon over a floating riskless interest rate. We use the Treasury Yield Curve to obtain riskless interest rates. However, although we know the fixed coupon payment for all future coupon payments, we do not know the future riskless interest rate for every future payment date. Following Fabozzi et al. (2000), we estimate unknown future riskless interest rates by generating the appropriate forward rate curve from the Treasury Yield Curve. Adding the estimated future riskless interest rate from the forward rate curve to the fixed coupon payment then yields the expected coupon payment for every determined coupon payment date.[69] After we have obtained this complete cash flow stream, determining the yield spread is straightforward: First, we determine the dirty price by adding the accrued interest to the clean price. Second, we numerically determine the same yield spread for each summand of the cash flow stream that results in the correct dirty price.

Risk modelling firms model the yearly loss distribution of cat bonds in relation to its inherent underwriting risk. The most important indicator for cat bond yield spreads is the first moment of this loss distribution, the EL.[70] Risk modelling firms only provide a static loss distribution for each calendar year. However, the likelihood of losses fluctuates dynamically for some peril types. For example, hurricanes do not occur in the first half of a calendar year and European winter storms do not occur in the summer,[71] so that the default risk of cat bonds can be zero outside of its respective risk season. Herrmann/Hibbeln (2021) offer a method to model seasonality effects in yield spreads for cat bonds. The methodology implements a fluctuating EL in accordance

[68] In our data set, 90.8% of all cat bonds pay a quarterly coupon, with monthly coupons and semiannual coupons trailing at 7.4% and 0.4%, respectively. 1.3% of all cat bonds are zero coupon bonds.

[69] For very few cat bonds, we have an additional assumption: We assume cat bonds to only pay a coupon of 0.5% in the last calendar month of maturity. Often, a cat bond's risk period has already ended during its last calendar month of maturity and it only pays a very reduced coupon. This assumption affects only 14 observations.

[70] We have three parameters from this loss distribution in our dataset: The EL, the probability of first loss (PFL), and the conditional expected loss (CEL), with EL = PFL*CEL (see also Lane 2000). We could also use the PFL instead of the EL as a measure for default risk throughout this paper but Galeotti et al. (2013) and Braun (2016) report that models that only employ the EL generally have a better model fit. Nevertheless, we have rerun our main regressions from Table 15 with PFL instead of EL but do not find any meaningful differences. Detailed results are available upon request.

[71] Other seasonal perils could include pacific typhoons and U.S. wildfires. However, typhoons and U.S. wildfires occur throughout the whole calendar year. Additionally, these peril types are very rare. Overall, we have four bonds in the dataset that insure against typhoons and six bonds that insure against U.S. wildfires. We do not have bonds in the dataset that insure against wildfires in other regions.

with seasonally fluctuating default risk:

$$EL_t = \frac{Remaining\ risk_t}{Remaining\ time_t} = \frac{EL_{initial} \cdot \int_{\tau=t}^{T} \lambda(\tau) d\tau}{T-t}, \tag{27}$$

where EL_{inital} is the yearly average EL as provided by risk modelers, $\lambda(\tau)$ is the density function of arrival frequencies, which varies depending on the point in time τ, and the time of maturity is denoted by T.

The relative shares of arrival frequency λ for hurricanes and European winter storms is provided by AIR on a monthly basis. To acquire a daily distribution of λ, we use linear interpolation. We do not directly use EL_t as Herrmann/Hibbeln (2021) but instead implement a seasonal EL adjustment variable $EL_{s,t}$:

$$EL_{s,t} = EL_t - EL_{initial} \tag{28}$$

This way, we can separate the general EL premium from the premium that is due to seasonal changes in EL. More importantly, it allows for an unhindered modelling of EL in single-peril earthquake bonds that are not affected by seasonality.

Herrmann/Hibbeln (2021) also identify a reduced seasonal fluctuation for multi-peril and/or multi-location bonds. A cat bond may fluctuate less strongly with the hurricane or winter storm season if it also insures against earthquakes or in locations without seasonal fluctuations in peril arrival frequency. To allow for a reduced seasonal fluctuation in multi-peril and/or multi-location bonds, we interact ELs,t with a multi-peril/multi-location dummy. Additionally, we use separate ELs,t for the U.S. hurricane season and the European winter storm season. For our purpose of identifying the liquidity premium for exogenous default risk, the present seasonality for cat bonds is a substantial advantage because it strongly increases heterogeneity in yield spreads and default risk. Hence, we are able to observe the liquidity premium for various different levels of default risk and its associated change in yield spreads.

3.3.4 Summary statistics

Table 12 describes the sample in terms of cat bond properties whereas Table 13 contains descriptive statistics on continuous variables. Over 90% of cat bonds protect against perils in North America, and the majority protects against wind perils including hurricanes. Peril categories add up to more than 100% because roughly half of all cat bonds protect against multiple perils. Almost 80% of all cat bonds are exposed to seasonally fluctuating perils, highlighting

Table 12: Cat bond specific information on 229 cat bonds.

Variable		No. of bonds	Percentage
Region			
	North America	207	90.39%
	Europe	25	10.92%
	Japan	18	7.86%
	Other	7	3.06%
Peril			
	Hurricane	77	33.62%
	Wind	145	63.32%
	Earthquake	152	66.38%
Peril number			
	Single-peril	106	46.29%
	Multi-peril	123	53.71%
Peril location			
	Single-location	204	89.08%
	Multilocation	25	10.92%
Peril number and peril Location			
	Single-peril and single-location	97	42.11%
	Multi-peril and/or multilocation	132	57.89%
Seasonality affected			
	Yes	181	79.74%
	No	48	21.15%
Rating			
	BB	42	18.50%
	B	29	12.78%
	NR	158	69.60%

Note: For region and peril, the percentages of the categories exceed 100% because multi-peril and multilocation bonds have multiple peril types and locations, respectively. All other categories add up to 100%.

Table 13: Summary statistics for continuous dependent and independent variables.

	n	Mean	SD	q1	q10	q50	q90	q99
Yield spread (bps)	3341	466	310	28	189	407	761	1564
Bid-ask spread (bps)	3341	9	5	3	5	10	10	25
Bid-ask spread market quarter (bps)	17	10	2	7	8	9	11	15
Market trading activity (Trades)	17	220	90	126	126	161	406	411
Maturity remaining (years)	3341	2.04	1.3	0.06	0.36	1.92	3.75	5.69
$\text{EL}_{initial}$ (bps)	229	260	242	21	63	177	564	1407
Coupon (bps)	229	622	355	0	250	525	1150	1750
EL seas. adj. US (bps)	2376	-25	89	-282	-128	-8	40	190
EL seas. adj. EU (bps)	309	-15	85	-263	-79	-20	52	378
GC reinsurance index (points)	5	180.9	8.7	170.6	170.6	177.4	182.2	194
SP500 90-day return (bps)	3341	152	540	-1403	-631	235	714	1482
BaAML BB index (bps)	3341	296	76	203	223	276	408	519
1-month T-bill yield (bps)	3341	104	90	0	2	89	236	246
Yield curve slope (bps)	3341	65	42	-14	2	58	123	142

Note: Summary statistics for continuous dependent and independent variables. Most variables are in basis points (bps). Remaining Maturity is in years. The GC Reinsurance Index represents the Guy Carpenter Global Property Catastrophe Rate-On-Line Index, where 100 points refer to reinsurance prices in the base year of 1990.

the importance of thoroughly modeling the seasonality in default risk and yield spread. Only a third of all cat bonds has received a rating. All of these ratings are in the non-investment grade category of either BB or B.

In line with economic theory, yield spreads are larger than ELs for all quantiles, which implies a risk compensation of investors beyond the actuarially fair premium. The seasonal EL adjustment factors reduce or increase the overall EL depending on the seasonal state of the hurricane season or the European winter storm season. Generally, the heterogeneity in bid-ask spreads is rather small, and 10 bps is the most commonly observed bid-ask spread.[72] However, there is no cat bond in the sample, where the bid-ask spread is constantly at 10 bps; hence, there is no bond in the data set, where the within bond heterogeneity is zero.

3.3.5 Econometric model

We explain two dimensions of liquidity effects in cat bond spreads: pooled ordinary least squares (OLS) regressions to incorporate between-bond differences and fixed effects (FE) regressions to explain within-bond changes and to account for unobserved bond properties. In all models, standard errors are clustered at bond level and robust to heteroscedasticity.

$$
\begin{aligned}
V_t = {} & \beta_0 + \beta_1 Liquidity_{it} + \beta_2 EL_i + \beta_3 EL_{s-us,it} + \beta_4 MultiP/L_i + \beta_5 MultiP/L_i \cdot EL_{s-us,it} \\
& + \beta_6 EL_{s-eu,it} + \beta_7 ReinsIndex_t + \beta_8 SP500Return_t + \beta_9 BBYieldIndex_t \\
& + \beta_{10} OneMonthTreasury_t + \beta_{11} SlopeYieldCurve_t + \beta_{12} Maturity_{it} + \beta_{13} IssuedVolume_i \\
& + \beta_{14} TriggerType_i + \beta_{15} US_i + \beta_{16} HU_i + \beta_{17} Coupon_i + \psi_t + \varepsilon_{it}
\end{aligned}
\tag{29}
$$

We regress the observed yield spreads on liquidity and various control variables including default risk measures, macroeconomic variables that affect the financial market, and bond specific information. As a liquidity measure, we use the relative bid-ask spread of a matched dealer buy and dealer sell pair (see Section 3.3.2). To control for exogenous default risk, we use the EL as provided by the risk modelling firms and implement the seasonal adjustment factors as well as an interaction term with a multi-peril/multi-location dummy $MultiP/L_i$. We use separate seasonal adjustment factors (see Section 3.3.3) for the U.S. hurricane season $EL_{s-us,it}$ and the European winter storm season $EL_{s-eu,it}$. There is no interaction term of the European season

[72]Cat Bonds are usually issued under SEC rule 144a. Edwards et al. (2007) report that bonds issued under SEC rule 144a have lower transaction costs, potentially manifesting in lower bid-ask spreads.

and the multi-peril/multi-location dummy because we do not have single-peril bonds in the sample that insure against European winter storms. To control for macroeconomic changes on the financial markets, we include the return of the S&P500 performance index over the past 90 days, the Merrill Lynch BB Yield Spread index, the 1-Month Treasury yield and the slope of the yield curve measured as the difference between the 1-Year and the 5-Year Treasury yield. To control for other bond specific information, we use the remaining maturity and issued volume. Following the established empirical cat bond literature such as Braun (2016) and Gürtler et al. (2016), we also control for cat bond specific properties. To control for possible moral hazard, we include an indemnity trigger dummy.[73] We include U.S. and hurricane dummy variables to control for peak locations and peak perils. Additionally, we include year-quarter fixed effects ψ_t to account for unobserved macroeconomic effects.

For our within-bonds analyses, we perform fixed effects transformations by demeaning all explanatory variables:

$$\begin{aligned} \widehat{YieldSpread}_{it} &= \eta_0 + \eta_1 \widehat{Liquidity}_{it} + \eta_2 \widehat{EL}_{s-us,it} + \eta_3 MultiP/L_i \cdot \widehat{EL}_{s-us,it} \\ &+ \eta_4 \widehat{EL}_{s-eu,it} + \eta_5 \widehat{ReinsIndex}_t + \eta_6 \widehat{SP500Return}_t + \eta_7 \widehat{BBYieldIndex}_t \\ &+ \eta_8 \widehat{OneMonthTreasury}_t + \eta_9 \widehat{SlopeYieldCurve}_t + \eta_{10} \widehat{Maturity}_{it} + \hat{\psi}_t + \hat{\varepsilon}_{it} \end{aligned} \tag{30}$$

Hence, all variables that have no heterogeneity across time are dropped. Fixed effects transformations also control for all unobserved constant properties on bond level.

3.3.6 Endogeneity in default risk and liquidity

For corporate bonds, the default risk premium and the liquidity premium are endogenously linked. Chen et al. (2007) highlight that much of the liquidity cost could be due to asymmetric information on the credit quality of a traded bond. Chen et al. (2018) describe a possible spiral of worsening credit and liquidity. According to Campbell/Taksler (2003), investors may also deduce credit risk information from observed yield spreads. Hence, it appears plausible that dealers set bid-ask spreads after they have deduced additional information on credit risk or other unobserved factors before the actual trade occurs. If this additional information is positively related to yield spreads, it drives bid-ask spreads upwards, which would lead to upward biased effects due to reversed causality. As stated before, there are various approaches in the literature

[73]For a discussion on trigger types and associated moral hazard, please refer to Finken/Laux (2009).

to address the endogeneity issue. While many approaches attempt to find two assets that have the same default risk but differ in liquidity (Longstaff et al. 2005, Kempf et al. 2012, Black et al. 2016, and Schwarz 2019), Chen et al. (2007) implement three structural equations to explain yield spreads, liquidity, and credit ratings. They estimate all three equations simultaneously through a simultaneous equations model (SEM). However, we believe the endogeneity problem is much less severe for cat bonds than it is for corporate bonds. It is plausible to assume that cat bond defaults are strictly exogenous events because the occurrence of natural catastrophes cannot be influenced by financial market conditions; neither is the likelihood of a natural disaster amplified by deteriorating liquidity nor does a change in investor sentiment make a natural catastrophe more likely. Hence for cat bonds, there is only one channel of causation between default risk and liquidity: The likelihood and the severity of natural catastrophes dictate cat bond trading. However, the trading of cat bonds does not influence the likelihood or severity of natural catastrophes in any way. This accounts for the endogeneity stemming from default risk and liquidity. Nevertheless, there could still be some endogeneity stemming from unobserved factors that dealers observe through the yield spread, which are unrelated to default risk. Dealers could set their bid-ask spread according to the expected yield spread from the trade. Yield spread and bid-ask spread would form simultaneously. To account for this endogeneity dimension, we alter the SEM from Chen et al. (2007) to reflect the exogeneity assumption of default risk in the cat bond market. Instead of using three equations to explain yield spread liquidity and credit rating, we use two equations to simultaneously estimate yield spread and liquidity. We use the EL and the seasonal EL adjustment factors as exogenous variables to reflect default risk.

$$\begin{aligned}
V_t = {} & \vartheta_0 + \vartheta_1 Liquidity_{it} \\
& + \vartheta_2 EL_i + \vartheta_3 EL_{s-us,it} + \vartheta_4 MultiP/L_i + \vartheta_5 MultiP/L_i \cdot EL_{s-us,it} \\
& + \vartheta_6 EL_{s-eu,it} + \vartheta_7 ReinsIndex_t + \vartheta_8 SP500Return_t + \vartheta_9 BBYieldIndex_t \\
& + \vartheta_{10} OneMonthTreasury_t + \vartheta_{11} SlopeYieldCurve_t + \vartheta_{12} TriggerType_i \\
& + \vartheta_{13} US_i + \vartheta_{14} HU_i + \vartheta_{15} Coupon_i + \psi_t + \varepsilon_{it}
\end{aligned} \tag{31}$$

$$\begin{aligned}
Liquidity_{it} = {} & \zeta_0 + \zeta_1 YieldSpread_{it} \\
& + \zeta_2 EL_i + \zeta_3 EL_{s-us,it} + \zeta_4 MultiP/L_i + \zeta_5 MultiP/L_i \cdot EL_{s-us,it} \\
& + \zeta_6 EL_{s-eu,it} + \zeta_7 Maturity_{it} + \zeta_8 IssuedVolume_i + \psi_t + \varepsilon_{it}
\end{aligned} \tag{32}$$

For the yield spread, we consider *Reinsurance Index*, *SP500 Return*, *BB Yield Index*, *One*

Month Treasury, *Slope Yield Curve*, *Trigger Indemnity*, *U.S.*, *HU* and *Coupon* as exogenous variables. For the liquidity, we use *Maturity* and *Issued Volume* as exogenous variables. We estimate the SEM with maximum-likelihood estimation. Standard errors are again clustered at bond level and robust to heteroscedasticity. Analogously to the FE model described in the previous section, we also apply fixed effects transformations to the SEM.

3.4 Empirical results

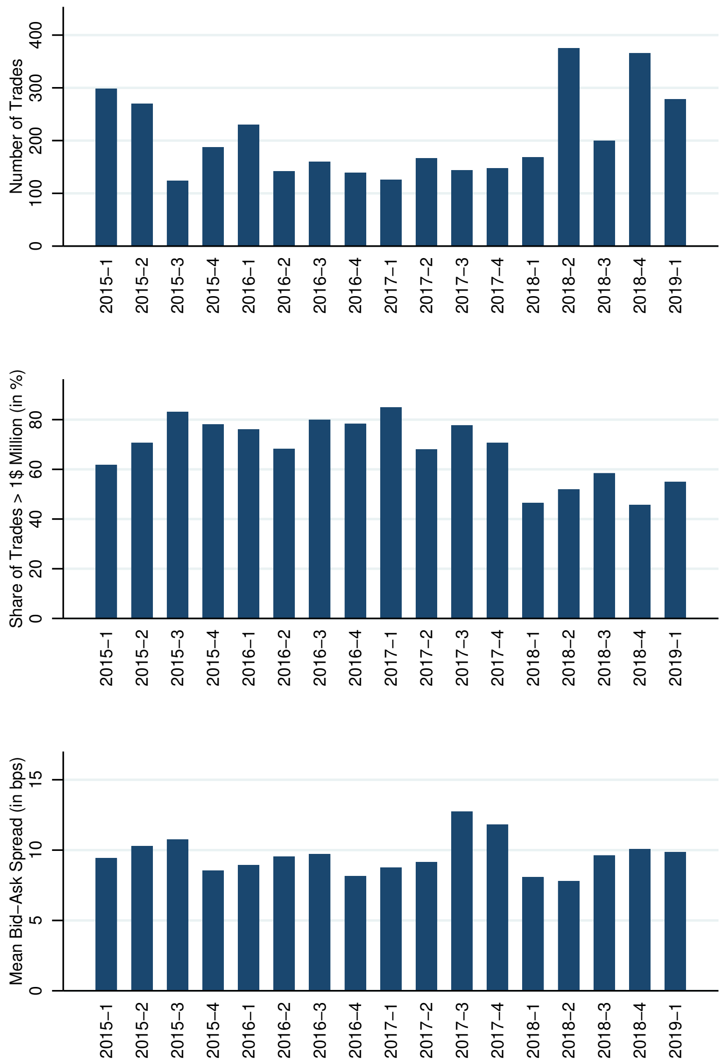
3.4.1 Secondary market cat bond trading - general patterns

Figure 2 and Figure 3 illustrate the number of trades, the share of large trades (> US$ 1 million) and the mean bid-ask spreads over the sample period on a quarterly basis as well as the monthly averages within a year. Figure 2 shows a strong fluctuation of trading activity over the sample period. Trading is relatively strong during the first half of 2015 but drops by more than 50% in the second half. From Q2-2016 to Q1-2018 trading fluctuates at a relatively low level before spiking in Q2-2018 and Q4-2018. Generally, we can see an increase in trades after Q1-2018. However, that does not necessarily imply an increased trading volume. The bottom panel indicates that the share of large trades has substantially declined just as the number of trades increased. The mean bid-ask spread fluctuates just below 10 bps for most quarters. However, Q3-2017 and Q4-2017 experienced a sudden spike in bid-ask spreads. This increase coincides with the landfall of hurricane Irma in September 2017 causing multiple cat bonds to default. For this month, the Eurekahedge ILS Advisers Index saw its worst monthly ILS return of -8.61%, with the second worst month being November 2018 trailing with -3.68%.[74]

Herrmann/Hibbeln (2021) highlight the importance of seasonality on the cat bond market. Cat bonds that insure against hurricanes are virtually risk free during the first half of a calendar year but are strongly exposed to default risk from the hurricane season in the second half. Figure 3 illustrates the within-year trading of cat bonds. The number of trades indicates that from March to June, in the prelude to the hurricane season, trading activity is high. From its peak in June, trading activity steadily declines to half its previous level in September until it recovers until December. The lowest point in September precisely coincides with the peak of the hurricane season. The trading activity is smaller during the peak months of the hurricane season – in August, September and October – with a joint significance at the 0.1%-level (F =

[74]Many defaulted cat bonds had already been affected by hurricane Harvey two weeks before hurricane Irma. In this context, it is important to note that we dropped all observations for defaulted cat bonds from 180 days before its default date. The observed spikes in bid-ask spreads are observed for bonds that did not default in the aftermath of the 2017 hurricane season.

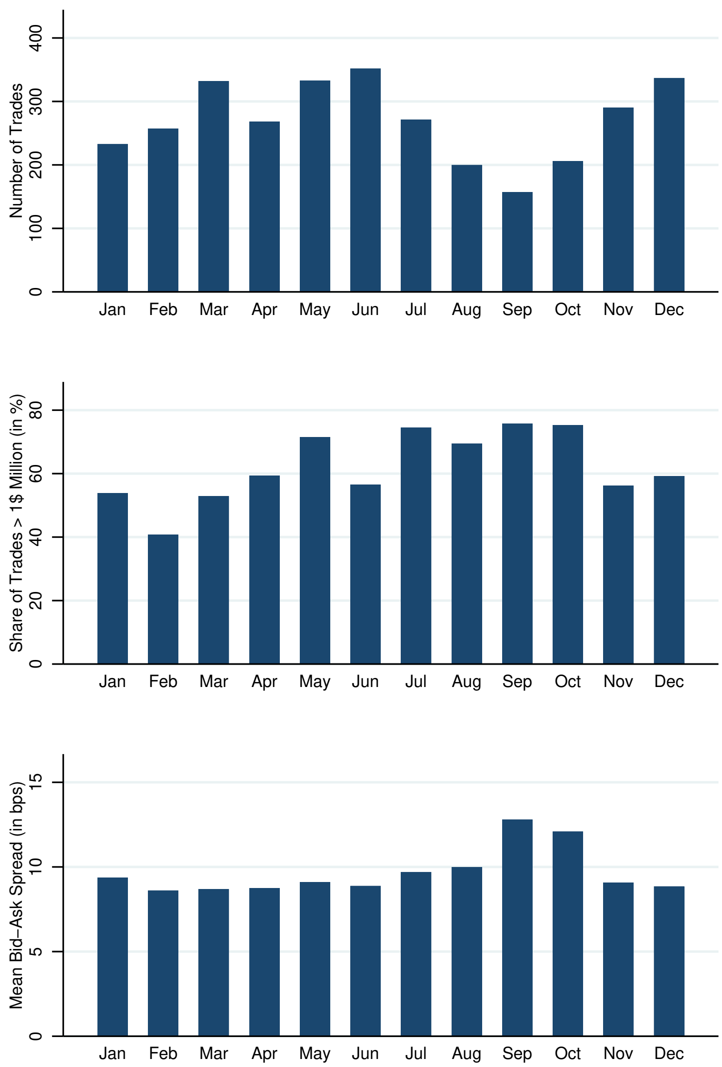
Figure 2: Trading activity per quarter year - cat bonds.



Note: This figure depicts trading The number of trades per quarter has been fluctuating strongly with peaks in the second and fourth quarter of 2018. Trading has generally been low from mid-2016 to early 2018. The mean bid-ask spread per trade has been fluctuation just below 10 bps with two peaks in the second half of 2017. The share of trades up US$1 million in size has been declining over the sample period.

11.16). Mean bid-ask spreads fluctuate slightly below 10 bps. Only September and October experience average bid-ask spreads that are larger than 10 bps. However, it is unclear whether this increase is due to increased default risk, lower trading activity or a combination of both. A one-way ANOVA test reveals that the differences in means of bid-ask spreads for these calendar months are significant at the 0.1%-level (F = 13.65).

Figure 3: Trading activity within year - cat bonds.



Note: This figure depicts trading activity on the secondary cat bond market within year. The share of trades fluctuates throughout the first half of each calendar year and rapidly declines throughout the first half of the risk season (June – September) to roughly half its previous size. Trading activity recovers throughout the remainder of the year as the risk season subsides. The mean bid-ask spread per trade fluctuates just below 10 bps through most of a calendar year but peaks in September and October before it declines as the risk season subsides. The share of trades up US$ 1 million in size is generally larger in the second half of a calendar year.

To compare some of these results to the corporate bond market, we have obtained an enhanced TRACE dataset from WRDS that spans the same sample period from January 2015 to March 2019. We apply the enhanced TRACE filter from Dick-Nielsen (2014) to account for artefacts in the dataset stemming from same-day corrections and cancelations or reversals.[75] The upper diagram in Figure 4 contains the number of trades in the corporate bond market for each quarter of the sample period. We can observe a clear trend over the sample period: While trading appears to be slightly more pronounced in the first quarter, the number of trades has generally increased throughout the sample period. In the first quarter of 2019 around 50% more trades were recorded than in the first quarter of 2015. This is quite contrary to the cat bond market, where we observe fluctuating trade numbers from one quarter to the next without a clear time trend. Not surprisingly, there are many more trades in the corporate bond market than in the cat bond market. The lower diagram contains the average number of trades per calendar month within each year. We observe slightly elevated trading in March and slightly depressed trading in April, July, and September. Overall, trading activity is quite constant irrespective of the calendar month. Compared to its median, it only drops by 9% to its lowest point in July. This is in stark contrast to the cat bond market, where we observe significantly reduced trading during the U.S. hurricane season: Compared to its median, trading declines by 42%. As trading is quite evenly distributed in corporate bonds, we conclude that the observed intra-year trading pattern is unique to the cat bond market.

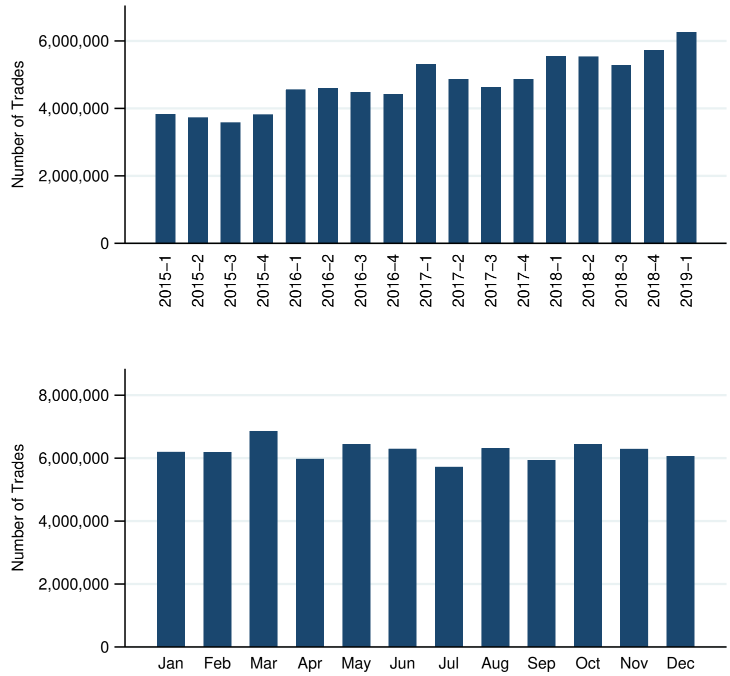
3.4.2 Trading and adverse events

Trading and adverse events - cat bonds

In this section, we investigate cat bond trading around adverse events. In terms of the numbers of defaults, 2017 and 2018 have been particularly bad years for the cat bond market. 2017 saw large losses from hurricanes Irma, Harvey, and Maria, while 2018 was strongly affected by hurricane Michael. These two hurricane seasons pushed multiple cat bonds into default according to the artemis.bm "Cat Bond Losses & Bonds at Risk" directory. Therefore, these events are well-suited to further investigate how the secondary market trading reacts to adverse events. In the following section, we further support this analysis by using enhanced TRACE data on corporate bonds to investigate the trading of corporate bonds of associated insurance

[75] For more details on the filter, please refer to Dick-Nielsen (2014).

Figure 4: Trading activity - corporate bonds.

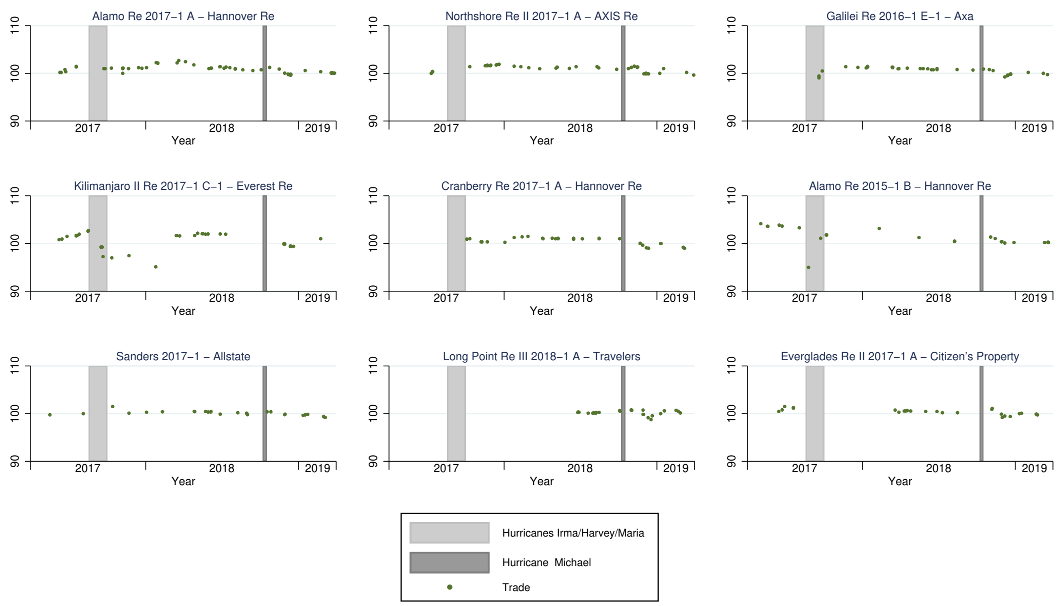


Note: Note: This figure depicts trading activity on the secondary corporate bond market over the sample period and within year. The two diagrams depict all OTC-trades reported in enhanced TRACE as provided by WRDS. As observable in the upper diagram, observable trades in enhanced TRACE have generally increased. The number of trades does not fluctuate strongly from one quarter to the next. In the lower diagram, we observe slightly elevated trading in March and slightly depressed trading in April, July and September.

companies.

First, we select a set of cat bonds from the dataset to illustrate actual trading around these events. Since many cat bonds are traded very rarely, we select cat bonds that are relatively often traded in the time frame form March 2017 to March 2019. In addition, the selected bonds must have exposure to U.S. hurricanes. Out of all cat bonds that meet these criteria, the nine cat bonds which were most often traded during this period are (in descending order): Alamo Re 2017-1 A, Northshore Re II 2017-1 A, Galilei Re 2016-1 E-1, Kilimanjaro II Re 2017-1 C-1, Cranberry Re 2017-1 A, Alamo Re 2015-1 B, Sanders 2017-1, Long Point Re III 2018-1 A, and Everglades Re II 2017-1. For example, we observe 54 trades for Alamo Re 2017-1 A and 26 trades for Everglades Re II 2017-1 A. Second, we mark the respective events: a) overlapping Hurricanes Harvey, Irma, and Maria and b) Hurricane Michael. Harvey formed 17 August 2017 and dissipated 2 September 2017, Irma formed 30 August 2017 and dissipated 14 September 2017, and Maria formed 16 September 2017 and dissipated 30 September 2017. Thus, we define the event horizon of "Harvey/Irma/Maria" from 17 August 2017 to 30 September 2017. Hurricane Michael formed 7 October and dissipated 16 October 2017; we define this event horizon as "Michael".

Figure 5: Trading around adverse events - cat bonds.



Note: This figure depicts the trades that have taken place between March 2017 – March 2019 for a set of nine cat bonds. These nine cat bonds were the cat bonds that were most often traded during this period. Two events are marked: a) Hurricanes Irma, Harvey, and Maria from 17 August 2017 to 30 September 2017 and b) Hurricane Michael from 7 October 2018 to 16 October 2018. Each dot represents one trade. Long Point Re II 2018-1 A was issued May 2018, Northshore Re II 2017-1 A and Cranberry Re 2017-1 A were issued in June 2017. All other bonds were issued May 2017 or earlier.

Figure 5 contains diagrams where each trade for these nine cat bonds is marked as a dot. The event periods "Harvey/Irma/Maria" and "Michael" are marked in gray. Similarly to evidence from the previous section, where we observed relatively few trades during the hurricane season in general, we observe almost no trades during adverse hurricane events for these nine bonds in particular: We only observe eight trades during Harvey/Irma/Maria across these bonds. We record these trades for only four bonds: Alamo RE 2017-1 A, Galilei Re 2016-1 E-1, Kilimanjaro II Re 2017-1 C-1, and Alamo Re 2015-1 B. For the latter two bonds, these trades highlight temporary losses, most notably for Alamo Re 2015-1 B. On 24 August 2017, its price is 95, which is a significant drop from the previous observable trade on 02 August 2017 at a price of 103.3. However, the bond quickly recovers to a price of 101.1 on 22 September 2017. It appears that one investor decided to reduce its exposure just as hurricane Harvey was about to make landfall in Texas. According to the Deal Directory on artemis.bm, Alamo Re 2015-1 B protects exclusively against named storms in Texas. This cat bond probably recovered after Harvey dissipated as it became apparent that it was not going to default. Alamo Re 2015-1 B matured 07 June 2019 without a loss. For other bonds, such as Alamo Re 2017-1 A and Northshore Re II 2017-1 A, it seems trading was very frequent before and after Harvey/Irma/Maria but almost paused completely during the event itself. Although we do not observe a single trade during Hurricane Michael, we can observe a cluster of trading just a few weeks later towards December 2019. During this time, some bonds such as Alamo Re 2017-1 A, Northshore Re II 2017-1 A, Galilei Re 2016-1 E-1 and Long Point Re III 2018-1 A experienced some price decline but quickly recovered just a few weeks later. It is possible that the market was first surprised by potential losses from hurricane Michael a few weeks after the events, which could explain the price decline but then recovered a few weeks later. To put these observations into perspective, we also look at selected corporate bond trading in relation to the two catastrophe events Harvey/Irma/Maria and Michael but also earnings announcements of the associated corporations.

Trading and adverse events - corporate bonds

We further investigate our observations from the previous section by investigating the trading of selected corporate bonds that most closely match the nine cat bonds from the previous section. We utilize corporate bonds from the same insurance companies that sponsored these nine cat bonds. This way, we can observe corporate bonds that are affected by the same adverse event information (Harvey/Irma/Maria and Michael);[76] similarly, we can study how these corporate bonds react to new corporate information in the form of regular earnings announcements. If possible, we select one corporate bond for each of the nine cat bonds. This corporate bond a) needs to be issued by the sponsoring insurance company, b) must be observable in the enhanced TRACE dataset from WRDS, and c) should be traded during the same sample period from March 2017 to March 2019. From the corporate bonds complying with these criteria, d) we choose the bond with the shortest remaining duration to achieve a similar duration as for the cat bonds.

[76]Strong catastrophe events can put (re-)insurance companies in jeopardy.

The nine aforementioned cat bonds were issued by the following seven (re-)insurance companies: Citizen's Property, Hannover Re[77], Everest Re, Allstate, XL Bermuda[78], Travelers, and Axis Re. In Refinitv Eikon, we do not find any corporate bonds for Citizen's Property matching the correct time period; its last corporate bond was called in 2007. For Hannover Re, we do not find any corporate bonds that are TRACE eligible because Hannover Re has only issued corporate bonds in European jurisdiction during our time period. This leaves us with Everest Re, Allstate, Axa, Travelers, and Axis Re. For each sponsoring entity, we select one corporate bond following the abovementioned criteria.[79]

Figure 6 depicts the trading of the five selected corporate bonds for the time frame of March 2017 to March 2019 as in the previous section. The catastrophe events Irma/Harvey/Maria and Michael are marked in gray. We additionally look at trading around earnings announcements, marked by dashed lines.[80] This allows us to compare the market's reaction to arrival of new information 1) from catastrophe events and 2) from the events of corporate disclosure.

Comparing the general trading for cat bond bonds in Figure 5 to the general trading for associated corporate bonds in Figure 6, we observe that corporate bonds are much more frequently traded than cat bonds. For Allstate, Axa, Travelers and Axis, their respective corporate bonds are so frequently traded during this two-year time period that we cannot make out any differences in trading during the catastrophe events. We also cannot observe any obvious market reaction to earnings announcements. However, for Everest Re, there is a very long period around Irma/Harvey/Maria in 2017 where its corporate bond was not traded. On the contrary, the same corporate bond was more strongly traded during Michael and experienced a strong price drop.

Since the multitude of trades makes a visual inspection of corporate bond trading so difficult, we also determine the specific trade during the catastrophe events and around earnings announcements. This means for the catastrophe events we use the previously specified event horizon and for earnings announcements, we define a time window of 15 days before and 15

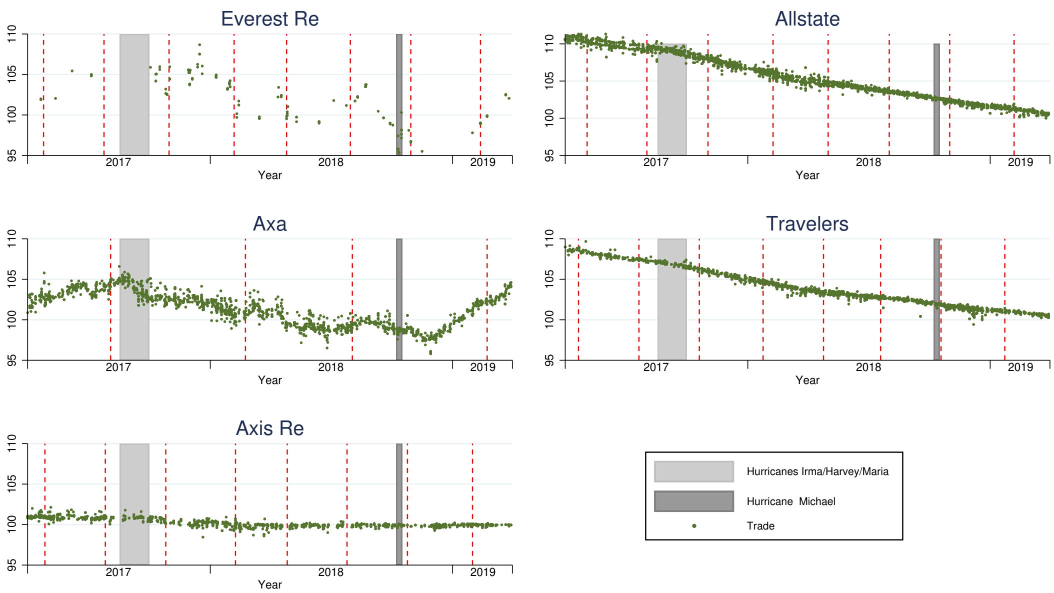
[77] Hannover Re has issued three of the nine cat bonds, while each of the remaining six (re-)insurance companies have issued one of the remaining cat bonds.

[78] XL Bermuda is a subsidiary of Axa. We mark this sponsor as "Axa" from here on.

[79] The selected corporate bonds have the following CUSIPs: Allstate (020002AX9), Travelers (020002AX9), Everest Re (020002AX9), Axa (020002AX9), and Axis Re (020002AX9).

[80] The dates of earnings announcements stem from Refinitiv Eikon. Axa only provides earnings announcements with semiannual frequency, whereas Allstate, Travelers, Everest Re, and Axis Re announce earnings with quarterly frequency.

Figure 6: Trading around adverse events - corporate bonds.



Note: This figure depicts the trades that have taken place between March 2017 – March 2019 for a set of five corporate bonds. These five corporate bonds belong to sponsoring entities of some of the cat bonds depicted in Figure 5. Two events are marked: a) Hurricanes Irma, Harvey, and Maria from 17 August 2017 to 30 September 2017 and b) Hurricane Michael from 7 October 2018 to 16 October 2018. The dashed lines mark earnings announcements. Each dot represents one trade.

days after the respective announcement.[81] Assuming that trades are evenly distributed across a calendar year as supported by Figure 4, we can expect roughly $44/365 \approx 12.1\%$ of all trades per bond in 2017 to take place during the defined time window of Irma/Harvey/Maria. If this share of trades is above (below) 12.1%, the specific corporate bond was more (less) often traded than expected. For Michael we expect $14/365 \approx 2.5\%$ of all trades in 2018 to take place during the defined time window, whereas for earnings announcements with four 30-day long time windows, we expect $4*30/365 \approx 32.9\%$ of all trades per year to take place during one of the earnings announcement time windows.[82]

For many corporate bonds, results are the opposite from cat bonds where we observed dampened trading during the catastrophe events. For Irma/Harvey/Maria, the shares of trades for each corporate bond as of the total trades in 2017 range from 12.8% for Axis Re up to 20.9%

[81] For earnings announcements, this time window is always 30 days long.

[82] For Axa, we expect only a share of 16.4% because Axa reports earnings on a semi-annual basis.

for Axa. The share for Allstate is 15.2%, while Travelers and Everest Re both have shares of 17.4%. All of these shares are above the 12.1% threshold.[83] For Michael, these shares fluctuate: Everest Re (2.7%) and Travelers (3.7%) have shares above the 2.5% threshold, while Allstate (2.4%), Axis Re (0.9%) and Axa (1.9%) are below the threshold.[84] However, the results for Michael are less reliable due to the relatively short time frame. During the 30-day time frame of earnings announcements, all four corporate bonds were more often traded than expected and surpass the 32.9% threshold. Shares range from 35.6% for Everest Re to 40.0% for Axis Re. The shares for Travelers and Allstate are 35.9% and 38.2%. Axa surpasses its 16.4% threshold with 17.4%.[85] Overall, we can conclude that corporate bonds are more often traded during catastrophe events and around earnings announcements. This means that corporate bonds of (re-)insurance companies are more frequently traded when new information arrives on the market in the form of catastrophe events or earnings announcements. Considering this result for corporate bonds, we could expect an elevated trading activity in the cat bond market during the hurricane season. However, we observe the contrary: Cat bonds are less frequently traded during the hurricane season when much new information arrives at the cat bond market, but at the same time the level of uncertainty is high during this period. This makes the reduced trading during the hurricane season, which is clearly visible in Figure 3 and discussed in Section 3.4.1, much more meaningful.

3.4.3 Determinants of liquidity

Next, we shed light on the drivers of liquidity on the cat bond market measured by bid-ask spreads. The models in Table 14 regress the bid-ask spreads on default risk and other liquidity related variables such as maturity and traded volume. The bid-ask spread in Table 14 is related to the EL, both measured by yearly $EL_{initial}$ but also the seasonal swing measured by EL_{s-us} and EL_{s-eu}. Models (1) and (2) show that a 100 bps seasonal swing in EL for the US season is associated with a 1 bps change in bid-ask spreads. This effect is smaller for multi-peril bonds and larger within bonds as indicated by the FE models (3) and (4). All coefficients on EL_{s-us} are highly statistically significant at the 0.1%-level. We see no such effect for EL_{s-eu}, possibly

[83]All differences in shares from 12.1% for Irma/Harvey/Maria are statistically significant at least at the 0.1%-level except for Axis Re, where the difference is not statistically significant.

[84]Differences in shares from 2.5% for Michael are statistically significant for Travelers, Axis Re and Axa at least at the 1%-level. Differences are not statistically significant for Everest Re and Allstate.

[85]All differences in shares from 32.9% (and 16.4% for Axa) are statistically significant at least at the 5%-level.

Table 14: Bid-ask spread determinants.

Dependent Variable	Bid-Ask spread			
	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
EL_{inital}	0.003*	0.003*		
	(2.02)	(1.98)		
EL_{s-us}	0.011***	0.010***	0.014***	0.016***
	(4.20)	(3.76)	(5.35)	(5.28)
EL_{s-eu}	0.008+	0.007	0.002	0.001
	(1.85)	(1.65)	(0.43)	(0.18)
Multi-P/L	-0.343	-0.192		
	(-1.32)	(-0.79)		
EL_{s-us} # Multi-P/L	-0.007+	-0.004	-0.010**	-0.008*
	(-1.96)	(-1.20)	(-2.85)	(-2.41)
Volume 1M	0.624**	0.510*	0.601**	0.485*
	(2.85)	(2.42)	(3.12)	(2.53)
Market Trading Activity	-0.006***		-0.007***	
	(-4.26)		(-4.66)	
Maturity	0.582***	0.562***	3.099***	2.317
	(5.56)	(5.64)	(5.07)	(0.98)
Constant	4.823+	16.497***	9.131**	9.450
	(1.76)	(5.22)	(3.25)	(1.27)
Observations	3341	3341	3341	3341
Number of bonds	229	229	229	229
R^2 / within R^2	0.070	0.106	0.064	0.096
Adj. R^2 / adj. within R^2	0.065	0.098	0.061	0.089
Financial market controls	Yes	Yes	Yes	Yes
Bond specific controls	Yes	Yes	Omitted	Omitted
Year-quarter FE	No	Yes	No	Yes

Note: This table shows the determinants of bid-ask spreads. Models (1) and (2) are pooled OLS models. Models (3) and (4) apply fixed effects transformations. In Models (2) and (4), year-quarter fixed effects capture common changes in market conditions. *Volume 1M* is a dummy variable, which is 1 if the volume of a trade is larger or equal to US$ 1 million and distinguishes between large trades and small trades. Due to limited data frequency, *Market Trading Activity* and *Reinsurance Index* are dropped in the presence of year-quarter fixed effects. All standard errors are clustered at bond level and robust to heteroscedasticity. t-values are shown in parentheses. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

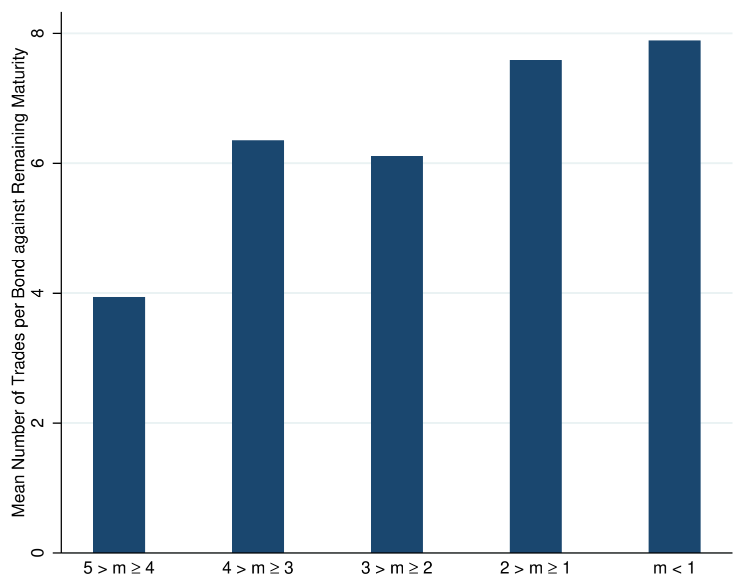
because cat bonds in the data set have only very limited exposure to the European catastrophe season.[86] These results confirm hypothesis H1.1 – liquidity is low if default risk is high –, which is in line with the order processing channel because search costs are higher for bonds with higher default risk, which in turn decreases liquidity.

As indicated by Huang/Stoll (1997), a large trade could have a larger bid-ask spread because brokers have disproportionally higher search costs to match larger orders. Standard TRACE provides trade volume that is capped at US$ 1 million. Hence, we define *Volume 1M* as a

[86] This seasonal effect is smaller for multi-peril US bond as indicated by the interaction term EL_{s-us} *# Multi-P/L*. We do not have a similar interaction term for the European season because there are no single-peril EU wind bonds in the sample that are affected by seasonality.

dummy variable that indicates if a trade is larger or equal to the US$ 1 million cap, and thus separates the trades into small and large trades. In this setting, we observe 1173 trades below and 2168 above the cap. We find a strong relationship between the bid-ask spread and trade size. In all four models, large trades have bid-ask spreads that are roughly 0.5 bps larger than for small trades, and the coefficients are highly statistically significant at the 0.1%-level.[87] Hence, in line with Huang/Stoll (1997) we can confirm that bid-ask spreads are higher for larger trades, which is in line with hypothesis H1.2.

Figure 7: Trading activity on the secondary cat bond market against the time to maturity.



Note: This figure depicts trading activity on the secondary cat bond market against the time to maturity (m, in years). The mean number of trades per bond increases the closer a bond gets to its maturity. For bonds with five years to maturity there are around four trades on average. The average number of trades per bond increases to around eight trades in the last year before maturity.

In order to relate a bond's liquidity to the overall market's trading activity, we define Market Trading Activity as the number of trades on the market for the current quarter. A one standard deviation increase in the quarterly Market Trading Activity is associated with a 0.12 (0.13)

[87]In this setting with a dummy variable for the US$ 1 million cap, we forgo the heterogeneity below the US$ 1 million cap. We can nevertheless use this heterogeneity by limiting the dataset to a subsample where all trades have a volume below the US$ 1 million cap. Models that use the specific trading volume in the subsample of these small trades further support H1.2: For small trades, the bid-ask spread increases with traded volume. The coefficients for the traded volume are significant on the 5%-level. Detailed results are available upon request.

standard deviation decrease in bid-ask spreads in the pooled OLS model (FE model). This result is highly statistically significant at the 0.1%-level. This indicates that observed bid-ask spreads are related to the general liquidity on the cat bond market. Furthermore, the bid-ask spreads fall as bonds near their maturity. For pooled OLS in models (1) and (2), a one-year lower time to maturity reduces the bid-ask spread by more than 0.5 bps. These results are highly statistically significant at the 0.1%-level. Within bond, this relationship increases to around three bps; however, this effect loses its statistical significance in the presence of year-quarter fixed effects, probably because year-quarter fixed effects capture most of within bond changes in maturity. Figure 7 provides further evidence: Cat bonds are more frequently traded the closer they get to their respective maturity date. In their last year of duration, cat bonds are twice as often traded as bonds with five years to maturity. Compared to three years to maturity, trading is still 25% higher in the last year to maturity. A one-way ANOVA test reveals that the differences in the mean number of trades w.r.t. the years of remaining maturity are significant at the 0.1%-level (F = 12.67). Overall, we accept hypothesis H1.3 meaning that a decreasing time to maturity is related to a decreasing bid-ask spread. An additional potential liquidity factor could be the issuance volume (see Braun 2016 or Gürtler et al. 2016). However, unreported in Table 14, we do not find a relationship between issuance volume and bid-ask spread.

3.4.4 Yield spreads and liquidity

Liquidity premium

We quantify the liquidity premium on the cat bond market through pooled OLS and SEM to capture differences between bonds but also FE models that quantify the liquidity effect for within bond changes and to control for unobserved constant bond properties. First, we illustrate results for pooled OLS and SEM with pooled observations (see Table 15, Models 1 and 2). All standard errors are clustered at bond level and robust to heteroscedasticity. The established literature highlights the relationship of the liquidity premium and the credit risk premium. Model (1) includes a series of variables to control for the default risk in cat bonds. $EL_{initial}$ represents the static level of EL, while EL_{s-us} and EL_{s-eu} account for seasonal fluctuations in EL induced by the U.S. hurricane and the European winter storm season. The interaction term of EL_{s-us} and $Multi-P/L$ accounts for lower seasonal fluctuation in multi-peril and/or

Table 15: Liquidity premium and other yield spread determinants.

Dependent variable	Yield spread	Yield spread	Bid-ask spread	Yield spread	Yield spread	Bid-ask spread
	OLS	SEM – pooled		FE	SEM – demeaned	
	(1)	(2a)	(2b)	(3)	(4a)	(4b)
Bid-ask spread	10.293*	11.638**		8.038*	9.254*	
	(2.54)	(2.77)		(2.12)	(2.40)	
Yield spread			-0.002			-0.002
			(-0.32)			(-0.19)
$EL_{initial}$	1.186***	1.192***	0.004			
	(9.03)	(9.44)	(0.60)			
EL_{s-us}	1.202***	1.211***	0.013*	1.252***	1.239***	0.019
	(4.88)	(4.83)	(2.03)	(5.19)	(5.31)	(1.23)
EL_{s-eu}	0.927***	0.919***	0.009	0.434**	0.438**	0.003
	(5.16)	(4.90)	(1.40)	(2.68)	(2.59)	(0.40)
Multi-P/L	25.791	30.645+	-0.009			
	(1.32)	(1.69)	(-0.03)			
EL_{s-us} # Multi-P/L	0.099	0.080	-0.004	-0.527+	-0.541*	-0.010
	(0.35)	(0.28)	(-0.93)	(-1.96)	(-1.98)	(-1.25)
Maturity	-0.041		0.583***	-10.161		0.910***
	(-0.01)		(5.86)	(-0.26)		(5.06)
Issued volume	-0.048+		-0.000			
	(-1.76)		(-0.03)			
Coupon	0.141	0.136				
	(1.57)	(1.58)				
Constant	-152.790+	-183.345+	8.549***	405.575*	192.590**	-0.128
	(-1.65)	(-1.66)	(7.18)	(2.16)	(2.93)	(-0.59)
Observations	3341	3341	3341	3341	3341	3341
Number of bonds	229	229	229	229	229	229
R^2 / within R^2	0.781	0.787	0.100	0.373	0.371	0.086
Adj. R^2 / adj. within R^2	0.778	0.785	0.094	0.368	0.366	0.080
Financial market controls	Yes	Yes	No	Yes	Yes	No
Bond specific controls	Yes	Yes	No	No	No	No
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the determinants of yield spreads. Model (1) applies OLS and model (2) is a simultaneous equations model: For the yield spread (2a), SP500 Return, BB Yield Index Models, 1-Month Treasury, Slope Yield Curve, Trigger Indemnity, U.S., HU, and Coupon are exogenous variables; for the bid-ask spread (2b), Maturity and Issued Volume are exogenous variables. Model (3) and (4) present corresponding results for an FE model and an SEM model with demeaned variables, respectively, to explain within bond variation. Explanatory variables correspond to the time-variant variables of model (1) and (2). Year-quarter fixed effects and controls capture common changes in market conditions. All standard errors are clustered at bond level and robust to heteroscedasticity. t-values are shown in parentheses. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

multi-location bonds.[88] As additional control variables, we include general market conditions

[88] A non-linear relationship between yield spread and EL could more accurately explain yield spreads if, for example, investors demand a higher compensation per unit of EL when the EL is small. However, Galeotti et al. (2013) find that a non-linear relationship only barely improves explanatory power and recommend using a linear relationship. Braun (2016) finds that predictive power is not higher for a non-linear relationship of yield spread and EL. Nevertheless, we have also implemented a quadratic EL variable to model a non-linear relationship of yield spread and EL. In this model, the quadratic term was not statistically significant and the coefficients of the EL and the bid-ask spread remained unchanged. Hence, a potential non-linear relationship of yield spread and EL does not bias our results. Detailed results are available upon request.

such as the S&P500 return over the last 90 days, the current yield on BB-rated corporate bonds, the 1-month treasury yield and the slope of the yield curve. Furthermore, we control for common bond properties such as the time to maturity, the issued volume and the coupon, but some control variables are also cat bond specific properties such as trigger type and peak peril regions. Year-quarter fixed effects capture unobserved heterogeneity in general market conditions. The coefficient of bid-ask spread implies that a 1 bp change of bid-ask spreads is associated with 10 bps change of yield spreads, which is statistically significant at the 5%-level.

Model (2) contains results for the SEM that pools all observations to account for possible remaining endogeneity between yield spreads and bid-ask spreads after we control for exogenous default risk. For the yield spread in column (2a), *Reinsurance Index*, *SP500 Return*, *BB Yield Index Models*, *1-Month Treasury*, *Slope Yield Curve*, *Trigger Indemnity*, *U.S.*, *HU* and *Coupon* are exogenous variables. For the bid-ask spread in column (2b), *Maturity* and *Issued Volume* are exogenous variables. In Model (2), the coefficient for bid-ask spread remains highly statistically significant at the 1%-level. Its magnitude increases to roughly 12 bps change of yield spreads per bp change of the bid-ask spread.[89] The similar coefficients indicate that endogeneity concerns – for example dealers incorporating some yield spread information in their transaction pricing – seem to be negligible in the presence of cat bonds with exogenous default risk. We therefore find strong evidence that liquidity is priced in the secondary cat bond market and materially impacts the bonds' yield spreads. Investors demand a compensation for a cat bond if this bond is more difficult to sell.

Previously, we quantified the liquidity premium for cat bonds with pooled OLS and pooled SEM. Next, we use FE models that quantify the liquidity effect for within bond changes and control for unobserved constant bond properties. Table 15 contains the results for an FE model (Model 3) and an SEM (Model 4) with demeaned variables. The FE model (3) is in line with our results for pooled OLS. However, the slightly lower coefficient implies that the change in liquidity within bonds has a smaller effect on yield spreads. According to the FE model, a 1 bp change in bid-ask spread within bond is associated with an 8 bps change in yield-spread as

[89] For bonds with an indemnity trigger, the default event is related to the actual losses of the sponsoring insurer. However, loss assessment can take months or even years. Hence, it can take a very long time till an indemnity bond is officially declared defaulted. Investors might want to trade on potential loss information during the period of loss assessment. For parametric bonds on the other hand, a cat bond default is determined almost immediately after the specified event. Hence, being able to buy and sell a cat bond quickly can be more appealing to investors of an indemnity bond than for non-indemnity bonds. Therefore, liquidity could be more strongly priced for indemnity bonds. In undisclosed results, where we include an interaction term of bid-ask spread and a dummy variable for the indemnity trigger, we find that liquidity is more strongly priced for indemnity bonds. Detailed results are available upon request.

opposed to 10 bps in model (1) for pooled OLS. This bid-ask spread coefficient is significant at the 5%-level.

Model (4) contains results for the SEM that uses demeaned variables to account for observed bond characteristics and explain within bond difference while accounting for possible endogeneity between yield spreads and bid-ask spreads. We consider the same exogenous variables as in model (2), except that time-invariant variables are omitted due to the within transformation. In model (4) the coefficient for bid-ask spread change remains highly statistically significant at the 1%-level. Its magnitude increases to roughly 9 bps change of yield spreads per bp change of bid-ask spread. In column (4b), the remaining maturity as the exogenous variable for bid-ask spreads has a highly statistically significant influence on bid-ask spread. For within bond changes, this connection is even larger than for the pooled models (1) and (2). Overall, we can identify a substantial impact of changes in liquidity on yield spreads within bonds.

It is interesting to relate the size of the pooled OLS and FE coefficients to Chen et al. (2007). In their pooled OLS setting, they find a bid-ask spread coefficient of 2.30. In their SEM setting, the bid-ask spread coefficient is 12.13 – almost five times the size of the pooled OLS coefficient – highlighting the severe endogeneity problem in their OLS estimation. Our results for bonds with exogenous default risk strongly support these results because our estimated coefficients in the pooled setting are close to the SEM result from Chen et al. (2007). For their FE models, Chen et al. (2007) report a coefficient of 2.46 in the OLS setting and 12.47 in the SEM setting. Although the coefficients we find in our FE models are smaller than the SEM coefficient from Chen et al. (2007), the similar magnitude still supports the overall notion of Chen et al. (2007). In line with Braun (2016) and Gürtler et al. (2016), who used issued volume and remaining maturity as liquidity measures, we do not find these variables to be strongly related to the yield spread. For remaining maturity, there is no statistically significant relation to the yield spread. For issued volume, we find a negative coefficient, which indicates that a one standard deviation increase in issued volume dampens yield spreads by 7 bps. However, we do not further investigate this result because this coefficient is only barely significant at the 10%-level. Instead, the bid-ask spread is the dominant liquidity variable.

Overall, we can confirm H2.1 on the general liquidity premium not only based on pooled OLS and FE regressions but also based on respective SEM models. Exploiting exogenous default risk from natural catastrophes, our results are not affected by endogeneity and therefore support the corporate bond literature on the liquidity premium. Since the estimated coefficients are relatively similar in the pooled models, we use the bid-ask spread coefficient for pooled OLS to quantify the liquidity premium on the cat bond market. Based on an average bid-ask spread in the sample of 9.5 bps and a bid-ask spread coefficient of 10.3 in model (1) of Table 15, we determine an average liquidity premium of 97.9 bps. Even if the magnitude of bid-ask spreads is mostly rather small, a large proportion of yield spreads – around 21% – can be attributed to the liquidity premium.

Liquidity Premium and Default Risk

Previous research has found the liquidity premium to be higher for bonds of low rating categories (e.g., Chen et al. 2007, Dick-Nielsen et al. 2012). To investigate liquidity effects for differing categories of riskiness, we have formed two subsamples, separated by a rating cutoff. Generally, the share of rated cat bond issues has declined substantially in the past: 70% of all cat bond issues that are contained in our TRACE subsamples have not received a rating. At the same time, the heterogeneity of ratings is very low; only BB and B ratings can be observed in the market. However, we acquired a second dataset from Lane Financials and artemis.bm that contains all cat bond issues from 2002 to 2019. This dataset contains 390 rated cat bond issues. We use this dataset to create a naïve binary rating model that allows us to assign the rating categories “BB rating or better” or “B rating or worse” to all cat bonds from the TRACE dataset. We assign these rating categories based on a probit regression that selects a cat bond into the BB rating or better category against the B rating or worse category depending on the EL at issue, its trigger type, coupon and volume, as well as peak peril, peak region and multi-peril dummies. The most important variable in this rating model is the EL.[90] After the application of the naïve rating model, 117 bonds of our sample have a “BB rating or better” and 112 have a “B rating or worse”.

Table 16 contains liquidity effects on yield spreads for the BB rating cutoff. All models include the same explanatory variables as Table 15. For pooled OLS in models (1) and (2) and FE regressions in models (3) and (4), the coefficients for bid-ask spreads increase more than threefold when comparing rating categories “B or worse” versus “BB or better”. This indicates that the liquidity effect is much more pronounced for cat bonds of a high-risk category. In models (5) – (8) we apply an alternative cutoff of 153 bps of $EL_{initial}$. This cutoff value was selected

[90]Detailed results on the naïve rating model are available upon request.

to separate the sample into two subsamples of roughly equal size.[91] Again, the coefficients for the bid-ask spreads increase more than threefold, indicating a liquidity effect that is much more pronounced for cat bonds of a high-risk category. Hence, we confirm H2.2 on a higher liquidity premium for risky bonds.

Table 16: Liquidity premium and default risk.

Dependent variable	Yield spread							
Cutoff	BB or better	B or worse	BB or better	B or worse	$EL_{initial}$ <153 bps	$EL_{initial}$ $\geq$153 bps	$EL_{initial}$ <153 bps	$EL_{initial}$ $\geq$153 bps
	OLS	OLS	FE	FE	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bid-ask spread	4.247* (2.47)	14.701* (2.34)	2.828+ (1.98)	12.447+ (1.95)	4.142* (2.20)	13.558* (2.31)	2.596 (1.64)	11.436+ (1.96)
Obs.	1943	1398	1943	1398	1666	1675	1666	1675
Number of bonds	117	112	117	112	97	132	97	132
R^2 / within R^2	0.413	0.839	0.270	0.518	0.411	0.805	0.316	0.453
Adj. R^2 / adj. within R^2	0.404	0.836	0.260	0.510	0.400	0.801	0.306	0.444
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the liquidity premium for subsamples of different rating classes and expected loss categories. Models (1) – (4) use the BB Rating as a cutoff. Models (5) – (8) use an $EL_{initial}$ of 153 bps as a cutoff. All standard errors are clustered at bond level and robust to heteroscedasticity. t-values are shown in parentheses. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

According to the results in Table 16, we can quantify different liquidity premiums for different default risk categories. Based on an average bid-ask spread in the low-risk "BB or better" subsample of 9.4 bps and a bid-ask spread coefficient of 4.3 in model (1), we determine an average liquidity premium of 39.5 bps. For this subsample, 11.3% of yield spreads can be attributed to the liquidity premium. For the high-risk "B or worse" subsample, the premium is much larger. Slightly higher average bid-ask spreads of 9.6 bps and a coefficient of 14.8 in model (2) result in an average liquidity premium of 141.1 bps, implying that 22.5% of yield spreads can be attributed to the liquidity premium.

Liquidity Premium and Market Liquidity

In Table 17, we investigate market liquidity effects that were previously absorbed in the year-quarter fixed effects in Table 15. To better control for reinsurance market conditions in the absence of year-quarter fixed effects, we have included the Guy Carpenter Rate-On-Line index, which controls for general reinsurance market prices. Braun (2016) and Gürtler et al.

[91] As an alternative to the EL cutoff, we also implemented a spread at issue cutoff. Results remained unchanged. Detailed results are available upon request.

Table 17: Liquidity premium and market liquidity.

Dependent variable	Yield spread			
	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
Bid-ask spread	11.199**	10.810**	8.747*	8.260*
	(2.80)	(2.73)	(2.36)	(2.25)
Bid-ask spread market quarter		8.032***		10.617***
		(3.76)		(5.95)
$EL_{initial}$	1.191***	1.190***		
	(9.12)	(9.07)		
EL_{s-us}	1.195***	1.192***	1.218***	1.219***
	(5.08)	(5.04)	(5.15)	(5.24)
EL_{s-eu}	0.878***	0.875***	0.347*	0.351*
	(4.70)	(4.67)	(1.98)	(2.08)
Multi-P/L	22.767	22.997		
	(1.16)	(1.17)		
EL_{s-us} # Multi-P/L	0.037	0.053	-0.551+	-0.526+
	(0.13)	(0.18)	(-1.94)	(-1.87)
Maturity	-1.481	-1.217	93.428***	109.873***
	(-0.23)	(-0.19)	(6.92)	(7.95)
Constant	-532.424***	-654.302***	28.723	-48.318
	(-3.88)	(-4.74)	(0.22)	(-0.38)
Observations	3341	3341	3341	3341
Number of bonds	229	229	229	229
R^2 / within R^2	0.771	0.773	0.336	0.349
Adj. R^2 / adj. within R^2	0.770	0.771	0.334	0.347
Financial market controls	Yes	Yes	Yes	Yes
Bond specific controls	Yes	Yes	No	No
Year-quarter FE	No	No	No	No

Note: This table shows regression results for yield spreads on market liquidity. Models (1) and (2) are pooled OLS models. Models (3) and (4) apply fixed effects transformations. All standard errors are clustered at bond level and robust to heteroscedasticity. t-values are shown in parentheses and. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

(2016) have shown that the level of reinsurance prices is positively related to the yield spreads on cat bonds. As a measure for market liquidity, we use the mean bid-ask spread of the current quarter. In model (1) and (3), we present the results for OLS and FE models without the market liquidity measure, whereas this measure is included in the corresponding models (2) and (4). Model (2) for OLS and model (4) for FE regressions indicate that the average bid-ask spread across all cat bond trades in the current quarter is positively related to the yield spread of cat bonds. As suggested by model (2), a 1 bp change in average market spreads is associated with 8 bps change in yield spreads. Similarly, according to model (4) a 1 bp change in average market spreads is associated with an 11 bps change in yield spreads within bond. Both coefficients are significant at the 0.1%-level. In line with H3, these results confirm that market wide liquidity has a substantial impact on the yield spread of cat bonds.

3.5 Conclusion

We provide first empirical insights into trading activity and liquidity of cat bonds. The trading activity on the secondary market of cat bonds fluctuates within a calendar year. We observe that trading is less frequent during the peak of the U.S. hurricane season from July to September; moreover, cat bonds are more often traded when they are closer to maturity. Considering that the most buy and sell orders are matched within a 60 minutes time window, this indicates the market is dominated by brokers without a proprietary inventory. This means the bid-ask spreads on the cat bond market mostly reflect broker search and execution costs, whereas they should not contain large markups for adverse selection costs or capital costs from inventories.

We find that a cat bond's liquidity is related to its current default risk, its remaining time to maturity and the market's current liquidity: Bid-ask spreads are lower when a bond is less risky and bonds are more frequently traded when a bond approaches its maturity, which results from lower order processing cost. Additionally, we find the bid-ask spread to be smaller when there is lots of trading in the current quarter. Regarding the liquidity premium, we find liquidity to be more strongly priced for bonds with high default risk. Moreover, we find the overall market liquidity to have an impact on the individual yield spreads.

In addition to providing novel insights into secondary market trading and liquidity for cat bonds, we contribute to the general corporate bond literature through the identification and quantification of liquidity effects for strictly exogenous default risk from natural catastrophes. Overall, we find strong evidence for a substantial liquidity premium on the cat bond market. These results are robust to endogeneity due to the exogenous nature of catastrophe events and hold after controlling for other potential sources of endogeneity between yield spreads and dealer setting of bid-ask spreads by employing simultaneous equations models. We find that a 1 bp change of bid-ask spread is associated with roughly 10 bps change of yield spread. We find that on average 97.9 bps of yield spread can be attributed to a cat bond's liquidity. Relatively speaking, 21.0% of the cat bond market's yield spread can be attributed to the liquidity premium. The magnitude of the liquidity premium varies substantially depending on the default risk of a bond: While the absolute (relative) liquidity premium accounts for 39.5 bps (11.3%) of yield spreads for bonds with low default risk ("BB or better"), this premium increases to 141.1 bps (22.5%) for bonds with high default risk ("B or worse"). Given a volume of US$ 40 billion for outstanding cat bonds, this means that the (re-)insurance industry paid a liquidity premium of US$ 391 million on transferred extreme event risk in 2019. If insurance companies want to take steps to reduce this substantial liquidity premium, they should work towards improving the aggregate liquidity of the market, for example, through a joint effort by setting up a central market maker or supporting existing dealers, as Eldor et al. (2006) find that market makers substantially improve the liquidity of a market. If an industry-wide cooperation is infeasible, they could improve their own issuances' liquidity by offering supporting dealer services. A further possibility to reduce the liquidity premium could be to issue rather low-risk or short-term cat bonds, which generally express lower bid-ask spreads; though, the additional fix costs for more frequent issues could eliminate the intended benefits.

Common Risk Factors in the Cross Section of Catastrophe Bond Returns

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Abstract

Historically, cat bonds have provided high single-digit average annual returns, paired with a low volatility and little correlation to other asset classes. While there is an extensive literature that explains (ex-ante) cat bonds spreads, there is no factor model in the academic literature that explains this (ex-post) realized return puzzle. Based on monthly quoted prices for the complete cat bond market from 2001 to 2020, we provide insights into relevant risk factors in the cross-section of cat bond returns. After investigating a battery of possible cat bond return factors in bivariate and multivariate portfolio sorts as well as Fama-MacBeth regressions, we propose a four-factor cat bond model. Its factors are the seasonality adjusted probability of first loss, a separate seasonality adjustment factor and the two corporate bond factors TERM and DEF from Fama & French. This novel four-factor model predicts 60% of the time series variation of the historical cat bond market returns - as opposed to 4% for the Fama & French three- or five-factor model - and substantially reduces the observable alpha of the cat bond market.

Keywords: catastrophe bonds, asset pricing, factor model

JEL: C12, G01, G11, G12, G17

4. Essay 3 – Common risk factors in the cross-Section of catastrophe bond returns

4.1 Introduction

Catastrophe bonds ("Cat Bonds") are securitized reinsurance contracts that offer valuable protection to (re-)insurance companies against natural disasters such as hurricanes, earthquakes and winter storms. Cat bonds belong to the broader asset class of Insurance-Linked Securities (ILS). The structure of a cat bond mainly consists of a special purpose vehicle (SPV) and the sponsoring (re-)insurance company (sponsor). The SPV engages in a reinsurance contract with the sponsor offering catastrophe risk protection. The SPV then issues a cat bond, whose default clauses mirror the reinsurance contract. This means that after a catastrophe, when the SPV has to make payments through the reinsurance contract, the issued cat bond's default is triggered and the cat bond's collateral is paid out to the sponsor.[92] The cat bond's collateral is held in a trust account separate from the sponsoring (re-)insurance company's balance sheet. Cat Bonds are not exposed to the sponsor's credit risk.

Between 2016 and 2020, the cat bond market grew at annualized compounding rate of 15% per year.[93] This additional reinsurance capacity is especially important to (re-)insurance: extreme event protection is notoriously expensive in the reinsurance industry because it is difficult to diversify. Historically, cat bonds have provided high single-digit average annual returns, paired with a low volatility and little correlation to other asset classes (Braun et al. 2019). This indicates surprisingly high abnormal returns compared to other classes of financial instruments such as corporate bonds. Thus, we investigate the returns of cat bonds to address this cat bond return puzzle (Bantwal/Kunreuther 2000).

In recent years, several papers helped to establish a broad understanding of cat bond spreads, both in the primary and secondary market (e.g., Galeotti et al. 2013, Braun 2016, Gürtler et al. 2016, Herrmann/Hibbeln 2021). To the best of our knowledge, however, only three papers to date have examined realized cat bond returns. Trottier (2019) analyze the risk-return profile of the Swiss Re Cat Bond Performance Indices. Drobetz et al. (2020) explore the role of cat bonds as a diversifier in multi-asset portfolios. Braun et al. (2019) develop a new breed of factor models for the ILS asset class, which succeed at explaining the historical returns of dedicated ILS funds based on the returns of the cat bond market. Therefore, they can serve as

[92]Cat bond defaults can be full or partial.

[93]According to the increasing market volume at www.artemis.bm.

a means for measuring investment performance or estimating capital costs in the ILS industry. Unfortunately, however, these ILS-specific factor models do not reveal the fundamental drivers of risk premiums in the cat bond market itself. Our work addresses this gap.

Based on a novel data set, provided by a global reinsurance brokerage firm, we contribute the first analysis of expected excess returns in the cat bond market. Our data comprises monthly secondary market prices and coupon payments for virtually all cat bonds that existed in the twenty years from 2001 to 2020.[94] This allows us to calculate realized excess returns on individual cat bonds and subsequently explore the cross-sectional determinants of cat bond risk premiums. Our analysis focuses on the return implications of bond-specific characteristics that are known to influence cat bond yield spreads and coupon spreads. Specifically, we explore whether the following factors explain the cross-section of cat bond returns: (1) event risk: the probability of first loss (PFL) and its seasonal adjustments, (2) downside risk: the conditional expected loss (CEL), (3) moral hazard: indemnity trigger-type bonds (IND), (4) complexity: multi-peril bonds (MP) and multilocation bonds (ML), (5) Peak peril: Hurricane Bonds (HU), (6) Peak territory: U.S. Bonds (US). For PFL, we build upon Herrmann/Hibbeln (2021) to develop two seasonality adjusted PFL measures: 1) the monthly seasonality adjusted PFL and 2) the associated seasonality adjustment factor. These capture the time variation of the PFL for U.S. hurricane and European wind bonds. We subject the proposed factors to a wide range of established asset pricing tests: univariate and bivariate portfolio sorts, Fama/MacBeth (1973) regressions to predict cross-sectional returns and time-series regressions of market returns on factors. Finally, we compare realized and predicted returns for a wide array of different test portfolios.

We find that event risk, as measured by the modeled PFL, is a strong predictor of future cat bond returns. In addition, we find a substantial impact of the seasonal event risk factors, constructed in the spirit of Herrmann/Hibbeln (2021). However, we do not find evidence that downside risk, moral hazard, complexity and peak risk is effectively priced. Furthermore, we confirm the (weak) link between ILS markets and fixed income markets uncovered by Braun et al. (2019). Specifically, the two classical corporate bond factors TERM and DEF (see Fama/French 1993) turn out to explain some variation of cat bond excess returns over our sample period, too.

Ultimately, we propose a four-factor model for the cat bond asset class, consisting of the time-varying (seasonally-adjusted) PFL (PFLS), a separate seasonality factor (SF), capturing

[94] This is the largest cat bond data set analyzed in the literature to date.

the extent of seasonal PFL fluctuations, as well as TERM and DEF. This novel factor model predicts 60% of the time series variation of the historical cat bond market returns. When controlling for a handful of categorically unpredictable catastrophe events during our sample period, the adjusted R-squared increases to 70%. In contrast, the standard Fama-French three-factor model (see Fama/French 1993) with TERM and DEF and the Fama-French five-factor model (see Fama/French 2015) applied to the cat bond market only yield adjusted R-squares of 4% and 3%, respectively. Compared to the same Fama-French models, our four-factor model substantially reduces the observable alpha on the cat bond market from roughly 0.38% per month to 0.16% per month; though, this remaining alpha is still statistically and economically significant. Applying this model to a set of 24 test portfolios, we also find statistically and economically significant alphas, which leaves room for future research.

We then offer various additional analyses and robustness checks: For example, we analyze the performance of the proposed four-factor cat bond model for different time periods, we investigate downside scenarios such as Hurricane Katrina, the default of Lehman Brothers or the Tohoku earthquake, and we analyze the stability of the model regarding different default cutoff points. These additional tests support our main findings.

The implications of our work reach beyond the cat bond literature. Specifically, we contribute to the general asset pricing literature (see, e.g., Fama/French 1992, Carhart 1997, Pastor/Stambaugh 2003, Fama/French 2015) by providing evidence that classical factor models cannot explain cat bond returns.[95] We also add to the literature on common factors in the cross-section of (corporate) bond returns (see, e.g., Fama/French 1993, Elton et al. 1995, Gebhardt et al. 2005, Jastova et al. 2013, Bai et al. 2019) by linking risk premiums on cat bonds to the wider fixed income markets. Finally, we enrich the more recent strand of the asset pricing literature, focusing on downside risk (see Jurek/Stafford 2015, Chabi-Yo/Ruenzi 2018, Chabi-Yo et al. 2019) by revealing the pricing dynamics behind traded natural disaster risk. Finally, we contribute to the rapidly growing literature on climate finance (see, e.g., Andersson 2016, Ilhan et al. 2021, Krueger et al. 2020, Bolton/Kacperczyk 2021). Catastrophe event losses are expected to rise in the wake of climate change. Ultimately, many catastrophe prone areas could become uninhabitable when insurance becomes unafforadable. Overall, cat bonds could be an important detail in the global effort to mitigate the effects of climate change, while offering high

[95] A first indication of this result was provided by Braun et al. (2019), who showed that classical factor models cannot explain the return variation of broad ILS portfolios.

returns to investors at low volatility and large diversification benefits.

The remainder of the paper is structured in the following way: Section 4.2 explains important characteristics of the cat bond market. In Section 4.3 we introduce the data set and the methodology we use to generate required variables. Section 4.4 presents results from portfolio sorts and Fama/MacBeth (1973) regressions. In Section 4.5 we illustrate the four cat bond factors and investigate their explanatory power in time-series regressions. Section 4.6 presents further empirical evidence, while Section 4.7 contains robustness checks. Section 4.8 concludes.

4.2 Cross-sectional catastrophe bond risk characteristics

4.2.1 Institutional background

In this section, we concisely revisit the general mechanics and characteristics of cat bonds. We deliberately restrict the discussion to those aspects that are known to influence primary and secondary market spreads and could therefore also drive returns in the cross-section.[96] Cat bonds are a type of structured finance security through which investors may obtain an almost pure exposure to natural catastrophe risk. The latter is cleanly defined in terms of reference perils (e.g., hurricanes, earthquakes) and covered territory (e.g., US, Japan). The inventors and most active users of cat bonds are large insurance and reinsurance companies (the sponsors/cedents), who seek to protect their property-casualty books from an accumulation of losses due to large-scale disasters. All cat bond issuances are fully collateralized. The principal paid by investors is held in highly-rated short term securities (US Treasury Money Market Funds) or structured notes of supranational institutions (IRBD or ERBD).[97] This insulates the structures against interest rate and counterparty default risk. The collateral account is administered by a bankruptcy-remote special purpose vehicle (SPV). The SPV also facilitates the actual risk transfer from the cedent to the investor. Specifically, it enters into an excess-of-loss (XL) reinsurance contract with the cedent, either on a per-occurrence or an annual aggregate basis.[98]

This reinsurance contract embedded in the cat bond pays out, if the so-called trigger conditions are fulfilled. Today, the cat bond market is dominated by the indemnity and industry loss index trigger (see Artemis Catastrophe Bond & ILS Market Dashboard). The former relates to insured losses in the cedent's portfolio and the latter to an index of insurance industry losses

[96] For a more detailed introduction to cat bonds, we refer to Braun (2016).

[97] See Swiss Re (2019) for a current breakdown of collateral types in the market.

[98] Per-occurrence cat bonds carry an embedded excess of loss per event (XL/E) reinsurance contract whereas annual aggregate cat bonds are based on a more comprehensive stop-loss reinsurance contract.

compiled by a third party calculation agent such as Property Claims Services (PCS). In both cases, underlying insured losses caused by the reference peril in the covered territory need to exceed the bond's attachment point for a trigger event to be called. The payout as a percentage of the principal then commonly develops proportionally to the losses above the attachment point, reaching 100 percent once losses hit the exhaustion point.

For bearing the natural disaster risk securitized in a cat bond, investors are compensated with a regular coupon that consists of a floating interest payment from the (almost) risk-free collateral and a risk spread that is fixed at issuance. Later on, when cat bonds trade in the secondary market, price fluctuations reflect the time-varying nature of trigger risk (see Beer/Braun 2021). This causes secondary market yield spreads to deviate from the fixed coupon spread. The cross-sectional variation of primary market coupon spreads and secondary market yield spreads have been the subject of extensive earlier work (see Braun 2016, Gürtler et al. 2016, Herrmann/Hibbeln 2021).

Despite these significant advances in the cat bond literature throughout recent years, however, the extent to which spread drivers translate into realized returns remains largely in the dark. So far, the only study of risk premiums in ILS markets based on realized returns is attributable to Braun et al. (2019). Their results link the expected excess returns on ILS portfolios managed by dedicated investment funds to returns on the cat bond market, the industry loss warranty market and to fund characteristics. However, they do not shed further light on the fundamental risk drivers that underpin the expected excess return on the cat bond market itself.

We fill this gap with a comprehensive analysis of common risk factors in the cross-section of cat bond returns. In the following, we identify potential factors based on the existing literature on coupon spreads and yield spreads, particular the work of Braun (2016) and Gürtler et al. (2016). These factors will then be subjected to a comprehensive battery of asset pricing tests in the empirical part of the paper.

4.2.2 Event risk

For corporate bonds, default risk is the primary determinant of yield spreads. This default risk is measured by a credit rating. For cat bonds, empirical research indicates that the expected loss (EL) is the primary driver of yield spreads and coupon spreads (see Lane/Mahul 2008, Galeotti et al. 2013, Braun 2016, Gürtler et al. 2016). EL is defined as the first moment of the cat bond's loss distribution. Due to the scarcity of extreme natural disasters, historical data cannot be used for risk assessment. Instead, specialized catastrophe risk modelling firms, such as RMS, AIR and EQECAT, fill in the data void in the tail of the insured loss distribution. Their models allow for the calculation of the key cat bond metrics EL, PFL, and CEL.[99] When a cat bond is issued, the risk modelling agent provides investors with a detailed report on the inherent underwriting risk and a modelled loss distribution for the bond. Rating as proxy for trigger risk is not suited: many cat bonds are not rated. Of those that are rated, most are BB rated with little variation. Unreported results indicate that the information conveyed by the rating does not add explanatory power over and above what is included in PFL. EL itself is the product of PFL and CEL (see, e.g., Lane 2000, Galeotti et al. 2013), so we can use EL or PFL as proxies for the event risk of a cat bond. We split EL into its components, since more recent work has shown that PFL is a key predictor of hazard rates (intensities) implied by secondary market cat bond prices (see Beer/Braun 2021).

4.2.3 Downside risk

Bai et al. (2019) find that downside risk is the strongest predictor of future corporate bond returns controlling for credit risk and liquidity risk. To proxy for downside risk they determine the 5% VaR as the second lowest monthly return observation over the past 36 months. However, the majority of cat bonds already matures after 36 months so that we are unable to determine their 5% VaR. Instead, we use the CEL as a proxy for downside risk. For two bonds of the same EL and different CELs, the cat bond with the higher CEL has a more left skewed loss distribution than the cat bond with the low CEL.

4.2.4 Moral hazard risk

Indemnity Triggers have repeatedly been associated with moral hazard risk for the cedent (see, e.g., Lee/Yu 2002, Götze/Gürtler 2020b). The payout of an indemnity trigger cat bond is directly attached to the actual catastrophe losses of the sponsoring (re-)insurance company. The (re-)insurer could decide to cut back on damage mitigation and loss adjustment expenses after its losses are close to or have surpassed the cat bond's threshold, after which additional losses are covered by the cat bond and not the sponsor. This behaviour could increase losses to the disadvantage of cat bond holders. A further detrimental effect could be adverse selection, where

[99]According to our data set, AIR has served as the risk modelling agent for 52% of all cat bond emissions, with RMS and EQECAT following at 14% and 11%, respectively. For the remainder, the risk modelling agent is unreported in the Artemis Catastrophe Bond & Insurance-Linked Securities Deal Directory. AIR has been the dominant risk modeller in recent years serving as the risk modelling agent for 80% of all cat bonds from 2016-2020.

investors cannot distinguish a good sponsor from a bad sponsor as in Finken/Laux (2009). However, this asymmetric information problem does not affect parametric trigger cat bonds, where payouts are independent from the actual sponsor. To offset these effects, investors could demand higher returns for indemnity trigger bonds. However, Braun (2016) and Gürtler et al. 2016 do not find evidence for higher coupon spreads or higher yield spreads associated with indemnity triggers. Nevertheless, if moral hazard realizes while yield spreads do not reflect it, the presence of an indemnity trigger could affect expected cat bond returns in the cross-section.

4.2.5 Complexity

A cat bond can offer protection against multiple perils and multiple locations. For example, a cat bond can protect against hurricanes and earthquakes (multi-peril) or against earthquakes in the U.S. and Europe (multilocation). Gürtler et al. 2016 state that investors may prefer single-peril over multi-peril bonds and single-location over multilocation bonds because it is easier to create a well-diversified portfolio using these bonds. They find higher yield spreads for multi-peril and multilocation bonds, while Braun (2016) finds higher coupon spreads for multilocation bonds.[100] These higher yield spreads could carry over to higher expected returns in the cross-section.

4.2.6 Peak risk

On the cat bond market, hurricane is the dominating peril and U.S. is the dominating location.[101] This could mean that rare bonds such as China earthquake and Turkey earthquake are sought after as diversifying element for ILS-only investors. U.S. perils are available in masses and therefore carry a markup in yield spread to offset their lack of diversification benefits. Braun (2016) finds higher coupon spreads for cat bonds that protect against hurricanes or whose perils are located in the U.S., while Gürtler et al. 2016 observe similar markups in yield spreads. Hence, bonds with peak locations and/or peak perils could have higher expected returns. Braun et al. (2019) find that expected excess returns for both single-peril U.S. hurricane and U.S. earthquake exposures are substantially higher than for the broad mix of perils inherent the cat bond market

[100] It is important to note that the event risk variables PFL and EL provided by the risk modelling firms already take multiple perils into account. A multi-peril bond is as likely to default as a single-peril bond if both have the same PFL.

[101] Table 18 reports that 80% of all cat bonds in the data set have exposure in North America. 38% protect exclusively against hurricanes, while a further 54% protect against wind perils which often also includes hurricanes.

portfolio. In addition, Beer/Braun (2021) find that peak and non-peak locations have an impact on time-varying trigger risk in the secondary market.

4.3 Data and sample selection

4.3.1 Cat bond data

The over-the-counter (OTC) character of the cat bond market makes it difficult to obtain pricing data of the secondary market. To the best of our knowledge there are only two public data sources: Lane Financial LLC for quoted spreads and Trade Reporting and Compliance Engine (TRACE) for trade prices. Lane Financial LLC surveys a group of dealers every quarter for the spreads on the secondary cat bond market, effectively reporting quoted spreads. However, the low quarterly frequency makes it difficult do investigate returns and estimate a pricing model. Instead of quoted spreads, TRACE reports the clean prices of actual trades on the secondary cat bond market. Unfortunately, cat bond trades have not been captured by TRACE before July 2014. In addition, the data exhibits an irregular spacing in time, which is disadvantageous when performing Fama/MacBeth (1973) regressions with Newey/West (1987) standard errors of multiple lags.

Rather than using one of these data sets, we were able to obtain a private data set from a large reinsurance brokerage firm. This data set comprises monthly quoted prices and spans the complete cat bond market from the beginning of 2001 to the end of a 2020 for a total of 757 cat bonds. We are thus examining the largest data set used in empirical cat bond research to date. To test how closely our quoted prices match actual traded prices from TRACE, we match each monthly observation of quoted prices with the mean price observed in TRACE during the same month. We then determine the correlation between the quoted price and the mean TRACE price for each bond. We only determine this correlation for bonds, for which we observe mean TRACE prices for at least ten months. The mean correlation coefficient we obtain with this procedure between our monthly quoted prices and the mean monthly TRACE prices is 0.92. Due to this extraordinarily high correlation, it is safe to continue with quoted prices.

In addition to the cat bond prices, the data set we obtained also contains other valuable information necessary to determine cat bond returns. This information includes each cat bond's issue and maturity dates, its yearly nominal coupon and its payment schedule with specific payment dates. Additionally, the data set includes information on its issue price, if the bond was issued below par. We use this information to determine each cat bond's specific cash flow. Additionally, the data set contains each cat bond's issued volume and its risk variables PFL, CEL and EL, as well as its rating if any rating was published. We supplement this data set with additional bond specific information from Artemis.bm. The Artemis Catastrophe Bond & Insurance-Linked Securities Deal Directory contains information such as the trigger type, the peril types (e.g., hurricane, wind or earthquake) and its location (e.g. U.S., Europe or Japan). Additionally, we mark a cat bond as defaulted when it appears on the "Catastrophe bond losses: cat bonds defaulted, triggered or at risk" list on artemis.bm.

To obtain our final data set we only have to drop very few bonds. We remove eight bonds, for which we lack important information such as peril types or important risk variables. We also drop one bond, which is perpetual, and one bond that has an implausible CEL of >1. We drop all observations that were recorded before the issue date or after the maturity date. In total 52 bonds have defaulted. Their returns remain in the data set up to the point where their price drops to or below 50. When a bond drops drops to or below 50, this first drop is still included in the data set, which ensures that there is no survivorship bias, but every consecutive observation is excluded. Essentially, we assume investors sell their bonds after it has dropped below this threshold.[102] Overall we have 23,176 monthly price observations for 747 cat bonds.

Table 18 contains basic information on the cat bond properties in the sample. More than 80% of all cat bonds have exposure to perils located in North America followed by only 21% for Europe and 13% for Japan. At first glance, the cat bond market is dominated by earthquake perils with 64%. However, wind bonds usually protect against a wide range of wind perils, which also includes hurricanes. Hence, hurricane is the dominant peril type on the cat bond market although only 38% of all cat bonds exclusively offer hurricane protection. The peril and region categories add up to more than 100%, because some bonds protect against multiple perils while others offer protection in multiple locations or both. 47% of all cat bonds are such multi-peril bonds and 19% offer protection in multiple locations. 42% of all cat bonds have an indemnity trigger, while the other 58% employ parametric, industry loss or modelled loss triggers (non-indemnity). Historically 7% of all cat bonds have defaulted. A bit less than half of all cat bonds are unrated, while most cat bonds received a non-investment grade rating highlighting their high-yield character. Historically the share of rated cat bond issues has declined so that most cat bonds in recent years have not received a rating.

Throughout this paper, we use the following supplementary data: U.S. Treasury yield curve,

[102] It is possible to use other thresholds in this context and we check all of our results for robustness with regard to this assumption. Figure 12 contains a sensitivity analysis in the Fama/MacBeth (1973) regression setting with respect to the estimated coefficients and their statistical significance. We discuss this figure in Section 4.7.1

Table 18: Cat bond specific information on 747 cat bonds.

Variable	Categories	No. of bonds	Percentage
Region	North America	602	80.59%
	Europe	155	20.75%
	Japan	98	13.12%
	Other	45	6.02%
Peril	Hurricane	281	37.62%
	Wind	402	53.82%
	Earthquake	476	63.72%
Peril number	Single-peril bond	395	52.88%
	Multi-peril bond	352	47.12%
Peril location	Single-location bond	602	80.59%
	Multilocation bond	145	19.41%
Indemnity	Indemnity trigger	310	41.50%
	Non-indemnity trigger	437	58.50%
Defaults	Defaulted	52	6.96%
	Not defaulted	695	93.04%
Rating	AA	4	0.54%
	A	5	0.68%
	BBB	21	2.86%
	BB	238	32.38%
	B	129	17.55%
	NR	338	45.99%

Note: For peril region and peril location, the percentages of the categories exceed 100% because some bonds have exposure to multiple peril types or locations. All other categories add up to 100%. The region denoted as "Other" contains, for example, bonds in Turkey or China.

S&P500 Performance Index, Barclays US Treasury Index (Bloomberg Ticker: LUATTRUU), Barclays US High Yield 1-3 Year Index (Bloomberg Ticker: BUH3TRUU), Bank of America Merrill Lynch Option-Adjusted Spread indices of various rating classes for corporate bond spreads and the Carpenter Global Property Catastrophe Rate-On-Line Index.

4.3.2 Cat bond returns

With very few exceptions, cat bonds are generally floating rate notes that pay coupons on a quarterly basis. Some bonds instead pay a semiannual or monthly coupon while very few bonds are issued as zero-coupon bonds.[103] Although we explain the cross-section of excess returns, we still determine the complete cat bond returns as precisely as possible by accurately tracking

[103] In the data set, 1.9% of all cat bonds are zero-coupon bonds, while 98.1% are floaters. 91.3% of all cat bonds pay coupons on a quarterly schedule.

coupon payments. From the data set, we know the specific coupon payment dates. Each coupon consists of a variable interest rate that resets on a regular basis as well as the coupon spread or quoted margin fixed at issuance. We extract the variable interest rates from the short end of the treasury yield curve.[104] At each payment date, a cat bond pays the T-Bill rate that was fixed on the previous previous payment date (e.g., if the last payment date was 3 months ago, the cat bond pays the 3-month T-Bill rate from the Treasury yield curve observed six months ago). For the first coupon payment, we use the reference rate from its issue date.

We make two additional assumptions concerning the coupon payments of cat bonds: First, a cat bonds maturity is typically a bit longer than its inherent reinsurance contract. For example, a cat bond with a so called risk period of three years often has a maturity of one or two extra months. In these extra months outside of the risk period, the cat bond only pays a reduced quoted margin or no quoted margin at all.[105] We assume that a cat bond only pays the risk-free interest rate in the first calendar month it was issued.[106]

Second, a cat bond usually pays a very reduced coupon after a default event occurred. However, a cat bond can remain in the data set for extended periods because loss assessment can take several years.[107] During this period, we assume that a cat bond does not pay any coupon.[108]

Once we have determined the specific cash flow stream of each cat bond, we can determine its monthly returns from the change in its clean prices, its accrued interest and its paid coupons between two observations. We determine the monthly return of a cat bond i at time t as the sum of its return due to its price return r^p and its coupon return r^c:

$$r_{i,t} = r^p_{i,t} + r^c_{i,t} \tag{33}$$

[104] We generally use excess returns throughout this paper, so that the choice of the risk free rate should not affect our results.

[105] All of this information is provided in the cat bond's offering circular. However, these offering circulars are unavailable to us and to the best of our knowledge have been unavailable to any other academic cat bond research.

[106] This assumption only affects the first observation in the data set for each bond.

[107] How long loss assessment takes is strongly related to a cat bonds trigger type. For example, defaults of cat bonds with a parametric trigger can be determined rather quickly: usually it is very easy to determine the magnitude of an earthquake or wind speeds of a hurricane and compare them to the default conditions. On the contrary, for cat bonds with an indemnity trigger bond, it can take years for actual losses for the protected (re-)insurance company to creep up to the default threshold. For a more in depth discussion on trigger types, please refer to Hagedorn et al. 2009

[108] This assumption only affects the very few observations in the data set because we drop all default observation after a cat bond's price has dropped below a threshold of 50.

We determine the price return through changes in the clean price P divided by its dirty price P^d:

$$r^p_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P^d_{i,t-1}}, \tag{34}$$

where the dirty price P^d is the sum of the clean price P and the accrued interest A:

$$P^d_{i,t} = P_{i,t} + A_{i,t} \tag{35}$$

We determine the coupon return through the paid coupon C (if there was any) and the change in accrued interest A:

$$r^c_{i,t} = \frac{C_{i,t}}{P^d_{i,t-1}} + \frac{A_{i,t} - A_{i,t-1}}{P^d_{i,t-1}} \tag{36}$$

Plugging equations (36) and (34) into equation (33) yields the simple expression for the total return:

$$r_{i,t} = \frac{P_{i,t} + A_{i,t} - P_{i,t-1} - A_{i,t-1} + C_{i,t}}{P_{i,t-1} + A_{i,t-1}} = \frac{P^d_{i,t} - P^d_{i,t-1} + C_{i,t}}{P^d_{i,t-1}} \tag{37}$$

When we determine a cat bond index or portfolio return, we use the methodology from Swiss Re (2014). Generally, we generate value-weighted indices and portfolios. Then the weight $w_{i,t}$ of a bond i at time t in an index or portfolio is as follows:

$$w_{i,t} = \frac{N_i \cdot P^d_{i,t-1}}{\sum_{k=1}^{n} N_{k,t-1} \cdot P^d_{k,t-1}} \tag{38}$$

where N_i (N_k) is the notional amount outstanding for cat bond i (k). Generally, a cat bond's notional amount is repaid at full at its time of maturity so that N_i remains constant throughout a cat bond's maturity.

Portfolios are always restructured at the previous month $t-1$. Index and portfolio returns are then determined by multiplying bond returns and their specific weights:

The return from changes in clean price:

$$r^p_{index,t} = \sum_{i=1}^{n} w_{i,t} \cdot r^p_{i,t} \tag{39}$$

and the return from coupon payments and changes in accrued interest:

$$r^c_{index,t} = \sum_{i=1}^{n} w_{i,t} \cdot r^c_{i,t} \tag{40}$$

add up to the monthly return of the index or portfolio:

$$r_{index,t} = r^{p}_{index,t} + r^{c}_{index,t} \tag{41}$$

Finally, to obtain a time series of excess returns, we subtract the one-month T-Bill rate from each monthly cat bond return.

4.3.3 Seasonal event risk

The PFL of many cat bonds fluctuates strongly throughout a calendar year (see Beer/Braun 2021, Herrmann/Hibbeln 2021). For example, the PFL of a single-peril U.S. hurricane bond is virtually zero outside the hurricane season, but increases drastically during the hurricane season. To draw on an analogy, such a cat bond can implicitly move, for example, from a B Rating to a AAA rating and vice versa within a single calendar year. This clear seasonal pattern repeats itself throughout the term of the bond.[109] In similar fashion, the expected returns of seasonality-affected cat bonds should change substantially from one calendar month to the next. Hence, it is important to specifically model seasonal fluctuations in event risk. To this end, we alter the conceptual framework from Herrmann/Hibbeln (2021) to fit a factor model that explains the cross-section of monthly cat bond returns.

Table 19: Modeled distribution of arrival frequencies.

	U.S. hurricanes ($\gamma_{t,us}$)	EU winter storms ($\gamma_{t,eu}$)
January	0.0%	26.0%
February	0.0%	16.5%
March	0.0%	11.5%
April	0.0%	0.0%
May	0.2%	0.0%
June	3.6%	0.0%
July	12.5%	0.0%
August	28.7%	0.0%
September	34.6%	0.0%
October	18.3%	11.0%
November	2.0%	14.0%
December	0.1%	21.0%

Note: Distributions of U.S. hurricanes and EU winter storms throughout a calendar year as modeled by AIR.

Table 19, taken from Herrmann/Hibbeln (2021), contains the relative distribution of U.S.

[109] Cat bond ratings are not updated when they move through their respective season. Thus, investors need to perform their own seasonal risk assessment.

hurricanes and EU winter storms as modelled by AIR.[110] As indicated by Table 19, there are no hurricanes from January to April. During this time a single-peril U.S. hurricane bond has a PFL of zero. During the hurricane season, the same cat bond is exposed to the highest PFL in September, when the hurricane season is at its peak. Similarly, the EU winter storm season peaks in January.

We determine the seasonal PFLs in three steps: First, we determine the constant hazard rates (on a p.a. basis) implied by the modeled PFL from the cat bond offering circular. Second, we transform this hazard rate into a monthly constant PFL (PFLC). Third, we estimate the monthly seasonal PFL (PFLS) through a heterogeneous hazard rate that fluctuates according to the seasonal distributions of perils in Table 19.

1. We determine every cat bond's hazard rate through a simple hazard rate model using the constant yearly PFL we have in our data set. This is the PFL provided by the risk modelling agent. In this hazard rate model the default events follow a Poisson process:

$$\mathrm{PFL} = 1 - \mathrm{P}[N(T) = 0], \tag{42}$$

where P[N(T) = 0] stands for the annual probability of survival, i.e., the probability that the number of trigger events is zero. In a hazard rate model with a Poisson process this probability of survival can be determined as follows:

$$\mathrm{P}[N(T) = 0] = \exp(-\lambda_h \Delta t), \tag{43}$$

where λ_h denotes the homogeneous hazard rate in p.a. terms and Δt is a day count fraction for calculation periods shorter than a year. We can then plug Equation (42) into Equation (43) and solve for λ_h:

$$\lambda_h = -\frac{\ln(1 - \mathrm{PFL})}{\Delta t}. \tag{44}$$

In our case, the provided PFL is the default probability for one year, so $\Delta t = 1$.

We use equation 44 to determine the homogenous hazard rate λ_h for all cat bonds in our data set.

[110]Herrmann/Hibbeln (2021) in turn obtained these distributions from Poliquin (2012) and a representative from AIR.

2. Since our data is of monthly frequency, we also want to obtain the monthly constant probability of first loss (PFLC). We obtain PFLC by utilizing the acquired λ_h in the hazard rate model from Equation (43) combined with Equation (42) and a time frame of one month $\left(\Delta t = \frac{1}{12}\right)$:

$$\text{PFLC} = 1 - \exp\left(-\lambda_h \frac{1}{12}\right). \tag{45}$$

3. We introduce the heterogeneous hazard rate λ_t:

$$\lambda_t = \lambda_h \cdot \gamma_t, \tag{46}$$

where γ_t stands for the relative share of the either the U.S. hurricane season ($\gamma_{t,us}$) or the EU winter storm season ($\gamma_{t,eu}$), yielding $\lambda_{t,us}$ or $\lambda_{t,eu}$, respectively. PFLS_t is defined as the resulting time-varying monthly PFL, which accounts for the modeled seasonality patterns from Table 19:

$$\text{PFLS}_t = 1 - \exp(-\lambda_t). \tag{47}$$

Additionally, we define SF_t as the seasonality adjustment factor, which reports how strongly PFLC is scaled for every individual cat bond in each calendar month:

$$\text{SF}_t = \frac{\text{PFLS}_t}{\text{PFLC}}. \tag{48}$$

So, for example, if the PFLS_t for a single-peril U.S. hurricane bond in September is four times the monthly constant PFLC, SF_t equals four.

With the above mentioned formulae, determining the PFLS_t of a single-peril U.S. hurricane bond is straightforward. However, every other cat bond type has its PFL spread out across different peril types.[111] Some of these perils, such as earthquake, do not change seasonally. Consequently, such a multi-peril U.S. hurricane/earthquake bond fluctuates less strongly with the U.S. hurricane season than a single-peril U.S. hurricane bond (see Herrmann/Hibbeln 2021). Additionally, multilocation bonds with wind exposure in the U.S. and Europe may mix both seasons. How strongly a cat bond fluctuates with one of the two seasons depends on how its PFL is divided between these two peril types and other peril types that are not affected by these two

[111] A multi-peril bond, including hurricane and earthquake risk, could be 1% hurricane and 99% earthquake or anything between.

seasons. In the absence of detailed information from offering circulars, we follow the econometric approach of Herrmann/Hibbeln (2021) to determine the average relative distribution of PFL between (1) U.S. hurricane risk, (2) European winter storm risk and (3) other perils for each bond. More specifically, we estimate yield spread models for different cat bond categories and compare their seasonal fluctuation to the baseline-maximum seasonal fluctuation of U.S. hurricane bonds. To this end, we run the following regression:

$$s_{it} = \beta_{us}\mathrm{EL}_{it,us} + \beta_{eu}\mathrm{EL}_{it,eu} + \eta' C_{it} + \alpha_i + \varepsilon_{it}, \tag{49}$$

where s_{it} is the yield spread of bond i at time t. C_{it} is a vector of control variables such as the Guy Carpenter Global Property Catastrophe Rate-On-Line Index as a proxy for reinsurance prices, the Bank of America Merrill Lynch Option-Adjusted Spread indices of various rating classes for corporate bond spreads, the return of the S&P500 performance index and the time to maturity. α_i stands for unobserved time-invariant bond properties. Herrmann/Hibbeln (2021) define EL_t as the seasonal yearly expected loss until maturity. They argue that investors evaluate the remaining amount of risk against the remaining time to maturity when valuing a cat bond:

$$\mathrm{EL}_t = \frac{\textit{Remaining risk}_t}{\textit{Remaining time}_t} = \frac{\mathrm{EL}_{initial} \cdot \int_t^T \lambda(\tau)d\tau}{\Delta t} \tag{50}$$

where T is the time of maturity, t is the current time and $\lambda(\tau)$ is the density function if arrival frequencies, which depends on the time of the season τ. For $\lambda(\tau)$ we use $\gamma_{t,us}$ and $\gamma_{t,eu}$ from Table 19.

The economic intuition behind this formula is as follows: If the remaining amount of risk declines at the same pace as the remaining time to maturity, EL_t does not change throughout a cat bond's lifetime. This is the case for earthquake bonds. However, if the remaining risk decreases at a faster or slower pace than the remaining time to maturity, EL_t increases or decreases depending on the seasonal state. For example, outside of the hurricane season, the amount of remaining risk of a cat bond does not decrease because no hurricanes can occur. This means, the remaining risk does not decline and EL_t increases as the remaining time to maturity decreases. On the contrary during the hurricane season, the remaining risk decreases very rapidly, because the cat bond is at a high default risk. In consequence, EL_t declines as the bond goes through the hurricane season. Herrmann/Hibbeln (2021) show that the seasonal changes in yield spreads are closely related to these seasonal changes in EL_t.

We use a fixed effects transformation version of this model to maximize the within bond explanatory power and control for α_i. Since cat bonds are floating rate notes, we draw on the U.S. treasury forward rate curves to determine the variable rates included in the unknown future coupons (see, e.g., Beer/Braun 2021, Herrmann/Hibbeln 2021). In combination with the coupon frequency and quoted margins from our data set, this allows us to generate the cash flow stream for each cat bond. Subsequently, we numerically solve for the yield spread that matches clean prices and the cash flow stream.[112]

We then estimate model (49) for subsamples that represent six different group categories of cat bonds. By dividing their coefficient estimates $\hat{\beta}_{us}$ and $\hat{\beta}_{eu}$ through the baseline coefficient from the regression of the single-peril U.S. hurricane subsample, we can determine how, on average, a cat bond's risk exposure is distributed among its peril types. Thereby, we assume that investors demand the same amount of risk premium per unit of risk irrespective of the peril type and its seasonal state, i.e. one unit of EL in U.S. hurricane risk translates into as much yield spread as one unit of EL in European winter storm risk or earthquake risk:

$$S_{c,z} = \frac{\hat{\beta}_{c,z}}{\hat{\beta}_{C_1,us}} \tag{51}$$

with $c \in \{\mathrm{C}_1, \mathrm{C}_2, \mathrm{C}_3, \mathrm{C}_4, \mathrm{C}_5, \mathrm{C}_6\}$ and $z \in \{us, eu\}$.

Overall, we have the following group categories, each with separate regressions:

- C_1: Single-peril U.S. hurricane bonds (benchmark category).
- C_2: Single-peril U.S. wind bonds.
- C_3: Multi-peril U.S. hurricane bonds without exposure to European winter storms.
- C_4: Multi-peril U.S. hurricane bonds with exposure to European winter storms.
- C_5: Single-peril EU wind bonds.
- C_6: Multi-peril EU wind bonds without exposure to U.S. hurricanes.

Table 20 reports the estimated seasonality coefficients regarding the exposure to U.S. hurricanes or EU winter storms for the six regressions and the resulting shares of peril types for the

[112] It should be noted that these yields are *promised* yields, i.e., we do not weight the cash flows with default probabilities. The promised yield is the maximally achievable yield, which materializes in case no trigger event occurs before maturity. It is higher than the *expected* yield, which can be calculated from the expected values of the cash flows.

Table 20: Modeled distribution of arrival frequencies.

Category	Coefficients U.S.	Coefficients EU	Share of peril type U.S. hurricane	Share of peril type EU winter storm	Share of peril type Other
C_1 - SP U.S. HU	2.15	-	100%	0%	0%
C_2 - SP U.S. Wind	1.42	-	66%	0%	34%
C_3 - MP U.S. HU without EU Wind	1.30	-	60%	0%	40%
C_4 - MP U.S. HU with EU Wind	0.94	0.81	44%	38%	19%
C_5 - SP EU wind	-	1.59	0%	74%	26%
C_6 - MP EU wind without U.S. HU	-	0.78	0%	36%	64%

Note: This table reports U.S. and EU seasonal coefficients of fixed effects transformation regressions of yield spreads on seasonality-adjusted EL variables strictly replicating Herrmann/Hibbeln (2021). Unreported control variables are the Guy Carpenter Global Property Catastrophe Rate-On-Line Index, the Bank of America Merrill Lynch Option-Adjusted Spread indices of various rating classes, the return of the S&P500 performance index and the time to maturity. Detailed regression results are available upon request. Additionally, this table reports the resulting estimated percentage exposure to U.S. hurricanes, EU winter storms, and other peril types, which includes other perils such as earthquakes, for the six cat bond categories.

six categories. The coefficient for C_1 is the baseline coefficient. All other seasonality coefficients are smaller than this coefficient for single-peril U.S. hurricane bonds. Obviously, bonds in C_1 fluctuate 100% with the U.S. hurricane season. Bonds from C_3, for example, fluctuate much less strongly with the U.S. hurricane season. We obtain their 60% share by dividing the U.S. coefficient from C_3 by the baseline U.S. coefficient from C_1. The remaining 40% of C_3 are other perils. We apply the same procedure to obtain the respective shares for all other categories. Overall, the mostly low shares of other perils highlight that the cat bond market is strongly affected by seasonality.

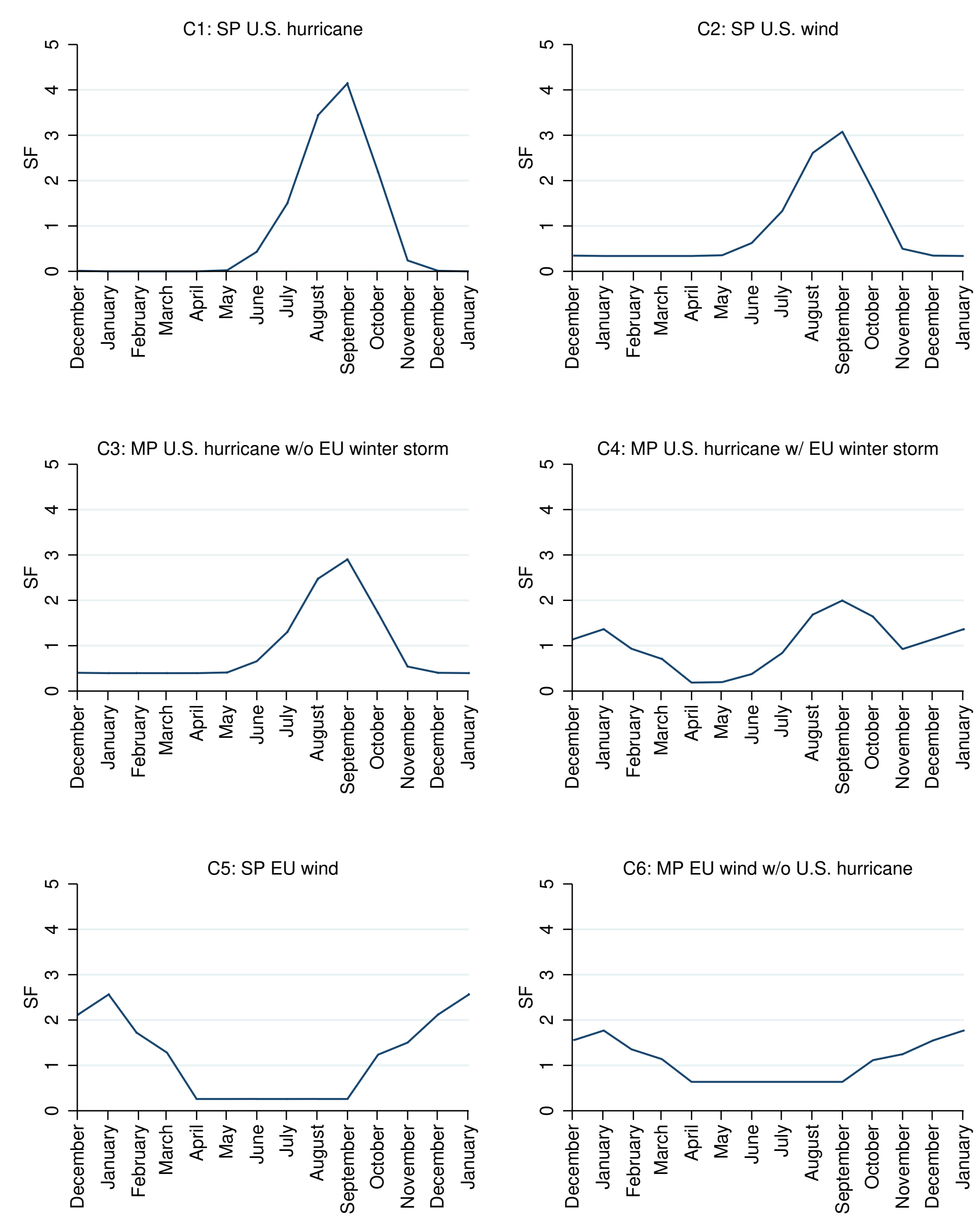
We can now estimate individual monthly hazard rates for every bond i at time t in these six categories using the respective shares $S_{c,z}$ for category c and geography z:

$$\lambda_{it} = \lambda_{it,us} \cdot S_{c,us} + \lambda_{ti,eu} \cdot S_{c,eu} + \frac{\lambda_{h,i}}{12} \cdot S_{c,ns} \tag{52}$$

We then use Equations (47) and (48) to determine the seasonality-adjusted PFL (PFLS) and the seasonality factor (SF), respectively.

Figure 8 illustrates the resulting SF for the six categories. SF $>$ 1 implies that a bond is exposed to a larger seasonal PFLS than its constant PFLC implies in the respective month, whereas SF $<$ 1 implies that a bond is exposed to a smaller seasonal PFLS. As expected, bonds of C_1 have the greatest exposure to the U.S. hurricane season. Their SF fluctuates between 0 and over 4, peaking in September. This means that their PFLS is more than four times as the constant monthly PFLC. Bonds from C_2 and C_3 fluctuate less strongly with the U.S. hurricane season and also contain other perils indicated by the flat line above 1 from January through

Figure 8: The seasonality adjustment factor SF for six cat bond categories.



Note: This figure illustrates the seasonality adjustment factor SF for the six bond categories. SF>1 implies that a bond is exposed to a larger seasonal PFLS than its constant PFLC implies in the respective month. SF<1 implies that a bond is exposed to a smaller seasonal PFLS than its constant PFLC implies in the respective month. If a bond is more strongly exposed to seasonality, its SF fluctates more strongly throughout a calendar year. For bonds of category 4, the graph illustrates the overlapping U.S. hurricane and EU winter storm seasons.

May. Bonds from C_4 mix the U.S. hurricane and EU winter storm seasons. Bonds from C_5 and C_6 are both exposed to the European winter storms season, but it is plausible that single-peril EU wind bonds in C_5 have a higher exposure to the EU winter storm season than multi-peril bonds.

4.3.4 Summary statistics

Table 21 reports summary statistics on the continuous variables, including the excess returns according to the methodology described in Section 4.3.2, event risk variables from Section 4.3.3, and the yield spread.

Table 21: Summary statistics for continuous variables.

	n	mean	sd	min	p25	p50	p75	max
Excess return (monthly in %)	22,423	0.42	3.90	-100.08	0.17	0.42	0.92	91.33
EL (monthly in %)	747	0.23	0.24	0.00	0.08	0.15	0.30	1.64
PFLC (monthly in %)	747	0.31	0.33	0.00	0.11	0.20	0.41	2.37
CEL (in %)	747	75.63	14.11	18.18	68.41	78.39	85.12	100.00
PFLS (monthly in %)	23,176	0.00	0.35	-2.14	-0.12	0.00	0.04	6.46
SF	23,176	1.01	0.82	0.00	0.40	1.00	1.30	4.15
Yield spread (monthly in %)	23,106	7.13	6.60	-75.13	3.48	5.54	8.71	87.37
Maturity (in years)	23,176	1.80	1.15	0.00	0.85	1.71	2.61	6.99
Coupon (yearly in %)	747	7.16	4.77	0.00	4.00	6.00	9.50	39.25
Volume (in USD mio.)	746	135.28	116.67	1.80	57.00	100.00	180.00	1500.00

Note: Summary statistics for the continuous variables. The event risk variables constant probability of first loss (PFLC), conditional expected loss (CEL) and constant expected loss (EL) on bond level are provided by the risk modeling firms. The seasonality adjusted PFL (PFLS) accounts for the seasonal fluctuations in PFL as described in Section 4.3.3. These event risk variables are on a monthly basis. SF is the seasonality adjustment factor. Additionally, this table reports the remaining time to maturity, the nominal yearly coupon and the issued volume.

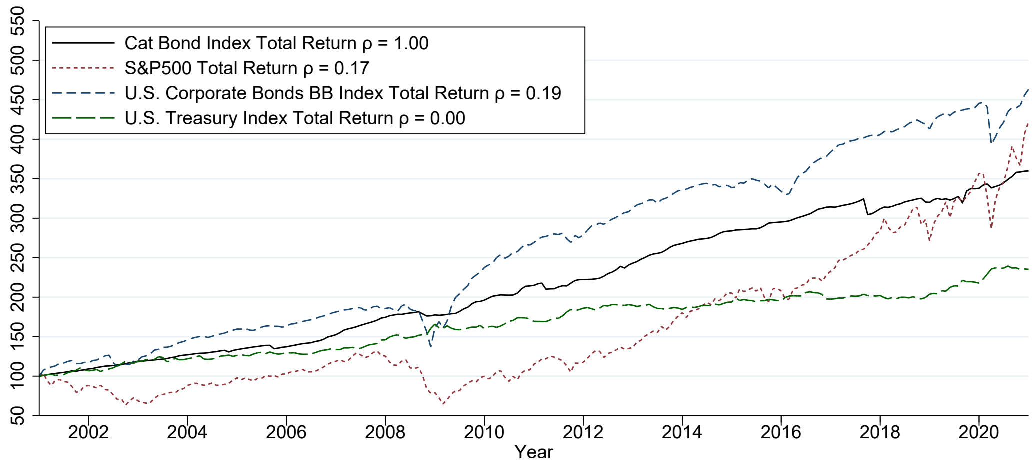
4.4 The cross-section of expected excess returns

In this section, we first discuss the characteristics of historical excess returns on cat bonds compared to other asset classes, we then perform univariate and bivariate portfolio sorts, before we investigate potential cat bond return factors in Fama/MacBeth (1973) regressions.

4.4.1 Historical cat bond returns

Following Braun et al. (2019), Figure 9 illustrates the returns of our cat bond market index in comparison to the other asset classes such as stocks, corporate bonds and treasuries. We generate the cat bond market index using all cat bonds in our sample as described in Section 4.3.1 and the methodology described in Section 4.3.2. We use the S&P500 Total Return Index for stock returns, the Barclays US High Yield 1-3 Year Total Return Index Unhedged for corporate

Figure 9: Cat bond returns compared to other asset classes.



Note: This figure illustrates the returns of the cat bond market as compared to other asset classes over the sample period. The cat bond index is generated from our sample using the methodology from Section 4.3.2. For stock returns, we use the S&P500 Total Return Index, for corporate bond returns, we use the Barclays US High Yield 1-3 Year Total Return Index Unhedged, for U.S. Treasury Returns, we use the Barclays US Treasury Index.

bond returns, because it most closely reflects the maturities in the cat bond market, and we use the Barclays US Treasury Index for treasury returns.

We find that, over the time period under consideration, both U.S. stocks and U.S. high-yield corporate bonds have generated a higher total return than the cat bond market. However, stocks only surpassed cat bonds in 2019. At the same time, the cat bond market has expressed much lower volatility than the other two asset classes. Additionally, its losses during the Financial Crisis in 2009 and the crash associated with the COVID-19 pandemic in 2020 were much lower than losses for the stock and high-yield corporate bond markets. Overall, it appears the cat bond market is quite resilient towards distress on the financial markets.

Previous publications discuss the cat bond market's low correlation with other financial markets and high potential for diversification (e.g., Dieckmann 2019, Cummins/Weiss 2009, Braun 2016). As indicated by earlier research, cat bonds do not appear to be a "zero-beta" asset class (see, e.g., Litzenberger/Beaglehole 1996, Carayannopoulos/Perez 2015, Gürtler et al. 2016). Instead, we find a small correlation of cat bond returns and stock returns ($\rho = 0.17$) or high-yield corporate bond returns ($\rho = 0.19$). Both of these correlation coefficients are statistically significant at the 1% level.[113] Overall, cat bonds are an asset class with relatively high returns, low volatility and a substantial diversification potential.

4.4.2 Uni- and bivariate portfolio sorts

Table 22 reports univariate portfolio sorts of the proposed cat bond return factors. These factors are derived from continuous variables (EL, PFLC, CEL, SF) and from binary variables (IND, MP, ML HU, US). In each monthly cross-section, we sort all cat bonds according to these variables. For the continuous variables, we then form five quintile portfolios P1 (lowest values) to P5 (highest values). For the binary variables, we naturally obtain two portfolios: P1 (P0) contains all cat bonds where the binary variable value is 1 (0). We then report the mean of the return of each portfolio across all cross-sections. Finally, we determine the difference between the mean returns of P5 and P1, as well as P1 and P0, respectively. The p-values for these differences, reported in parentheses, were determined with Newey/West (1987) standard errors with four lags. A positive return difference between the portfolios that is statistically significant could indicate first evidence that these potential factors are positively priced in the cat bond market.

Table 22: Univariate portfolio sort.

Panel A	EL	PFLC	CEL	SF	Yield
P5	0.90	0.80	0.36	0.55	0.85
P4	0.55	0.46	0.53	0.50	0.54
P3	0.34	0.48	0.49	0.51	0.46
P2	0.30	0.32	0.46	0.45	0.33
P1	0.26	0.27	0.36	0.24	0.13
Difference: P5 - P1	0.64***	0.53***	0.00	0.31***	0.72***
	(.000)	(.000)	(.976)	(.000)	(.000)
Panel B	IND	MP	ML	HU	US
P1	0.37	0.53	0.67	0.47	0.48
P0	0.46	0.35	0.38	0.31	0.27
Difference: P1 - P0	-0.09	0.18**	0.29***	0.15*	0.20**
	(.348)	(.002)	(.000)	(.028)	(.003)

Note: This table reports mean returns for univariate portfolio sorts. For Panel A, P5 represents the mean returns for the portfolios with the highest values for the respective variable, P1 contains the lowest variable values. For Panel B, P1 contains the portfolio were the respective dummy variable has the value 1, P0 contains the dummy variable value 0. To assess the potential impact of the respective variables on returns, we determine the difference in mean returns between P5 and P1, and P1 and P0, respectively. p-values in parentheses were determined with Newey/West (1987) standard errors with four lags. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

[113] We further investigate this link in Section 4.5.

For the event risk variables EL and PFLC, we find P5 has a much larger return than P1. We observe a large return difference of 0.64% per month for EL and 0.53% of PFLC. Both are highly statistically significant, which is first evidence that event risk is strongly priced in the cat bond market. On the contrary, the downside risk as measured by CEL appears not to be priced in the cat bond market. For the seasonality adjustment factor SF, we find that P5 has a much larger return than P1 and observe a relatively large return difference of 0.31%, which is highly statistically significant. This suggests that the seasonal fluctuation in event risk for cat bonds is strongly priced in the cat bond market.

Although we do not use yield as a separate factor in this article, we use this variable to relate our research to the historically dominant empirical yield spread literature on cat bonds. We find that P5 has a much larger return than P1. In fact, this difference is larger than for EL and PFL and is highly statistically significant. This indicates that higher yield spreads actually materialize in higher returns even if we take negative realizations such as defaults into account. So far the cat bond literature could only show that risky bonds with a high EL have higher yield spreads but they could still have larger or smaller returns than low risk bonds depending on actual default events. Here it appears that instead, high yield cat bonds have much larger realized returns than low risk cat bonds.

Concerning the binary portfolio sorts, we find larger average excess returns of P1 for MP, ML, HU and US of a magnitudes between 0.15% and 0.29% per month. These differences are statistically significant. Only P1 and P0 for IND do not have a return difference that is statistically significant. However, all of these differences must be interpreted with care, because they do not control for differences in event risk. For example, HU bonds tend to generally have a higher PFL than non-HU bonds.

Against this background, we additionally calculate the corresponding returns for bivariate portfolio sorts controlling for event risk through PFL. Overall, we do not find strong evidence for the binary non-event risk factors when controlling for PFL, and we find that results are not always consistent across PFL categories.[114] This can have several reasons: First, dividing the cat bond market in ten portfolios each (5x2), can leave each portfolio with relatively few bond observations making it more difficult to find differences that are statistically significant. Second, the number of defaults is so small that it is not spread out enough to correctly resemble the expected number of defaults according to PFL in the ten bins. Hence, we do not further restrict

[114] Detailed results are available upon request.

the number of potential factors but move on with all the binary factors to the Fama/MacBeth (1973) regressions.

4.4.3 Fama/MacBeth (1973) regressions for event risk variables

Next, we investigate the event risk variables to determine which event risk variable to use. We use Fama/MacBeth (1973) regressions where we predict the cross-section of one-month ahead bond returns to determine the event risk variables that are most suitable from EL, PFLC and CEL. For each Model in the Fama/MacBeth (1973) regressions in Table 23, we first run separate cross-sectional regressions of the model on one-month ahead returns. We then take the mean of each coefficient and the adj. R^2 across all cross-sectional regressions and determine the associated p-values with t-statistics from Newey/West (1987) standard errors with four lags. For each model, we have 240 seperate regressions.

Table 23: Fama/MacBeth (1973) regressions for event risk variables.

	Intercept	EL	PFLC	CEL	adj. R^2
(1)	.262***	1.498***			0.186
	(0.000)	(0.000)			
(2)	.103		1.12***	.002	0.192
	(.51)		(0.000)	(.247)	
(3)	.264***		1.108***		0.184
	(0.000)		(0.000)		

Note: This table reports mean coefficients for Fama/MacBeth (1973) cross-sectional regressions of explanatory event risk variables on one-month ahead cat bond returns. p-values in parentheses were determined with Newey/West (1987) standard errors with four lags. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

Model (1) of Table 23 regresses the monthly constant EL on one-month ahead returns. We obtain a coefficient of 1.50, which is highly statistically significant at the 0.1% level. The mean adj. R^2 is 0.186. Model (2) contains the PFLC and CEL as variables to explain one-month ahead returns. While the monthly PFLC is highly statistically significant, CEL does not appear to explain the cross-section of one-month ahead cat bond returns. Taking Table 22 into account, where the return difference of P5 and P1 for CEL is close to zero, we conclude that downside-risk as measured by CEL is not priced in the cat bond market. Because CEL does not appear to be priced, Model (3) contains PFLC as the only event risk variable. PFLC is highly statistically significant at the 0.1% level. Compared to Model (1) with EL, Model (3) has almost the same explanatory power. The coefficient is smaller for PFLC than for EL, because PFLC is on average larger than EL.

Since EL does not have a significantly higher explanatory power than PFLC and CEL does not appear to be priced in the cat bond market, we continue to use PFLC as the event risk variable for the remainder of the paper. At the same time, this means we do not find any evidence that downside risk is priced in the cat bond market.

4.4.4 Fama/MacBeth (1973) regressions for additional cat bond variables

Table 24 reports results for Fama/MacBeth (1973) regressions of various additional cat bond variables controlling for probability of default, as well as time to maturity in years and size in USD 100 mio. Again, we first run cross-sectional regressions of factor variables on one-month ahead returns for each month in the data set and report mean coefficients with p-values from Newey/West (1987) standard errors with four lags.

Model (1) represents the baseline model, where we only use PFLC to explain one-month ahead returns. As compared to Model (1) in Table 23, the PFLC remains virtually unchanged after the inclusion of maturity and size as controls. Generally, maturity and size remain statistically insignificant throughout all models of this table.

In Model (2) we include the seasonality adjustment factor SF. We find that it is strongly related to cross-sectional one-month ahead returns with a statistical significance on the 0.1% level. This means, that bonds at the peak of their respective season have much higher returns than during the seasonal lowpoint.[115] For all models including SF, we regress one-month ahead returns on next month's expected SF because investors on the cat bond market should be able to make the same prediction. Hence, we do not use unknown information in the cross-sectional regression of the current month. Overall, the R^2 increases from 0.217 in Model (1) to 0.274 after including SF in the regression.

In Models (3) through (7), we include IND, MP, ML, HU and US, respectively, while controlling for PFLC, Maturity and Size. First, we find higher one-month ahead returns for multi-peril (MP) and multilocation (ML) cat bonds. On average, monthly returns are roughly 0.17% larger for these bond types. Both coefficients are statistically significant at the 1% level. Second, for HU we do not observe returns that are statistically significantly larger that for non-HU bonds. Third, returns for US are roughly 0.12%-points larger. This coefficient is significant at the 5% level. Ultimately, we also find smaller returns for IND. However, this coefficient is only significant at the 10% level. To investigate if one of these variables dominates other variables or if the indications from the previous models hold in a larger setting, we use Model (8) with all

[115] Figure 8 illustrates how SF fluctuates for the six cat bond categories. For single-peril HU bonds, where seasonal fluctuation is largest, SF fluctuates between 0 outside the hurricane season and reaches 4.15 in September. This means that the returns for a single-peril HU bond is 4.15*0.26 = 1.08% larger per month during the peak of the hurricane season than outside the hurricane season.

Table 24: Fama/MacBeth (1973) regressions for other factors.

	Intercept	PFLC	SF	IND	MP	ML	HU	US	Maturity	Size	adj. R^2
(1)	.133	1.088***							.007	.021	0.217
	(.413)	(0.000)							(.826)	(.523)	
(2)	−.146	1.085***	.257***						0	.025	0.274
	(.407)	(0.000)	(0.000)						(.992)	(.466)	
(3)	.287*	1.058***		−.145+					.008	.009	0.230
	(.029)	(0.000)		(.089)					(.803)	(.787)	
(4)	.045	1.019***			.167**				0	.028	0.228
	(.795)	(0.000)			(.004)				(.992)	(.396)	
(5)	.158	1.002***				.168**			.006	.014	0.229
	(.338)	(0.000)				(.003)			(.849)	(.668)	
(6)	.037	1.073***					.098		.001	.029	0.258
	(.834)	(0.000)					(.125)		(.984)	(.413)	
(7)	.013	1.066***						.124*	.009	.026	0.244
	(.936)	(0.000)						(.044)	(.78)	(.442)	
(8)	−.169	.989***	.36***	−.128+	.117	−.015	.051	.065	−.008	.013	0.325
	(.328)	(0.000)	(0.000)	(.094)	(.12)	(.834)	(.749)	(.374)	(.803)	(.697)	

Note: This table reports mean coefficients for Fama/MacBeth (1973) cross-sectional regression of explanatory event risk variables on one-month ahead cat bond returns. p-values in parentheses were determined with Newey/West (1987) standard errors with four lags. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

the different variables. While the coefficient of PFLC remains almost unchanged, the coefficient for SF increases, both staying significant at the 0.1% level; the other coefficients become generally smaller and lose their statistical significance. IND stays significant at the 10% level, which could indicate that moral hazard problems related to the indemnity trigger indeed reduce realized returns (and are not compensated in terms of a higher ex-ante risk premium); though, the significance level is only 9.4%, so we do not want to stress this finding.

Together with mixed results from binary portfolio sorts we interpret the results from the Fama/MacBeth (1973) regressions in the following way: First, PFLC and SF appear to be priced in the cat bond market. We already excluded CEL as a downside risk measure in the previous section based on Table 23, which investigated the event risk variables. Additionally, we dismiss the other cat bonds specific variables IND, MP, ML, HU and US. Although previous empirical research on yield spreads has shown that cat bonds with these properties have higher spreads, we find no evidence that these higher yields associated with these variables materializes in higher returns. This could have two reasons: a) The larger returns are too small for our models to detect, or b), these variables are correctly priced by investors because they actually reflect higher riskiness, so that higher yields and the higher likelihood of defaults cancel each other out.

We use Table 25 to investigate the ability of yield spread to explain one-month ahead cat bond returns in the already proposed Fama/MacBeth (1973) setting. In this context Table 25 repeats Table 24 adding the yield spread to each model.

The coefficient for yield spread is highly statistically significant on the 5% level and fluctuates between roughly 0.4 and 0.5 depending on the model. This means that roughly half the yield spreads materializes in actual returns. All other coefficients except for SF lose their statistical significance when the yield spread is present. However, this is not very surprising considering that investors take all these variables into account when their trading determines the yield spread. In other words: the information in PFLC, IND, MP, ML, HU and US is already reflected in the yield spread. Only SF remains statistically significant. A likely explanation is that the seasonality factor strongly reflects a cat bond's seasonally changing event risk for the upcoming month, while the yield spread in terms of the seasonality of event risk reflects somewhat of an average over the entire remaining time to maturity.[116] For example, the yield spread reacts much less strongly to a change in the seasonal state than the return of the respective month. Generally, the explanatory power of the models including the yield spread is larger than the

[116]Please refer to Herrmann/Hibbeln (2021) for an in-depth discussion of yield spreads and seasonality.

Table 25: Fama/MacBeth (1973) regressions for other factors - yield spread.

	Intercept	Yield	PFLC	SF	IND	MP	ML	HU	US	Maturity	Size	adj. R^2
(1)	.075	.493*	.042							-.015	.022	0.336
	(.402)	(.019)	(.857)							(.618)	(.286)	
(2)	−.125	.437*	.125	.215***						−.022	.022	0.384
	(.264)	(.034)	(.576)	(0.000)						(.442)	(.309)	
(3)	.201$^+$	.496*	.029		−.156$^+$					−.012	.014	0.347
	(.055)	(.017)	(.905)		(.061)					(.675)	(.504)	
(4)	.002	.48*	.023			.096$^+$				−.02	.031	0.344
	(.984)	(.027)	(.92)			(.085)				(.504)	(.138)	
(5)	.125	.475*	.014				.102			−.016	.012	0.346
	(.209)	(.026)	(.952)				(.109)			(.583)	(.604)	
(6)	.025	.489*	.032					.056		−.022	.028	0.368
	(.818)	(.025)	(.897)					(.364)		(.466)	(.235)	
(7)	.026	.439*	.082						.091	−.019	.023	0.355
	(.803)	(.039)	(.719)						(.125)	(.523)	(.286)	
(8)	−.115	.381$^+$	.194	.286**	−.133$^+$	.066	−.049	.041	.079	−.032	.013	0.426
	(.374)	(.081)	(.491)	(.001)	(.085)	(.348)	(.454)	(.795)	(.182)	(.304)	(.562)	

Note: This table reports mean coefficients for Fama/MacBeth (1973) cross-sectional regression of explanatory event risk variables on one-month ahead cat bond returns. This table includes the yield spread in every model. p-values in parentheses were determined with Newey/West (1987) standard errors with four lags. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

explanatory power of Model (8) in Table 24 without the yield spread. Overall we find the yield to be a strong variable to explain the cross-section of one-month ahead returns, but it is not suitable as a factor following the general finance literature on corporate bonds.

4.5 A cat bond factor model

In the previous section we investigated potential cat bond pricing factors through uni- and bivariate portfolio sorts and Fama/MacBeth (1973) regressions. We found that PFLC and SF explain the cross-section of one-month ahead cat bond returns. So we propose a factor model based on factors derived from these variables. Additionally, we supplement these two factors with the two bond factors TERM and DEF from Fama/French (1993) to see if they are also priced in the cat bond market. Ultimately, we propose a five cat bond pricing factors model that includes four factors: PFLC, SF, PFLS, TERM and DEF.

For F_PFLC as the return factor for PFLC, we use the quintile portfolio sorts. For each month F_PFLC is the return difference of the highest PFLC quintile portfolio and the lowest PFLC quintile portfolio. We determine F_SF in the same fashion as F_PFLC. Each month, F_SF is the return difference of the highest SF quintile portfolio and the lowest SF portfolio. As an additional event risk alternative to the combination of PFLC and SF, we also use PFLS as the seasonality adjusted PFL as defined in Section 4.3.3 and construct the corresponding return factor F_PFLS accordingly. We define TERM as the return difference between the monthly return of the Barclays US Treasury Index and the one-month T-Bill rate. We define DEF as the return difference between the monthly return of the Barclays US High Yield 1-3 Year Total Return Index and monthly return of the Barclays US Treasury: 1-3 Year Total Return Index.

Table 26: Descriptive statistics for the proposed factors

Factor	N	Mean	Volatility	t-stat.	Min	Q25	Median	Q75	Max
F_PFLC	240	0.53	1.88	4.94***	-19.73	0.22	0.56	1.06	9.11
F_SF	240	0.31	1.41	3.58***	-14.11	-0.07	0.21	0.62	10.40
F_PFLS	240	0.28	1.75	2.23*	-15.93	-0.28	0.12	0.92	9.28
TERM	240	0.25	1.27	3.17**	-4.46	-0.48	0.18	0.91	5.30
DEF	240	0.45	2.55	2.45*	-13.69	-0.10	0.48	1.17	17.36

Note: This table reports descriptive statistics on the proposed factors. All reported values, except for the t-statistics and N, are in %. t-statistics were determined with Newey/West (1987) standard errors with four lags. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

Table 26 reports descriptive statistics of the proposed factors. All of these factors exhibit a positive average return that is statistically significant at least at the 5% level. Table 27 reports the correlation matrix of the proposed factors. As expected, F_PFLC and F_PFLS are strongly correlated. Generally, the three cat bond factors F_PFLC, F_SF and F_PFLS have only a low

Table 27: Correlation matrix for the proposed factors

	F_PFLC	F_SF	F_PFLS	TERM	DEF
F_PFLC	1.00				
F_SF	0.09	1.00			
F_PFLS	0.83	0.26	1.00		
TERM	-0.03	-0.03	-0.05	1.00	
DEF	0.03	0.02	0.04	-0.30	1.00

Note: This table reports correlation coefficients on the proposed factors.

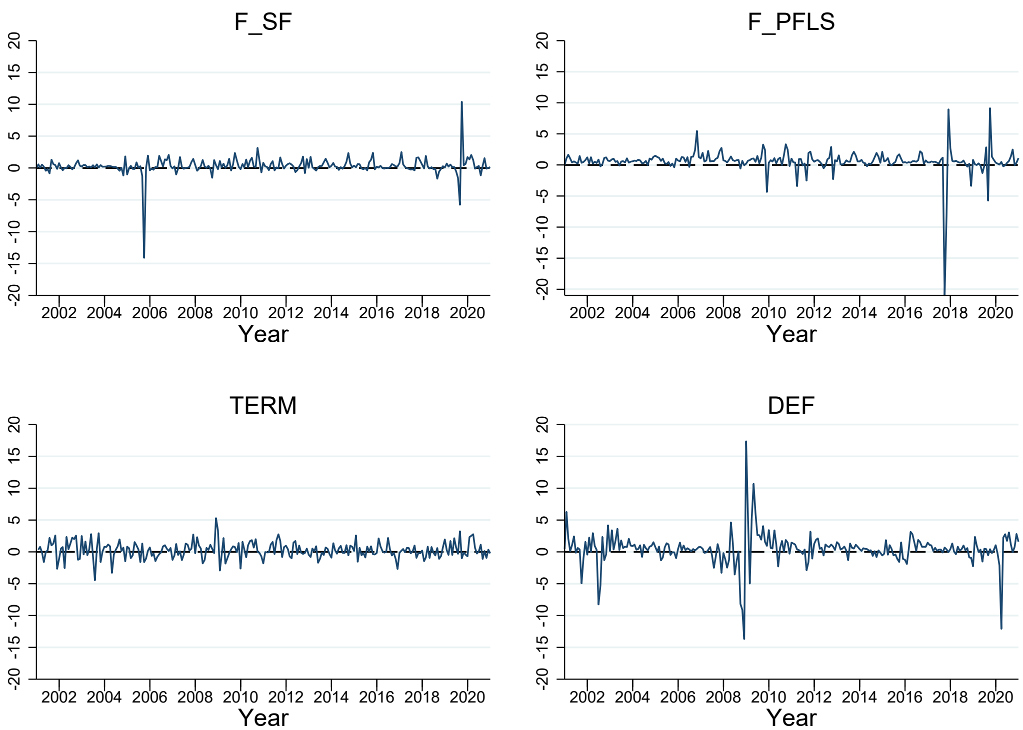
correlation with the two corporate bond factors TERM and DEF. Additionally, F_SF is only mildly correlated with P_PFLS and almost uncorrelated with F_PFLC.

Figure 10 plots the monthly time-series of the four factors F_PFLS, F_SF, TERM and DEF over the sample period from 2001-2020. While DEF strongly reflects the general financial market with the Financial Crisis 2009 and the crash associated with the Covid-19 pandemic in 2020, F_PFLC and F_SF strongly reflect adverse events in the cat bond market: In 2005, Hurricane Katrina adversely affected the cat bond market; although no cat bond ultimately defaulted,[117] we can observe a large draw down for F_SF. U.S. hurricane bonds during this 2005 hurricane season incurred large temporary losses when SF was naturally high for these bonds. Strikingly, F_PFLS does not show any sign of Hurricane Katrina. This indicates that not the most risky bonds in terms of PFLS were affected by these temporary losses but there was a markdown for U.S. HU bonds regardless of their PFLS. Next, we cannot observe the Tohoku Earthquake from 2011 in the F_PFLS time-series. The event caused two Japanese earthquake bonds to default. However, they were not part of the PFLS long or PFLS short portfolios. For F_PFLS, we observe its biggest draw down during the hurricane season of 2017, when hurricanes Irma, Harvey and Maria caused a multitude of cat bond defaults. Our cat bond index experiences its biggest draw down in September 2017. High PFLS bonds over-proportionally experienced losses because we do not observe a draw down in F_SF. Additionally, we can observe a partial bounce-back in the following month. F_SF highlights that the 2019 hurricane season only saw temporary draw downs on hurricane bonds so that these temporary losses were recovered in the consecutive month when feared losses did not materialize.

Now, we want to investigate if these factors actually explain the time-series of cat bond market returns and how much of the observable market return remains unexplained, i.e. how much alpha the market still exhibits after we use our factors to explain its returns. Table 28

[117] See the artemis.bm "Catastrophe bond losses: cat bonds defaulted, triggered or at risk" list.

Figure 10: The return of the four factors F_SF, F_PFLS, TERM and DEF.



Note: This figure shows the monthly returns of the four factors F_SF, F_PFLS, DEF and TERM over the time period 2001-2020.

contains time-series regressions of the monthly excess returns of the cat bond market index on different cat bond factor models.

In Model (1) we propose a simple one-factor cat bond model that only utilizes F_PFLC. Although this simple model does not account for seasonality, it already explains roughly a quarter of the cat bond market's returns expressed by its adjusted R^2 of 0.28. However, we observe a very large and significant alpha of 0.3% per month that we cannot explain with this model. Next, we include the F_SF that reflects the seasonality adjustment factor in Model (2). Its coefficient is highly statistically significant at the 0.1% level and increases the adjusted R^2 to 0.44. The remaining alpha drops to 0.23% per year. Now we add the seasonally adjusted monthly F_PFLS factor in Model (3) to see if it better explains market returns than F_PFLC and F_SF. Because PFLS essentially contains all information from PFLC and seasonally adjusts it, we are not surprised that the coefficient of F_PFLC is almost 0 and not statistically significant.

Instead, F_PFLS is highly statistically significant at the 0.1% level. At the same time F_SF remains statistically significant at the 5% level. This suggests that investors also price the general state of the season on top of the individual cat bond's exposure to the the same season as already captured by F_PFLS.[118]

Considering the previous result, we examine a two-factor cat bond model, whose factors are F_SF and F_PFLS. In Model (4), we observe that the adjusted R^2 increases to 0.56, which means that the model explains more than half the return variation observable on the cat bond market. The remaining alpha diminishes further to 0.21% but remains statistically significant. Next, we add the two corporate bond factors TERM and DEF from Fama/French (1993). We find that the cat bond market is related to TERM and DEF but these two factors have much less explanatory power than the cat bond factors PFLS and SF. The adjusted R^2 increases by roughly 3%-points as compared to Model (4), and the alpha diminishes by 0.05%-points to 0.16%.

Finally, we propose a four-factor cat bond pricing model consisting of the factors PFLS, SF, TERM and DEF. In the robustness check of Section 4.7.2, we also apply the Fama-French three-factor model (see Fama/French 1993) and Fama-French five-factor model (see Fama/French 2015) to the returns of the cat bond market. Except for the stock market factor, none of the Fama-French factors explains cat bond returns. We believe the stock market factor has a very small explanatory power because it captures some of the losses during the Financial Crisis in 2009 and the crash associated with the COVID-19 pandemic in 2020 that spilled over to the cat bond market.

In Figure 11 we illustrate the actual mean returns of 24 cat bond portfolios against the mean return predicted by two different cat bond factor models: the one-factor model with PFLC, and the four-factor model with PFLS, SF, TERM and DEF. The portfolios are the long portfolios, short portfolios and long-short portfolios of IND, MP, ML, HU, US, Maturity and Size. In addition, we generate two portfolios where we randomly draw ten bonds from the market; new bonds are randomly drawn when one of the ten bonds matures. For one portfolio, we use equal weighting, for the other portfolio we use value weighting. Finally, we include the market portfolio.

We can interpret these diagrams in the following way: Each marking represents one of the 24 portfolios and illustrates their mean actual return against their mean predicted return. The

[118]PFLS is essentially PFLC*SF.

Table 28: Explaining the market using a cat bond factor model.

	(1)	(2)	(3)	(4)	(5)
F_PFLC	0.242**	0.225**	-0.016		
	(0.001)	(0.004)	(0.897)		
F_SF		0.253***	0.180***	0.183***	0.183***
		(0.000)	(0.000)	(0.000)	(0.000)
F_PFLS			0.282*	0.269***	0.267***
			(0.016)	(0.000)	(0.000)
TERM					0.062**
					(0.008)
DEF					0.066**
					(0.005)
Constant	0.298***	0.227***	0.206***	0.205***	0.160***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Observations	240	240	240	240	240
R^2	0.279	0.447	0.565	0.565	0.601
Adjusted R^2	0.276	0.443	0.560	0.561	0.594

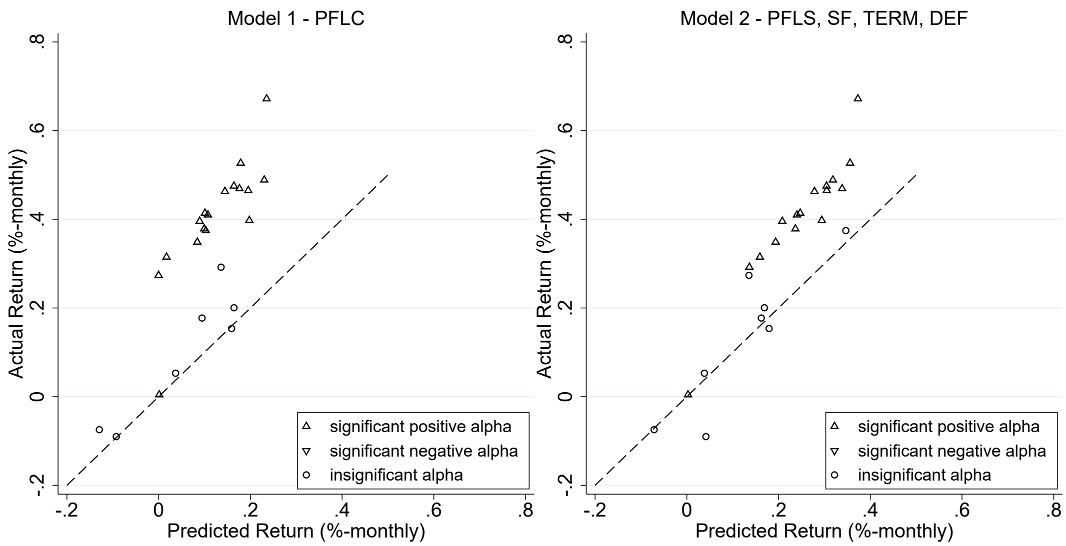
Note: This table reports time-series regressions of the monthly excess returns of the cat bond market index on different factor models. All factor returns are generated using long-short portfolios. The factors TERM and DEF are taken from Fama/French (1993). The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

distance to the bisector marks a portfolio's alpha. The further away it is from the bisector, the larger its alpha. If a portfolio is above the bisector, its alpha is positive; its alpha is negative if it is below the bisector. An upward (downward) pointing triangle marks a portfolio with an alpha that is positive (negative) and statistically significant, at least on the 10% level, whereas a circle marks portfolios with an alpha that is not statistically significant. Overall, a model is more accurate in terms of explaining more of a portfolios return, i.e. reducing alpha, if the markings in the diagram are closer to the bisector.

Generally, the portfolios move closer to the bisector as we go from Model 1 to Model 2. As already expected from Table 28, alphas appear to be smallest for the four-factor model (Model 2). Additionally, it becomes evident that most portfolios exhibit a positive alpha. Only two portfolios are below the bisector in Model 2. It is also quite interesting that most positive-alpha portfolios are clustered around a line almost in parallel to the bisector. This could indicate that investors demand a general fixed premium for holding one of these portfolios. This could be some form of cat bond surcharge or there could be more cat bond pricing factors that we have not discovered, yet.

Ultimately, we propose a four-factor cat bond pricing model that connects the two cat bond factors PFLS, as the seasonally adjusted probability of default, and SF, as the seasonality adjustment factor, with the two financial market bond factors TERM and DEF. Although this model already explains a very large proportion of the cat bond market returns, we still observe

Figure 11: Predictability of 24 cat bond portfolios with cat bond factor models.



Note: This figure illustrates the actual mean returns of 24 cat bond portfolios against the mean return predicted by two different cat bond factor models. Model 1 only includes the one-factor model with PFLC, and Model 2 the four-factor model with PFLS, SF, TERM and DEF. The bisector is drawn as the dashed line. The further away a portfolio is from the bisector, the larger its mean unexplained return, i.e. its alpha. A triangle that is pointing upwards represents a positive alpha that is statistically significant at least at the 10% level. Downward pointing triangles mark negative alphas that are significant at least at the 10% level. Circles mark portfolios with insignificant alphas.

alphas that are statistically significant and economically meaningful. This leaves room for future research: a) Cat bond returns could be more closely related to the general financial markets than anticipated by TERM, DEF and the other five Fama-French stock market factors. b) Due to data availability, we do not include a liquidity factor in our model. Illiquidity could explain a large proportion of the remaining alpha on the cat bond market.

4.6 Further empirical evidence

4.6.1 Time splits

We investigate how our cat bond factor model performs in different time periods. Table 29 contains results of the four-factor cat bond model for four sub-samples. Each of these sub-samples covers a time frame of 5 years: (1) 2001 - 2005, (2) 2006 - 2010, (3) 2011 - 2015, (4) 2016 - 2020.

Time split (1) from 2001 to 2005 is very close to the cat bond markets inception. Hurricane Katrina puts many cat bonds at risk but ultimately does not cause any losses to the cat bond market. It appears plausible, investors still grew accustomed to the new asset class and not many large loss events had yet taken place: PFLS is not strongly priced yet. Instead, it seems

Table 29: Performance of the cat bond factor model for different time periods.

	(1)	(2)	(3)	(4)
	2001-2005	2006-2010	2011-2015	2016-2020
F_SF	0.265***	-0.050	-0.247	0.162***
	(0.000)	(0.762)	(0.285)	(0.000)
F_PFLS	0.088	0.307**	0.627**	0.264***
	(0.341)	(0.009)	(0.005)	(0.000)
TERM	0.008	0.122*	0.124*	0.050
	(0.712)	(0.011)	(0.012)	(0.439)
DEF	0.027	0.059+	0.008	0.178***
	(0.345)	(0.066)	(0.913)	(0.000)
Constant	0.294***	0.223	0.232+	0.051
	(0.000)	(0.192)	(0.073)	(0.306)
Observations	60	60	60	60
R^2	0.678	0.374	0.524	0.819
Adjusted R^2	0.655	0.328	0.489	0.806

Note: This table reports time-series regressions of the monthly excess returns of the cat bond market index on the four-factor cat bond model. The sample is split into four sub samples of equal length: 2001-2005, 2005-2010, 2011-2015, 2016-2020. All factor returns are generated using long-short portfolios. The factors TERM and DEF are taken from Fama/French (1993). The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

investors demand a general seasonality surcharge as expressed by SF that does not take the individual cat bonds riskiness into account. This is supported by the market's tremendous alpha of 0.29 % per month. This alpha is highly statistically significant. TERM and DEF are positive but not statistically significant.

Time split (2) from 2006 - 2010 is characterized by the financial crisis. Investors appear to evaluate the individual cat bond's riskiness more strongly expressed by the now significant PFLS. Instead, SF becomes insignificant. The financial crisis could highlight the connection of cat bond market and other financial markets: TERM and DEF are positive and significant. At the same time, the alpha becomes insignificant with a value of 0.22% per month.

Time split (3) from 2011 - 2015 sees high returns. The Tohoku earth quake from 2011 causes some losses but generally the market proves very resilient. SF is strongly priced and the cat bond market is still connected to the financial markets as expressed by the statistically significant TERM coefficient.

Time split (4) from 2016 - 2020 suffers from increasing cat losses and temporary losses from the crash associated with the Covid-19 pandemic. Interestingly, we observe the highest adjusted R^2 of more than 0.80 during this difficult market phase. PFLS, SF and DEF are highly statistically significant. Probably due to high losses, alpha shrinks to only 0.05% per month and is not statistically significant.

Overall, the four-factor cat bond model performs well throughout the four time splits. It seems that each of the four factors is able to capture different market characteristics. The explanatory power varies but remains high throughout the four time periods.

4.6.2 Downside scenarios

Table 30: Cat bond returns in downside scenarios.

	(1)	(2)	(3)
F_SF	0.183***		0.193**
	(0.000)		(0.006)
F_PFLS	0.267***		0.170*
	(0.000)		(0.011)
TERM	0.062**		0.037+
	(0.008)		(0.095)
DEF	0.066**		0.045*
	(0.005)		(0.015)
Katrina		-3.918***	-0.945
		(0.000)	(0.335)
Lehman		-2.078***	-1.101***
		(0.000)	(0.000)
Tohoku		-4.051***	-3.188***
		(0.000)	(0.000)
Irma/Maria		-6.728***	-3.232*
		(0.000)	(0.033)
California wildfires		-0.226***	-0.113*
		(0.000)	(0.025)
Michael		-2.163***	-1.395***
		(0.000)	(0.000)
Covid-19		-2.048***	-1.704***
		(0.000)	(0.000)
Constant	0.160***	0.515***	0.281***
	(0.001)	(0.000)	(0.000)
Observations	240	240	240
R^2	0.601	0.498	0.700
Adjusted R^2	0.594	0.482	0.686

Note: This table reports time-series regressions of the monthly excess returns of the cat bond market index on the four-factor cat bond model. In addition, several event variables are introduced. All factor returns are generated using long-short portfolios. The factors TERM and DEF are taken from Fama/French (1993). The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

We further investigate downside scenarios in Table 30 where we introduce various event risk dummies to capture the effects of adverse events on market returns. For each event, we define a dummy variable that a) takes a value of one in the month where the respective event occurs and b) is zero otherwise. We analyze the impact of the following events: Hurricane *Katrina* (September 2005), the default of *Lehman Brothers* (September 2008), the *Tohoku* earthquake (March 2011), hurricanes Irma and Maria (September 2017), the *California wildfires* (July 2018), hurricane *Michael* (which occurred in October 2018 but we mark it in November 2018 because most losses materialized there), and the crash associated with the *Covid-19* pandemic (March 2020).

Model (1) contains the four-factor cat bond model. Model (2) uses the event variables without the four-factor cat bond model, while Model (3) combines both. In Model (2), we find that roughly half of the cat bond market's returns can be explained by the event variables. The market saw the largest losses from hurricanes Irma and Maria in 2017. The coefficient indicates that this effect depressed returns by 6.7%-points for this month. Hurricane Katrina and the Tohoku earthquake also had strong negative effects on the market (-3.9%-points and -4.1%-points, respectively). On the contrary, the default of Lehman Brothers in the 2008 and the crash associated with the Covid-19 pandemic only had a negative impact on returns of -2.1%-point and -2.0%-points, respectively. Hurricane Michael in 2018 had an effect of the same magnitude as Lehman, while the California wildfires of 2018 dampened returns only very mildly (-0.23%-points). In Model (3), we combine the cat bond four-factor model with the event variables. Compared to Model (1), the adjusted R^2 increases only by 0.10, although the event variables alone in Model (2) have an adjusted R^2 of 0.48. This indicates that much informational content of these event variables is already captured in our four-factor cat bond model. This notion is further supported by the fact that the coefficients of the event variables decline substantially from Model (2) to Model (3). Additionally, all factors from our four-factor model remain statistically significant when we include the event variables.

4.6.3 Liquidity

The role of liquidity as a relevant state variable for the cross-section of expected asset returns dates back to the seminal work of Pastor/Stambaugh (2003). Herrmann/Hibbeln (2020) show that a cat bond's yield spread is related to its liquidity. They quantify a liquidity premium of roughly 20% relative to the entire yield spread, using observable bid-ask spreads from actual trades reported in TRACE as a liquidity measure. Although the time frame of TRACE data is relatively short (July 2014 to December 2020) and some bonds go for many months without an observable trade leaving gaps in the panel data set, we investigate illiquidity as a potential factor driving cat bond returns.

As a measure for illiquidity, we use the realized bid-ask spreads observable in TRACE data. Higher bid-ask spreads indicate higher illiquidity, which in turn could be associated with higher expected cross-sectional returns. We obtain the Standard TRACE data set from WRDS for BTDS-144A type bonds, which contains cat bonds. For each trade, we observe the CUSIP of the bond traded, the date and time of each trade, its price, and the reporting side of the trade ("buy" or "sell"). Every transaction that passes through a dealer is recorded twice: 1. The dealer buys the bond from an investor ("buy") and then sells it to another investor ("sell"). The difference between buy price and sell price then yields the bid-ask spread. Since we lack a unique identifier that directly connects these buys and sells, we instead rely on the matching algorithm from Herrmann/Hibbeln (2020) to match buys and sells. The five matching criteria are as as follows:

1. Both associated trades have to be from the same bond.
2. One "buy" is matched to one "sell" and vice versa.
3. The volume of both trades has to be the same.[119]
4. Both trades have to occur in a time window of 60 min.
5. Every trade must not already have another match.

In TRACE, we observe 18627 trades for 335 cat bonds in the given time frame. We do not observe 83 cat bonds of the corresponding broker data set because these bonds are mostly European bonds and not TRACE eligible. We then apply the Dick-Nielsen (2014) filter to this raw TRACE data set and are left with 18147 trades.[120] After applying the matching algorithm outlined above, we obtain 14776 bid-ask spreads. As our final measure, we use the bid-ask spread relative to the midpoint between buy and sell price. To account for outliers and potential mismatches, we winsorize these bid-ask spreads at the 2.5% and 97.5% levels. Since we otherwise still rely on the monthly broker data set for cat bond returns and return factors, we determine the mean bid-ask spread per month for each cat bond to obtain monthly bid-ask spreads for TRACE eligible cat bonds. For these 335 TRACE eligible cat bonds, this yields 3675 bond-month observations of mean bid-ask spreads. On the contrary, we have 9672 bond-month observation for the same cat bonds within the given time frame in the broker data set. This means that cat bonds can go for multiple months without any recorded trades highlighting their illiquid nature. However, this lack of trades also leaves large gaps in the monthly panel data set. To cope with this issue of missing bid-ask spreads, we backfill missing values with the last known bid-ask spread of the corresponding bond. We then use the established method of sorting bonds according to their illiquidity to obtain an illiquidity factor:We determine the return difference between the quintile portfolios of the cat bonds with the highest and the lowest bid-ask spreads

[119]For Standard TRACE trading volume is capped at USD 1 million.

[120]We use this filter to correct for cancellations, corrections, and reversals in the raw TRACE data. The Dick-Nielsen (2014) filter originally applies to Enhanced TRACE data, while Dick-Nielsen (2014) filters Standard TRACE data. Although we have a Standard TRACE data set, we decided to use the Dick-Nielsen (2014) filter because it is more recent and accounts for structural changes in TRACE reporting in 2012.

for each calendar month. As usual, these portfolios are readjusted on a monthly basis.

If we find evidence for an illiquidity premium in the cross-section of cat bond returns, we should observe a positive and statistically significant coefficient for the illiquidity factor (F_ILLIQ). Table 31 compares the established four-factor model to a potential five-factor model that adds the illiquidity factor (F_ILLIQ); both of these models are applied to the limited time frame of July 2014 to December 2020. The established four-factor model in Model (1) performs quite well during this period. The adjusted R^2 is very high while alpha is low and statistically insignificant. The factors, except TERM, are strongly statistically significant. On the contrary, adding the illiquidity factor in Model (2) does not lead to substantial changes. The adjusted R^2, alpha, and factor coefficients remain almost unchanged. The added illiquidity factor is positive but small and not statistically significant. Hence, we do not find any evidence for an illiquidity premium in the cross-section of cat bond returns.[121] Though, we note that this result does not imply that there is no illiquidity premium in the cross-section of cat bond returns. As Herrmann/Hibbeln (2020) have identified a significant liquidity premium in yield spreads, we rather believe that TRACE data for cat bonds is still too scarce to identify an illiquidity premium in the cross-section of cat bond returns in a factor model setting.

Table 31: Explaining the market using a cat bond factor model including a liquidity factor.

	(1)	(2)
F_SF	0.265***	0.268***
	(0.000)	(0.000)
F_PFLS	0.157***	0.162***
	(0.000)	(0.000)
TERM	0.060	0.059
	(0.261)	(0.280)
DEF	0.163***	0.163***
	(0.000)	(0.000)
F_ILLIQ		0.039
		(0.606)
Constant	0.065	0.061
	(0.160)	(0.193)
Observations	78	78
R^2	0.801	0.803
Adjusted R^2	0.790	0.789

Note: This table reports time-series regressions of the monthly excess returns of the cat bond market index on different factor models including a liquidity factor based on bid-ask spreads from TRACE. The time period is limited to July 2014 to December 2020. All factor returns are generated using long-short portfolios. The factors TERM and DEF are taken from Fama/French (1993). The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

[121] We also used an illiquidity factor without backfilling bid-ask spreads in months where no bid-ask spreads could be observed. Here, the coefficient for F_ILLIQ is negative but also small and not statistically significant.

4.7 Robustness checks

4.7.1 Default cutoff

In Section 4.3.1 we discuss the default cutoff of 50, which means we drop all observation of a bond after its prices drops to or below 50, essentially assuming investors would sell a bond immediately when it reaches or breaches this threshold of 50. Generally, a higher cutoff means that default observations are less present in the data set. Since this cutoff appears arbitrary, we run a sensitivity analysis of the multivariate Fama/MacBeth (1973) regression of Model (8) as reported in Table 24 with respect to the default cutoff. In Figure 12, we increase the cutoff from 5 to 90 in steps of five. The thick line marks the estimated coefficients for each cutoff point. The dashed lines mark the 90% confidence interval. Generally, the Fama/MacBeth (1973) results are insensitive to the choice of the default cutoff as we do not observe strong changes in coefficient size when we increase the cutoff. Only HU becomes significant as the cutoff surpasses 75. IND is just barely significant for some cutoff values and becomes insignificant after a cutoff of 55. This supports our decision to exclude IND as a priced cat bond factor. Its statistical significance is generally low.[122]

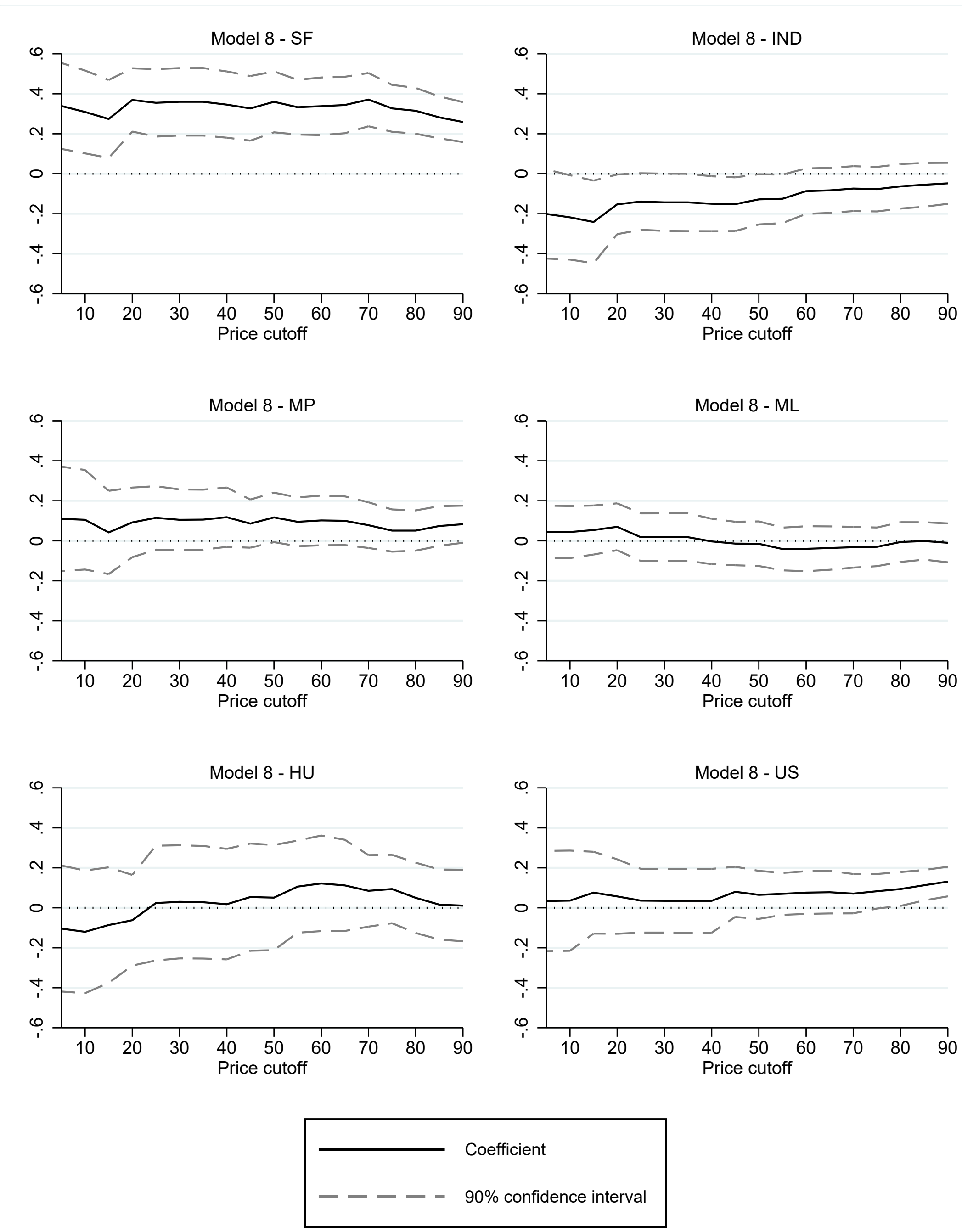
4.7.2 Fama-French factor models

We apply the Fama-French three-factor model (Mkt-RF, SMB, HML) with TERM and DEF from Fama/French (1993) and the Fama-French five-factor model (Mkt-RF, SMB, HML, RMW, CMA) to the cat bond market returns to see if these stock market factors are related to cat bond returns. We compare the performance of these models to our four-factor cat bond model. All Fama-French factors are directly taken from the Keneth R. French data library. Table 32 uses the same setting as Table 28 as it reports time-series regressions of the monthly excess returns of the cat bond market index on different factor models.

Model (1) reports results on the cat bond four-factor model, while Model (2) applies the Fama-French three-factor model complemented with Term and DEF. We observe a very low adjusted R^2 of 0.04 in Model (2). Only the market factor Mkt-RF is statistically significant. Model (3) uses the five stock market factors from the Fama-French five factor model. Again, Mkt-RF is statistically significant. In addition, RMW is slightly significant at the 10% level but

[122] We also run the same sensitivity analysis for the bivariate models (2) - (7) in Table 24. Again, results are insensitive to the choice of the default cutoff. In addition, we perform this sensitivity analysis for PFLC across all models in Table 24. The coefficient for PFLC increases slightly as the cutoff increases and remains highly statistically significant for all cutoff values. Detailed results are available upon request.

Figure 12: Sensitivity analysis regarding varying default cutoffs (multivariate).



Note: This figure reports the coefficient of the the Fama/MacBeth (1973) from Table 24 with respect to different default cut offs for the complete Model (8), where all variables are used at once. The thick line marks the coefficients. The dashed line marks the 90% confidence intervals.

Table 32: Explaining the market return using different factor models.

	(1)	(2)	(3)	(4)	(5)
F_SF	0.183***			0.182***	0.183***
	(0.000)			(0.000)	(0.000)
F_PFLS	0.267***			0.268***	0.268***
	(0.000)			(0.000)	(0.000)
TERM	0.062**	0.062		0.088***	0.087***
	(0.008)	(0.208)		(0.000)	(0.001)
DEF	0.066**	0.043		0.034+	0.031
	(0.005)	(0.123)		(0.094)	(0.103)
Mkt-RF		0.029**	0.045**	0.029**	0.030**
		(0.008)	(0.001)	(0.005)	(0.007)
SMB		-0.008	0.001	0.001	0.003
		(0.725)	(0.978)	(0.944)	(0.833)
HML		0.021	0.014	0.021*	0.025
		(0.409)	(0.596)	(0.046)	(0.125)
RMW			0.038+		0.010
			(0.056)		(0.522)
CMA			0.005		-0.016
			(0.811)		(0.512)
Constant	0.160***	0.376***	0.386***	0.151**	0.150**
	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)
Observations	240	240	240	240	240
R^2	0.601	0.059	0.050	0.618	0.619
Adjusted R^2	0.594	0.039	0.030	0.607	0.604

Note: This table reports time-series regressions of the monthly excess returns of the cat bond market index on different factor models. These factor models are the Fama-French three-factor model (Mkt-RF, SMB, HML) with TERM and DEF from Fama/French (1993) and the Fama-French five-factor model (Mkt-RF, SMB, HML, RMW, CMA). All factor returns are generated using long-short portfolios or directly taken from the Keneth R. French data library. The symbols +, *, ** and *** indicate statistical significance at the 10%, 5%, 1% and 0.1% levels, respectively.

we believe this is a random artifact. Overall the five stock market factors in Model (3) only lead to an adjusted R^2 of 0.03. In Models (4) and (5), we combine the Fama-French three-factor model and the Fama-French five-factor model with our four-factor cat bond model. For both models, the adjusted R^2 barely increases by 0.01 compared to Model (1). All Fama-French factors except for Mkt-RF remain statistically insignificant. DEF loses its statistical significance, which could be due to the correlation with Mkt-RF.

To sum up, we do not find an economically meaningful relation of stock market factors and the cat bond market returns. The Fama-French three-factor model and the Fama-French five-factor model have very low explanatory power and do not explain the returns on the cat bond market, so we do not include any of these stock factors into our cat bond factor model. However, there appears to be a very small exposure to the Mkt-RF factor, even if its explanatory power is small. Further investigation of this relation can be topic for future research.

4.8 Conclusion

Although the asset class of cat bonds have achieved exceptional high returns associated with low volatility and low correlation to other asset classes during the last 20 years, there exists no cat bond factor model to explain actual observable returns in the literature. We fill this gap by exploiting a unique cat bond data set of monthly quoted cat bond prices. This data set spans the complete cat bond market over the 20 years from 2001-2020. Hence, we propose the first cat bond factor model to explain the cross-section of cat bond returns. From a large group of candidates we select four factors to propose a four-factor cat bond pricing model. These four factors are: first, the seasonality adjusted probability of first loss (PFLS), second, the seasonality adjustment factor (SF) and third, the corporate bond market factors TERM and DEF.

PFLS and SF are unique to the cat bond market. As opposed to corporate bond ratings, the PFL in cat bonds is a continuous variable modelled by specialized risk modelling firms.[123] PFLS and SF are formed through the introduction of seasonal fluctuations in the peril events U.S. hurricanes and European winter storms. In the language of corporate bond ratings, a cat bond can move from AAA outside its respective season to "junk" and back within a calendar year. We used the following four steps to ultimately propose our four-factor cat bond model:

First, we created a group of candidates of potential cat bond factors. These candidates were composed of event risk variables (PFLC, PFLS, SF), a downside risk factor (CEL), and the bond property factors indemnity, multi-peril, multilocation, hurricane and U.S. (IND, MP, ML, HU, US). Second, we used independent univariate and bivariate portfolio sorts as well as Fama/MacBeth (1973) regressions to restrict this field of candidates to the candidates, that are able to explain the cross-section of one-month ahead returns. Here, we did not find any evidence that the downside risk factor and the bond property factors predict the cross-section of cat bond returns. Third, we created factor returns for the leftover candidates PFLC, PFLS and SF by creating long-short portfolios for these factors. We find that only PFLS and SF explain the time-series of the cat bond market returns if all three event risk factors are included. Fourth, we add the corporate bond factors DEF and TERM from Fama/French (1993) to the preliminary two-factor cat bond model and find that they also explain a small proportion of the cat bond market returns. Ultimately, we propose the four-factor cat bond model that consists of PFLS, SF, TERM and DEF.

[123] For a detailed discussion on seasonality in yield spreads on the secondary cat bond market, please refer to Herrmann/Hibbeln 2021.

Using the cat bond four-factor model, we are able to explain roughly 60% of the time-series of cat bond market returns. However, even if the alpha is substantially reduced, we still observe a statistically significant and economically meaningful abnormal return of 0.16% per month. This indicates the existence of other risk factors such as an illiquidity factor, which is supported by Herrmann/Hibbeln (2020) who find that roughly 20% of the cat bond market's yield spread can be explained by illiquidity. Even if we did not find statistical evidence for this factor in a preliminary analysis, this could easily result from current data restrictions.[124] An alternative explanation for these abnormal returns is that the cat bond market is more closely related to other financial markets than captured by the two corporate bond market factors from Fama/French (1993) and the five stock market factors from Fama/French (2015). The illiquidity premium in cat bond returns and the relation of cat bond returns to other financial markets leave room for future research.

[124] TRACE data only begins in July 2014, leading to a very short time period for creating a cat bond factor model. However, this will eventually change in the future.

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Erklärung nach § 10 (6) PromO der Mercator School of Management

Hiermit versichere ich, dass ich die vorliegende Dissertation selbständig und ohne unerlaubte Hilfe angefertigt und andere als die in der Dissertation angegebenen Hilfsmittel nicht benutzt habe. Alle Stellen, die wörtlich oder sinngemäß aus anderen Schriften entnommen sind, habe ich als solche kenntlich gemacht.

Wuppertal, 15. April 2021 Markus Herrmann

DOI: 10.17185/duepublico/75011
URN: urn:nbn:de:hbz:464-20211209-092619-7