Catastrophe and Corporate Bonds: A Unified Approach to Pricing Natural Disaster Risks

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Abstract

This paper derives a unified model for both catastrophe and corporate bonds to study the implications of natural disaster risks. We obtain arbitrage-free valuations that are intuitive and easy to implement empirically. We illustrate their application to quantify financial risks from hurricanes and wildfires. Results show that market implied catastrophe (cat) event probabilities are materially larger than the corresponding statistical probabilities, especially for wildfires, implying significant cat event risk premium. These cat event probabilities are used to decompose corporate bond default probabilities into business and cat risks (with extension to municipal bonds). We show that cat risks in exposed corporate bonds are time varying, and that they increase and remain persistent after major cat events, reflecting heightened market uncertainty. Our approach can be used by investors and policymakers to understand the broader financial implications of natural disaster risks.

Keywords: Catastrophe bonds, Corporate bonds, Natural disaster risk, Default risk, Catastrophe risk premium.

JEL Codes: G12, G22

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1 Introduction

The increasing frequency and severity of natural disasters such as hurricanes, floods, and wildfires are generating correspondingly increasing economic and financial losses. There is a growing body of literature studying the effects of climate-related risks and natural disasters on the overall economy and different segments of the financial markets. In particular, evidence continues to grow that natural catastrophe risks significantly increases the credit (and potentially bankruptcy) risks of corporations, municipalities, and sovereigns exposed to these hazards, subsequently raising their funding costs, with potential for financial stability implications (see Acharya et al. (2024), Kruttli et al. (2025), Goldsmith-Pinkham et al. (2023), Giglio et al. (2021)). However, at present, there is a lack of analytically tractable and easily implemented valuation models that decompose a corporate bond's credit risks into those due to natural disasters and those due to ordinary business operations.

The purpose of this paper is to provide such a framework and illustrate its empirical application. This is done by exploiting the information contained in catastrophe (cat) bond markets to identify the relevant cat event probabilities, which are then used to help quantify the credit risks of bonds issued by corporations that are exposed to these cat events (with extension to municipal bonds). Historically, these two bond markets have been studied separately in the literature. In contrast, this paper provides a unified framework for simultaneously studying both markets.

Cat bonds are risk-transfer instruments in the class of insurance-linked securities, that enable re/insurance companies and other economic entities to transfer risks from natural catastrophes such as hurricanes, earthquakes, and wildfires to the capital markets. The cat bond market has seen exponential growth in recent years, approaching \$57 billion notional in 2025, with \$21 billion of issuance compared to \$7 billion issuance a decade earlier (see Artemis.bm). This signals the growing importance of cat bonds in reducing insurance protection gaps from natural disasters. In addition, a critical feature of cat bond returns is that they are largely uncorrelated to traditional asset returns (equities, derivatives, bonds etc.) and broader macro-financial conditions, thereby facilitating portfolio diversification, as the risks are driven by referenced natural disasters. Because of the risks, although cat bonds are fully collateralized and generally offer higher (double-digit) returns, if the cat event occurs the entire principal can get wiped out (see Braun and Kousky (2021), Cummins (2008), Chicago Fed Letters (2018) for general details on cat bond markets).

Valuation models are available for both cat bonds (see Jarrow (2010), Ma and Ma (2013), Beer and Braun (2022)) and corporate bonds based on the well established reduced-form credit risk model (see Jarrow and Turnbull (1995), Jarrow (2009), Bakshi et al. (2022), Hilscher et al. (2025)). Our paper extends the model in Hilscher et al. (2025) to include the impact of cat risks by decomposing the firm's default probabilities into those due to ordinary business operations and those due to catastrophe events. We also extend the cat valuation model in Jarrow (2010) by modifying its assumption in two ways to facilitate computation and empirical estimation. The cat and default events in catastrophe and corporate bonds, respectively, are captured by suitably modeled Poisson intensities along with loss rates, under the standard martingale pricing framework. As such, we provide a unified, intuitive and simple arbitrage-free pricing methodology for both corporate and cat bonds, that is directly useful to practitioners and policy makers.

We first illustrate the model numerically with respect to cat bond prices. We show that the relation among cat risks, time to maturity, and spreads is highly nonlinear. While a cat bond's price is generally sensitive to maturity, declining as maturity increases (consistent with findings in the literature), this holds only for bonds with relatively lower spreads. For cat bonds with larger spreads, the impact is reduced, and in fact, the bond value may increase if the catastrophe risk is relatively low. However, if cat risk and maturity both increase, the bond values decline uniformly, and this impact is more pronounced for bonds with lower spreads. For corporate bonds, we find that long maturity bonds are more responsive to larger risk exposures, consistent with the empirical findings that lower-quality and longer maturity bonds generally exhibit higher yield spreads or face larger issuance costs (see Acharya et al. (2024) and Painter (2020)).

The sample period for our empirical analysis is from April 2018 to the end of 2025. For the cat bond model, we focus on two categories of cat bonds referencing risks from US named storms/hurricanes and wildfires. These two perils are arguably the most important and represent the largest segments of the cat bond markets in the US, thereby providing an ideal setting for our investigation (see Section 4 for more details on the data).

Using our closed form solution, we calculate market implied cat event intensities/probabilities at the individual cat bond-tranche level for both hurricanes and wildfires. We find that these market implied cat event probabilities and expected losses are significantly larger than those indicated by the initial modeled estimates contained in issuance documents relating to the attachment probability (i.e. probability of first loss) and the expected loss.[1] In particular, the

[1]These modeled risk metrics are provided by specialized scientific modeling firms as part of investor disclosures during cat bond issuance. Thus, these represent benchmark statistical estimates against which the analogous metrics from our model can be compared to compute risk premium. See Section 4.1 for more details.

average market implied cat risk in hurricane-linked cat bonds is about 3 times larger than the ones implied by the corresponding statistical estimates, showing significant hurricane-linked cat risk premium. For the wildfire-linked cat bonds, the market implied risk is even larger, about 6 times the statistical estimates.[2] This distinction between hurricane and wildfires is also visible in the corporate/municipal credit risk decomposition. Since cat event intensities correspond to a given region, the implied cat bond risk premium can be applied to other financial assets/instruments exposed to same peril in the same region (e.g., equities, bonds, mortgages, borrowing/funding rates etc.). We apply this insight to corporate bonds.

From the individual cat bonds, we construct a monthly index of implied cat risk for both hurricane and wildfire risks, as bond tranche weighted averages. Because cat bond prices reflect risks from natural disasters, our estimated aggregate market implied cat event intensities can be used to obtain the market implied cat risks embedded in the corporate bonds from the same region. Using this cat risk index, we decompose a corporate bond's credit risk into two independent components: (i) standard business risks, and (ii) cat risks. Note that, while the model is described with reference to a corporation, it is generally applicable to other credit risky entities such as municipalities and sovereigns. To illustrate this, we also apply our approach to municipal bonds.

Almost all hurricane linked cat bonds reference Florida (the state prone to hurricane risks) and all wildfire cat bonds reference California (the state prone to wildfire risks). Therefore, to illustrate the empirical implementation of our model we find large firms that have: (i) predominant business activities in Florida (for hurricanes) or California (for wildfires risk), and (ii) actively traded bonds. We obtain six such representative bonds in our sample period (2018 to 2025) issued by firms and municipalities: two firms in Florida, including Miami-Dade county's municipal bond, and two firms in California, including a municipal bond in the Los Angeles (LA) region. Since the revenues and/or productive assets of the entities issuing these bonds are within these locations, we can quantify the relevant cat risks embedded in these bonds. A benefit of this approach is that the estimated cat event intensities can be used to understand the potential impact of cat risks on other firms in the same region without actively traded bonds or financial instruments.[3]

Results on Florida hurricane risks in the corporate/municipal bonds show that on average

[2]This might be attributable to relatively less advanced wildfire risk modeling capabilities relative to hurricanes (see Section 4.1), and greater uncertainty since wildfires can last for months while hurricane durations are relatively shorter. These differences may prompt investors to demand a larger risk premium.

[3]For firms whose assets/revenues are geographically diversified, isolating the impact of cat risks from total credit risk becomes empirically challenging. The reason is that a single cat event in one region alone is very unlikely to affect the default probabilities significantly enough to be empirically discernible.

cat risk accounts for about 7-13% of the bond's total credit risk over our full sample period. This shows the heterogeneous effects of hurricanes for entities within the region facing the same risks. In our sample period, hurricane Ian is the most damaging (it is the third most costly hurricane in US history (see National Oceanic and Atmospheric Administration (NOAA)). We show that after hurricane Ian, there are significant and persistently larger cat event intensities, consistent with the large damages experienced. In particular, during the 3-month period after Ian's landfall, the bonds' credit risks increased sharply, where the embedded cat risk accounts for over 30-40% of the total risks on average. This is due to a significant increase in the market's risk aversion via increased cat risk premium since the cat event statistical probabilities as given in the cat bond issuance market do not change. This outcome has practical implications because it implies larger credit spreads and greater funding costs for both the corporates and municipalities.

Similar results are observed for wildfire risks in California, except that the effects are more persistent. Over our sample period, the average cat risk accounts for about 6-18% of a bond's credit risk for corporates, but about 55% for LA municipal bonds (although the credit risk levels are much smaller when compared to corporate bonds). Our time period includes the recent 2025 Palisades and Eaton wildfires in the LA region, which to date are the most damaging wildfires in global history (see Gallagher Re (2025)). We see large spikes in the cat event intensities near this period and elevated risks in the aftermath. For the 3-month period after the Palisades fire, 23% of risks in corporate bonds are attributable to cat events, and about 55% for LA municipal bonds. Relative to hurricanes, the market implied wildfire risks in California exhibit a persistence over time reflecting the market's concern about wildfires. This is also consistent with the observation that the average risk premium in wildfire cat bonds are significantly larger than those in hurricane cat bonds, thereby reflecting larger uncertainty surrounding the impact of wildfires.

Our model (see expressions (7) and (12) in Section 2.3) also has practical implications for investors, industry practitioners, and policy makers. First, the market implied cat event intensities can be used for other firms and businesses, including small-and-medium enterprises (SMEs), in the same region to estimate the impact of cat events on their default probabilities. Second, banks can use our model to quantify the impact of disaster risks on their loan/bond portfolios and loss provisions. Last, our model can also be used by policymakers to estimate the impact of natural disasters on market-wide credit and funding risks, and therefore financial stability.

Related Literature and Policy Discussion: This paper contributes to two separate strands of the literature: (i) the growing literature studying the effects of climate-related physical risks from natural disasters and extreme weather events (e.g., hurricanes, wildfires, heatwaves, floods etc.) in different segments of financial markets, and particularly on credit spreads and funding costs of corporates and municipalities, and (ii) the catastrophe bond pricing and derivatives literature.[4]

With respect to the first strand of the literature, Acharya et al. (2024) find economically substantial effects on credit spreads for corporate and municipal bonds, and higher conditional expected stock returns, for entities exposed to heat stress. Jeon et al. (2024) find that municipalities exposed to higher wildfire risks face increased borrowing costs. Painter (2020) finds that municipal bonds more exposed to a rise in sea level face higher spreads and cost of capital. Goldsmith-Pinkham et al. (2023) show that municipal bond markets began pricing sea-level increase risk around in 2013.[5] Kruttli et al. (2025) show a large and persistent equity option implied volatility increase for firms with establishments in a hurricane's landfall area, indicating that investors account for NOAA's hurricane forecasts when pricing options. We contribute to this literature by showing the impact of cat risk on corporate and municipal bond default risk intensities and equivalently on the credit spreads, using an arbitrage-free, reduced form credit risk valuation model (see Duffie (1999), Duffie et al. (2003), Driessen (2005), Bakshi et al. (2006), and Jarrow (2009) and Bakshi et al. (2022) for reviews) as applied to cat bonds. In particular, our findings on the persistently larger cat risk reflected in corporate/municipal bond prices in the aftermath of major hurricanes is consistent with similar findings from Kruttli et al. (2025) using equity options. In addition, our results document a greater degree of persistence in cat event risk premium due to wildfire risks.

With respect to the cat bond pricing literature, Jarrow (2010) introduced the first general methodology for arbitrage-free cat bond valuation by applying the reduced form credit risk pricing model to cat risk events under a general stochastic interest rate process. Beer and Braun (2022) use the Jarrow (2010) model to compute implied Poisson intensities from a cross-section of cat bond market prices obtained from a global reinsurance brokerage firm.

[4]See survey articles by Giglio et al. (2020), Hong et al. (2020), Acharya et al. (2023) for comprehensive reviews on the asset pricing implications and see Cummins (2008), Braun (2016), Major (2019) for the general catastrophe bond market literature.

[5]Similarly, Nguyen et al. (2022) find that real estate exposed to greater seal level increases face higher interest rates, after controlling for borrower creditworthiness, whereas Giglio et al. (2021), Bernstein et al. (2019) and Baldauf et al. (2020) show that exposure to sea level increases are reflected in residential house prices. Hong et al. (2019) show food industry stock prices react slowly to projected increases in drought exposure while Alok et al. (2020) document overreaction to natural disasters by exposed mutual funds.

Our paper generalizes the Jarrow (2010) model in two ways. First, we remove assumptions concerning the floating rate and its approximate value in the original formulation. Second, we add a conditional independence assumption (explained in the text), analogous to that in Hilscher et al. (2025), to simplify the valuation formulas. The resulting valuation expressions are intuitive and easy to compute. Similar to Beer and Braun (2022) we obtain market implied cat event Poisson intensities from hurricane and wildfire cat bonds and further document the impact of cat risk on bond prices (funding risk) and the existence of significant cat event risk premium, which is especially pronounced in the wildfire cat bonds.[6]

We note that the empirical cat bond literature has found the statistical expected loss as a key driver of cat bond spreads in primary markets (see Lane and Mahul (2008), and Dieckmann (2009)), Braun (2016)) for more details). We find that market implied expected losses (which directly related to market spreads and cat event intensities) are highly correlated with the statistical expected losses. However, a large portion of the variation in estimated market implied cat intensities are not explained by the statistical expected losses, confirming the presence of significant risk premium in cat bond markets.

Our paper also contributes to ongoing discussions on the financial stability implications from the growing frequency and severity of natural disasters (see Adrian et al. (2022) New York Fed (2024), FSB (2025), ECB (2025)). For example, concentration of exposed borrowers in high-risk areas can affect the banking sector's health when natural disasters occur (e.g. due to increased borrower credit risk, reduced debt collateral value etc.). BIS (2025) recently noted a lack of methodologies for factoring in cat risks when valuing risky debt instruments like bonds and loans, and for determining loss provisions and capital. Our valuation model fills this gap, as discussed above, while also providing policymakers with an intuitive and easy to implement approach to investigate such issues. In this context, an emerging area of concern relates to the financial stability implications due to cat risk insurance protection gaps (i.e. portion of economic losses not covered by insurance), see ECB (2025). This is because cat risk protection gaps in a region can cause significant losses that strain the balance sheets of corporates, local and national governments, and banks, and this effect can

[6]Relatedly, Ma and Ma (2013) price cat bonds using a one-factor Cox-Ingersoll-Ross model in an incomplete market setting assuming the cat event is diversifiable risk. There are also papers related to cat option pricing where the markets modeled are incomplete because the underlying cat event loss process is not traded. Bakshi and Madan (2002) price assuming a complete market. Chang et al. (2010) use indifference pricing based on a power utility function. Dassios and Jang (2003) and Braun (2011) assume a martingale measure exists, but do not specify the unique measure to use in pricing. In a related paper, Zanjani (2002) prices insurance contracts in a single period equilibrium model. All of these papers assume interest rates are constant.

also spillover into adjacent or far-away locations.[7] To reduce these insurance gaps, one of the EU-level solutions proposed by the ECB-EIOPA (2024) calls for issuing catastrophe bonds (and further developing the markets in Europe) to transfer cat risks to capital markets. Our paper is useful for obtaining insights into these issues as well.[8]

An outline for this paper is as follows. Section 2 presets the model of cat and corporate bonds, Section 3 provides numerical illustrations, Section 4 discusses the data and estimation, Section 5 presents the empirical analysis, and Section 6 concludes. All proofs and derivations of the theoretical results are contained in Appendix A.

2 The Model

This section derives the arbitrage-free valuation formulas for catastrophe (cat) bonds and ordinary coupon bearing bonds issued by a credit risky entity, e.g. corporations and municipalities. These are extensions of Hilscher et al. (2025) and Jarrow (2010).

2.1 The Set-up

We consider a continuous trading model on a finite horizon $[0, T^*]$. The uncertainty in the model is characterized by a complete filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\in[0,T^*]}, \mathbb{P})$ where $\mathbb{P}$ is the statistical probability measure and the filtration $\mathbb{F} \coloneqq (\mathcal{F}_t)_{t\in[0,T^*]}$ satisfies the usual hypotheses with $\mathcal{F} = \mathcal{F}_{T^*}$.

Traded are a term structure of default-free zero-coupon bonds, a cat bond, and a coupon bearing bond. The time t price of a default-free zero-coupon bond paying a dollar at time T is denoted by $p(t, T) > 0$. The default-free zero-coupon bond price process is assumed to be a $\mathbb{F}$ adapted semimartingale. The default-free spot rate of interest, r_t, is $\mathbb{F}$ adapted. The money market account's time t value is $B(t) = e^{\int_0^t r_s ds}$. Of course, we assume the necessary measurability and integrability such that the integral is well-defined.

[7]For example, about 75 percent of Euro area bank exposures to firms facing higher flood risks is either uncollateralized or secured by vulnerable physical assets (ECB-EIOPA (2023)). Relatedly, Munich Re (2024) estimates that the global economic losses from natural disasters was about \$320 billion (with \$176 for the US) of which only \$140 billion were insured (\$99 billion for US).

[8]In fact, the market implied cat event intensities obtained in our paper directly reflect the costs of closing/reducing the insurance protection gap. This is a key reason why cat bonds were introduced in the aftermath of hurricane Andrew in 1992.

2.1.1 The Cat Bond

A cat bond is simply an ordinary floating rate bond with an embedded insurance policy written by the bond holder (i.e. investor) to the bond issuer/sponsor (such as a (re)insurance company) that seeks to transfer cat risks to the capital markets. The cat bond is designed to insure damages and losses from a catastrophe event, like hurricanes and wildfires. The principal from the investors is held in a special purpose vehicle (SPV) which is bankruptcy remote, protecting both parties. The SPV invests the principal in a highly-rated and liquid collateral such as US Treasury securities. That cat bond pays floating interest rate payments, in addition to the fixed insurance premium (i.e. the spread) over the life of the bond. However, if a predefined catastrophe trigger event occurs, the collateral held by the SPV is liquidated to cover the losses to the sponsor (up to the principal of the bond). We now present an analytic model of a cat bond.

Traded is a cat bond with time t value denoted $v_{cat}(t)$, assumed to be a $\mathbb{F}$ adapted semimartingale. Let τ_{cat} be a stopping time with respect to the filtration $\mathbb{F}$ representing the occurrence of the cat event. This represents the random future time when the cat event occurs, and thus, triggers the losses from the principal to the investors, which is subsequently paid out to the cat bond sponsor.[9]

The cat bond has the following terms.

- It has a maturity of T, a face value equal to L dollars, and pays floating interest rate payments at the intermediate dates $\{t_1, ..., t_m = T\}$, but only up to a catastrophe event time τ_{cat}. For notational convenience, let the current time be denoted t_0. We let the time period between interest payments be equal to $\Delta := t_i - t_{i-1}$ for $i = 1, ..., m$.

- Floating payments are based on the default-free simple Δ-period interest rate

$$R_{t_{k-1}}\Delta := \frac{1}{p(t_{k-1}, t_k)} - 1. \tag{1}$$

  plus a constant spread $c > 0$. As seen, the floating rate over $[t_{k-1}, t_k]$ is known at time t_{k-1}.

- If the cat event happens in the time interval $(t_{k-1}, t_k]$, then the bond receives a constant loss rate of $\delta_{cat} \in [0, 1]$ at time t_k on the notional of L dollars. The, loss $\delta_{cat}L$ is paid

[9] In practice, there are various types of triggers (indemnity, industry loss, parametric, and modeled loss triggers) depending on the exact definition of the cat bond's qualifying event. See Braun (2016) for more details. Our formulation of event trigger as a random stopping time τ_{cat} is quite general as is applicable to the different triggers.

by the cat bond holder/investor and subtracted from the cat bond's face value. It is important to note that the cat event can happen anytime within this interval, but the payment only occurs at the end.

- If the cat event does not happen, the face value of L dollars is paid at time T.
- For future use, define the cumulative payments received up to time t given no cat event as[10]

$$G_{cat}(t) := \left(\sum_{k=1}^{m} \frac{(R_{t_{k-1}} + c)\Delta L}{B(t_k)} \cdot 1_{\{t_k \leq t < \tau_{cat}\}} \right) B(t).$$

We assume that there can be two different types of cat events based on the severity of the catastrophe, indexed $i = 1, 2$, with event $i = 2$ being the most severe. Each is modeled as the the first jump time of a Poisson process $N_{cat\, i}(t)$ starting at $N_{cat\, i}(0) = 0$ with deterministic intensities $\lambda_{cat\, i}(t) > 0$ for $i = 1, 2$. The cat intensities are deterministic to simplify the analytics while also allowing for seasonality in cat events. This is not a limitation for our application, because we estimate the intensities monthly, which allows us to obtain time varying estimates. We assume that $N_{cat\, i}(t)$ for $i = 1, 2$ are independent under $\mathbb{P}$.

The cat event time is the first time one of these cat events occur, i.e.

$$\tau_{cat} := min\{\tau_{cat\,1}, \tau_{cat\,2}\}.$$

It follows that the cat event intensity is

$$\lambda_{cat}(t) = \lambda_{cat\,1}(t) + \lambda_{cat\,2}(t). \tag{2}$$

Note the generality of expression 2. Considering two types of cat events recognizes the fact that different catastrophe events can lead to the occurrence of different triggers and principal losses. This is because when cat events occur, different tranched cat bonds may not get triggered if the event is not severe enough. This formulation is quite general and it can be used to value cat bonds with independent cat risks, such as bonds that reference multiple perils (e.g., hurricanes, wildfires, and earthquakes). Given the objective of this paper, we focus only on single-peril cat bonds and leave the extension to multi-peril bonds for future research.

[10]Note that $v_{cat}(T) = L$, if no cat event before or at time T.

2.1.2 The Coupon Bond

We assume that traded is a coupon bond issued by a credit entity, which we call a firm. While the presentation below refers to a firm or corporation, the model is more generally applicable to bonds issued by other credit risky entities such as municipalities or sovereigns. The time t price of the bond is denoted $v_{bond}(t)$, also assumed to be a $\mathbb{F}$ adapted semimartingale. Let τ_{bond} be a stopping time with respect to the filtration $\mathbb{F}$ representing the occurrence of a default on the coupon bond. The coupon bond has the following terms.

- It has a maturity of T, a face value equal to L dollars, and pays fixed interest rate payments of $C > 0$ dollars at the intermediate dates $\{t_1, ..., t_m = T\}$, but only up to the default time τ_{bond}. Note that for notational simplicity we use T for the corporate bond's maturity as well. However, this is easily generalized.

- If default happens in the time interval $(t_{k-1}, t_k]$, then the bond pays a constant recovery rate of $(1 - \delta_{bond}) \in [0, 1]$ at time t_k on the notional of L dollars where $\delta_{bond} > 0$ is the loss rate. It is important to note that default can happen anytime within this interval, but the payment only occurs at the end.

- If default does not happen, the face value of L dollars is paid at time T.

- For future use, define the cumulative payments received up to time t given no default as[11]

$$G_{bond}(t) := \left(\sum_{k=1}^{m} \frac{C}{B(t_k)} \cdot 1_{\{t_k \leq t < \tau_{bond}\}} \right) B(t).$$

We assume that the firm can default for two reasons. One, its ordinary business activities fail. This is modeled as the first jump time of a Poisson process $N_{bus}(t)$ with $N_{bus}(0) = 0$ and intensity $\lambda_{bus}(t) > 0$. Two, the more severe cat event of type 2 causes the firm to default. Note that the cat event of type 1 is not severe enough to cause default. This possibility is the reason for introducing two distinct cat events.[12] We assume that the two default events, $N_{bus}(t)$ and $N_{cat\,2}(t)$, are independent under $\mathbb{P}$.

Hence, the default time is

$$\tau_{bond} := min\{\tau_{bus}, \tau_{cat\,2}\}.$$

[11] Note that $v_{bond}(T) = L$, if no default before or at time T.

[12] We introduce only two cat events for simplicity of presentation and estimation, although it is easy to generalize to any finite number of such events.

and it follows that the default intensity for the firm is

$$\lambda_{bond}(t) = \lambda_{bus}(t) + \lambda_{cat\,2}(t).$$

We can rewrite this as

$$\lambda_{bond}(t) = \lambda_{bus}(t) + \alpha(t)\lambda_{cat}(t) \tag{3}$$

where

$$\alpha(t) := \frac{\lambda_{cat\,2}(t)}{\lambda_{cat}(t)} < 1.$$

In a subsequent section, we estimate expression (3) empirically using corporate bond prices given an estimate of λ_{cat} from the cat bond markets. Note the role of $\alpha(t)$ as a proportional factor in the above equation. λ_{cat} represents the cat intensities implied by cat bonds, which we use to characterize the corresponding cat event intensities affecting corporate bonds, i.e. $\alpha(t)\lambda_{cat}(t)$.

The assumption here is that default intensities in corporate bonds are affected by cat events if their operations are located in the same region insured by the relevant cat bonds. This is a realistic assumption given that λ_{cat} is an independent risk in addition to λ_{bus}, and it reflects the degree to which the cat event affects default risk of the bond λ_{bond}.

Remark. Alternative ($\alpha(t) > 1$)

Here the cat event only affects the cat bond if it is a cat event of type 2, but any cat event causes the firm to default. This is the other possibility.

1) Assume that the cat event for the cat bond is $\tau_{cat\,2}$, i.e. only a cat event of type 2 causes the investor to lose principal on the cat bond (based on attachment and detachment points). Note that here, $\lambda_{cat\,2}(t)$ is implicitly estimated from cat bond prices.

2) Assume that

$$\tau_{bond} := min\{\tau_{bus}, \tau_{cat}\}$$

i.e. both types of cat events cause the firm to default.

Note that here, λ_{cat}, is implicitly estimated from coupon bond prices. Then, we have that

$$\lambda_{bond}(t) = \lambda_{bus}(t) + \lambda_{cat}(t) = \lambda_{bus}(t) + \alpha\lambda_{cat\,2}(t)$$

where

$$\alpha(t) := \frac{\lambda_{cat}(t)}{\lambda_{cat_2}(t)} > 1.$$

Thus, this alternative condition implies that the corporate bond is highly vulnerable to cat event risks, thereby making the weight α more sensitive to the possibility any cat event λ_{cat}. This completes the remark.

2.2 The Market Structure

We assume that the markets for the traded securities are arbitrage-free.

Assumption. (Existence of an Equivalent Martingale Measure)

There exists an equivalent probability measure $\mathbb{Q}$ such that

$$\frac{p(t,T)}{B_t}\ for\ all\ T \in [0,T^*], \quad \frac{v_{cat}(t)+G_{cat}(t)}{B_t}, \quad \frac{v_{bond}(t)+G_{bond}(t)}{B_t}$$

are $\mathbb{Q}$ martingales.

It is important to note that we are not assuming that the market is complete. Hence, there can exist a continuum of martingale measures. The implication of the assumption that the cat bond trades in an arbitrage-free market is that one obtains the same time 0 arbitrage-free prices under all equivalent martingale measures. This follows directly from the fact that the normalized cat bond price process is a uniformly integrable martingale, given the bond's random value at time T.[13]

Next, given an equivalent martingale measure $\mathbb{Q}$, the risk-neutral default intensities are

$$\widetilde{\lambda}_{cat}(t) := \lambda_{cat}(t)\kappa_{cat}(t) \tag{4}$$

$$\widetilde{\lambda}_{bus}(t) := \lambda_{bus}(t)\kappa_{bus}(t) \tag{5}$$

where $\kappa_{cat}(t) > 0$, $\kappa_{bus}(t) > 0$ are deterministic functions representing cat event and default jump risk premiums, respectively. Note that equation 4 will be directly used for obtaining cat risk event premium given the proxy for the corresponding statistical intensities λ_{cat} as discussed in Section 4.1 below.

We add the following assumption to simplify the analytic formulas.

Assumption. (Conditional Independence)

For all t, the default-free spot rate process $(r_s)_{s\geq t}$, the cat event time $\tau_{cat} > t$, and the

[13]This handles the fact that the loss process itself does not trade. In the cat derivatives literature, because the loss process does not trade, the markets are incomplete, and incomplete arbitrage-free pricing methods need to be used. Here, however, because the cat bond trades, even if the market is incomplete, all martingale measures give the same cat value under the above assumption.

default time $\tau_{bond} > t$ are independent under $\mathbb{Q}$ given the filtration $\mathcal{F}_t$.

This assumption states that given the information at time t, the default-free spot rate process, the cat event, and the default event are independent under the martingale measure. This is a mild assumption because it does not imply that these quantities are independent under $\mathbb{P}$. This condition effectively states that the risk adjustments embedded in the risk neutral measure $\mathbb{Q}$, removes the (future looking) dependencies under $\mathbb{P}$. This is analogous to (and only slightly stronger than) the implication that asset returns under $\mathbb{Q}$ are uncorrelated, due to the risk adjustment, where they are correlated under $\mathbb{P}$.

2.3 The Valuation Formulas

The existence of a martingale measure implies

$$\begin{aligned} v_{cat}(t) = \textstyle\sum_{k=1}^{m} E^{\mathbb{Q}} \left[(R_{t_{k-1}} + c)\Delta L 1_{\{\tau_{cat} > t_k\}} e^{-\int_t^{t_k} r_u du} \,|\mathcal{F}_t \right] \\ + L E^{\mathbb{Q}} \left[1_{\{\tau_{cat} > T\}} e^{-\int_t^{T} r_u du} \,|\mathcal{F}_t \right] \\ + \textstyle\sum_{k=1}^{m} L E^{\mathbb{Q}} \left[1_{\{t_{k-1} < \tau_{cat} \leq t_k \leq T\}} (1 - \delta_{cat}) e^{-\int_t^{t_k} r_u du} \,|\mathcal{F}_t \right]. \end{aligned} \tag{6}$$

The Appendix A shows that under the above structure, this expression simplifies to

$$\begin{aligned} v_{cat}(t) = \textstyle\sum_{k=1}^{m} \left[c + f(t; t_{k-1}, t_k) \right] \Delta L z_{cat}(t, t_k) + L z_{cat}(t, T) \\ + L(1 - \delta_{cat}) \textstyle\sum_{k=1}^{m} x_{cat}(t, t_k) \end{aligned} \tag{7}$$

where

$$f(t; t_{k-1}, t_k)\Delta := \frac{p(t, t_{k-1})}{p(t, t_k)} - 1 \tag{8}$$

$$Q_{cat}(t, t_i) := Prob^{\mathbb{Q}} \left[\tau_{cat} \leq t_i \,|\mathcal{F}_t \right] = 1 - e^{-\int_t^{t_i} \tilde{\lambda}_{cat}(s) ds} \tag{9}$$

$$z_{cat}(t, t_k) = p(t, t_k)[1 - Q_{cat}(t, t_k)] \tag{10}$$

$$x_{cat}(t, t_k) = p(t, t_k)[Q_{cat}(t, t_k) - Q_{cat}(t, t_{k-1})] \tag{11}$$

where $\tilde{\lambda}_{cat}(t) = \tilde{\lambda}_{cat\,1}(t) + \tilde{\lambda}_{cat\,2}(t)$.

It is shown in the Appendix that $z_{cat}(t, t_k)$ is the time t value of a survival digital, a security that pays \$1 at time t_k only if a cat event occurs after t_k. And, $x_{cat}(t, t_k)$ is the time t value of a cat event digital, a security that pays \$1 at time t_k if a cat event occurs within $(t_{k-1}, t_k]$.

Hence, the first term in expression (7) is the present value of the floating rate payments, if there is no cat event. The second term is the present value of the principal payment, if there is no cat event. And, the third term is the present value of the recovery rate, if there is a cat event.

Analogously for the coupon bond we have

$$v_{bond}(t) = \sum_{k=1}^{m} C z_{bond}(t, t_k) + L z_{bond}(t, T) + L\left(1 - \delta_{bond}\right) \sum_{k=1}^{m} x_{bond}(t, t_k) \tag{12}$$

where

$$Q_{bond}(t, t_i) \coloneqq Prob^{\mathbb{Q}}\left[\tau_{bond} \leq t_i \,|\mathcal{F}_t\right] = 1 - e^{-\int_t^{t_i}\left(\tilde{\lambda}_{bus}(s) + \tilde{\alpha}(t)\tilde{\lambda}_{cat}(s)\right)ds} \tag{13}$$

$$z_{bond}(t, t_k) = p(t, t_k)[1 - Q_{bond}(t, t_k)] \tag{14}$$

$$x_{bond}(t, t_k) = p(t, t_k)[Q_{bond}(t, t_k) - Q_{bond}(t, t_{k-1})]. \tag{15}$$

where $\tilde{\alpha}(t) \coloneqq \frac{\tilde{\lambda}_{cat\,2}(t)}{\tilde{\lambda}_{cat}(t)} < 1$, $\tilde{\lambda}_{cat}(t) = \tilde{\lambda}_{cat\,1}(t) + \tilde{\lambda}_{cat\,2}(t)$, with $\tilde{\lambda}_{bond}(t) = \tilde{\lambda}_{bus}(t) + \tilde{\alpha}(t)\tilde{\lambda}_{cat}(t)$.

The key difference between the bond valuation formula and the cat bond valuation formula is that the bond valuation formula has no floating rate payments and for the coupon bond, default is generated by either a cat event or a business default event.

3 Numerical Illustrations

This section provides numerical examples to illustrate properties of the model. This helps build an understanding of the model and subsequent empirical results. Recall that the key valuation equation for cat bonds is expression (7) and expression (12) for corporate bonds.

For cat bonds, we consider maturities from 1 to 3 years (consistent with predominantly 3 years maturity of cat bonds in our sample Table 1) with coupon payments in quarterly frequency, as standard in the cat bond market. For our parameters, we vary the cat event intensity λ_{cat} from 0.05 to 0.20 and set the recovery rate at 20% (i.e., loss rate of 80%). We consider two different spreads, 5% and 10% above the default-free floating rate. All of these values are broadly reflective of the values observed in our sample as discussed in Section 4 below. For corporate bonds, we set the total default intensity λ_{bond} up to 0.1, a coupon rate of 5% paid semi-annually (as standard in corporate bonds), a recovery rate between 0.1 to 0.8, and maturities of 5 and 10 years. The risk-free term structure is assumed flat at 1%.

Figure 1 shows the cat bond price surface across maturity and catastrophe risk. The lower surface corresponds to a 5% spread and the upper surface corresponds to a 10% spread. As

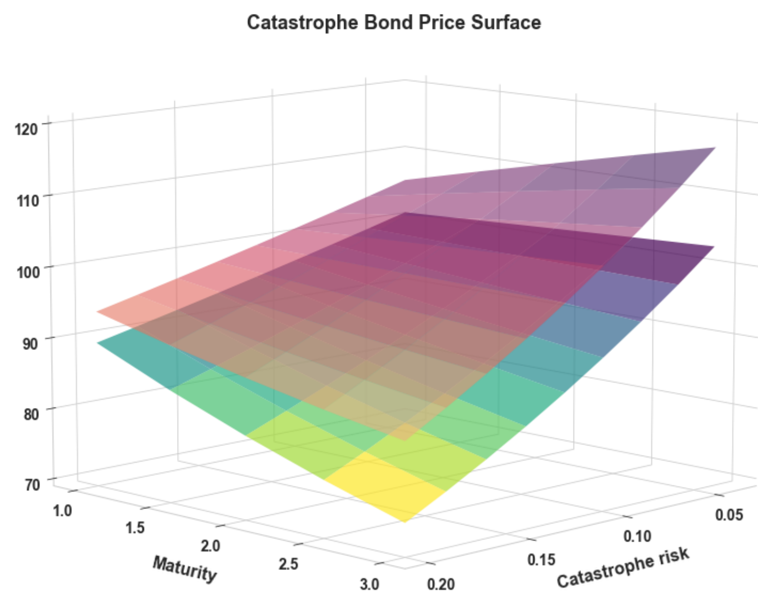

Figure 1: This figure numerically illustrates the impact on the catastrophe bond price surface across a range of maturities T and catastrophe intensities λ_{cat} using equation (7). The top surface corresponds to a higher spread (10%) and the bottom surface corresponds to a lower spread (5%).

one would expect, as the catastrophe risk decreases (moving from 0.2 to 0.05 in the figure), the value of the cat bond increases uniformly, all else equal. However, the relation among catastrophe risks, time to maturity, and spreads is highly nonlinear. As seen, a cat bond's price is more sensitive to maturity, and declines rapidly as maturity increases, but only for a bond with a relatively lower spread (the lower surface). For cat bonds with relatively larger spreads (the top surface), the impact is not as strong. In fact, for a larger spread bond, the bond value may increase if the catastrophe risk is relatively lower. However, as catastrophe risk and maturity both increase, the bond values decline uniformly, with the impact more pronounced for bonds with lower spreads.

Figure 2 shows the corporate bond price surface across default risks and recovery rates, for two different maturities. The bond price surface declines uniformly as total risk increases and/or recovery rates decrease. Further, we see that long maturity bonds are relatively more responsive to larger risk exposures. This is consistent with empirical findings in the corporate bond literature, as well as in the climate-related literature. For example, Acharya et al. (2024) document that lower-quality and longer-maturity bonds across asset classes

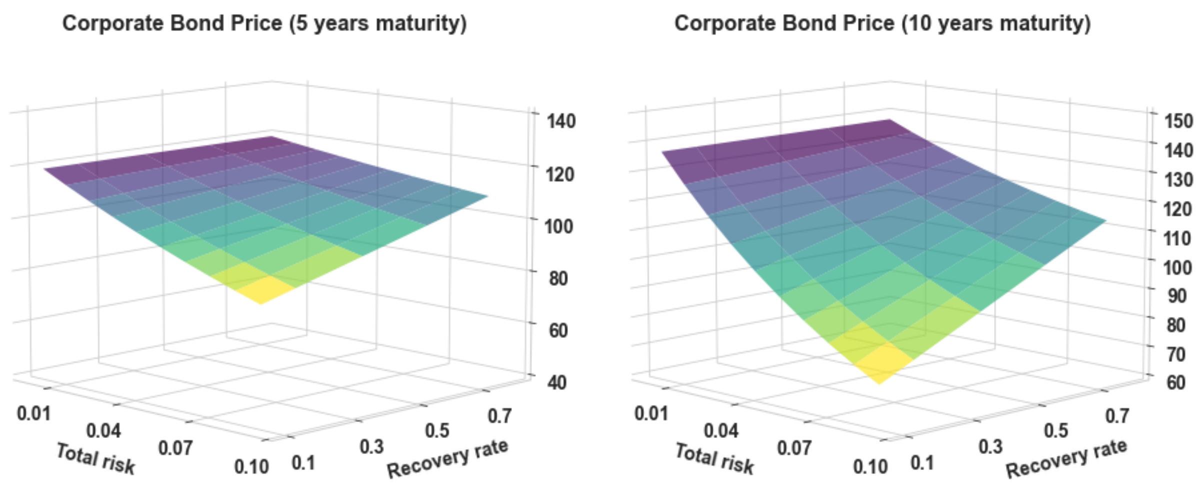

Figure 2: This figure numerically illustrates the impact on the corporate bond price surface across a range of recovery rates δ_{bond} and total default intensities λ_{bond} using equation (12). The left figure corresponds to the 5 year maturity bond and right figure corresponds to the 10 year maturity bond.

exposed to local heat stress exhibit higher yield spreads, while Painter (2020) finds that higher climate-risk exposure is significantly associated with larger issuance costs for long-term maturity municipal bonds, but not as much for short-maturity bonds.

4 Data and Estimation

This section describes our cat and corporate bond data, and the empirical methodology.

4.1 Catastrophe Bonds

Although growing, the cat bond market is relatively small when compared to traditional equity and bond markets. Further, most cat bonds are not publicly listed, but trade over-the-counter and generally held-to-maturity by investors. Nevertheless, given the growing interest in this asset class, the first exchange traded fund (ETF) on catastrophe bonds was launched in early 2025, opening access to a wider range of investors. Despite this, the secondary market is still relatively illiquid (see FT 2025 for more details). For the purposes of our paper, we focus on primary market data.

We obtain catastrophe bond issuance information from the Artemis.bm deal directory and cross-check against other sources as needed (BSX exchange, rating agency reports etc.)

to compile our data sample.[14] For this paper, we restrict our attention to two categories of risks/perils: (i) US named storm and hurricanes,[15] and (ii) wildfires. For these perils, we collect data on rule 144a catastrophe bonds. Regulation 114 Trust requires a cat bond's collateral to be invested in cash-like liquid securities (e.g. US Treasuries). These bonds dominate the market, are generally more liquid, they are held by qualified (large) institutional investors, and they have more transparency on structuring provided to investors (see Captive International and Guy Carpenter).

We initially focus on a sample of cat bonds from 2011 to 2025, available at monthly frequency (data before this period is sparse and missing critical information on spreads). In particular, the cat bond market for US named storm and hurricane risks has experienced exponential growth after the 2017-2018 period. Of the approximate \$21 billion total cat bond issuance in 2025, about \$6.5 billion are from US hurricane related risks. There were 20 or more unique issuances per-year since 2023, double from the 11 issuances in 2022. For our final empirical application, we will focus on the period from 2018 onward, given the steadily growing cat bond issuance and sizes,[16] increasing recognition of climate-related risks around this period as discussed above, as well as availability of suitable corporate bond data.

To understand the data availability in cat bond markets (and in relation to wildfire risks), it is important to recognize that issuing cat bonds involves engaging highly specialized third-party modeling firms (e.g. AIR, RMS, EQECAT), that use complex scientific models of hazards/perils, coupled with exposures and vulnerabilities, to determine the security's cat risks. These firms are central in providing objective statistical estimates of various risk metrics such as the attachment probability (the probability of seeing some principal loss) and the expected loss (average annual loss of principal). Consequently, these catastrophe models for specific perils are critical to the growth of the cat bond market.

In this context, hurricanes and earthquakes are the two main perils for which catastrophe risk modeling is quite mature and well-established. However, for other perils such as wildfires, the risk modeling is not as advanced. This relates to the fact that hurricane related cat bonds dominate the market, whereas cat bonds issued for wildfires are relatively fewer, especially given the difficulty in modeling. Nevertheless, recent reports suggest advancements in modeling due to the increasing notional of wildfire cat bonds issued (see Bloomberg News

[14]Compiling data from different sources is quite common in the literature given the relative scarcity of publicly available granular/transactions data on cat bonds (see Braun (2016), Beer and Braun (2022)).

[15]This also includes the U.S. flood risk (from named storms) category but this sample is quite small.

[16]During the 2011-2017 period, the average number of issuances and issuance size per-year were 5 and \$1.16 billion, respectively. However, during 2018-2015, the average issuance number and size per-year had significantly grown to 12 and \$3.38, respectively. See Artemis.bm for a range of cat bond market data.

(2025)).[17] As such, our wildfire sample is relatively small but spread out over 2018 and 2025. However, this is not an issue for the purpose of this paper because the initially estimated catastrophe intensities are only used to characterize and determine the subsequent impact on corporate bonds exposed to the same cat event risk as implied from the corporate bond prices.

The key variables we obtain for each cat bond are the following: Issuer (sponsor/cedent), peril category and US regions referenced, total issuance size (million USD), and date issued. For each issuance, we obtain the following at a single bond or tranche level (for multi-tranche issuance): coupon spreads, the discount price for zero-coupon issuance, maturity term, attachment probability, expected loss, and trigger type. Since the key risk metrics on initial attachment probability and expected loss are provided by specialized modeling firms as discussed above, we take these metrics as good approximations under the statistical probability against which we compare the analogous market implied quantities. We assume a 3 month coupon payment schedule (for coupon paying bonds) and use the historical US Treasury yield curve (monthly average given cat bond observations) to derive the corresponding 3-month forward rate curves to value the floating rate payoffs from the collateral (see Jarrow (2019) for methodological details, and Jarrow and Lamichhane (2022) for an example of a corresponding implementation of the US Treasury yield curve). Although we calculate implied catastrophe risks at the individual tranche level, we eventually derive a monthly index of implied catastrophe risks, which is calculated as a tranche size weighted average.

Lastly, we obtain the historical losses on the triggered catastrophe bonds from Artemis.bm bond losses repository. We only keep those losses corresponding to hurricanes, storms, typhoons, and wildfires, either when triggered on a standalone basis or as part of the multi-peril aggregated losses. Our sample is dominated by losses due to US hurricanes and also wildfire risks as part of the aggregated losses category, thereby providing us with representative loss rates to directly use in our estimates.

Table 1 presents the cat bond summary statistics for a sample of 195 unique observations (tranches) over the sample period 2011-2025. Offerings range from a low of \$6.75 million to \$1.5 billion with a median of about \$135 million. The increased number and amounts of cat bond offerings are because of the growing demand. The average insurance spread is 9%, with some outliers over 25%. Most of the cat bonds have 3 year maturities. With respect to the values, the lowest maturities are driven by the 16 zero-coupon bonds with an average

[17] While wildfire specific cat bonds are limited given the modeling challenges discussed, many multi-peril cat bonds that cover losses from a range of perils such as hurricanes, earthquakes, do include wildfires. However, our paper focuses on implied cat risks that reference a specific peril.

Table 1: Summary Statistics of Hurricane-Linked Catastrophe Bonds

	Obs.	Mean	SD	Min	p25	p50	p75	Max
Tranche Size (USD mln)	195	180.49	159.51	6.75	100	135	225	1500
Spread	179	0.090	0.043	0.022	0.060	0.080	0.111	0.255
Term (years)	195	2.76	0.75	0.50	3.00	3.00	3.00	4.00
Zero Coupon Bond Price	16	90.68	2.88	84.00	89.56	91.50	91.93	95.00
Attachment Probability	153	0.030	0.024	0.002	0.016	0.023	0.038	0.173
Expected Loss	190	0.024	0.018	0.001	0.013	0.019	0.030	0.103
Loss Rate	70	0.78	0.28	0.12	0.68	0.92	1.00	1.00

Note: This table reports the summary statistics on the hurricane-linked catastrophe bond specific variables (at bond-tranche level) over 2011 to 2025 period: number of observations (Obs.), mean, median (p50), standard deviation (SD), minimum, maximum, 25th, and 75th percentiles (p25, p75), along with the modeled attachment probability and expected loss. Tranche size is in millions of USD. The loss rate sample is from 2005 to 2025 and contains losses from single peril and multi-peril bonds as discussed in the main text. Digits are rounded to 2-3 decimal places.

price of 90.68, representing a significant discount. These zero-coupon bonds have maturities of 0.5 to 1.5 years, with the majority at 1 year.

The attachment probability (also described as the probability of the first loss (PFL)) and the expected loss refer to the initial modeled values (from specialized firms) provided in the cat bond bond offering disclosures to investors. As seen, except for one outlier with an initial attachment probability of 17% and an expected loss of 10%, the median attachment probability and expected loss is approximately 2%.[18] These two variables represent the statistical/actuarial measures, which we subsequently compare to the analogous risk-neutral counterparts to quantify the risk premium reflected in cat bond markets. Hereafter, we refer to these statistical quantities as modeled, and the analogous quantities (obtained from the implied Poisson intensities and expected losses) as market implied.

For the 11 wildfire cat bonds in our sample over (2018-2025), the average spread is about 9%, with a high of 11% and a low of 4%, all with 3 year maturities. While the overall sample size for wildfire cat bonds is small, the average spreads, which are the key inputs to the subsequent analysis for corporate bonds, are reliable and not driven by outliers, especially since the range is well within that of hurricane cat bonds. The average modeled attachment probability is 1.6%, and the modeled expected loss is 1.4%.[19]

[18] Note that the discrepancy between the number of cat bond observations of 195 and spreads, attachment probability and expected loss is due to missing information, especially in early parts of the sample period.

[19] Note that unlike in hurricane linked cat bonds that provide single modeled values of expected losses,

Figure 3 shows the distribution of the cat bond spreads (for both hurricanes and wildfires) and the historical loss rates on the principal (Table 1 describes the statistics). The average loss rate is near 80%, the median is 92%, and the 75th percentile is 100%. This is much larger than average loss rate ranges of 40% to 50% for corporate bonds.

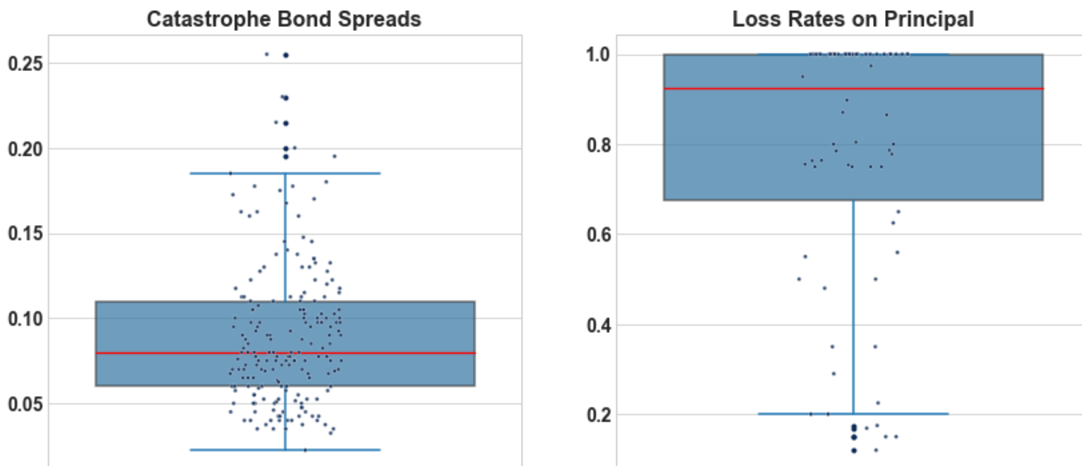

Figure 3: This figure shows the distribution of all available catastrophe bond spreads (both hurricane and wildfires) and loss rates as reported in Table 1. The solid red lines indicate corresponding median values.

Finally, about 84% of the hurricane cat bond sample (163 out of 195) consists of indemnity triggers, followed by industry loss index triggers (31 out of 195), with one parametric trigger. A similar pattern holds for wildfire cat bonds with about 82% of sample (9 out of 11) with indemnity triggers and one each with industry loss and parametric triggers. This pattern is consistent with the overall catastrophe bond market where indemnity triggers constitute about 75% of the bonds followed by about 18% industry loss index triggers (see Artemis.bm).

4.2 Corporate Bonds

The primary purpose of this section and the subsequent corporate bond results is to illustrate the application of our model to corporates, using the estimated cat event intensities from the cat bond market. Future research can use the blue print presented herein to apply this model to larger and granular data sets and alternate cat events and locations.

To implement our valuation model, we need to select bonds issued by firms or municipalities whose revenues and/or productive assets would be significantly impacted by a cat

some earlier observations for wildfire cat bonds instead provide a small range of modeled expected losses (indicating average versus high risk). This is likely due to the modeling challenges discussed above. For those bonds, we take the range mid-point to report the averages here.

event. Default probabilities of firms whose revenues and assets are diversified across regions may be affected by natural disasters, but the impact would be less than those whose risks are geographically concentrated. Because almost all the hurricane linked catastrophe bonds in our sample reference Florida (within the broader US Eastern Coast and Northern Atlantic that is subject to most hurricane risks), and all the wildfire risks reference California, we focus our attention to catastrophe risks attributable to these two states. Consequently, we search for large firms with two conditions: (i) the firm has its predominant business activities in Florida (for hurricanes) or California (for wildfires risk), and (ii) the firm has actively traded bonds.

Applying our filter, we identify four large firms whose bonds are actively traded. For hurricane risks in Florida, we select: Florida Power & Light (FPL) and Duke Energy Florida (DukeFL). For wildfire risks in California, we select: Southern California Edison (SCE) and San Diego Gas & Electric (SDGE). As utilities and infrastructure based companies, they are exposed to the specific natural hazards in their region of operation. Since the revenues and/or productive assets of these bonds are fully located within their respective states, this sample allows us to quantify the relevant cat risks embedded in these bonds. A benefit of this approach is that the estimated cat risks can be used for understanding similar cat event implications for other firms, including SMEs, operating in the same region without actively traded bonds or financial instruments.[20]

We obtain the information on these firms' traded bonds from Cbonds. The sample period is from April 2018 to the end of 2025. This sample period allows us to exploit the available catastrophe bond data. We collect closing bond prices, at a daily frequency, along with bid and ask prices, coupon rates, maturities, and payment schedules.

Table 2 presents the corporate bond summary statistics over 2018-2025. Due to the absence of trading in certain periods, specially periods following the covid-19 shock, and missing observations, we see a different total number of daily observations among the four bonds. The coupon rates range between 3-4 percent and the yield-to-maturity (YTM) is around 4%. The median bid-ask spread (in dollar terms) is between 0.3 to 0.6, suggesting a relatively liquid sample. We subsequently compare our estimated mean absolute pricing errors with those in this table. Finally, all of these bonds have a maturity of about 25 years,

[20]This methodology can also be applied to firms that may have only a certain portion of their total revenues and/or productive assets in such regions. However, for such firms, estimating the size of the cat event risk sensitivity factor α will be empirically challenging because of data limitations with potentially noisy estimations, depending on the degree of geographical diversification. Nevertheless, our subsequent results can be seen as providing an upper bound on the impact of cat events on the firm's default intensities if diversified firms have a sufficient degree of business concentration in the exposed regions.

Table 2: Summary Statistics of Corporate Bond Characteristics

	Obs.	Coupon	YTM	BidAskSp	Maturity
Hurricane risks (in Florida):					
Florida Power & Light (FPL)	1975	3.95	4.25	0.45	25.9
Duke Energy Florida (DukeFL)	2007	3.40	4.32	0.53	25.4
Wildfire risks (in California):					
Southern California Edison (SCE)	1968	4.13	4.84	0.34	25.9
San Diego Gas & Electric (SDGE)	1648	3.75	4.50	0.59	25.3

This table reports the summary statistics of the variables representing corporate bond characteristics over the period from April 2018 to end 2025: number of daily observations (Obs.), coupon rate (%), average yield-to-maturity (YTM, %), bid-ask spread (BidAskSp, in dollars), and average maturity (years). The top panel shows representative firms for analyzing hurricane risk in Florida. The top panel shows representative firms for analyzing wildfire risks in California.

i.e. these are long-term bonds maturing between 2046 to 2048.

4.3 Calibration

The goal of this section is to estimate corporation default probabilities, using the cat bond's implied intensities. Although we estimate the market implied risk neutral quantities, $\widetilde{\lambda}_{bus}(t)$, $\widetilde{\lambda}_{cat}(t)$, and $\widetilde{\lambda}_{bond}(t)$, for ease of notation we drop the tilde in the subsequent presentation. The equation we estimate, expression (3), is reproduced here for convenience:

$$\lambda_{bond}(t) = \lambda_{bus}(t) + \alpha(t)\lambda_{cat}(t) \tag{16}$$

The loss rate used for cat bonds is 80%, which is close to the historical average as seen in Table 1 but still lower than the median at 92%. For the corporate bonds, we also tested various values in the range 40% to 80%, and found the 40% loss rate (i.e. recovery rate of 60%) to be optimal. This is also consistent with average recovery values of around 54% as discussed in Bakshi et al. (2022). Given these loss rates, we estimate $\lambda_{bus}(t)$, $\lambda_{cat}(t)$, and $\alpha(t)$ for each bond in a three step sequence.

First, we estimate the cat event intensity $\lambda_{cat}(t)$ by its implied value based on the prices contained in the primary market issuance information. The estimate is obtained by finding the root of the equation (7) in $\lambda_{cat}(t)$ that prices the bonds at par, given the inputs on spreads, maturity, quarterly payment frequency, and the benchmark US Treasury risk-free term structure discussed before. Recall that our cat bond issuance information is monthly. To obtain daily estimates of the implied cat event intensity, we use the estimated monthly value for all days in a given month. For the months where there are no issuance prices due to the absence of an issuance, we use the previous month's implied estimate. For our application, this is reasonable because the initial estimate of the weighted average cat event intensities λ_{cat} are primarily used to help anchor and characterize the overall market implied cat risks in the corporate bond markets.

Second, we estimate the corporate default intensity λ_{bond} by its implied value based on the daily market prices of the bonds using expression (12). This estimation employs a non-linear optimization routine that minimizes the mean absolute errors (MAE) between the model value and market prices (following Bakshi et al. (2006) who also employ mean absolute pricing errors to compare model fit) along with other inputs of principal, coupon rate, payment schedule, remaining maturity, and the benchmark US Treasury term structure.[21]

Third, using the implied intensities λ_{bond} and λ_{cat}, we jointly estimate the business risk intensity λ_{bus} and the multiplier α using expression (16). Here, the estimate of λ_{bond} is used to set upper bounds for α and λ_{bus}. Subject to the upper bound constraints, we find the best fitting parameters λ_{bus} and α to minimize the MAE between the model value in expression (12) and the market prices. This estimation also uses same non-linear optimization routine, along with the inputs from step two.[22]

Because we are using individual bond issues for each corporate/municipality, we perform our estimations using a 5 day rolling window. For each bond, we estimate two parameters. Thus, for each time t, we take 5 daily data points at times $\{t, t-1, ..., t-4\}$ and estimate the parameters for time t. This allows sufficient data for each day's estimation.

Given the above setup, the median MAEs from the daily estimations for FPL, DukeFL, SCE, and SDGE are 0.28, 0.28, 0.27, 0.42, respectively. These errors are smaller than the median bid-ask price differences as contained in the corporate bond data Table 2, confirming the model convergence.

[21] As noted in Hilscher et al. (2025), credit spreads should not be used to price risky corporate bonds due to an implied assumption in its application that coupons after default receive recovery payments, which is counterfactual.

[22] Although it is possible to further impose the hard constraint of the equation $\lambda_{bond} = \lambda_{bus} + \alpha\lambda_{cat}$ in step three in addition to upper bounds during optimization routine, we instead let the parameters λ_{bus} and α vary freely within their upper bounds. Because of the linear relation between these quantities, we get the same (unique) value for λ_{bond} as in step two.

5 The Empirical Investigation

This section presents the empirical results. We first present the results for catastrophe bonds and subsequently discuss the results for corporate bonds, followed by an extension to municipal bonds. We also present some additional discussion on the broader implications and applicability of our model.

5.1 Market Implied Risks from Catastrophe Bonds

Figure 4 top panel shows an index of the spread on the hurricane cat bonds above the floating rate, along with the average market implied cat event intensity λ_{cat}. For easy comparison, we also include the 3 month Treasury rates and some major destructive named-hurricanes along with their landfall dates (all in Florida). As noted before, although we calculate implied cat event intensities at the individual tranche level, we compute a monthly index of the implied cat risks. This is calculated as a tranche size weighted average. These are depicted in Figure 4. As seen the market implied cat event intensity closely follows the levels of spreads. For subsequent discussion, we note that spreads are driven by cat risks and the market's risk premium for cat risk.

Figure 4 bottom panel shows the relationship between our market implied cat event intensities and the modeled expected loss (as provided during the bond issuance by the modeling firms as discusses above). As seen, while there is a strong relationship between these two variables, only about 40% of the variations in the market implied cat event intensities are explained by the expected loss (i.e., the R^2 on regression line). While this is consistent with the finding in the literature that modeled statistical expected losses are a key driver of the spreads, these results point to the fact that a large portion of implied cat event intensities are not explained by expected losses, thereby suggesting a significant cat event risk premium in the market.

The presence of a cat event risk premium is clearly seen in Figure 5. The right side panel shows the same descriptive data as in Table 1 and the left side panel shows the market implied quantities from our model. As seen, the market implied cat event intensity is significantly larger than the ones implied by the initial attachment probability, which is the cat risk premium.[23] The risk premium is given by the ratio of the market implied cat risk probability and the modeled attachment probability, which is the term κ_{cat} in equation

[23] Since the modeled attachment probabilities are standard annualized quantities, the translation of λ_{cat} into a corresponding probability is straightforward using $1 - e^{-\lambda_{cat}T}$ with $T = 1$ as in the model section above.

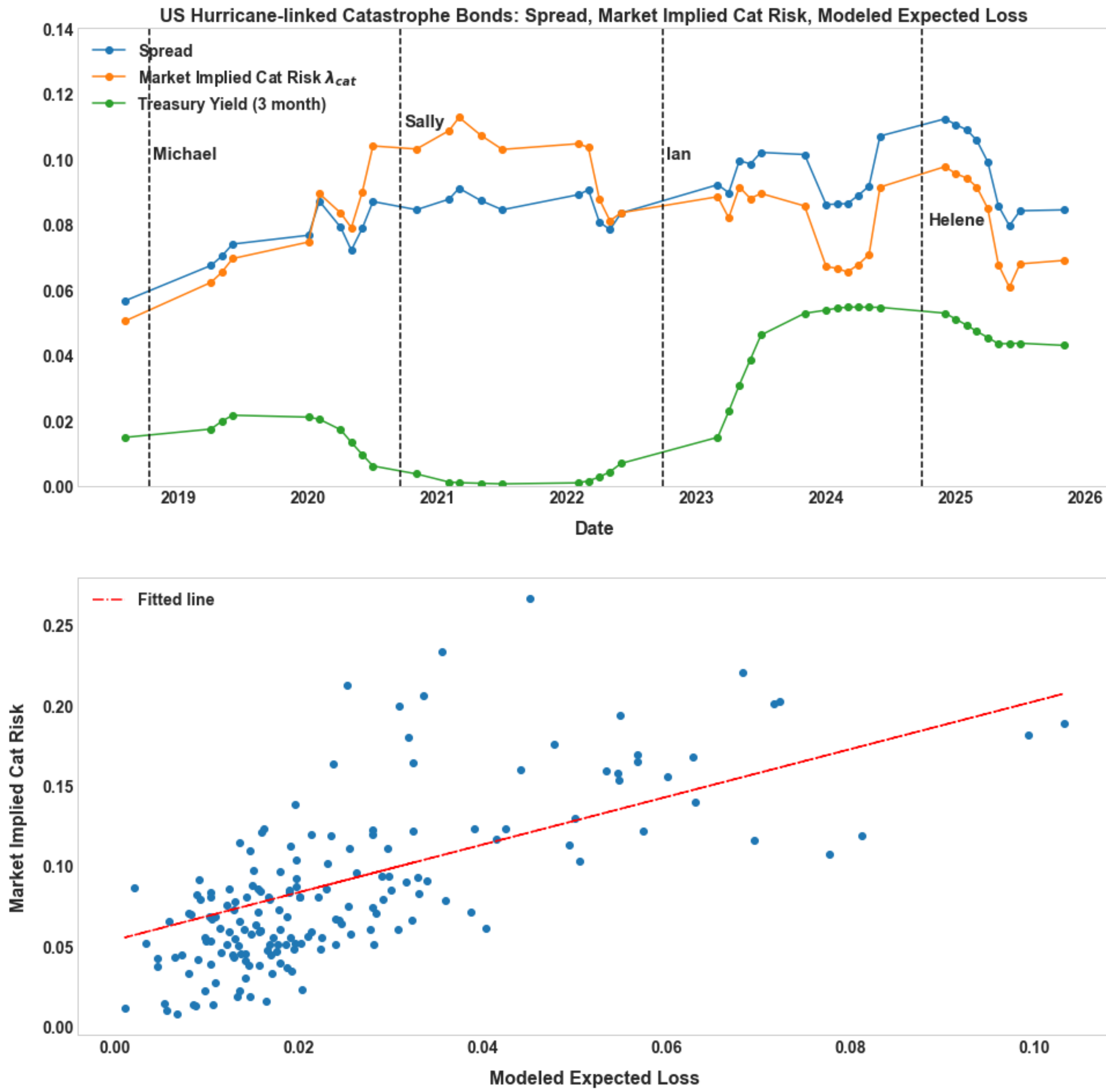

Figure 4: **Cat Spread, Market Implied Cat Risk, and Modeled Expected Loss:** The top panel shows the index of catastrophe bond intensities constructed as monthly weighted averages of individual tranche level market implied cat bond intensities λ_{cat} along with the analogously constructed insurance spread, and the 3 month US Treasury yield. The bottom panel shows the scatter plot of λ_{cat} and the corresponding modeled expected losses.

4. In particular, the average market implied cat event intensity is more than 3 times larger than the modeled attachment probability (which is our benchmark measure of statistical probability). Since the market implied expected loss is directly driven by the implied cat event intensities (i.e. $EL_{implied} = Prob_{cat} * lossrate$, where the loss rate is 0.8 as discussed above), these observations are consistent with Figure 4 bottom panel.

Finally, for wildfire risks, the average market implied cat event intensity is about 6 times

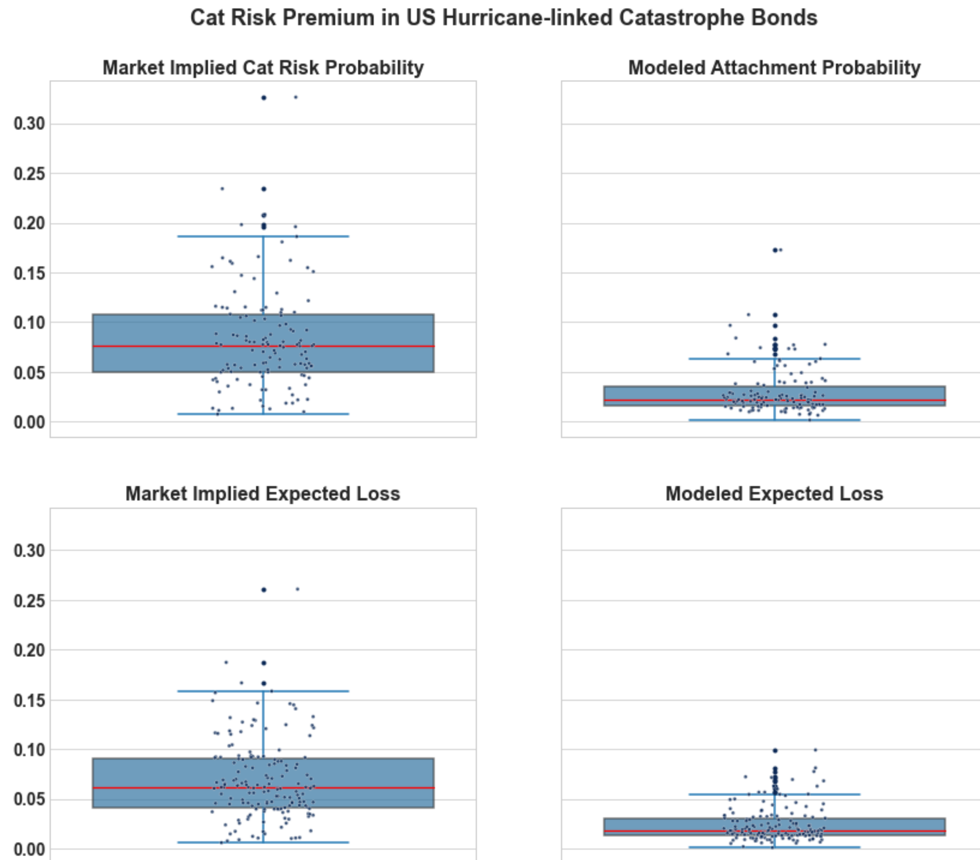

Figure 5: **Cat Risk Premium:** This top panel shows the distributions of the market implied cat risk probability (left) and modeled attachment probability (right). The bottom panel shows the distributions of the market implied expected loss, obtained directly from the corresponding estimated cat probability (left) and modeled expected loss (right). The solid red lines indicate corresponding median values.

larger than the modeled attachment probability (after removing the low outlier probability in the data). This shows that the average risk premium in wildfire cat bonds is significantly larger than those in hurricane cat bonds. This might be due to a lack of robust modeling relative to hurricanes along with the relatively longer duration of wildfires as discussed above, thereby prompting investors to demand more premium for the higher uncertainty. The distinction between hurricane and wildfires will also be seen in our corporate/municipal bond estimations.

As noted earlier, because the cat event intensities are specific to a given region, the estimated cat bond risk premium can be used to provide an upper bound for the cat risk premium in various financial assets/instruments exposed to the same peril in the same region (e.g., equities, bonds, mortgages, borrowing/funding rates etc.).

5.2 Catastrophe Risks in Corporate Bonds

We now discuss the implications for corporate bond default intensities, starting first with hurricanes and then wildfires. For simplicity of exposition and discussion related to the Figures below, we refer to λ_{bond} as total risk, λ_{bus} as standard business risk, and $\alpha\lambda_{cat}$ as cat risk.

5.2.1 Hurricanes

Figure 6 shows the corporate bonds prices for both FPL and DukeFL, along with model predicted bond prices on the left axis. As seen, the model and data prices are nearly identical. The right axis shows the bond's total implied default intensity λ_{bond} and its dynamics closely captures the risks in bond prices. A negative shock to bond prices generally implies a larger default intensity λ_{bond}. In particular, notice the sharp increase in default risk around the covid-19 period in early 2020, followed by a slow decline in the total risks afterwards up to 2022 as the general economic uncertainty from covid slowly unwound. The model captures overall economic risks quite well. Further, note the continued decline in both bond prices after 2022. This is largely due to the tightening of monetary policy by the Federal Reserve. During this period, credit risk concerns generally increased, given the rapid pace of interest rate increases, which consequently raised borrowing costs.[24]

Figure 7 depicts the decomposition of the total default intensity into business risk λ_{bus} and catastrophe risk $\alpha\lambda_{cat}$. The green filled area shows the proportion of total risks that can be attributed to catastrophe risks from hurricanes. The vertical lines indicate some of the major damaging hurricanes during our sample period. While hurricanes generally affect parts of Florida in different ways, we see a uniform increase in cat event intensities due to the hurricanes (either sharp spike or gradual increase).

Note that hurricane Ian was the third most damaging and costly hurricane in Florida and US history with (inflation-adjusted 2025) damages totaling about \$120 billion (see NOAA Billion-Dollar Weather and Climate Disasters Dashboard). Consequently, in our sample period, Ian is the most damaging hurricane and our model is able to pick up these cat event risks, consistent with the reported damages. As seen in Figure 7, our model also reflects the risks in the aftermath of Ian, as we observe persistently higher cat event intensities post hurricane Ian, relative to other hurricanes. Table 3 further decomposes the magnitudes. It shows the average default intensity λ_{bond} and the ratio of $\alpha\lambda_{cat}$ to λ_{bond}, i.e. the proportion

[24]See Jarrow and Lamichhane (2025) for more discussion on the impact of monetary policy regime shifts on funding costs.

Figure 6: **Risks from Hurricanes:** This figure shows the 20-day moving average of the bond prices (blue line), overlaid with model predicted prices (orange line) and the total risk λ_{bond} (on the right axis) over the sample period 2018 to 2025. The dotted vertical lines show landfall dates of some major hurricanes in the US/Florida region. The top figure is for Florida Power & Light and the bottom figure is for Duke Energy Florida.

of cat risk attributable to the total risk (referencing the shaded green area in Figure 7). The comparison is shown for the full sample period and till 3-months after hurricane Ian's landfall (September 28, 2022).

As seen, over the full sample, the average of total FPL default risk is at 2.3% of which cat risk accounts for about 10.7% of the total risk. DukeFL has a slightly larger default risk of about 3.2% on average, but cat risk only accounts for about 7.7% of the total risk. However, in the period of 3-months post Ian, both FPL and DukeFL exhibit persistent cat risks. FPL's total risk is 3.3% of which cat risk accounts for about 32% of the total risk. DukeFL has a slightly larger default risk of about 5.2%, where cat risk accounts for about 33% of the

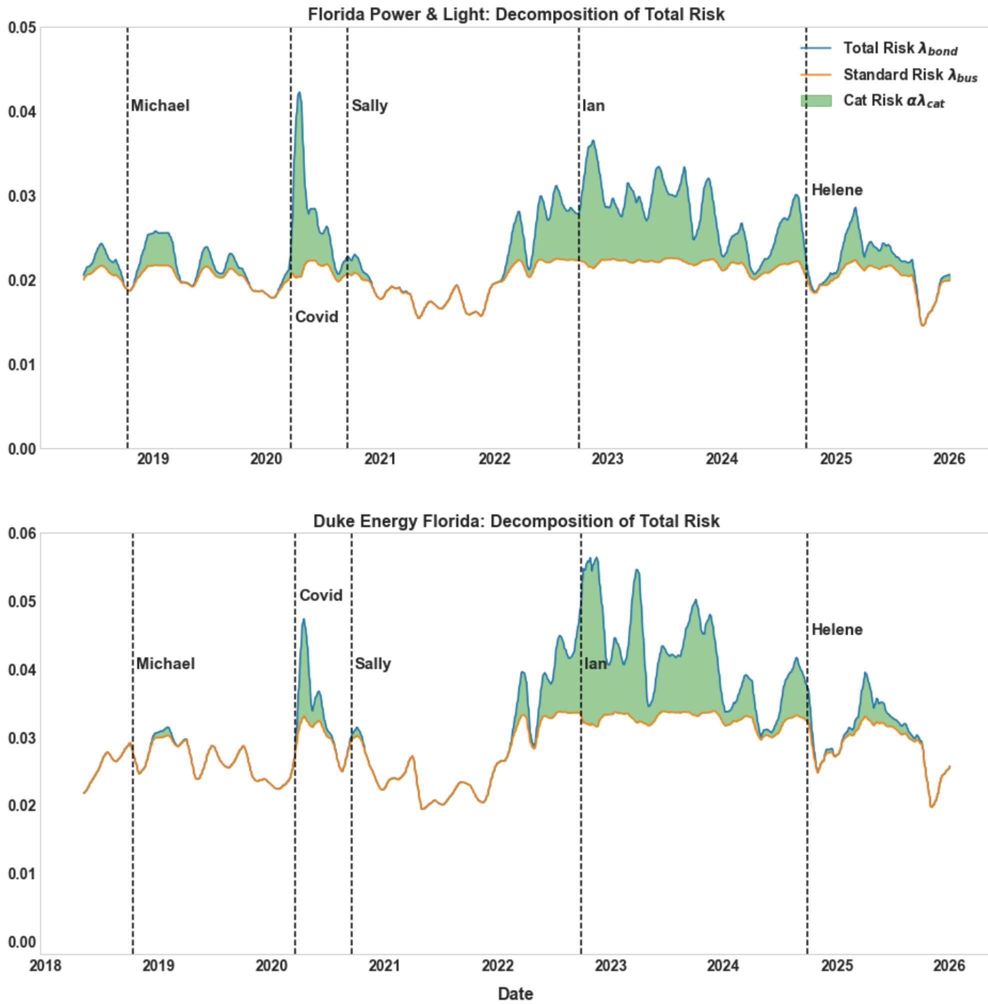

Figure 7: **Decomposition of Hurricane Risks:** This figure shows the 20-day moving average of the total risk λ_{bond} (blue line), the standard business risk λ_{bus} (orange line), and the decomposition of total risk into cat event risk $\alpha\lambda_{cat}$ (shaded green area) over the sample period of 2018 to 2025. The dotted vertical lines show landfall dates of some major hurricanes in the US/Florida region. The top figure is for Florida Power & Light and the bottom figure is for Duke Energy Florida.

total. These results illustrate the heterogeneous effects of hurricanes for firms within the same broader location facing the same risks. DukeFL seems to be relatively less exposed to catastrophe risks than is FPL on average, even though DukeFL's default risk is generally at elevated levels. However, both firms faced a significant rise in cat risks post hurricane Ian, showing the impact of historically significant cat event on bond prices and risks.[25] We see

[25]This is also consistent with the fact that FPL could be more exposed to hurricane risks relative to DukeFL. FPL is the largest utility provider in Florida with assets along large parts of hurricane prone Florida coastlines. DukeFL mostly services broader inland and western Florida. See news release from Florida Public Service Commission 2024 and 2025 for more information, including recent storm related impacts, where FPL received approval to recover $1.2 billion hurricane related damages and DukeFL for

Table 3: Decomposition of Total Risks and Comparison to Hurricane Ian

	Full sample	3-months after Ian
FPL:		
Total Risk	0.023	**0.033**
Cat Risk-to-Total Risk	0.107	**0.320**
Duke Energy:		
Total Risk	0.032	**0.050**
Cat Risk-to-Total Risk	0.077	**0.330**

This table shows the averages of the total risk λ_{bond} along with the corresponding ratio of cat risk attributable to the total risk, i.e. the ratio of cat risk-to-total risk, $\frac{\alpha\lambda_{cat}}{\lambda_{bond}}$. First column is for the full sample period and second column is for total 3-months after hurricane Ian landfall.

similar results in the Miami-Dade county municipal bonds in the next section.

For subsequent use, we highlight a subtle economic channel through which natural disasters affect credit risks. The above results indicate that periods of general economic stress (irrespective of natural disasters) with elevated risk aversion, can lead to larger business risk and cat event risk premium. This is seen from a spike in credit risk, from both business as well as catastrophic risk during the covid stress and periods of rapidly rising interest rates. In other words, during periods of economic stress, credit risk and premiums for natural disaster risk can actually rise, even if the statistical probabilities of default and cat events remain unchanged.

5.2.2 Wildfires

We now turn our discussions to wildfire risks in California. As with hurricanes, Figure 8 shows the corporate bond market and model prices, along with the default intensities, while Figure 9 shows the corresponding decomposition. Similar trends in the bond prices and the dynamics of the default intensities are evidenced as for hurricanes, including responses to the covid shock and interest rate spikes.

Figure 9 provides the decomposition of the default intensities, where the dotted lines indicate major and damaging wildfires in California. Similar to hurricanes, the model picks up the risks from wildfires, and is heterogeneous across the two corporate bonds, since they are differently exposed to different wildfires. One notable feature relative to hurricanes in Figure 7 is that the cat event default intensities from wildfire seem relatively more persistent.

$1.09 billion in costs.

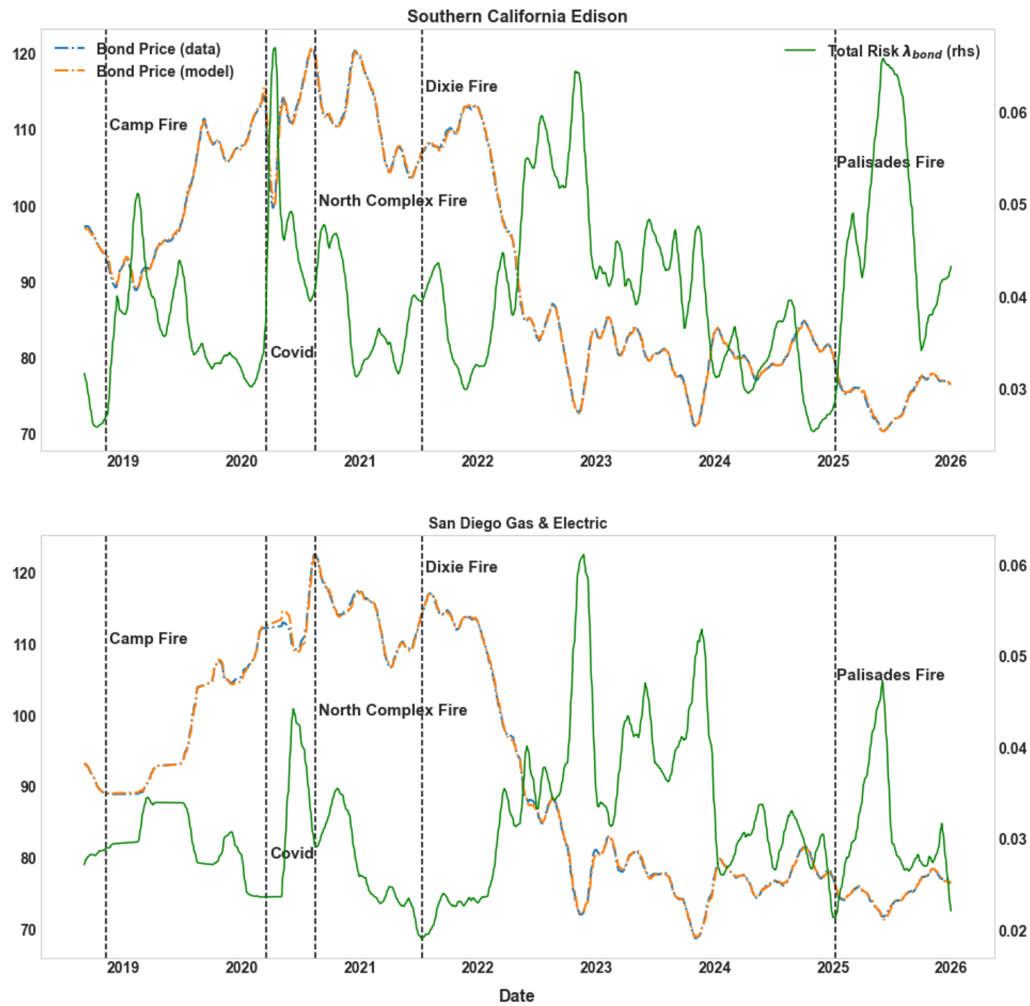

Figure 8: **Risks from Wildfires:** This figure shows the 20-day moving average of the bond prices (blue line), overlaid with model predicted prices (orange line) and the total risk λ_{bond} (on the right axis) over the sample period of 2018 to 2025. The dotted vertical lines show start dates of some major wildfires in the US/California region. The top figure is for Southern California Edison and the bottom figure is for San Diego Gas & Electric.

This is consistent with the fact that while both hurricanes and wildfires are acute risks, wildfires can last for a few months at a time, whereas the duration of hurricanes is much less (leaving aside the damaging effects).[26]

The Palisades and Eaton wildfires in Los Angeles which started in early January 2025, were the most damaging wildfires in global history, which lead to over $65 billion in total

[26]Relatedly, there is also a precedent of corporate bankruptcy from wildfires in California. In 2019 Pacific Gas & Electric (PG&E) filed for bankruptcy due to multi-billion dollar liabilities from wildfires in 2017 to 2018 in Northern California (see information on California Public Utilities Commission webpage and Columbia University Center on Global Energy Policy report (2019). It is reasonable to believe that markets might be more attentive to similar future risks for exposed corporations in the region.

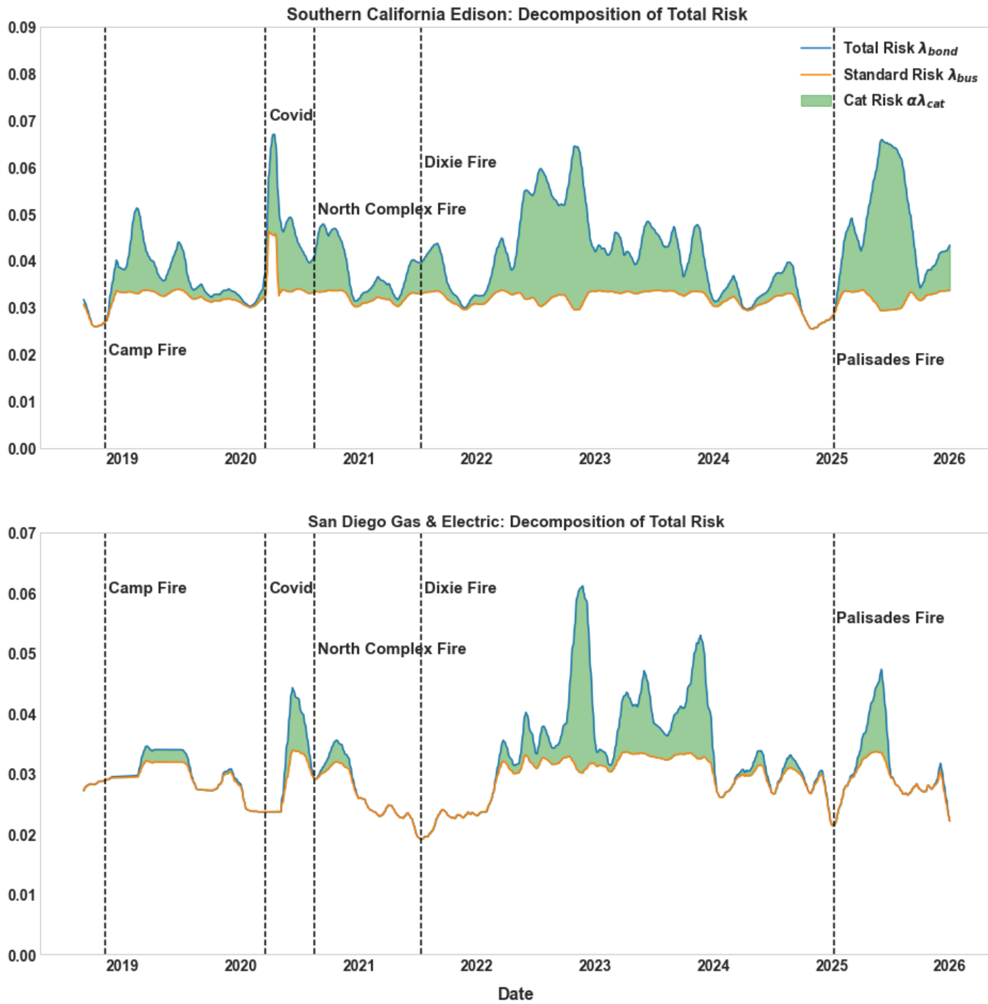

Figure 9: **Decomposition of Wildfire Risks:** This figure shows the 20-day moving average of the total risk λ_{bond} (blue line), the standard business risk λ_{bus} (orange line), and the decomposition of total risk into wildfire cat event risk $\alpha\lambda_{cat}$ (shaded green area) over the sample period of 2018 to 2025. The dotted vertical lines show start dates of some major wildfires in the US/California region. The top figure is for Southern California Edison and the bottom figure is for San Diego Gas & Electric.

losses according to insurance report by Gallagher Re (2025). Consistent with this evidence, we do see a large spike in the cat event intensities, especially in SCE which was directly exposed to the Palisades wildfires given that it serves the Southern California region. While the risks increased for SDGE as well, it was relatively smaller compared to that for SCE as seen in the Figure 9. It is also evidenced that SCE has a relatively larger exposure to cat event risks as perceived by the market.

Table 4 shows the decomposition of the default intensities with a comparison to the Palisades wildfire. Over the full sample the average default intensity for SCE was about

Table 4: Decomposition of Total Risks with Comparison to Palisades Fire

	Full sample	3-months after Palisades
SCE:		
Total Risk	0.041	**0.044**
Cat Risk-to-Total Risk	0.181	**0.238**
SDGE:		
Total Risk	0.032	**0.031**
Cat Risk-to-Total Risk	0.067	**0.037**

This table shows the averages of the total risk λ_{bond} along with the corresponding ratio of cat risk attributable to the total risk, i.e. the ratio of cat risk-to-total risk, $\frac{\alpha\lambda_{cat}}{\lambda_{bond}}$. First column is for the full sample period and second column is for total 3-months after the start of Palisades wildfire in January 2025.

4.1% and 18.1% of that was attributable to the cat risks. Comparing that with the three month period after the Palisades fire, we see larger cat risks attribution at 23.8%. For SDGE, the average default intensity is about 3.2%, of which about 6.7% can be attributed to cat risks. Further, during the 3-months period after the Palisades fire, cat risk was just 3.7% of the total. Thus, although SDGE was not directly exposed to the Palisades fire which was contained in the LA region, this reflects the risk premium related to fires given the market's sensitivity to the possibility of similar events. In contrast, SCE was directly exposed to the LA wildfires. But, the relatively mild increase from 18.1% to 23.8% suggests that the SCE bond markets in the past had similar concerns about wildfire risks. In the municipal bond results reported subsequently, we will see similar results for the LA municipal bond. Thus, relative to hurricanes, the wildfire risks in California seem to reflect a persistent concern about the effects of wildfires. This is also consistent with the previous results that the average risk premium in wildfire cat bonds is significantly larger than those in hurricane cat bonds. This reflects the larger uncertainty surrounding wildfires and the underdeveloped scientific modeling capacity relative to hurricane risks.

Given the above illustration, it is easy to see that for firms and businesses fully located in the same region, including SMEs, without actively traded bonds/financial instruments, our results apply directly. For firms with only a portion of their business activities in the exposed region, actively traded or not, our results can be used to provide an upper bound on the cat risks embedded in their default probabilities.

5.3 Extension to Municipal Bonds

This section discusses results on municipal bonds. Although the credit risk and default for municipalities are generally much lower than those for corporations, some municipalities are directly exposed to natural disasters, which affect credit spreads. Unfortunately, relative to corporate bond markets, municipal bonds are relatively illiquid and trade infrequently (see Jeon et al. (2024)). We select two municipalities that are active in municipal bond markets with a relatively large bond issuance outstanding. For hurricanes we select the municipal revenue bonds from Miami-Dade county in Florida, as it is directly exposed to hurricane risks. For wildfires in California, we select the bond from the Los Angeles Department of Water and Power (LADWP), which is also directly exposed to wildfire risks.

The available sample of municipal bonds from our data source Cbonds is only from late 2020. Note that Cbonds has its own methodology for constructing reliable indicative bond prices, with relevant measures of bid and ask prices (see Cbonds Estimation). This is helpful given that municipal bonds trade infrequently and are relatively illiquid. The daily sample size for Miami-Dade County municipal bond is 1240, with an average maturity of 26.3 years (maturing in 2049), a coupon rate of 5%, and an average YTM of 4%. Similarly, the daily sample size for the LADWP municipal bond is 1269, with an average maturity of 24 years (maturing in 2047), a coupon rate of 5%, and an average YTM of 4.5%. The median bid-ask spread is about 0.5 for both municipal bonds.

We applied the same estimation methodology as with corporate bonds. The estimates converged and we get a MAE for both at about 0.48, which is near the bid-ask spread.

Figure 10 shows the decomposition of the default intensities for the Miami-Dade county bond (top figure) and for the LADWP bond (bottom figure). Note the consistently declining default intensities since 2022 for both bonds. This reflects the fact that post-covid risks were subsiding. However, business risks for these municipal bonds reduced to being nearly negligible in recent years, as seen from the Figure.

For Miami-Dade county, consistent with the impact of hurricane Ian as seen in the corporate bonds discussed above, we do see elevated risks. Table 5 shows the full decomposition. The average default intensity is 2%, mostly driven by post-covid period risks but overall much lower than that for FPL/DukeFL as expected, and the risks are almost negligible at times since late 2023. About 13% of default intensity is attributable to cat event risks over the entire sample whereas that proportion jumps to about 42% in the aftermath of hurricane Ian. The bond shows a small spike in the more recent 2024 hurricane Helen, but then it subsided quickly.

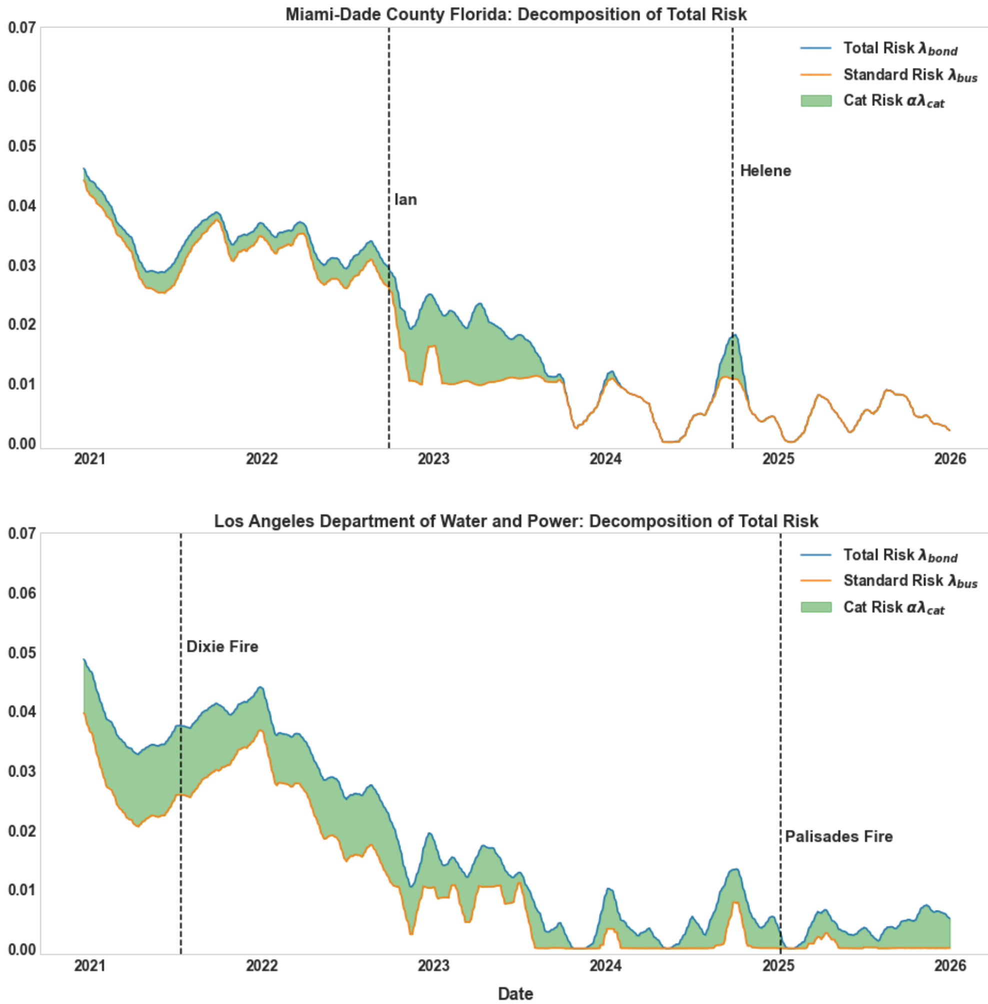

Figure 10: **Decomposition of Hurricane and Wildfire Risks in Municipal Bonds:** This figure shows the 20-day moving average of the total risk λ_{bond} (blue line), the standard business risk λ_{bus} (orange line), and the decomposition of total risk into cat event risk $\alpha\lambda_{cat}$ (shaded green area) over the sample period from late 2020 to 2025. The top figure corresponds to Miami-Dade county municipal bond, where the dotted vertical lines show landfall dates of some major hurricanes in the US/Florida region. The bottom figure is for LADWP municipal bond where the dotted vertical lines show start dates of some major wildfires in the US/California region.

Similarly, for LADWP, even though the average default intensity is about 1.7% and the business risks are almost negligible at times since late 2023, about 55% of the risk is attributable to cat event risks, including the 3 months after the Palisades fire. Thus, while the default intensity is small in absolute value, the wildfire risk remains quite persistent, exactly as for SCE which is also exposed to wildfires in the LA region. It is also consistent with the significant risk premium observed in the wildfire cat bonds as discussed above.

Table 5: Decomposition of Total Risks in Municipal Bonds

	Full sample	3-months after
Miami-Dade County Florida: Comparison to Hurricane Ian		
Total Risk	0.02	**0.02**
Cat Risk-to-Total Risk	0.13	**0.42**
LADWP California: Comparison to Palisades Fire		
Total Risk	0.017	**0.003**
Cat Risk-to-Total Risk	0.557	**0.558**

This table shows the averages of the total risk λ_{bond} in the municipal bonds along with the corresponding ratio of cat risk attributable to the total risk, i.e. the ratio of cat risk-to-total risk, $\frac{\alpha\lambda_{cat}}{\lambda_{bond}}$. The first column is for the full sample period. The second column, top panel is for the total 3-months after hurricane Ian landfall and the second column bottom panel is the total 3-months after the start of the Palisades wildfire.

6 Conclusion

This paper derives a unified model for both catastrophe and corporate bonds to study the implications of natural disaster risks. The arbitrage-free valuations obtained in this paper are intuitive and easy to implement. We illustrate the application of our approach to quantify the financial risks from hurricanes and wildfires. Our results show that the market implied cat event probabilities are materially larger than the corresponding statistical probabilities, which are especially pronounced for wildfire risks, implying the presence of significant cat event risk premium.

These estimated cat event intensities are used to decompose the credit risk embedded in corporate bonds into that due to ordinary business operations and cat events (with extension to municipal bonds). Our results show that the cat risks in corporate bonds are time varying, which increase and remain persistent after major catastrophe events, reflecting increased market risk aversion. Our methodology applies to other entities such as municipalities or sovereigns that may be exposed to natural disaster risks. Lastly, our paper can be used by both practitioners and policymakers to quantify the impact of natural catastrophe risks on portfolio values, and to better understand implications for credit and funding risks, and financial stability.

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A Appendix

A.1 Cat Formula

The following formula follows directly from the assumption that $\frac{v_{cat}(t)+G_{cat}(t)}{B_t}$ is a $\mathbb{Q}$ martingale.[27]

$$
\begin{aligned}
v_{cat}(t) = \textstyle\sum_{k=1}^{m} E^{\mathbb{Q}} \left[(R_{t_{k-1}} + c)\Delta L 1_{\{\tau_{cat} > t_k\}} e^{-\int_t^{t_k} r_u du} | \mathcal{F}_t \right] \\
+ L E^{\mathbb{Q}} \left[1_{\{\tau_{cat} > T\}} e^{-\int_t^{T} r_u du} | \mathcal{F}_t \right] \\
+ \textstyle\sum_{k=1}^{m} L E^{\mathbb{Q}} \left[1_{\{t_{k-1} < \tau_{cat} \le t_k \le T\}} (1 - \delta_{cat}) e^{-\int_t^{t_k} r_u du} | \mathcal{F}_t \right]
\end{aligned}
$$

We consider each term separately.

For future use we define

- (A Survival Digital) This security pays \$1 at time t_k only if a cat event occurs after t_k. The value of this security at time $t < t_k$ is

$$
z_{cat}(t, t_k) = E^{\mathbb{Q}} \left[1_{\{\tau_{cat} > t_k\}} e^{-\int_t^{t_k} r_u du} | \mathcal{F}_t \right]
$$

$$
= E^{\mathbb{Q}} \left[1_{\{\tau_{cat} > t_k\}} | \mathcal{F}_t \right] E^{\mathbb{Q}} \left[e^{-\int_t^{t_k} r_u du} | \mathcal{F}_t \right] = [1 - Q_{cat}(t, t_k)] p(t, t_k)
$$

- (A Default Digital) This security pays \$1 at time t_k if a cat event occurs within $(t_{k-1}, t_k]$. The value of this security at time $t < t_k$ is

$$
x_{cat}(t, t_k) = E^{\mathbb{Q}} \left[1_{\{t_{k-1} < \tau_{cat} \le t_k\}} e^{-\int_t^{t_k} r_u du} | \mathcal{F}_t \right]
$$

$$
\begin{aligned}
&= E^{\mathbb{Q}} \left[1_{\{t_{k-1} < \tau_{cat} \le t_k\}} | \mathcal{F}_t \right] E^{\mathbb{Q}} \left[e^{-\int_t^{t_k} r_u du} | \mathcal{F}_t \right] \\
&= [Q_{cat}(t, t_k) - Q_{cat}(t, t_{k-1})] p(t, t_k)
\end{aligned}
$$

A.1.1 Fixed Rate Spread Payments

$$
\begin{aligned}
&E^{\mathbb{Q}} \left[c\Delta L 1_{\{\tau_{cat} > t_k\}} e^{-\int_t^{t_k} r_u du} | \mathcal{F}_t \right] = c\Delta L E^{\mathbb{Q}} \left[1_{\{\tau_{cat} > t_k\}} | \mathcal{F}_t \right] E^{\mathbb{Q}} \left[e^{-\int_t^{t_k} r_u du} | \mathcal{F}_t \right] \\
&\quad = c\Delta L [1 - Q_{cat}(t, t_k)] p(t, t_k) = c\Delta L z_{cat}(t, t_k).
\end{aligned}
$$

[27] Note that there is a typo in Hilscher et al. (2025), it omits the cash flows. As noted in the text, we do not need complete markets for this formula to hold.

A.1.2 Floating Rate Payments

Standing at time t_{k-1}.

$$E^{\mathbb{Q}}\left[R_{t_{k-1}}\Delta e^{-\int_{t_{k-1}}^{t_k} r_u du}\middle|\mathcal{F}_{t_{k-1}}\right] = E^{\mathbb{Q}}\left[\left(\frac{1}{p(t_{k-1},t_k)}-1\right)e^{-\int_{t_{k-1}}^{t_k} r_u du}\middle|\mathcal{F}_{t_{k-1}}\right]$$
$$= E^{\mathbb{Q}}\left[\left(\frac{1}{p(t_{k-1},t_k)}\right)e^{-\int_{t_{k-1}}^{t_k} r_u du}\middle|\mathcal{F}_{t_{k-1}}\right] - E^{\mathbb{Q}}\left[e^{-\int_{t_{k-1}}^{t_k} r_u du}\middle|\mathcal{F}_{t_{k-1}}\right]$$
$$= \frac{1}{p(t_{k-1},t_k)}E^{\mathbb{Q}}\left[e^{-\int_{t_{k-1}}^{t_k} r_u du}\middle|\mathcal{F}_{t_{k-1}}\right] - p(t_{k-1},t_k)$$
$$= \frac{p(t_{k-1},t_k)}{p(t_{k-1},t_k)} - p(t_{k-1},t_k) = 1 - p(t_{k-1},t_k).$$

Next, standing at time $t \leq t_{k-1}$.

$$E^{\mathbb{Q}}\left[R_{t_{k-1}}\Delta e^{-\int_t^{t_k} r_u du}\,|\mathcal{F}_t\right] = E^{\mathbb{Q}}\left[E^{\mathbb{Q}}\left[R_{t_{k-1}}\Delta e^{-\int_t^{t_k} r_u du}\middle|\mathcal{F}_{t_{k-1}}\right]|\mathcal{F}_t\right]$$
$$= E^{\mathbb{Q}}\left[E^{\mathbb{Q}}\left[R_{t_{k-1}}\Delta e^{-\int_{t_{k-1}}^{t_k} r_u du}e^{-\int_t^{t_{k-1}} r_u du}\middle|\mathcal{F}_{t_{k-1}}\right]|\mathcal{F}_t\right]$$
$$= E^{\mathbb{Q}}\left[e^{-\int_t^{t_{k-1}} r_u du}E^{\mathbb{Q}}\left[R_{t_{k-1}}\Delta e^{-\int_{t_{k-1}}^{t_k} r_u du}\middle|\mathcal{F}_{t_{k-1}}\right]|\mathcal{F}_t\right]$$

Using the above, we get

$$= E^{\mathbb{Q}}\left[e^{-\int_t^{t_{k-1}} r_u du}\left(1-p(t_{k-1},t_k)\right)|\mathcal{F}_t\right]$$
$$= E^{\mathbb{Q}}\left[e^{-\int_t^{t_{k-1}} r_u du}\,|\mathcal{F}_t\right] - E^{\mathbb{Q}}\left[p(t_{k-1},t_k)e^{-\int_t^{t_{k-1}} r_u du}\,|\mathcal{F}_t\right]$$
$$= p(t,t_{k-1}) - LE^{\mathbb{Q}}\left[p(t_{k-1},t_k)e^{-\int_t^{t_{k-1}} r_u du}\,|\mathcal{F}_t\right]$$

But, because $\frac{p(t,t_k)}{B(t)}$ is a $\mathbb{Q}$- martingale,

$$E^{\mathbb{Q}}\left[p(t_{k-1},t_k)e^{-\int_t^{t_{k-1}} r_u du}\,|\mathcal{F}_t\right] = E^{\mathbb{Q}}\left[\frac{p(t_{k-1},t_k)}{B(t_{k-1})}\,|\mathcal{F}_t\right]B(t) = Lp(t,t_k)$$

Hence, by substitution

$$E^{\mathbb{Q}}\left[R_{t_{k-1}}\Delta e^{-\int_t^{t_k} r_u du}\,|\mathcal{F}_t\right] = L\left(p(t,t_{k-1}) - p(t,t_k)\right)$$

Finally,

$$E^{\mathbb{Q}}\left[R_{t_{k-1}}\Delta L 1_{\{\tau_{cat}>t_k\}}e^{-\int_t^{t_k} r_u du}\,|\mathcal{F}_t\right]$$
$$= E^{\mathbb{Q}}\left[R_{t_{k-1}}\Delta L e^{-\int_t^{t_k} r_u du}\,|\mathcal{F}_t\right]E^{\mathbb{Q}}\left[1_{\{\tau_{cat}>t_k\}}\,|\mathcal{F}_t\right]$$
$$= L\left(p(t,t_{k-1}) - p(t,t_k)\right)\left[1 - Q_{cat}(t,t_k)\right] = L\left(\frac{p(t,t_{k-1})}{p(t,t_k)} - 1\right)z_{cat}(t,t_k)$$

A.1.3 Principal Payment

$$LE^{\mathbb{Q}}\left[1_{\{\tau_{cat}>T\}}e^{-\int_t^T r_u du}\,|\mathcal{F}_t\right] = LE^{\mathbb{Q}}\left[e^{-\int_t^T r_u du}\,|\mathcal{F}_t\right]E^{\mathbb{Q}}\left[1_{\{\tau_{cat}>T\}}\right]$$
$$= Lp(t,T)[1 - Q_{cat}(t,t_k)] = Lz_{cat}(t,T)$$

A.1.4 Recovery Rate Payments

$$\sum_{k=1}^{m} LE^{\mathbb{Q}}\left[1_{\{t_{k-1}<\tau_{cat}\leq t_k\leq T\}}(1-\delta_{cat})e^{-\int_t^{t_k} r_u du}\,|\mathcal{F}_t\right]$$

$$= L(1-\delta_{cat})\sum_{k=1}^{m} E^{\mathbb{Q}}\left[1_{\{t_{k-1}<\tau_{cat}\le t_k \le T\}}\,|\mathcal{F}_t\right] E^{\mathbb{Q}}\left[e^{-\int_t^{t_k} r_u du}\,|\mathcal{F}_t\right]$$
$$= L(1-\delta_{cat})\sum_{k=1}^{m}[Q_{cat}(t,t_k)-Q_{cat}(t,t_{k-1})]p(t,t_k)$$
$$= L(1-\delta_{cat})\sum_{k=1}^{m} x_{cat}(t,t_k).$$

A.2 Bond Valuation Formula

The same mathematics as above yields the bond valuation formula, replacing "cat" with "bond" for the appropriate payments. Note that for fixed rate corporate bonds, the floating rate payment component is removed.