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PAPER

An asset-level analysis of financial tail risks under extreme weather events

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Abstract

Extreme weather events pose a risk to the economic and financial system. To understand the materiality of these risks, financial institutions are beginning to conduct climate stress testing exercises. This requires climate risk models to be integrated with financial risk models. In this paper, we introduce an open, modular, and reproducible framework for the assessment of asset-level physical risk and the translation of these risks into portfolio-level impacts. The proposed framework addresses key limitations of previous research by including multiple financial transmission channels, and the incorporation of spatial correlations between weather events for bottom-up, asset-level, estimation of portfolio-level tail risks. By incorporating direct capital damages, business disruptions, and insurance coverage, we provide an overview of the direct financial impact of extreme weather events. Through an application of the framework for the assessment of flood risk to a portfolio of power firms located in India, we show that these extensions have material impacts on the risk estimates. We further show how different assumptions related to spatial correlations can lead to large under- or overestimations of portfolio-level tail risks.

1. Introduction

Extreme weather events have material financial impacts on firms causing substantial damages to assets and disrupting operations. These economic impacts subsequently propagate to the financial system [1] [2], and financial markets [3]. As a result, financial institutions are using climate stress testing to assess, manage, and disclose their climate-related risks [4] which has led to a proliferation of climate service providers that offer convenient out-of-the-box physical climate risk assessment solutions. These solutions often lack transparency and show substantial divergence in risk scores [5], which are quantitative indicators that estimate an asset's or firm's exposure and vulnerability to physical climate hazards, often generated using proprietary models. The lack of transparency, combined with the disconnect between the granularity of data that financial institutions need and what climate science can reliably provide [6], makes it difficult to assess their usefulness. This has led to increasing calls for climate risk data and models to be offered as an open, public good [7][8].

Existing academic research in the domain of physical climate financial risk assessments has primarily led to the development of macro-economic models to assess the impact of both chronic and acute climate risks [9]. The projections of economic variables generated by these models are subsequently used as inputs into sectoral or regional decomposition models to conduct stress testing exercises [10]. These models are useful for describing impacts on the overall economy; but lack the granularity to accurately describe the physical risk of specific assets or firms. More recently, Bressan, *et al* have introduced an asset-level framework for the quantification of chronic and acute climate risks [11]. They provide a detailed approach based on the dividend discount model (DDM) that considers direct asset damages from tropical cyclones, and chronic losses estimated from a macro-economic model. This type of bottom-up, asset-level methodology provides an alternative for physical risk stress testing by aggregating asset-level results to financial portfolio- and system-level impacts. In this research, we contribute to a specific part of bottom-up climate stress testing, i.e. the assessment of asset-, firm- and portfolio-level tail risks.

Central banks have developed their own approaches for climate stress testing. Most notably, the European Central Bank's (ECB) economy-wide climate stress test includes damages to physical capital and production disruptions due to extreme weather events, and changes in insurance premiums because of the changing frequency and intensity of extreme weather events [12]. Other central banks, including the Bank of England [4], Dutch Central Bank [13], the People's Bank of China [14], the Federal Reserve [15], the Bank of Japan [16], and the Bank of Thailand [17] also conducted or proposed climate stress tests. Some of these exercises exclusively focus on the quantification of transition risks and none of them provide a detailed asset-level framework for physical risks. Further, the approaches of central banks and financial institutions often rely on proprietary data from data providers which makes it difficult to reproduce their results.

Even though previous literature has provided models for asset-level physical risk assessments, there are limitations to this work. First, empirical studies have provided evidence for multiple financial transmission channels of physical risks including direct capital damages, business disruptions [18], and increased costs of insurance following natural disasters [19, 20]. Existing models of asset-level assessments do not provide a comprehensive framework that includes all channels. Secondly, portfolio-level tail risks and average impacts are computed by taking a weighted sum of asset-level impacts. Distributions and/or estimates of asset-level impacts are derived independently. Therefore, assumptions regarding the correlations between asset-level impacts are required to obtain portfolio-level risks. Often the assumptions of complete independence or complete dependence[6] are taken which can lead to under- or overestimations of the financial risks, especially financial tail risks. Lastly, these approaches often still rely on physical risk scores obtained through data vendors.

This research addresses some of these limitations. Firstly, the framework introduces an open, modular, and reproducible approach based on freely available data. This approach aims to reduce the significant cost barrier currently associated to bottom-up physical risk assessments whilst allowing financial institutions to use proprietary data and models for certain parts of the analysis.

Secondly, the paper significantly extends current approaches with regards to modeling insurance impacts after physical weather events by not only including changes in fair premiums, but also including temporary changes in insurance premiums due to severe weather events.

Third, the paper introduces a Monte Carlo approach for estimating portfolio-level risks, in which spatial correlations between weather events and their financial impacts are explicitly modeled. The inclusion of such correlations is a core feature of insurance models and has also been applied in the context of financial stress testing [21].

A core distinction in the treatment of climate-related physical risks lies between these scenario-based approaches and probabilistic risk analysis. Scenario-based approaches, used in many central-bank stress testing exercises, typically define specific events (e.g. a 1-in-100 year flood) [12] or narrative-driven pathways and estimate financial impacts based on those assumptions. This approach aligns with the recommendations of the Task Force on Climate-Related Financial Disclosures (TCFD) [22] for scenario-driven financial stress testing but is less suitable for evaluating market risk and other commonly used techniques in finance.

In contrast, probabilistic approaches, such as Monte Carlo simulations, model the likelihood and correlation structure of extreme events to generate outcome distributions. Our framework adopts this probabilistic perspective, making it well-suited for estimating tail risk metrics such as Value at Risk (VaR) and expected shortfall which are calculated using quantiles of estimated return distributions of financial portfolios. These measures are widely used in financial risk management and are directly tied to bank capital requirements under the Basel regulatory framework [23][7].

By aligning the modeling of physical climate risks with existing practices in financial risk management, the framework provides a foundation for integrating climate tail risks into financial regulation. Moreover, because it captures dependencies through correlation models, the framework can also support techniques such as portfolio optimization, hedging, and securitization, where correlations play an important role.

While the framework is generalizable to multiple hazards and sectors, it is demonstrated on a case study of flood risk for Indian power firms. Floods have been reported to constitute the largest percentage (41%) of

[6] The assumption of complete dependence assumes that all assets are hit by the same natural disasters at the same time. The complete independence assumption assumes that all asset impacts are independent from each other. The complete dependence assumption is an upper bound, whereas the complete independence assumption is a lower bound.

[7] The Basel Framework sets international standards for banking system resilience. VaR is one of the core tools used to determine capital adequacy in response to market risks.

all known disasters between 2008 and 2017 with India being one of the most severely affected countries [24]. By focusing our case study on power firms, we can leverage publicly available data sources and use results from previous literature to calibrate asset-level damages.

The remainder of the paper is structured as follows. The methodology section provides an overview of the modeling framework which is based on the discounted cash flow model and Monte-Carlo simulation. Then, the results section discusses a case study on power assets located in India. We highlight the impact of our modeling decisions related to the spatial correlation structure of weather events and compare portfolio-level results. Finally, the discussion will highlight the key results, discuss limitations, and provide guidance for further research.

2. Methods

The paper introduces a simulation-based, end-to-end, modular, and reproducible framework for the translation of asset-level physical risk impacts into portfolio-level financial risks using only freely available data. As this research is interested in portfolio-level tail risk estimations, we currently only consider acute impacts and refer to Bressan [11], for the incorporation of chronic impacts.

In this section, we first discuss the incorporation of spatial correlations in the impacts of extreme weather events. Because the case study focuses on flood risks, the approach described below is most applicable to this type of risk but can be generalized to other extreme weather events. Secondly, we discuss how to translate these weather impacts into financial impacts to finally discuss how these asset-level financial impacts are translated into portfolio-level risk.

2.1. Extreme weather events

The simulation of weather events is based on the work of Bernhofen [25]. Maps for physical hazards with various return periods (RP) (5, 10, 25, 50, 100, 200, 500, 1000) are obtained from the Global Infrastructure Resilience Index (GIRI) [26]. These maps provide values for both the extent, the intensity, and the frequency at which these events occur and can be obtained for one historical and two future scenarios: an optimistic and a pessimistic scenario. These two future scenarios cover the period 2051–2100 and represent the 20th percentile and 80th percentile of an ensemble of 30 climate model runs consisting of 10 climate models and 3 shared socioeconomic pathways (SSPs) scenarios [27].

The simulation of extreme events is done using a multivariate distribution with univariate homogeneous Poisson processes and a copula correlation structure. Each Poisson process corresponds to a single hazard type and RP at a specific geographic location. As a result, the probability of an event with hazard type h and return period rp in region $\mathcal{R}$ occurring in an individual year corresponds to

$$P(N_{h,\mathcal{R}} \geqslant 1) = 1 - \mathrm{e}^{-\frac{1}{rp}}.$$

The intensity of the weather events is obtained from the hazard maps.

The correlation between the occurrences of weather extremes across different geographical areas is modeled using a copula function. Previous literature has discussed various approaches for modeling these correlations [28]. A naïanve implementation assumes independent events across geographical regions and hazard types. This approach leads to an underestimation of portfolio-level financial impacts (see results). Copulas can be used to provide an explicit specification of the correlation structure across different regions. A key advantage of using copulas is that they can be used for a variety of weather extremes, including floods [29] and droughts [30, 31], storms [32], and heatwaves [33]. Alternatively, simulation-based approaches like for example the simulation of tropical cyclone paths as discussed in [34] have the potential to introduce correlations between asset impacts as well.

Correlations between multiple hazard types can also be modeled using copula functions. For example, Lan, [28] and Guo, [33] modeled respectively the correlation between floods and winds [28], and droughts and heatwaves [33] using copula functions. Various authors have also used copulas to model correlations between characteristics of weather events like for example the duration and intensity of droughts [35, 36].

A disadvantage of the copula method is that the calibration is done based on historical information. Therefore, the application of copulas in the context of scenario analysis requires the specification of copula parameters based on expert opinion or the assumption that the correlation structure does not depend on scenario parameters. In the context of this paper, which models the financial impact of flood events, the correlations between these events are calibrated using daily discharge data from 1979 until 2016 obtained from the Global Flood Awareness System (GloFAS) v4.0 [37].

The discharge data is transformed into a set of binary indicators representing the occurrence of extreme discharge events on each date. To account for potential time lags in the joint occurrence of flooding across basins, a three-day window is applied around each extreme event. Extreme discharge events are defined using the 99th percentile of daily discharge values. These events do not represent the full set of flood occurrences but rather a practical threshold for identifying extreme events used in the calibration of the copula function. Based on the resulting binary event matrix, three types of copulas are fitted to capture the spatial dependence structure: Gaussian, t-Copula, and R-vine copula.

The Gaussian copula models the correlation between flood events based on the multivariate normal distribution [38]

$$C_R^G(u_1,\ldots,u_d) = \Phi_R\left(\Phi^{-1}(u_1),\ldots,\Phi^{-1}(u_d)\right)$$

with R the correlation matrix and $\Phi(-1)$ the inverse of the standard normal cumulative distribution function. The main advantage of the Gaussian copula is that it only requires a single input, which is the correlation matrix. A key disadvantage of the method is the asymptotic independence of extreme events [39] meaning that as events get more extreme, the correlations become weaker. This limitation of the Gaussian copula was widely discussed in the aftermath of the 2008 financial crisis [39].

An alternative copula function that introduces tail dependence whilst still being easily fitted based on the correlation matrix is the T-Copula. This copula is defined by [40]

$$c^t_{\nu,R}(\mathbf{u}) = \int^{t_\nu^{-1}(u_d)} \cdots \int^{t_\nu^{-1}(u_d)} \frac{\Gamma(\frac{\nu+d}{2})}{\Gamma(\frac{\nu}{2}\sqrt{(\pi\nu)^d|P|}} \quad \left(1+\frac{\mathbf{x}'P^{-1}\mathbf{x}}{\nu}\right)^{-\frac{\nu+d}{2}} \mathrm{d}x.$$

With R the correlation matrix and ν the degrees of freedom. The tail dependence λ of the T-copula is given by

$$\lambda = 2t_{\nu+1}\left(-\sqrt{\nu+1}\sqrt{1-\rho}/\sqrt{1+\rho}\right)$$

where ρ is the off-diagonal element of R. The degree of freedom is therefore an additional parameter that needs to be estimated and is directly related to the degree of tail risk. Since the t-distribution is elliptically symmetric; the level of upper- and lower-tail dependence are the same.

A more flexible copula that allows for differing upper- and lower tail dependencies is the R-vine copula. Vine copulas are built out of bivariate copulas. A tree structure combined with conditioning is used to transform these bivariate copulas into a single multivariate version. In the tri-variate case,

$$f(x_1,x_2,x_3) = f(x_3|x_1,x_2)\times f(x_2|x_1)\times f(x_1).$$

Following [40], a pair copula decomposition represents f as

$$\begin{aligned} f(x_1,x_2,x_3) = c_{1,3|2}&\left(F(x_1|x_2),F(x_3|x_2)|x_2\right)f(x_2)\\ &\times c_{2,3}\left(F(x_2),F(x_3)\right)f(x_3)\\ &\times c_{1,2}\left(F(x_1),F(x_2)\right)f(x_1)\end{aligned}$$

showing that the joint density can be expressed in terms of bivariate copulas, marginal densities and conditional distributions. Because each bivariate copula can be parameterized differently, vine copulas allow each pair to have different strengths and types of correlation [41]; however, the number of parameters in the copula model increases quadratically with the dimension, posing challenges in high dimensional applications [41].

Previous studies exploring the spatial correlation of flooding have made use of the vine copula [42]. However, these applications typically deal with a small number of correlations that need to be modeled. In our assessment, 126 different basins are included. The large number of basins make it difficult to obtain stable parameterizations of the copula. As a result, the analysis compares the result for the three copulas.

2.2. Asset-level financial impacts

The financial impact of simulated weather events is estimated using a discounted cash flow (DCF) model. Previous literature has used the Discounted Dividend Model (DDM) [11]. Even though a major advantage of the DDM is that it directly estimates equity value (and hence share prices), previous literature has viewed the approach to be problematic [43] and not commonly used in practice [44]. In the DCF model, the value of a firm is determined based on the future free cash flows that will be earned. The value of a firm's i assets j $(A_{i,j})$

is given by[8] [45]

$$A_{i,j} = \sum_{t=0}^{T} \frac{FCF_t{}^t}{1+r} + TV$$

where FCF_t is the free cash flow generated by the asset at time t. The discount rate r is assumed to be constant over time and equal to 5%. The robustness checks (appendix B) show that the conclusions are robust against different specifications of the discount rate. The terminal value is given by [45]

$$TV = \frac{FCF_T}{r-g}.$$

With g being the growth rate of free cash flows. The free cash flows FCF_t depend on the revenue REV_t and costs C_t related to the asset's activities. The value T denotes the total number of cash flows that are taken into consideration. In the remainder of this paper, we assume that cash flows are computed on a yearly basis; however, the methods are applicable for other time scales. To allow for sufficient extreme weather events to occur in the simulation periods, we use a time horizon T of 25 years for the computation of the cash flows.

Based on this general framework, three transmission channels of acute weather events are modeled: (1) direct damages to the asset, (2) production disruptions following weather events, and (3) the insurance premium for protection against direct and production impacts. For each of these impacts, we differentiate between insured and uninsured assets. The framework does not include supply chain dependencies, critical infrastructure, or financial contagion between firms even though these can also have a material impact on the level of physical risk. In this context, we use *materiality* to refer to whether the financial impact of a climate-related risk is large enough to affect business valuations and investments.

2.2.1. Direct asset damages

Weather events cause physical damages to the asset that need to be repaired. Uninsured firms will need to cover the replacement costs in full, whereas insurance companies will cover the cost of replacement for insured assets. The proportional damages to the asset with respect to the asset's replacement value $RV_{i,j}$ can be computed using damage curves $f_d(x)$ obtained from previous literature [46, 47]. The financial impact of direct damages resulting from a weather event with characteristics ϵ is therefore given by

$$\Delta FCF_t = -f_d\left(x_\epsilon\right) RV_{i,j}\left(1 - I_{i,j}\right)$$

where the indicator function $I_{i,j}$ is 0 if the asset is not insured and 1 if the asset is insured against capital damages. The input for the damage function x_ϵ represents a vector of event characteristics that are used to obtain damages. For our analysis of floods, we use the damage curve provided by Nirandjan *et al* [46] in which x_ϵ corresponds to a single element representing the flood depth. In practice, however, flood damages are a function of additional characteristics.

2.2.2. Production disruptions

Weather events can prevent assets from producing services or goods and therefore impact both the revenue and costs of the asset. The impacts arising from these business disruptions are modeled using damage functions $f_b(x_\epsilon)$ that link weather event characteristics to disruption days. These damage curves are obtained from Luo [48]. The lost revenues of the asset are a combination of the reduced production volumes ΔVOL_t and price changes $\Delta\pi_t$ characterized by a price-supply elasticity function:

$$\Delta VOL_t = -\frac{f_b\left(x_\epsilon\right)}{CH_{i,j}} VOL_t$$

$$\Delta\pi_t = \frac{\partial\pi_{i,j}}{\partial VOL_{i,j}} \Delta VOL_t.$$

With CH denoting the capacity hours of the asset. The use of capacity hours is specific for generating assets but similar approaches can be taken for other case.

The revenue of the firm $(VOL_t * \pi_t)$ is impacted by these changes. Using the above equations, we obtain the aggregate impact on the firm's revenue

$$\Delta REV_t = VOL \times \Delta\pi + \pi \times \Delta VOL + \Delta VOL \times \Delta\pi.$$

[8] The subscripts i and j are dropped wherever it is clear from context that they relate to a specific asset.

Similarly, assuming constant unit costs, the costs are reduced according to the change in volume and the unit cost $u_{i,j}$ of production

$$\Delta C_t = -\Delta VOL_t \times u_{i,j}.$$

As a result, the impact on the free cash flows is given by

$$\Delta FCF_t = (\Delta REV_t - \Delta C_t)\left(1 - I_{i,j}\right) \tag{1}$$

with the indicator function $I_{i,j}$ representing the presence of insurance against business disruptions.

2.2.3. Cost of insurance

The impact of direct damages and production disruptions can be mitigated through insurance. By paying a fixed premium, firms can offset the negative impacts of direct asset damages and production disruptions. The premium that is charged by the insurance companies consists of three components: (1) the actuarially fair insurance premium based on the expected damages incurred by the asset, (2) the markup charged by insurance companies, and (3) short-term deviations from the fair insurance premium as a result of the insurance cycle. The fair insurance premium $p_{f,t}$ of an asset is computed by the total expected damages $\tilde{D}_{i,j}$ [12, 49]. The expected direct asset damages are given by:

$$\tilde{D}_{i,j} = \sum_{rp}^{RP}\left(1 - \mathrm{e}^{-\frac{1}{rp}}\right) f_d\left(x_{rp}\right) RV_{i,j}.$$

The markup charged by insurance companies is typically assumed to be a fixed percentage. In this study, we assume that insurance companies do not charge a mark-up; however, we allow changes in the cost of capital to influence the price of insurance.

To model these short-term fluctuations in the price of insurance, we base ourselves on the approach of Heinrich *et al* [49]. In this model, the insurance premium p_t depends on the total capital K in the insurance industry. High levels of capital will have a downward impact on insurance premiums, and low levels of capital will lead to increased premiums:

$$p_t = \tilde{D}_{i,j} \times \left[1 + s\left(\frac{K_0}{K_{t-1}}\right)\right].$$

The insurance premium therefore depends on the total expected damages $\tilde{D}_{i,j}$ and the ratio between the capital available in the insurance industry K_{t-1} and the start capital K_0. The capital K_t is equal the capital at the end of the previous year K_{t-1} with the collected premiums added and the total payouts deducted for the current year. The parameter s denotes the sensitivity of the insurance premium to the capital. Following Heinrich, *et al*, we also employ an upper and lower bound for the insurance premium which are respectively $1.35 \times \tilde{D}_{i,j}$ and $0.7 \times \tilde{D}_{i,j}$.

A limitation of this insurance pricing model is that it does not account for insurers' investment income. In periods of high capital returns, insurance firms may be able to absorb larger losses without increasing premiums. This model focuses on the loss-driven capital constraint channel and short-term premium dynamics, and does not aim to fully capture insurer balance sheet behavior or asset-side effects.

By including the link between insurance premiums and the capital available in the insurance industry, we incorporate the short-term impact of weather events on insurance premiums. When a severe weather event occurs, insurers will be forced to payout a significant number of claims. If this amount is larger than the premiums they collect, the total capital will go down which subsequently pushes the price of insurance up. During the following years, the insurance firms will collect higher premiums which pushes their capital up ultimately stabilizing the price of insurance around the fair insurance premium.

In practice, insurance capital is globally diversified and supported by reinsurance markets, which means that localized shocks are typically absorbed with limited impact on industry-wide premium levels. In our model, however, we adopt a stylized representation of the insurance capital pool, which reflects the capital available to the subset of firms and risks considered in the analysis. This approach allows us to investigate how repeated, concentrated losses might lead to temporary pricing pressures, even in a simplified setting. While not intended to represent the full dynamics of global insurance and reinsurance markets, this modeling choice provides a useful tool for exploring stress scenarios. Future work could incorporate more granular assumptions about regional or sectoral diversification.

2.3. Firm- and portfolio-level impacts

The impact of weather events on assets is translated into firm- and portfolio-level impacts. The framework considers impacts on the firm value and the probability of default. Due to the stochastic nature of the climate events simulation, Monte-Carlo simulation needs to be used to obtain a distribution of firm- and portfolio-level impacts. To accurately reflect the role of spatial correlations between events, aggregation to the firm and portfolio level is performed within each individual Monte Carlo simulation, rather than simulating asset-level impacts independently and aggregating afterward. This ensures that correlated shocks are propagated consistently through the system and that nonlinear joint impacts, particularly relevant in the tails of the distribution, are fully captured. The following subsections discuss each individual step of the Monte-Carlo simulation.

2.3.1. Impact on firm value

The value of the firm V_i is computed using ownership O information on assets and the asset values obtained from the DCF modeling,

$$V_i = \sum_{j=0}^{N} O_{i,j} A_{i,j}.$$

To quantify the level of climate risk of a firm, we compare the firm value V_i with a baseline scenario. The baseline scenario can either be defined as the current world scenario that considers current acute risks, following the work of Bressan [11], or use a synthetic scenario in which no weather events occur, following the suggestion of Hallegatte and Przyluski *et al* [50].

In both cases, the level of physical risk $PRISK_i$ can be defined as,

$$PRISK_i = \frac{V_{i,\mathcal{S}}}{V_{i,\mathcal{B}}}$$

with $V_{i,\mathcal{S}}$ the value of firm i in the modeled scenario and $V_{i,\mathcal{B}}$ the value of firm i in the baseline scenario. To arrive at a portfolio-level impact, we use the weighted sum of firm-level impacts:

$$V_{pft} = w_i \sum_{i=0}^{M} PRISK_i$$

where the weight w corresponds to the percentage exposures and M the number of positions, that is, the number of distinct investment holdings or exposures. For non-equity instruments, additional steps in the valuation of the instrument are needed. Note that for each step of the Monte-Carlo simulation, a portfolio value is obtained. Since the asset-level (and hence firm-level) impacts have correlations that arise from the flood correlation model, the portfolio-value distribution obtained through the Monte-Carlo simulation will also incorporate these correlations. As a result, we can define the VaR of the portfolio using the quantiles of portfolio values:

$$VaR_\alpha = Q_{V_{pft}}(1-\alpha).$$

To obtain interval estimates for the VaR, we make use of m out of n bootstrapping following the procedure of Bickel and Anat [51]; however, we note that alternative methods based on extreme value theory exist [52, 53].

2.3.2. Impact on default probability

The impact of weather events on firm default probabilities is computed in two different ways: (1) a Merton-based model in which the asset value is adjusted for the weather events, and (2) an approach based on empirical research in which fundamental metrics of firms are used to obtain an estimate of default probabilities. Both of these models are used in the previous literature and have benefits and limitations discussed in the results and discussion section. In the Merton framework the probability of default of a firm is given by [54],

$$PD_i = \phi\left(-\frac{\ln\left(\frac{V_i}{D}\right) + \left(\mu - \sigma^2\right) T}{\sigma\sqrt{T}}\right).$$

With, D the face value of the firm's debt, μ the drift rate of the firm's asset values, σ the volatility of asset values and T the time to maturity of the debt, and ϕ the cumulative standard normal distribution. The ΔPD_i can then be computed using the firm value in the baseline and the scenario's firm value:

$$\Delta PD_i = PD_i\left(V_{i,\mathcal{S}}\right) - PD_i\left(V_{i,\mathcal{B}}\right).$$

There are various limitations to the Merton model. For example, it requires an estimation of the asset volatility. This volatility is not directly observed. As a result, a calibration procedure like the one described in Bharath and Shumway [59] needs to be used. This calibration can be a cumbersome exercise and cannot be done for non-listed firms.

Even if the volatility can be calibrated, it is still unclear how that volatility should be adjusted for the increased levels of shocks. The literature has provided some proposals regarding these adjustments, for example Aguais and Forest (2023) use a climate-change volatility multiplier based on global mean temperatures. In this paper, we use a constant volatility. Similar limitations exist for the estimation on the drift parameter which we also assume to be constant.

Alternatively, the probability of default can be expressed as a linear function of fundamental firm metrics. As proposed in the *ECB's economy-wide climate stress test*, one such formulation looks as follows [12],

$$PD_i = \alpha + \beta_1 LEV_i + \beta_2 PROF_i + \beta_3 \ln(GDP) + \beta_4 \ln(GDP)^2 + \beta_5 AGE_I + \epsilon_i.$$

The profitability and leverage ratios are

$$LEV_i = \frac{\text{Total debt}_i}{\text{Total assets}_i} = \frac{D_i}{V_i}$$
$$PROF_i = \frac{\text{Earnings}_i}{\text{Total assets}_i} = \frac{E_i}{V_i}.$$

In the framework introduced in sections 2.2 and 2.3.1, the total assets correspond to V_i, and the earnings to the weighted sum of average revenues over the simulation period,

$$E_i = \sum_{j=0}^{N} O_j \frac{1}{T} \sum_{t=0}^{t} REV_t.$$

Then, the change in default probability is given by,

$$\Delta PD_i = \beta_1 \left(\frac{D}{V_{i,\mathcal{S}}} - \frac{D}{V_{i,\mathcal{B}}}\right) + \beta_2 \left(\frac{E_{i,\mathcal{S}}}{V_{i,\mathcal{S}}} - \frac{E_{i,\mathcal{B}}}{V_{i,\mathcal{B}}}\right).$$

Parameter estimates for β_1 and β_2 are provided in Alagoskoufis *et al* (2021); however, more precise values for these parameters can be obtained by performing an empirical estimation. The main advantage of this approach is that it can be applied to both public and private firms and the PD changes can easily be obtained from the *prisk* model framework. In the results section, we compare the results obtained through both approaches.

2.4. Data

Our case study focuses on India (see figure 1), and we set up the modeling framework using various publicly available data sources. In the appendix, we also provide the results for Thailand. Both India and Thailand are highly exposed to flood risk making these countries an interesting case study for this analysis. The focus on power assets is mostly driven by the availability of geographic and ownership data, as well as sector-specific damage curves. The framework can be extended to different geographical areas or sectors.

River flood extent and depth maps are obtained from the GIRI for a baseline (historical) scenario and a future (pessimistic) scenario. This future scenario is centered around the year 2075 and represents a high emission, SSP 585 scenario. The methodology to generate flood maps is described in detail in Alfieri *et al* [27]. The flood maps are global in scale, with a resolution of 3 arcseconds (90 m at the equator). Flooding is modeled for all rivers with an upstream catchment area greater than 500 m^2. Although multiple global flood hazard models are available [55] we chose to use the GIRI model because it models flooding on more (smaller) river channels than other openly available global flood model datasets, and therefore is less likely to miss potential upstream flood exposure, especially in India where previous research has shown that over half of all flood exposure is to rivers with upstream catchment areas less than 1000 m^2 [56].

Data on the location, ownership tree and production capacity of power assets are obtained from the global integrated power tracker of Global Energy Monitor [57]. This dataset contains 80 729

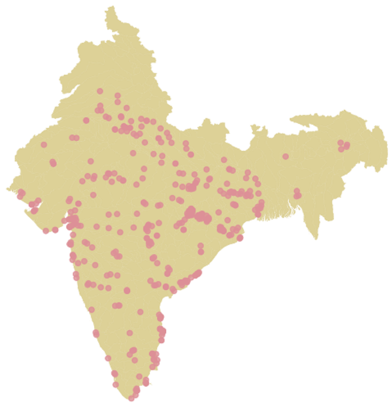

Figure 1. The distribution of power plants across India. In total, there are 437 basins and 424 power assets belonging to 188 firms spread across 126 basins.

power-producing assets of which 424 assets located in India belong to 126 firms. A selection of assets classified as coal, oil/gas, bioenergy, and nuclear was made. Nuclear facilities of any capacity are included in the dataset, whereas for coal and bioenergy data a capacity of at least 30 MW is needed. For oil and gas companies, the threshold for inclusion is 50 MW or more globally and 20 MW or more in the European Union [57]. The dataset used in our analysis represents 93.27% of the production of all operating plants and plants under construction with type bioenergy, coal, nuclear, oil, or gas in India.

To account for the size of these assets, a buffer zone of 0.01° is created around their geographic location. The maximum flood depth within this buffer zone for each scenario and RP is used in this assessment. To link flood depths with capital damages and business disruptions, we use damage curves obtained from Nirandjan *et al* and Luo *et al* respectively, but robustness tests are provided for the damage curves from Huizinga *et al* [47] (appendix B). An estimation of replacement values for the power assets are obtained from Nirandjan *et al* [46].

Discharge data to calibrate the copulas was taken from GloFAS v4 [37] for the years 1979-2016, as this was the same historical period for the meteorological forcing used for the GIRI baseline flood hazard maps. We use HydroATLAS river basins [58] at the Level 6 categorization and manually select basin outlet points from the GloFAS river network for each basin. The Level 6 categorization was used as it was the smallest basin classification for which one could reliably extract points on the GloFAS river network. In our analysis of the spatial correlation of flooding between basins we therefore assume that flood risk within Level 6 basins is fully dependent.

To ensure that the data can be made publicly available, financial leverage data and ownership data of firms is manually collected through the exploration of annual reports, sec filings, and voluntary disclosures. For 82% of the firms in the case study, we managed to obtain the necessary financial information. For firms of which no data was obtained, we used the median value of the other firms. As an alternative, established data vendors can be used to obtain the necessary financial information.

3. Results

The above methodology is applied on a case study. This case study discusses the physical risk of flood events on an equally weighted financial portfolio consisting of power firms operating in India. Robustness checks for these results are provided in appendices A and B. To illustrate the contributions of this framework with respect to the previous literature, we show (1) the impact of the correlation modeling framework on portfolio-level tail risks, (2) the materiality of all financial transmission channels, and (3) a comparison between the default modeling frameworks.

3.1. Impact of spatial correlations on portfolio-level risks

The simulation approach introduces spatial correlations between extreme weather events using a copula-based model. These correlations propagate through the framework and have an impact on the distribution of firm-level and portfolio-level impacts. To highlight the materiality of these correlations, we compare four modeling techniques in the context of flood simulations (see figure 2):

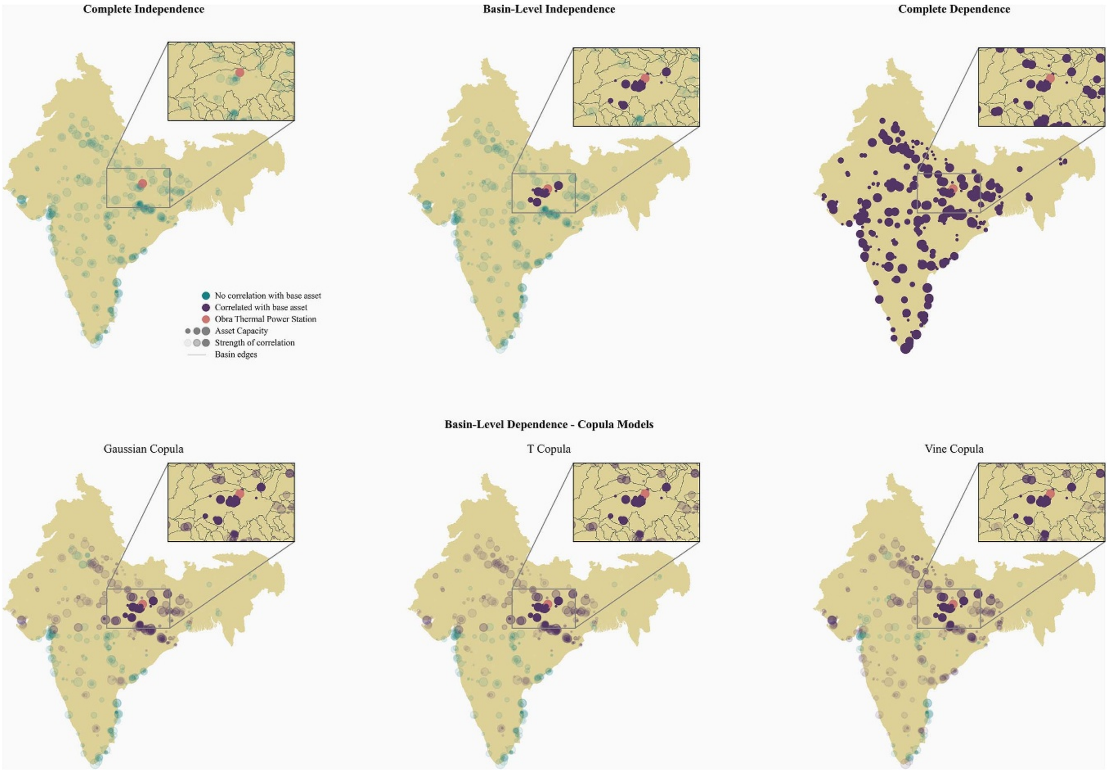

Figure 2. An example of the different correlation models applied to the Obra Thermal Power Station. The colors indicate the strength of the correlation of weather extremes between the Obra Thermal Power Station and the other assets in the dataset. The size of the dots denotes the capacity of the asset.

(i) Complete independence—the floods occurring at an asset are assumed to be independent from the floods occurring at any other asset. This approach can be considered a lower-bound estimate.

(ii) Basin-level independence—each asset is located in a basin (see figure 2). Flood events are simulated at the basin-level instead of the individual asset level. When a flood occurs in a basin, all assets located in that basin are impacted. Floods across different basins are assumed to be independent.

(iii) Basin-level dependence—the same approach is taken as in the basin-level independence; however, the joint occurrence of floods between basins is modeled using various copula functions. As mentioned in the methodology; the investigated copula functions are: (a) the Gaussian copula, (b) the T-copula, and (c) the vine copula.

(iv) Complete dependence—all assets are impacted by floods of the same return period at the same time. This approach can be considered an upper-bound estimate.

The result of this comparison is provided in table 1. The table shows the average impact of flood events on the portfolio value as well as a measure for the VaR that corresponds to the 0.05 and 0.01 quantiles. All results are communicated compared to a baseline scenario where no weather shocks occur.

The results in table 1 show how the inclusion of correlations between weather events has a material impact on the estimation of financial tail risks. The assumptions of complete independence or dependence can lead to large under- or overestimations of portfolio-level tail risks. The results are robust against different specifications of the copula model. The complete independence assumption can underestimate tail risks by up to 20% compared to the Gaussian copula model, and the complete dependence assumption can overestimate tail risks by 207% compared to the independence assumption.

These results vary from portfolio to portfolio; but the robustness checks show that the conclusions are very similar for a portfolio using power assets located in Thailand (appendix A). This comparison further shows that the materiality depends on the spatial concentration of the assets. For highly concentrated assets (e.g. Thailand), the estimated tail risks move closer to the upper-bound estimate whereas for lower levels of concentration (e.g. India) the estimated tail risks are closer to the lower-bound. In Thailand the complete dependence is 5% higher compared to the basin-level model, whereas in India, it is 127% higher.

The Gaussian copula provides a similar result as the basin-level independence setting. This is expected because the Gaussian copula has asymptotically independent tails. The t- and vine copulas provide the largest tail risks of the copula models; however, two notes should be made.

Table 1. Portfolio value changes (%) for the Indian portfolio under different specifications of the correlation structure between weather events. The values are expressed as a percentage change in value compared to the baseline scenario where no weather events occur. The Q5 and Q1 columns corresponds to 95% and 99% Value at Risk (VaR) metrics. The simulations for the table above assume insurance against capital damages and flood protections equal to 100Y flooding events. Robustness checks are provided in appendix B.

	Average impact	Median impact	Q5	Q1	Q5 interval	Q1 interval
Complete independence	−0.715 990	−0.710 000	−0.927 000	−1.013 200	[−0.91, −0.94]	[−0.99, −1.06]
Basin-level independence	−0.699 930	−0.680 000	−1.045 100	−1.203 600	[−1.02, −1.07]	[−1.15, −1.27]
Gaussian copula	−0.701 580	−0.670 000	−1.102 900	−1.255 900	[−1.05, −1.14]	[−1.21, −1.29]
T copula	−0.705 810	−0.660 000	−1.146 800	−1.396 400	[−1.09, −1.18]	[−1.28, −1.47]
Vine copula	−0.717 500	−0.680 000	−1.154 600	−1.323 500	[−1.12, −1.18]	[−1.28, −1.38]
Complete dependence	−0.671 050	−0.350 000	−2.375 800	−3.862 600	[−2.08, −2.7]	[−3.54, −4.26]

First, the degrees of freedom of the t-copula, which determines the level of tail dependence, has been estimated at 20. This naturally leads to lower levels of tail dependence. In the robustness tests (appendix A) where we apply the methodology on Thailand, we noticed an estimated degrees of freedom of 5 which led to higher tail dependence. In both cases, the vine copula seemed to capture these differing levels of tail dependence.

Second, due to a limited number of extreme observations, the parameters of the vine copula are relatively unstable. In some robustness checks, the vine copula turned out to have the highest tail risks (see appendix B). In other checks the level of tail risks was highest for the t-copula.

The results also show how the inclusion of correlations across assets have a negligible impact on the average portfolio-level impacts. This is because joint extreme events, which are shaped by the copula function, occur infrequently in the Monte Carlo simulations and therefore have limited influence on the mean. The average is dominated by more frequent, lower-impact events, whose marginal distributions are not affected by the choice of copula. Another insight gained from these results is the impact of the correlation structure on median values. It can be observed how the median impact remains relatively stable with respect to the correlation specification except for the complete dependence assumption. This is also expected as we are dealing with extreme events and only simulating a time horizon of 25 years.

We further find that the values for the tail risks obtained from the framework are similar to values obtained in previous literature even though they cannot be compared directly due to differences in selected RCP scenarios. The results in section 3.3 also show that the conclusions are valid for the average probability of default.

Overall, these results highlight the importance of considering correlations between impacts of extreme events for the computation of portfolio-level tail risks, but also show that for average risk computations these correlations do not need to be considered. Using upper or lower bound estimates like the complete (in)dependence assumptions can lead to material overestimations (underestimations) of financial tail risks.

While these upper and lower bound estimates can still be useful for defining the extremes of potential outcomes, we provide more targeted estimates that identify where portfolio-level risks are likely to fall within that range. This approach can offer additional context to the upper- and lower bound estimates provided by previous literature.

3.2. Materiality of financial transmission channels

The framework includes financial impacts of direct asset damages, business disruptions, and insurance premiums. An analysis of the materiality of these impacts shows that, under the current assumption, 83.2% of calculated average impacts are a result of direct asset damages , and the remaining 16.8% for business disruptions. The business disruptions currently do not incorporate disruptions due to the failure of critical infrastructure or supply chain disruptions. If these impacts would be included, the materiality would significantly increase. Given the large proportion of capital damages, there is a clear need for the inclusion of insurance information in the modeling framework. The materiality of each of these transmission channels is strongly dependent on the assumed damage curves; as a result, these conclusions cannot be generalized towards other asset types and geographic locations.

There is no impact of short-term insurance premium effects on average asset values because they cancel out over the simulation period; however, increased tail risks due to these short-term effects can be observed in the modeling results (see appendix B). Because the insurance premium paid by firms is the same as their expected damages, the presence of insurance in general does not significantly impact average portfolio risks.

Table 2. Portfolio value changes (%) under the same assumptions as table 1 but without insurance showing a substantial increase in the levels of tail risk.

	Average impact	Median impact	Q5	Q1	Q5 interval	Q1 interval
Complete independence	−0.718 920	−0.710 000	−1.074 800	−1.241 500	[−1.06, −1.1]	[−1.21, −1.27]
Basin-level independence	−0.687 220	−0.650 000	−1.278 800	−1.563 400	[−1.25, −1.31]	[−1.51, −1.6]
Gaussian copula	−0.693 200	−0.630 000	−1.393 500	−1.728 600	[−1.36, −1.44]	[−1.69, −1.8]
T copula	−0.702 090	−0.610 000	−1.480 600	−2.062 800	[−1.47, −1.52]	[−1.92, −2.12]
Vine copula	−0.728 260	−0.650 000	−1.450 600	−1.880 700	[−1.44, −1.47]	[−1.82, −1.93]
Complete dependence	−0.767 670	−0.100 000	−4.365 100	−7.575 500	[−4.09, −4.68]	[−7.17, −7.92]

Table 3. Portfolio value changes (%) under the same assumptions as table 1 but with insurance companies dropping out after 3 years.

	Average impact	Median impact	Q5	Q1	Q5 interval	Q1 interval
Complete independence	−0.722 260	−0.720 000	−1.031 100	−1.193 000	[−1.02, −1.05]	[−1.17, −1.22]
Basin-level independence	−0.684 150	−0.640 000	−1.184 700	−1.393 200	[−1.16, −1.2]	[−1.35, −1.43]
Gaussian copula	−0.686 850	−0.640 000	−1.238 500	−1.585 300	[−1.22, −1.25]	[−1.54, −1.63]
T copula	−0.701 250	−0.615 000	−1.386 600	−1.862 900	[−1.34, −1.41]	[−1.81, −1.94]
Vine copula	−0.716 210	−0.660 000	−1.344 200	−1.731 200	[−1.32, −1.36]	[−1.63, −1.84]
Complete dependence	−0.730 930	−0.170 000	−3.858 800	−6.831 100	[−3.53, −4.17]	[−6.24, −7.23]

However, firms take insurance to protect themselves against large capital expenses and/or losses due to weather events. By taking insurance, firms pay an annual premium to prevent these large, unexpected losses.

The results of our framework, nicely illustrate this trade-off. Average risks are hardly impacted by the presence of insurance whereas tail risks have decreased substantially. Indeed, when we assume that no firm in the portfolio is insured against capital damages, we observe tail risks of 23%–96% higher compared to a fully insured portfolio (see table 2). This result highlights the importance of including insurance coverage information into portfolio-level risk assessments as they significantly impact the levels of tail risks observed for financial portfolios.

By incorporating insurance, the modeling framework further allows for more advanced scenarios to be designed. For example, an analysis can be made regarding the impact of insurance dropping out of certain markets at a certain time in the future. Table 3 provides an example where insurance drops out of the Indian Power Industry after 3 years in the simulation and investigates how this impacts current portfolio-level risks. In this scenario, tail risks have increased by 16%–77% which is in between the scenario with no insurance and the scenario with insurance against capital damages. Alternatively, scenarios considering partial coverage of assets can be developed as well. The impact of partial coverage would be similar to modeling insurance dropouts, i.e. it would lead to an increase in tail risks compared to a full coverage scenario.

Both the insurance dropout and partial insurance scenarios could provide insights to policy makers. This highlights the need for models that incorporate insurance protection gaps into physical risk assessments. Again, insurance dropping out of the market does not impact average impacts but only influences portfolio-level tail risks.

3.3. Impact on probability of default

The framework provides two approaches related to the quantification of default probabilities: (1) a structural credit risk model based on the Merton framework, and (2) an empirical approach based on fundamental firm metrics. The results of both frameworks are provided in table 4. Overall, both approaches have similar behavior regarding the portfolio-level tail risks; however, there are also some key differences between both models.

Both models show changes in the estimated probability of default that align well (see table 4). For both the Merton and the empirical model, a change in the correlation structure between financial impacts effectively triple (quadruple) the estimated 95th (99th) percentile probability of default changes. These are financially material impacts as the probability of default is related to the cost of borrowing for firms. Overall,

Table 4. Average change in probability of default of firms in the portfolio according to the empirical and Merton model. The change is expressed in basis points (bps). The volatility of the Merton model has been fixed to 20% to avoid using proprietary financial data sources and make the results fully reproducible. Since financial institutions will be able to access financial data, we refer to Bharath and Shumway [59] for the methodology of how to calibrate the volatilities.

	Average impact	Median impact	95th percentile	99th percentile
Empirical model				
Complete independence	2.427 581	2.351 657	3.916 751	4.793 613
Basin-level independence	2.296 293	2.105 603	4.753 375	6.563 792
Gaussian copula	2.342 580	2.086 982	4.886 011	6.798 184
T copula	2.391 865	2.027 901	5.227 664	7.215 472
Vine copula	2.391 865	2.027 901	5.227 664	7.215 472
Complete dependence	2.376 268	0.264 190	14.197 431	25.497 104
Merton model				
Complete independence	3.215 419	2.789 105	6.981 805	8.797 749
Basin-level independence	3.031 876	2.297 572	7.996 213	11.157 796
Gaussian copula	3.117 071	2.288 987	8.395 543	13.425 415
T copula	3.247 501	2.305 818	9.627 927	13.967 070
Vine copula	3.247 501	2.305 818	9.627 927	13.967 070
Complete dependence	3.216 539	0.088 155	21.113 898	41.622 030

we notice that the Merton model provides higher estimates for the probability of default. There are two explanations for this. First, the observed debt ratios of the firms in the portfolio are quite high with an average of 56.66%. These high levels of debt influence the Merton model but not the empirical model (see below). Secondly, as discussed in the methodology, the parameters used in the empirical model need to be empirically estimated which may change these results.

A key practical limitation of the Merton model is its requirement to specify a default barrier. Even though this default barrier is theoretically well defined, due to data quality issues it is difficult to obtain realistic values. Under relatively small misspecifications of the default barrier, very different changes in default probabilities can be observed. The empirical model seems to be more robust against misspecifications of the firm characteristics providing practical benefits.

Secondly, both models have different biases. In the Merton model, the change in default probability is strongly dependent on the current financial health of the firm expressed as the distance to default. For large distances to default, even firms that are highly exposed to physical climate risks do not experience a significant change in default probability. This is of course a realistic result. In the empirical model, the change in probability of default is independent from current profitability and leverage ratios. Only absolute changes in these parameters are used to determine changed probabilities of default. Depending on the financial health among the set of firms under investigation, this assumption can have a material impact on the results.

Thirdly, the parameters of the Merton model need to be obtained from external sources and calibrations of both the default barrier and asset volatility can be made to account for additional risk exposures. Like mentioned earlier, it can be difficult in practice to obtain high-quality data, and it is unclear how these calibrations should consider different scenarios for physical risks. In the empirical model, the financial ratios can be obtained from within the framework. However, one needs to assume that the sensitivities (β's) obtained from the empirical assessment are still valid for the framework parameters.

To summarize, the Merton-model provides results with the realistic assumption that current financial health of firms should be considered when assessing impacts on firm defaults, but it is very sensitive to misspecifications of the model parameters which is problematic given the practical difficulty of obtaining high quality data. The empirical model can provide less sensitive results; but, it does not take into account the current financial health of firms and it is unclear how well the empirical estimates apply to the framework setting. Overall, in practice, the Merton model is still preferable as the empirical approach does not consider the financial health of firms and it is difficult to empirically derive its parameters. However, more research is needed related to the relations between the Merton and scenario parameters.

4. Discussion

Extreme weather events can cause material impacts on the economic system through various transmission channels. As a result, there has been a growing need for open and publicly available methodologies for physical risk assessments. In this research, we outlined an end-to-end methodology from the estimation of asset-level flood impacts to portfolio-level risks using only publicly available data. The framework is applied on both India and Thailand (appendix A). Through the incorporation of direct asset damages, business disruptions, and insurance impacts, we show that each of these transmission channels has a material impact on average portfolio-level impacts, and/or portfolio tail risks.

The results of the framework further highlight the importance of modeling spatial correlations as previously established [60, 61], which has been well established in the insurance literature [29] and applied to financial stress testing [21]. We show how different assumptions related to the correlation models can lead to material under- and overestimations of portfolio-level tail risks. Whereas all models agree that physical risk impacts are not negligible, the complete (in)dependence assumptions can lead to material over(/under)estimations. The materiality of these under- and overestimations depends on the spatial concentration of the portfolio assets. By combining models for spatial correlations with hazard maps, we can obtain more informative estimates for portfolio-level tail risks. A comparison of different approaches regarding the modeling of spatial correlations shows that these models largely agree on the estimates of acute climate risk.

Furthermore, the framework shows the importance of modeling insurance coverage and impacts. Even though the impact of insurance on average portfolio-level impacts is small, it has a material impact on tail risks. The incorporation of insurance in the modeling framework can lead to richer scenario designs including for example insurance dropouts.

Finally, the comparison of default models and robustness checks provide an overview of the impact of modeling decisions and parameter choices on the estimated levels of physical risks. These results can guide empirical research and practitioners.

Even though the research contributes to the existing work, there are still some limitations. For example, the model does not include indirect sources of financial impacts like financial contagion across firms and supply chain disruptions even though previous research has shown their importance [62, 63]. Additional research is needed in this area.

The incorporation of spatial correlation also complicates the scenario analyses as spatial correlations can change depending on climate pathways [64]. Even though the framework provides a first step towards including these changing correlations, it is still challenging to incorporate them.

In terms of financial impacts, the framework is currently limited to average impacts, tail risks, and probability of default of equity portfolios. In practice, financial institutions make use of a broader collection of financial instruments. The application of the framework to other asset classes requires additional valuation steps that are currently not part of the framework.

A further limitation of our framework lies in its treatment of investor and market behavior. The model assumes that physical climate risks are reflected in firm and asset valuations as they materialize, rather than being anticipated and priced in advance. This reactive valuation approach does not account for the possibility that investors or lenders may incorporate long-term climate risks into current asset prices. Therefore, the framework may underestimate the degree to which market participants adjust valuations proactively in response to anticipated climate trends and can hence overestimate market risks. On the other hand, irrational behavior of investors, e.g. overreactions following weather events, could also increase market risks. Future research could extend the framework by incorporating alternative assumptions about investor foresight and climate risk pricing dynamics.

Additional research is also needed related to the interactions between physical and transition risk. Currently, most research focuses on one or the other, whereas in practice, these risks are related to each other. Similarly, more research is needed to estimate compound impacts including interactions between multiple types of acute risks and economic risks which can lead to greater insights regarding system-level impacts.

Data availability statement

The data that supports the findings of this study are openly available in the supplementary files of this article.

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Conflict of interest

The authors declare no conflicts of interest.

Data access

All data and code will be available on Github following the release of this paper and can be accessed through the following link.

Appendix A. Comparison with Thailand

The case study was also performed for Thailand. In this appendix, we discuss the main results for Thailand and compare them to the observed results of India. The conclusions for both India and Thailand are the same; however, there are some interesting differences between both case studies. We start by outlining the key differences between both countries and afterwards discuss the impact of these differences on the results.

A.1. Correlation structure

Both countries have similar correlation structures regarding climate extremes between different basins. In both cases, correlations are clustered (see figures B6 and B7). However, it can be seen that the overall correlations in India are less extreme compared to the correlations in Thailand. This is likely explained by geological differences between both countries. For starters, Thailand is a much smaller country compared to India. This difference in correlation structure can have an impact on the results as stronger correlations can significantly increase tail risks.

A.2. Geographic spread of power assets

The power assets in Thailand are very much clustered around Bangkok (see figure B5) whereas power assets in India are much more spread across the country. This lack of geographic diversification in Thailand significantly increases tail risks but reduces average risks.

A.3. Debt levels

The Indian firms included in the analysis sometimes had extreme levels of debt, whereas the Thai firms typically had more moderate debt levels. As a result, the Indian firms were much more sensitive to climate impacts under the Merton model compared to Thai firms.

A.4. Tail and average risk-levels

The results for Thailand are provided in table B2. These results show how the average risk in Thailand is lower compared to the average risk in India; however, the tail risks in Thailand is higher compared to the tail risk in India. The explanation for this is the lack of geographic diversification in Thailand. Because the assets are so concentrated, the probability of an extreme event occurring in Thailand at any asset is relatively small; however, the impact of such an event would be extreme. This low probability but high impact situation results in low average impacts but high tail risks. In India, the assets are much more geographically dispersed meaning that the probability of an extreme event occurring at any of the assets is relatively high; however, the probability of an extreme event occurring that affects a large proportion of assets is low. Therefore, the average risk in India is relatively high; but the tail risks are lower.

Another interesting result is the difference in risk for the complete dependence assumption. In India, the complete dependence risk is 6 times the complete independence risk. In Thailand, the multiplier is only equal to 4. This is due to the number of assets in the portfolio. Thailand only has 93 power assets in the database, whereas India has 424. The complete dependence assumption is therefore much more unrealistic for the larger portfolio of Indian firms.

Finally, the difference between the tail copulas (T and vine) and the Gaussian copula is larger for Thailand compared to India. This is because the tail dependence of climate extremes in Thailand seemed to be stronger. Again, this can be linked to the differences in size of both countries.

Appendix B. Robustness checks

Given the specification of various model parameters, the results of the analysis can change. In this appendix, we investigate the robustness of the key model conclusions under various model specifications. Detailed results for all of these robustness checks are available for download in an Excel file posted on the Github repository.

B.1. Flood damage curves

The flood damage curves in the study are obtained from Nirandjan *et al* [46]; however, alternative specifications like for example Huizinga *et al* [47] exist. To represent both the differences between these damage curves; as well as the uncertainty for each damage curves, robustness checks are provided in which slight variations of these damage curves are used (see figure B1).

The robustness checks show that the conclusions of the paper are robust against specifications of the damage curves. Both the insurance and correlation modeling still have a material impact on the financial tail risks. Table B1 provides the range of Q1 tail risks obtained.

The results between the damage curve specifications differ materially due to the different shapes of the curves. Whereas the Huizinga *et al* damage curves allow damages up to 100% of the asset value, the Nirandjan *et al* cap the damages to 30%. As a result, the Huizinga *et al* damage curves are more penalizing.

B.2. Flood protection levels

The flood protection levels are an important parameter that determines the overall level of physical risk. Depending on the assumptions related to this parameter, the 99% tail risk could be anywhere between −27% in the case of no flood protections at any asset and −0.48% when assets are protected to a 1 in 500 year flood event. Figure B2 shows how the risk-levels change for different flood protection levels and copula models. Even though, the flood protection level is an important parameter for the risk-levels, it does not influence the conclusions for this study.

B.3. Insurance sensitivity

The difference between insured and uninsured settings have already been discussed in the results section; however, the impact of the insurance sensitivity parameter s has not yet been discussed. Note that the impact of the insurance sensitivity and insurance industry capital are the same. The insurance sensitivity parameter seems to have a negligible impact on the results of the model with only very small changes observer (<0.01%).

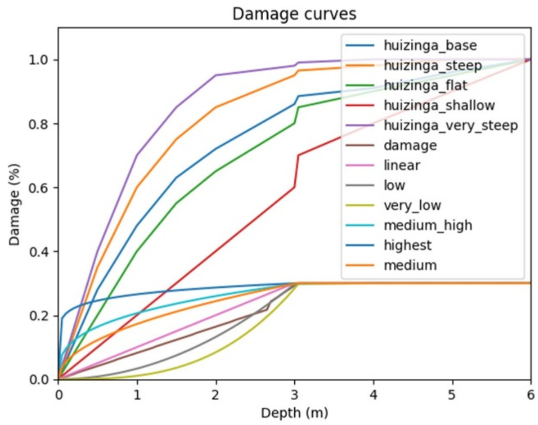

Figure B1. Different specifications of the damage curves used in the robustness checks.

Table B1. Range of Q1 risks obtained under different damage curves.

	Nirandjan (2024)	Huizinga (2017)
Complete indep.	[0.54, 3.27]	[1.47, 4.25]
Basin-level indep.	[0.81, 5.97]	[2.83, 8.52]
Gaussian Copula	[0.79, 6.44]	[2.64, 7.97]
T Copula	[1.03, 8.30]	[3.58, 11.03]
Vine Copula	[1.09, 7.79]	[3.52, 9.20]
Complete dep.	[1.83, 13.39]	[6.18, 18.38]

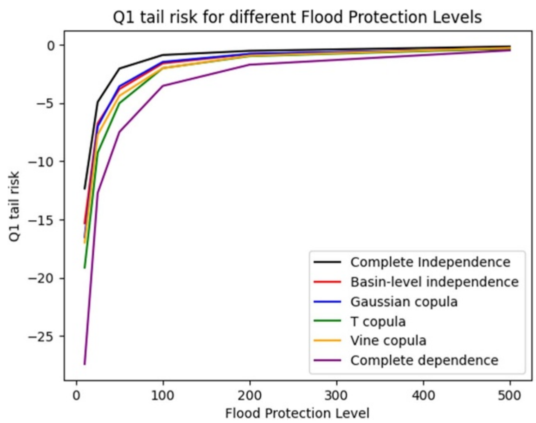

Figure B2. The Q1 tail risk for different flood protection levels. The complete dependence and independence assumptions are always the upper and lower bound and the order between the copula models and relative positions stay the same.

Table B2. The results for Thailand in the case of no insurance. This table should be compared to table 2 for India.

	Average impact	Median impact	Q5	Q1	Q5 interval	Q1 interval
Complete independence	−0.266 260	−0.210 000	−0.651 000	−0.884 200	[−0.58, −0.7]	[−0.81, −0.96]
Basin-level independence	−0.318 580	−0.190 000	−1.084 200	−1.602 000	[−1.0, −1.15]	[−1.34, −1.8]
Gaussian copula	−0.268 100	−0.155 000	−0.884 100	−1.478 100	[−0.82, −0.94]	[−1.38, −1.68]
T copula	−0.252 220	−0.080 000	−1.101 600	−2.013 100	[−1.01, −1.18]	[−1.84, −2.35]
Vine copula	−0.251 840	−0.100 000	−0.946 500	−2.013 100	[−0.87, −1.01]	[−1.68, −2.53]
Complete dependence	−0.215 260	0.000 000	−1.381 800	−3.538 200	[−0.87, −2.06]	[−2.98, −4.22]

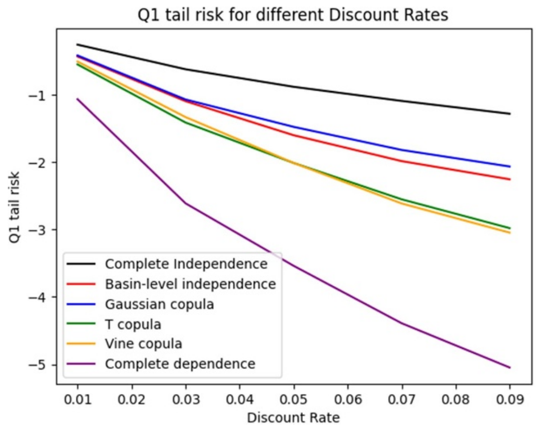

Figure B3. The Q1 tail risk for different discount rates. As the discount rate increases, the tail risk increases.

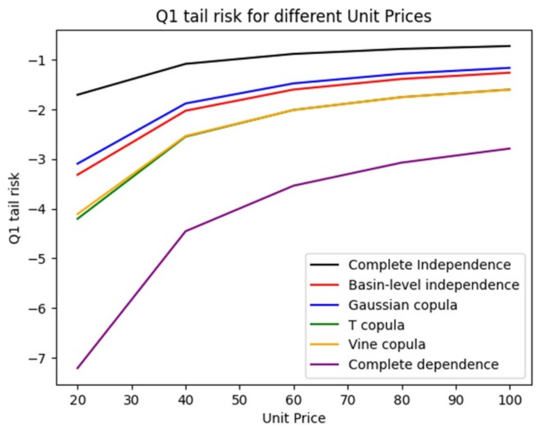

Figure B4. The Q1 tail risk for different unit prices that are directly related to the revenue. Increased revenue reduces tail risk.

B.4. Discount rates

The discount rate is used in the DCF model to determine the impact of a cash flow disruption on the value of the asset. Figure B3 shows the impact of this parameter on the observed tail risks.

B.5. Unit prices

The unit price is used to determine the revenue of the firm based on its production levels. Higher revenues decreases the importance of capex damages, as a result, higher revenue levels (due to higher prices) result in smaller tail risks (see figure B4).

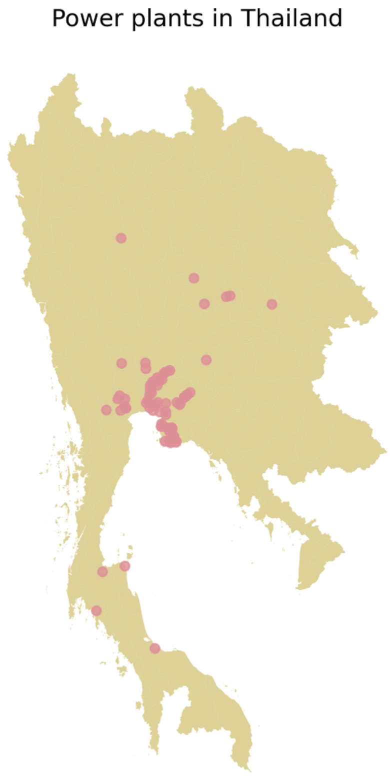

Figure B5. Power plants in Thailand.

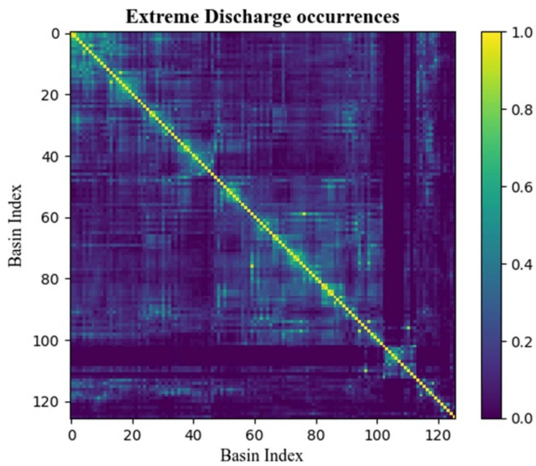

Figure B6. Correlation between extreme discharge levels in Indian basins.

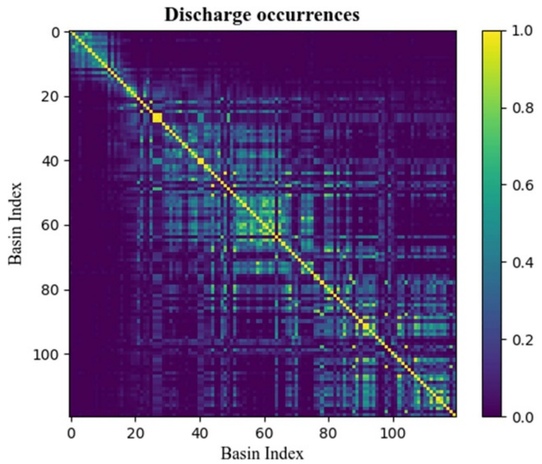

Figure B7. Correlation between extreme discharge levels in Thai basins.

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