Systemic Risk under Joint Market and Climate Stress

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Outline

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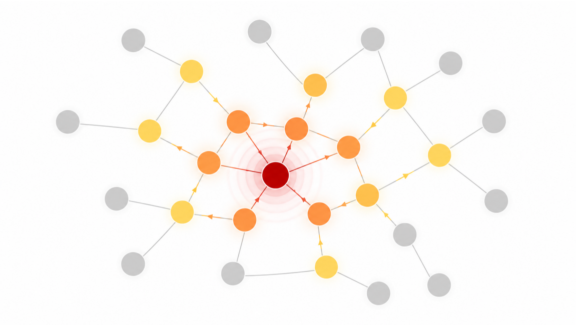
Systemic risk

- Systemic risk refers to the risk that:
  - distress in one financial institution, sector, or market segment propagates through financial channels;
  - impairs the stability of the broader financial system;
  - potentially generates spillovers to the real economy.



- In the aftermath of the GFC, a rich body of research on systemic risk has emerged.

Systemic climate risk

- Climate change poses an additional source of systemic risk to financial stability.
  References from industry: Carney (2015), NGFS (2019), FSB (2020)
  References from academia: Dafermos et al. (2018), Monasterolo (2020), Battiston et al. (2021), Curcio et al. (2023), Pacelli et al. (2025)
- Relatively limited attention has been paid to measuring the systemic contribution of climate-related financial risks until Jung et al. (2025).
- We aim to quantify the systemic climate risk of a sector across different market and climate stress scenarios.

Market vs. climate stress

- Market stress: market-wide financial distress
- Climate stress: the manifestation of climate-related risks in financial markets
- Climate stress can trigger or exacerbate episodes of market stress, thereby constituting a distinct source of systemic risk
- Market stress may also arise from a broad range of non-climate factors.
- We examine systemic risk under a unified framework that accommodates different configurations of market and climate stress.

Compounding effect

- When climate stress and market stress materialize concurrently, it gives rise to compound climate–financial stress scenarios, with nonlinear amplification effects.
- Acharya et al. (2023) identify three mechanisms through which climate and financial crises may interact:
    - coincidental occurrence
    - shared underlying causes
    - causal propagation
- **References:** NGFS (2019), FSB (2020), Acharya et al. (2023), Engle (2023), de Bandt et al. (2025)

Physical vs. transition risk

- Within climate change risk, we focus on transition risk rather than physical risk.
- While physical risks may generate significant losses, their effects are often geographically concentrated and therefore less likely to trigger system-wide financial stress.
- By contrast, a disorderly transition to a low-carbon economy can have substantial systemic consequences through abrupt and unanticipated changes in climate policy.
- **References:** FSB (2020), Semieniuk et al. (2022), Faccini et al. (2023)

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- While physical risks may generate significant losses, their effects are often geographically concentrated and therefore less likely to trigger system-wide financial stress.
- By contrast, a disorderly transition to a low-carbon economy can have substantial systemic consequences through abrupt and unanticipated changes in climate policy.
- **References:** FSB (2020), Semieniuk et al. (2022), Faccini et al. (2023)
- **Question**: How to model transition risk?

The market-based approach

- Engle et al. (2020) build climate-news hedge portfolios.
- Jung et al. (2025) construct climate transition risk factors by forming portfolios designed to decline in value as transition policy risk rises.
- Alekseev et al. (2026) construct similar climate hedge portfolios.
- We follow this literature in adopting a market-based measure of systemic climate risk.
- **Comments:**
  - Pros: does not require internal balance-sheet data, but instead relies on market returns, hence **forward-looking and time-varying**
  - Cons: Are the proxies accurate?

Outline

Three negative returns

- We focus on the systemic impact on a sector under joint market and climate stress.
- Three return rates, all to be specified:
  - the sector: r_i
  - the overall market: r_m
  - a transition risk portfolio: r_c
- Negative returns:

$$X_t = -r_i, \qquad Y_t = -r_m, \qquad Z_t = -r_c$$

The stress scenario

- For a distribution fucniton F, its quantile at level $0 < p < 1$ is defined by

$$F^{\leftarrow}(p) = \mathrm{VaR}_q[X] = \inf\{x \in \mathbb{R} : F(x) \geq p\}.$$

- Give a set $A \subset \mathbb{R}^2_+$, called stress set, define a stress scenario as

$$A_p = \left\{ \left(\frac{Y}{F_Y^{\leftarrow}(p)}, \frac{Z}{F_Z^{\leftarrow}(p)} \right) \in A \right\}.$$

- Typical examples for A: With suitable thresholds y_0 and z_0,
  - $(y_0, \infty) \times \mathbb{R}$: market stress
  - $\mathbb{R} \times (z_0, \infty)$: climate stress
  - $\mathbb{R}^2 \setminus \{(-\infty, y_0] \times (-\infty, z_0]\}$: either market or climate stress
  - $[y_0, \infty) \times [z_0, \infty)$: joint market–climate stress
  - $[y_0, \infty) \times (-\infty, z_0)$: market-only stress
  - $(-\infty, y_0) \times [z_0, \infty)$: climate-only stress

Conditional expected shortfall (CoES)

- Given the stress scenario A_p for (Y, Z), define the CoES as

$$\mathrm{CoES}_{p,q}\left[X \middle| Y, Z\right] = E\left[X \,\middle|\, X > \mathrm{VaR}_q[X], A_p\right], \qquad 0 < p, q < 1,$$

  where p controls the stress level and q controls confidence level.

- $\mathrm{CoES}_{p,q}$ measures the expected loss in the upper tail of X relative to the marginal threshold $\mathrm{VaR}_q[X]$, conditional on the stress scenario A_p.

- We have followed the spirit of Adrian and Brunnermeier (2016) but adopted a *slightly different* form for the threshold.

- **Question:** How to model X, Y, Z? **Empirical insights**: Negative returns, particularly during market downturns, exhibit heavy-tailed behavior and strong tail dependence.

Univariate regular variation

- A nonnegative random variable X, or its tail distribution function F, is said to have a regularly varying tail with index $0 < \alpha_X < \infty$, written $\overline{F} \in \mathrm{RV}_{-\alpha_X}$, if

$$\lim_{x\to\infty} \frac{\overline{F}(xy)}{\overline{F}(x)} = y^{-\alpha_X}, \qquad y > 0,$$

- Let $p = F(x) \in (0,1)$. Then we can rewrite this limit relation as

$$\lim_{p\uparrow 1} \frac{P(X > xy)}{1-p} = \lim_{p\uparrow 1} \frac{1}{1-p} P\left(\frac{X}{F_X^{\leftarrow}(p)} > y\right) = y^{-\alpha_X}.$$

- This gives hints how to extend the concept to multi-dimensions.

Multivariate regular variation (MRV)

Definition

Let $(X, Y, Z)^{\intercal} \in \mathbb{R}_+^3$ be a nonnegative random vector with marginal tail functions F, G, and H. The vector is said to follow a MRV structure if there exists a non-degenerate sigma-finite measure ν on $\mathbb{R}_+^3 \setminus \mathbf{0}$ such that

$$\lim_{p \uparrow 1} \frac{1}{1-p} P\left(\left(\frac{X}{F_X^{\leftarrow}(p)}, \frac{Y}{F_Y^{\leftarrow}(p)}, \frac{Z}{F_Z^{\leftarrow}(p)}\right) \in B\right) = \nu\{B\},$$

for every Borel set $B \subset \mathbb{R}_+^3$ that is bounded away from $\mathbf{0}$ and is a continuity set of ν.

Notes:

- Heavy tails: Necessarily, $\overline{F} \in \mathrm{RV}_{-\alpha_X}$, $\overline{G} \in \mathrm{RV}_{-\alpha_Y}$, and $\overline{H} \in \mathrm{RV}_{-\alpha_Z}$ for some $\alpha_X, \alpha_Y, \alpha_Z > 0$
- Tail dependence: embedded in ν

Reference: Resnick (2007)

Asymptotic estimates for the CoES

Assumption: The vector (X^+, Y^+, Z^+) jointly follows an MRV structure with indices $\alpha_X > 1$, $\alpha_Y > 0$, $\alpha_Z > 0$, and with limit ν exhibiting upper tail dependence.

Theorem

As $p \uparrow 1$ and $1 - q \sim c(1-p)$ for $c > 0$, we have

$$\lim_{p \uparrow 1} \frac{\mathrm{CoES}_{p,q}\left[X \mid Y, Z\right]}{F_X^{\leftarrow}(p)} = c^{-\frac{1}{\alpha_X}} + \frac{\int_{c^{-\frac{1}{\alpha_X}}}^{\infty} \nu\left\{(y, \infty) \times A\right\} dy}{\nu\left\{\left(c^{-\frac{1}{\alpha_X}}, \infty\right) \times A\right\}}.$$

Notes:

- The $\mathrm{CoES}_{p,q}$ is of the order of $F_X^{\leftarrow}(p)$.
- The right side does not involve rarity.
- Key to the right side is to estimate ν.
- Provide a theoretical foundation for estimation.

Outline

Data

Market-based framework: all risk measures are inferred from traded sector and factor returns.

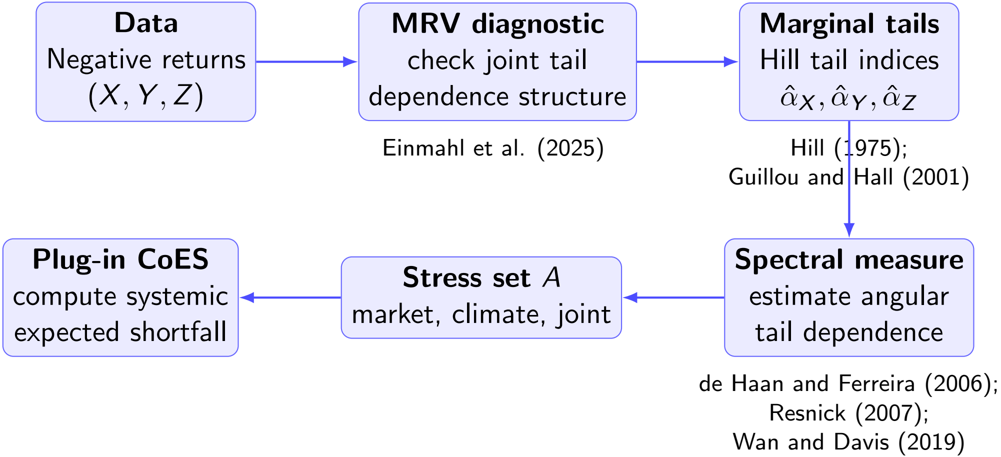
- **Sample:** daily returns from 2008-01-02 to 2026-03-17.
- **Subperiods:** crisis and early post-crisis period (2008–2013), the calm pre-COVID period (2014–2019), and turbulent post-2020 period marked by COVID, inflation, political and energy shocks (2020–2026).
- **Sector ETFs:** Energy, Materials, Financials, Industrials, Technology, Consumer Staples, Utilities, Health Care, Consumer Discretionary, Transportation, and Oil and Gas.
- **Market factors:** SPDR S&P 500 ETF Trust (**SPY**) as baseline, and iShares MSCI ACWI ETF (ACWI).
- **Climate transition factors:** a low return corresponds to an increase in transition risk.
    - **EMIT:** emissions-weighted transition-risk factor; baseline
    - SA: stranded-asset factor focused on fossil-fuel-related assets
    - CEP: climate-efficient portfolio factor linked to climate news
    - SUB: brown-minus-green relative repricing factor

Sector exposure

Climate betas (126-day rolling window, controlling for SPY)

- Sectors more exposed to transition risk, such as brown sectors, are expected to have positive climate betas.
- Systemic risk rankings need not be obvious from exposure to transition climate risk alone.

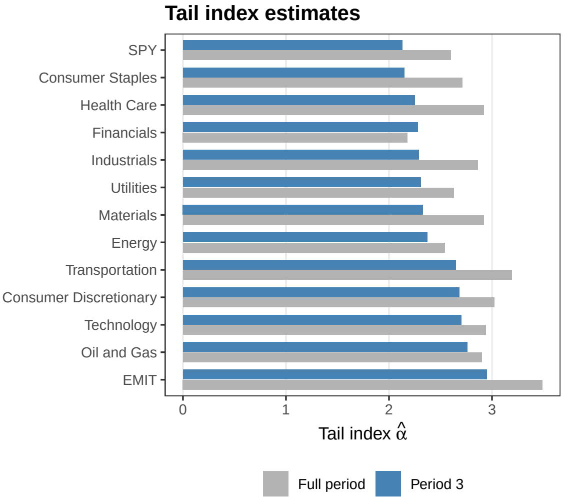
Estimation workflow



Tail inputs: Marginal tails

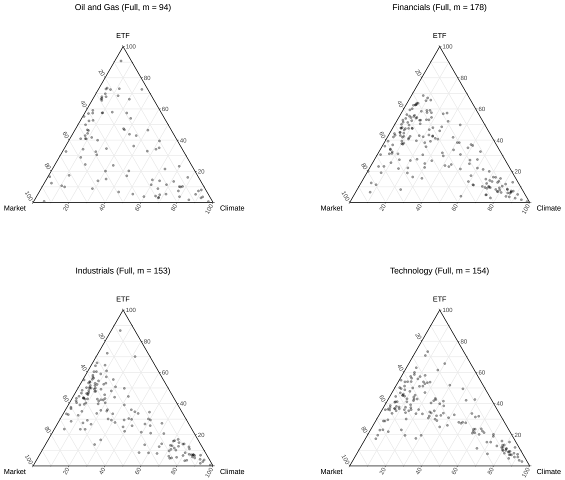
Marginal tails

- Heavy tails of sectoral losses justify an extreme-value approach.
- Full-sample: Financials and Energy have particularly heavy sector-loss tails.
- Post-2020: Tails are often heavier across many ETFs.



Tail dependence

- Spectral mass is concentrated along the sector–market edge and in the simplex interior.
- Simultaneous sector–market and joint extremes.



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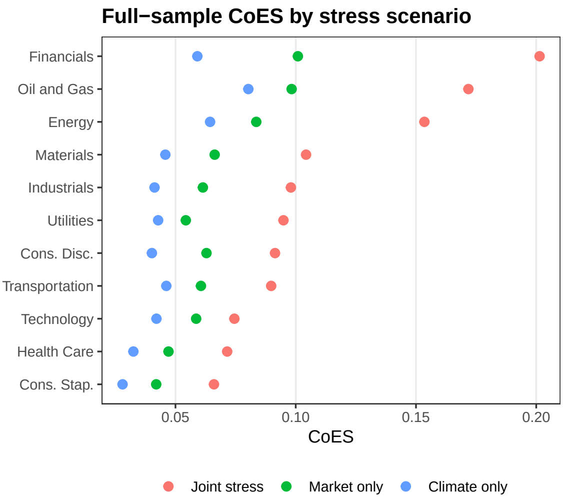
Main CoES result

CoES: Set stress level $p = 0.99$ and confidence level $q = 0.95$.

- Joint stress is more severe than standalone market or climate stress for every sector.
- Financials rank highest under joint stress.
- Oil and Gas and Energy rank highest under climate-only exposure.
- Robust under alternative combinations of market and climate factors.

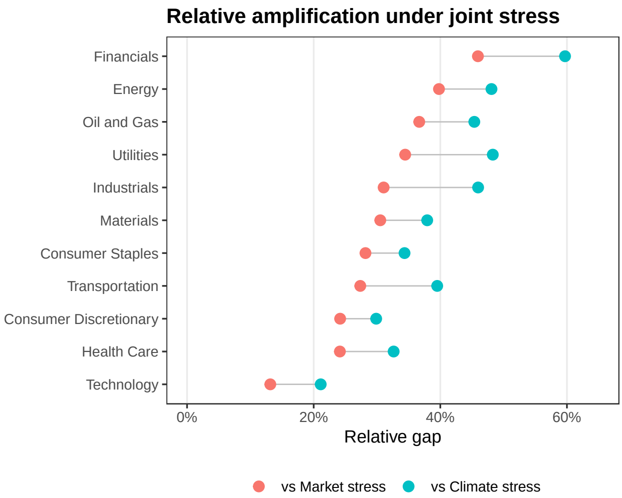


Scenario amplification: Joint vs. standalone stress

Relative gap: Full sample

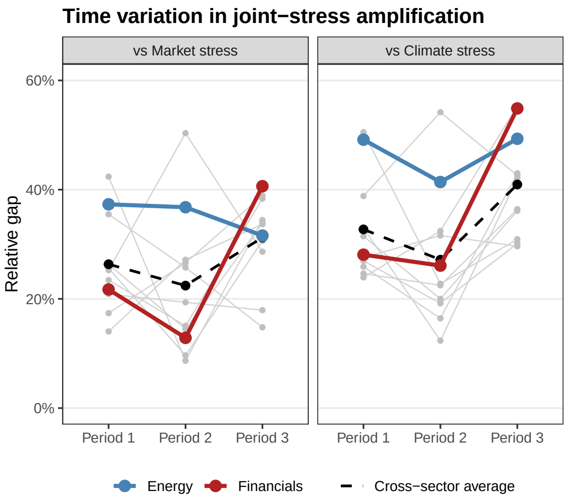
$$\frac{\mathrm{CoES}^J - \mathrm{CoES}^M}{\mathrm{CoES}^M}, \frac{\mathrm{CoES}^J - \mathrm{CoES}^C}{\mathrm{CoES}^C}.$$

- Joint-stress CoES exceeds standalone benchmarks by economically meaningful margins.
- Treating market and climate shocks separately can materially understate sector tail risk.



Relative gap: Subperiods

- Amplification is time-varying, not a fixed sector ranking.
- Period 2 shows a relative calmer environment of amplification on average, but remains sector-specific.
- Period 3, compound vulnerability becomes broader across Energy, Financials, Industrials, Materials, and Transportation.



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Concluding remarks

- Theoretical contributions:
  - Focus: climate-specific sectoral systemic risk
  - Developed a market-based CoES framework
  - Conducted extreme value analysis

- Empirical findings:
  - Joint market–climate stress raises CoES for every sector and period.
  - Compound climate risk is not just a carbon-intensity ranking: Financials can be most vulnerable under joint stress.
  - Since 2020, compound vulnerability appears more broad-based across sectors.

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- Empirical findings:
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  - Compound climate risk is not just a carbon-intensity ranking: Financials can be most vulnerable under joint stress.
  - Since 2020, compound vulnerability appears more broad-based across sectors.

Thank you very much!!

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