Are Transition and Physical Climate Risks Priced? Evidence from Directional News-Based Measures

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Motivation

An empirical puzzle in climate finance:

- Engle et al. (2020): "[...] *there is more climate change discussion when climate risk is elevated.*" $\rightarrow$ **more news = higher risk**.
- Faccini et al. (2023): "[...] *news has typically signalled a reduction in transition risks* [...]" $\rightarrow$ **more news = lower risk**.

Two issues in the literature

- Existing indicators are **unidirectional**: they require *a priori* assumptions to be interpreted (no direction signal in the data itself).
- ICAPM (Merton, 1973) interpretations remain **implicit** — testable restrictions are not assessed (*"fishing license"*, Fama (1991))

This paper: I build **directional** climate-risk indicators and discipline the interpretation via **ICAPM sign tests** (Maio and Santa-Clara, 2012).

Contributions

1. **A novel directional measure of climate risk.**
   - Daily transition (TRI) and physical (PRI) risk indicators based on 100K+ news articles
   - LLM-based classification captures **direction**, intensity, and horizon — absent from existing measures (Engle et al., 2020; Ardia et al., 2023; Faccini et al., 2023; Bua et al., 2024)

2. **New cross-sectional evidence on transition risk pricing.**
   - Exposure to TRI innovations carries a **negative and significant** risk premium
   - Physical risk **not priced** in the US cross-section

3. **ICAPM discipline: a remedy to the "*fishing-license*" (Fama, 1991) problem.**
   - First joint test of cross-sectional pricing $\times$ aggregate predictability $\times$ implied risk aversion (Maio and Santa-Clara, 2012)
   - Only **directional** indicators pass the sign consistency $\rightarrow$ **direction matters**

Newspaper Articles Corpus

Step 1 — Outlet selection. 7 major English-language outlets, balanced across political orientation and geography:

Daily Mail, Los Angeles Times, New York Post, National Public Radio (NPR), The Globe and Mail, The Guardian, The Washington Post

Step 2 — Article retrieval (MediaCloud). Articles containing at least one of 10 climate-related keywords:

climate change, global warming, climate crisis, carbon emissions, Paris Agreement, renewable energy, climate policy, climate risk, sea level rise, carbon tax

Step 3 — Web scraping of full article texts from retrieved URLs.

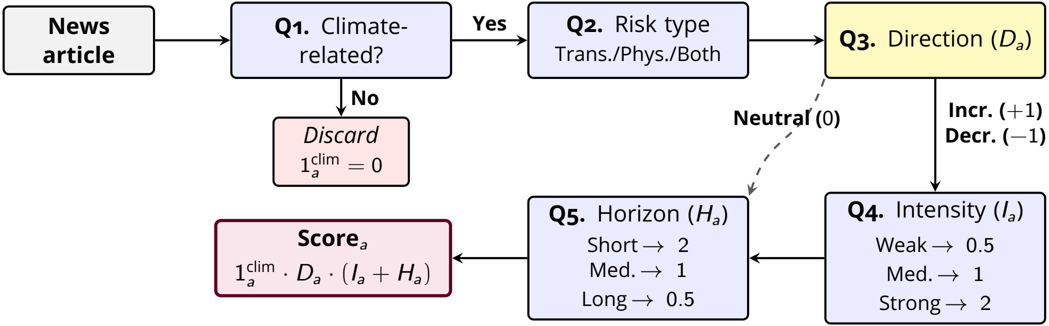
Final corpus:

- **161,962** articles retrieved
- **101,456** (63%) labeled as *climate-related* by the LLM

Stats per Outlet | Alluvial Plot

Measuring Climate Risk: LLM Annotation Pipeline

For each news article a (2010–2024), **GPT-5-mini** answers 5 multiple-choice questions, mapped to an article-level score:



I address two potential concerns:

- **Classification accuracy:** F1 $>$ 85% on Q1–Q3 ▸ Details
- **Forward-looking bias:** pre/post cut-off test rules out memorization ▸ Details

From Annotations to Daily Indicators

Article-level score:

$$\text{Score}_a = 1_a^{\text{clim}} \cdot D_a \cdot (I_a + H_a) \tag{1}$$

where $D_a \in \{-1, 0, +1\}$ (Direction), $I_a \in \{0.5, 1, 2\}$ (Intensity), $H_a \in \{0.5, 1, 2\}$ (Horizon).

Daily aggregation (Ardia et al., 2023; Baker et al., 2016):

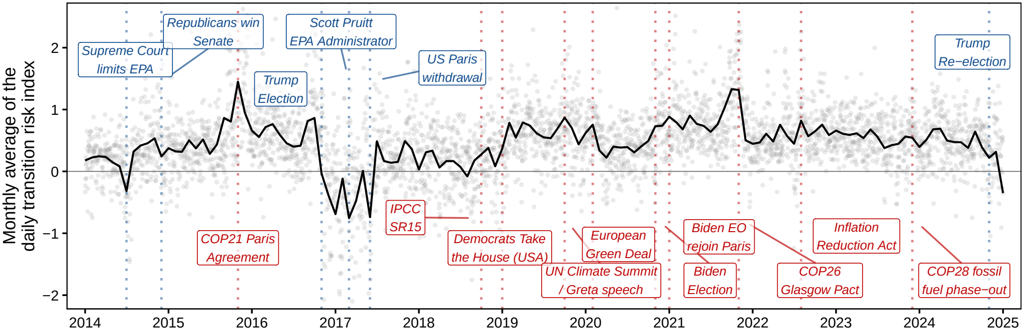
1. Sum article scores per outlet $\times$ day
2. Normalize by outlet-specific standard deviation
3. Average across outlets publishing on day t
4. Calendar completion via Kalman smoother (1.5% of days)

Two indicators:

TRI **Transition Risk Indicator**: aggregated transition-risk articles

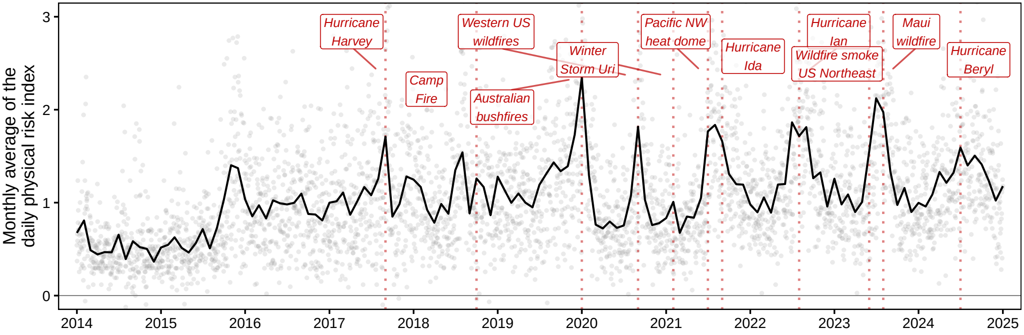
PRI **Physical Risk Indicator**: aggregated physical-risk articles

Transition Risk Indicator Time Series



Notes: This figure displays the transition risk indicator (TRI) from January 2014 to December 2024. **Gray dots represent daily values**; the **black line shows the monthly average**. Vertical lines indicate major climate-related events, colored by their expected effect on risk: **red for risk-increasing events**, **blue for risk-decreasing events**.

Physical Risk Indicator Time Series



Notes: This figure displays the physical risk indicator (PRI) from January 2014 to December 2024. **Gray dots represent daily values**; the **black line shows the monthly average**. Vertical lines indicate major climate-related events, colored by their expected effect on risk: **red for risk-increasing events**, **blue for risk-decreasing events**.

Financial Data

Stock sample (Sharadar, 2014–2024)

- Domestic common stocks listed on NYSE/NASDAQ, includes delisted firms
- Standard filters: excl. penny stocks ($p < \$5$) and microcaps (below NYSE 20th percentile of market cap.)
- **5,125 unique firms**; ~2,140 firms per month on average

Test assets and factors (Kenneth French Data Library)

- Test portfolios: 25 Size–Book-to-Market (BM), 30 and 49 industry portfolios
- Factors: FF3, FF5, and UMD (momentum).

Controls (EPU Website, Amit Goyal's Website, FRED)

- *Economic Policy Uncertainty* (EPU) index innovations (Baker et al., 2016)
- Predictive controls: TERM, DEF, DY (Welch and Goyal, 2008); VIX, WTI

Correlation matrix

Fama–MacBeth Regression (1/2): Methodology

First stage (rolling betas): 12-month rolling regressions on daily excess returns,

$$r^e_{i,t} = c_i + \beta^{\tilde{F}\,\prime}_{i,t}\tilde{\boldsymbol{F}}_t + \beta^{X\,\prime}_{i,t}X_t + \varepsilon_{i,t}$$

yielding $\hat{\beta}^{\tilde{F}}_{i,t-1}$ and $\hat{\beta}^{X}_{i,t-1}$ at each month-end.

Second stage (monthly cross-sectional pricing):

$$r^e_{i,t} = \lambda_{0,t} + \boldsymbol{\lambda}'_{\tilde{F},t}\,\hat{\beta}^{\tilde{F}}_{i,t-1} + \boldsymbol{\lambda}'_{X,t}\,\hat{\beta}^{X}_{i,t-1} + u_{i,t}$$

$\hat{\lambda}$ obtained as the time-series average of $\hat{\lambda}_t$, with Newey and West (1987) t-statistics (lag 6).

Notation:

- $\tilde{\boldsymbol{F}}_t = (\widetilde{\text{TRI}}_t, \widetilde{\text{PRI}}_t)'$: climate-risk innovations (AR(8) residuals)
- X_t: MKT, SMB, HML, UMD, EPU innovations (Baker et al., 2016)

Fama–MacBeth Regression (2/2): Results

	74 Portfolios			55 Portfolios		
	(*i*)	(*ii*)	(*iii*)	(*i*)	(*ii*)	(*iii*)
TRI Innov.	-1.339		**-1.612***	**-1.823****		**-1.893****
	(-1.59)		**(-1.94)**	**(-2.00)**		**(-2.25)**
PRI Innov.		-0.624	-0.500		-0.848	-0.757
		(-0.63)	(-0.51)		(-0.74)	(-0.70)
MKT	0.010	0.009	0.008	**0.014****	0.010	**0.012***
	(1.37)	(1.18)	(1.13)	**(2.33)**	(1.57)	**(1.77)**
Controls	✓	✓	✓	✓	✓	✓
Sample Period	2015 – 2024 (120 months)					

Notes: *74 Portfolios* = 49 industry + 25 Size–BM; *55 Portfolios* = 30 industry + 25 Size–BM. Controls: SMB, HML, MOM, EPU innov. Newey and West (1987) t-stats (lag 6). *, **, *** = 10%, 5%, 1%.

Negative TRI shocks risk premium (-1.6 to -1.9), robust to portfolio choice.

PRI shocks are not priced in either universe.

Assets hedging transition risk shocks earn **lower expected returns**

▸ Univ. Sorts

ICAPM Consistency (1/3): Methodology

Maio and Santa-Clara (2012): for $z_t \in \{\text{TRI}, \text{PRI}\}$ to be a valid ICAPM state variable:

1. z_t shocks command a significant risk premium (λ_z)
2. z_t predicts the future investment opportunity set, with a slope sign consistent with the sign of λ_z
3. the implied market price of risk is plausible

Empirical test of condition (2): predictive regressions of q-month aggregate market returns on z_t,

$$r_{t \to t+q} = \alpha_q + \beta_q \, z_t + \varepsilon_{t,t+q} \tag{2}$$

$$r_{t \to t+q} = \alpha_q + \beta_q^{\text{TRI}} \, \text{TRI}_t + \beta_q^{\text{PRI}} \, \text{PRI}_t + \boldsymbol{\gamma}_q' \boldsymbol{X}_t + \varepsilon_{t,t+q} \tag{3}$$

Notation: $r_{t \to t+q}$ = compounded value-weighted U.S. market return from t to $t+q$; $\boldsymbol{X}_t$ = controls (TERM, DEF, DY, RF, VIX, WTI). Tested at $q \in \{1, 3, 12, 24, 36, 48\}$ months.

ICAPM Consistency (2/3): Single Predictive Regressions

$q =$	1	3	12	24	36	48
TRI	-1.085	-1.798	-6.526	2.235	-3.996	**-8.145*** **
t-stat$_{\text{Newey-West}}$	(-1.47)	(-1.07)	(-0.88)	(0.15)	(-0.69)	**(-2.92)**
t-stat$_{\text{Hansen-Hodrick}}$	(-1.39)	(-1.20)	(-1.06)	(0.27)	(-0.73)	(-1.98)
Adj. R^2 (%)	-0.03	0.14	2.30	-0.62	1.33	7.78
PRI	**-2.532** **	-3.594	1.669	9.972	-1.768	5.397
t-stat$_{\text{Newey-West}}$	**(-2.54)**	(-1.48)	(0.26)	(1.42)	(-0.43)	(0.73)
t-stat$_{\text{Hansen-Hodrick}}$	(-2.53)	(-1.48)	(0.29)	(1.89)	(-0.40)	(0.80)
Adj. R^2 (%)	3.84	3.47	-0.61	5.12	-0.66	2.28

Notes: Single-predictive regressions of the value-weighted U.S. market return compounded over horizons of q months on the current level of TRI or PRI. Sample: Jan. 2014 to Dec. 2024. Coefficients in %. *, **, *** denote significance at 10%, 5%, 1%.

- **Higher TRI predicts lower market returns** at the 4-year horizon, consistent with the timeframe required for climate policy implementation
- **PRI is significant only at the 1-month horizon**, reflecting the immediate impact of physical climate events
- Long-horizon TRI predictability is the relevant condition for ICAPM consistency

Multiple Predictive Reg.

ICAPM Consistency (3/3): Summary

Maio and Santa-Clara (2012) require three conditions for a candidate state variable to be ICAPM-consistent. I compare **directional** indicators (TRI, PRI) with their **non-directional** counterparts (AT, AP), built without the Q3 direction signal.

	Directional		Non-directional	
Restriction	TRI	PRI	AT	AP
Forecasts future investment opportunities	✓	✓	✓	✓
Sign consistency (λ_z vs. β_q)	✓	✗	✗	✗
Plausible market price of risk	✓	✓	✓	✓
ICAPM-consistent?	✓	✗	✗	✗

- **Transition Risk can be interpreted as an ICAPM state variable**
- Non-directional measures (AT, AP) **fail the sign condition**
- **Direction matters**: only signed indicators reconcile cross-sectional pricing with ICAPM theory

AT/AP Figures

Conclusion

Main Takeaway

Transition risk (TRI) behaves as an ICAPM state variable:

- TRI predicts lower future market returns (worse investment opportunities),
- Exposure to TRI innovations carries a negative and significant risk premium,
- consistent with intertemporal hedging of transition-risk shocks.

$\rightarrow$ **Intertemporal hedging of transition risk.**

- **Direction matters:** only directional measures satisfy the ICAPM sign restriction.
- **Physical risk (PRI):** no robust long–short alpha / no robust pricing evidence in these tests.

Next steps: local physical-risk proxies; comparing existing transition-risk proxies in the literature.

Thank you for your attention.
Questions & comments welcome.

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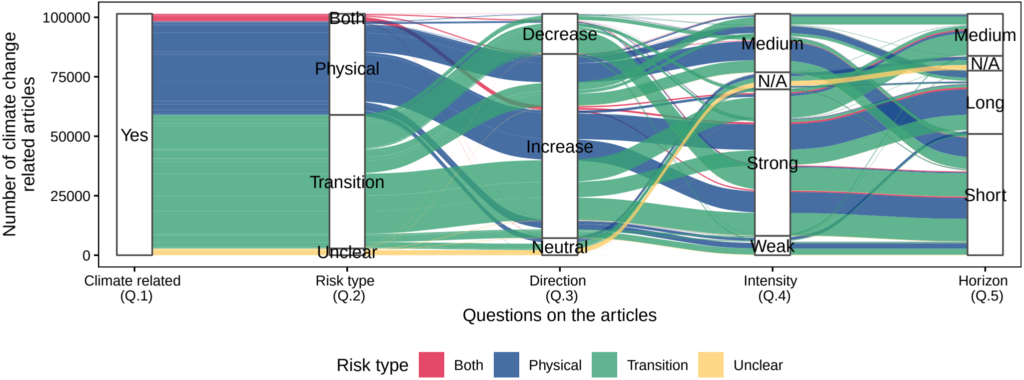
Table: Descriptive Statistics per Outlet

Outlet	Country	Articles			Indicators	
		Total	Green	% Green	Av. Transition Risk Score	Av. Physical Risk Score
Los Angeles Times	USA	13,170	8255	62.68	0.86	2.53
New York Post	USA	5,566	3,459	62.15	1.68	2.56
NPR	USA	6,463	4,477	69.27	1.02	2.66
Washington Post	USA	25,382	14,710	57.95	0.42	2.63
The Guardian	UK	51,130	36,965	72.30	1.11	2.67
Daily Mail	UK	52,186	28,175	53.99	1.51	2.56
The Globe and Mail	Canada	8,065	5,415	67.14	1.81	2.77
Total		161,962	101,456	62.64		

Notes: This table reports outlet-level descriptive statistics. *Total* is the number of collected articles; *Green* is the number of articles classified as climate-related by the LLM (Q1 = Yes); *% Green* is the corresponding share. *Av. Transition Risk Score* and *Av. Physical Risk Score* are the mean article-level scores computed over climate-related articles classified as transition risk (Q2 = Transition) and physical risk (Q2 = Physical), respectively.

Back

Figure: Alluvial Representation of the LLM-Based Classification of News Articles



This alluvial diagram shows article classifications across the five LLM questions, from climate relevance to time horizon. Flow widths reflect article counts, and colors indicate risk type: transition, physical, both, or unclear. The green flows show that most transition-risk articles are classified as risk-increasing, strong-intensity, and short-horizon.

Back

Table: LLM Classification Performance on Manually Annotated Articles

Question	Support	Micro (%)			Macro (%)			MAE	nMAE
		F1	P	R	F1	P	R		
Q1	271	86.7	86.7	86.7	86.3	88.5	85.9		
Q2	141	87.9	87.9	87.9	62.7	63.9	62.3		
Q3	141	88.7	88.7	88.7	64.7	67.6	62.9	0.184	0.092
Q4	135	61.5	61.5	61.5	42.3	45.5	43.3	0.474	0.237
Q5	135	55.6	55.6	55.6	31.4	31.4	35.4	0.556	0.278

Notes: This table reports the performance of the LLM-based classification on the manually annotated newspaper sample. Q1–Q5 correspond to the five annotation tasks. For each task, the table reports F1-score, precision (P), and recall (R), computed using both micro- and macro-averaging; all values are expressed in percentages. Micro-averaged metrics weight observations by their frequency, while macro-averaged metrics give equal weight to each class. For the ordinal classification tasks (Q3–Q5), the table additionally reports the mean absolute error (MAE) and the normalized MAE (nMAE). Support denotes the number of manually annotated articles used for evaluation.

Back

Table: Pre- vs Post–Training Cut-off Performance of the LLM Classification

Grp.	Prompt	Q.	N	Micro (%)			Macro (%)			MAE	nMAE
				F1	P	R	F1	P	R		
G.1	P.2	Q1	174	77.0	77.0	77.0	74.9	82.3	75.0		
		Q2	92	80.4	80.4	80.4	49.5	49.1	57.6		
		Q3	91	58.2	58.2	58.2	31.4	39.4	35.4	0.538	0.269
		Q4	68	41.2	41.2	41.2	24.0	21.8	26.7	0.632	0.316
		Q5	72	43.1	43.1	43.1	29.7	31.2	32.1	0.764	0.382
G.2	P.2	Q1	98	75.5	75.5	75.5	73.7	82.2	74.6		
		Q2	50	76.0	76.0	76.0	46.2	45.2	47.8		
		Q3	49	71.4	71.4	71.4	36.2	36.2	58.3	0.327	0.163
		Q4	37	40.5	40.5	40.5	21.1	20.4	24.5	0.649	0.324
		Q5	40	62.5	62.5	62.5	29.0	29.5	31.7	0.525	0.263

Notes: Classification performance on manually annotated articles, split by publication date relative to GPT-3.5-Turbo's training cut-off (Sept. 2021). Q1–Q5 report micro/macro F1, precision (P), recall (R) in %; ordinal tasks (Q3–Q5) also report MAE and normalized MAE. GPT-3.5-Turbo chosen for its earlier cut-off, allowing a larger post-cutoff sample.

Back

Table: Correlation Matrix of Daily TRI/PRI Innovations and Financial Variables

	TRI*	PRI*	MKT	SMB	HML	RMW	CMA	MOM	EPU*	WTI	VIX
TRI*	1.00	0.04	-0.02	-0.03	0.01	-0.02	-0.00	0.01	-0.03	-0.01	0.02
PRI*		1.00	-0.00	-0.01	0.00	-0.01	0.00	-0.00	0.02	-0.01	-0.01
MKT			1.00	**0.22**	-0.07	**-0.20**	**-0.30**	**-0.13**	0.01	**0.12**	**-0.16**
SMB				1.00	-0.01	**-0.41**	**-0.14**	**-0.20**	-0.00	0.00	-0.00
HML					1.00	**0.32**	**0.59**	**-0.33**	-0.07	0.08	-0.03
RMW						1.00	**0.30**	-0.03	-0.04	0.03	0.03
CMA							1.00	0.02	-0.04	0.05	0.06
MOM								1.00	0.05	-0.08	-0.00
EPU*									1.00	-0.03	0.08
WTI										1.00	-0.09
VIX											1.00

- TRI/PRI/EPU innovations: residuals from AR(8) (BIC-selected)
- TRI* and PRI* show **near-zero correlation** with all factors and EPU
- Confirms TRI/PRI capture distinct climate-risk shocks

Back

Univariate Sorts (1/3): Methodology

Step 1 — Estimate exposure to climate risk shocks. For each asset i, run a 12-month rolling regression on daily data:

$$r^e_{i,t} = c_i + \beta_{i,t}\,\tilde{F}_t + \gamma_i'\,\boldsymbol{X}_t + \varepsilon_{i,t} \tag{4}$$

where $\boldsymbol{X}_t$ are factor controls and $\tilde{F}_t \in \{\widetilde{\mathrm{TRI}}_t, \widetilde{\mathrm{PRI}}_t\}$ denotes daily innovations, defined as residuals from a daily $AR(8)$ model[1].

Step 2 — Form quintile portfolios. At each month-end, sort assets into 5 value-weighted portfolios by $\hat{\beta}_{i,t-1}$:

- Q1: lowest exposure (*brown* — adversely affected by climate shocks)
- Q5: highest exposure (*green* — benefits from climate shocks)
- Q5–Q1: long-short return spread

Step 3 — Estimate alphas for quintile and long-short portfolios under Fama and French (1993) 3-factor, Carhart (1997) 4-factor, and Fama and French (2015) 5-factor models.

Back

[1]The lag order is selected by minimizing the BIC.

Univariate Sorts (2/3): Alphas on TRI Innovation Betas

	1	2	3	4	5	5-1
			January 2015 – December 2024 ***(120 months)***			
Fama-French 3-factor alpha	**-0.45***	0.04	-0.06	0.06	0.10	**0.55****
	(-1.83)	(0.43)	(-0.79)	(0.63)	(0.83)	**(2.04)**
Carhart 4-factor alpha	**-0.39****	0.09	-0.13	0.07	0.07	**0.47***
	(-1.96)	(1.07)	(-1.52)	(0.78)	(0.56)	**(1.92)**
Fama-French 5-factor alpha	**-0.47****	-0.02	0.09	-0.10	**0.23***	**0.70*****
	(-1.98)	(-0.24)	(1.38)	(-1.05)	**(1.80)**	**(2.69)**

Notes: Stocks sorted monthly into value-weighted quintiles by TRI innovation betas (1 = lowest, 5 = highest). Betas estimated on a 12-month rolling window of daily returns. Alphas in monthly %. t-statistics based on Newey and West (1987) standard errors (lag 6). *, **, *** denote significance at 10%, 5%, 1%.

- **Takeaway:** TRI beta–sorted portfolios display an increasing pattern in alphas, with a positive and significant Q5–Q1 spread ($\simeq$0.5–0.7% per month) across models.
- **Explanation:** Short-leg driven: low-TRI-beta ("*brown*") stocks underperform when TRI shocks are frequent; high-TRI-beta stocks hedge (Pástor et al., 2021).

Back

Univariate Sorts (3/3): Alphas on PRI Innovation Betas

	1	2	3	4	5	5-1
		January 2015 – December 2024 *(120 months)*				
Fama-French 3-factor alpha	**-0.57****	0.02	-0.03	**0.24****	-0.09	0.48
	(-2.13)	(0.25)	(-0.30)	**(2.49)**	(-0.64)	(1.40)
Carhart 4-factor alpha	**-0.59****	-0.06	-0.00	**0.24*****	-0.02	0.57
	(-2.15)	(-0.53)	(-0.04)	**(3.04)**	(-0.10)	(1.64)
Fama-French 5-factor alpha	**-0.59****	0.03	0.07	0.14	-0.07	0.52
	(-2.14)	(0.27)	(0.76)	(1.56)	(-0.49)	(1.50)

Notes: Stocks sorted monthly into value-weighted quintiles by PRI innovation betas (1 = lowest, 5 = highest). Betas estimated on a 12-month rolling window of daily returns. Alphas in monthly %. t-statistics based on Newey and West (1987) standard errors (lag 6). *, **, *** denote significance at 10%, 5%, 1%.

Back

- **Takeaway:** No robust long–short alpha for physical risk, as proxied by PRI innovations.
- **Potential explanation:** PRI is *aggregate* but physical risk is *local* $\rightarrow$ weak signal in *beta-sorted* portfolios.

Table: Multiple Predictive Reg. of Aggregate Market Returns

	(i)	(ii)	(iii)	(iv)
Panel A: $q = 1$				
TRI	-0.005	-0.003	-0.005	-0.003
	(-1.21)	(-0.64)	(-1.24)	(-0.69)
PRI	**-0.015*****	**-0.012*****	**-0.015*****	**-0.012*****
	(-3.75)	(-2.71)	(-3.81)	(-2.78)
Panel B: $q = 12$				
TRI	**-0.036*****	**-0.028*****	**-0.036*****	**-0.028*****
	(-3.63)	(-3.35)	(-3.52)	(-3.32)
PRI	-0.011	0.002	-0.012	0.001
	(-0.90)	(0.15)	(-0.98)	(0.10)
Panel C: $q = 48$				
TRI	**-0.034*****	**-0.029*****	**-0.034*****	**-0.029*****
	(-5.77)	(-5.69)	(-5.78)	(-5.86)
PRI	0.031	0.045*	0.029	0.044*
	(1.11)	(1.80)	(1.01)	(1.65)
VIX		✓		✓
WTI			✓	✓
Other controls	✓	✓	✓	✓

Other controls:

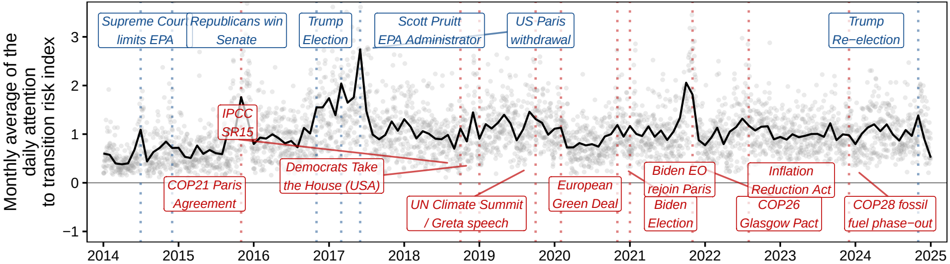
- TERM: term spread
- DEF: default spread
- DY: dividend yield
- RF: risk-free rate

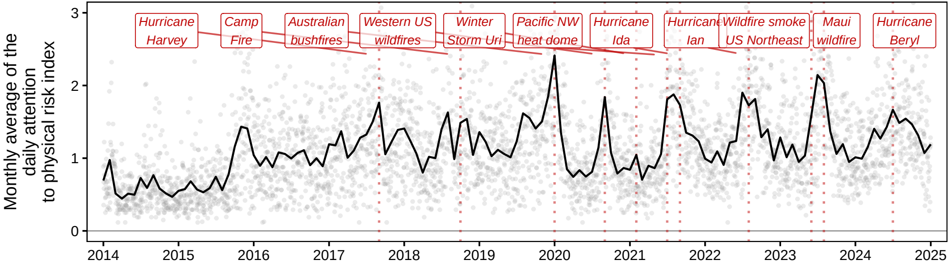
Notes:

- Standardized regressors
- NW (·) and HH [·] t-stats
- Sample: 2014–2024
- *, **, *** = 10%, 5%, 1%

Back

Attention to Transition (AT) and Physical (AP) Risks





Back

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