International Climate News


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NBER Summer Institute
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Broad Motivation

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↪ **Equity Returns:** do **green** and **brown** stock returns respond differently after a climate news shock?
↪ **Current Accounts:** do climate news shocks matter for int'l trade flows?

Preview of Findings

Empirical:
↪ **Novel dataset:** high-frequency, large cross section of countries, based on 24,000,000 tweets (2014-2022) ⇒ **Climate Attention Index (CAI)**

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The model drives our empirical strategy & explains our results

Literature Review

- **FX literature:** *among others,* Lustig, Roussanov, Verdelhan (2011), Della Corte, Sarno, and Tsiakas (2011), Mano et al (2019), ...
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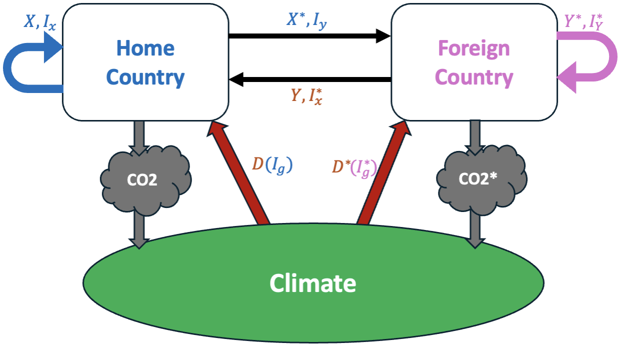
- **Macrofinance models of international finance:** *among others,* Bansal and Shaliastovich (2013); Colacito, Croce, Gavazzoni, Ready (2018) Lewis and Liu (2014), Zviadadze (2014) ...
  - **Here:** Heterogeneous exposures to both global growth and climate spillovers

Predictions from GE:

Flows & Prices

Basic Model Setup

- Two countries with trade on both consumption and investment goods (Colacito et al., 2018)
- Production generates emission ⇒ worsening climate condition ⇒ higher climate damage
- Damage/Vulnerability is distinct from climate sentiment shocks



Horizon and Shocks

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Time 1: Both the Home and Foreign (*) agent receive news about:
- 1. **global** climate news shock g;
- 2. local productivity shock θ

Time 2: No additional shocks, endogenous production and climate damages realized.

Preferences

Time $t \in \{0, 1, 2\}$, recursive preferences identical between two countries:

$$u_t = (1-\beta)\log\left(\widetilde{C}_t \cdot \mathcal{G}_t\right) + \frac{\beta}{1-\gamma}\log E_t\left[\exp\left\{(1-\gamma)u_{t+1}\right\}\right], \quad t = \{0, 1, 2\},$$

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- C_1, C_2, and D_2 are endogenous, i.e., depends on the shocks.

Time 1: Get News and Trade Goods!

After receiving the news shocks, both countries choose maximizes time-1 utility subject to the following resource constraints:

$$\begin{aligned} \text{Home:} \quad & 1 = X_1 + X_1^* + I_{x,1} + I_{y,1} + I_{g,1}, \\ \text{Foreign:} \quad & 1 = Y_1 + Y_1^* + I_{y,1}^* + I_{x,1}^* + I_{g,1}^*. \end{aligned}$$

e.g., for the home country:

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- $I_{g,1}$ and $I_{g,1}^*$ refers to green investments.

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- Output materializes, subject to productivity shock θ, and use of brown capital:

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- Economic-induced climate damage realized and mitigated by green capital:

$$D_2 = \left(\frac{GDP_2^{\lambda_g} \cdot GDP_2^{*1-\lambda_g}}{G} \right)^a, \qquad D_2^* = \left(\frac{GDP_2^{*\lambda_g} \cdot GDP_2^{1-\lambda_g}}{G^*} \right)^a$$

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$$G = I_{g,1}^{\lambda_g} I_{g,1}^{*1-\lambda_g}, \qquad G^* = I_{g,1}^{*\lambda_g} I_{g,1}^{1-\lambda_g}.$$

- $\lambda_g > .5$ implies that domestic disruption matters more.

FX & Asset Prices

- Let $Q_{i,t}$ denote the time-t ex-dividend value of the marginal cash-flows paid out by investment in the final period of the model:

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- By complete markets, the FX is determined by the $\log SDF - \log SDF^*$ and

$$\Delta e_{H|F} > 0 \rightarrow \text{appreciation of Home currency}$$

Model Predictions ▸ details

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Proposition 3. When $b > 1$, a **global** climate news shock $g > 0$ **decreases** the home country's net exports.

Data Collection

Data from X (formerly Twitter)

Table 1. Dataset Summary

Country	Tot. no. News Outlets	Tot. no. Tweets	Tot. no. Words	Tot. no. Terms	Language
AR	4	1,892,464	16,592,918	50,513	Spanish
AU	4	539,792	5,805,411	46,253	English
BR	3	1,091,173	9,157,179	46,841	Portuguese
CA	5	1,071,360	9,662,873	48,695	English
CH	4	312,897	2,477,651	40,932	German and French
CL	3	1,088,455	9,422,589	48,409	Spanish
CN	3	488,076	6,786,626	53,342	English
CO	3	1,291,773	10,348,974	55,984	Spanish
DE	4	708,692	6,779,556	31,190	German
ES	4	1,484,502	13,662,696	61,176	Spanish
FR	4	1,004,595	8,950,751	54,021	French
HK	2	305,490	2,982,160	28,143	English
IN	4	1,909,474	22,370,252	71,505	English
IT	3	1,268,190	10,209,216	42,084	Italian
JP	4	353,247	3,819,349	36,544	English
KR	4	302,946	2,814,363	28,923	English
MX	4	2,041,505	19,553,684	70,880	Spanish
NO	3	152,521	921,258	13,022	Norwegian
NZ	3	147,218	1,156,784	20,538	English
PT	3	802,011	6,102,651	40,929	Portuguese
SA	3	914,623	8,754,709	44,571	Arabic
SE	4	190,493	1,607,852	19,201	Swedish
UK	4	791,929	6,978,125	46,460	English
US	11	2,735,338	29,141,511	72,662	English
ZA	3	453,135	3,945,579	33,473	English
Total	**96**	**23,341,899**	**220,004,717**	**1,106,291**	

Tweet-level observations between 2014 and 2022

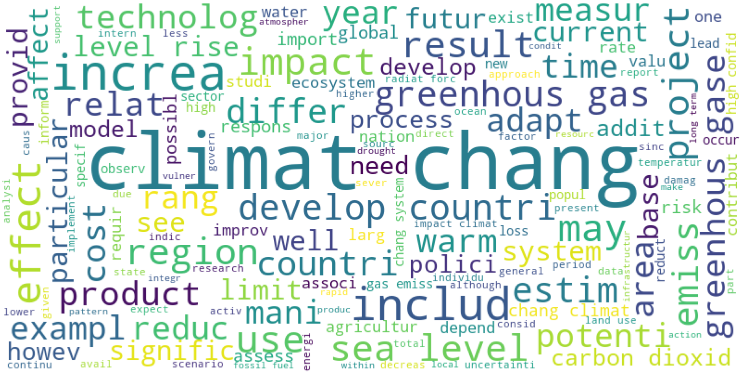
25 main economies (both developed and developing), $>$ 80% world GDP

96 newspapers

Takeaway: very large sample!

Newspapers

Text Analysis: Corpus & Documents



Methodology: Engle et al (2020)
- same corpus of authoritative text
- cosine similarity of merged tweets (documents)
- Google translate API applied to the corpus

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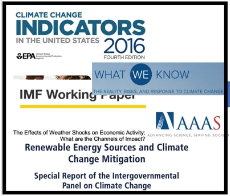
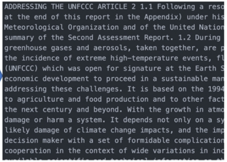


White Papers


ADDRESSING THE UNFCCC ARTICLE 2 1.1 Following a reso
at the end of this report in the Appendix) under his
Meteorological Organization and of the United Nation
summary of the Second Assessment Report. 1.2 During
greenhouse gases and aerosols, taken together, are p
the incidence of extreme high-temperature events, fl
(UNFCCC) which was open for signature at the Earth S
economic development to proceed in a sustainable man
addressing these challenges. It is based on the 1994
to agriculture and food production and to other fact
the next century and beyond. With the growth in atmo
damage or harm a system. It depends not only on a sy
likely damage of climate change impacts, and the imp
decision maker with a set of formidable complication
cooperation in the context of wide variations in inc

Single *Corpus* (English)

***tf-idf* vectorize**

$$Similarity = \frac{Corpus \cdot Document}{|Corpus| \cdot |Document|}$$

	corpus	0	1	2	3	4	5	6	7	8	...
congression	1.0	25.0	20.0	16.0	13.0	16.0	11.0	7.0	7.0	13.0	...
...	...	...	...	...	...	...	...	...	...	...	...
emiss	2699.0	3.0	25.0	3.0	8.0	3.0	8.0	3.0	4.0	23.0	...
climat chang	2822.0	24.0	36.0	18.0	32.0	24.0	34.0	31.0	29.0	71.0	...
increas	2941.0	74.0	79.0	68.0	59.0	59.0	65.0	54.0	75.0	85.0	...
chang	5751.0	186.0	192.0	197.0	185.0	151.0	225.0	244.0	235.0	275.0	...
climat	5978.0	28.0	66.0	37.0	81.0	38.0	44.0	43.0	34.0	93.0	...

year	month	country	lang	tweet_pp
2014	10	USA	en	small spici start prepar demand eggnog season ...
2014	11	USA	en	hour hanoi photo jame wasserman nyt virgin gal...
2014	12	USA	en	two year colleg student vanish upstat new york...
2015	1	USA	en	new year day bowl game dealbook huge ski resor...
2015	2	USA	en	snow forecast mayor blasio say new york citi s...

```
'small spici start prepar demand eggnog season entrepreneur
ann ward nyt third day job afghan presid dig bank fraud cas
ravel websit best bit blog facebook agre eas rule real name
famili teenag pregnanc abort rate plummet long act femal cc
t compani singl purchas made appl pay technolog industri al
ong protest photograph creatur might never see otherwis phc
otest hong kong target phish attack smartphon homeland rein
rocess brooklyn beer list section label import florida man
```

"document": country-month merged text

***tf-idf* vectorize**

Tweet-Level Examples

High Similarity Tweets (score > 0.5)

Washington Post Opinions
@PostOpinions

Trump is isolationist, protectionist and a climate denier. @MaxBoot writes that voters aren’t. wapo.st/2UIj0oE

9:56 PM · Sep 9, 2019

The Boston Globe
@BostonGlobe

Is climate denial contagious? | Editorial Cartoon by @WassermanToons in @GlobeOpinion bos.gl/g52mwXj

6:02 AM · Mar 12, 2019

The Washington Post
@washingtonpost

Opinion: Once again, the U.S. embarrasses itself on climate change wapo.st/2H5kovh

9:46 AM · May 7, 2019

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The Boston Globe
@BostonGlobe

Is climate denial contagious? | Editorial Cartoon by @WassermanToons in @GlobeOpinion bos.gl/g52mwXj

6:02 AM · Mar 12, 2019

The Washington Post
@washingtonpost

Opinion: Once again, the U.S. embarrasses itself on climate change
wapo.st/2H5kovh

9:46 AM · May 7, 2019

Low Similarity Tweets (score $= 0$)

The Washington Post
@washingtonpost

Donald Trump masqueraded as a spokesman to brag about himself
wapo.st/1TeAcvk

9:10 PM · May 13, 2016

The New York Times
@nytimes

Three doses of Pfizer-BioNTech's Covid vaccine give significant protection against Omicron, the companies said, but two doses alone "may not be sufficient to protect against infection" by the fast-spreading variant.
nyti.ms/3IldRMg

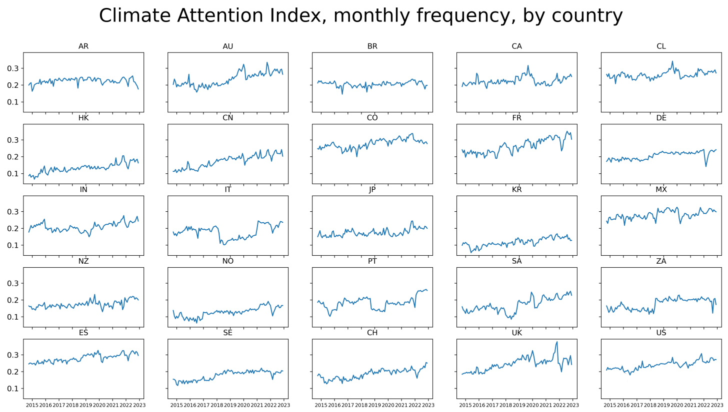
9:15 PM · Dec 8, 2021

Houston Chronicle
@HoustonChron

Softball playoffs: Schaeffer, Friendswood topple Crosby, 7-3
bit.ly/3MduLgK

10:32 AM · May 13, 2022

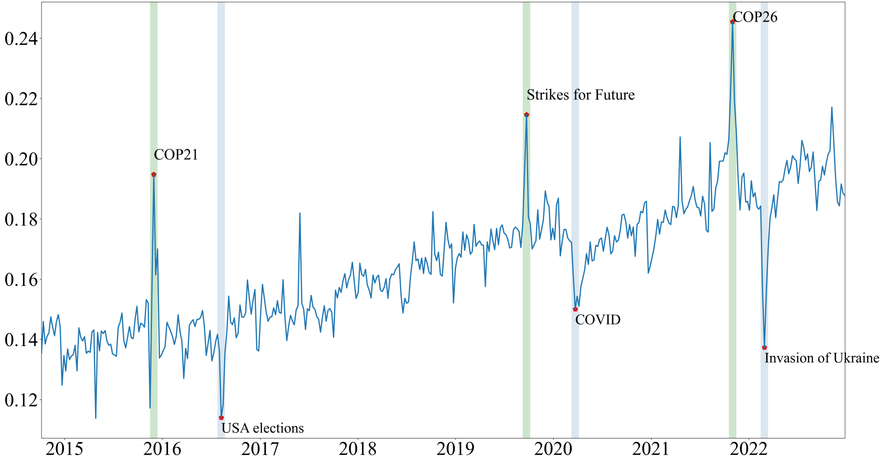
Climate Attention Index by Country



Takeaway: Granular but with a common component.

World Climate Attention (CAI)

$$\overline{CAI}_t = \sum_i \omega_{i,t} CAI_t^i, \quad \omega_{i,t} \in \{1/N;\ \text{Volume Share};\ \text{GDP share}\}$$



Takeaway: Our index effectively reflects major global events.

Heterogeneous Exposure to World CAI

TABLE 2. ESTIMATED β FOR EACH COUNTRY

	Equally weighted		GDP weighted		Volume weighted	
Country code	β	s.e.	β	s.e.	β	s.e.
AR	0.932	0.213	0.573	0.153	1.021	0.250
AU	1.420	0.197	0.932	0.190	1.362	0.209
BR	0.615	0.293	0.470	0.218	0.688	0.290
CA	1.711	0.224	1.313	0.138	1.752	0.228
CL	0.241	0.284	0.113	0.175	0.251	0.289
HK	2.104	0.325	1.196	0.326	1.596	0.503
CN	2.015	0.344	1.787	0.142	1.827	0.454
CO	0.678	0.180	0.561	0.115	0.670	0.206
FR	0.663	0.247	0.320	0.243	0.718	0.270
DE	0.363	0.122	0.236	0.074	0.309	0.154
IN	1.408	0.367	1.143	0.184	1.532	0.331
IT	0.982	0.592	0.624	0.473	1.520	0.682
JP	1.895	0.271	1.470	0.236	1.715	0.221
KR	2.414	0.395	1.624	0.280	1.864	0.318
MX	0.610	0.242	0.375	0.141	0.799	0.240
NZ	0.811	0.293	0.428	0.223	0.770	0.305
NO	0.345	0.321	0.245	0.267	0.178	0.320
PT	0.469	0.662	0.083	0.432	0.125	0.623
SA	2.270	0.572	1.112	0.249	2.227	0.605
ZA	0.198	0.466	-0.029	0.466	0.065	0.593
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UK	0.993	0.269	0.798	0.214	0.958	0.335
US	0.767	0.143	0.743	0.083	0.872	0.133

$$\Delta CAI_{i,t} = \underbrace{\beta_i}_{\text{exposure}} \cdot \underbrace{\Delta \overline{CAI}_t}_{\text{global shock}} + \underbrace{u_{i,t}}_{\text{Local shock}}$$

Takeaway #1:
Heterogeneous exposure in the cross section! That is, $b \neq b*$!

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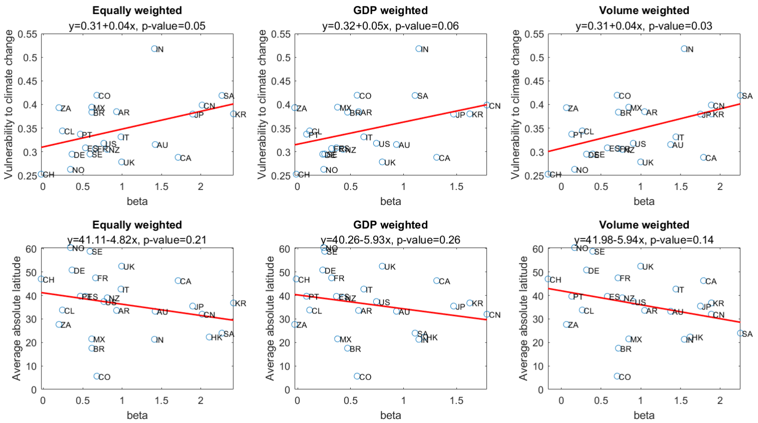
Takeaway #2:
Results robust across aggregation schemes

β: a Novel Source of Heterogeneity



Takeaway #1: β weakly related to vulnerability score (top panels) and absolute latitude (bottom panels). Details Other Vars

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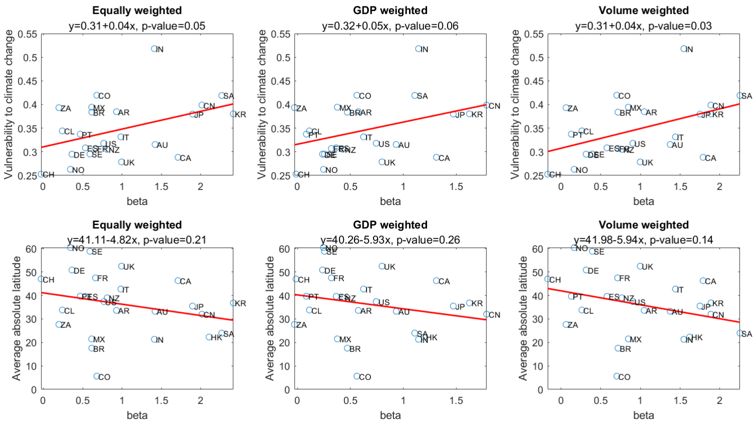

Takeaway #1: β weakly related to vulnerability score (top panels) and absolute latitude (bottom panels). Details Other Vars

Takeaway #2: Our results hold when we take the **orthogonalized part** of the βs (additional information).

CAI, FX, & Stock Returns

Top-days

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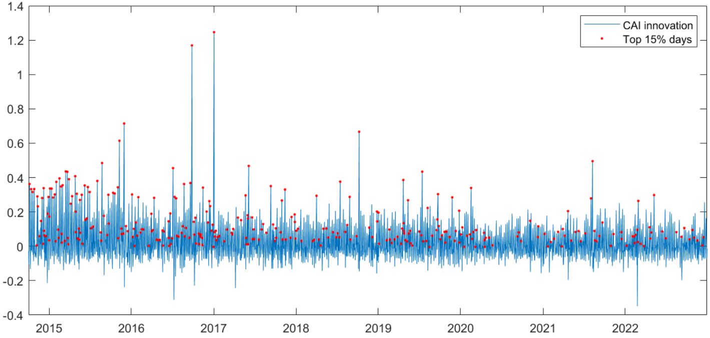
2. **High-frequency identification** of climate news shock responses
3. Our results are probably **downward biased** (other important days did not make it!)

Innovations to World CAI



Takeaway: evenly spread out across years (business days only; conditional on day of the week).

From Tweets to Topics

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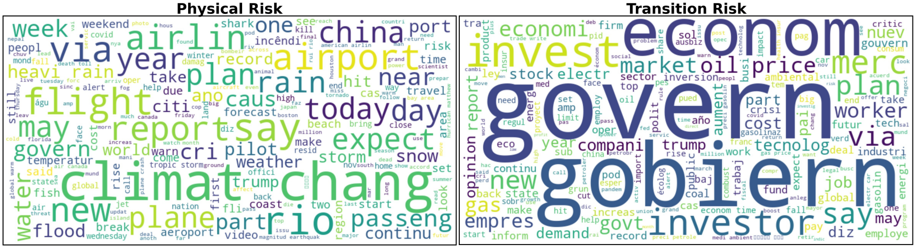
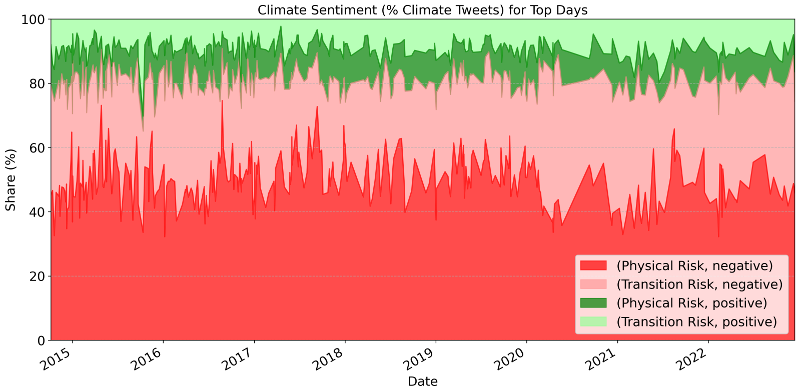
4. Climate-related topics: similarity score in the top 0.1% percentile
5. If the high score comes from physical (transition) sentence, classify the tweets in that topic as physical (transition)

Word Clouds and Topics



Takeaway: our classification delivers a good fit.

From Attention to Sentiment for Top-Days



Takeaway: top-attention days are associated to bad news

FX and CAI News

$$\Delta e^{i,j}_{t,t+k} = a^{i,j}_k + b_k \cdot \mathbb{1}^{Top}_t + \epsilon^{i,j}_{t,k}$$

where we include country pairs (i, j) such that β_i **is significantly larger than** β_j pairs

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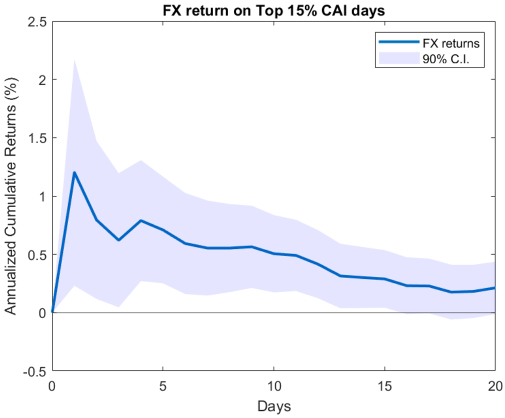

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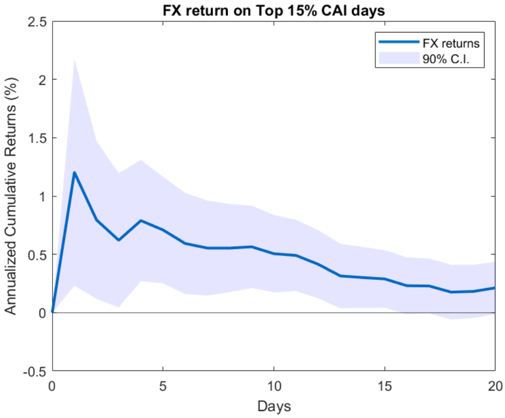

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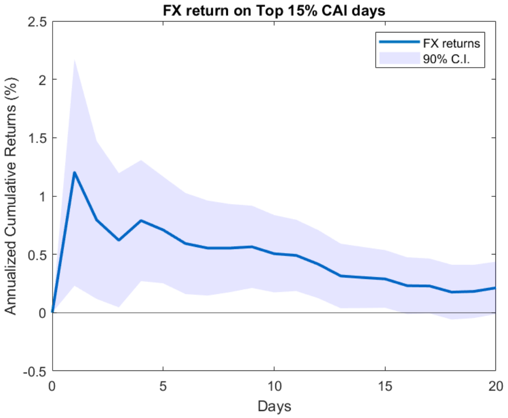

1. In total 138 country-pairs and 322 top-days.
2. Net of cumulative returns in all other days ('DiD')
3. Average cumulative returns after days with top-15% positive news in CAI

Takeaway: Currencies of high-β countries appreciate.

Weights Top βs Freq. Other

FX and CAI News: Transition & Physical Risks

Let S_t denote the share of tweets talking about transition risks at day t, normalized between 0 and 1.

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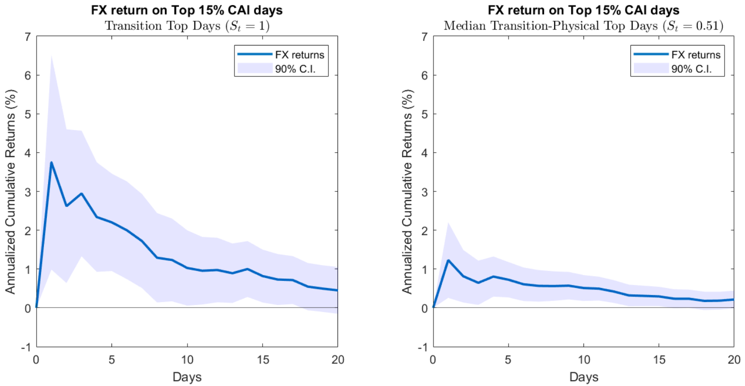
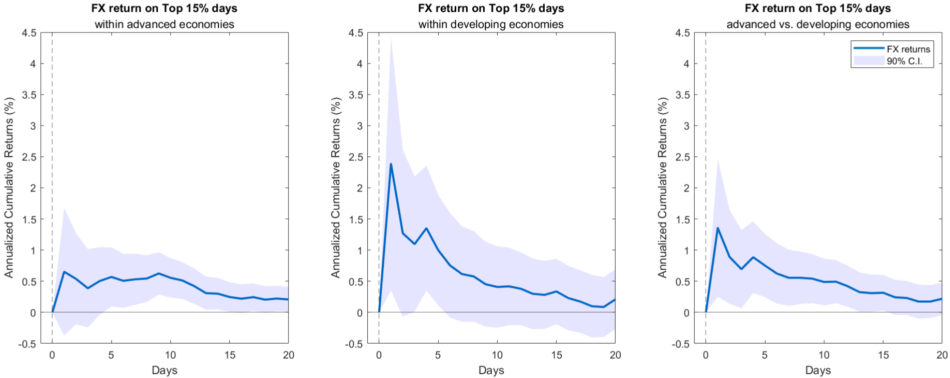


Takeaway: Transition Risks dominate. Local

FX and CAI News: Developing vs Advanced Economies



Takeaway: Developing Economies experience more persistent appreciations.

Equity Returns Sensitivity to CAI

Data set comprising 16,774 firms and a total of 23,305,563 firm-day observations:

$$r^{i,c}_{t,t+k} = \alpha^i_t + \zeta^{i,c}_{t,k} \cdot \mathbb{1}^{Top}_t + \epsilon^{i,c}_{t,k}, \quad (1)$$

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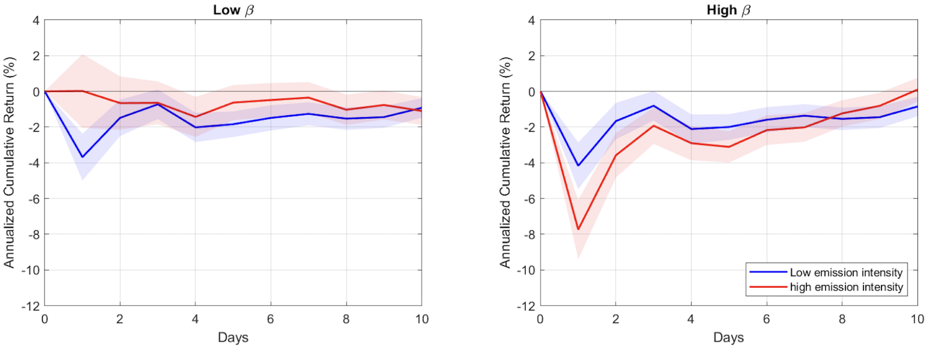
- E_{i,t_a} is our stock level-specific emission intensity in the previous year (Trucost)

Equity Returns Sensitivity to CAI



95% C.I. constructed using standard errors clustered at the industry*date and firm level.

Takeaways: 1. stock returns depreciate after top climate days; 2. "brown" stocks depreciate more in countries with high β

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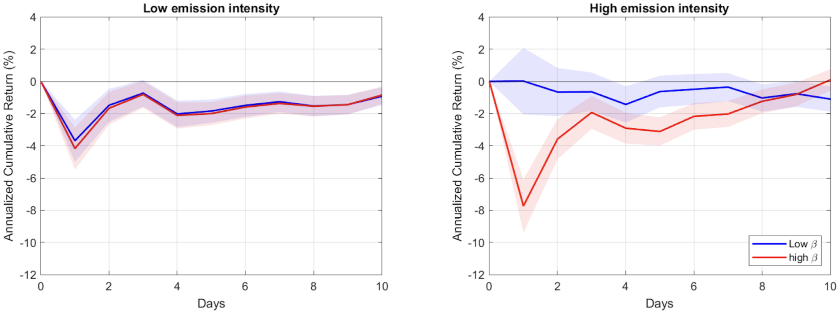

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Takeaway #1: High-β countries make high-emission firms more exposed

Weights Top Other

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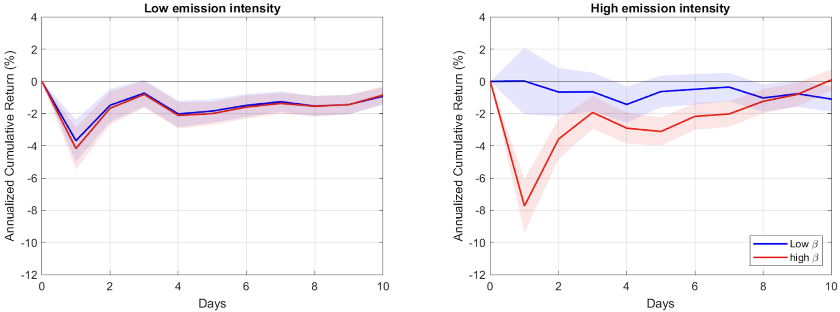

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Takeaway #1: High-β countries make high-emission firms more exposed ▸▸ Weights ▸▸ Top ▸▸ Other

Takeaway #2: FX and phisical damage news not first-order ▸▸ Local Units ▸▸ Topic

Empirical Investigation about Flows

- Due to the low-frequency nature of trade data, we switch to **quarterly** frequency of our index.
- To correct the error-in-variable bias, we estimate the following system of equations by GMM:

$$\begin{aligned} \Delta CAI_{i,t} &= \beta_i \cdot \overline{\Delta CAI}_t + u_{i,t} && (3) \\ \Delta\left(\frac{NX_{i,t}}{GDP_{i,t}}\right) - \Delta\left(\frac{NX_{j,t}}{GDP_{j,t}}\right) &= \Gamma \cdot (\beta_i - \beta_j) \cdot \overline{\Delta CAI}_t \ldots \\ & \quad + \theta' \cdot (control_{i,t} - control_{j,t}) + \epsilon_{ij,t}, && (4) \end{aligned}$$

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- $(\beta_i - \beta_j)$ is country i's sensitivity to climate news shocks, with i and j sorted such that $\beta_i > \beta_j$

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$$+\theta' \cdot (control_{i,t} - control_{j,t}) + \epsilon_{ij,t}, \quad (4)$$

- $\frac{NX_{i,t}}{GDP_{i,t}}$ is the net export over GDP of country i at time t
- $\overline{\Delta CAI}_t$ is our 'global' attention index
- $(\beta_i - \beta_j)$ is country i's sensitivity to climate news shocks, with i and j sorted such that $\beta_i > \beta_j$
- Γ is the coefficient for the differential sensitivity

Empirical Investigation about Flows

- Due to the low-frequency nature of trade data, we switch to **quarterly** frequency of our index.
- To correct the error-in-variable bias, we estimate the following system of equations by GMM:

$$\Delta CAI_{i,t} = \beta_i \cdot \overline{\Delta CAI}_t + u_{i,t} \tag{3}$$

$$\Delta\left(\frac{NX_{i,t}}{GDP_{i,t}}\right) - \Delta\left(\frac{NX_{j,t}}{GDP_{j,t}}\right) = \Gamma \cdot (\beta_i - \beta_j) \cdot \overline{\Delta CAI}_t \ldots$$

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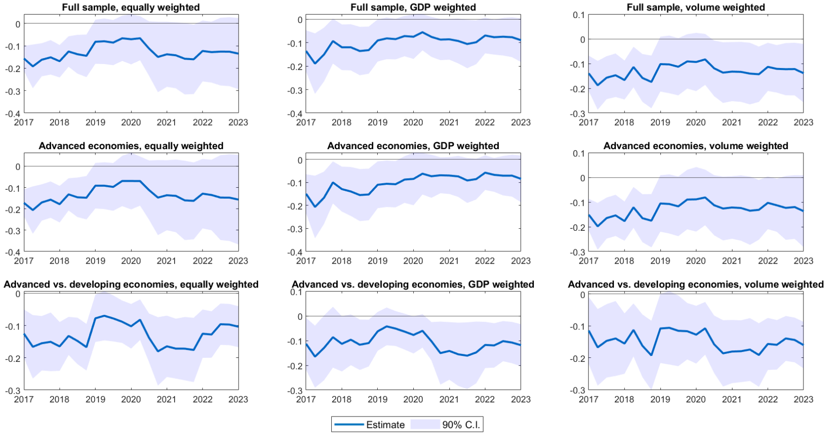
- Γ is the coefficient for the differential sensitivity
- *control* includes: change in the country-level industrial production index & the share of Twitter volume on days when the CAI is at the bottom 5% (other events that affect Twitter activity).

Empirical Results about Flows (I)

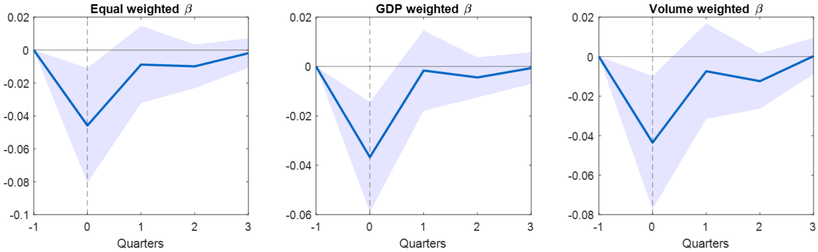
Estimates of Γ across country-pairs and samples:



Takeaways: Highly exposed countries receive resources (decline in CA).

Empirical Results about Flows (II)

Estimates of Γ over horizon k across 190 country-pairs when we do **not** use $\beta_i - \beta_j$:



Takeaways: Effects may last 3-6 months.

Conclusions

1. **Novel & BIG dataset** on climate news comprising AEs and EEs.

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Conclusions

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- **FX markets**,
- **Intl. Equity markets** &
- **Current Accounts**

3. An **International EZ-IAM** model rationalizes many of our empirical patterns.

Our Climate Attention Index is available for download at:
https://sites.google.com/view/internationalclimatenews

Thank you!

Any comment are welcome:

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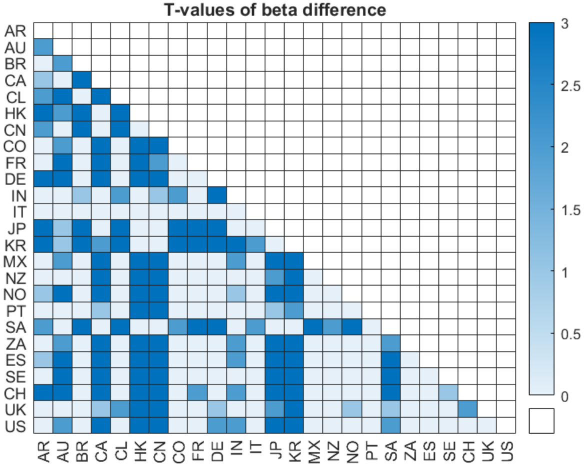
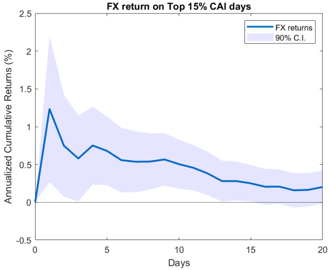
biao.yang@sjtu.edu.cn majo_arteaga@hotmail.com

Significant βs ⏩ Back

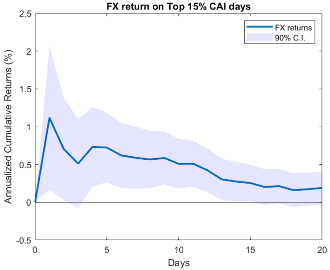


FX and CAI News: GDP- and Volume-weighted

Back

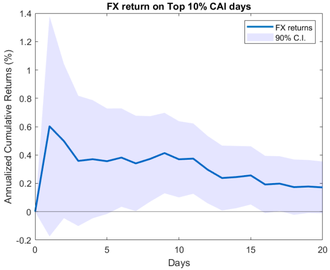


(a) GDP-Weighted

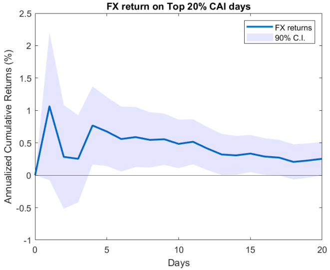


(b) Volume-Weighted

FX and CAI News: top-10 and top -20% ▸▸ Back

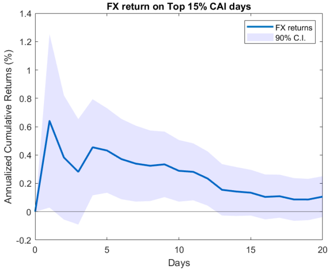


(c) Top 10% Days

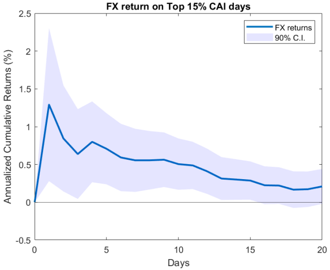


(d) Top 20% Days

FX and CAI News: the Role of β Back

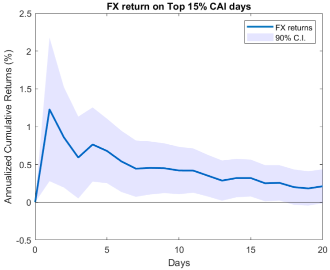


(e) All Country Pairs

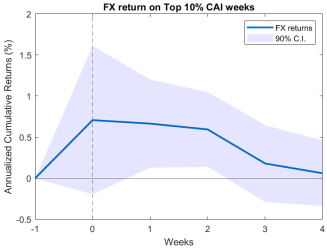


(f) β Different at 5%

FX and CAI News: the Role of Freq. ⏩ Back

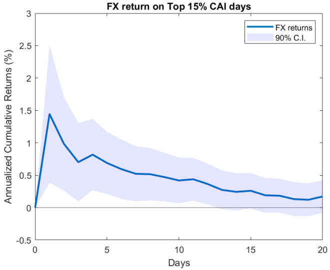


(g) Monthly Data

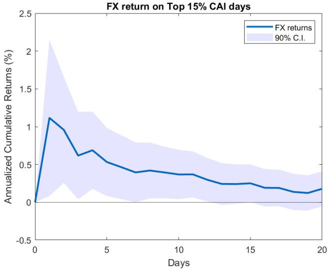


(h) Weekly Data

FX and CAI News: Additional Robustness ⏩ Back



(i) Combine EU

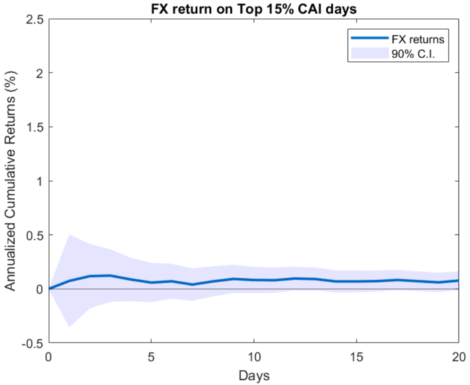


(j) Residual Betas

FX and Innovations to Local CAI. Back

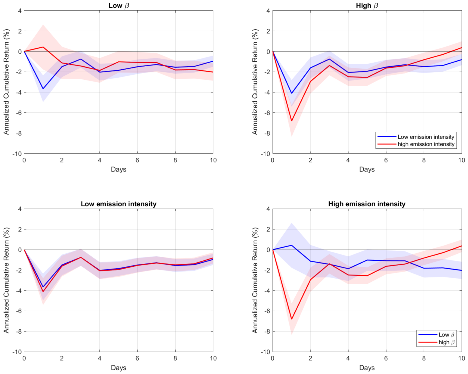
$$\Delta e^{i,j}_{t,t+k} = a^{i,j}_k + b_k \cdot \left(\mathbb{1}^{Top}_{i,t} - \mathbb{1}^{Top}_{j,t}\right) + \epsilon^{i,j}_{t,k}.$$

For each country i, the local top-day dummy $\mathbb{1}^{Top}_{i,t}$ is based on the top-15% days of the country's local CAI.

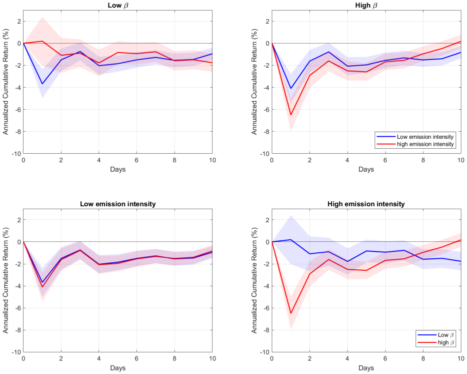


Equity returns and World CAI: the Role of Weighting

Back



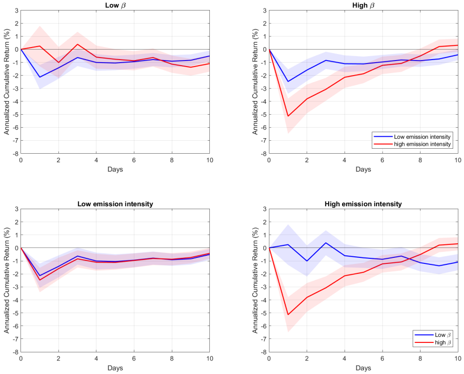
(k) GDP-Weighted



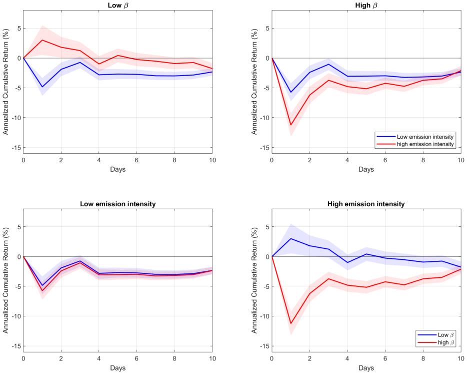
(l) Volume-Weighted

Equity returns and World CAI: top 10% and 20% Days

Back



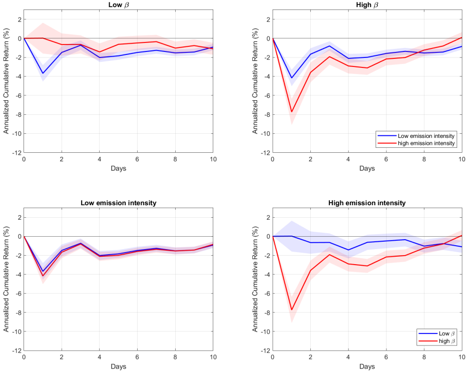
(m) Top 10% Days



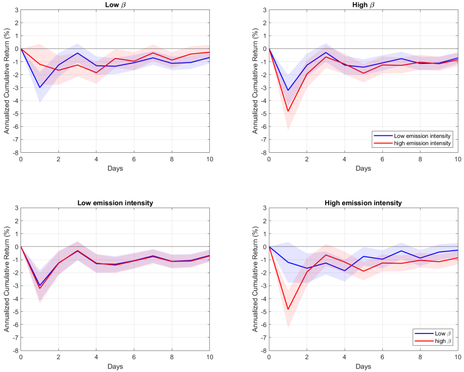
(n) Top 20% Days

Equity returns and World CAI: Additional Results

Back



(o) Clustering at the country×industry×date and firm level



(p) Residual Betas

Ratio of Pareto Weights ▸ back

- Let $\lambda = \lambda_g = \lambda_l$, $a \in (0,1)$, $b > 1$, $\gamma > 1$, $\lambda \in (1/2, 1)$ and $\beta \in (0,1)$.
- The log-ratio of the Pareto weights at time $t = 1$ is equal to:

$$\tilde{s}_1 = \bar{s} + \tilde{\beta} \cdot \underbrace{(\gamma - 1)}_{>0} \cdot \left[\underbrace{\left(\frac{(b-1)a}{1 + 2(\gamma - 1)\lambda_u^s} \right)}_{>0} \cdot g - \underbrace{\left(\frac{(1-a)(2\lambda - 1)}{1 + 2(\gamma - 1)\lambda_u^s} \right)}_{>0} \cdot 2\theta \right],$$

where $\tilde{\beta} = \beta(1-\beta)$, and

$$\lambda_{lx}^S = \frac{\beta}{1+\beta}(1-\lambda)(2\lambda - 1)(1-a) > 0$$

$$\lambda_u^s = (1-\beta)\left\{(1-\lambda)\left[2\lambda(1+\beta) + \beta(2\lambda-1)^2(1-a)\right] + (2\lambda - 1)\left[1 + a\beta + (1-a)(2\lambda-1)\beta\right]\lambda_{lx}^S\right\} > 0.$$

Exchange Rates back

- Let $\lambda = \lambda_g = \lambda_l$, $a \in (0,1)$, $b > 1$, $\gamma > 1$, $\lambda \in (1/2, 1)$ and $\beta \in (0,1)$.
- The log-growth rate of the exchange rate at date $t = 1$ is equal to:

$$\Delta e_1 = \overline{\Delta e} + \lambda_e^s \cdot \tilde{s}_1,$$

where

$$\lambda_e^s = (2\lambda - 1)^2 \cdot [1 - 2 \underbrace{\frac{\beta}{1+\beta}}_{<1/2} (1-\lambda)(1-a)] > 0.$$

- The exchange rate appreciates in response to a positive sentiment shock ($g > 0$) and it depreciates in response to a positive productivity shock ($\theta > 0$).

Net Exports ▸ back

- Let $\lambda = \lambda_g = \lambda_I$, $a \in (0,1)$, $b > 1$, $\gamma > 1$, $\lambda \in (1/2, 1)$ and $\beta \in (0,1)$.
- Net exports of consumption and investment goods at time $t = 1$ are equal to:

$$\frac{NX_1^C}{X_1} = -\left(\frac{1-\lambda}{\lambda}\right)\left[\frac{(\exp\{\tilde{s}_1\} - 1)}{1 + (\exp\{\tilde{s}_1\} - 1)}\right]$$
$$\frac{NX_1^I}{I_x} = -\left[\frac{(2\lambda - 1)(1-\lambda)}{\lambda}\right]\left[\frac{(\exp\{\tilde{s}_1\} - 1)}{1 + \lambda(\exp\{\tilde{s}_1\} - 1)}\right]$$

- Both net export functions are decreasing in $(\exp\{\tilde{s}_1\} - 1)$.
- NX decline in response to a positive sentiment shock ($g > 0$) and increase in response to a positive productivity shock ($\theta > 0$).

Excess Returns ▸ back

- Let $\lambda = \lambda_g = \lambda_l$, $a \in (0,1)$, $b > 1$, $\gamma > 1$, $\lambda \in (1/2, 1)$ and $\beta \in (0,1)$.
- The log-return of brown stocks in excess of green stocks at date $t = 1$ is equal to:

$$r_{b,1} - r_{g,1} = \bar{r} + \lambda_r^s \cdot \tilde{s}_1,$$

where

$$\lambda_r^s = -2(1-\lambda)[\lambda - \underbrace{\left(\frac{\beta}{1+\beta}\right)}_{<1/2}(1-\lambda)(2\lambda-1)(1-a)] < 0.$$

- Excess return declines in response to a positive sentiment shock ($g > 0$) and it increases in response to a positive productivity shock ($\theta > 0$).

Equity Returns Sensitivity to CAI: Topics

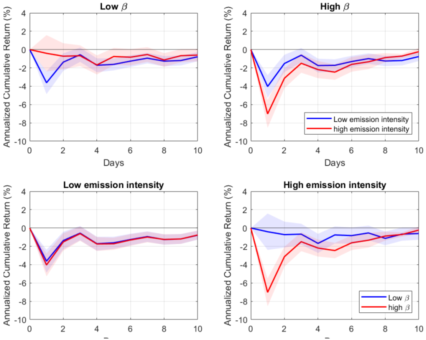
Back

$$r^{i,c}_{t,t+k} = \alpha^i_k + \zeta^{i,c}_{t,k} \cdot 1^{Top}_t + \epsilon^{i,c}_{t,k}, \quad \zeta^{i,c}_{t,k} = (\gamma_{0,k} + (\gamma_{1,k} + \gamma_{2,k} \cdot \beta_c) \cdot E_{i,t_a}) + \underbrace{(\kappa_{0,k} + (\kappa_{1,k} + \kappa_{2,k} \cdot \beta_c) \cdot E_{i,t_a}) \cdot S_t}_{topic-sensitive},$$

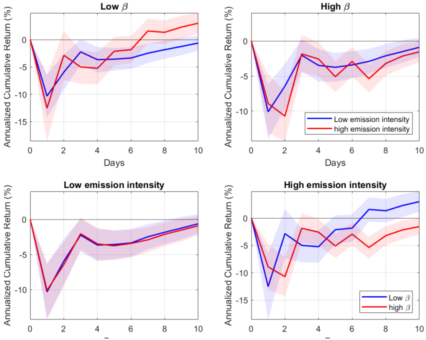
Equity Returns Sensitivity to CAI: Topics

Back

$$r^{i,c}_{t,t+k} = \alpha^i_k + \zeta^{i,c}_{t,k} \cdot 1^{Top}_t + \epsilon^{i,c}_{t,k}, \quad \zeta^{i,c}_{t,k} = \left(\gamma_{0,k} + (\gamma_{1,k} + \gamma_{2,k} \cdot \beta_c) \cdot E_{i,t_a}\right) + \underbrace{\left(\kappa_{0,k} + (\kappa_{1,k} + \kappa_{2,k} \cdot \beta_c) \cdot E_{i,t_a}\right) \cdot S_t}_{topic-sensitive},$$



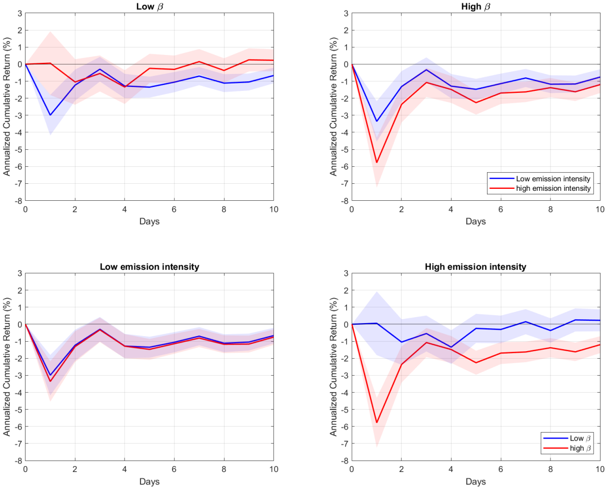
(s) Median Transition/Physical Top Days



(t) Transition Top Days

Takeaways: Transition news dominates.

Equity Returns Sensitivity to CAI (in local currency) ⏩ Back



Takeaways: Not just driven by the FX!

Newspapers' coverage (non-exhaustive)

Back

Country	Newspaper name	Twitter handle	Language
Argentina	Clarín	clarincom	Spanish
	Diario Crónica	cronica	
	Infobae	infobae	
	La Nación	LANACION	
Australia	The Australian	australian	English
	The Daily Telegraph	dailytelegraph	
	The Australian Financial Review	FinancialReview	
	The Age	theage	
Brazil	Estadão	Estadao	Portuguese
	Folha de S.Paulo	folha	
	-	GauchaZH	
	Jornal O Globo	JornalOGlobo	
Canada	The Globe and Mail	globeandmail	English
	Montreal Gazette	mtlgazette	
	Ottawa Citizen	OttawaCitizen	
	Toronto Star	TorontoStar	
	The Vancouver Sun	VancouverSun	
Switzerland	20 Minuten	20min	German
	24 heures	24heuresch	
	Le Temps	LeTemps	French
	Neue Zürcher Zeitung	NZZ	
Chile	El Mercurio	ElMercurio_cl	Spanish
	El Mostrador	elmostrador	

ND-GAIN

Back

ND-GAIN
Notre Dame Global Adaptation Initiative

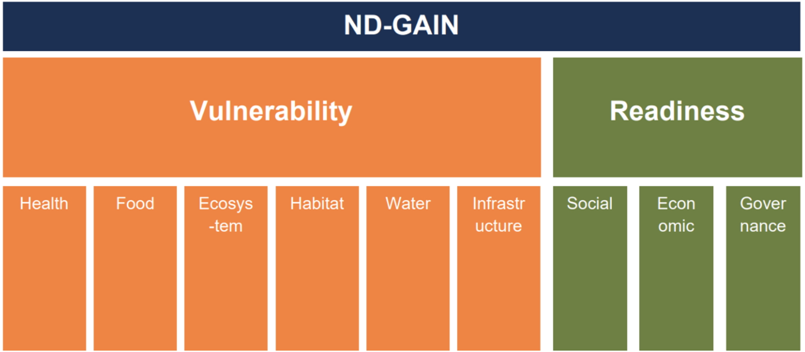


Figure 1. Summary of ND-GAIN Vulnerability and Readiness Indicators

Vulnerability is composed of 36 indicators. Each component has 12 indicators, crossed with 6 sectors. Readiness is composed of 9 indicators.

Other Associations ⏩ Back

We find that our β_c coefficients are associated to:
- real total GDP and population (size) $+$
- total emissions $+$
- democracy index (https://ourworldindata.org/) $-$
- vulnearbility to storms (https://ferdi-indicators.shinyapps.io/PVCCI/) $+$