Virality to Vulnerability: Reverse Stress Testing Emerging Risks

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[Preliminary: Please do not circulate.]

Abstract

Investor beliefs can play a central role in how emerging risks– such as climate risk, characterized by high uncertainty and limited historical data– affect financial markets. The perception of these risks, rather than realized outcomes alone, can drive market reactions and amplify vulnerabilities, potentially affecting financial stability. This makes it challenging to incorporate emerging risks into traditional stress tests which typically focus on shocks to fundamentals. We address this gap by proposing a reverse stress testing framework that uses social media virality to capture shifts in beliefs and identify points of fragility. Our methodology consists of three steps. First, we construct a virality index based on the intensity of reposts of postings from influential accounts and interpret innovations in the index as belief shocks. We empirically validate the index and suggest that stock market responds more strongly and persistently to large changes in virality index than to those in a news-based index. Second, we design a risk portfolio that mimics the virality index and estimate financial institutions' stock return sensitivity to it. Finally, we quantify the magnitude of belief shocks needed to trigger stress across financial institutions.

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1 Introduction

Emerging risks, such as climate risk, can be characterized by high uncertainty and limited historical data. A key feature of these risks is that investor beliefs can play a central role in how emerging risks affect financial markets and the broader economy. Perceptions about the likelihood and consequences of these risks—rather than realized outcomes alone—can drive market reactions and potentially escalate into financial stability concerns. Therefore, it is important to understand what kinds of events trigger shift in belief, and how large a shift must be to affect financial stability.

Despite of importance of the question, it is difficult to address within traditional stress testing frameworks. The challenges are threefold. First, while stress scenarios are well defined with respect to traditional risk factors, such as market risk, interest rate risk, or credit risk, designing plausible yet severe scenarios for assessing emerging risks is difficult due to their inherent uncertainty. Second, since market reactions may be driven by changes in perception, not necessarily involving realization of the risks, it is critical to incorporate belief shifts, which are hard to measure. Third, because perceptions evolve over time, the standard assumption of a static balance sheet in traditional stress tests may not be suitable for analyzing emerging risks.

We address the first challenge by flipping the question: instead of starting with uncertain scenarios, we ask what kind of scenario would cause emerging risks to significantly weaken financial institutions' capital positions. This reverse approach is particularly useful when past realizations are scarce and when changes in beliefs, not necessarily involving realizations of risks, may be the key driver of stress. To address the second challenge, we use social media activity to proxy for belief shifts. By tracking reposts from influential accounts, we capture both the content of the information and how it spreads. We address the third challenge by dynamically estimating financial institutions' stock return sensitivities to belief shocks, as measured by our social media virality index.

Why is social media activity suitable for measuring beliefs? Social media has become

a major channel for information exchange, with over 5.2 billion users worldwide (Kepios, 2024). In the United States, one-third of adults regularly get news from social media, and adults under 30 are nearly as likely to trust it as national news outlets (Pew Research Center, 2024). By enabling users to rapidly share, amplify, and react to information, social media provides a useful proxy for measuring shifts in investor beliefs. Prior studies have shown that beliefs can be shaped through social media by trusted peers (Bailey et al., 2018, 2024), institutional investors (Kuchler et al., 2022), professional forecasters and public institutions (Carroll, 2003), and influencers with large followings (Muller and Schwarz, 2023). Moreover, social media has emerged as a powerful amplification channel for financial risk. Cookson et al. (2023) find that collapse of Silicon Valley Bank in 2023 was accelerated by viral content urging withdrawals on social media, leading to a sharper decline in stock prices in regions with high social media engagement.

How could virality become financial system vulnerability? Financial institutions holding assets (or liabilities) that are sensitive to sharp shifts in beliefs may be exposed to sudden losses. In a frictionless setting, they could immediately adjust their portfolios in response. However, Jung et al. (Forthcoming) suggest that such adjustments take time due to frictions such as relationship lending and specialization. As a result, emerging risks can affect the future profitability of financial institutions and their stock returns. When large institutions experience prolonged declines in stock prices, these losses can pose a broader financial stability risk.

The key to assessing this mechanism lies in quantification: *how large* must a shift in beliefs about emerging risks be to pose a threat to financial stability? We propose a novel approach to answer this question. Our methodology proceeds in three steps. First, we use social media data from Twitter and Bluesky to construct measures of belief dynamics. Second, we implement factor-mimicking portfolios to hedge the risk of beliefs shifting over short horizons. Third, we apply a market-based reverse stress testing framework to quantify the size of belief shocks that could generate systemic stress.

Our proposed approach can be applied to various contexts, including climate change risk, socioeconomic risk, and geopolitical risk. In this paper, we show an application to climate change risk, as the academic literature highlights the important role of investor and household beliefs in asset pricing in the context of climate change (e.g., Howe et al. 2015; Baldauf et al. 2020; Stroebel and Wurgler 2021; Acharya et al. 2023). In practice, although many regulators have conducted climate stress tests, there has been no consensus on what constitutes a severe yet plausible scenario.[1] Most commonly, regulators use scenarios from the Network for Greening the Financial System (NGFS), but they lack assigned probabilities. Therefore, our proposed reverse stress testing offers a practical alternative by avoiding the need for predefined scenarios or probabilities and instead identifying the critical stress levels that matter most.

Moreover, there has been great interest in measuring the "Minsky moment" in climate risk, in which a sharp shift in climate beliefs results in a substantial impact on asset prices (e.g., Alogoskoufis et al. 2021; Gautam 2024; Kaldorf and Rottner 2024). However, existing "green swan" scenarios involve significant uncertainties and rely on granular data, limiting their practical application (Bolton et al., 2020). In contrast, our forward-looking, time-varying approach identifies relevant scenarios by reverse-engineering key stress factors using only publicly available data. While we focus on climate risk as the main application, we also provide an application to geopolitical risk in the Appendix.

To implement our approach, we first construct a *climate virality index* by measuring retweets of influential climate accounts in the United States. These accounts include US politicians active between 2017–2021, trending accounts during climate conferences collected by Falkenberg et al. 2022 (e.g., Greta Thunberg), government agencies (e.g., the EPA and 14 regional accounts), nonpartisan news (e.g., Carbon Brief), disaster risk monitors (e.g., Readygov), and academic institutions (e.g., Earth Institute at Columbia) collected by snowball-sampling user profile recommendations. We find that most of the spikes in the

[1] At least 23 jurisdictions, including the European Union, have conducted in total 35 climate stress tests (Acharya et al., 2023).

climate virality index correspond to climate events related to both transition risk (e.g., the US exit from the Paris Agreement) and physical risk (e.g., major hurricanes and wildfires). The index identifies the US exit from the Paris Agreement as by far the most significant transition event between 2016–2022, followed by the UN Climate Change Conference in 2021, Green New Deal congressional resolutions in 2019, and Trump's rollback of climate rules following his inauguration in 2017. The index also responds to major physical disasters, including Hurricanes Dorian and Irma as well as the Australian wildfires in 2020.

How do viral climate risk events on social media compare with events identified by news articles? Interestingly, we find that only a subset of events deemed "important" by news articles went viral on Twitter, while some events not flagged as important by news articles also gained significant traction on Twitter. Specifically, we compare the climate virality index with a news-based climate risk index from Engle et al. (2020). They construct a "cosine similarity" index by assigning a textual similarity score between term frequencies appearing in daily news articles and term frequencies in twelve authoritative white papers on climate change. Our comparison with the New York Times (NYT) cosine similarity index reveals three main findings. First, the climate virality index and NYT index commonly identify 11 of 21 climate events, with both indices identifying the Paris Agreement transitions as highly significant. Second, whereas the NYT index consistently captures attention to climate reports (e.g., the 2020 UN emission gaps report and the 2021 NOAA report on record CO2 levels), the climate virality index additionally identifies natural disasters (e.g., US hurricanes, European heatwaves, and Australian wildfires) and viral domestic events such as the Dakota Access Pipeline protests. Third, the climate virality index identifies a wider range of positive brown shocks, including Trump's rollback of EPA emission rules.

Next, we estimate how asset prices respond as climate virality index changes. In event studies, we find that cumulative abnormal stock returns on brown sectors increase by 3% in the first two weeks after the US exit from the Paris Agreement, consistent with investor

expectations of lower transition risk.[2] Conversely, cumulative abnormal returns on brown stocks fall by 8% in the first two weeks after the US re-entry to the Paris Agreement, consistent with expectations of higher transition risk driven by regulatory tightening.

More interestingly, we find that events that were followed by higher retweets tend to have a larger and longer impact on affected stock returns than those that were covered by news articles but did not become viral. While cumulative abnormal returns on brown stocks fall by 7% in the first two months after a viral retweet event that increased climate risk, cumulative abnormal returns after news-based events only fall by 2% over the same time horizon. Furthermore, cumulative abnormal returns remain significantly negative for at least four months after a viral retweet event, yet cumulative abnormal returns are close to zero by the third month after a news event. Our findings imply that the climate virality index we developed differs from news-based indices, and can be valuable for identifying potential "Minsky moments."

There are two potential explanations for the stronger and more persistent stock market reactions to the events that went viral compared to similar events covered by traditional news outlets that did not. First, investors are not confident about their own interpretation of the event, and thus rely on the reactions of others. When the event becomes viral, investors revise their own beliefs based on the direction of the responses they observed on social media. Reliance on such unverifiable information exposes investors to confirmation bias, and can lead to overreaction relative to the true gravity of the underlying event.

Second, investors may face very high uncertainty regarding how other investors would react to climate related events. In the context of analyzing emerging risks, virality can provide more direct sense of how other investors' beliefs get updated by the events than the information covered by news articles. As a result, virality would invite stock market participation by investors who are averse to uncertainty with respect to other investors' beliefs.

[2]We identify brown sectors using the top 50 SIC industry codes by scope 1 and 2 emission rankings (Ilhan et al., 2023). Results are robust to restricting the sample to the top 10 or 25 industries.

Using the climate virality index, we construct a factor mimicking portfolio to hedge against climate beliefs shifting rapidly. Motivated by our event study results, we focus on brown sectors whose returns are highly sensitive to the climate virality index. To construct a hedge portfolio, we follow the factor mimicking portfolio methodology of Engle et al. (2020) and DeNard et al. (2023). We regress industry returns on the climate virality index and control factors to obtain time-varying estimates of industry climate exposure. From these estimates, we construct hedge targets and solve a quadratic portfolio optimization problem with a constrained minimum-variance objective and maximum hedge criterion that depends linearly on the hedge targets. We control the trade-off between the two objectives with a risk preference parameter, which is selected to maximize the portfolio's sensitivity to the climate virality index.

By flipping the sign of climate belief *hedge* portfolio, we obtain a climate belief *risk* portfolio. That is, climate belief risk portfolio falls in value as the risk goes up. To identify potential vulnerability of financial institutions to climate belief risk, we estimate their stock return sensitivity to the climate belief risk portfolio return, *climate beta*. As a result, we find that the climate beta increased during 2020 and 2021 across all financial institutions. In the cross section of 898 financial institutions, we find higher climate beta for smaller, more leveraged financial institutions with lower returns on assets and operating profits.

Finally, we use the CRISK framework of Jung et al. (Forthcoming) to reverse engineer the level of stress that can lead to a financial stability concern. Jung et al. (Forthcoming) propose a methodology to compute the expected capital shortfall in a climate stress scenario (CRISK), which can be thought of as a market-based climate stress test. In this paper, we formalize a methodology for reverse stress testing. We posit a regulator's problem as finding the level of stress that leads to a "too risky" level of leverage, where the stress scenario in consideration is the shift in climate beliefs over a short period of time (e.g., six months). In line with the Basel III minimum leverage ratio (BIS), we set the stressed leverage ratio as 4%. To solve the regulator's problem, we first derive the equity loss conditional on climate

stress required to reach a stressed leverage. Next, we use each financial institution's climate beta to estimate the level of climate stress associated with the target level of equity loss.

Our reverse stress testing reveals that 1% of financial institutions are expected to have leverage fall below prudential levels if the climate belief risk portfolio declines by 3% over six months. A back-of-the-envelope calculation suggests that this level of stress is equivalent to a shock ten times the magnitude of the US re-entering the Paris Agreement. These findings remain robust after controlling for aggregate demand shocks and COVID-related factors.

Contributions to the Literature This paper relates to several strands of literature. First, this paper contributes to the literature that studies the effect of shifts in the beliefs of investors, households, and supervisors on financial stability. On the institutional investor side, Kelly and O'Grada (2000), Iyer and Puri (2012), and Acemoglu et al. (2015) highlight the role of institutional networks in amplifying bank contagion. On the household side, Cookson et al. (2023) suggest that social media posts mentioning the word "withdrawal" accelerated deposit outflows and stock responses during the Silicon Valley Bank collapse in regions with high social media participation. Jiang et al. (2023) explore complementary mechanisms, such as beliefs about bank health and uninsured leverage, which may drive self-fulfilling solvency runs. Aldama-Navarrete et al. (2024) find that media sentiment, particularly negative sentiment, influences bank supervisory ratings. We contribute to this literature by providing a quantitative framework to evaluate the resilience of financial institutions to shifts in investor and household beliefs.

Second, this paper contributes to the climate finance literature in two key ways. We make a direct contribution to a growing literature developing climate risk indices (e.g., Engle et al. 2020; Gavriilidis 2021; Caldara and Iacoviello 2022; Bua et al. 2022; Ardia et al. 2023; Giglio et al. 2023; Jung and Hannaoui 2024). Compared to existing studies, we introduce a novel index derived from social media that reflects how investors absorb and further distribute climate-related information. Furthermore, we contribute to the work studying the impact of

climate change risk on financial stability (e.g., Jung et al. Forthcoming, 2023; Alogoskoufis et al. 2021; Kaldorf and Rottner 2024) by offering a reverse climate stress test methodology.

Third, this paper adds to the growing literature studying the impact of social networks on financial decisions and asset prices. Giannini et al. (2018) find that investor opinions, mediated by Twitter activity, either converged or diverged around earnings announcements, with convergence associated with negative stock return shocks. More broadly, studies have documented the effects of social networks on financial decisions, including investment behavior among both institutional and retail investors (e.g., Kuchler et al. 2022), housing and mortgage choices (e.g., Bailey et al. 2018), and product adoption (e.g., Bailey et al. 2022). We add to this literature by documenting that viral events on social media have larger and more persistent effects on asset prices than events reported by traditional news outlets.

Fourth, this paper adds to the extensive literature on investor learning and information processing. Blankespoor et al. (2020) surveys the literature and documents that even relatively well-understood traditional financial information, such as earnings announcements, imposes significant processing costs on investors. On this note, Jung (2020) structurally estimates the extent of learning frictions from post-earnings-announcement drifts and finds that it takes weeks for investors to fully reflect earnings information in prices. We add to this literature by suggesting that stock market reactions to climate news tends to be stronger and more persistent if it becomes viral on social media. This indicates a new channel through which investor learns about risks involving high uncertainty and limited historic realizations.

Outline of Paper Section 2 describes the social media and financial datasets used for analysis. Section 3 outlines the construction of the climate virality index, event studies validations, and comparisons with news-based indices. Section 4 constructs the factor-mimicking portfolio. Section 5 details the reverse-stress testing framework and reports results. Section 6 performs robustness checks and section 7 concludes.

2 Data

We use various datasets, including social media data and financial market data.

Social Media Data We use Twitter data to measure shifts in household and investor beliefs. Twitter is a social media platform where users post short messages called tweets, which can include text, images, or links, and are visible to their followers. Retweets allow users to quote other tweets in their posts or directly share tweets with their own followers, making the original tweet accessible to a broader audience.[3]

We use tweets and retweets retrieved from the Internet Archive. The Internet Archive team collects tweets through Twitter's "Spritzler" streaming API, which returns a 1% random sample of global tweets in real-time.[4] Our main sample consists of 1.8 billion tweets between 2016–2022, which is the longest sample period with consistent data we can obtain from the Internet Archive.[5] Our textual analysis focuses on retweets of influential public accounts in the United States, including government agencies, news, non-profit organizations, politicians, and celebrities.

Financial Market Data To measure stock market response to risk factors, we retrieve daily stock-level returns and market cap data from the CRSP-Compustat merged data set. We also retrieve Fama-French factors and a risk-free rate from the Kenneth R. French Data Library. To construct industry returns, we pulled all stocks that are traded on NYSE, AMEX, or NASDAQ, sorted by SIC codes. To analyze financial institutions, we focus on

[3]Twitter data provides a reasonable representation of how American public discourse evolves over time. Survey estimates indicate that one in five American adults uses Twitter (Smith and Anderson, 2018). Nearly half of users use Twitter daily, with nearly one-third using the platform multiple times per day. Two-thirds of US adults who engage in political discussions online do so using Twitter (Sam Bestvater and Smith, 2022).

[4]Prior studies (e.g., Morstatter et al., 2013; Pfeffer et al., 2018) confirm that the Spritzler stream is highly correlated with the full sample in terms of daily tweet volumes, topics and hashtags, as well as the spatial distribution of geo-tagged tweets. Our analysis of geo-tagged tweets based in the US further confirms that the geographical distribution of the Spritzler sample is consistent with census population estimates (Figure A1).

[5]We truncate years before 2016 due to a readjustment in Twitter's streaming architecture. Twitter discontinued the Spritzler stream in January 2023.

firms whose SIC codes are between 6000 and 6799. The sample period covers 2016–2022.

3 Measuring Beliefs with Social Media Data

3.1 Risk Virality Index

We construct an index of public attention to climate risk by measuring retweets of influential climate accounts in the United States. The internal validity of our attention index exploits the assumption that retweeting behavior signals beliefs attached to the original tweet.

Our methodology is motivated by the fact that it is easier to identify public figures and institutions who influence the direction of climate discourse than to directly characterize climate discourse itself. For example, Jung and Hannaoui (2024) show that existing textual indices that attempt to identify documents relevant to climate risk are highly sensitive to the authors' choice of reference keywords and documents (e.g., Engle et al. 2020; Gavriilidis 2021; Bua et al. 2022; Ardia et al. 2023; Giglio et al. 2023). Moreover, these measures often have limited out-of-sample performance when the vocabulary used to describe a topic changes significantly over time.[6] This empirical challenge is particularly pertinent on social media, where the vocabulary usage is highly varied. Conversely, the collection of influential climate accounts is arguably slow-changing, and thus can produce more robust indices.

To construct the climate virality index, we first retrieve the Twitter handles of US politicians who took office between 2017–2021 from the Twitter Parliamentarian Database.[7] Next, we retrieve Twitter handles from Falkenberg et al. (2022) corresponding to the most retweeted accounts during UN's Climate Change Conferences in 2015 and 2021 (COP21 and COP26 respectively). Falkenberg et al. (2022) manually labels the top 300 most retweeted

[6]For instance, Google Trends indicate that search interest in "climate change" has increased substantially relative to "global warming" in the past ten years (Jung and Hannaoui, 2024). Indices constructed using exclusively one word or the other would lead to incomplete estimates of public attention to climate risk.

[7]http://twitterpoliticians.org. The database scrapes social media handles from publicly listed government profiles, sorted by constituency and political affiliation.

accounts with their ideological leanings. We retrieve these accounts. Finally, we complement political and celebrity accounts by compiling a seed list of policy-neutral institutional accounts with a climate focus, including nonpartisan government agencies (e.g., EPA and its regional accounts), international agencies with a strong US presence (e.g., the IPCC and UN Climate Change), nonpartisan news sources (e.g., Climate Desk and Carbon Brief), disaster monitors(e.g., NOAA Climate and FEMA), and academic institutions (e.g., Earth Institute and the Union of Concerned Scientists). We augment this list through snow-ball sampling. Specifically, we retrieve the top five recommended accounts listed on the Twitter profiles for each seed account, and repeat this process for five cycles.[8] By this process, we identify 68 climate institutional accounts (Table A2).

Our climate virality index counts the number of retweets of climate institutions, politicians, and viral celebrity accounts. To ensure the retweets are relevant to climate discussion, we further filter retweets of political and celebrity accounts using climate keywords.[9] These keywords include "climate", "global warming", and 33 hashtags identified by Falkenberg et al. (2022) as viral during COPs 21 and 26 (Table A1). The index plots the weekly count of climate retweets.

3.1.1 Viral Events

The climate virality index captures public attention to both transition and physical climate risk (Figure 1). The index identifies the US exit from the Paris Agreement as by far the most significant transition event with 54,318 retweets. The index also responds to major physical disasters, including Hurricane Dorian (18,868 retweets), Hurricane Irma (17,145 retweets), and the Australian wildfires (16,386 retweets). A random sample of user texts verify that the index identifies relevant discussions around the climate events (Table 1).

Our climate virality index captures significant positive and negative shocks to brown

[8]By the fifth cycle, no new accounts appear in the top five recommendations.
[9]We assume retweets of climate institutions are always relevant.

sectors.[10] As an illustrative example, We estimate event studies of the top 50 brown industry returns around the US exit from and re-entry to the Paris Agreement:

$$R_t = \alpha + \sum_{n=0}^{3} \gamma_n shock_{t-n} + \mathbf{X}_t'\delta + \varepsilon_t, \tag{1}$$

where CAR_t is the six-month cumulative abnormal return, $shock_t$ is an indicator equal to 1 if a retweet event occurs during week t, and $\mathbf{X}_t$ are controls for market return MKT as well as Fama-French factors SMB and HML. Standard errors are Newey-West with an optimally chosen lag.[11]

Figure 2 plots the cumulative coefficient on $\hat{\gamma}_n$ with 95% confidence intervals. Event study estimates verify that the returns on the top 50 brown sectors react positively to the US exit from the Paris Agreement, consistent with investor expectations of lower transition risk (Panel A). Cumulative abnormal returns increase by 3.3% in the first two weeks after the US exit (significant at 1%) and plateau by the third week. Conversely, brown sector returns respond negatively to the US re-entry to the Paris Agreement, consistent with expectations of regulatory tightening (Panel B). Cumulative abnormal returns fall by 8.4% in the first two weeks since the US re-entry (significant at 5%) and plateau by the third week. Cumulative changes in returns on all other "non-brown" industries are close to zero, motivating our focus on brown stocks.

3.1.2 Virality Index vs. News Index

To illustrate how social media attention differs from news attention, we compare differences in events identified by our climate virality index with the New York Times cosine similarity index (Engle et al., 2020). Figure A2 plots the two standardized indices with event annotations and Table 2 categorizes events identified by both indices, social media only, and news only. This analysis reveals several key findings. First, the indices commonly identify 11 of 21

[10] Defined as top SIC4 industries by scope 1 and scope 2 emissions (Ilhan et al., 2023). See Table A3.

[11] Lag is $\lfloor \frac{4T}{100} \rfloor^{\frac{2}{9}}$, where T is the number of days in the sample period.

climate events (52%). In particular, both indices identify the Paris Agreement transitions as significant. Second, whereas the NYT index consistently identifies climate reports authored by authoritative agencies (e.g., the UN emission gaps report in 2020 and NOAA report on record CO2 levels in 2021), the climate virality index additionally identifies natural disasters (e.g., US hurricanes, European heatwaves, and Australian wildfires) and viral domestic events with a focus on Trump's legislations. Third, the climate virality index identifies a wider range of positive and negative brown shocks. All positive brown events identified by the NYT index are also identified by the retweets index. However, not all positive brown retweet events are identified by the NYT index, such as the 2016 presidential election of Donald Trump.

To compare how stock responses differ around retweet and news events, we re-estimate monthly regressions of equation 1 separately for positive and negative brown shocks identified by the indices. Event study estimates indicate that the decline in brown returns is far more persistent after a negative shock *only* identified by retweets (Figure 3 Panel A). Cumulative abnormal returns decrease by 7.3% in the first two months after a viral retweet event (significant at 1%), while returns after news events that did not become viral only decrease by 1.7% ($p = 0.412$) over the same time horizon. Events commonly identified by both indices do not correspond with significant changes in cumulative abnormal returns on the monthly level. Moreover, changes in stock returns after positive brown shocks are statistically different from zero and more drastic for retweet-only events (Panel B).

3.2 More Applications

Our approach can be applied to other types of risk as well. In the Appendix, we show an application to geopolitical risk. Following similar steps, we construct a tariff virality index and empirically validate it. We show that following a sharp change in the tariff virality index, stock returns of the affected sectors move as expected.

One could apply our framework to social uncertainty. As an example, we construct

a social uncertainty index by filtering retweets of US politicians for keywords related to activism and lobbying. By using politicians as the account universe, the index captures attention risk from the political constituency. The social uncertainty index spikes during presidential elections and key social movements such as the Women's Marches and the Black Lives Matter movements (Figure A3).

As another example, we construct a meme stock attention index by incorporating methods from Muller and Schwarz (2023) and Cookson et al. (2023). First, we extract all retweets containing cashtags of meme stocks (e.g., $GME) identified by Muller and Schwarz (2023). Second, we identify influencer accounts whose follower count exceeds 10,000 and whose profile descriptions contain keywords used in the startup and retail investor communities (Cookson et al., 2023). Finally, we construct the meme stock index by filtering meme stock retweets of these influencer accounts. The meme stock index gains significant traction in late-2020, which coincides with the retail investing boom (Figure A4). While this paper focuses on climate risk, these two applications show that researchers can easily adapt our approach to hedge against other types of social media shocks.

4 Constructing Hedge Portfolios

4.1 Factor Mimicking Portfolio

In this section, we follow the factor-mimicking approach of Engle et al. (2020); DeNard et al. (2023) to construct a factor-mimicking portfolio that hedges against climate risk becoming viral. Motivated by previous results, we construct a short-only portfolio of the top 50 brown industries whose returns are highly sensitive to the climate virality index.[12]

To construct the portfolio, we first estimate time-varying exposure to attention risk by sector. For each brown industry i, we estimate six-month rolling window regressions of daily

[12]See Table A3. Our selection of the stock universe is robust to the number of industries (top 20, 30, 50) and the emissions metric (scope 1, scope 2, or combined).

returns $R_{i,t}$ on the climate virality index CC_t and Fama-French factors $\mathbf{X}_t$:

$$R_{i,t} = \beta_{i,t} CC_t + \mathbf{X}_t' \delta_{i,t} + \varepsilon_{i,t}. \tag{2}$$

We use estimates of daily climate exposure $\hat{\beta}_{i,t}$ and Newey-West standard errors $\hat{\sigma}_{i,t}$ to construct a hedge signal $\tilde{b}_{i,t}$:

$$\tilde{b}_{i,t} = -1 \times \frac{\tilde{\beta}_{i,t}}{\sum_j \tilde{\beta}_{j,t}}, \qquad \tilde{\beta}_{i,t} = (\min(\hat{\beta}_{i,t}, 0))^2 / \hat{\sigma}_{i,t}. \tag{3}$$

In words, we first truncate the estimated climate exposure $\hat{\beta}_{i,t}$ to non-positive values since brown returns tend to respond negatively to attention risk (Table 2). We then scale estimated exposure by the t-statistics to obtain $\tilde{\beta}_{i,t}$. On each day t, we scale each sector's exposure by the total brown exposure to climate attention. We flip the sign to ensure brown stock returns respond negatively to increases in the climate signal.

Next, for each day t we optimize:

$$\min_{w_t \leq 0, \sum_i w_{it} = -1} \left\{ w_t' \hat{\Sigma} w_t - \lambda w_t' \tilde{b}_t \right\}, \tag{4}$$

where $\hat{w}_t$ are short-only weights on the brown industries on day t, λ is a risk preference parameter, $\tilde{b}_t$ is the hedge signal, and $\hat{\Sigma}$ is the estimated variance-covariance matrix of brown industry returns R over the whole sample period 2016–2022.[13] Finally, the daily portfolio return is $R_t^{FMP} = \hat{w}_t' R_t$.

[13] To address estimation error of the covariances when the sample period is relatively short, we implement a Ledoit and Wolf (2022) shrinkage estimator with linear constant variance-covariance shrinkage (DeNard et al., 2023). Specifically, we shrink the sample covariance S_{sample} to a matrix $Target$ with the grand mean variance along diagonals and grand mean covariance everywhere else: $\hat{\Sigma} = \hat{\theta} S_{sample} + (1 - \hat{\theta}) Target$, where $\hat{\theta}$ is inversely proportional to the Perron-Frobenius distance $||S_{sample} - Target||_F$ and bounded in $[0, 1]$. See Appendix A of DeNard et al. (2023).

4.2 Portfolio Performance

The risk preference parameter λ in problem 4 must be chosen. If $\lambda = 0$, the optimal weights correspond to a constrained minimum-variance portfolio. If $\lambda = 2$, the optimal portfolio sets industry weights identically equal to the hedge signal. If $\lambda = \infty$, the optimal portfolio consists of the industry that reacts most negatively to $\tilde{b}$ on each day. We select the optimal value of λ that maximizes the sensitivity of the hedge portfolio returns to the climate virality index. Following DeNard et al. (2023), we estimate the following OLS regression:

$$R_{t,\lambda}^{FMP} = \beta_\lambda CC_t + \mathbf{X}_t' \delta_\lambda + \varepsilon_{t,\lambda}, \tag{5}$$

where $R_{t,\lambda}^{FMP}$ is the return on day t of a hedge portfolio constructed with risk-preference λ, CC_t is the weekly average of the standardized climate virality index, $\mathbf{X}_t$ are controls for MKT, HML, SMB. Standard errors $\varepsilon_{t,\lambda}$ are Newey-West. We use $\hat{\beta}_\lambda$ as the portfolio metric: the larger and more significant the better. By this test, $\hat{\beta}_\lambda^*$ is maximized at $\lambda^* = 0.1$ (Figure 5). $\hat{\beta}_\lambda$ is positive and statistically different from zero across all tested values of λ, suggesting robust performance of the brown portfolio under different risk preferences.

DeNard et al. (2023) constructs a hedge portfolio for the NYT index using green stocks with an optimal $\lambda^* = 0.002$. In contrast, our brown hedge portfolio requires a value of $\lambda^* = 0.1$ to optimally hedge fluctuations in the climate virality index, implying 50 times greater weight on the hedge signal. These results suggest that relative to climate news, hedging social media attention requires a more risk-controlled but less diverse portfolio.

5 Reverse Stress Testing

5.1 Framework

We use the CRISK framework to reverse engineer the level of stress that can lead to a financial stability concern. Following Jung et al. (Forthcoming), we define CRISK as the

expected capital shortfall of a financial institution i in a climate stress scenario at time t:

$$CRISK_{it} = \mathbb{E}_t[CS_{it}|R^{climate}_{t+1,t+h} = -\theta, R^{MKT}_{t+1,t+h} = 0], \tag{6}$$

where CS_{it} is the firm's capital shortfall and θ is stress level, measured as the decrease in return $R^{climate}_{t+1,t+h}$ on the climate risk factor over a long period h. We define a financial institution's capital shortfall as the difference between the prudential level of equity, measured as 8% of quasi-assets, and the equity that the institution holds:

$$CS_{it} = k(D_{it} + W_{it}) - W_{it},$$

where $k = 0.08$ is the prudential ratio of equity to assets, D_{it} is the book value of debt for institution i at time t, and W_{it} is market value of equity. Assuming that firm debt is relatively immune to stress, CRISK can be re-expressed as:

$$CRISK_{it} = kD_{it} - (1-k)(1 - LRMES_{it})W_{it}, \tag{7}$$

where $LRMES_{it}$ is the long-run marginal expected shortfall (LRMES), defined as the expected firm equity multi-period arithmetic return conditional on climate stress θ. We assume that firm i's stock returns follow a factor model:

$$r_{it} = \beta^{climate}_{it} r_{climate,t} + \beta^{MKT}_{i,t} MKT_t + \varepsilon_{it}, \tag{8}$$

where $r_{it} = \log(1 + R_{it})$ is the firm's stock return, $r_{climate,t}$ is the climate risk factor, and MKT_t is market return.[14] $\beta^{climate}_{it}$ captures the sensitivity of an institution's stock returns

[14]We include MKT to control for confounding factors such as the COVID shock and aggregate demand shock. In robustness checks, we include additional controls.

to the climate risk factor. Using equation 8, we can express CRISK and LRMES as:

$$CRISK_{it} = kD_{it} - (1-k)W_{it}\exp(\beta_{it}^{climate}\log(1-\theta)) \tag{9}$$

$$LRMES_{it} = 1 - \exp(\beta_{it}^{climate}\log(1-\theta)). \tag{10}$$

Under the CRISK framework, a climate stress test amounts to estimating the CRISK of financial institutions using equation 9 for given values of the prudential ratio k and climate stress θ.

A *reverse* stress test aims to find the level of climate stress necessary to reach a target level of financial stress. First, we solve for the maximum long-run marginal expected shortfall $LRMES_{it}^{*}$ needed to reach a target equity-to-debt ratio $\kappa^{target} = 0.04$ for each institution:

$$\frac{D_{it}}{(1-LRMES_{it})W_{it}} \leq \frac{1}{\kappa^{target}} \tag{11}$$

$$LRMES_{it}^{*} = 1 - \kappa^{target}\frac{D_{it}}{W_{it}}. \tag{12}$$

Next, we define $\tilde{\beta}_i^{climate}$ for each financial institution i as its highest recorded value estimated from the data, since risk factor sensitivity tends to increase during periods of stress. Finally, we solve for the level of climate stress $\theta_{it}^{climate*}$ that satisfies equation 10:

$$LRMES_{t}^{*} = 1 - \exp(\tilde{\beta}_i^{climate}\log(1-\theta_{it}^{climate*})) \tag{13}$$

$$\theta_{it}^{climate*} = 1 - \exp\left(\frac{1}{\tilde{\beta}_i^{climate}}\log(1-LRMES_{it}^{*})\right) \tag{14}$$

$$\approx \frac{LRMES_{it}^{*}}{\tilde{\beta}_i^{climate}}. \tag{15}$$

Intuitively, a financial institution with higher stock return sensitivity $\tilde{\beta}_i^{climate}$ to the risk factor requires lower levels of climate stress to reach a stressed level of leverage.

5.2 Empirical Analysis

5.2.1 Climate Beta

In this section, we estimate the climate betas of all financial institutions using daily stock return data.[15] We construct the climate risk factor from the returns of a *long* position in the brown hedge portfolio (section 4). For each institution i, we obtain $\hat{\beta}_{it}^{climate}$ from 252-day rolling-window OLS regressions of equation 8.

Figure 6 plots the climate betas for the top 10 US banks by total assets between 2016–2022. Figure 7 plots the daily distribution of climate betas across all financial institutions. These results indicate that while the levels of climate beta vary across institutions, trends in climate beta are parallel over time, with notable increases across all institutions in 2020 and 2021. Increases in climate betas coincide with aggregate demand shocks associated with oil uncertainty and COVID, which we control for in section **??**.

To understand which institutional characteristics are associated with sensitivity to climate attention risk, we estimate the following OLS regression:

$$\hat{\beta}_{it}^{climate} = \alpha_i + \mathbf{X}'_{it}\beta + \gamma_t + \varepsilon_{it}, \tag{16}$$

where $\mathbf{X}_{it}$ are institution characteristics including the log of total assets, leverage, return on assets, and the ratio of operating profits to book value of equity. α_i and γ_t are firm and time fixed effects. Standard errors are clustered on the institution level. OLS estimates indicate higher climate betas for financial institutions with lower returns on assets and lower operating profit to book ratios (Table 3).[16]

[15] Financial institutions are firms whose SIC is between 6000 and 6799.

[16] Controlling for either firm or time fixed effects, climate betas are also associated with smaller and more leveraged firms. Controlling for both firm and time fixed effects flips the estimates.

5.2.2 CRISK

Using the climate betas, we compute the CRISK for the top 10 US banks between 2016–2022 (Figure 8). Estimated CRISKs are mostly negative until 2020 and increased substantially in 2020–2021. These estimates imply that among the largest US banks, the risk of capital shortfall from viral climate retweet events became prevalent only after 2020.

5.2.3 Marginal CRISK

By construction, CRISK is a function of climate betas as well as size and leverage. Thus, lower estimated values of CRISK may reflect firm under-capitalization unrelated to climate stress. To isolate baseline levels of systemic risk from climate stress, we compute marginal CRISK as the difference between stressed CRISK when $\theta = 50\%$ and un-stressed CRISK when $\theta = 0\%$:

$$mCRISK_{it} = (1 - k) \cdot W_{it} \cdot LRMES_{it}. \tag{17}$$

In words, the marginal CRISK of a financial institution $mCRISK_{it}$ is the difference between the institution's CRISK and its under-capitalization when there is no climate stress. We truncate $mCRISK_{it}$ at zero because an increase in climate risk is unlikely to lead to capital surplus during periods of distress.

Estimates of equation 17 indicate that among the top 10 US banks, marginal CRISK was minimal between 2018–2019 and re-surged in 2020 (Figure 9). Marginal CRISK peaked in 2020 despite rebounds in oil prices and temporarily flattened to zero in the last month of 2020, reflecting aggregate COVID shocks unrelated to climate risk. Marginal CRISK quickly rose once more in 2021, highlighting the need to manage systemic climate risk in the long run.

5.2.4 Reverse Stress Test

Using equation 14, we estimate the value of climate stress θ^*_{it} required for financial institutions to reach a stressed leverage of $\kappa^{target} = 0.04$ over a six-month period (Figure 10). To reach the stressed leverage, the bottom 1% of financial institutions require 3% decline in the climate risk factor over six-months *without any market stress*. Analogously, the bottom 5% require a 21% decline, the bottom 10% require a 34% decline, and the bottom 25% require a 56% decline in the climate risk factor over six months respectively.

Estimated values of $\theta_i^{climate*}$ imply that daily declines in the climate risk factor by 0.03%, 0.19%, 0.33%, and 0.65% for six months will pose a financial stability concern to the bottom 1%, 5%, 10% and 25% of financial institutions, respectively.

As an illustrative example, six-month returns on the climate risk factor following the US re-entry to the Paris Agreement imply a decline of about -0.31% per day. These estimates imply that a shock 10 times as big as the US re-entry to Paris Agreement will pose a financial stability concern to the bottom 1% of financial institutions. A shock 67 times as big will pose a financial stability concern to the bottom 5%. Table B7 reports the most vulnerable 1% of financial institutions to climate attention risk.

6 Robustness Tests

In main specifications, we estimate climate betas of financial institutions with the climate attention factor and a market factor. These results indicated significant increases in CRISK and marginal CRISK between 2020–2022, and one might be concerned about the potentially confounding effect of the COVID pandemic. To address this concern, we add additional factors related to COVID:

$$r_{it} = \beta_{it}^{climate} r_t^{climate} + \mathbf{X}_t' \beta_{it}^{\mathbf{X}} + \varepsilon_{it}, \tag{18}$$

where $r_t^{climate}$ is the return on the long-only brown hedge portfolio and $\mathbf{X}_t$ are controls for MKT and COVID exposure of brown industries between 2020–2022. These additional factors measure total employment and industry shares of workers in team-work intensive, customer-facing, and physically-proximate jobs (Fahlenbrach et al., 2021).

Controlling for COVID factors, increases in climate betas during 2020–2022 remain large and persistent for the top US banks (Figure A5) as well as the full distribution of financial institutions (Figure A6). These estimates imply similar calculations for CRISK and marginal CRISK (Figures A7 and A8 respectively). With COVID controls, estimated climate betas for the largest US banks are *even larger* during 2020–2021, suggesting that the COVID is unlikely the primary driver behind the substantial rise in climate beta.

7 Conclusion

This paper introduces a market-based approach to reverse stress testing financial institutions. Exploiting the increasingly relevant role of social media in shaping investor beliefs, we construct measures of social media virality using retweets of influential accounts. Focusing on climate stress testing as one important application, we construct a factor-mimicking portfolio using brown stocks to hedge against the risk of climate going viral. Using the hedge portfolio return as a risk factor, we estimate the expected capital shortfall (CRISK) of financial institutions conditional on climate going viral. We develop a reverse stress test by deriving the minimum level of climate stress necessary for financial institutions to reach a stressed level of leverage. Our estimates imply that a climate event with a 10 times stronger impact on climate belief than the US re-entry to Paris Agreement can push a small fraction (1%) of financial institutions having a leverage higher than a prudential level.

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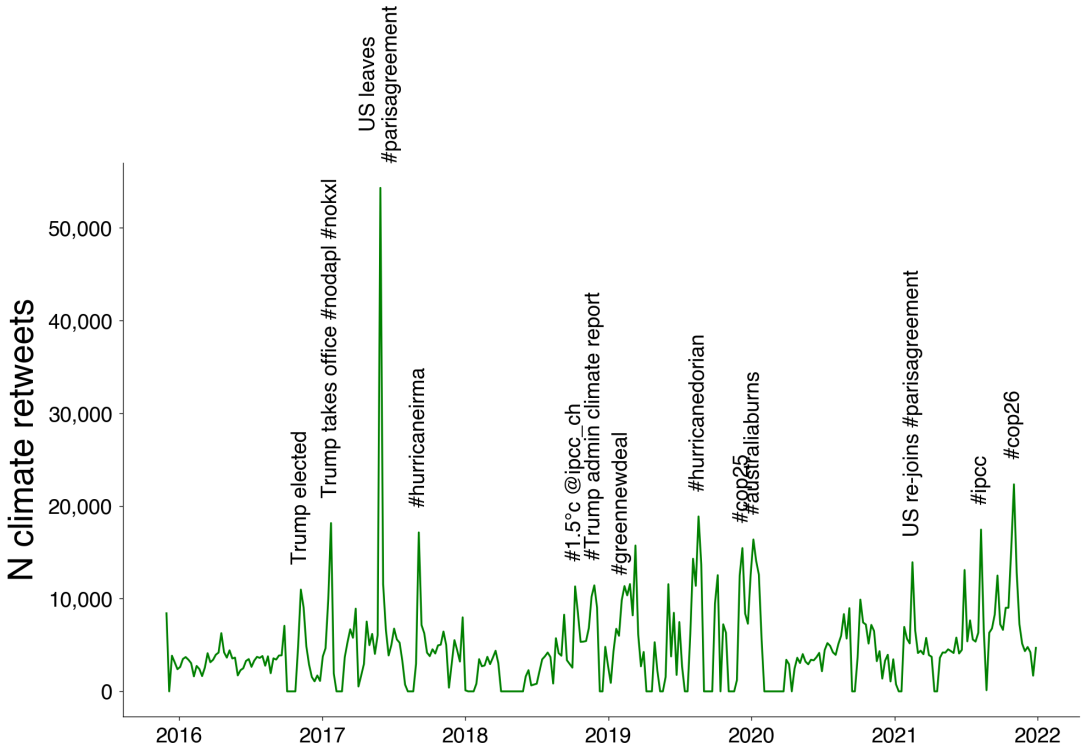
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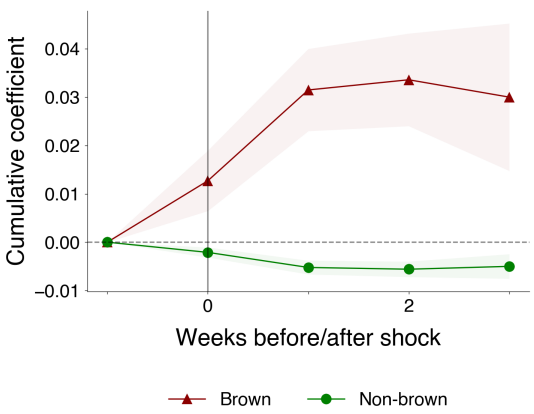
Figures

FIGURE 1: CLIMATE VIRALITY INDEX

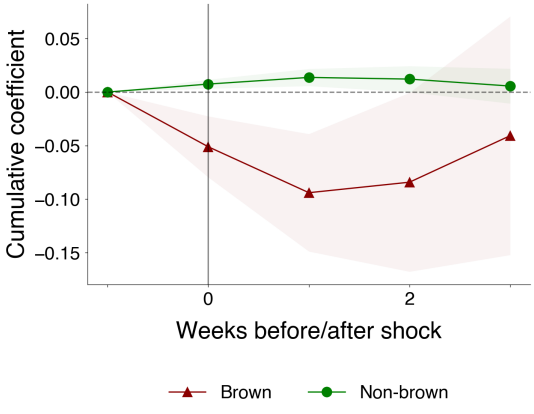


Note: Figure plots the weekly climate virality index. Index counts retweets of influential climate accounts, including 68 institutional profiles, viral accounts during COP21 and COP26, and US politicians who took office between 2017–2021. We filter retweets of viral COP and political accounts using climate hashtags from Falkenberg et al. 2022.

Figure 2: Stock Response Around Climate Retweet Events



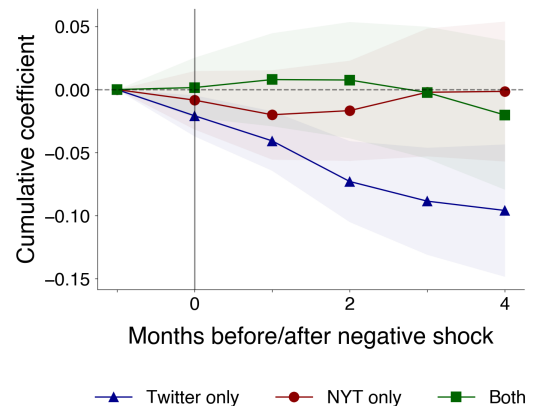
a) US leaves Paris Agreement



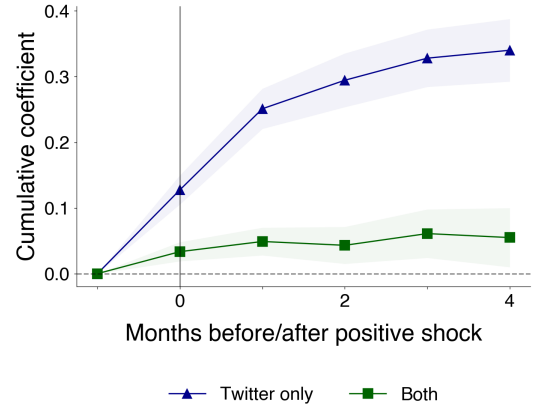
b) US rejoins Paris Agreement

Note: Figure plots cumulative $\hat{\gamma}$ and 95% CI from the OLS regression: $CAR_t = \alpha + \sum_{n=0}^{3} \gamma_n shock_{t-n} + \mathbf{X}_t'\delta + \varepsilon_t$. CAR_t is the six-month cumulative abnormal return in week t, $shock_t$ is a dummy equal to 1 if a retweet event occurred in week t, $\mathbf{X}_t$ are controls for MKT, HML, SMB. Standard errors are Newey-West. Estimates reported separately for the top 50 industries by scope 1&2 emissions ("brown") and others (Ilhan et al., 2023).

Figure 3: Brown Stock Response Around Retweet v News Events



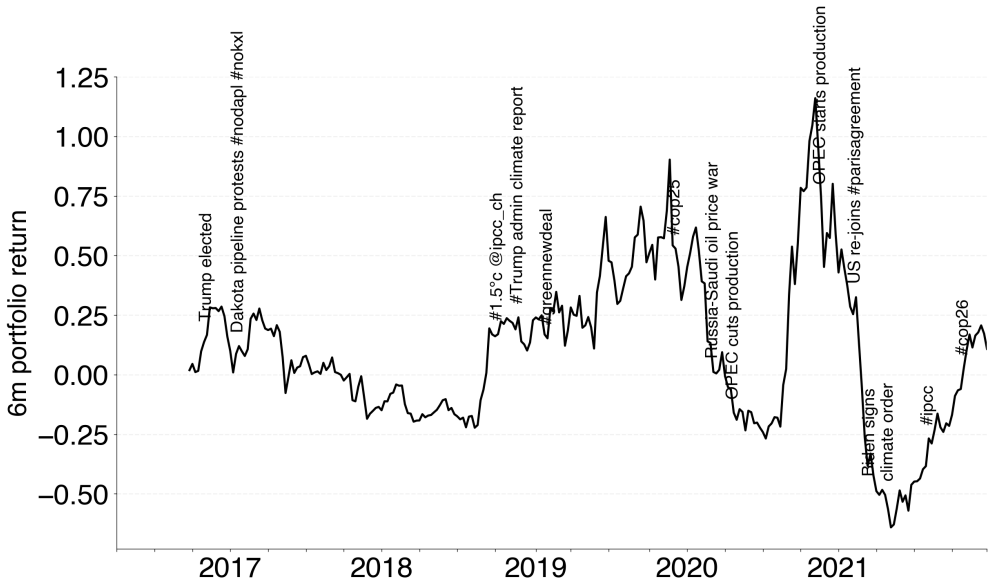
a) Negative Brown Events



b) Positive Brown Events

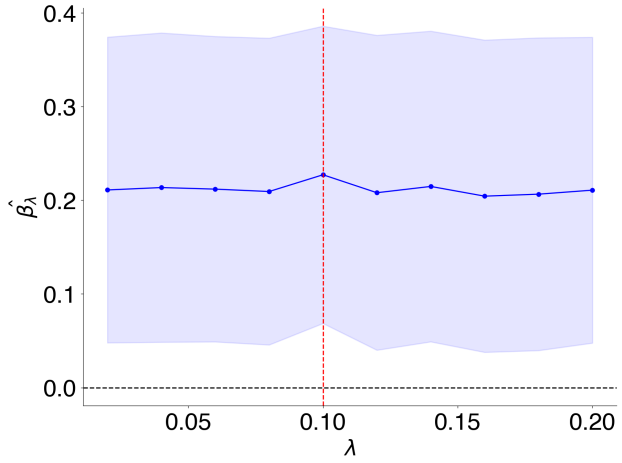
Note: Figure plots cumulative $\hat{\gamma}$ and 95% CI from the OLS regression: $CAR_t = \alpha + \sum_{n=0}^{4} \gamma_n shock_{t-n} + \mathbf{X}_t'\delta + \varepsilon_t$. CAR_t is the six-month cumulative abnormal return in month t for the top 50 industries by scope 1&2 emissions (Ilhan et al., 2023). Other variables are defined in Figure 2. Panel A plots stock response around negative brown shocks and Panel B plots stock response around positive brown shocks (Table 2).

FIGURE 4: HEDGE PORTFOLIO RETURN



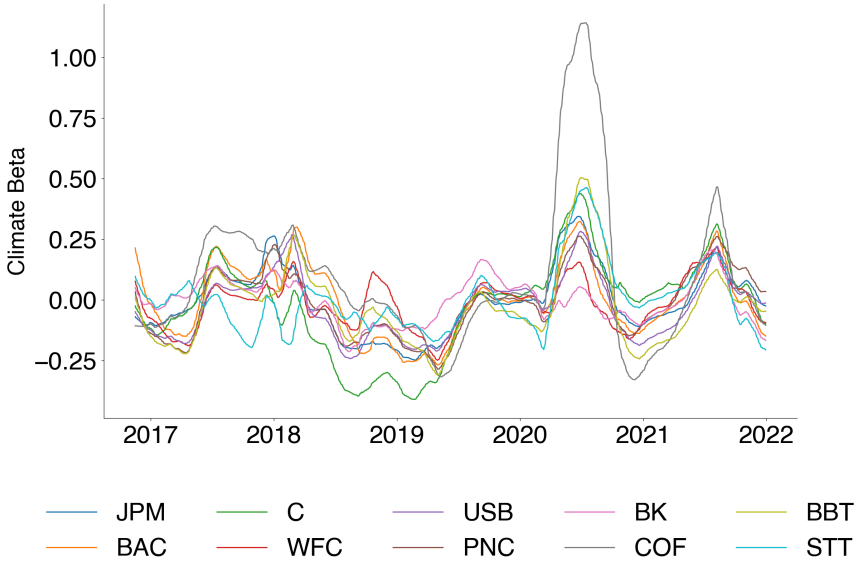
Note: Figure plots six-month simple return on the short-only brown portfolio. Increasing returns corresponds with higher attention risk from the climate virality index. Daily portfolio weights $\hat{w}_t$ over the top 50 brown industries solve the following optimization problem: $\min_{w_t \leq 0, \sum_i w_{it} = -1} \left\{ w_t' \hat{\Sigma} w_t - \lambda w_t' \tilde{b}_t \right\}$. $\hat{\Sigma}$ is the estimated variance-covariance matrix of brown industry returns R over the whole sample period 2016–2022, λ is a risk preference parameter, and $\tilde{b}_t$ is the hedge signal on day t. Daily portfolio return is $R_t^{FMP} = \hat{w}_t' R_t$.

FIGURE 5: HEDGE PORTFOLIO PERFORMANCE



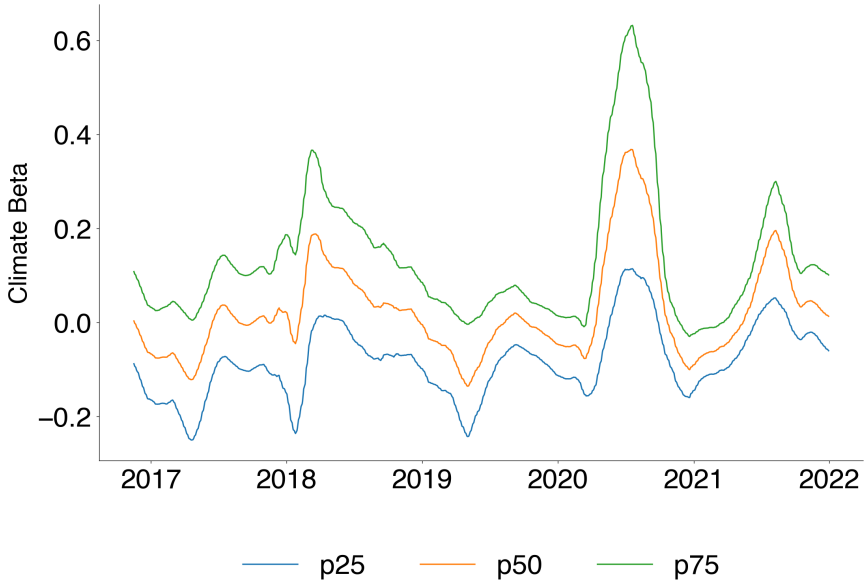
Note: Each point plots the annualized $\hat{\beta}_\lambda$ and 95% CI from a short-only portfolio with risk parameter λ, where $\hat{\beta}_\lambda$ are obtained from the OLS regression: $R_{t,\lambda}^{FMP} = \beta_\lambda CC_t + \mathbf{X}_t' \delta_\lambda + \varepsilon_{t,\lambda}$. $R_{t,\lambda}^{FMP}$ is the return on day t of a hedge portfolio constructed with risk-preference λ, CC_t is the weekly average of the standardized climate virality index on day t, $\mathbf{X}_t$ are controls for MKT, HML, SMB. Standard errors $\varepsilon_{t,\lambda}$ are Newey-West. $\hat{\beta}_\lambda^*$ is maximized at $\lambda^* = 0.1$.

FIGURE 6: CLIMATE BETAS FOR TOP 10 US BANKS



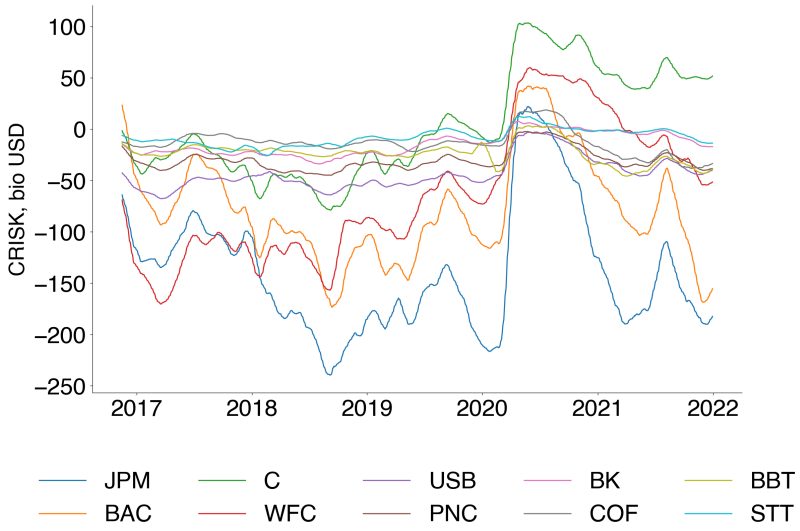
Note: Figure plots $\hat{\beta}_{it}^{climate}$ from 252-day rolling window OLS regressions for each bank: $r_{it} = \beta_{it}^{climate} r_t^{climate} + \beta_{it}^{MKT} MKT_t + \varepsilon_{it}$, where r_{it} is the stock return of bank i on day t and $r_t^{climate}$ is the climate risk factor, defined as the return of a long-position brown hedge portfolio on day t.

FIGURE 7: CLIMATE BETAS FOR ALL FINANCIAL INSTITUTIONS



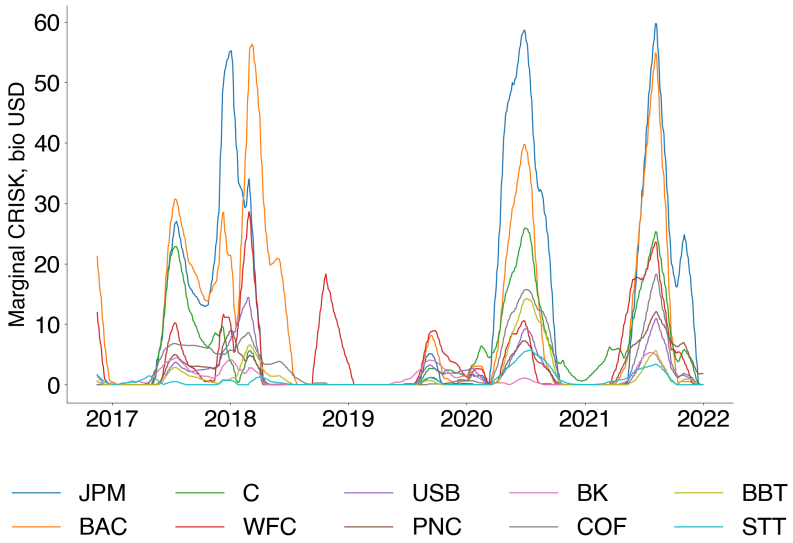
Note: Figure plots the pth percentile of climate betas $\hat{\beta}_{p,t}^{climate}$ on each day t across all financial institutions (SIC between 6000 and 6799).

Figure 8: CRISK for Top 10 US Banks



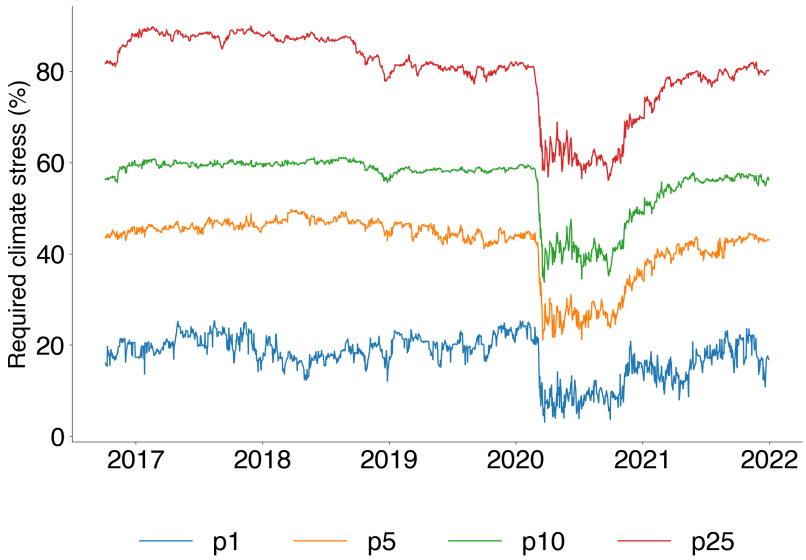
Note: Figure plots the expected capital shortfall (CRISK) of the top 10 banks in a climate stress scenario. CRISK of bank i on day t is defined by: $CRISK_{it} = kD_{it} - (1-k)W_{it}\exp(\hat{\beta}_{it}^{climate}\log(1-\theta))$, where $k = 0.08$ is the prudential ratio, D_{it} is debt, W_{it} is market equity, $\theta = 50\%$ is climate stress level, measured by the decrease in return on the climate risk factor.

Figure 9: Marginal CRISK for Top 10 US Banks



Note: Marginal CRISK is defined as the difference between stressed CRISK ($\theta = 50\%$) and un-stressed CRISK ($\theta = 0\%$). Other variables defined in Figure 8.

FIGURE 10: ESTIMATES OF REQUIRED CLIMATE STRESS



Note: Figure plots the required climate stress $\theta^{climate*}$ to make the pth percentile of financial institutions reach a stressed leverage of $\kappa^{target} = 0.04$. $\theta_{it}^{climate*}$ for each firm i on day t is computed from: $\theta_{it}^{climate*} \approx \frac{LRMES_{it}^{*}}{\tilde{\beta}_i^{climate}}$, where $LRMES_{it}^{*} = 1 - \kappa^{target}\frac{D_{it}}{W_{it}}$ is the maximum long-run marginal expected shortfall (LRMES) needed to make the institution reach the stressed leverage. $\tilde{\beta}_i^{climate}$ is the maximum recorded estimate of climate beta between 2016–2022.

Tables

Table 1: Climate Risk Retweet Events

Event	Date	Sample Tweet
Trump Election	11/08/16	From Sept, but relevant: Trump's pick to lead EPA transition team is Myron Ebell, a well-known climate skeptic.
Trump Takes Office; Dakota Access Pipeline	01/23/17	We will resist! We will fight these pipelines every step of the way, @realDonaldTrump! #NoDAPL #NoKXL
US Withdrawal from Paris Agreement	06/01/17	#EPA Head Continues to Defend #Trump's Historic Mistake #Paris-Agreement @SierraClub @bruneski @maryannehitt
Hurricane Irma	09/10/17	What else does nature have to do to wake us up to the horror of #climate breakdown? #Irma
Trump Admin Releases Climate Report	11/23/18	One encouraging sign in this latest climate report is that, compared to the 2014 version, there are many more examples of communities starting to think about and prepare for climate change. But the report also makes clear that we're not even close to what's needed.
Green New Deal	02/07/19	No, the #GreenNewDeal doesn't ban beef. And while cutting back on burgers can help your own health and the planet's, getting rid of cows entirely is another question.
Hurricane Dorian	08/24/19	Tropical Storm #Dorian Advisory 5A: Dorian Getting a Little Better Organized.
COP25	12/02/19	Y'all really got 8th graders out here fighting for #ClimateJustice & y'all won't give us a #GreenNewDeal nationally & y'all won't make #Chicago 100% renewable by 2025? Y'all really out here heartless af, no cap! #ClimateStrike
Australia Wildfires	01/06/20	In fire-ravaged Australia, climate denial goes up in smoke #ClimateEmergency #AustraliaBurns
US Rejoins Paris Agreement	02/19/21	US formally rejoins #ParisAgreement today - prompting further climate action in India and across the globe
IPCC Report	08/09/21	The IPCC report is out today. It's brutal. It reaffirms what we know so clearly already: the climate emergency is painfully real & indisputably caused by human activity. Many climatic changes are inevitable and 'irreversible', and many tipping points have been reached.
COP26	11/01/21	Is it possible the climate crusaders jetting into #COP26 truly don't understand the depths of their hypocrisy?

Table 2: Climate Retweet and News Events

Date	Event	Both	Twitter Only	NYT Only	Positive for Brown
2016-11	Trump Election		✓		✓
2017-01	Trump Takes Office; Dakota Access Pipeline Protests		✓		✓
2017-03	Trump Signs Rollback of Climate Rules	✓			✓
2017-06	US Withdrawal from Paris Agreement	✓			✓
2017-09	Hurricane Irma		✓		
2017-11	NCEI Climate Report	✓			
2018-01	Australia Reports Record Heat			✓	
2018-07	Europe Heat Waves		✓		
2018-10	1.5°C IPCC Report	✓			
2018-11	Trump Admin Releases Climate Report		✓		
2019-02	Green New Deal	✓			
2019-06	Trump Repeals Clean Power Plan + Heat Waves	✓			✓
2019-08	Hurricane Dorian		✓		
2019-12	COP25	✓			
2020-01	Australia Wildfires		✓		
2020-09	Trump Rolls Back Methane Rules	✓			✓
2020-12	UN Emission Gaps Report			✓	
2021-02	US Rejoins Paris Agreement	✓			
2021-04	NOAA Reports Record CO2 Levels			✓	
2021-08	IPCC Report	✓			
2021-11	COP26	✓			

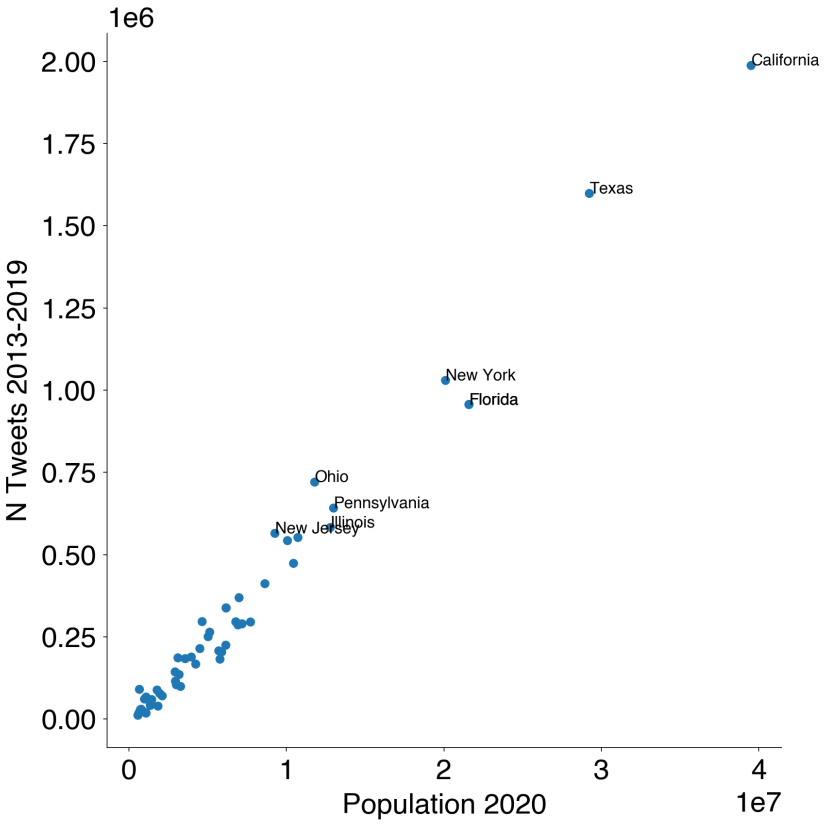
Table 3: Climate Betas of Financial Institutions

	$\hat{\beta}_{it}^{climate}$	$\hat{\beta}_{it}^{climate}$	$\hat{\beta}_{it}^{climate}$
Log Assets	-0.0236***	-0.0056	0.0022
	(0.0005)	(0.0174)	(0.0291)
Leverage	0.0003***	0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)
ROA	-0.6598***	-0.4383	-0.3799
	(0.0459)	(0.3289)	(0.3105)
Operating Profit/Book Equity	-0.0010***	-0.0000	-0.0006***
	(0.0000)	(0.0001)	(0.0001)
Firm FE		✓	✓
Time FE	✓		✓
N	898	898	898
T	1253	1253	1253

Note: Table reports estimated $\hat{\Gamma}$ from $\hat{\beta}_{it}^{climate} = \alpha_i + \mathbf{X}'_{it}\Gamma + \gamma_t + \varepsilon_{it}$, where $\hat{\beta}_{it}^{climate}$ is the estimated sensitivity of firm i on day t to the climate risk factor, $\mathbf{X}_{it}$ are firm characteristics including the log of total assets, leverage, return on assets, and the ratio of operating profits to book value of equity. α_i and γ_t are institution and day fixed effects respectively. Standard errors are clustered at the firm-level if firm fixed effects are included and at the day-level otherwise. Sample period consists of 2016–2022. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

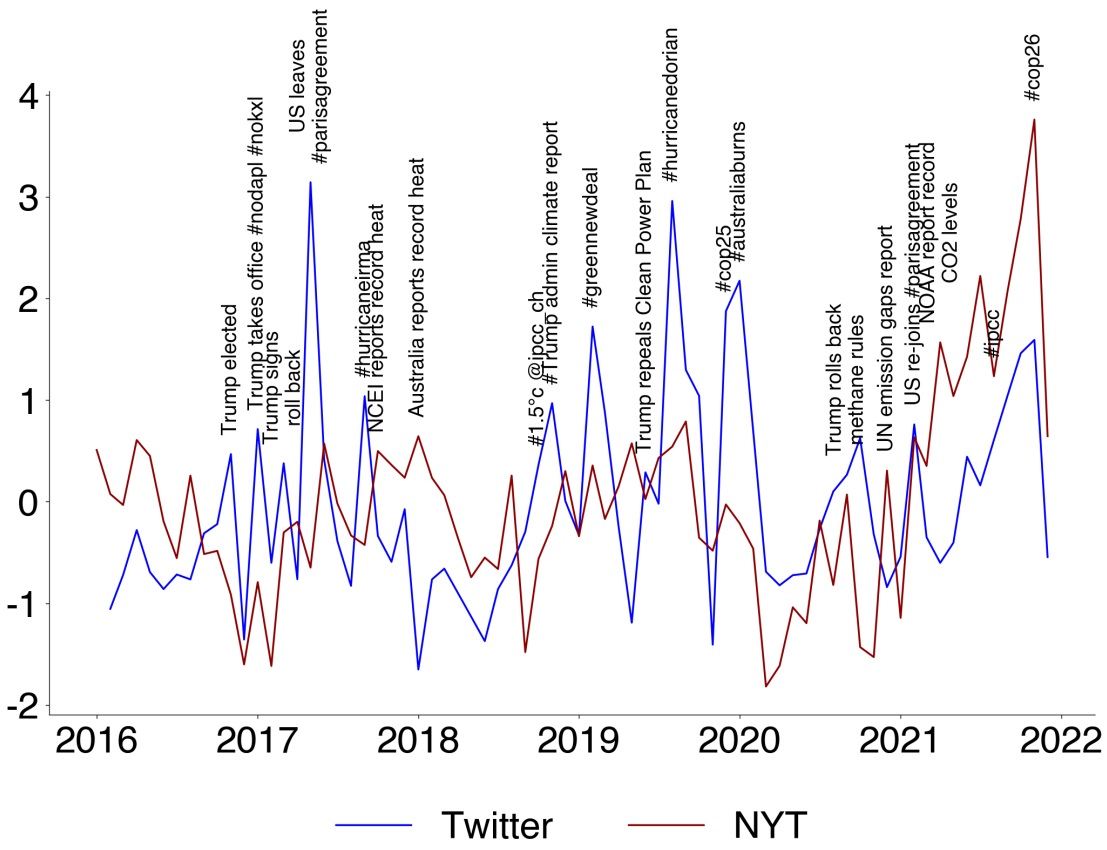
Appendix A. Supplementary Figures and Tables

Figure A1: Geographical Distribution of the Spritzler Sample



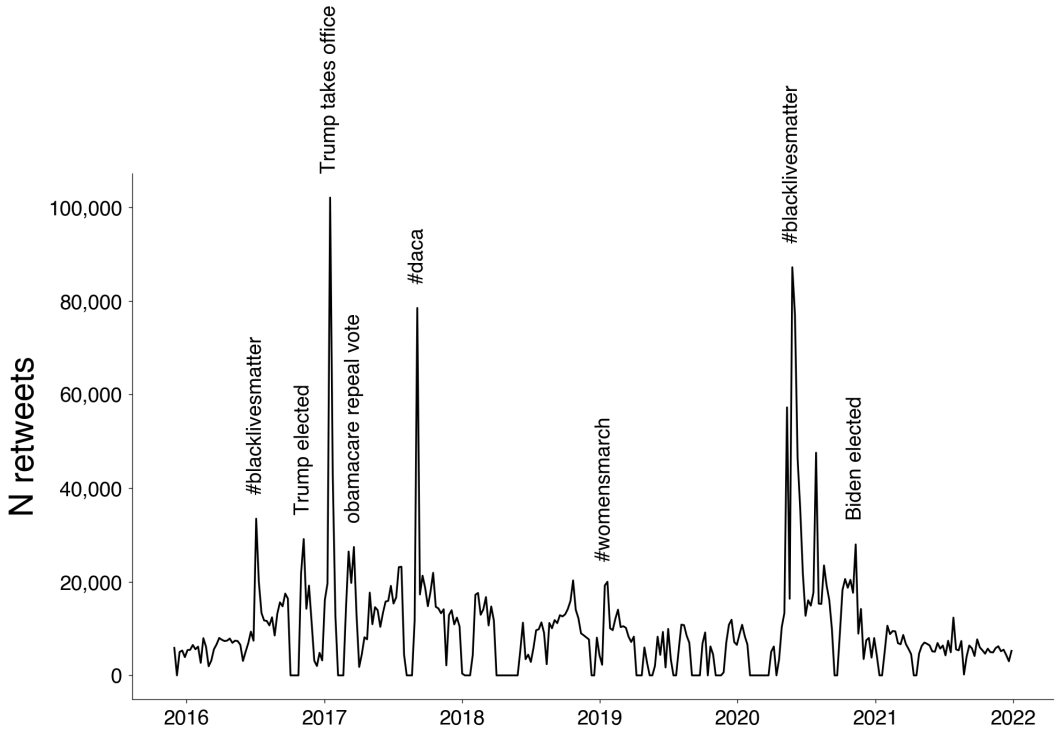
Note: Figure plots 15M geo-tagged tweets in the United States from the Spritzler stream against 2020 census population estimates. Twitter discontinued the collection of geo-tagged tweets in 2019.

FIGURE A2: RETWEET VS. NEWS INDICES



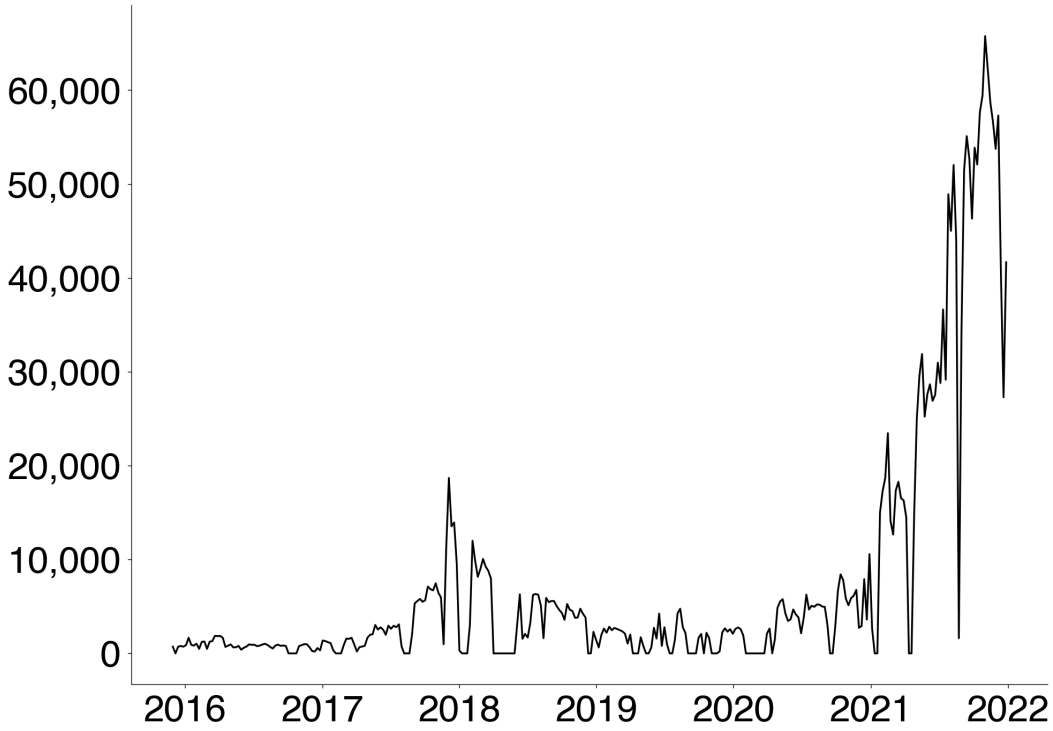
Note: Figure plots the monthly climate retweet and news indices. News index plots the monthly cosine similarity of NYT articles to climate topics (Engle et al., 2020).

Figure A3: Social Uncertainty Index



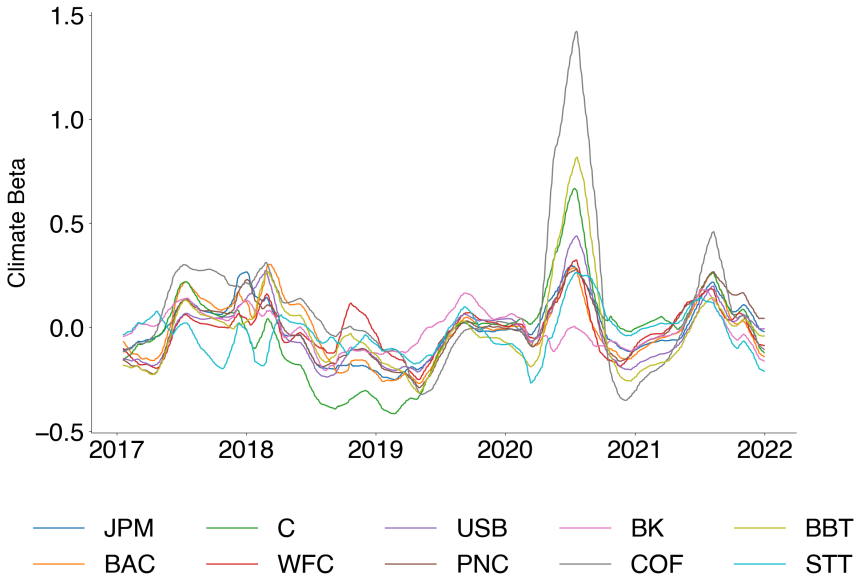
Note: Figure plots the social uncertainty index. Index counts retweets of US politicians containing keywords "protest", "demonstration", "boycott", "lobbying", "advocacy", "activism", "civil right", "human right", "social justice", "fightfor15", "generalstrike", "workersrights", "unionstrong", "womensmarch", "daywithoutimmigrants", "nodapl", "standwithstandingrock", "waterislife", "blacklivesmatter", "metoo", "timesup", "saytheirnames", "daca", "muslim ban", "maga", "title 42", "obamacare".

Figure A4: Meme Stock Attention Index



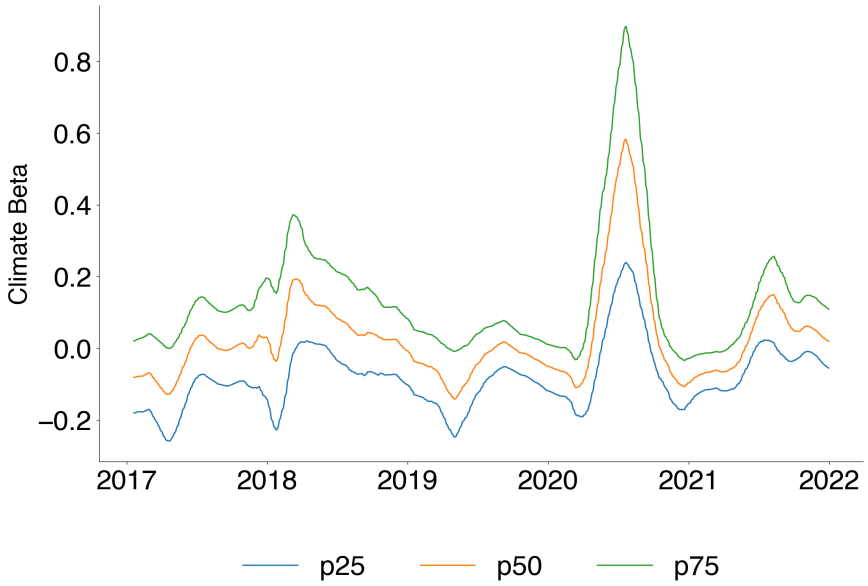
Note: Figure plots the meme stock attention index. Index counts retweets of influencer accounts containing keywords "$gme", "$amc", "$upst", "$bbby", "$bbig", "$bb", "$nok", "$sava", "$clov", "$pltr", "$spce", "$lcid", "crypto", "coinbase", "bitcoin", "meme stock", "memestock", "wallstreetbets" (Muller and Schwarz, 2023). Startup influencers are accounts with over 10,000 followers and whose profile descriptions contain "VC", "entrepreneur", "startup", "start up", "founder", "_venture", or "venture capital" (Cookson et al., 2023).

FIGURE A5: ROBUSTNESS OF CLIMATE BETAS, TOP 10 US BANKS



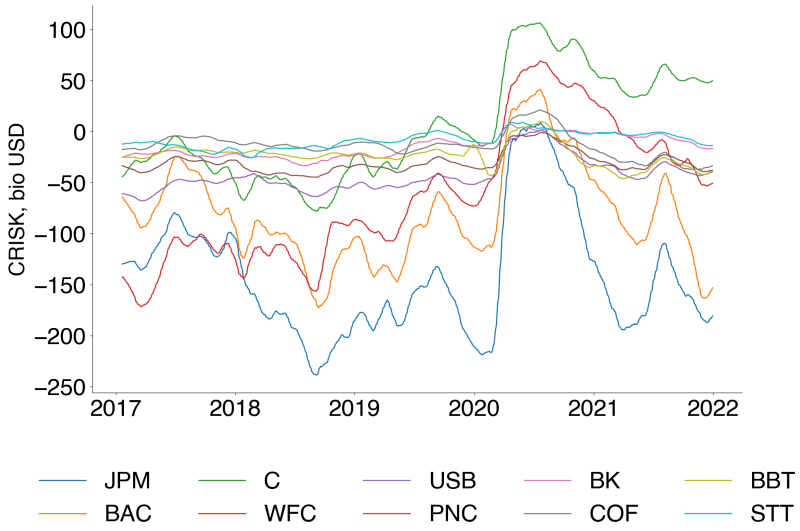
Note: Plot replicates $\hat{\beta}_{it}^{climate}$ from Figure 6 with the inclusion of COVID factors in the 252-day rolling-window OLS regression for each bank: $r_{it} = \beta_{it}^{climate} r_t^{climate} + \mathbf{X}_t' \beta_{it}^{\mathbf{X}} + \varepsilon_{it}$, where $\mathbf{X}_t$ are controls for MKT and other factors that measure COVID exposure in brown industries between 2020–2022. These factors measure total employment, industry shares of workers in team-work intensive, customer-facing, and physically-proximate jobs (Fahlenbrach et al., 2021). Other variables are defined in Figure 6.

FIGURE A6: ROBUSTNESS OF CLIMATE BETAS, ALL FINANCIAL INSTITUTIONS



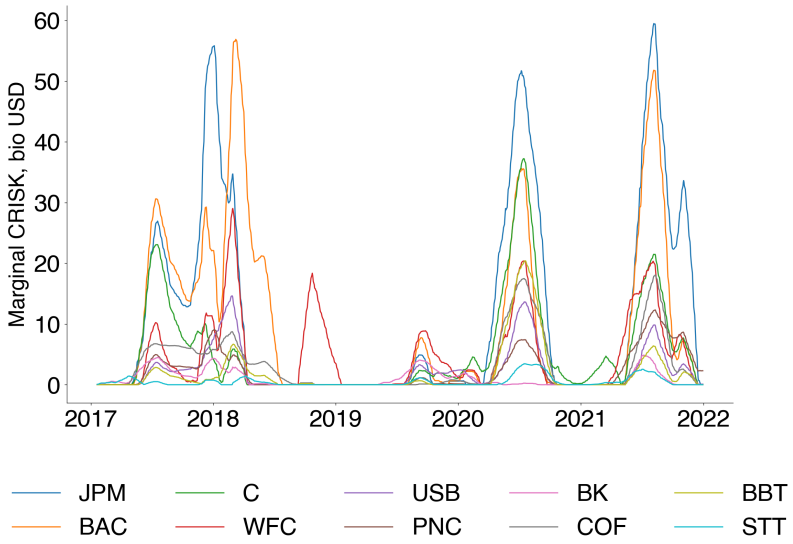
Note: Plot replicates Figure 7 with COVID controls in 2020–2021.

FIGURE A7: ROBUSTNESS OF CRISK FOR TOP 10 US BANKS



Note: Plot replicates Figure 8 with COVID controls.

FIGURE A8: ROBUSTNESS OF MARGINAL CRISK FOR TOP 10 US BANKS



Note: Plot replicates Figure 9 with COVID controls.

Table A1: Viral Hashtags During COP21 and COP26

climate, global warming, climateaction, climatechange, climatecrisis, climateemergency, togetherforourplanet, climatejustice, netzero, climateactioninyourarea, fridaysforfuture, parisagreement, lossanddamage, climatefinance, blackpinkclimateadvocates, racetozero, agw fraud, climate lies, agw hoax, climatefraud, fakeweather, greathunbergexposed, noclimateemergency, climatescam, globalwarmingfraud, climateconspiracy, forcedclimatechange, climatecult, carbonkeptomania, forced electrification, blame climate change, climate hoax, climate panic, climate fearmongering, climate deception

Note: Table reports viral hashtags related to climate during COP21 and COP26 from Falkenberg et al. (2022). Hashtags that are neutral or express climate belief in bold.

Table A2: Snowball-Sampled Climate Accounts

EPA, US Climate Alliance, IPCC, UN Climate Change, Inside Climate News, Grist, Carbon Brief, Climate Desk, NOAA Climate, Readygov, FEMA, Climate Central, ClimateCoLab, Earth Institute, Union of Concerned Scientists, UN Environment Programme, Yale Program on Climate Change Communication, UNDP Climate, UN Biodiversity, FAO Climate Change & Biodiversity, NYT Climate, Climate Connections, EcoWatch, World Resources Institute, Climate Group, The Nature Conservancy, Sierra Club, Yale Environment 360, 350 dot org, NWS Climate Prediction Center, NOAA Communications, NOAA Research, NASA Climate, NOAA National Severe Storms Laboratory, National Hurricane Center, National Weather Service, Climate Connections, RMI, Bloomberg Green, Climate Reality, Partnership for Policy Integrity, WRI Climate, Green Climate Fund, Climate Investment Funds, Adaptation Fund, Global Center on Adaptation, E&E News, Daily Climate, Columbia Climate School, Earthjustice, National Wildlife Federation, Greenpeace USA, NRDC, EDF, World Bank Climate, NWS Storm Prediction Center, NWS Central Region, NWS LMRFC, NWS Southern Region, NWS OHRFC, NWSFlashFlood, BloombergNEF, Climate Home News, Global Environment Facility (GEF), Cipher News, Energy Impact Partners, On Capitol Hill, Save The Arctic

Note: 68 influential institutional Twitter accounts and regional affiliates. Snowball samples collected through top 5 recommended Twitter profiles per account page. Sampling repeated after each augmentation up to five times. Seed accounts in bold.

Table A3: Brown Industries

SIC	Industry
2911	Petroleum Refining
4991	Cogeneration Utilities
4911	Electric Services
3312	Steel Works
4512	Air Courier Services
4931	Electric and Other Services Combined
2810	Industrial Chemicals
4953	Refuse Systems
2070	Fats and Oils
4932	Gas and Other Services Combined
2820	Plastics Materials
4513	Airline Operations
2631	Paperboard Mills
1311	Crude Petroleum and Natural Gas
5331	Variety Stores
4210	Trucking and Courier Services
4812	Telephone Communications
4400	Water Transportation
1000	Metal Mining
4923	Gas Transmission and Distribution
2650	Paperboard Containers
4011	Railroads
2821	Plastic Resins
3221	Glass Containers
3711	Motor Vehicles
9997	Nonclassifiable Establishments
2080	Beverages
2621	Paper Mills
1040	Gold Ores
2840	Soap and Other Detergents
1389	Oil and Gas Field Services
5411	Grocery Stores
7011	Hotels and Motels
3011	Tires and Inner Tubes
2670	Converted Paper Products
2273	Carpets and Rugs
5211	Lumber and Building Materials
2870	Agricultural Chemicals
100	Agricultural Production
2851	Paints and Coatings
2011	Meat Packing
3724	Aircraft Engines
5399	Miscellaneous General Merchandise
2000	Food Products
5812	Eating Places
4213	Trucking
3679	Electronic Components
2400	Logging
4813	Telecommunications
2086	Soft Drinks

Note: Table reports the top 50 industries by scope 1 and 2 emissions (Ilhan et al., 2023).

Table A4: Institutions Most Vulnerable to Climate Stress

Ticker	HCOMNAM	Type
OPHC	Optimumbank Holdings Inc	Bank
CARV	Carver Bancorp Inc	Bank
BKU	Bankunited Inc	Bank
PNBK	Patriot National Bancorp Inc	Bank
FRBK	Republic First Bancorp Inc	Bank
RDIB	Reading International Inc	Bank
FBC	Flagstar Bancorp Inc	Bank
CUBI	Customers Bancorp Inc	Bank
INBK	First Internet Bancorp	Bank
ALLY	Ally Financial Inc	Bank
BHLB	Berkshire Hills Bancorp Inc	Bank
COOP	Mr Cooper Group Inc	Bank
CADE	Cadence Bancorp	Bank
TCBI	Texas Capital Bancshares Inc	Bank
C	Citigroup Inc	Bank
CIT	C I T Group Inc New	Bank
AMTB	Amerant Bancorp Inc	Bank
ASRV	Ameriserv Financial Inc	Bank
CNBKA	Century Bancorp Inc	Bank
PBHC	Pathfinder Bancorp Inc Md	Bank
FFIC	Flushing Financial Corp	Bank
HAFC	Hanmi Financial Corp	Bank
PTVCA	Protective Insurance Corp	Insurers
DGICB	Donegal Group Inc	Insurers
AEL	American Equity Invt Life Hldg C	Insurers
LNC	Lincoln National Corp	Insurers
EQH	Equitable Holdings Inc	Insurers
VOYA	Voya Financial Inc	Insurers
HALL	Hallmark Financial Services Inc	Insurers
PFG	Principal Financial Group Inc	Insurers
FNHC	Fednat Holding Co	Insurers
PRU	Prudential Financial Inc	Insurers
UNM	Unum Group	Insurers
AIG	American International Group Inc	Insurers
RIVE	Riverview Financial Corp	Other
GWGH	G W G Holdings Inc	Other
FTFT	Future Fintech Group Inc	Other
AGM	Federal Agricultural Mort Corp	Other
SBT	Sterling Bancorp Inc	Other
IMH	Impac Mortgage Holdings Inc	Other
CPSS	Consumer Portfolio Svcs Inc	Other
MFIN	Medallion Financial Corp	Other
FXCM	Global Brokerage Inc	Other
OCN	Ocwen Financial Corp	Other
MGI	Moneygram International Inc	Other
SQBG	Sequential Brands Group Inc New	Other
APEX	Apex Global Brands Inc	Other
ZAIS	Zais Group Holdings Inc	Other
AMBC	Ambac Financial Group Inc	Other
ICON	Iconix Brand Group Inc	Other
NAVI	Navient Corp	Other
AINC	Ashford Inc	Other
VEL	Velocity Financial Inc	Other
UIHC	American Coastal Insurance Corp	Other
HGSH	Green Giant Inc	Other
HVBC	H V Bancorp Inc	Other
TSC	Tristate Capital Holdings Inc	Other
IBKR	Interactive Brokers Group Inc	Other
RLGY	Anywhere Real Estate Inc	Other

Note: This table reports the bottom 1% of financial institutions by climate stress required to reach a stressed leverage of 0.04 over six months.

Table A5: Correlations of risk betas and thetas (firm × day)

Panel A: Value-based correlations

	β^v	β^c	θ^v_{max}	θ^v_{ave}	θ^c_{max}	θ^c_{ave}
β^v	—	0.144				
β^c	0.144	—				
θ^v_{max}			—			
θ^v_{ave}			-0.315	—		
θ^c_{max}			0.848	-0.180	—	
θ^c_{ave}			-0.119	-0.251	-0.390	—

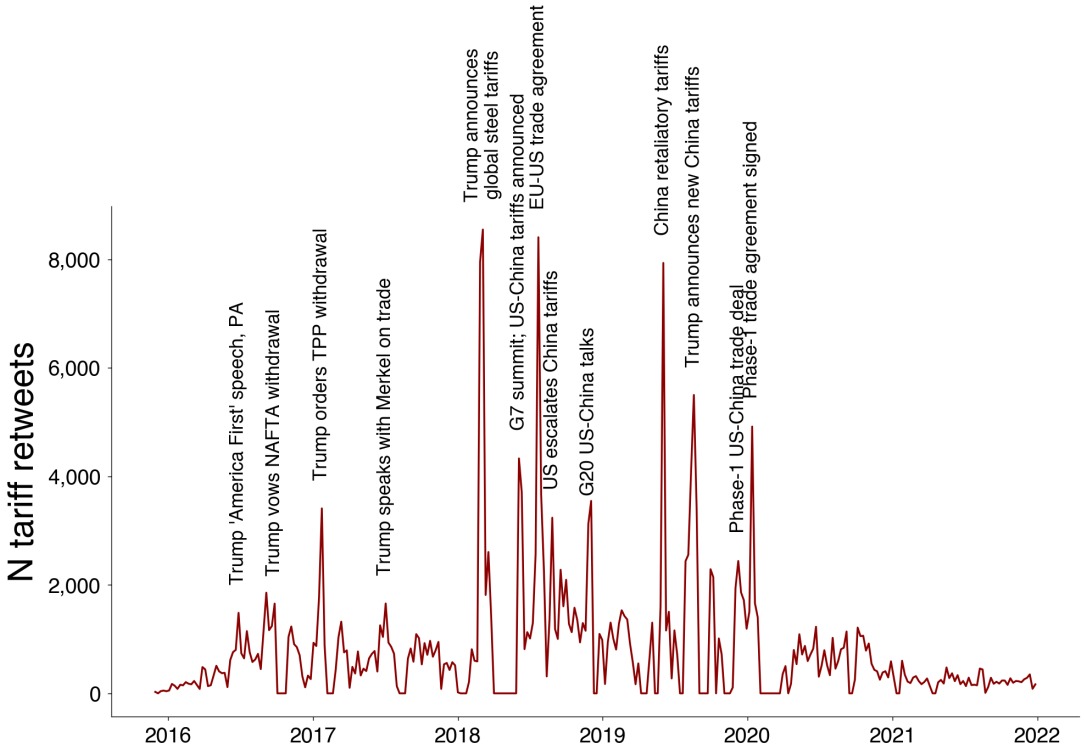
Panel B: Rank-based correlations

	β^v_{rank}	β^c_{rank}	$\theta^v_{\text{max,rank}}$	$\theta^v_{\text{ave,rank}}$	$\theta^c_{\text{max,rank}}$	$\theta^c_{\text{ave,rank}}$
β^v_{rank}	—	0.767				
β^c_{rank}	0.767	—				
$\theta^v_{\text{max,rank}}$			—			
$\theta^v_{\text{ave,rank}}$			0.865	—		
$\theta^c_{\text{max,rank}}$			0.915	0.640	—	
$\theta^c_{\text{ave,rank}}$			0.946	0.602	0.535	—

Note: Cross-sectional correlations of firm-day risk exposure measures under stressed conditions. Panel A displays value-based correlations across betas (β) and thetas (θ), with beta–theta blocks omitted. Panel B displays correlations based on within-day ranks.

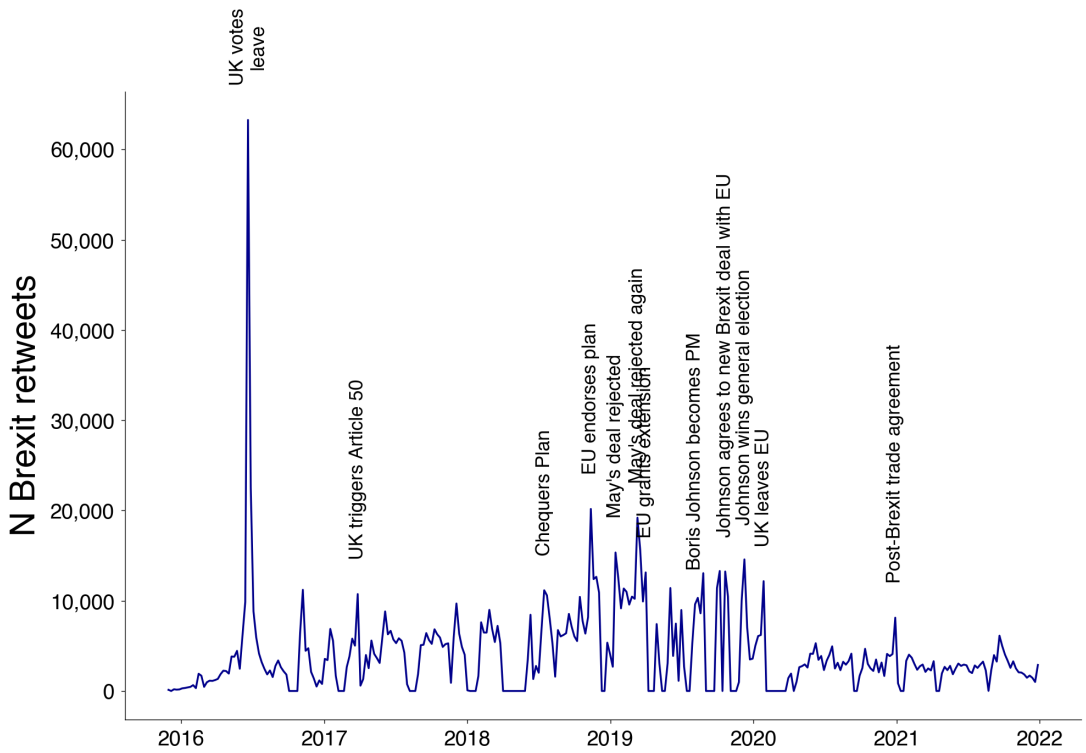
Appendix B. Geopolitical Risk Indices

FIGURE B1: TRADE UNCERTAINTY INDEX



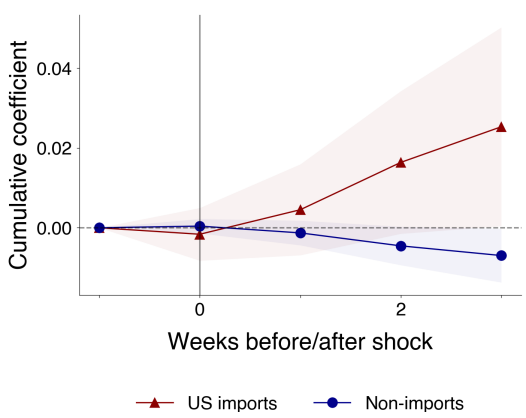
Note: Figure plots the weekly tariff virality index. Index counts retweets of influential geopolitical accounts, including 243 institutional profiles, trade experts and economist accounts, and US politicians who took office between 2017–2021. We filter retweets using the keywords: tariff, trade, #americafirst, tradewar, #tariffpain, #trumptariffsfail.

FIGURE B2: BREXIT VIRALITY INDEX

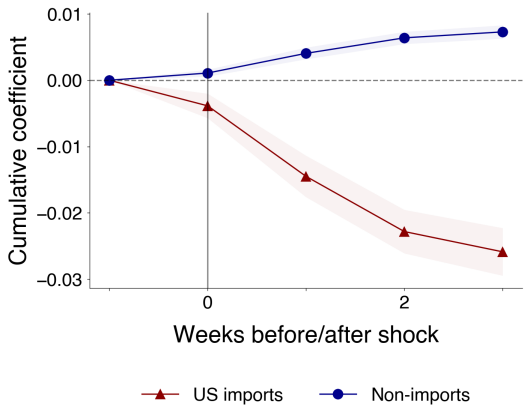


Note: Figure plots the weekly Brexit virality index. Index counts retweets of influential Brexit accounts, including 572 institutional profiles, influencer accounts, and UK politicians who took office between 2017–2021. We filter retweets using the hashtags: #brexit, #leaveeu, #voteleave, #takebackcontrol, #strongerin, #remain, #stopbrexit, and #fbpe.

FIGURE B3: STOCK RESPONSE AROUND GEOPOLITICAL TWEET EVENTS



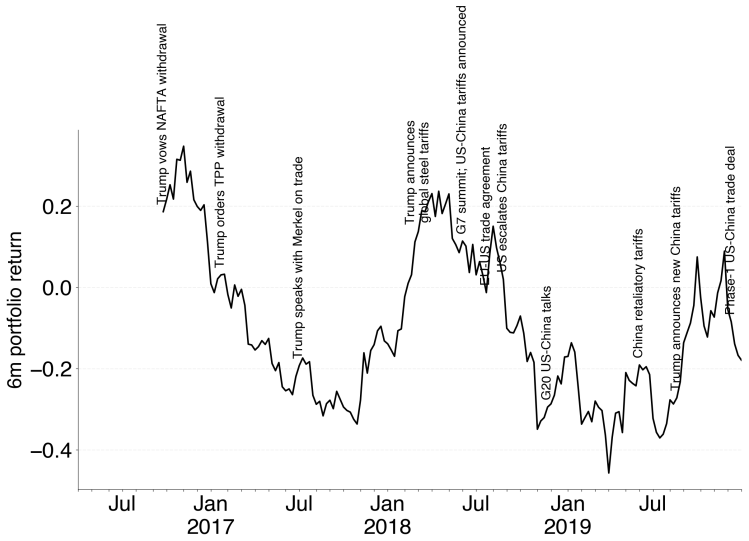
a) Trump speaks with Merkel on trade



b) Trump announces global steel tariffs

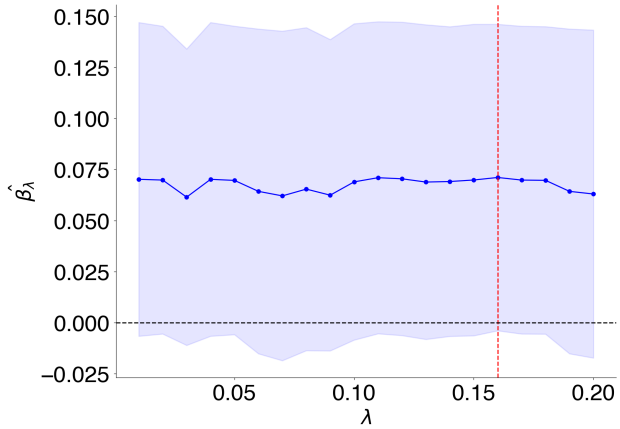
Note: Figure plots cumulative $\hat{\gamma}$ and 95% CI from the OLS regression: $CAR_t = \alpha + \sum_{n=0}^{3} \gamma_n shock_{t-n} + \mathbf{X}_t'\delta + \varepsilon_t$. CAR_t is the six-month cumulative abnormal return in week t, $shock_t$ is a dummy equal to 1 if a retweet event occurred in week t, $\mathbf{X}_t$ are controls for MKT, HML, SMB. Standard errors are Newey-West. Estimates reported separately for the top 50 US industries by import-value 2016–2021 (4-digit SIC code) and other non-import industries.

FIGURE B4: GEOPOLITICAL RISK HEDGE PORTFOLIO RETURN



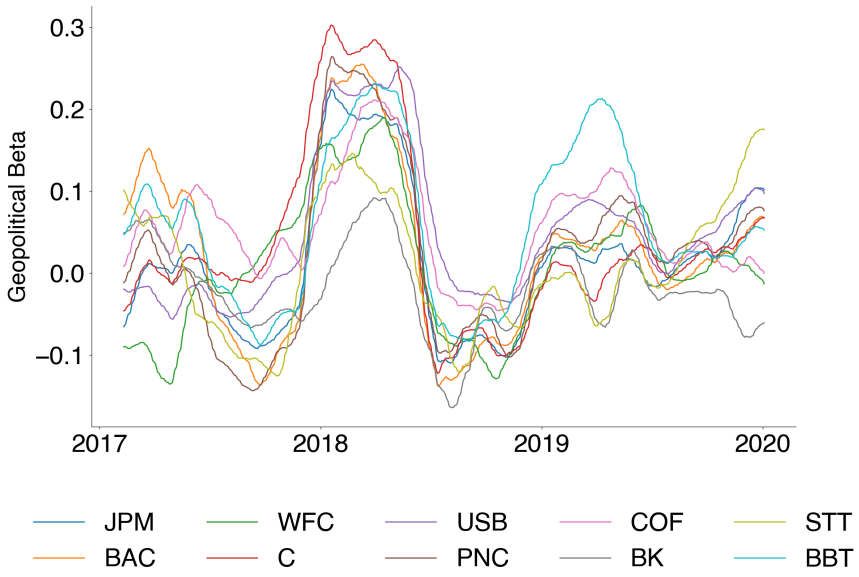
Note: Figure plots six-month simple return on the short-only geopolitical risk portfolio. Increasing returns corresponds with higher attention risk from the geopolitical risk index. Daily portfolio weights $\hat{w}_t$ over the top 50 importing industries solve the following optimization problem: $\min_{w_t \leq 0, \sum_i w_{it} = -1} \left\{ w_t' \hat{\Sigma} w_t - \lambda w_t' \tilde{b}_t \right\}$. $\hat{\Sigma}$ is the estimated variance-covariance matrix of import industry returns R over the whole sample period 2016–2022, λ is a risk preference parameter, and $\tilde{b}_t$ is the hedge signal on day t. Daily return is $R_t^{FMP} = \hat{w}_t' R_t$.

FIGURE B5: GEOPOLITICAL RISK HEDGE PORTFOLIO PERFORMANCE



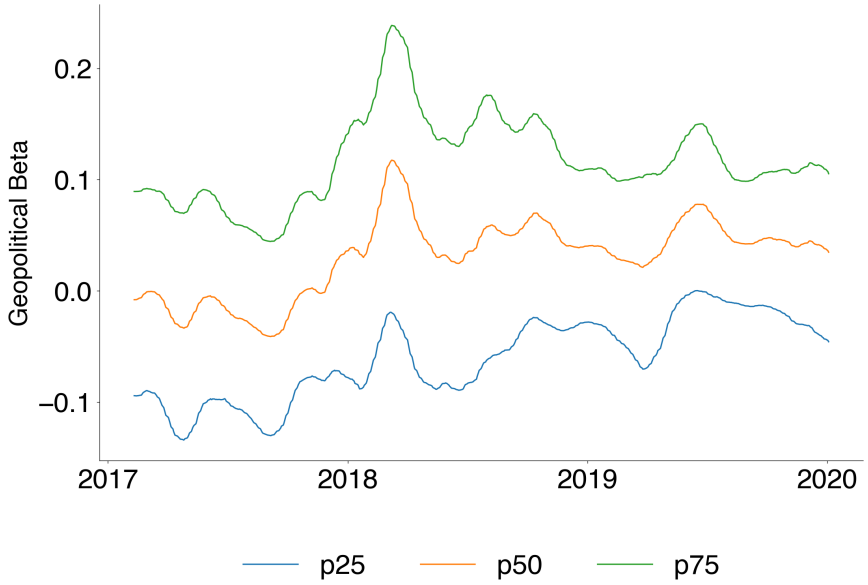
Note: Each point plots the annualized $\hat{\beta}_\lambda$ and 95% CI from a short-only portfolio with risk parameter λ, where $\hat{\beta}_\lambda$ are obtained from the OLS regression: $R_{t,\lambda}^{FMP} = \beta_\lambda Index_t + \mathbf{X}_t' \delta_\lambda + \varepsilon_{t,\lambda}$. $R_{t,\lambda}^{FMP}$ is the return on day t of a hedge portfolio constructed with risk-preference λ, $Index_t$ is the weekly average of the standardized geopolitical risk index on day t, $\mathbf{X}_t$ are controls for MKT, HML, SMB. Standard errors $\varepsilon_{t,\lambda}$ are Newey-West. $\hat{\beta}_\lambda^*$ is maximized at $\lambda^* = 0.1$.

FIGURE B6: GEOPOLITICAL BETAS FOR TOP 10 US BANKS



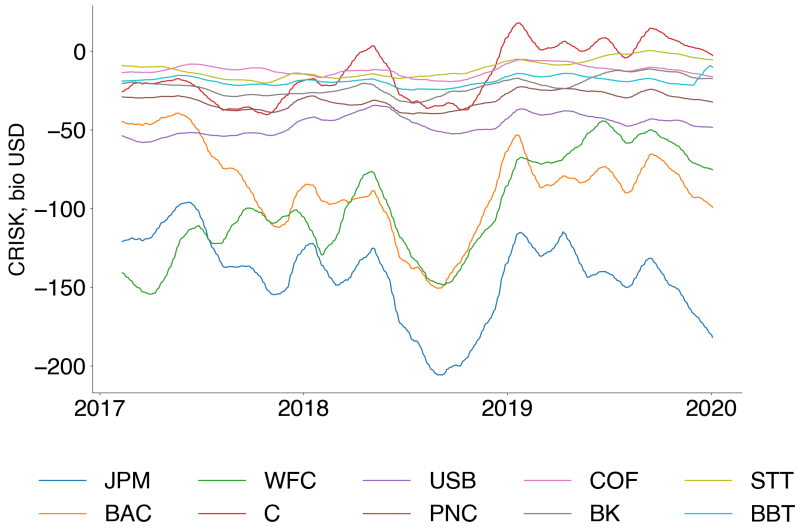
Note: Figure plots $\hat{\beta}_{it}^{geo}$ from 252-day rolling window OLS regressions for each bank: $r_{it} = \beta_{it}^{geo} r_t^{geo} + \beta_{it}^{MKT} MKT_t + \varepsilon_{it}$, where r_{it} is the stock return of bank i on day t and r_t^{geo} is the geopolitical risk factor, defined as the return of a long-position geopolitical risk hedge portfolio on day t.

FIGURE B7: GEOPOLITICAL BETAS FOR ALL FINANCIAL INSTITUTIONS



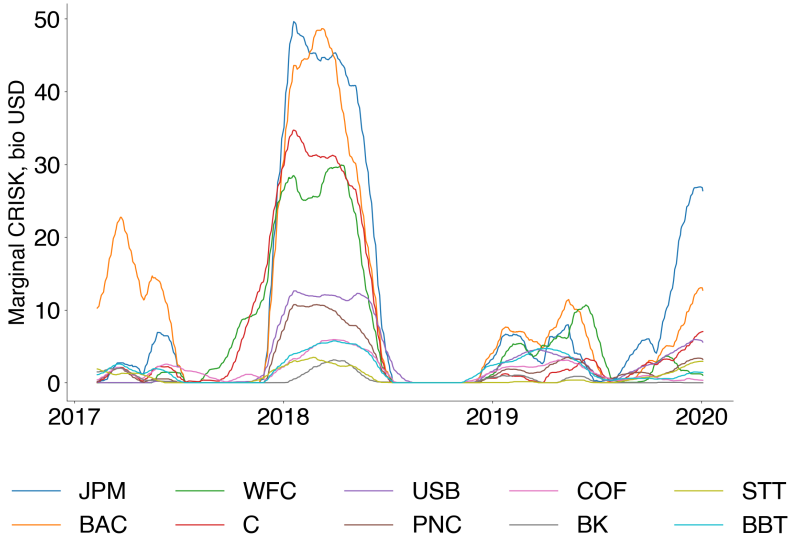
Note: Figure plots the pth percentile of geopolitical betas $\hat{\beta}_{p,t}^{geo}$ on each day t across all financial institutions (SIC between 6000 and 6799).

Figure B8: Geopolitical RISK for Top 10 US Banks



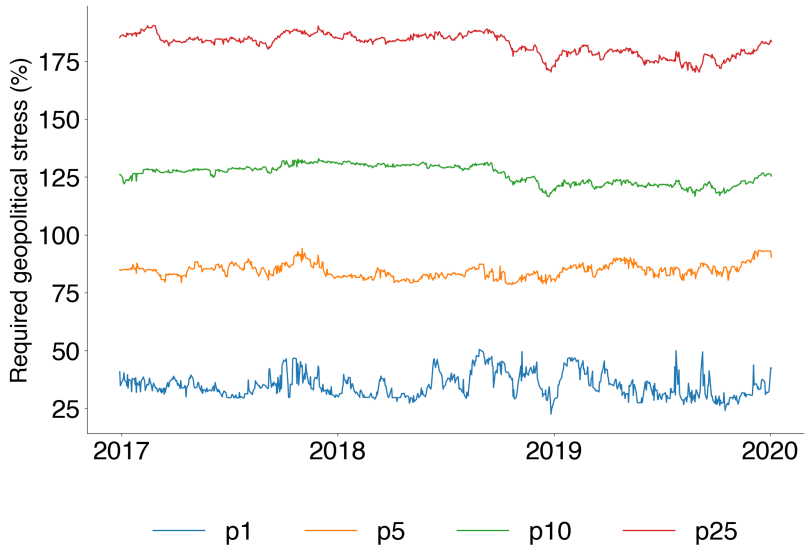
Note: Figure plots the expected capital shortfall (Geopolitical RISK) of the top 10 banks in a geopolitical stress scenario. Geopolitical RISK of bank i on day t is defined by: $RISK_{it} = kD_{it} - (1-k)W_{it}\exp(\hat{\beta}_{it}^{geo}\log(1-\theta))$, where $k = 0.08$ is the prudential ratio, D_{it} is debt, W_{it} is market equity, $\theta = 50\%$ is geopolitical stress level, measured by the decrease in return on the geopolitical risk factor.

Figure B9: Marginal Geopolitical RISK for Top 10 US Banks



Note: Marginal Geopolitical RISK is defined as the difference between stressed Geopolitical RISK ($\theta = 50\%$) and un-stressed RISK ($\theta = 0\%$). Other variables defined in Figure B8.

FIGURE B10: ESTIMATES OF REQUIRED GEOPOLITICAL STRESS



Note: Figure plots the required geopolitical stress $\theta^{climate*}$ to make the pth percentile of financial institutions reach a stressed leverage of $\kappa^{target} = 0.04$. θ_{it}^{geo*} for each firm i on day t is computed from: $\theta_{it}^{geo*} \approx \frac{LRMES_{it}^{*}}{\tilde{\beta}_i^{geo}}$, where $LRMES_{it}^{*} = 1 - \kappa^{target}\frac{D_{it}}{W_{it}}$ is the maximum long-run marginal expected shortfall (LRMES) needed to make the institution reach the stressed leverage. $\tilde{\beta}_i^{geo}$ is the maximum recorded estimate of climate beta between 2016–2022.

Table B1: Tariff Risk Retweet Events

Event	Date	Sample Tweet
Trump "America First" speech, PA	06/27/16	Trump: If China doesn't stop illegal activities, including theft of US trade secrets, I will use presidential power to remedy trade disputes
Trump vows NAFTA withdrawal	09/26/16	#DonaldTrump makes no sense right now companies are leaving because taxes are too high but yet you claimed tariffs and tax increase keeps jobs
Trump orders TPP withdrawal	01/23/17	So not only is trump threatening a trade war with our neighbors, he's now "taking names" of any country who doesn't bow to him
Trump speaks with Merkel on trade	07/03/17	Merkel says finding a G-20 agreement on trade is proving difficult
Trump announces global steel tariffs	03/08/18	GOP know that #Trump's tariff plan is terrible, but they are refusing to stand up to him because they are scared
G7 Summit	06/08/18	Trump's surprise G-7 pitch: 'We should at least consider no tariffs'
EU-US trade agreement	07/25/18	Trump tweet as Juncker arrives in DC: "I have an idea ... Both US and EU. Drop all Tariffs, Barriers and Subsidies! ... Hope they do it, we are ready — but they won't!" Truth is, neither Trump nor Juncker could deliver this.
US-China escalate tariffs	08/23/18	Ford Just Canceled Production Of New Car, Cites Trump's Tariffs As The Reason: "Our viewpoint on Focus Active was that, given the tariffs, obviously our costs would be substantially higher"
G20 US-China trade talks	12/01/18	Prime Minister Justin Trudeau Confronts President Donald Trump On Tariffs At the G20 Summit
China retaliatory tariffs	06/01/19	The trade war comes to Louisville—and Jack Daniel's takes a tariff hit.
Trump announces new China tariffs	08/01/19	Some context on the possible impact of the new China oil tariff from @catkngai and @alexlongley1
Phase-1 US-China trade deal	12/13/19	Another sign of America's leverage over #China - and another reason for #Trump to keep the #tariffs pressure on rather than accept any rollbacks w/o adequate (meaning unilateral) verification of a #tradedeal's terms
Phase-1 trade deal signed	01/15/20	Landmark US, China deal signing will give Trump a trade war victory

Table B2: Geopolitical Betas of Financial Institutions

	$\hat{\beta}_{it}^{geo}$	$\hat{\beta}_{it}^{geo}$	$\hat{\beta}_{it}^{geo}$
Log Assets	-0.0175***	-0.0987***	-0.0858***
	(0.0002)	(0.0274)	(0.0295)
Leverage	0.0003***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)
ROA	-0.8466***	-0.9074***	-0.8823***
	(0.0405)	(0.3058)	(0.2999)
Operating Profit/Book Equity	-0.0076*	0.0444	0.0403
		(0.0302)	(0.0298)
Firm FE		✓	✓
Time FE	✓		✓
N	898	898	898
T	1253	1253	1253

Note: Table reports estimated $\hat{\Gamma}$ from $\hat{\beta}_{it}^{geo} = \alpha_i + \mathbf{X}'_{it}\Gamma + \gamma_t + \varepsilon_{it}$, where $\hat{\beta}_{it}^{geo}$ is the estimated sensitivity of firm i on day t to the geopolitical risk factor, $\mathbf{X}_{it}$ are firm characteristics including the log of total assets, leverage, return on assets, and the ratio of operating profits to book value of equity. α_i and γ_t are institution and day fixed effects respectively. Standard errors are clustered at the firm-level if firm fixed effects are included and at the day-level otherwise. Sample period consists of 2016–2022. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B3: Brexit Retweet Events

Event	Date	Sample Tweet
06/20/16	UK votes leave	Amanpour horrified over #Brexit. I love it.
03/29/17	UK triggers Article 50	Do not say, 'The British people voted for Brexit, not hard Brexit.' There is no other kind available. Do not deceive people.
07/06/18	Chequers Plan	Nobody is coming up with an alternative to May's Brexit.
11/19/18	EU endorses plan	I stayed up late reading the Brexit Withdrawal Agreement. Here's 585 pages in 2 mins.
01/14/19	May's deal rejected	Anyone worried about a No Deal Brexit should be grateful to Jeremy Corbyn. Theresa May knows she can't get any deal through parliament without help from Corbyn. That gives him leverage. And he's using that leverage to get No Deal off the table. Thank him. #Newsnight #Peston
03/11/19	May's deal rejected again	Simple version: In a no deal Brexit, goods entering Northern Ireland from the Republic would not face tariffs (while negotiations take place with the EU and Irish Govt); but goods entering the rest of the UK from the Republic of Ireland would face high tariffs.
03/29/19	UK misses Brexit deadline	Theresa May's #Brexit process is a complete mess & MPs are now having to do in a few days what PM should have done 2 yrs ago to find compromise
consensus		
08/05/19	Boris Johnson becomes PM	I am interested to know, in light of Boris Johnson's 31st. October Brexit deadline what people actually want to happen before/on that date
10/21/19	Johnson agrees to new Brexit deal with EU	Work permits could be required to do business in the EU after Brexit.....No longer Project Fear. It's Project Reality ... Also may need to pay 2 lots of National Insurance and possess a Work Permit and/or Residence Permit.
12/09/19	Johnson wins general election	If you voted conservatives to 'Get Brexit Done' then you are the worst kind of person. LOOK AT THE BIGGER PICTURE.
01/27/20	UK leaves EU	"This is our star. Look after it for us". #NotMyBrexit
12/28/20	Post-Brexit trade agreement	France will be vigilant on post Brexit deal implementation, minister says

Table B4: Snowball-Sampled US Tariff Accounts

donald j. trump, peter navarro, sec. wilbur ross, chuck schumer, paul krugman, dani rodrik, lou dobbs, fareed zakaria, wto, US chamber, america first policy institute, joe rogan, eric trump, candace owens, ron desantis, maureen bannon, jason miller, greg kelly, lauren boebert, patrick byrne, steven mnuchin, lara trump, kellyanne conway, US commerce dept., john bolton, kamala harris, nancy pelosi, bernie sanders, elizabeth warren, adam schiff, the new yorker, politico, joseph e. stiglitz, ezra klein, thomas l. friedman, nber, olivier banchard, lawrence h. summers, dacemoglumit, mariana mazzucato, mark r. levin, tom fitton, maria bartiromo, rep. jim jordan, sebastian gorka drg, christiane amanpour, chelsea clinton, foreign policy, council on foreign relations, chuck todd, un trade and development, ifc, asian development bank, bloomberg markets, usagov, US department of labor, roll call, US house updates, peter schweizer, rob schmitt, rep andy biggs, real america's voice (rav), tucker carlson, georges st-pierre, danawhite, matt walsh, mike pence, kevin mccarthy, sean hannity, jesse watter, dan bongino, rep. marjorie taylor greene, james wood, ben shapiro, benny johnson, newsmax, kari lake, ted cruz, jayne zirkle, stephen miller, chuck callesto, james bradley, ben bergquam, steven cheung, sarah huccabee sanders, rsbn, dan scavino jr., john solomon, sosh hawley, leoterrell, sen. marsha blackburn, matt gaetz, josh hawley, leo terrell, laura ingraham, rand paul, melania trump, ivanka trump, kevin sorbo, ann vandersteel, praying medic, ezra a. cohen, general mike flynn, tracy beanz, treasury department, judicial watch, oversight committee, kayleigh mcenany, lindsey graham, jeanine pirro, department of state, dept. of agriculture, department of defense, marco rubio, judge napolitano, bill o'reilly, gop, fox news, the white house, alexandria ocasio-cortez, joe biden, bill clinton, bill maher, michelle obama, jill biden, stacey abrams, al franken, pete buttjigieg, alexander s. vindman, neal katyal, rep. jamie raskin, adam kinzinger, time, the wall street journal, the washington post, the atlantic, the hill, cnn politics, msnbc, cbs news, usa today, thomas piketty, voxeu, cepr, nate silver, fivethirtyeight, yamiche alcindor, vox, jake tapper, al gore, david brooks, richard n. haass, qje, aea journals, econometrica, the review of economics and statistics, josh angrist, ricardo reis, markus brunnermeier, peterson institute, mohamed a. el-erian, robin brooks, lloyd blankfein, hyun song shin, jeffrey gundlach, ucl institute for innovation and public purpose, doughnut economics action lab, kate raworth, tim jackson, carlota perez, dinesh d'souza, charlie kirk, greggutfeld, terrence k. williams, jack poso, jonathan turley, john kennedy, monica crowley, mollie, tomi lahren, donald trump jr., breitbart news, diamond and silk, juanita broaddrick, sara a. carter, richard engel, cnn, wiolf blitzer, ali velshi, the democrats, karine jeane-pierre, maxine waters, hillary clinton, foreign affairs, the diplomat, al jazeera english, national interest, csis, catham house, carnegie endowment, andrea mitchell, joe scarborough, kasie hunt, morning joe, lawrence o'donnell, unctad trade, unido, sinical, asean, david malpass, world bank data, bloomberg economics, blackrock, bloomberg asia, seeking alpha, finance news, ft economics, oecd statistics, christine lagarde, european central bank, national journal, post politics, mike allen, cspan, meet the press, republican cloakroom, US senate updates, house republicans, catherine herridge, sean davis, kimberley strassel, brian cates, rep. darrell issa, miranda devine, ronny jackson, scott baio, gianno caldwell, chuck grassley, brigitte gabriel, citizen free press, just the news, act for america, the first

Note: 243 influential institutional Twitter accounts and regional affiliates. Snowball samples collected through top 5 recommended Twitter profiles per account page. Sampling repeated after each augmentation up to three times. Seed accounts in bold.

Table B5: Snowball-Sampled Brexit-EU Accounts

boris johnson, nigel farage mp, michael gove, allison pearson, andrew neil, leave.eu, vote leave, scrutari semper, david cameron, nicola sturgeon, mark carney, carole cadwalladr, robert peston, carolyn fairbairn, richard branson, best for britain, jean-claude juncker, bbc breaking news, bbc news, jeremy clarkson, rishi sunak, sir gavin williamson cbe mp, gb news, the gateway pundit, reform uk, emerald robinson, the reclaim party, matt hancock, jacob rees-mogg, sajid javid, laura kuenssberg, toby young, julia hartley-brewer, isabel oakeshott, darren grimes, richard tice mp, nick robinson, guido fawkes, alastair campbell, andrew marr, alex phillips, john longworth, ben habib, priti patel mp, michael heaver, andrea leadsom, daniel hannan, annunziata rees-mogg, kate hoey, better off out with brexit, douglas murray, thomas sowell quotes, niall ferguson, matt goodwin, g. k. chesterton, uk prime minister, sky news, guardian news, mayor of london, sadiq khan, uk parliament, gov.uk, theresa may, harriet harman, mhairi black, scottish government, bbc scotland news, stv news, angela rayner, rosemary barton, bbc radio cumbria, channel 4 news, resolution foundation, cbi, institute for government, john pienaar, faisal islam, gina miller, chris bryant, pippa crerar, european movement, caroline lucas, antónio costa, european commission, european parliament, eu council, council of europe, Reuters, CNN, Mail+, financial times, james may, jeremy hunt, sir mark spencer, steve barclay, rt hon nadine dorries, rt hon michelle donelan, sir liam fox, gillian keegan, active patriot, andrew bridgen, lee anderson mp, laurence fox, isabel webster, spiked, michelle dewberry, defund the bbc, june slater, the free speech union, neil oliver, reclaimthemedia, keir starmer, dominic raab, john redwood, kemi badenoch, penny mordaunt, james cleverly, amber rudd, suella braverman mp, nadhim zahawi, uk house of commons, marina hyde, private eye magazine, yvette cooper, mahyar tousi, peter hitchens, nick ferrari, dan wootton, sophie corcoran, andrew pierce, martin daubney, tom harwood, jo coburn, fr calvin robinson, turning point uk, mike graham, mark dolan, beth rigby, jonsnowc4, fraser nelson, the rest is politics, marina purkiss, ed miliband, ed balls, gordon brown, alice grant, belinda de lucy, emily hewertson, peter bone, claire fox, peter whittle, aman bhogal, leavemeansleave, chris heaton-harris, esther mcvey, kate andrews, tim montgomerie, chris rose, standup4brexit, jon cruddas, rushanara ali mp, meg hillier, global guido, uk independence party, brexit facts4eu.org, freedom Association - join @ tfa.net, katharine birbalsingh, tim shipman, nick timothy mp, christopher hope, londonist, home office, the independent, jeremy corbyn, rachel reeves, angela eagle dbe, polly toynbee, chukaumunna, stephen flynn mp, john nicolson, glasgow times, scotland tonight, clyde 1, edinburgh evening news, lisa nandy mp, nia griffith mp, chrystia freeland, terry milewski, adrienne arsenault, hannah thibedeau, the standard, torsten bell, IPPR, institute for fiscal studies, IoD, commons library, policy exchange, michael crick, patrick wintour, james landale, katya adler, adam fleming, ian dunt, sam coates sky, jim pickard, jo maugham, femi, dr rakib ehsan, charlotte gill, ash hirani, david foxx, alex deane, moggmentum, sheryll murray, christopher pincher, sir conor burns, rt hon andrew stephenson cbe, james sunderland, dr kieran mullan mp, mark harper, giles watling, madeline grant, liam halligan, institute of economic affairs, katy balls, (((dan hodges))), conservativehome, john rentoul, alastair stewart, samantha smith, rebecca ryan, brexit home, sir stephen timms, catherine mckinnel mp, andy slaughter, wayne david, seema malhotra mp, tlip siddiq, rupa huq mp, rt hon valerie vaz mp, kate hollern for blackburn, vicky foxcroft, steve mccabe, clive efford, karen buck, media guido, steven edginton, douglas carswell, briefings for britain, nick marcel tenconi, ben walker, breitbart london, neil hamilton, bob for a full brexit, gully foyle, david c bannerman, reform uk grassroots, bruges group, adam smith institute, taxpayers' alliance, tcw, centre for policy studies, ruth lea, steven swinford, mattchorley, paul waugh mp, alex wickham, stephen bush, susan hall am, david frost, james heale, calgie, robert colvile, jason groves, john stevens, howard beckett, louis theroux, bridget phillipson, paul blomfield, jonathan ashworth, labour press, maria eagle mp, liz kendall, stellacreasy, margaret hodge, owen jones, jonathan freedland, the new statesman, david miliband, muciana berger, tommy sheppard, kirsty blackman, màiri mcallan, pete wishart, angus robertson, the national, what's on glasgow, the scotsman, mike galsworthy, tim walker, jessica simor kc, dawn butler, 4th july - tory wipe out, bladeofthesun, jonathan pie, haggis_uk, hugh grant, peter jones, chris packham, theo paphitis, peter kyle, richard burgon mp, dr rosena allin-khan, ava-santina, alexandra hall hall, sam bright, brexit bin, chris grey, ciaran the euro courier, peter jukes, dick mackintosh, britain people, paul schleifer, matthiasmueller, science magazine, martin wolf, dr dan goyal, kevin anderson, dg meme, digital eu, european research executive agency, nabila massrali, margrethe vestager, adina valean, terence zakka, nicolas schmit, world bank, oecd, real time economics, bank of england, kristina georgieva, eu_eurostat, politicoeurope, eu economy & finance, ceps thinktank, european economic and social committee, euractive, floridian eder, euwatchers, european ombudsman, manfred weber, ylvia johansson, oliver varhelyi, vera jourová, epp, s&d group, martin schulz, european parliamentary research service

Note: 572 influential institutional Twitter accounts and regional affiliates. Snowball samples collected through top 5 recommended Twitter profiles per account page. Sampling repeated after each augmentation up to three times. Seed accounts in bold.

Table B6: Top Import Industries

SIC	Industry
3663	Radio and T.V. Communications Equipment
2834	Pharmaceutical Preparations
3571	Electronic Computers
3429	Hardware
3069	Fabricated Rubber Products
1311	Crude Petroleum and Natural Gas
2911	Petroleum Refining
3674	Semiconductors and Related Devices
2499	Wood Products
3172	Personal Leather Goods
2836	Biological Products, Except Diagnostic
2869	Industrial Organic Chemicals
3331	Primary Copper
3651	Household Audio and Video Equipment
3312	Blast Furnaces and Steel Mills
3021	Rubber and Plastics Footwear
3575	Computer Terminals
3577	Computer Peripheral Equipment
3531	Construction Machinery
3647	Vehicular Lighting Equipment
3724	Aircraft Engines and Engine Parts
3592	Carburetors, Pistons, Rings, Valves
3629	Electrical Industrial Apparatus
3714	Motor Vehicle Parts and Accessories
3829	Measuring and Controlling Devices
2531	Public Building and Related Furniture
3728	Aircraft Parts and Equipment
2821	Plastics Materials and Resins
3292	Asbestos Products
3011	Tires and Inner Tubes
2819	Industrial Inorganic Chemicals
3711	Motor Vehicles and Car Bodies
3634	Electric Housewares and Fans
2421	Sawmills and Planing Mills, General
2833	Medicinals and Botanicals
3621	Motors and Generators
3559	Special Industry Machinery
3519	Internal Combustion Engines
3721	Aircraft
3842	Surgical Appliances and Supplies
3291	Abrasive Products
3613	Switchgear and Switchboard Apparatus
2391	Curtains and Draperies
175	Deciduous Tree Fruits
3523	Farm Machinery and Equipment
3631	Household Cooking Equipment
3491	Industrial Valves
3356	Nonferrous Rolling and Drawing
2812	Alkalies and Chlorine

Note: Table reports the top 50 US industries by import value 2016–2021. Data from the US International Trade Commission.

Table B7: Institutions Most Vulnerable to Geopolitical Stress

Ticker	HCOMNAM	Type
OPHC	Optimumbank Holdings Inc	Bank
COOP	Mr Cooper Group Inc	Bank
CARV	Carver Bancorp Inc	Bank
AMTB	Amerant Bancorp Inc	Bank
BYFC	Broadway Financial Corp Del	Bank
PBIB	Limestone Bancorp Inc	Bank
RDIB	Reading International Inc	Bank
TBBK	Bancorp Inc	Bank
CNBKA	Century Bancorp Inc	Bank
DGICB	Donegal Group Inc	Insurers
PTVCA	Protective Insurance Corp	Insurers
AEL	American Equity Invt Life Hldg C	Insurers
LNC	Lincoln National Corp	Insurers
PRU	Prudential Financial Inc	Insurers
VOYA	Voya Financial Inc	Insurers
EQH	Equitable Holdings Inc	Insurers
GWGH	G W G Holdings Inc	Other
FTFT	Future Fintech Group Inc	Other
AGM	Federal Agricultural Mort Corp	Other
FXCM	Global Brokerage Inc	Other
CPSS	Consumer Portfolio Svcs Inc	Other
SQBG	Sequential Brands Group Inc New	Other
IMH	Impac Mortgage Holdings Inc	Other
ZAIS	Zais Group Holdings Inc	Other
OCN	Ocwen Financial Corp	Other
AMBC	Ambac Financial Group Inc	Other
ICON	Iconix Brand Group Inc	Other
NAVI	Navient Corp	Other
MGI	Moneygram International Inc	Other
APEX	Apex Global Brands Inc	Other
LMFA	L M Funding America Inc	Other
SES	Synthesis Energy Systems Inc	Other
AFSI	Amtrust Financial Services Inc	Other
IBKR	Interactive Brokers Group Inc	Other
NNI	Nelnet Inc	Other
ATLC	Atlanticus Holdings Corp	Other
ARL	American Realty Investors Inc	Other
XELB	Xcel Brands Inc	Other

Note: This table reports the bottom 5% of financial institutions by geopolitical stress required to reach a stressed leverage of 0.04 over six months.