



Empty pledges and powerless conventions: How transition climate risks are disrupting financial markets?

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ABSTRACT

We propose mention volume index (MVI) as a novel alternative measure of attention to Google's search volume index (SVI). We construct several physical and transition climate risk indexes as shocks to corresponding climate MVIs that we construct by employing textual analysis on climate change narratives on social media between July 2010 and 2022. Using predictive regressions and several test assets, we investigate the response of asset prices to our climate risk indexes at the market level and the asset level. The predictions of our physical climate risk indexes support three stylized findings in the climate finance literature: (i) the carbon premium hypothesis, (ii) the rise in investors' awareness after the Paris Agreement, and (iii) the prediction that green firms outperform brown firms when concerns about weather risk increase unexpectedly. The predictions of our transition climate risk indexes provide new evidence documenting noise trading behavior in the form of return reversal an excess volatility in aggregate market level indexes following unexpected increases in attention to climate pledges and conventions. Moreover, at the asset-level, a rise in attention to climate pledges today is associated with an initial increase (decrease) in the returns of green (brown) firms on the second day. These responses are reversed on the fourth day. Peak and sentiment analyses of climate mentions around these events show that the return reversal is due to the backtracking and the lack of credibility of these promises. Finally, we find that the ineffectiveness of the U.S. carbon policy triggers flight to safety to the bond mutual fund market and disrupts the performance of green (but not brown) firms' stock prices. Unexpected increases in concerns about carbon policy risk on social media today is associated with an initial increase in green returns on the third day that is almost entirely reversed on the fourth day.

"It is a file of shame, cataloguing the empty pledges that puts us firmly on track toward an unlivable world"

—Antonio Guterres, U.N. Secretary General, on the latest sixth assessment IPCC report.

1. Introduction

The salient impacts of climate change are driven by physical events (e.g., floods, hurricanes, and rising sea levels) and regulatory actions (e.g., climate summits, pledges, policies, and solutions) that generate broad waves of public attention in the news and on social media. It is, therefore, plausible to expect the associated physical and transition risks to disrupt financial markets. These disruptions could be either reflected in asset prices or manifested in the form of noise trading. The main objective of this paper is to test this hypothesis. Using a set of physical and transition climate risk indexes, which we construct from a novel measure of

attention to climate change, we assess this hypothesis at the aggregate market level by employing predictive time series regressions to different test assets including clean energy exchange traded funds (ETFs), highly liquid equity ETFs, and mutual funds flows. We supplement this macro analysis with a micro (cross-section) analysis, where we assess the performance of green versus brown firms' stock prices following spikes in our climate risk indexes. More specifically, this paper seeks (i) to empirically investigate the contemporaneous and future positive or negative responses of asset prices to contemporaneous shocks to attention to climate change, which are captured by our physical and transition climate risk indexes, and (ii) to identify which type of risk is causing noise trading, i.e., price reversal and excess volatility, in financial markets. We run our macro and micro analyses before and after the Paris Agreement (PA) to assess the validity of [Fahmy's \(2022\)](#) recent finding that documents a rise in investors' awareness of climate risks after the PA.

The first challenge is to measure climate risk. We propose to use mention volume as a novel measure of attention to climate change

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mentions on social media. We quantify different types of physical and transition climate risks as innovations, i.e., shocks, to this attention measure. We consider these innovations as good proxies for climate risks. Using peak and sentiment analyses, we uncover the root causes, i.e., the main drivers, of these innovations and the sentiment that they carry. Finally, guided by the results of these analyses and the empirical findings, we provide a rationale of the mechanism via which physical and transition climate risks affect financial markets.

Since Da, Engelberg, and Gao (2011)'s first demonstration that search volume is a direct and unbiased measure of attention, some studies in the climate finance literature have relied on using the search volume index (SVI) in Google Trends as a proxy for investor attention. For instance, Choi, Gao, and Jiang (2020) use Google SVI of the term "global warming" to study investors' reactions to rising temperatures. Fahmy (2024a, 2024b) uses Google SVI to construct several measures of physical and regulatory climate risks using search volume as a proxy for attention. Ilhan, Sautner, and Vilkov (2021) use Google search volume data for the topic "climate change" as a proxy for attention to climate change. Fahmy (2022) also demonstrates the rise in investors' awareness of climate risks after the Paris Agreement using Google SVI. We contribute to this strand of literature by proposing *mention volume* as an alternative direct measure of attention. We demonstrate the advantages of using the mention volume index (MVI) as opposed to the SVI in measuring attention. We then construct several climate MVIs as measures of attention to different aspects of climate change by performing textual analysis on millions of climate mentions on major social media platforms. We restrict our search to the U.S. Thus, our climate MVIs reflect U.S. household attention to climate change on social media.

The key to the construction of our climate MVIs is the identification of relevant climate terms that we collect in a climate mention list (CML) by performing peak analysis of climate-related mentions on social media and by examining several white papers on climate change from sources such as the Intergovernmental Panel on Climate Change (IPCC) and the Environmental Protection Agency (EPA). To capture public attention to different physical and transitional aspects of climate change, we classify the terms in our CML in two broad categories: *physical* climate terms and *transition* climate terms. We further divide each category into several sub-categories. In particular, following the EPA's climate indicators classification, we break down the physical category into six sub-categories: carbon emissions and greenhouse gases (CARBON), weather and climate (WEATHER), sea and oceans (OCEANS), snow and ice (SNOW), health and society (SOCIETY), and ecosystems (ECOSYSTEM). Similarly, following the IPCC reports, we break down the transition category into four sub-categories: namely, climate summits and conventions (CONVENTIONS), policies related to carbon emissions and greenhouse gases (carbon POLICY), climate promises and pledges (PLEDGES), and clean and renewable energy solutions to climate change (SOLUTIONS).

We use the terms in each climate classification in our CML to construct a corresponding climate MVI as a measure of attention. Our approach is inspired by Engle, Giglio, Kelly, Lee, and Stroebel (2020), who construct two monthly media-based climate risk measures. The first is an aggregate attention measure about climate change, which is constructed by performing textual analysis on the news content of the Wall Street Journal (WSJ). The second is a proprietary sentiment measure that captures the negative attention about climate change in a large set of news outlets provided by the data analytic vendor Crimson Hexagon, which was recently acquired by Brandwatch.¹

Our approach, however, differs in three key aspects. First, rather than only developing an aggregate measure of risk from attention to climate change, we construct measures of different types of physical and transition climate risks, and we test their impacts on financial markets. The rationale for constructing a wide variety of climate risk indexes rather than an aggregate measure is twofold. First, this disaggregation allows us

to identify which type of risk is more prominent in causing disruptions in the form of price reversal and excess volatility in asset prices. Second, as stated in Fahmy (2024a, 2024b), in an aggregate index, the positive and negative impacts of different types of climate risks may cancel out. Thus, individual indexes are more suitable especially if one wishes to study the heterogeneous impacts of climate risk on asset prices.

Second, instead of performing textual analysis on newspapers as in Engle et al. (2020) and in Ardia, Bluteau, Boudt, and Inghelbrecht (2022), we analyze millions of climate mentions on major social media platforms. There are several advantages of using social media content rather than news. First, analyzing climate mentions on social media is more suitable for our proposed MVI as a proxy for climate attention. Second, performing sentiment analysis on climate mentions on social media provides an accurate reflection of how the public feel about the impacts of climate change. Third, we find that climate mentions on social media (especially Twitter) are more pronounced compared to news mentions. For instance, we find that 72.5 % (35.8 million) of the total 49.35 million mentions of the general term "climate change" on all content sources of Brandwatch between July 2010 and June 2022 are on Twitter platform while 10.7 % (5.3 million) of these mentions belong to online news articles. This means that approximately 83 % of all mentions of "climate change" belong to online news websites and Twitter with the latter being significantly dominant. This fact, which is consistent across every term and every search query in our CML, suggests that social media is an important content source in capturing the tone of public climate conversations. This rationale is consistent with several studies that find that investors communicate and learn from a combination of news media and social networks, and that the social influence is a significant factor in information dissemination (Chen & Hwang, 2022; Shive, 2010). For these reasons, we use Twitter in this paper as the social media data source in all empirical analyses. Our results, however, are robust to the use of news only as a content source or to an aggregate content that combines both news and Twitter.²

Third, we perform peak analysis on our constructed MVIs to understand the root causes of concern in U.S. public attention to climate change. We find that public perception of climate change is significantly shaped by actions and statements of climate deniers and supporters. This shaped perception, in turn, causes sudden shifts in investors' preferences. This behavioral change can cause asset prices to respond either positively or negatively or it can induce temporary mispricing and excess volatility. We supplement our peak analysis with a sentiment analysis. More specifically, we employ Brandwatch's sentiment classifier to detect the tone in the corpus of text corresponding to our MVIs' search queries. The classifier, which was used to develop the aggregate sentiment index of Engle et al. (2020), determines whether the sentiment corresponding to a search query is positive, negative, or neutral. It uses artificial intelligence models, also known as Transformer Architecture Language (TAL) models, that are pre-trained on billions of words to have a deep general knowledge of over 100 languages before being applied to sentiment analysis. TAL models offer a more sophisticated understanding of context, slang, and dialects. In addition to words, phrases, and sentence structure, these models can detect sentiment indicated by Emojis, emoticons, and multiword hashtags. Our peak and sentiment analyses allow us to provide an explanation of the positive and negative responses of asset prices to climate risks.

² It is worth noting that, in the empirical analyses, experimenting with one-day lag news MVI did not produce any significant results. We did so to rule out the possibility that climate news concerns that predate today's tweets are the actual drivers of asset prices. We have also obtained similar results when considering Twitter MVI that matches the characteristics of the test assets, i.e., when considering Twitter MVI pertaining only to trading days (excluding weekends and holidays) and restricting the volume only to trading hours. We did this to rule out the possibility that the contemporaneous market impacts are due to pre-dated climate Twitter concerns rather than same day effects.

¹ <https://www.brandwatch.com>.

Our approach of constructing MVIs as measures of climate attention has several appealing features. First, much like Google Trends, which permits downloading the SVI of one search term at a time, Brandwatch platform permits downloading the MVI of any search query. However, unlike the SVI, the search query of the MVI is not restricted to one term. It could consist of one or several search terms or phrases joined by textual operators (e.g., OR, AND, and NEAR). This feature, along with textual analysis, allows the construction of more precise measures of attention. Second, as opposed to climate search terms, climate *mentions*, especially on social media, reveal public perception of climate change, which is useful in understanding investors' behavior in financial markets. In particular, by analyzing the peaks of the climate MVI, one can identify the main drivers of public climate conversations. This is important in understanding the factors shaping attention to climate change. Third, one can capture the tone of climate conversations by performing sentiment analysis on the MVI search queries. This analysis is helpful in explaining the positive or negative response of asset prices to shocks in attention to climate events.

Our CARBON MVI, which measures U.S. public attention to greenhouse gases and carbon emissions, is a good example that illustrates the previous advantages of using MVI as a measure of attention. The CARBON MVI is constructed by applying textual operators to the terms in the CARBON category in our CML (see Panel A in Table 1) to compose a query that captures public attention to carbon emissions.³ Fig. 1 plots the monthly MVI of this search query broken down by different content sources from Brandwatch between July 2010 and June 2022. Twitter and online news are the two most significant content sources with the former being more prominent than the latter as shown from the plots in Panel A in Fig. 1. Out of the approximate 1236 K mentions of the CARBON query, 848 K come from Twitter and 278 K come from news articles. Brandwatch platform allows us to use textual analysis to obtain the main topics and sub-topics of each search query. Panel B in Fig. 1 shows the topics wheel of the CARBON MVI search query. To understand the sources of U.S. public attention to carbon emissions, we perform peak analysis on our Twitter CARBON query to identify the main drivers behind the high swings in the Twitter CARBON MVI. At the monthly frequency, we analyze the main drivers of the peaks in the MVI by first comparing the volume of each point on the MVI to the monthly median volume of the time series. We mark any significant monthly deviation as peak (see the capital letters on the chart in Panel A in Fig. 1). Next, we identify potential drivers for each peak. We analyze the millions of mentions on Twitter and compare the volume of mentions for each potential driver to the three weeks days preceding the peak. We consider both the percentage increase from the norm and the volume of the driver relative to the volume of the whole search. We find that the MVI of the CARBON query tends to peak following denial statements from executives and politicians regarding carbon emissions. For instance, in March 2017 (point K on the Twitter monthly MVI in Panel A in Fig. 1), we find that CARBON Twitter MVI is 1151 % higher than the median monthly mention volume. Our analysis reveals that this peak is driven by several drivers including 5029 mentions sharing several news links reporting a statement by EPA Chief Scott Pruitt saying that carbon dioxide is not a primary contributor to global warming. In June 2017, we document a 426 % increase in the CARBON Twitter MVI relative to the median monthly volume (point V). We find that this spike is driven by another denial statement, which posits that humans are not the main cause of climate change. This statement, which is made by Energy Secretary Rick Perry, generated 2706 mentions sharing several links on this story from

³ The exact search query is documented in the Internet Appendix. In addition to stop words and hashtags, the query includes terms like "greenhouse gas*" OR "carbon dioxide" OR "CO2" OR "carbon emission*" OR "carbon footprint" OR "methane emission*" OR "greenhouse effect*" and their variations, which are mentioned within 10 words of the general terms "climate change" OR "global warming."

different news outlets. We document the rest of the drivers of this peak and the drivers of other peaks in the Twitter MVI below the graph in Panel A in Fig. 1.

The importance of this peak analysis is twofold. First, in addition to topic analysis, it serves as another robustness check for the constructed query. In case we detect peak drivers that are unrelated to the query topics, we revise the query to exclude these drivers. Second, it reveals the prominent drivers of each search query. Across most of our search queries, we find that actions and statements by politicians, policy makers, and executives are the most influential drivers of attention to climate change.

Identifying climate attention drivers from analyzing the peaks of our MVIs is important in understanding the transmission mechanism of climate risks from attention to climate change events to financial markets. This is crucial in managing (Fahmy, 2024b) and hedging (Engle et al., 2020) such risks. We also argue that this analysis is useful in designing and implementing effective climate mitigation and adaptation policies that can change the way investors perceive climate risks and, thus, are likely to cause stability in financial markets. Details regarding the Twitter peak analysis of the CARBON query as well as other queries are found in the Internet Appendix.

Finally, we employ Brandwatch's sentiment classifier on the CARBON MVI query to analyze the sentiment of the CARBON mentions. The results of the sentiment analysis, as documented in Panel C in Fig. 1, reveal that, excluding the percentage of neutral sentiment, CARBON mentions carry a dominant negative sentiment.

We make three contributions to the literature. First, we contribute to attention theory in finance by proposing *mention volume* as an alternative measure of attention to the conventional search volume measure in Google Trends. We demonstrate the advantages of using our measure. Notably, we show that peak and sentiment analyses can be easily performed on this measure. The results of these analyses are useful in providing a rationale for the positive/negative responses of asset prices to shocks to this attention measure.

Second, we contribute to the burgeoning climate finance literature that investigates the impacts of climate risks on financial markets (e.g., Ardia et al., 2022; Balvers, Du, & Zhao, 2017; Bansal, Kiku, & Ochoa, 2019; Bolton & Kacperczyk, 2021; Fahmy, 2024a; Pastor, Stambaugh, & Taylor, 2021; among others). This strand of literature shares the common methodology of analyzing the cross-section of stock returns using standard factor models. In this paper, in addition to analyzing the impacts of climate risks in the cross-section of green and brown stocks, we also provide a market level analysis of clean energy and highly liquid equity ETFs' returns. Our macro analysis provides empirical evidence on the clean energy-climate connection (Fahmy, 2024a). As for the cross-section analysis, our results contribute to the findings of Ardia et al. (2022), who test the prediction of Pastor et al. (2021)'s model, which posits that green stocks outperform brown stocks amid unexpected concerns about climate change. The authors construct an aggregate news-based measure of climate concerns and test its predictive power on the performance of green and brown stocks in the S&P500. They find that on days with unexpected increase in climate change concerns, green firms' stock prices tend to increase whereas brown firms' prices decrease. While our study differs from Ardia et al. (2022) in (i) using attention to climate change on social media (as opposed to news) to construct climate risk measures, and (ii) disaggregating climate risk into several types, our results are consistent with their findings. We find that green stocks outperform brown stocks when concerns about WEATHER risk on social media strengthen unexpectedly.

Third, our results contribute to a large strand of literature on sentiment theory, which has its roots in De Long, Shleifer, Summers, and Waldmann (1990)'s first demonstration that sentiment change can lead to more noise trading, price reversal, and excess volatility if uninformed retail traders base their decisions on sentiment and there exist limits to arbitrage.⁴ Sentiment studies differ in the way they measure sentiment

⁴ See Backer and Wurgler (2007) for a literature review.

Table 1
Climate mentions list and sentiment analysis.

(1)	(2)			(3)	(4)	(5)	(6)
	Sentiment (%)						
Climate risk classification	+	–	Neutral	Total mentions	Topics wheel	Topics growing in volume	MVI statistics
Panel A: Physical climate terms							
CARBON				Total 10.8M			<i>MVI^{CARBON}</i>
“greenhouse gas*” OR “greenhouse-gas*” OR GHG OR GHGs	1%	13%	86%	2.85M		Climate crisis/carbon emissions	Mean: -0.0006
“carbon dioxide” OR carbon OR CO2	2%	11%	87%	2.85M		Reducing the carbon footprint	Sd: 0.35
“emission*” OR “carbon emission*”	2%	14%	84%	2.55M		Climate action/Electric vehicles	Min: -1.30
“carbon footprint*”	5%	14%	81%	1.83M		Carbon Emissions	Max: 1.78
methane OR “methane emission*”	1%	13%	86%	359.33K		Trump Administration/Oil & gas	
“greenhouse effect”	3%	12%	85%	220.58K		Natural Resources/Carbon dioxide	
(“anthropogenic activit*” OR anthropogenic) NEAR/10 (“climate change” OR “global warming”)	1%	25%	74%	91.31K		Anthropogenic climate change is real	
WEATHER				Total 3.02M			<i>MVI^{WEATHER}</i>
flood* NEAR/10 (“climate change” OR “global warming”)	1%	30%	69%	1.1M		Green new deal/Climate effects	Mean: 0.002
(hurricane* OR cyclone*) NEAR/10 (“climate change” OR “global warming”)	2%	28%	70%	736.31K		Climate change deniers	Sd: 0.28
“extreme weather” NEAR/10 (“climate change” OR “global warming”)	1%	23%	76%	588.27K		Climate crisis/Climate effects	Min: -1.74
“drought*” NEAR/10 (“climate change” OR “global warming”)	1%	27%	72%	383.61K		Climate crisis/Climate effects	Max: 1.43
(“heat wave*” OR “heatwave*”) NEAR/10 (“climate change” OR “global warming”)	1%	28%	71%	179.6K		Climate effects	
(“extreme precipitation*” OR “heavy precipitation*”) NEAR/10 (“climate change” OR “global warming”)	2%	28%	70%	23.4K		Climate change is real/Climate change effects	
OCEANS				Total 0.32M			<i>MVI^{OCEANS}</i>
(“sea level* rise” OR “rise in sea level” OR “rising sea” OR “rising seas” OR “rising sea level*”) NEAR/10 (“climate change” OR “global warming”)	1%	13%	86%	327.25K		Rising seas/Green new deal/Coastal communities	Mean: 0.006
(“ocean heat” OR (heat NEAR/2 ocean*) OR “ocean heat content”) NEAR/10 (“climate change” OR “global warming”)	1%	10%	89%	18.29K		Ocean heat waves due to climate change	Sd: 0.45
“sea surface temperature” NEAR/10 (“climate change” OR “global warming”)	0%	5%	95%	8531		Rising seas due to climate change	Min: -1.54
“coastal flood*” NEAR/10 (“climate change” OR “global warming”)	0%	13%	87%	4107		Greenhouse gas emissions/Rising seas	Max: 2.48
SNOW				Total 0.25M			<i>MVI^{SNOW}</i>
((Arctic OR Antarctic) NEAR/2 (sea OR ice or glacier*)) NEAR/10 (“climate change” OR “global warming”)	1%	17%	82%	113.67K		Starve to death/ Polar bears/ Climate change is real	Mean: 0.004
((glacier* OR “ice sheet*” OR snow) NEAR/2 melt*) NEAR/10 (“climate change” OR “global warming”)	1%	14%	85%	90.94K		Glaciers lost to climate/ Farewell to the first Icelandic glacier	Sd: 0.57
(snowfall* OR “snow fall*”) NEAR/10 (“climate change” OR “global warming”)	2%	16%	82%	64.99K		Winter storms/Warmer planet	Min: -1.87
SOCIETY				Total 0.19M			<i>MVI^{SOCIETY}</i>
((society OR societies OR societal OR social) NEAR/2 (risk* OR impact* OR effect*)) NEAR/10 (“climate change” OR “global warming”)	2%	11%	87%	125.58K		Climate action/ Climate science	Max: 2.44
((“human health”) NEAR/2 (risk* OR impact* OR effect*)) NEAR/10 (“climate change” OR “global warming”)	2%	13%	85%	62.79K		Climate crisis/Impact on human health/Climate science	Mean: 0.004
ECOSYSTEM				Total 0.17M			<i>MVI^{ECOSYS}</i>
(ecosystem OR ecosystems) NEAR/10 (“climate change” OR “global warming”)	2%	18%	80%	153.31K		Mass extinction of entire ecosystem/ Climate change is a hoax	Sd: 0.47
(“specie OR species) NEAR/2 extinction*) NEAR/10 (“climate change” OR “global warming”)	4%	16%	80%	17.75K		Species extinction due to climate change	Min: -1.69
							Max: 1.96

Panel B: Transition climate terms

(continued on next page)

Table 1 (continued)

(1)	(2)			(3)	(4)	(5)	(6)
	Sentiment (%)						
Climate risk classification	+	–	Neutral	Total mentions	Topics wheel	Topics growing in volume	MVI statistics
CONVENTIONS				Total 4.02M 2.49M			MVI^{CONVENTIONS}
“Paris Agreement” OR “Paris Accord” OR “Paris Climate Accord”	3%	24%	73%			Trump withdrawal	Mean: 0.003
“Intergovernmental Panel on Climate Change” OR IPCC OR “IPCC report”	1%	16%	83%	885.54K		CO2 budget/Climate crisis	Sd: 0.27
(convention* OR summit* OR agreement OR protocol OR portocols OR treaty OR treaties OR accord OR accords OR COP*) NEAR/10 (“climate change” OR global warming*)	2%	10%	88%	1.52M		Climate crisis/Paris Agreement/COP25/ COP23 / COP26	Min: -1.44 Max:1.58
Carbon POLICY				Total 1.9M 1.01M			MVI^{POLICY}
(carbon OR CO2 OR emission* OR greenhouse gas*) NEAR/2 (pric* OR tax* OR fee*)	2%	23%	75%			Carbon pricing/Carbon taxes	Mean: 0.005
((carbon NEAR/2 (credit OR credits OR market OR markets OR trade OR trading OR policy OR policies)) NOT (token* OR DEFI OR “defi-carbon”))	3%	23%	74%	804.31K		Green New Deal/Climate crisis	Sd: 0.21
(“feed-in tariff” OR “feed in tariff” OR feed-in-tariff*) NEAR/10 (“climate change” OR “global warming”)	2%	13%	85%	33.42K		Carbon markets Solar energy/Power panels	Min: -1.16 Max:1.29
PLEDGES				Total 1.4M 422.8K			MVI^{PLEDGES}
(“Energy transition” OR “Just transition”) NEAR/10 (“climate change” OR “global warming”)	6%	4%	90%			Energy transition	Mean: 0.004
(“sustainable development goals” OR SDG OR SDGs OR sustainab*)	4%	1%	95%	402.34K		Sustainable future/climate action	Sd: 0.23
(“net zero” OR net-zero)	5%	3%	92%	237.60K		Net-zero emission by 2050	Min: -1.04
(“climate resilience”) NEAR/2 (fund* OR strategy OR strategies OR project OR projects)	4%	3%	93%	154.01K		Clean energy/Clean water	Max: 1.08
climate NEAR/2 (plan OR plans OR promise OR promises OR pledge OR pledges OR target OR targets)	3%	2%	95%	148.22K		Fight climate change	
Climate NEAR/2 (adaptation OR mitigation OR transition)	5%	4%	91%	24.68K		Just transition/Climate mitigation	
SOLUTIONS				Total 0.4M 263.34K			MVI^{SOLUTIONS}
(“renewable energy” OR renewables) NEAR/10 (“climate change” OR “global warming”)	2%	7%	91%			Carbon capture and storage	Mean: 0.005
((carbon OR CO2) NEAR/2 (captur* OR utiliz* OR stor*)) NEAR/10 (“climate change” OR “global warming”)	1%	4%	95%	65.23K		Energy efficiency and sustainable energy	Sd: 0.39
(“energy efficiency” OR “energy efficient”) NEAR/10 (“climate change” OR “global warming”)	2%	7%	91%	39.03K		Renewable energy	Min: -1.64 Max: 1.98
(“electric vehicles” OR “electric vehicle” OR EV OR E.V. OR EVs) NEAR/10 (“climate change” OR “global warming”)	2%	14%	84%	38.87K		100% renewable energy/ clean energy/combating climate change	
(“solar energy” OR “solar power” OR “solar energy fuel” OR “solar solution” OR “solar solutions”) NEAR/10 (“climate change” OR “global warming”)	2%	8%	90%	24.12K		Clean energy/Solar power/ Fossil fuels	
(“wind energy” OR “offshore wind power” OR “wind farm” OR “off-shore wind farm”) NEAR/10 (“climate change” OR “global warming”)	2%	14%	84%	11.44K		Wind power/Renewable energy	
(“solar radiation management” OR “greenhouse gas removal” OR “climate engineering” OR “geo-engineering”) NEAR/10 (“climate change” OR “global warming”)	2%	14%	84%	8357		Reverse climate change/ Solar radiation/Climate change is real	
“Bionenergy with carbon capture and storage” OR BECCS	0%	2%	98%	2182		Carbon storage/Climate crisis	
(geothermal NEAR/2 (energy OR technology OR technologies OR system OR systems)) NEAR/10 (“climate change” OR “global warming”)	3%	4%	93%	1114		Geothermal energy sources	
“Stratospheric Aerosol Injection” NEAR/10 (“climate change” OR “global warming”)	1%	10%	89%	951		Controversial spraying methods to curb global warming	
“afforestation” NEAR/10 (“climate change” OR “global warming”)	4%	7%	89%	827		Tackle climate change	

This table documents the terms in our climate mentions list (CML) and the corresponding sentiment analysis. Column (1) shows the terms in the physical (Panel A) and transition (Panel B) climate risk classification. Column (2) displays the sentiment analysis using Brandwatch’s sentiment classifier. Column (3) documents the total number of mentions in millions (M) or thousands (K) that correspond to each individual term in Column (1) over the period between July 11, 2010, and June 26, 2022. Column (4) displays the topics wheel for each sub-category. Column (5) includes the topics which are growing fastest in volume over the analysis period. Column (6) contains descriptive statistics of each mention volume index (MVI) in each sub-category. The MVIs are constructed by composing search queries that include the corresponding terms in Column (1) using several operators such as “OR,” “NOT,” and “NEAR/x.” The NEAR/x operator brings preceding terms that are within x words from the proceeding terms. An * tagged to a term brings all term variations. The exact queries are found in the Internet Appendix.

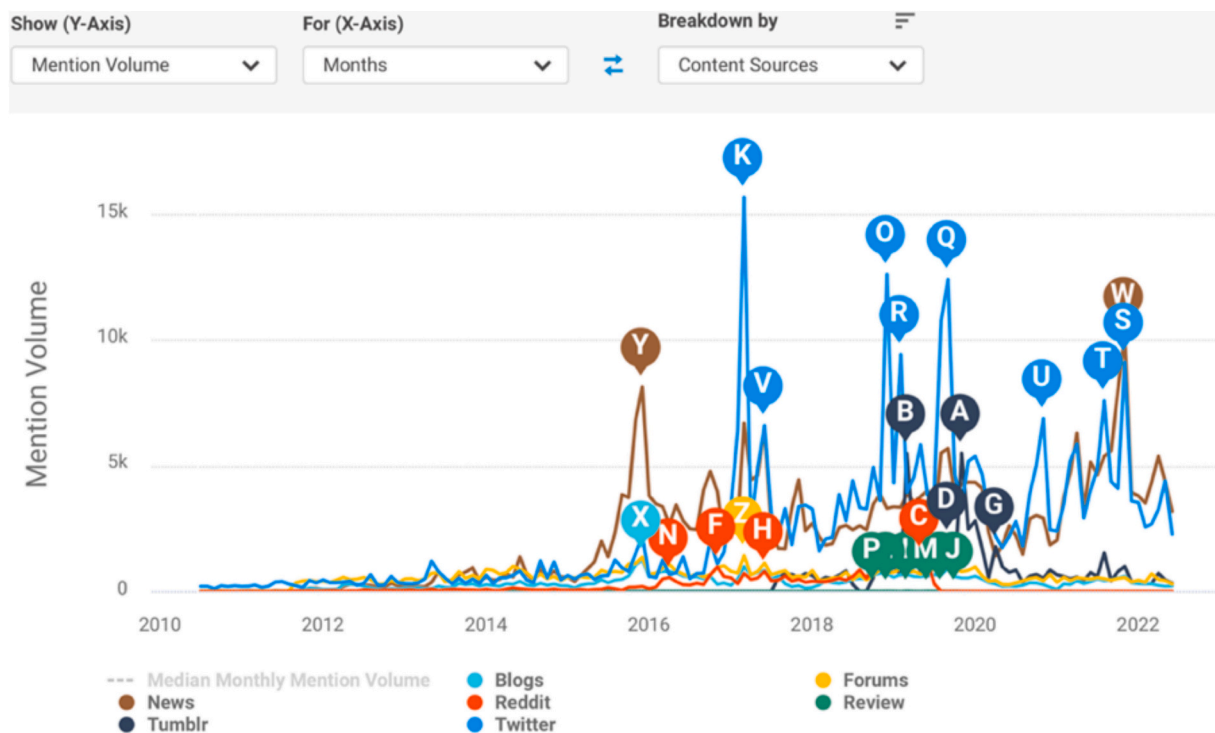
and in the choice of financial markets. [Da, Engelberg, and Gao \(2015\)](#), for instance, use SVIs on Google Trends to measure investor sentiment toward economic and financial events. [Brown and Cliff \(2005\)](#) and [Lemmon and Portniaguina \(2006\)](#), among others, use survey-based measures to approximate investor sentiment. Other studies use market-based measures, such as trading volume, consumer confidence, option implied volatility (VIX), or mutual funds flow, as proxies for investor sentiment (e.g., [Aboody, Even-Tov, Lehavy, & Trueman, 2018](#); [Baker & Wurgler, 2006](#); [Huang, Jiang, Tu, & Zhou, 2015](#)). Our climate risk measures, which are constructed as shocks to U.S. public attention to climate mentions on social media, are considered as market-based measures that approximate investor climate perception. As for the choice of financial markets, we consider three test assets as our aggregate market level indexes: namely, the clean energy ETFs that are considered in [Engle et al. \(2020\)](#), and the highly liquid equity ETFs and mutual fund flows that are investigated in [Da et al. \(2015\)](#), [Edelen and Warner \(2002\)](#) and [Greene and Hodges \(2002\)](#). The choice of the highly liquid equity ETFs and the mutual fund flows as test assets follows the sentiment literature that posits that the return reversal in the highly liquid equity ETFs and the flight to safety from equities to bonds in the mutual fund flows are common indicators of noise trading behavior of uninformed retail investors following economic and financial events ([Da et al., 2015](#); [Edelen & Warner, 2002](#); [Greene & Hodges, 2002](#)). We extend this strand of literature by investigating the behavior of retail traders amid climate events.

At the aggregate market level, we find that our physical climate risks (including CARBON and WEATHER risks) predict a negative response in clean energy ETFs and a positive response in highly liquid equity ETFs in the period before the PA. The finding that liquid equity ETFs outperform clean energy ETFs indicates that investors were not paying attention to the issue of climate change during this period. This reflects the lack of awareness or care about climate change before the PA. After the PA, however, we find a positive and significant relation between CARBON and WEATHER risks and clean energy ETFs' returns. The negative and positive responses of clean energy ETFs' returns to CARBON and

WEATHER risks before and after the PA respectively confirm the noticeable shift in investors' preference toward clean energy assets after the PA ([Fahmy, 2022](#)).

The cross-sectional analysis of the impacts of CARBON and WEATHER risks on the performance of green and brown stocks provides two key results. First, we find that brown stocks outperform green stocks amid unexpected shocks in attention to carbon emissions and greenhouse gases on social media. This result is consistent with the finding of [Bolton and Kacperczyk \(2021\)](#), who document that carbon emissions affect the cross section of U.S. stock market and find that stocks with higher emissions earn higher returns. The high returns of the brown stocks reflect investors' demand to be compensated for carbon risk. Second, we find that green stocks outperform brown stocks when concerns about WEATHER risk on social media strengthen unexpectedly. Peak and sentiment analyses of U.S. climate mentions around physical climate events after the PA show that these mentions are driven by climate denial statements and that they carry a prominent negative sentiment in the post-PA period. This negative sentiment prompts conscious investors to hold green stocks causing their returns to rise. This result is consistent with [Fahmy \(2022\)](#), who documents a rise in investors' awareness of climate risks after the PA, and with [Choi et al. \(2020\)](#)'s finding, who document that U.S. households revise their beliefs about climate change upward when experiencing abnormal temperatures (heat waves in our WEATHER category in the climate classification in [Table 1](#)). The previous result is also consistent with [Ardia et al. \(2022\)](#)'s recent assessment of the performance of green versus brown stocks amid climate change concerns in U.S. newspapers.

As for transition climate risks, we find that climate PLEDGES and CONVENTIONS are sources of noise trading in clean energy markets. Increases in attention to climate PLEDGES, in the period after the PA, cause an initial contemporaneous positive response in clean energy returns that is reversed in the next five days. The initial positive response of clean energy returns to PLEDGES risk indicates that investors, who believe in climate change and feel good after a spike in attention to a climate promise or a pledge, are keen to hold clean energy assets. Our



(caption on next page)

sentiment analysis confirms this conjecture. We find that mentions related to climate PLEDGES carry a dominant positive sentiment after the PA. The backtracking and lack of credibility of such promises, however, lead to return reversal during the next five days. This behavioral bias is also apparent in the performance of green versus brown portfolios. Our cross-section analysis documents an initial increase (decrease) in green (brown) returns following increases in attention to climate PLEDGES on social media. These responses are reversed after two days.

Another key finding from our cross-section analysis is that carbon POLICY risks, e.g., carbon tax, feed-in-tariff, and carbon credit policies, disrupt green (but not brown) firms' stock prices. We found evidence of price reversal in green portfolios' returns following increases in climate POLICY risk. Peak analysis of climate policy mentions and further exploration of the climate sentiment corresponding to our carbon POLICY MVI show that these mentions carry a prominent negative sentiment. The return reversal in green stocks indicates that U.S. public believe that carbon policies are ineffective and lack credibility (e.g., the withdrawal of the Trump administration from the PA in 2017 and the dismantling of environmental regulations governing clean energy, water, and land during this period). The previous results are consistent with the recent findings of [Fahmy and Apergis \(2024\)](#) about the ineffectiveness of the U.S. climate policy.

The previous sentiment-induced temporary mispricing, which is reflected in the spike-reversal patterns in clean energy and green portfolios' returns, following increases in our climate PLEDGES, CONVENTIONS, and carbon POLICY risk indexes indicates disruptions in these markets in the form of noise trading. However, we perform a more direct test of the noise trading hypothesis by examining the daily bond and equity mutual fund flows ([Da et al., 2015](#)). Since individual investors hold most of total mutual fund assets, then negative (positive) sentiment-induced temporary mispricing following increases in climate concerns can be detected by movements of funds from the riskier (safer) fund, i.e., equity (bond), to the safer (riskier) fund. We find that unexpected concerns about climate policies, which are captured by the shocks to our carbon POLICY MVI, cause investors to switch in the long-term from equity to bond market. This flight to safety to the bond market reflects investors' worries about the ineffectiveness of climate policies ([Fahmy & Apergis, 2024](#)). The negative dominant sentiment corresponding to mentions related to carbon POLICY in our social media corpus validates this explanation. On the other hand, unexpected increases in climate PLEDGES on social media prompt investors, who feel good about these promises, to switch money from the bond mutual fund market to the equity fund market. This movement to a relatively riskier investment is justified by our sentiment analysis, which shows that mentions of climate pledges on social media carry a dominant positive sentiment. This positive climate sentiment reflects retail investors' belief that regulators and decision makers' promises are expected to successfully combat climate change and in consequence it justifies the movement of funds from the low-return but relatively safer bond market.

Since investment decisions that lead to noise trading can affect both the level and the volatility of asset prices, we conduct a volatility analysis to confirm the validity of our return reversal results. We fit a regime switching GARCH model to the conditional volatility of aggregate asset returns using our climate risk indexes as exogenous regime-driving variables. Within this framework, we test which type of climate risk is causing a nonlinear regime switching behavior in volatility. Our nonlinearity test results confirm that the innovations, i.e., shocks, to attention to climate CONVENTIONS and climate PLEDGES are the volatility drivers of all clean energy and highly liquid ETFs with the former type of risk being more prominent than the latter. Both risks drive the conditional volatility to oscillate between two (low and high) attention GARCH (1,1) regimes with different degrees of persistence.

The remainder of the paper is organized as follows. [Section 2](#) discusses the construction of our climate MVIs and risk measures. [Section 3](#) describes the data. [Section 4](#) documents the results of employing

predictive regressions to our test assets at the aggregate market level. [Section 5](#) discusses the construction of green and brown portfolios and documents the impacts of our climate risk indexes on the performance of green versus brown stocks. [Section 6](#) discusses the response of mutual funds flow to our climate risk measures. [Section 7](#) presents the volatility analysis and the results of the regime switching GARCH model. Finally, [Section 8](#) gives a concise conclusion that summarizes the results and provides a rationale, which is founded on peak and sentiment analyses of climate mentions on social media, of how shocks to attention to climate-related mentions on social media are transmitted in financial markets.

2. Construction of social media-based measures of climate risks

2.1. Classification of climate risks and textual analysis

The first step in the construction of our climate attention measures is the development of a climate mention list (CML) that includes terms which reflect different aspects of climate change. We first construct a preliminary CML that includes climate terms (unigrams, bigrams, and n-grams and their variations) that are most mentioned on Twitter amid major climate events (e.g., summits, conventions, and IPCC reports). We also supplement the list with terms that we collect from white papers on climate change from sources such as the IPCC, EPA, and other authoritative texts. The Internet Appendix gives a summary of these documents. It is worth noting that the terms "climate change" and "global warming" are the most mentioned terms in our data set with 49.35 million (M) and 14.5 M mentions, respectively, between 2010 and 2022. We find that one of these terms (or both) is (are) always mentioned within 10–15 words nearby almost every term in our preliminary CML. For that reason, in composing our search queries, we employ the "NEAR/10" operator to the word set ("climate change" OR "global warming") to confine the results of our query to climate-related conversations.⁵ We group the terms in the CML into physical and transition climate risk terms as shown in Column (1), Panel A, in [Table 1](#). Guided by the climate change indicators classification suggested by the EPA, we further divide the physical category into six groups: CARBON, WEATHER, OCEANS, SNOW, SOCIETY, and ECOSYSTEM. Following the IPCC reports, we divide the climate transition category into PLEDGES, CONVENTIONS, carbon POLICY, and SOLUTIONS as shown in [Table 1](#).

Our next step is to refine the preliminary terms in each of the previous categories. First, we exclude the terms that yield no mentions over the analysis period. We find that most of these terms are new clean technology terms in the SOLUTIONS category such as "concentrated solar power or photovoltaic systems," "tidal range energy," and "ocean thermal energy conversion." These terms describe new clean technologies that are in their early stage of development. Second, to eliminate terms that are used in contexts unrelated to climate change, for each climate term or search query, we ask two research assistants to draw independently 1000 excerpts that include the term or the query under consideration, and to manually verify the suitability of the context. We exclude the terms that are used in different contexts using the "NOT" operator in the revised search query. We repeat the previous manual verification on the revised query and keep revising until we are satisfied with the results. Third, in addition to manual checks, we also perform topic analysis on each search query to identify the climate topics which are growing in volume over the analysis period. We notice that some terms are mentioned in both climate and non-climate related topics. To exclude non-climate conversations that contain these terms, we revise our search queries by applying the "NEAR/10" operator to the word set ("climate change" OR "global warming"). We verify the validity of the revised search queries by re-executing the topic analysis to confirm that the resulting topics are climate related. For instance, the term

⁵ For robustness, we also experiment with 8- and 15-words proximity and document similar results.

“stratospheric aerosol injection” generates 7416 K mentions, making it the most mentioned term in the SOLUTIONS category in our preliminary CML. However, by examining the mentions’ topics, we find that most of the resulting mentions are related to solar dimming and military weapons but not climate change. When we restrict the search to terms near (“climate change” OR “global warming”), our query only generates 951 relevant mentions.

Table 1 documents the climate terms in our final CML after all eliminations and refinements. Column (2) reports the percentage of negative, positive, and neutral sentiments corresponding to the search queries in Column (1), which we obtain from running each query on Brandwatch’s sentiment classifier. We find that negative climate sentiment dominates positive sentiment in all groups of our classification. The only notable exception is the dominant positive sentiment of climate PLEDGES over the entire analysis period. Column (3) in Table 1 documents the total mentions of each term on all content sources in our data base over the analysis period. We find that the climate terms that are most mentioned by U.S. households in the physical category are the terms in the CARBON and WEATHER groups whereas the terms that are most mentioned in the transition category are those in the CONVENTIONS, carbon POLICY, and PLEDGES groups. This means that attention of U.S. households to physical climate impacts is mostly triggered by mentions of carbon emissions and tangible weather events whereas attention to regulatory impacts is triggered by climate promises, conventions, and carbon policies. This result confirms the importance of these regulatory events in shaping public opinion about climate change. Column (4) summarizes the climate topics in each category in a topics wheel and Column (5) lists the topics that are growing in volume over the analysis period.

2.2. Climate MVIs and risk measures

We use the search terms in each physical and regulatory sub-category to construct several search queries that capture public attention to various aspects of climate change. In each query, we include all stop words and other refinements from our preliminary analysis of each term in the CML. We provide the exact search queries in the Internet Appendix for researchers who are interested in replicating the results of the paper or for those who are interested in studying a specific type of climate risk from our classification.

We focus our empirical analysis on climate mentions on Twitter since it is the most prominent content source among all social media sources available on Brandwatch’s platform. We obtain the daily Twitter mention volume (MV) of each query over the analysis period (between July 2010 and June 2022). We winsorize the raw mentions series at the 5 % level (2.5 % in each tail). Finally, we transform each winsorized mention volume (WMV) series into percentage by taking the difference in logs. The result is a set of daily Twitter mention volume indexes (MVIs) defined as

$$MVI^{CLIMATE} = \Delta \log(WMV)^{CLIMATE}, \quad (1)$$

where *CLIMATE* is a generic term that represents one climate classification, i.e., one sub-category, in our CML. Column (6) in Table 1 summarizes the descriptive statistics of our climate MVIs. We make our climate MVIs freely available for download on the data repository Mendeley Data.⁶ Finally, we extract the innovations series of each $MVI^{CLIMATE}$, denoted by $I^{CLIMATE}$, as residuals from an autoregressive model of order 1 (AR1). The resulting series act as good proxies for

⁶ The MVIs are available for download from the following link: <https://data.mendeley.com/datasets/j6mmn4jdct/1>. Please cite this dataset as: Fahmy, H. (2024), “Empty Pledges and Powerless Conventions: Daily Climate Attention Mention Volume Indexes (MVIs) Data from Twitter,” Mendeley Data, V1, DOI: 10.17632/j6mmn4jdct.1

physical and transition climate risks. Table 2 documents the cross-correlations among the previous risk indexes. We do not report any significant pairwise correlation among the series. This implies that our climate risk proxies are distinct. Fig. 2 plots all our daily climate risk indexes.

2.3. Performance of our climate risk measures

Although the literature on quantifying and measuring climate risks is in its early stage of development, few studies have produced some interesting measures. We find that, at the monthly frequency, our MVIs correlate well with these measures. For instance, Gavriilidis (2021) constructs a Climate Policy Uncertainty (CPU) index by searching the content of eight leading U.S. newspapers for climate change terms related to policy uncertainty.⁷ The search query used in constructing the CPU includes most of the carbon POLICY terms in our CML. It is no surprise, therefore, to find high correlation between the CPU index and our carbon POLICY MVI. The correlation coefficient between the two series is 0.66. Fig. 3 plots the two series (at the monthly frequency) between July 2010 and December 2021. When we use this month’s AR1 innovation in our climate POLICY MVI, denoted by I^{POLICY} in the text, to predict this month’s percentage change (first difference in logs) in climate policy uncertainty, we find a positive and significant relation at the 5 % level (t -value = 2.02). An increase in our I^{POLICY} index by 2.6 % predicts a one standard-deviation (approximately 93 points of the CPU or 6 % of the percentage change in CPU) increase in contemporaneous policy uncertainty. This statistically significant relation suggests that shocks to U.S. public attention to mentions related to climate policy have an immediate effect on policy uncertainty at the monthly frequency.

Another measure related to our climate MVIs is Engle et al. (2020)’s monthly climate change news index from January 1984 to June 2017. To construct this index, the authors use unigrams and bigrams climate tokens to perform textual analysis on the climate news content of the WSJ. They take the AR1 innovation in this index as a proxy for aggregate climate risk. Although the authors only provide an illustration of their vocabulary list in the form of a word cloud (and not an extensive list), we find that most of the unigrams and bigrams terms in the word cloud are included in our CML. When we regress this month’s percentage change in our aggregate MVI, which is the MVI of all physical and regulatory terms in our CML, on this month’s AR1 innovation in the WSJ climate index, we find a highly statistically significant positive relation (t -value = 3.14). An increase in this month’s climate news risk, measured as AR1 innovation in WSJ climate index, by one standard-deviation causes a contemporaneous increase in attention to climate change, measured as percentage change in physical and regulatory climate MVIs, by 2.3 %. In other words, climate news shocks contemporaneously predict U.S. household attention to climate change. Fig. 4 plots both time series between July 2010 and June 2017.

3. Data and study variables

We measure different types of climate risks as innovations, i.e., shocks, to measures of attention to climate mentions. Since we mostly use U.S. financial data, we confine the geographic search for climate mentions to the U.S. The data analytic vendor Brandwatch provides access to several social media content sources. The social media platforms used in this study include Twitter, YouTube, LinkedIn, Reddit, Tumblr, Flickr, and QQ. It is worth noting that Twitter is responsible for almost 96 % of all social media content and is, therefore, considered the main social media source. All empirical analyses are performed using Twitter mention volume. The aggregate mention volume of all social

⁷ The search query and the CPU index are available on the Economic Policy Uncertainty website: www.policyuncertainty.com

Table 2
Correlations (Panel A) and summary statistics (Panel B) of the daily physical and transition climate risk indexes between July 11, 2010, and June 26, 2022.

Panel A: Cross-correlations										
	ρ^{CARBON}	ρ^{WEATHER}	ρ^{OCEANS}	ρ^{SNOW}	ρ^{SOCIETY}	ρ^{ECOSYS}	$\rho^{\text{CONVENTIONS}}$	ρ^{POLICY}	ρ^{PLEDGES}	$\rho^{\text{SOLUTIONS}}$
ρ^{CARBON}	1									
ρ^{WEATHER}	0.07	1								
ρ^{OCEANS}	0.06	0.18	1							
ρ^{SNOW}	0.02	0.02	0.06	1						
ρ^{SOCIETY}	0.03	0.04	0.04	0.02	1					
ρ^{ECOSYS}	0.04	0.06	0.05	0.05	0.05	1				
$\rho^{\text{CONVENTIONS}}$	0.08	0.11	0.10	0.04	0.05	0.05	1			
ρ^{POLICY}	0.09	0.06	0.07	0.01	0.09	0.08	0.15	1		
ρ^{PLEDGES}	0.07	0.09	0.07	0.01	0.10	0.04	0.12	0.17	1	
$\rho^{\text{SOLUTIONS}}$	0.05	0.04	0.05	0.05	0.06	0.03	0.07	0.07	0.15	1

Panel B: Summary statistics				
	Mean	Std. Dev.	Max	Min
ρ^{CARBON}	0.0	0.33	1.67	−1.16
ρ^{WEATHER}	0.0	0.28	1.44	−1.78
ρ^{OCEANS}	0.0	0.43	2.06	−1.42
ρ^{SNOW}	0.0	0.54	2.56	−1.69
ρ^{SOCIETY}	0.0	0.43	2.12	−1.27
ρ^{ECOSYS}	0.0	0.43	1.69	−1.45
$\rho^{\text{CONVENTIONS}}$	0.0	0.20	1.06	−0.92
ρ^{POLICY}	0.0	0.17	0.86	−0.65
ρ^{PLEDGES}	0.0	0.22	1.10	−0.84
$\rho^{\text{SOLUTIONS}}$	0.0	0.37	1.61	−1.52

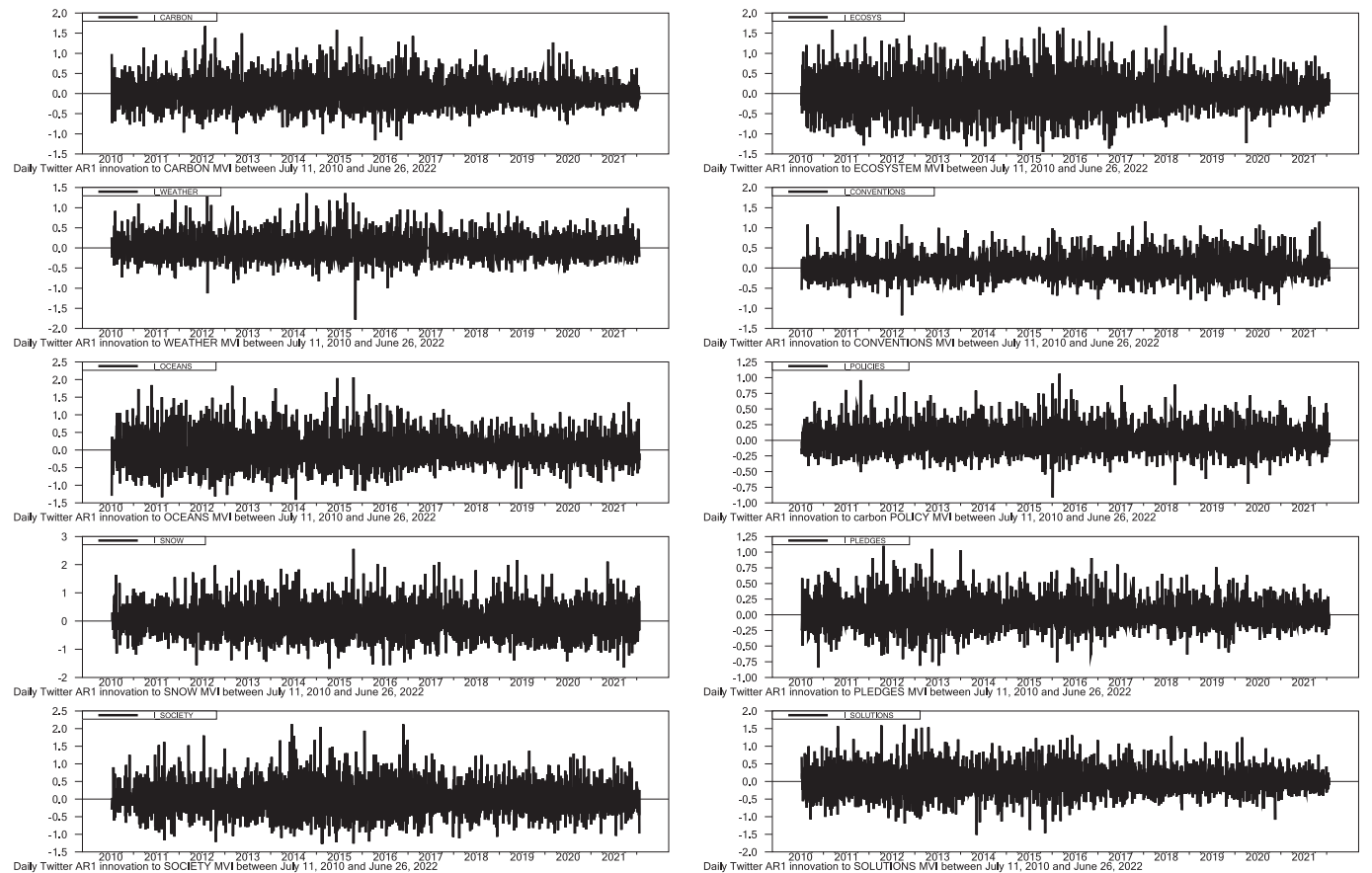


Fig. 2. Daily AR1 innovations, i.e., shocks to Twitter climate mention volume indexes (MVIs) as proxies for physical and transition climate risks between July 11, 2010, and June 26, 2022.

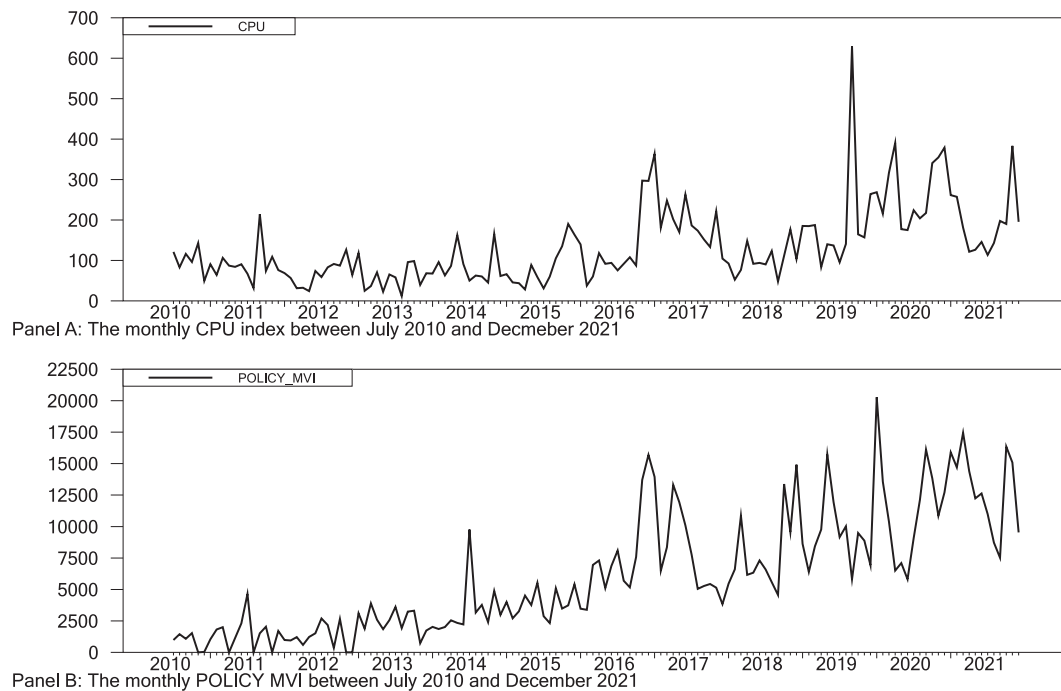


Fig. 3. Gavriilidis (2021)' monthly Climate Policy Uncertainty (CPU) index (Panel A) and our monthly carbon POLICY mention volume index (MVI) (Panel B) over the period between July 2010 and December 2021.

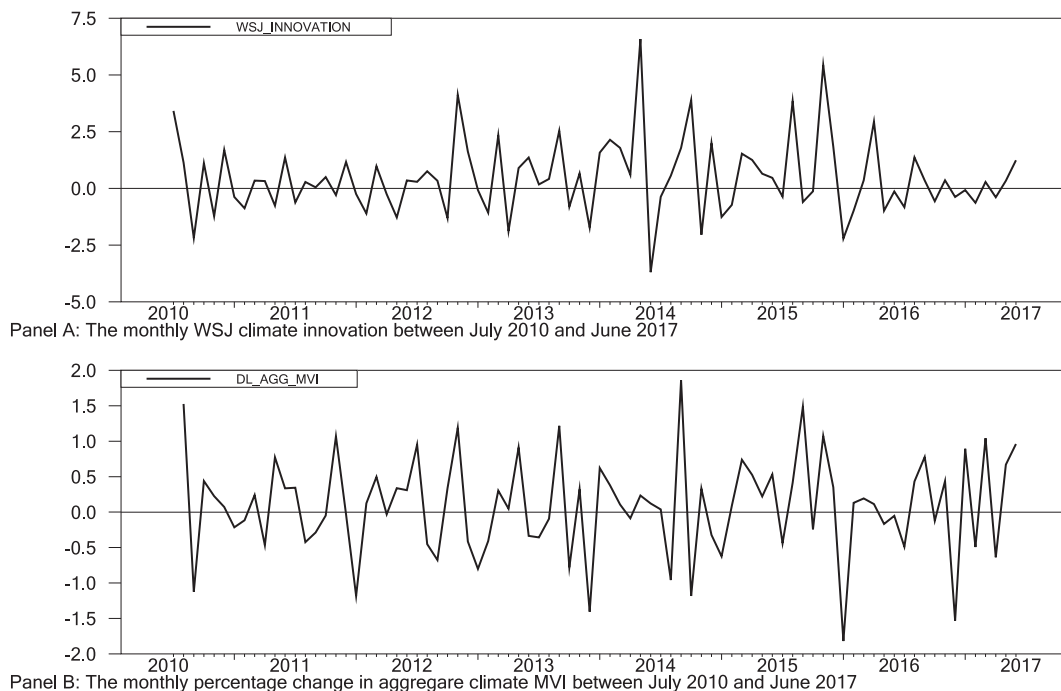


Fig. 4. Engle et al. (2020)'s monthly ARI innovation in the WSJ climate index (Panel A) and our monthly percentage change (first difference of logs) of the aggregate (physical and regulatory) climate mention volume index (MVI) (Panel B) over the period between July 2010 and June 2017.

media content sources is used for robustness checks. The content sources on Brandwatch's platform go back as far as July 11, 2010. Therefore, our full sample analysis period is between July 11, 2010, and June 26, 2022.

We run the macro empirical analysis on a wide range of asset classes including clean energy ETFs, highly liquid ETFs, and mutual fund flows. We measure the aggregate performance of clean energy assets via the

WilderHill Clean Energy (ECO) index and its underlying ETFs. The ECO index is commonly used in the literature (e.g., Engle et al., 2020; Fahmy, 2022) as a representative of the clean energy market as it focuses on companies listed on the NASDAQ and the NYSE that benefit from the shift toward cleaner energy use and zero carbon renewables. The ECO index includes 71 constituents that are mostly U.S. (52 members) and

Canadian (8 members) companies. It has two underlying ETFs: namely, the Invesco WilderHill Clean Energy ETF (PBW) and the Invesco Global Clean Energy ETF (PBD). Both PBW and PBD ETFs include stocks of publicly traded U.S. companies that are engaged in the business of advancement of clean energy and conservation. As opposed to PBW, PBD offers a more global exposure to clean energy investment.⁸ Daily closing prices of the ECO index and its two ETFs are sourced from DataStream over the analysis period. Equity ETF data is also sourced from DataStream. We examine four highly liquid ETFs; namely, SPDR S&P 500 (NYSEARCA: SPY), PowerShares QQQ Trust (NASDAQ: QQQQ), Russel 1000 Index ETF (NYSEARCA: IWB), and Russell 2000 Index ETF (NYSEARCA: IWM).

We obtain daily mutual fund data from Informa. The Emerging Portfolio Fund Research (EPFR) data set sources directly net asset value (NAV) files from fund managers, fund administrators, and custodians for mutual funds and ETFs that cover over 52 trillion in fund flows. Following several studies that have previously employed this data set (Da et al., 2015; Edelen & Warner, 2002 and Greene & Hodges, 2002), we focus on the daily flow of the equity (EQ) group and the intermediate treasury bonds (BOND) group. We use the EQ (and) BOND fund flows data as our last set of test assets.

Our micro empirical analysis focuses on the S&P500 firms over the analysis period (July 2010 – June 2022). To assess the performance of green and brown stocks amid unexpected shocks in our climate MVIs, we require a measure that defines the firm's greenness characteristic. We follow the literature (Ardia et al., 2022; Drempetic, Klein, & Zwergel, 2020; Ilhan et al., 2021) and use greenhouse gas (GHG) emissions intensity, which is defined as the number of tonnes of CO₂-equivalent GHG emissions necessary for a firm to generate \$1 million in revenue, as a measure of a firm's greenness. We construct this measure by scaling the firm's total GHG emissions by its total revenue. We obtain the carbon-dioxide-equivalent (CO₂-equivalent) GHG emissions data from Refinitiv. We define the total GHG emissions variable as the sum of Scope 1, 2, and 3 emissions.⁹ We obtain the firms' annual revenue figures from Compustat.

We use several control variables that are known to predict stocks and ETFs' returns. It is well documented in the energy economics literature that the stock prices of clean energy companies are directly connected to the price of crude oil and the stock prices of related clean technology companies (e.g., Fahmy, 2022; Henriques & Sadosky, 2008; Kumar, Managi, & Matsuda, 2012). To control for the impact of these variables on clean energy ETFs, we use the crude oil spot price index for the West Texas Intermediate (WTI) as a proxy for oil prices and the NYSE Arca Technology Index (PSE) as a proxy for technology prices. The PSE index is a price weighted index of 100 multi-industry technology companies.¹⁰ The wide scope of the PSE makes it a good representative of the stock prices of technology-related companies. We also control for market volatility and policy uncertainty using the Chicago Board Options Exchange (CBOE) daily volatility index (VIX) and the U.S. Economic Policy Uncertainty (EPU) daily index respectively. The VIX index captures the extent of implied volatility in options markets of the S&P 500 over the next 30 days period. It is broadly recognized as a measure of investor fear in financial markets. We include this index as a control variable in most specifications. The EPU index, which is constructed by Baker,

Bloom, and Davis (2015), is a news-based measure of economic policy uncertainty that is commonly used to control for the impact of economic policy on asset prices.¹¹ Daily closing spot prices of the WTI are sourced from the U.S. Energy Information Administration.¹² All other indexes are sourced from DataStream. In addition to the previous control variables, we include conventional control variables that are known to predict returns in finance: namely, we include the excess market return, MKT, the high-minus-low (HML) factor, and the small-minus-big (SMB) factor of Fama and French (1992); the robust-minus-weak (RMW) and the conservative-minus-aggressive (CMA) factor of Fama and French (2015), and the momentum (MOM) factor of Carhart (1997).¹³

In the cross-section regressions in Section 5, we include, in addition to the previous control variables, Henry Hub natural gas spot price (NG), Mont Belvieu, Texas, propane price (PROP), and the TED spread (TED), which is calculated as the spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. The three variables are sourced from the Federal Reserve Bank of St. Louis (FRED). More details about the data sources are found in the Internet Appendix.

4. Climate risks and aggregate market level returns

In this section, we test whether our climate risk indexes are able to predict asset prices at the aggregate market level or are sources of noise trading. Unsophisticated retail investors, who suffer from behavioral biases, make decisions based on personal judgement rather than rigorous financial analysis. In the presence of limits to arbitrage, this behavior causes asset prices to fluctuate away from fundamentals. Asset prices could be temporarily high following high swings in attention amid physical or regulatory climate events but later become low when the burst in attention fades away. We investigate this price reversal behavior using several test assets.

To reveal the existence of price reversal following changes in climate risks, measured as shocks to public attention, we run the following regression on each asset class i :

$$r_{t+k}^i = \psi_0 + \psi_1 I_t^{CLIMATE} + \Psi' CONTROL_t^i + \varepsilon_{t+k}^i, \quad (2)$$

where r_{t+k}^i is the return on asset class i on day $t+k$, where $k = 0, 1, \dots, 5$, ε_{t+k}^i is an error term on day $t+k$, Ψ is a parameter vector, $CONTROL_t^i$ is a vector of controls that includes five lags of asset i 's returns, MKT, HML, SMB, CMA, RMW, MOM, and percentage change (first difference of logs) in EPU, VIX, WTI, and PSE. The variable $I_t^{CLIMATE}$ is a generic climate risk index, which is constructed as innovations, i.e., AR1 residuals series, to the percentage change (first difference of logs) of CLIMATE MVI on day t . The coefficient of interest is ψ_1 .

4.1. Climate risks and clean energy returns

Our first test asset is the class of clean energy ETFs. Table 3 documents how our physical (Panel A) and transition (Panel B) climate risk indexes predict the daily returns of the ECO index, which represents the clean energy market at the aggregate market level. The climate risk indexes are those obtained from Twitter MVIs.¹⁴ For robustness, we also run the regressions in Eq. (2) on ECO's underlying ETFs; namely, on PBD and PBW ETFs' returns. In each case, we run the regressions before the

⁸ Source: <https://www.ishares.com>; <https://www.invesco.com>.

⁹ According to the GHG Protocol Corporate Standard, Scope 1 emissions are direct emissions from owned or controlled sources. Scope 2 emissions are indirect emissions from the generation of purchased energy. Scope 3 emission are all indirect emissions (not included in Scope 2) that occur in a firm's value chain. These are reported in tonnes of CO₂-equivalents.

¹⁰ The WTI index is commonly used in the literature as a benchmark for oil price. For robustness, however, we experiment with the Brent crude oil price index as a proxy for oil price and document similar findings. We choose not to report these results for space limitation.

¹¹ The EPU index is available at <https://www.policyuncertainty.com>.

¹² Source: <https://www.eia.gov>.

¹³ This data is available from Keneth French's website. See the Internet Appendix for the exact link.

¹⁴ In this empirical analysis and throughout all empirical analyses in this paper, we use climate risk indexes from Twitter MVIs. For robustness, we repeat all analyses using the aggregate search volume of all social media content sources and document similar results. We do not report these results to conserve space.

Table 3

Climate risks and clean energy ETF returns.

Panel A: Physical climate risks and clean energy assets					
CARBON risk					
	ECO returns		PBD ETF returns		PBW ETF returns
Column	(1)		(1)		(1)
Period	r_t^{ECO}		r_t^{PBD}		r_t^{PBW}
	B	A	B	A	B
I^{CARBON}	−0.0014** (0.0006)	0.002*** (0.0009)	−0.0096* (0.0005)	0.0015** (0.0007)	−0.0013* (0.0007)
Control	Yes	Yes	Yes	Yes	Yes
N	1401	1603	1401	1603	1401
$\bar{R}^2$	0.74	0.71	0.77	0.62	0.72
WEATHER risk					
	ECO returns		PBD ETF returns		PBW ETF returns
Column	(1)		(1)		(1)
Period	r_t^{ECO}		r_t^{PBD}		r_t^{PBW}
	B	A	B	A	B
$I^{WEATHER}$	−0.0014* (0.0008)	0.0026** (0.0012)	−0.0012** (0.0006)	0.0013* (0.0007)	−0.0011* (0.0006)
Control	Yes	Yes	Yes	Yes	Yes
N	1401	1603	1401	1603	1401
$\bar{R}^2$	0.75	0.71	0.77	0.62	0.71
SNOW risk					
	ECO returns		PBD ETF returns		PBW ETF returns
Column	(4)		(4)		(4)
Period	r_{t+3}^{ECO}		r_{t+3}^{PBD}		r_t^{PBW}
	B	A	B	A	B
I^{SNOW}	−0.0016*** (0.0005)		−0.0006** (0.0003)		−0.0016*** (0.0005)
Control	Yes		Yes		Yes
N	1398		1398		1398
$\bar{R}^2$	0.74		0.76		0.71
SOCIETY risk					
	ECO returns		PBD ETF returns		PBW ETF returns
Column	(5)		(5)		(5)
Period	r_{t+4}^{ECO}		r_{t+4}^{PBD}		r_{t+4}^{PBW}
	B	A	B	A	B
$I^{SOCIETY}$	−0.0009* (0.0005)		−0.0007** (0.0003)		−0.0009* (0.0005)
Control	Yes		Yes		Yes
N	1397		1397		1397
$\bar{R}^2$	0.74		0.77		0.70

Panel B: Transition climate risks and clean energy assets

PLEDGES risk					
	ECO returns		PBD ETF returns		PBW ETF returns
Column	(1)		(1)		(1)
Period	r_t^{ECO}		r_t^{PBD}		r_t^{PBW}
	A	A	A	A	A
$I^{PLEDGES}$	0.0035** (0.0015)	−0.002** (0.001)	0.0021** (0.001)	−0.0022** (0.001)	0.003** (0.0015)
Control	Yes	Yes	Yes	Yes	Yes
N	1603	1603	1603	1603	1603
$\bar{R}^2$	0.70	0.71	0.62	0.62	0.70
CONVENTIONS risk					
	ECO returns		PBD ETF returns		PBW ETF returns
Column	(1)		(2)		(1)
Period	r_t^{ECO}		r_{t+1}^{ECO}		r_t^{PBW}
	F	F	F	F	F

Table 3 (continued)

Panel B: Transition climate risks and clean energy assets				
	ECO returns		PBD ETF returns	
Column	(1)		(1)	
Period	r_{t+4}^{ECO}		r_{t+4}^{PBD}	
	A	F	A	F
$I^{CONVENTIONS}$	0.0014* (0.0008)	−0.0013* (0.0007)	0.0016** (0.0008)	
Control	Yes	Yes	Yes	Yes
N	3003	3002	3002	3003
$\bar{R}^2$	0.72	0.72	0.72	0.70
POLICY risk				
	ECO returns		PBD ETF returns	
Column	(5)		(5)	
Period	r_{t+4}^{ECO}		r_{t+4}^{PBD}	
	A	F	A	F
I^{POLICY}	0.0026* (0.0015)	0.002** (0.0009)	0.002** (0.001)	
Control	Yes	Yes	Yes	Yes
N	1603	2999	1603	1603
$\bar{R}^2$	0.71	0.71	0.69	
SOLUTIONS risk				
	ECO returns		PBD ETF returns	
Column	(1)		(1)	
Period	r_t^{ECO}		r_t^{PBD}	
	F	F	F	F
$I^{SOLUTIONS}$	0.0013*** (0.0005)	0.001** (0.0004)	0.0013** (0.0005)	
Control	Yes	Yes	Yes	Yes
N	3003	3003	3003	3003
$\bar{R}^2$	0.72	0.68	0.70	

This table documents how our daily physical (Panel A) and transition (Panel B) climate risk indexes, measured as innovations, i.e., shocks to attention to climate mentions on Twitter, predict the daily returns on clean energy ETFs at the aggregate market level. The dependent variables are contemporaneous returns (column (1)) and future returns (columns (2)–(6)) of the WilderHill Clean Energy (ECO) index, Invesco Global Clean Energy (PBD) ETF, and Invesco WilderHill Clean Energy (PBW) ETF. The control variables are the five lags of the returns, MKT, SMB, HML, CMA, RMW, MOM, the daily percentage change (first difference of the logs) in the NYSE Arca Technology Index (PSE), the daily percentage change (first difference of the logs) in the crude oil spot index for the West Texas Intermediate (WTI), the daily percentage change (first difference of the logs) in the CBOE volatility index (VIX), and the daily percentage change (first difference of the logs) in the economic policy uncertainty (EPU) index. In each case, we run the regressions in Eq. (2) before (B) the Paris Agreement (between July 11, 2010, and December 31, 2015), after (A) the Paris Agreement (between January 1, 2016, and June 26, 2022), and on the full (F) sample. We only report the significant risk coefficients. Newey and West (1987, 1994) standard errors of the estimators are reported in parentheses beneath the coefficients. ***, **, and * denote significance at the 1%, 5 %, and 10% levels respectively. N is the number of usable observations and $\bar{R}^2$ is the adjusted coefficient of determination.

PA, after the PA, and on the entire analysis period (between July 11, 2010, and June 26, 2022). In all regressions, we control for five lags of returns, clean technology stock prices (PSE index), oil prices (WTI index), economic policy uncertainty (EPU index), market uncertainty (VIX index), and standard return factors (MKT, HML, SMB, CMA, RMW, and MOM). To conserve space, we only report the significant risk coefficients in all regressions.

The results in Panel A in Table 3 show a negative and significant relation between CARBON and WEATHER risk indexes, which are denoted by I^{CARBON} and $I^{WEATHER}$ respectively, and clean energy ETFs' returns in the period before the PA. During this period, a contemporaneous increase in I^{CARBON} by one-standard deviation is associated with a

contemporaneous decrease in ECO ETF's returns by 4.6 basis points.¹⁵ In the period after the PA, the relation is positive and significant (at the 5 % level). An increase in I^{CARBON} today by one-standard deviation is associated with a contemporaneous (i.e., day $k = 0$) increase in ECO returns by 6.6 basis points. The negative and positive responses to CARBON risk before and after the PA respectively are robust across all clean energy ETFs (see the results for PBD and PBW in Panel A in Table 3). We also find the response of clean energy ETFs to WEATHER risk to be negative in the period before the PA and positive after the PA. A contemporaneous increase in $I^{WEATHER}$ by one-standard deviation is associated with a negative and significant (at the 5 % level) contemporaneous decrease in ECO returns by 11.2 basis points in the period before the PA whereas the impact of the same shock on ECO returns is positive (8.4 increase in basis points) and significant (at the 5 % level) after the PA. These results are robust for PBD and PBW as shown from Panel A in Table 3.

The negative and positive responses of clean energy ETFs to CARBON and WEATHER risks before and after the PA respectively suggest a change in investors' preference after the PA in favor of clean energy assets. This evidence points to a rise in investors' awareness of physical climate risks during this period. The peak analysis of our physical climate MVIs, which is documented in the Internet Appendix, confirms this conjecture. The analysis shows no significant spikes in attention to physical climate events during the period before the PA. All the peaks of our physical climate MVIs correspond to events that have occurred after the PA. The analysis of climate mentions on Twitter around the peaks of our CARBON and WEATHER MVIs reveal that these mentions are driven by climate denial statement from politicians and government officials. Further sentiment analysis of these mentions show that they carry a prominent negative sentiment in the post-PA period. This negative sentiment prompts conscious investors to prefer holding clean energy assets causing their returns to rise. This result is consistent with Fahmy (2022), who documents a rise in investors awareness of climate risks after the PA.¹⁶

As for the remaining physical climate risks in our classification, we find a negative and significant (at the 1 % and 10 % levels respectively) relation between SNOW and SOCIETY risks and clean energy ETFs' returns in the period before the PA. An increase in I^{SNOW} by one-standard deviation today is associated with a decrease in ECO returns on the third day by 8.6 basis points in the period before the PA. This result is robust for PBW and PBD as shown from Panel A in Table 3. An increase in $I^{SOCIETY}$ by one-standard deviation today is associated with a decrease in ECO, PBD, and PBW returns on the fourth day, i.e., on day $k = 4$, by 3.87, 3.01, and 3.87 basis points respectively in the period before the PA. OCEAN and ECOSYSTEM risks have no impact on clean returns.

The previous results share the common observation that clean energy ETFs' returns respond negatively to physical climate risks in the period before the PA and positively to CARBON and WEATHER risks after the PA. These results, along with our peak and sentiment analyses, confirm the absence of climate awareness in the period before the PA and the noticeable change in investors' behavior toward clean energy assets especially amid unexpected concerns about carbon emissions and weather events on social media after the PA.

When examining the predictions of our transition climate risk indexes, we observe return reversal in all clean energy ETFs' returns following spikes in attention to climate PLEDGES and CONVENTIONS. When $k = 0$, the positive and significant (at the 5 % level) coefficient on the $I^{PLEDGES}$ index confirms the existence of a positive contemporaneous relationship between innovations/shocks to attention to climate PLEDGES and the ECO returns. As we document in Panel B in Table 3, a

standard-deviation increase in $I^{PLEDGES}$ today predicts a contemporaneous increase in the ECO returns by 7.7 basis points. More than half of this increase, however, is reversed on the second day, i.e., when $k = 2$, as the returns on the ECO index drop by 4.4 basis points. This return reversal is also observed in the PBD and PBW ETFs. One standard-deviation increase in $I^{PLEDGES}$ today causes a contemporaneous increase in PBD and PBW returns by 4.6 and 6.6 basis points respectively. This impact is totally reversed on the fourth day in the case of PBD and partially reversed (4.4 basis points drop) on the second day in the case of PBW. The previous analysis shows that climate pledges lead to noise trading in the clean energy market. Investors, who feel good after a rise in attention following a climate pledge or a government promise to fight climate change, rush to hold clean energy ETFs causing their prices to rise. Our sentiment analysis (see Column 2 in Table 1) shows that climate pledges carry a positive sentiment. This explains the initial increase in clean energy returns following a rise in attention to climate pledges. This increase, however, is temporarily as it is reversed on the following two or four days. A plausible explanation of this price reversal is that investors believe that climate pledges and promises are not backed up by government actions.

We also find evidence of noise trading following spikes in attention to climate CONVENTIONS. Panel B in Table 4 documents the predictions of $I^{CONVENTIONS}$ using the full analysis sample. An increase in $I^{CONVENTIONS}$ by one-standard deviation today is associated with a significant (at the 5 % level) increase in the ECO returns by 2.8 basis points. This increase in returns, however, is totally reversed on the first day. Our sentiment analysis demonstrates that the sentiment corresponding to climate CONVENTIONS is predominantly negative. Thus, a plausible explanation of the previous return reversal result, which is robust across all clean energy ETFs except for PBD, is that investors are not confident in the ability of climate summits and conventions to deliver regulatory mandates that are powerful enough to combat climate change.

Finally, we find that clean energy ETFs' returns respond positively to carbon POLICY risk after the PA and over the full sample period as shown from Panel B in Table 3. This positive response suggests that carbon risk is priced, i.e., positively reflected, in clean energy returns. As for climate SOLUTIONS, as one would expect, the response of clean energy ETFs' returns to unexpected shocks in attention to clean energy solutions is instantaneously positive over the entire analysis.

4.2. Climate risks and highly liquid equity returns

Our second test asset is the class of highly liquid equity ETFs. Table 4 documents how our physical (Panel A) and transition (Panel B) risk indexes predict the daily returns on four highly liquid equity ETFs (SPY, QQQ, IWB, and IWM). For each risk type, we run the regressions in Eq. (2) before the PA, after the PA, and on the entire sample. According to the results in Panel A in Table 4, there is no evidence to support return reversal following spikes in attention to physical climate risks across all highly liquid equity ETFs. All physical climate risks (except OCEANS and SOCIETY risks) can predict equity ETFs' returns in the period before the PA. We find a positive and significant (at the 5 % and 1 % levels) relation between our CARBON, WEATHER, SNOW, and ECOSYSTEM risk indexes, which are captured by I^{CARBON} , $I^{WEATHER}$, I^{SNOW} , and $I^{ECOSYSTEM}$ respectively, and all future equity ETFs during this period.

A contemporaneous increase in attention to carbon emissions and greenhouse gases by one standard deviation is always associated with a contemporaneous increase in SPY returns by 0.4 basis points. The fifth day also carries an increase in SPY returns by 0.5 basis points. Impacts of similar magnitude on IWB and IWM ETFs' returns are also documented in the period before the PA. The positive response of equity ETFs' returns to CARBON risk and the negative response of clean energy ETFs' returns that we documented in the previous section (see Panel A in Table 3) provide evidence, albeit from a macro perspective, that is consistent with some recent cross-sectional analyses documenting that carbon-

¹⁵ Standard deviations of our risk indexes are documented in Table 2.

¹⁶ It is worth noting that the negative and positive responses of clean energy prices to CARBON and WEATHER risks before and after the PA is not a sign of price reversal since the changes in sign occur over two different periods and not within the same period.

Table 4
Climate risks and highly liquid equity ETF returns.

Panel A: Physical climate risks and high liquid ETFs' returns								
CARBON risk								
	SPY ETF returns				IWB ETF returns	IWM ETF returns		
Column	(1)	(6)			(1)	(1)		
	r_t^{SPY}	r_{t+5}^{SPY}			r_t^{IWB}	r_t^{IWM}		
Period	B	B			B	B		
J^{CARBON}	0.00012** (0.0006)	0.00015* (0.0008)			0.00014** (0.00006)	0.0003*** (0.00009)		
Control	Yes	Yes			Yes	Yes		
N	1401	1396			1401	1401		
$\bar{R}^2$	0.99	0.99			0.99	0.99		
WEATHER risk								
	SPY ETF returns		QQQ ETF returns		IWB ETF returns			
Column	(1)		(1)		(2)			
	r_t^{SPY}		r_t^{QQQ}		r_{t+1}^{IWB}			
Period	B		B		B			
$J^{WEATHER}$	0.00017** (0.00008)		0.0005** (0.0002)		0.00016** (0.00007)			
Control	Yes		Yes		Yes			
Ns	1401		1401		1400			
$\bar{R}^2$	0.99		0.92		0.99			
SNOW risk								
	SPY ETF returns				IWM ETF returns			
Column	(1)				(1)			
	r_t^{SPY}				r_t^{IWM}			
Period	B				B			
J^{SNOW}	0.00011** (0.00004)				0.00012** (0.00006)			
Control	Yes				Yes			
N	1401				1401			
$\bar{R}^2$	0.99				0.98			
ECOSYSTEM risk								
	SPY ETF returns		QQQ ETF returns		IWM ETF returns			
Column	(1)		(1)		(3)			
	r_t^{SPY}		r_t^{QQQ}		r_{t+2}^{IWM}			
Period	B		B		B			
J^{ECOSYS}	0.00013** (0.0005)		0.0002** (0.0001)		0.0002*** (0.00007)			
Control	Yes		Yes		Yes			
N	1401		1401		1399			
$\bar{R}^2$	0.99		0.93		0.98			
Panel B: Transition climate risks and highly liquid equity ETFs' returns								
PLEDGES risk								
	SPY ETF returns		QQQ ETF returns		IWB ETF returns	IWM ETF returns		
Column	(1)	(3)	(4)	(5)	(1)	(6)	(1)	(2)
	r_t^{SPY}	r_{t+2}^{SPY}	r_{t+3}^{QQQ}	r_{t+4}^{QQQ}	r_t^{IWB}	r_{t+5}^{IWB}	r_t^{IWM}	r_{t+1}^{IWM}
Period	A	A	A	A	A	A	A	A
$J^{PLEDGES}$	0.0002** (0.0001)	−0.0002** (0.0001)	0.0007** (0.0004)	−0.0005** (0.0003)	0.0002** (0.0001)	−0.0001** (0.000)	0.0004** (0.0002)	−0.0004** (0.0002)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1605	1605	1605	1605	1605	1605	1605	1605
$\bar{R}^2$	0.99	0.99	0.95	0.95	0.99	0.99	0.98	0.98
CONVENTIONS risk								
	SPY ETF returns		QQQ ETF returns		IWM ETF returns			
Column	(1)	(6)	(1)	(2)	(1)	(4)		
	r_t^{SPY}	r_{t+5}^{SPY}	r_t^{QQQ}	r_{t+1}^{QQQ}	r_t^{IWM}	r_{t+3}^{IWM}		
Period	B	B	B	B	F	A		
$J^{CONVENTIONS}$	0.0003*** (0.0001)	−0.00012** (0.00007)	0.0004** (0.0002)	−0.0007** (0.0003)	0.00002** (0.00001)	−0.0002** (0.0001)		
Control	Yes	Yes	Yes	Yes	Yes	Yes		
N	1401	1396	1401	1400	3005	3002		
$\bar{R}^2$	0.99	0.99	0.92	0.93	0.98	0.98		

(continued on next page)

Table 4 (continued)

Panel B: Transition climate risks and highly liquid equity ETFs' returns								
POLICY risk	SPY ETF returns		QQQ ETF returns		IWB ETF returns		IWM ETF returns	
	(6)	(1)	(6)	(6)	(1)	(1)	(1)	(1)
Column	r_{t+5}^{SPY}	r_t^{SPY}	r_{t+5}^{QQQ}	r_t^{QQQ}	r_t^{IWB}	r_t^{IWM}	r_t^{IWM}	r_t^{IWM}
Period	A	F	A	F	F	A	F	F
I^{POLICY}	0.0002** (0.0001)	0.0002** (0.0001)	0.0007** (0.0003)	0.0007** (0.0002)	0.00017** (0.0008)	0.0005** (0.0002)	0.0004** (0.00015)	
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1695	3005	1605	3000	3005	1605	3005	
$\bar{R}^2$	0.99	0.99	0.95	0.94	0.93	0.98	0.98	

This table documents how our daily physical (Panel A) and transition (Panel B) climate risk indexes, measured as innovations, i.e., shocks to attention to climate mentions on Twitter, predict the daily returns on four highly liquid ETFs; namely, S&P500 ETF (SPY), PowerShares QQQ trust (QQQ), Russel 1000 Index ETF (IWB), and Russel 2000 Index (IWM). The dependent variables are contemporaneous ETFs' returns (column (1)) and future returns (columns (2)–(6)). The control variables are the five lags of the returns, MKT, SMB, HML, CMA, RMW, MOM, the daily percentage change (first difference of the logs) in the CBOE volatility index (VIX), and the daily percentage change (first difference of the logs) in the economic policy uncertainty (EPU) index. In each case, we run the regressions in Eq. (2) before (B) the Paris Agreement (between July 11, 2010, and December 31, 2015), after (A) the Paris Agreement (between January 1, 2016, and June 26, 2022), and on the full (F) sample. We only report the significant risk coefficients. Newey and West (1987, 1994) standard errors of the estimators are reported in parentheses beneath the coefficients.

***, **, and * denote significance at the 1 %, 5 %, and 10 % levels respectively. N is the number of usable observations and $\bar{R}^2$ is the adjusted coefficient of determination.

intensive stocks, which are among this asset class, show higher returns than low-emission stocks (e.g., Bolton & Kacperczyk, 2021).

A contemporaneous increase in $I^{WEATHER}$ by one-standard deviation is associated with a contemporaneous increase in SPY and QQQ ETFs' returns by 0.5 and 1.4 basis points respectively, and an increase in IWB ETF's returns by 0.4 basis points, the next day, i.e., on day $k = 1$. A contemporaneous increase in I^{SNOW} is associated with a contemporaneous increase in SPY and IWM ETFs' returns by 0.6 basis points approximately (at the 5 % level). ECOSYSTEM risk also has a positive and significant impact on highly liquid ETF returns on days $K = 0$ and $K = 2$ during the pre-PA period.

The previous results suggest that investors prefer to invest in highly liquid equity ETFs amid physical climate events during the period before the PA. The peak analysis of our physical climate MVIs, which is documented in detail in the Internet Appendix, shows no significant spikes in attention to physical climate events during this period. Together the positive response of highly liquid equity ETFs' returns and the negative response of clean energy ETFs' returns that we documented in the previous section confirm the lack of awareness of the impacts of climate change before the PA.

We document the impacts of shocks to attention to transition climate aspects on equity ETFs' returns in Panel B in Table 4. Contrary to physical risks, we find that certain transition risks: namely, climate PLEDGES and CONVENTIONS, cause mispricing and noise trading in equity markets. A contemporaneous increase in attention to mentions related to climate promises or to climate conventions on social media is always associated with a contemporaneous increase in SPY, IWB, and IWM ETFs' returns. This increase is, however, partially or totally reversed during the next five days. We deduce, therefore, that climate PLEDGES and CONVENTIONS risks are sources of noise trading and mispricing in equity markets. This new evidence contributes to the climate finance literature that studies the impact of climate risk on asset prices.

5. Climate risks and the performance of green versus brown stocks

We analyze the performance of green versus brown stocks in the cross-section of equity firms in the S&P500. We focus on this index because surveys of GHG emissions typically target these firms. To identify green versus brown stocks, we retrieve Scope 1, 2, and 3 emissions (in tonnes of carbon-dioxide-equivalents) disclosed by the S&P500 firms from the Asset4/Refinitiv database. We focus on total

GHG emissions, which is the sum of Scope 1, 2, and 3. We scale the total GHG emissions by the firm's annual revenue to account for the economic value resulting from a firm's GHG emissions. The resulting variable is referred to as GHG emissions intensity (Ardia et al., 2022; Drempetic et al., 2020; Ilhan et al., 2021). Whether a firm is classified as green or brown depends on its position within the distribution of firms by their emission intensities at any point in time. GHG emissions are typically reported with a one-year delay. We account for this by shifting the GHG emissions intensity variable by 12 months in our analysis as in Ilhan et al. (2021) and Ardia et al. (2022).

We construct portfolios of green, brown, and green minus brown (GMB) stocks as follows. Each day in the sample, we divide stocks into green and brown. Green stocks are firms with a GHG emissions intensity variable in the lowest quartile of all firms' values available on that day whereas brown stocks are those in the highest quartile. For each day, we build equally weighted portfolios for these groups of firms. To construct the GMB portfolio, we long the green stocks and short the brown stocks.

We test the predictive power of our climate risk indexes on the performance of green versus brown portfolios by running the following regression:

$$r_{t+k}^i = \gamma_0 + \gamma_1 I_t^{CLIMATE} + \Gamma' CONTROL_t^i + \varepsilon_{t+k}^i, \quad (3)$$

where r_{t+k}^i is the return on portfolio $i \in \{\text{GMB, Green, Brown}\}$ on day $t + k$, where $k = 0, 1, \dots, 5$, ε_{t+k}^i is an error term on day $t + k$, Γ is a parameter vector, $CONTROL_t^i$ is a vector of controls that includes five lags of portfolio i 's returns, MKT, HML, SMB, CMA, RMW, MOM, and percentage change (first difference of logs) in EPU, VIX, WTI, NG, PROP, and TED. The variable $I_t^{CLIMATE}$ is defined as before. The coefficient of interest is γ_1 . We run the regressions before and after the PA, and over the entire sample. We only report the significant coefficient γ_1 in Table 5.

The results in Panel A in Table 5 show that brown stocks outperform green stocks amid unexpected shocks in attention to carbon and GHG emissions on social media in the period after the PA. An unexpected increase in attention to carbon emissions today by one unit causes an increase in brown firms' stock returns by 10 basis and a decrease in green firms' stock returns by 11 basis points on the fifth day. The return on the GMB portfolio also drop by 19 basis points on the fifth day. This result supports the carbon risk premium hypothesis and contributes to an emerging strand of literature on this topic, which has so far produced mixed results. More specifically, Pàstor et al. (2021)'s model supports the carbon risk premium hypothesis as it predicts that green stocks have

Table 5

This table documents how our daily physical (Panel A) and transition (Panel B) climate risk indexes, measured as innovations, i.e., shocks to attention to climate mentions on Twitter, predict the daily returns on green, brown, and GMB portfolios. The dependent variables are contemporaneous portfolio return (column (1)) and future returns (columns (2)–(6)). The control variables are the five lags of the returns, MKT, SMB, HML, CMA, RMW, MOM, the daily percentage change (first difference of the logs) in EPU, VIX, WTI, PROP, NG, and TED. In each case, we run the regressions in Eq. (3) before (B) the Paris Agreement (between July 11, 2010, and December 31, 2015), after (A) the Paris Agreement (between January 1, 2016, and June 26, 2022), and on the full (F) sample. We only report the significant risk coefficients. Newey and West (1987, 1994) standard errors of the estimators are reported in parentheses beneath the coefficients. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels respectively.

Panel A. Physical climate risks and the performance of green versus brown portfolios							
	Column	(1)	(2)	(3)	(4)	(5)	(6)
	Five days portfolio returns	r_t	r_{t+1}	r_{t+2}	r_{t+3}	r_{t+4}	r_{t+5}
CARBON risk	Analysis period						A
	GMB						−0.19*** (0.068)
	Green						−0.11** (0.04)
	Brown						0.10** (0.05)
WEATHER risk	Analysis period			A			
	GMB			0.21** (0.089)			
	Green			0.10** (0.05)			
	Brown			−0.10* (0.06)			
Panel B. Transition climate risks and the performance of green versus brown portfolios							
	Column	(1)	(2)	(3)	(4)	(5)	(6)
	Five days portfolio returns	r_t	r_{t+1}	r_{t+2}	r_{t+3}	r_{t+4}	r_{t+5}
PLEDGES risk	Analysis period		F			F	
	GMB		0.16** (0.08)			−0.14* (0.08)	
	Green		0.02 (0.05)			−0.05 (0.05)	
	Brown		−0.13** (0.06)			0.10** (0.05)	
CONVENTIONS risk	Analysis period	B	A				
	GMB						
	Green	0.14** (0.06)	−0.10** (0.05)				
	Brown		−0.15** (0.06)				
Carbon POLICY risk	Analysis period			A	A	A	
	GMB				0.09** (0.05)	−0.07** (0.03)	
	Green				0.05* (0.03)	−0.06* (0.035)	
	Brown			−0.05* (0.03)			

lower expected returns due to investors' preference for green stocks and the ability of green stocks to better hedge climate risk. Bolton and Kacperczyk (2021)'s study also supports this hypothesis. The authors find that stocks with higher emissions earn higher returns to compensate investors for bearing carbon risk. Görgen et al. (2020), however, do not find evidence of a carbon risk premium.

During the period after the PA, a shock in attention to a weather event, which is intensified by climate change, by one unit today triggers a significant (at the 5 % level) rise in GMB and green portfolios' returns by 21 and 10 basis points respectively on the second day, and a significant (at the 10 % level) drop in brown returns by 10 basis points on the second day. Thus, green stocks outperform brown stocks when concerns about WEATHER risk on social media strengthen unexpectedly in the

period after the PA. This result is consistent with Fahmy (2022), who documents a rise in investors awareness of climate risks after the PA. The results are also consistent with Choi et al. (2020)'s finding, who document that U.S. households revise their beliefs about climate change upward when experiencing abnormal temperatures.

We document the predictive power of our transition climate risk indexes on the performance of green versus brown stocks in Panel B in Table 5. Using the entire analysis period, we find that a rise in attention to climate PLEDGES by one unit today is always associated with a significant (at the 5 % level) increase in GMB returns by 16 basis points on the first day. This increase, however, is almost totally reversed on the fourth day. The green portfolio exhibits a similar behavior. The brown portfolio, however, displays an initial significant (at the 5 % level) drop

by 13 basis points on the first day and a later significant (at the 5 % level) rise by 10 basis points on the fourth day. The initial positive response of green returns to PLEDGES risk is consistent with the initial positive response of clean energy ETFs' returns that we documented in Section 4. This means that investors, who believe in climate change and feel good after a spike in attention to a climate promise or a pledge, are keen to hold green stocks and short brown stocks. The positive sentiment associated with mentions related to climate pledges (see Column (2) in Table 1) confirms this conjecture. The lack of credibility of such promises, however, lead to return reversal on the fourth day.

An unexpected rise in attention to climate CONVENTIONS on social media by one unit today is associated with a significant (at the 5 % level) contemporaneous increase in green stocks' returns by 14 basis points before the PA. The impact of a similar shock is, however, negative (drop by 10 basis points) on the first day after the PA. This result points to the ineffectiveness of climate conventions. Our sentiment analysis in Column (2) in Table 1 shows that mentions related to climate summits, conventions, and IPCC reports carry a negative sentiment.

Unexpected shocks in attention to carbon POLICY today are associated with a significant (at the 10 % level) drop in brown returns on the second day. POLICY risk, however, disrupts green stocks. A contemporaneous increase in POLICY risk by one unit is associated with an initial rise in GMB and green returns by 9 and 5 basis points respectively on the third day. This initial rise in green returns is, however, reversed on the following day. This result confirms the recent conjecture of Fahmy and Apergis (2024) regarding the ineffectiveness of U.S. climate policy.

6. Climate risks and fund flows

Mutual fund flows are commonly used in the literature to make inference regarding investment decisions that are fueled by behavioral biases. Individual retail investors hold about 90 % of total mutual fund assets. Therefore, they are more likely to be noise traders (Da et al., 2015). Following this rationale, we directly examine the effect of our climate risk indexes on daily mutual fund flows in our last set of asset tests.

We obtain daily mutual fund data from Informa on two groups of funds; an equity group that specializes in equity (EQ) and an intermediate treasury bonds (BOND) group. Several studies (e.g., Da et al., 2015; Edelen & Warner, 2002; Greene & Hodges, 2002) investigate an earlier version of this data set from Trim Tabs. In particular, Da et al. (2015) find strong persistence and long-memory components in the daily fund flows of this data set. The authors demean each of the daily fund flow series and apply the autoregressive fractionally integrated moving average ARFIMA(1, d , 1) model to extract the daily fund flow innovations. We find that the updated version of this data set from Informa does not suffer from this problem. When we fit the ARFIMA(1, d , 1) model to this data set, the results yield insignificant coefficients on the moving average and the autoregressive components of the model. For that reason, rather than using the innovations from the AFRIMA model, we directly use the fund flow of fund class i , denoted by $flow^i$, which is defined as the ratio of the daily fund flow in U.S. dollars over the fund's daily total net assets. In addition to persistence, the previous studies report that it is possible that this fund flow data set suffers a one-day reporting delay, that is, fund flow in day $t + 1$ may contain flow in day t . Therefore, we follow these authors and run the following fund flows regression:

$$flow_{t+k}^i = \varphi_0 + \varphi_1 I_t^{CLIMATE} + \Phi' CONTROL_t + u_{t+k}^i, \quad (4)$$

where $flow_{t+k}^i$ is the fund flow of fund class i , where $i \in \{EQ, BOND\}$, on day $t + k$, where $k = 0, 1, \dots, 4$, Φ is a parameter vector, $CONTROL_t$ is a vector of controls that includes five lags of the fund flow, and the percentage change (first difference of logs) in the EPU and the VIX indexes, $I_t^{CLIMATE}$ is a generic climate risk index on day t , and u_{t+k}^i is an error term on day $t + k$.

We document the results of the flow regressions in Table 6. We find that all types of physical climate risks, which are measured as innovations in attention to physical climate mentions, have no significant incremental predictive power for future daily fund flows of both bond and equity funds. This result confirms our earlier findings that physical climate risks are not a source of noise trading. Climate PLEDGES and climate POLICY, on the other hand, are the two types of transition climate risks that can predict future daily flows of bond and equity funds. In the bond market flow regressions (Panel A in Table 6), the coefficient on $I^{PLEDGES}$ is negative and statistically significant at the 10 % and 5 % levels on days $t = 1$ (Column 1) and $t = 2$ (Column 2) respectively.¹⁷ This result suggests that investors immediately start to withdraw from bond market mutual funds following a rise in attention to climate pledges. This outflow persists on days $t = 1$ and $t = 2$. An increase in $I^{PLEDGES}$ by one standard-deviation (0.22) corresponds to bond market outflows of 1.22×10^{-5} ($= 5.56 \times 10^{-5} \times 0.22$) on day $t = 1$, and 1.60×10^{-5} ($= 7.25 \times 10^{-5} \times 0.20$) on day $t = 2$. Given that the average daily bond market flow is 10.2×10^{-5} , we consider these outflows to be mild as they are about 15 % of the average daily flows. The coefficient on $I^{POLICIES}$ is positive and statistically significant (at the 5 % level of significance) on the fifth day (column (5) in Panel A). This means that, following a rise in attention to carbon POLICY, emotionally driven investors deposit money in the bond market mutual funds on the fifth day. One standard deviation increases in I^{POLICY} today corresponds to 1.32×10^{-5} ($= 7.74 \times 10^{-5} \times 0.17$) bond market inflows on day $t = 5$, which is equivalent to 14 % of the average daily flows.

In the equity market flow regressions (Panel B in Table 6), the coefficient on $I^{PLEDGES}$ is positive and statistically significant only on the fifth day. The coefficient on the I^{POLICY} index is negative on days $t = 0, 1, 5$, and is statistically significant (at the 5 % level) only on the fifth day. Thus, a rise in attention to mentions of climate PLEDGES causes unsophisticated retail investors to deposit money in the equity mutual fund market in the long-term whereas a rise in attention to mentions of carbon POLICY has the opposite effect.

Taken all together, the previous results suggest that, on the one hand, mounting worries about carbon POLICY causes investors to switch in the long-term from equity to bond market. This flight to safety to bond markets reflects investors' perception of the ineffectiveness and potential disruptions of carbon policies (Fahmy & Apergis, 2024). On the other hand, unexpected increases of mentions of climate PLEDGES on social media are associated with movements of funds from the bond mutual fund market to the relatively riskier equity market. A plausible explanation of this finding is that narratives related to climate promises and pledges on social media influence retail investors' belief that such promises are expected to successfully curb emissions and combat climate change. This perception, in turn, prompts retail investors to move their funds from the bond market to the relatively higher-return and higher-risk mutual equity market. Indeed, our sentiment analysis confirms this rationale as it shows that our climate PLEDGES MVI carries a dominant positive sentiment.

7. Climate risks and volatility

The empirical analysis in Section 4 shows that transition climate risks (particularly climate PLEDGES and CONVENTIONS) are sources of disruption and noise trading in clean energy and highly liquid equity markets. Since investment decisions that lead to noise trading can affect both the level and the volatility of asset prices, we expect both our climate PLEDGES and climate CONVENTIONS risk indexes to drive volatility in aggregate asset prices. By construction, our risk indexes capture high, low, and in-between attention to climate mentions regimes. Our mention volume analysis (see the peak analysis on CARBON

¹⁷ Recall that day $t = 1$ outflow may contain outflow in day $t = 0$.

Table 6

Climate risks and fund flows.

Panel A: Transition climate risks and bond flows					
Column	(1)	(2)	(3)	(4)	(5)
	$flow_t^{BOND}$	$flow_{t+1}^{BOND}$	$flow_{t+2}^{BOND}$	$flow_{t+3}^{BOND}$	$flow_{t+4}^{BOND}$
$I^{PLEDGES}$	$-5.56e^{-05*}$ ($3.40e^{-05}$)	$-7.25e^{-05**}$ ($3.28e^{-05}$)			
Controls	Yes	Yes			
Observations	3006	3005			
Adjusted R^2	0.46	0.43			
I^{POLICY}					$7.74e^{-05**}$ ($3.97e^{-05}$)
Controls					Yes
Observations					3002
Adjusted R^2					0.30

Panel B: Transition climate risks and equity flows					
Columns	(1)	(2)	(3)	(4)	(5)
	$flow_t^{EQ}$	$flow_{t+1}^{EQ}$	$flow_{t+2}^{EQ}$	$flow_{t+3}^{EQ}$	$flow_{t+4}^{EQ}$
$I^{PLEDGES}$					$5.9e^{-05**}$ ($2.87e^{-05}$)
Controls					Yes
Observations					3002
Adjusted R^2					0.12
I^{POLICY}					$-7.03e^{-05**}$ ($3.16e^{-05}$)
Controls					Yes
Observations					3002
Adjusted R^2					0.10

This table documents how the daily climate risk indexes predict mutual funds flows. We consider two groups of fund flows; an intermediate treasury bonds (BOND) group (Panel A) and an equity group (EQ) that specializes in equity (Panel B). The dependent variables are the contemporaneous and day 1 flows (column (1)), and the next four days flows (columns (2), (3), (4), and (5)). The control variables include five lags of the fund flows, the daily CBOE volatility index (VIX), and the daily economic policy uncertainty (EPU) index. All exogenous control variables are in percentage change (first difference of logs). Newey and West (1987, 1994) standard errors of the estimators are reported in parentheses beneath the coefficients. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels respectively.

risk below Panel A in Fig. 1 and the analysis of other risk indexes in the Internet Appendix) shows that attention to climate mentions intensifies amid a physical weather event or a political statement or a government action. This intensity in attention, however, is not long lasting. It fades away fairly quickly before the next event takes place and creates another wave in attention to climate mentions.

The previous behavior suggests that the conditional variance of returns switches between high and low equilibria following changes in innovations in attention to climate mentions, which are captured by our climate risk indexes. To model this regime switching dynamic and to test which type of climate risk is responsible for driving the volatility in asset returns, we employ an exogenous smooth transition GARCH (EX-STGARCH) model, which is essentially a modified version of González-Rivera (1998) and Lanne and Saikkonen (2005)'s STGARCH model, to the conditional variance of asset class i 's returns.

Our base regression equation is

$$r_t^i = \theta + \Theta' CONTROL_t^i + \epsilon_t^i, \quad (5)$$

where r_t^i is the return on asset class i , and $CONTROL_t^i$ is a vector of control variables that includes percentage change (first difference of logs) in EPU, VIX, WTI, PSE, and n lags of asset i 's returns, where n is the number that minimizes the Schwarz information criterion. We define $\epsilon_t^i = Z_t^i \sqrt{h_t^i}$ with $Z_t^i \sim i.i.d.(0, 1)$ so that the conditional variance equation is

$$h_t^i = \omega_1 + \alpha_1 \epsilon_{t-1}^{2i} + \beta_1 h_{t-1}^i + (\omega_2 + \alpha_2 \epsilon_{t-1}^{2i} + \beta_2 h_{t-1}^i) F(s; \gamma, c), \quad (6)$$

where $F(s; c, \gamma)$ is a first order logistic function bounded between 0 and 1 and defined as

$$F = \frac{1}{1 + \exp\{-\gamma(s - c)\}}, \quad (7)$$

where $\gamma > 0$ is the slope of the function, c is a threshold parameter, $s \in \Omega$ is the transition (or regime-driving) variable, and Ω is a transition set. We also impose the restrictions that ω_1 and $\omega_1 + \omega_2$ are positive, the α 's, β 's, and their sums are nonnegative, $\alpha_1 + \beta_1 < 1$, and $\alpha_1 + \alpha_2 + \beta_1 + \beta_2 < 1$ to ensure the non-negativity of the conditional variance.

The class of smooth transition regression models in the mean (Granger & Teräsvirta, 1993; Teräsvirta, 1994) or in the conditional variance (González-Rivera, 1998; Lanne & Saikkonen, 2005; Lee & Degennaro, 2000) or in both the mean and variance of the data generating process (Lundbergh & Teräsvirta, 1998) commonly employs a logistic smooth transition regression function in the transition variable s , which is usually taken to be one of the lags of the data generating process; that is, in the present context, $s_t = \epsilon_{t-d}^2$ as in González-Rivera (1998), where d is the delay. In the proposed EX-STGARCH model, however, the regime driving variable is an exogenous variable; namely, s is any climate risk index or one of its lags (up to 5 lags); that is, the set of potential transition candidates is

$$\Omega = \{I_t^{CLIMATE}, \dots, I_{t-5}^{CLIMATE}\}, \quad (8)$$

where CLIMATE is a generic term that represents any type of physical or transition climate risk.

One appealing feature of the EX-STGARCH model is that it allows us to test statistically whether a climate risk index, i.e., an exogenous regime driving variable, is causing the conditional volatility of returns to oscillate nonlinearly between two regimes defined by the value taken by the threshold parameter c . When γ is large and the transition variable

Table 7
Nonlinearity tests results.

(1)	(2)	(3)
Dependent variable	Transition variable	p-value
Panel A: Results of testing linearity against EX-STGARCH in the conditional variance of the highly liquid ETFs with our climate risk indexes as exogenous regime-driving variables		
h_t^{SPY}	$I_t^{CONVENTIONS***}$	1.1760×10^{-5}
	$I_t^{POLICY**}$	0.0176
	$I_t^{PLEDGES**}$	0.0272
	$I_t^{CONVENTIONS**}$	0.0412
h_t^{QQQ}	$I_t^{CONVENTIONS***}$	3.9998×10^{-6}
	$I_t^{POLICY***}$	0.0018
	$I_t^{PLEDGES***}$	0.0080
	$I_t^{CONVENTIONS*}$	0.0699
h_t^{IWB}	$I_t^{CONVENTIONS***}$	2.2370×10^{-6}
	$I_t^{PLEDGES***}$	0.0024
	$I_t^{POLICY***}$	0.0067
	$I_t^{CONVENTIONS*}$	0.0587
h_t^{IWM}	$I_t^{CONVENTIONS***}$	1.3609×10^{-5}
	$I_t^{POLICY***}$	0.0073
	$I_t^{PLEDGES***}$	0.0087
	$I_t^{CONVENTIONS*}$	0.0963
Panel B: Results of testing linearity against EX-STGARCH in the conditional variance of the clean energy assets with our climate risk indexes as exogenous regime-driving variables		
h_t^{ECO}	$I_t^{CONVENTIONS***}$	8.6167×10^{-5}
	$I_t^{PLEDGES***}$	1.45×10^{-3}
	$I_t^{CONVENTIONS**}$	0.021
	$I_t^{SOLUTIONS**}$	0.038
h_t^{PBD}	$I_t^{CONVENTIONS***}$	2.1283×10^{-5}
	$I_t^{PLEDGES***}$	3.1518×10^{-4}
	$I_t^{POLICY***}$	0.002
	$I_t^{CONVENTIONS***}$	2.1728×10^{-4}
h_t^{PBW}	$I_t^{PLEDGES***}$	1.21×10^{-3}
	$I_t^{CONVENTIONS**}$	0.0291
	$I_t^{SOLUTIONS**}$	0.0419

This table documents the results of testing which climate risk index nonlinearly drives the regime-switching behavior in the conditional volatility of asset returns. The test is based on the idea of replacing the transition function in Eq. (7) by a third order Taylor approximation and testing the null hypothesis $H_0 : \gamma = 0$. A rejection of H_0 implies the existence of an EX-STGARCH model in the conditional variance. This test, which is founded on Luukkonen et al. (1998)'s procedure, is detailed in Fahmy (2012). Panel A summarizes the results of the test when applied to the conditional volatility of four highly liquid ETFs; namely, S&P500 ETF (SPY), PowerShares QQQ trust (QQQ), Russel 1000 Index ETF (IWB), and Russel 2000 Index (IWM). For each ETF, we run the regression in Eq. (5) and extract the conditional variance as in Eq. (6). The control variables are n lags of daily returns, where n minimizes the Schwarz information criterion, percentage change (first difference of logs) in the Economic Policy Uncertainty (EPU) and the CBOE volatility index (VIX). For each ETF, we repeat the test for each climate risk index (up to 5 lags) and report the p-values ranked from the smallest (highest rejection of linearity) to the largest value in column (3). To converse space, we only report the climate risk indexes that yield significant results. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels respectively. Panel B summarizes the results of the test when applied to the conditional volatility of clean energy assets; namely, we consider the WilderHill Clean Energy (ECO) index, Invesco Global Clean Energy (PBD) ETF, and Invesco WilderHill Clean Energy (PBW) ETF. The control variables in the regression in Eq. (5) are the n lags of daily returns, where n minimizes the Schwarz information criterion, the daily NYSE Arca Technology Index (PSE), the daily crude oil spot index for the West Texas Intermediate (WTI), the daily VIX index, and the daily EPU index. All exogenous control variables are in percentage change (first difference of the logs).

$I_{t-d}^{CLIMATE} > c$, for any d between 1 and 5, then $F = 1$ and the conditional variance in Eq. (5) is

$$h_t^i = (\omega_1 + \omega_2) + (\alpha_1 + \alpha_2)\epsilon_{t-1}^{2i} + (\beta_1 + \beta_2)h_{t-1}^i. \quad (9)$$

This defines the high attention regime. If the exogenous transition variable is below the threshold, i.e., $I_{t-d}^{CLIMATE} < c$, and γ is large, then $F = 0$ and

$$h_t^i = \omega_1 + \alpha_1\epsilon_{t-1}^{2i} + \beta_1h_{t-1}^i. \quad (10)$$

This defines the low attention regime. Thus, the parameters of the conditional variance change monotonically as a function of the generic climate risk index from $\omega_1, \alpha_1, \beta_1$ to $(\omega_1 + \omega_2), (\alpha_1 + \alpha_2)$, and $(\beta_1 + \beta_2)$. As usual, the GARCH reaction parameters, i.e., the alphas, capture the extent of market stability in both regimes whereas the betas capture the degree of persistence in the conditional volatility.

The previous framework has two key advantages. First, the model allows us to capture the asymmetric response of the conditional variance equation to high versus low attention to climate mentions regimes. Second, and more importantly, the inclusion of our climate risks as potential exogenous regime-driving variables in the transition set Ω permits us to statistically test which type of climate risk is driving the nonlinear volatility in asset returns. This nonlinearity test, which is detailed in Fahmy (2012), follows the same procedure of Luukkonen, Saikkonen, and Teräsvirta (1998), where the null hypothesis of linearity, $H_0 : \gamma = 0$, i.e., $F = 0$ in Eq. (6), is tested against the alternative that h_t^i follows a nonlinear EX-STGARCH model for each transition candidate $s \in \Omega$.¹⁸ The transition variable that yields the highest rejection of H_0 , measured in the p-value, is considered the best regime-driving variable that captures the nonlinear regime-switching behavior of the conditional variance of asset returns. For each asset class i , we run the base regression in Eq. (5), extract the residuals series, and define the conditional variance as in Eqs. (6) and (7). We run the nonlinearity test for each exogenous climate risk index in Ω and record the p-values of the tests. To conserve space, we only report in Table 7 the significant exogenous risk indexes, i.e., the risk indexes in the set Ω that yield the highest rejection of the null-hypothesis (lowest p-values). We rank the values based on the strongest rejection of H_0 in Column (3). We document in Panel A the results of running the nonlinearity tests on the highly liquid equity ETFs. We find that the $I_{t-5}^{CONVENTIONS}$ index is the regime driving variable that shows the highest rejection of H_0 in the conditional variance of the SPY ETF returns. Nonlinearity is also rejected with I_{t-2}^{POLICY} , $I_t^{PLEDGES}$, and $I_{t-1}^{CONVENTIONS}$ (in that order) and, thus, they are also possible regime-driving variables. The previous results are robust across all highly liquid ETFs. This means that the conditional volatility in the aggregate returns of this asset class on day t is driven by (i) innovations in public attention to climate conventions on days $t-1$ and $t-5$, (ii) contemporaneous innovations in attention to climate pledges, and (iii) innovations in attention to climate policies on day $t-2$. These results are consistent with our earlier return reversal predictions in the highly liquid ETFs' returns that are documented in Table 4, Panel B.

Panel B in Table 7 documents the results of our nonlinearity tests when applied to the conditional volatility of clean energy assets. We find that contemporaneous innovations in attention to climate mentions related to pledges and conventions, i.e., $I_t^{CONVENTIONS}$ and $I_t^{PLEDGES}$ respectively, are the two exogenous regime-driving risk indexes that yield the highest rejection of the linearity hypothesis in the conditional variance of all clean energy assets. These results are consistent with our earlier return reversal regressions in Table 3, Panel B. It is clear from these regressions that $I_t^{CONVENTIONS}$ and $I_t^{PLEDGES}$ predict return reversal in all clean energy assets. Our nonlinearity tests reveal that they are also

¹⁸ In the test, the function $F = 1 + \exp\{-\gamma(s - c)\}^{-1} - 1/2$ in Eq. (7) is replaced by a third order Taylor approximation about the null hypothesis $\gamma = 0$. The $1/2$ is subtracted from F to facilitate the approximation.

Table 8

Estimation and dynamic analysis of volatility driven by our climate risk indexes.

Dependent variable	Panel A: Conditional volatility of highly liquid equity ETFs				Panel B: Conditional volatility of clean energy assets		
	h_t^{SPY}	h_t^{QQQ}	h_t^{IWB}	h_t^{IWM}	h_t^{ECO}	h_t^{PBD}	h_t^{PBW}
Regime-driving risk: s	$I_{t-5}^{CONVENTIONS}$	$I_{t-5}^{CONVENTIONS}$	$I_{t-5}^{CONVENTIONS}$	$I_{t-5}^{CONVENTIONS}$	$I_{t-5}^{CONVENTIONS}$	$I_{t-5}^{CONVENTIONS}$	$I_{t-5}^{CONVENTIONS}$
Threshold value: c	-0.06** (0.02)	-0.10** (0.04)	-0.02** (0.009)	-0.12*** (0.03)	-0.05*** (0.016)	0.44*** (0.03)	-0.10*** (0.02)
Slope of transition function: γ	29.7** (11.7)	12.2** (4.7)	15.2** (6.7)	12.6** (4.8)	159* (97.2)	95* (55.8)	82* (48.1)
ω_1	0.000001*** (0.0000002)	0.000002*** (0.0000003)	0.000001*** (0.0000002)	0.000002*** (0.0000004)	0.000027*** (0.000003)	0.000002*** (0.000001)	0.000006*** (0.000001)
α_1	0.14*** (0.013)	0.10*** (0.011)	0.13*** (0.013)	0.07*** (0.009)	0.02*** (0.003)	0.09*** (0.02)	0.07*** (0.01)
β_1	0.77*** (0.02)	0.81*** (0.018)	0.78*** (0.019)	0.83*** (0.017)	0.76*** (0.006)	0.90*** (0.07)	0.90*** (0.02)
ω_2					0.03*** (0.009)		
β_2	0.078** (0.03)	0.076** (0.03)	0.080*** (0.023)	0.09*** (0.03)	-0.16*** (0.02)	-0.12* (0.07)	-0.11*** (0.03)
Observations	3110	3110	3110	3110	3117	3117	3117
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diagnostics							
Q(1)	0.47	0.30	0.75	0.65	0.35	0.05	0.08
Q(10)	0.56	0.10	0.12	0.27	0.87	0.06	0.38
Q(20)	0.10	0.06	0.21	0.73	0.66	0.06	0.32
ML(10, 2)	0.30	0.23	0.30	0.17	0.92	0.09	0.37
ML(20, 2)	0.77	0.29	0.69	0.13	0.95	0.29	0.74
Dynamic analysis							
Characterization of the low attention regime L: $s < c$; $F = 0$							
Model	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
GARCH market reaction parameter: α_1	0.14	0.10	0.13	0.07	0.02	0.09	0.07
GARCH market persistence parameter: β_1	0.77	0.81	0.78	0.83	0.76	0.90	0.90
Characterization of the high attention regime H: $s > c$; $F = 1$							
Model	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
GARCH market reaction parameter: $\alpha_1 + \alpha_2$	0.14	0.10	0.13	0.07	0.05	0.09	0.07
GARCH market persistence parameter: $\beta_1 + \beta_2$	0.85	0.89	0.86	0.92	0.60	0.78	0.79

the regime drivers of the conditional volatility of this asset class.

Guided by the results of the nonlinearity tests in Table 7, we fit the EX-STGARCH model to the conditional variance of each asset class using the exogenous regime-driving variables that showed the highest rejection of linearity, i.e., $I_{t-5}^{CONVENTIONS}$ for the volatility of the highly liquid ETFs and $I_{t-5}^{CONVENTIONS}$ for the conditional volatility of clean energy assets. We report the estimation results in Table 8.¹⁹

The estimation results in Panel A in Table 8 show that high swings in the climate conventions risk index on day $t - 5$ drive the conditional volatility of all equity ETFs in this asset class on day t . Consider, for instance, the conditional volatility of the SPY ETF. The significant (at the 5 % level) estimated value of the threshold parameter $c = -0.06$ implies that when $I_{t-5}^{CONVENTIONS}$ drops below -6% , the transition function F approaches 0 and the conditional volatility of the SPY ETF returns displays a low attention GARCH(1,1) regime with a relatively high reaction parameter $\alpha_1 = 0.14$ and low volatility persistence parameter $\beta_1 = 0.77$; that is,

$$h_t^{SPY} = 0.000001 + 0.14e_{t-1}^{2SPY} + 0.77h_{t-1}^{SPY}. \quad (11)$$

When $I_{t-5}^{CONVENTIONS}$ exceeds the -6% threshold value, i.e., when attention to climate conventions is high, the transition function approaches 1 and the conditional volatility of the SPY ETF returns displays

a high attention GARCH(1,1) regime with higher degree of persistence as

$$h_t^{SPY} = 0.000001 + 0.14e_{t-1}^{2SPY} + 0.85h_{t-1}^{SPY}. \quad (12)$$

The previous results indicates that the conditional variance of the SPY ETF returns oscillates between two GARCH(1,1) regimes following changes in the climate conventions risk index above and below a threshold value of -6% . Fig. 5 shows this dynamic behavior. Panel A plots the daily conditional variance of the SPY ETF returns, h_t^{SPY} , over the sample period. Panel B plots the transition variable, $I_{t-5}^{CONVENTIONS}$. The large and significant (at the 5 % level) estimated value of the slope of the transition function, $\gamma = 29.7$, indicates that the transition of the conditional volatility of the SPY ETF returns between the low and high attention regimes is swift as shown from the transition plot in Panel C in Fig. 5 and from its dot plot in the left panel in Fig. 7. The previous dynamic behavior is robust across all highly liquid ETFs. We deduce, therefore, that a rise in climate conventions risk, measured as spikes in public attention to climate summits, meetings, and authoritative climate reports, increases the degree of persistence in the volatility of the highly liquid equity ETFs' returns.

In contrast to the previous dynamic behavior, conventions risk has the opposite impact on the conditional volatility of clean energy assets. The results in Panel B in Table 8 show that a rise in contemporaneous conventions risk decreases the degree of persistence in the conditional volatility of the ECO returns. In particular, h_t^{ECO} oscillates between a low attention GARCH(1,1) regime defined by the equation

$$h_t^{ECO} = 0.0000027 + 0.02e_{t-1}^{2ECO} + 0.76h_{t-1}^{ECO} \quad (13)$$

¹⁹ Since $I_{t-5}^{PLEDGES}$ also shows high rejection to the linearity hypothesis (see Panel B in Table 7), we repeat the estimation of the conditional variance of clean energy assets with $I_{t-5}^{PLEDGES}$ as exogenous transition variable and find the same regime switching dynamic as in the case of $I_{t-5}^{CONVENTIONS}$. We do not report these results to conserve space.

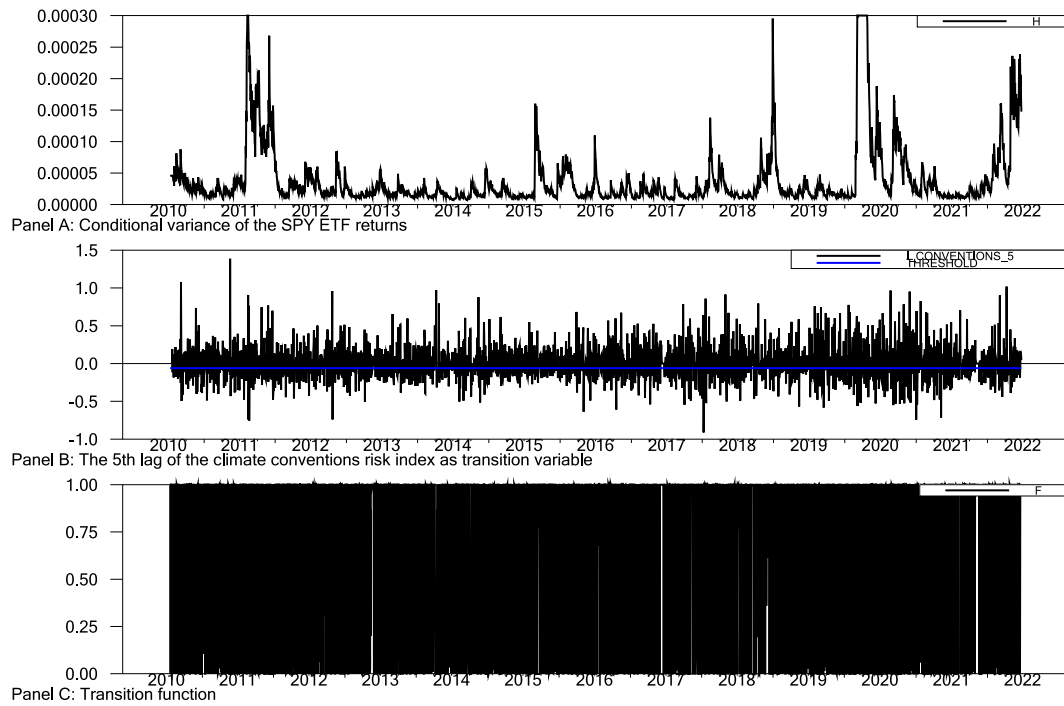


Fig. 5. Panel A depicts the daily conditional variance of the SPY ETF returns, h_t^{SPY} , between July 11, 2010, and June 26, 2022. Panel B depicts the fifth lag of the climate conventions risk index, $I_{t-5}^{CONVENTIONS}$, as the exogenous transition variable in the EX-STGARCH model fitted to h_t^{SPY} over the sample period. The blue line is the estimated threshold value $c = -6\%$. Panel C plots the transition function $F(\gamma, c, I_{t-5}^{CONVENTIONS})$ over the sample period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

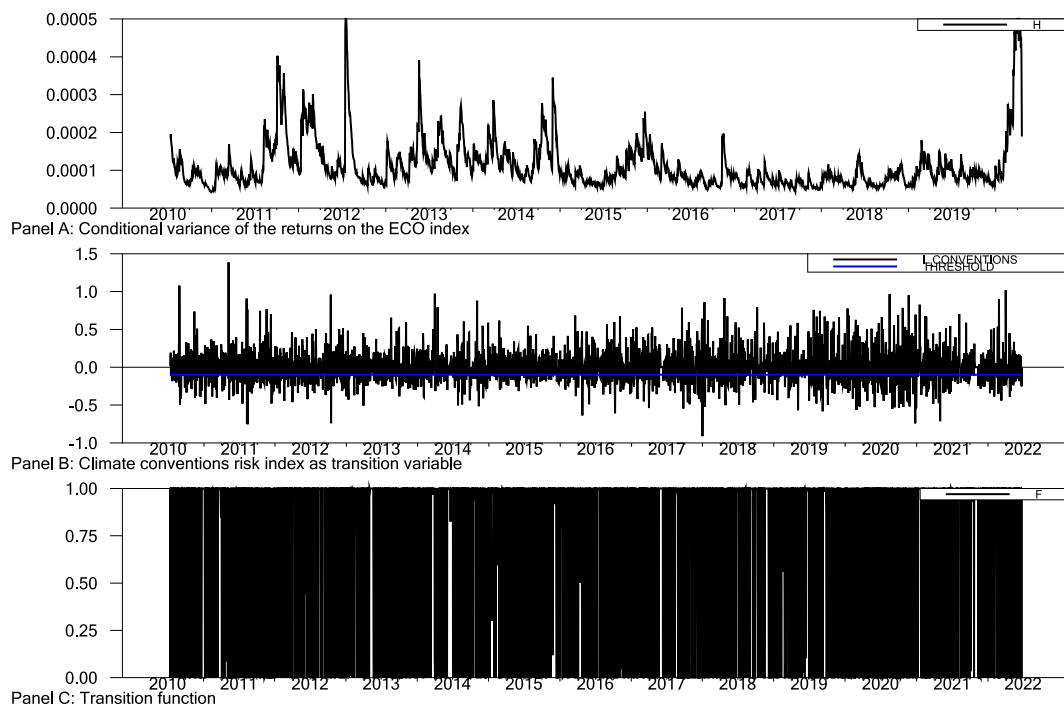


Fig. 6. Panel A depicts the daily conditional variance of the returns on the ECO index, h_t^{ECO} , between July 11, 2010, and June 26, 2022. Panel B depicts the climate conventions risk index, $I_t^{CONVENTIONS}$, as the exogenous transition variable in the EX-STGARCH model fitted to h_t^{ECO} over the sample period. The blue line is the estimated threshold value $c = -10\%$. Panel C plots the transition function $F(\gamma, c, I_t^{CONVENTIONS})$ over the sample period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

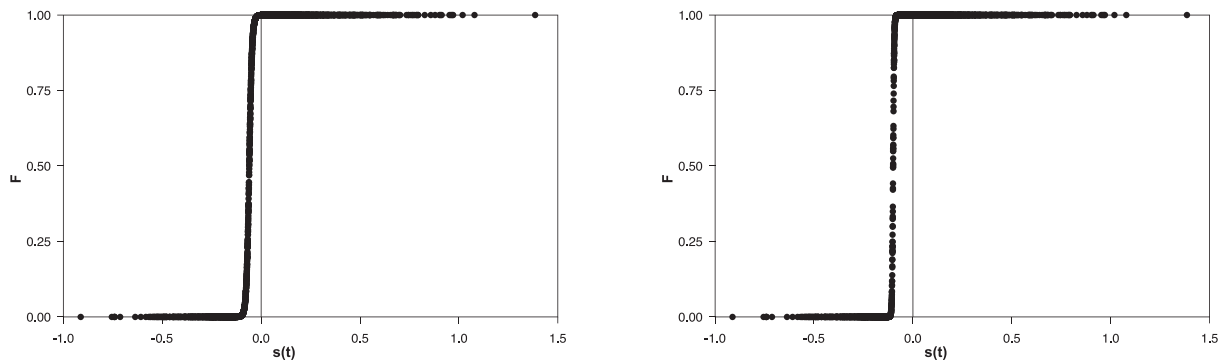


Fig. 7. The left panel shows a plot of the transition function $F(\gamma, c, I_{t-5}^{CONVENTIONS})$ of the EX-STGARCH model fitted to the conditional volatility of SPY ETF returns. The right panel shows a plot of the transition function $F(\gamma, c, I_t^{CONVENTIONS})$ of the EX-STGARCH model fitted to the conditional volatility of the returns on the ECO index. Each dot corresponds to one observation.

and a high attention GARCH(1,1) regime defined by the equation

$$h_t^{ECO} = 0.0000027 + 0.05\epsilon_{t-1}^{2ECO} + 0.61h_{t-1}^{ECO} \quad (14)$$

following changes in the $I_t^{CONVENTIONS}$ below and above a threshold value $c = -10\%$. The large value of the slope of the transition function indicates a swift transition between the two regimes. This behavior, which is robust across all clean energy ETFs, implies that high attention to climate conventions lowers the degree of persistence in the conditional volatility of this asset class. Fig. 6 and the right panel in Fig. 7 depict this behavior.

Panel A documents the results of fitting the EX-STGARCH model in Eq. (4), after dropping all insignificant coefficients, to the conditional volatility of the highly liquid ETFs; namely, S&P500 ETF (SPY), PowerShares QQQ trust (QQQ), Russel 1000 Index ETF (IWB), and Russel 2000 Index (IWM) using the exogenous transition variables proposed by the nonlinearity tests results in Table 7. Panel B documents the results of fitting the same model to the conditional variance of clean energy assets; namely, the WilderHill Clean Energy (ECO) index, Invesco Global Clean Energy (PBD) ETF, and Invesco WilderHill Clean Energy (PBW) ETF. The low attention regime (L) is: $h_t^i = \omega_1 + \alpha_1 \epsilon_{t-1}^{2i} + \beta_1 h_{t-1}^i$. The high attention regime (H) is: $h_t^i = (\omega_1 + \omega_2) + (\alpha_1 + \alpha_2) \epsilon_{t-1}^{2i} + (\beta_1 + \beta_2) h_{t-1}^i$. We carry out the estimation individually for each transition variable using maximum likelihood method conditional on γ (the slope of the transition function) and c (the threshold parameter). We maximize the log-likelihood function of the EX-STGARCH model using the iterative Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. We obtain the starting values of the algorithm by constructing a two-dimensional grid in γ and c . The values that minimize the residuals sum of squares are taken be the starting values of the procedure. $Q(q)$ are the p -values of Ljung and Box (1978) test of no serial correlation of order q in the standardized residuals. $ML(10, 2)$ and $ML(20, 2)$ are the test statistics of McLeod and Li (1983) test for nonlinearity (ARCH effects) in the squared standardized residuals with 10 and 20 correlations respectively and a degrees of freedom correction of 2. The standard errors are between brackets beneath the coefficients. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels respectively.

8. Concluding remarks

In this paper, we propose climate mention volume as a proxy for attention to climate change concerns on social media. We show that the proposed mention volume index (MVI) has several appealing features as opposed to Google SVI. Building directly on a novel climate risk classification, we construct several physical and transition climate risk measures as innovations, i.e., shocks to their corresponding MVIs. We investigate the predictive power of these risk measures on the performance of several asset classes at the market level and on the

performance of green versus brown portfolios in a cross-sectional analysis of the stocks in the S&P500.

Our results that document the impacts of *physical* climate risks on asset prices support three stylized empirical findings in the climate finance literature. First, at the aggregate market level, we find a contemporaneous positive and significant relation between clean energy ETFs' return and WEATHER risk after the PA. In the cross-section, we find that green stocks outperform brown stocks when concerns about WEATHER risk on social media intensifies unexpectedly. These results are consistent with studies that document rise in green returns amid unexpected abnormal temperatures (Choi et al., 2020) or climate change concerns in the news (Ardia et al., 2022; Pástor et al., 2021). Second, we find that brown stocks outperform green stocks amid unexpected shocks in attention to carbon emissions in the period after the PA. This finding is consistent with the carbon premium hypothesis (Bolton & Kacperczyk, 2021; Pástor et al., 2021). Third, we find that CARBON and WEATHER risks predict a negative response in clean energy ETFs' returns and a positive response in highly liquid equity ETFs' returns in the period before the PA. After the PA, however, we find positive and significant contemporaneous relations between these types of risks and clean energy returns. These findings confirm the rise in awareness of climate risks after the PA that is documented by Fahmy (2022).

Our results that document the inpts of *transition* climate risks on asset prices contribute to the climate finance literature by providing new evidence documenting the noise trading (return reversal and excess volatility) impacts of unexpected increases in climate CONVENTIONS and PLEDGES on aggregate market level prices after the PA. Furthermore, our cross-section analysis reveals that carbon POLICY risk disrupts green (but not brown) firms' stock prices in the long term. An unexpected increase in concerns about carbon POLICY on social media today is associated with an initial increase in green returns on the third day. This increase, however, is almost entirely reversed on the fourth day. Further sentiment analysis of the major peaks in our carbon POLICY MVI reveals that U.S. policy narratives on social media carry a dominant negative sentiment. A plausible explanation of this return reversal phenomenon, therefore, is that green investors perceive U.S. climate policy to be ineffective and that it is failing to achieve successful transition to a low-carbon economy. This interpretation is in line with the recent findings of Fahmy and Apergis (2024), who document that shocks to U.S. transition climate policies in the news and on social media induce higher volatility in green returns and promote stability in emission firms. They also document that U.S. climate policies carry a negative sentiment and deduce that the excess volatility reflects green investors' belief that such policies are ineffective and lack credibility.

Panel A in Table 9 summarizes our methodology by providing a description of the transmission of climate risks from climate attention shocks on social media to financial markets. Panels B and C summarize the main results and provide a rationale explaining the impacts of

Table 9

Panel A provides a description of the transmission process of climate risk from attention to climate mentions on social media to financial markets. Panels B and C summarize the empirical findings concerning the impacts of physical and transition climate risks, respectively, on asset prices. We document the responses of asset prices and the corresponding analysis period. $-/+$ indicates negative or positive response. $(+, -)$ indicates return reversal. B, A, F denote the periods before the Paris Agreement (PA), after the PA, and the entire analysis period respectively. SR and LR denote short- and long-run respectively.

Panel A. Transmission process of climate risks from climate attention on social media to financial markets							
Process		Description/measure					
1. Measure attention to climate change		MVI ≡ Mention volume index on social media					
2. Quantify climate risk		I ≡ Shocks/innovations to the MVI					
3. Identify two types of response to climate risk		Response type: (1) Climate risk is reflected in asset prices: returns show + or − response to I (2) Climate risk is a source of disruption: I causing return reversal (+, −) or (−, +) and excess volatility					
4. Impacts on financial markets		Analysis using predictive regressions and regime switching GARCH models					
5. Test assets		Market level (macro) analysis: clean energy ETFs, highly liquid equity ETFs, and mutual fund flows					
6. Explanation		Cross section (micro) analysis: brown, green, and green minus brown portfolios Peak and sentiment analyses					

Panel B. Response of asset prices to physical climate risks								
	Clean energy ETFs	Highly liquid equity ETFs	Mutual fund flows		Green stocks	Brown stocks	Empirical findings and related literature	Rationale (MVI drivers and sentiment)
			Bond flow	Equity flow				
Climate risk								
CARBON	− B and + A	+ B			− A	+ A	Carbon premium (Bolton & Kacperczyk, 2021)	MVI drivers: • Denial statements by U.S. politicians • U.S. Administration announcements • Skeptical climate statements by politicians and government executives Sentiment: Negative
WEATHER	− B and + A	+ B			+ A	− A	Rise in investors’ awareness of climate risks after PA (Fahmy, 2022) Upward beliefs amid unexpected rise in abnormal temperature (Choi et al., 2020)	MVI drivers: • Denial statements following actual weather events (e.g., hurricanes, droughts, and wildfires) • Concerns about weather events Sentiment: Negative

Panel C. Response of asset prices to transition climate risks								
	Clean energy ETFs	Highly liquid equity ETFs	Mutual fund flows		Green stocks	Brown stocks	Empirical findings and related literature	Rationale (MVI drivers and sentiment)
			Bond flow	Equity flow				
Climate risk								
PLEDGES	(+, −) A	(+, −) A	Outflow in SR (on days 0,1,2)	Inflow in LR (on day 5)	(+, −) F	(−, +) F	Empty pledges causing noise trading and disruptions in financial markets at the market level and in the cross-section.	MVI drivers: Mixed beliefs about climate change causing noise trading behavior in the form of return reversal. Some investors believe that climate promises and conventions lack credibility after the PA
CONVENTIONS	(+, −) F	(+, −) A/ F			+ B − A		Powerless climate conventions causing disruptions in clean energy markets	Sentiment: Positive MVI drivers: Mixed beliefs about climate change causing noise trading behavior in the form of return

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(continued on next page)

Table 9 (continued)

Panel C. Response of asset prices to transition climate risks							
	Clean energy ETFs	Highly liquid equity ETFs	Mutual fund flows		Green stocks	Brown stocks	Empirical findings and related literature
			Bond flow	Equity flow			Rationale (MVI drivers and sentiment)
Carbon POLICIES	+ A/F	+ A/F	Inflow in LR (on day5)	Outflow in LR (on day 5)	(+, −) A	− A	reversal. Some investors believe that climate promises and conventions lack credibility after the PA Sentiment: Negative MVI drivers: • U.S. Trump Administration withdrawal from the PA • U.S. Trump Administration rolling back environmental regulations in the period after the PA Sentiment: Negative
							Flight to safety in mutual funds and noise trading in green portfolios indicating the ineffectiveness of U.S. climate policy. (Fahmy & Apergis, 2024)

physical (Panel B) and transition (Panel C) climate risks on asset prices from our peak and sentiment analyses. A contemporaneous increase in a climate risk factor that causes a return reversal in the next five days indicates that the climate risk factor is a source of disruption. On the other hand, a contemporaneous increase in a climate risk factor that causes asset prices to respond either positively or negatively indicates that the corresponding risk factor is priced in the market under investigation. The reason that, amid increases in climate change news risk, asset prices respond with a delay is justified by Fahmy's (2024b) recent stochastic model that captures the dynamic of the latent process of attention to climate change news risk. The author shows that, after an increase in concerns about climate change events in the news, asset prices respond in an interval of time strictly below the time where attention failure rate reaches a maximum. In other words, investors make decisions amid climate news events in an interval of time before their attention to the climate news dies out. This time is shown to be approximately between a minimum of 0 and a maximum of 3 days in the events tested in the paper.

It is worth noting that we rely on textual analysis of climate Twitter mentions to explain the transmission mechanism from the climate risk factor to financial markets. We use the proprietary sentiment analysis provided by the data analytic vendor, Crimson Hexagon, to support this explanation. Having said that, we believe that formally testing the impact of climate social media sentiment on financial markets is an interesting topic on its own and is worth further investigation. However, we leave this connection for future research.

While most studies in the climate finance literature document the impacts of carbon and weather on the cross-section of stock prices, to the best of our knowledge, the impacts of climate conventions, pledges, and policies have not been explicitly studied. One exception is Fahmy's (2024a) recent work, which accounts for such risks. However, the analysis uses Google's SVI and solely focuses on the clean energy market. It is worth noting that other studies hint to the role of such events in shaping investor's preference. For instance, Santi (2023) studies the connection between investor climate sentiment and the cross-section of stock prices and argues that attention-grabbing events such as the release of a climate report may lead investors to update their beliefs and correct the mispricing of emission and clean stocks. Our analysis provides preliminary evidence that climate reports, conventions, summits, and pledges are causing mispricing and excess volatility in financial markets. These events do indeed cause retail investors to update their beliefs. However, judging by our return reversal and volatility analysis,

this shift in belief is a cause of mispricing and not a correction.

In conclusion, our mispricing tests and the results of our peak textual analysis reveal that transition climate risks lead to return reversal and excess volatility in financial markets due to the lack of credibility of climate pledges and the ineffectiveness of climate conventions. These disruptions can be reversed if politicians, governments, top executives, and policy makers work together to enhance the credibility of their climate actions, pledges, and policies. The sixth IPCC assessment report highlights the potential of behavioral changes in significantly lowering global emissions. The financial system can play a prominent role in promoting this pathway. However, as a first step, this requires a clear understanding of how investors perceive climate risks. The results of the present paper contribute to designing and implementing effective climate mitigation and adaptation policies that can change the way investors perceive climate risks and, thus, are likely to cause stability in financial markets.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material to this article, including the exact search queries, textual analysis methodology, peak analysis, and data sources, can be found in an Internet Appendix online at <https://doi.org/10.1016/j.irfa.2025.104384>.

Data availability

I have shared a link to mention volume data, which are freely available on the data repository Mendeley Data.

Empty Pledges and Powerless Conventions: Daily Climate Attention Mention Volume Indexes (MVIs) Data from Twitter (Original data) (Mendeley Data)

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