Dissecting Causal Linkages among International Climate Risk Measures

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Abstract. The paper uncovers causal linkages within a tangle of eight international climate risk measures from January 2005 to June 2023 by employing Granger causality tests based on high-dimensional VAR models. We account for the median, high and low regimes of climate risk and conduct the analysis for two sub-periods, conditional on the signing of the Paris Agreement, i.e. January 2005-December 2015 and January 2016-June 2023. The measures capturing public sentiment about the physical dimension of climate risk have more outgoing and fewer incoming causal linkages compared to the measures accounting for the transition climate risk. The most influential measure within our tangle is public sentiment about natural disasters, playing the pivotal role under the median and above-the-median risk regimes. Also, it appears the most influential in the aftermath of signing the Paris Agreement. It is only under the low-risk regime that a measure capturing the transition dimension of climate risk, marginal expected capital shortfall of world financial firms, appears the most significant in the respective causal network. The findings are relevant for international climate risk monitoring and for the investors hedging this risk in financial markets.

Keywords: climate risk, Granger causality, Paris Agreement, physical risk, transition risk.

JEL codes: G01, C32, Q54.

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1 Introduction

A lot of attention across different research fields, including economics and finance, is now riveted on climate risk (Giglio et al., 2021; Campiglio et al., 2023; Zhou et al., 2023; De Bandt et al., 2024; Albanese et al., 2025). Since its materialization can be quite costly, it is crucial to monitor the build-up of climate risk across firms, industries, countries and regions, thereby preventing or at least mitigating potential losses. To accomplish this goal, there is a need for empirical measures enabling to quantify climate risk from the economic perspective. Recently, an increasing number of such indicators has been proposed, though most of them are computed on the firm level, e.g. Ginglinger and Moreau (2023), Li et al. (2024). Meanwhile, climate risk measures seeking to capture the build-up of climate risk in the international framework are scarce.

The limited set of existing measures assessing climate risk internationally includes eight indicators extensively used in the research on climate finance, sustainable development and environmental economics in the recent years. The vast majority of these measures capture the economic agents' perception of exposure to climate risk based on the textual analysis of the media news (Faccini et al., 2023; Giglio et al., 2023; Bua et al. 2024), while only one, marginal expected capital shortfall of world financial firms under a climate stress scenario (MCRISK) introduced by Jung et al. (2023), builds on balance sheet and financial market data. Due to the distinctive methodologies underpinning these measures, they may naturally capture different facets of climate risk, e.g. considering climate risk as a whole, attaching more attention to physical risk which pins down the physical impacts of climate change or, conversely, to the transition one related to the transition to the low-carbon economy. Thus, by tracking these measures individually, policymakers may receive inconclusive and even potentially controversial information regarding the international stance of climate risk. Against this backdrop, it appears essential to dissect lead-lag relationships among the international climate risk measures and identify the most influential ones which have the biggest predictive power for the peer measures.

In this study, we perform such analysis for the period between January 2005 and June 2023 by underscoring Granger causal linkages within the aforementioned set of measures. These linkages are derived after controlling for a number of confounding economic and financial factors and are based on the high-dimensional vector autoregression models (HD-VARs). Such approach allows to overcome the dimensionality curse, a typical drawback of VAR estimation with multiple variables and relatively short time series. Besides the HD-VAR estimation, the novelty of our methodological approach rests on two more pillars. First, we examine the lead-lag relationships among the international climate risk measures in terms of three risk regimes: at the median level, when climate risk is above and below the median. Second, we identify the most influential measures for two sub-periods, i.e. January 2005-December 2015 and January 2016-June 2023, to test if signing the Paris Agreement leads to any change in the salience of the risk measures.

We document that the measures gauging public sentiment about the physical dimension of climate risk are more salient within our set of measures, exhibiting more outgoing and fewer incoming causal linkages, compared to the measures accounting for the transition climate risk. The most influential measure appears public sentiment about natural disasters, playing the pivotal role under the median and above-the-median risk regimes. This risk measure is also found the most influential in the aftermath of signing the Paris Agreement. However, under the low-risk regime a measure capturing the transition dimension of climate risk, marginal expected capital shortfall of world financial firms under a climate stress scenario, appears the most significant in the causal network. The results survive a number of robustness checks accounting for alternative approaches to deriving causal linkages among the climate risk measures.

Overall, we contribute to the extant literature by shedding light on the information flow among the international climate risk measures, thereby helping policymakers improve the monitoring of climate risk and elaborate economic policies which should account for this type of risk. In this realm, the results may be of a particular interest for national central banks implementing macroprudential policy instruments, including green ones, and international financial regulators, i.e. BIS and IMF, which are keen on investigating “green swans” - highly disruptive climate-related events potentially translating into financial crises. At the micro-level, our findings can be useful for investors assessing the pricing of climate risk and hedging it in financial markets.

The remainder of the paper is as follows: Section 2 describes the data, Section 3 presents the methodology, Section 4 displays the results and its policy implications, Section 5 describes the robustness checks, while Section 6 concludes.

2 Data

In a recent paper, Salisu and Oloko (2023) review the literature on climate risk measures and assert that they can be divided into three broad categories: (i) measures based on weather conditions; (ii) measures quantifying weather-related losses and (iii) text-based measures. Although the measures pertinent to the first two categories are directly linked to climate change, they largely build on the data describing the events which have already occurred. Therefore, such measures are available with a certain time lag. Besides, they are often collected and reported on a lower-frequency basis, i.e. quarterly and yearly. Conversely, text-based measures allow to gauge the public perception of exposure to climate risk in a more timely manner and using higher-frequency data. Such measures can be useful to assess the pricing of climate risk in financial markets and ways to hedge it, e.g. Engle et al. (2020), Ardia et al. (2023). We believe that such text-based measures can complement those based on weather-related data as regards climate risk monitoring and elaborating economic policies to curb it.

In this study, we adopt seven text-based measures of international climate risk. Faccini et al. (2023) propose a set of four measures capturing public sentiment about two dimensions of physical climate risk - natural disasters (NATDIS) and global warming (GLOBWARM), and about two dimensions of transition risk - international summits (INTSUM) related to climate issues and US climate policy (CLPOL). The measures gauge the intensity of news coverage along the four dimensions in the Refinitiv News Archive during 2000-2018. The news refer to policy debates, news on natural disasters, climate-change legislation across different countries, etc. Bua et al. (2024) compute two measures of climate risk - for its physical (PRI) and transition (TRI) dimensions, building on the news from Reuters News during 2005-2021. The news has a prevailing regional focus on the EU countries. One more text-based measure of climate risk, the New York Times Climate News Index (NYTCR), comes from Giglio et al. (2023). The indicator captures the intensity of climate-related news coverage in one of the leading US newspapers, though the news is not necessarily confined to the USA. The NYTCR measure encompasses both physical and transition dimensions of international climate risk.

Our set of international climate risk measures also includes a metric building on balance sheet and financial data, marginal expected capital shortfall of a financial firm under a climate stress scenario (MCRISK), introduced by Jung et al. (2023). The measure isolates the effect of climate stress from the financial firm's concurrent undercapitalization, i.e. from the pure financial stress. The MCRISK measure perceived mostly as a transition risk indicator is computed for a large number of international banks and it is aggregated at the international level.

Since the measures coming from Bua et al. (2024) begin in January 2005, while those borrowed from Faccini et al. (2023) are available until June 2023, our analysis is conducted for the period January 2005-June 2023.

Table 1 presents descriptive statistics for the data, while Table 2 reports a correlation matrix among the international climate risk measures.

Table 1. Descriptive statistics for international climate risk measures

Variable	Mean	Median	Maximum	Minimum	Standard Deviation	Observations
CLPOL	0.95	0.74	5.10	0.05	0.77	222
GLOBWARM	0.62	0.49	4.35	0.07	0.51	222
INTSUM	0.53	0.20	7.26	0.01	0.81	222
MCRISK	354.08	211.56	2791.16	-2812.90	798.98	222
NYTCR	-0.03	-0.41	4.66	-1.11	0.99	222
NATDIS	0.98	0.77	4.33	0.15	0.66	222
PRI	0.00	0.00	0.02	-0.02	0.01	222
TRI	0.00	0.00	0.03	-0.02	0.01	222

Table 2. Correlations among international climate risk measures

Correlation	CLPOL	GLOBWARM	INTSUM	MCRISK	NATDIS	NYTCR	PRI	TRI
CLPOL	1							
GLOBWARM	0.67	1						
INTSUM	0.24	0.34	1					
MCRISK	0.37	0.14	-0.20	1				
NATDIS	0.37	0.53	0.16	0.06	1			
NYTCR	0.48	0.35	-0.12	0.38	0.44	1.00		
PRI	0.09	0.31	0.27	-0.20	0.30	-0.07	1	
TRI	0.17	0.29	0.39	-0.07	0.26	-0.18	0.61	1

3 Methodology

We pursue a three-step methodology to test for causal linkages among the international climate risk measures.

At a preliminary stage, we standardize the international climate risk measures so that they have a a mean of zero and a standard deviation of one. Then, we isolate “pure” changes in climate risk from the shocks driven by global economic performance, volatility and policy uncertainty. To this end, we run an OLS regression for each of the climate risk measures on the dynamics of world industrial production index, the VIX index, and global economic policy uncertainty index. The world industrial production index is borrowed from Baumeister and Hamilton (2019). The VIX index, a recognized “fear gauge” in international financial markets, is retrieved from the CBOE Global Markets, capturing the international stock market’s expectation of 30-day volatility. The global economic policy uncertainty index is a newspaper-based measure accounting for the adverse perception of economic policy uncertainty across nearly 30 countries (Baker et al., 2016). After estimating the OLS regressions, we extract the residuals which proxy the “pure” changes in climate risk.

At the next stage, we assume that the patterns of causal linkages and, therefore, the most influential measures are not necessarily the same under different regimes of climate risk. Thus, deriving Granger causalities for the series “as is” may be insufficient. Building on such premise, we additionally decompose all the international climate risk measures into a below- and above-the-median components. Following Danielsson et al. (2018), we carry out this transformation by applying a one-sided Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997) represented as follows:

$$\min_{\{\tau_t(\lambda)\}_{t=1}^{T}} \sum_{t=1}^{T} [\sigma_t - \tau_t(\lambda)]^2 + \lambda \sum_{t=2}^{T-1} \{[\tau_{t+1}(\lambda) - \tau_t(\lambda)] - [\tau_t(\lambda) - \tau_{t-1}(\lambda)]\}^2 \quad (1)$$

where σ_t denotes a corresponding climate risk measure and $\tau_t(\lambda)$ is a trend, which is a function of λ.

We define these components as the deviations of each variable from above and below the trend, where the latter is derived by means of the HP filter with a smoothing parameter λ = 14400 which usually applies to monthly data:

$$\delta_t^{high}(\lambda) = \begin{Bmatrix} \sigma_t - \tau_t \; if \; \sigma_t \geq \tau_t(\lambda) \\ 0 \quad otherwise, \end{Bmatrix} \quad (2)$$

$$\delta_t^{low}(\lambda) = \begin{Bmatrix} \sigma_t - \tau_t \; if \; \sigma_t < \tau_t(\lambda) \\ 0 \quad otherwise \end{Bmatrix}$$

where δ_t^{high} and δ_t^{low} are above- and below-the-trend components of the corresponding variables and $\tau_t(\lambda)$ denotes the trend.

At the third stage, we obtain Granger causalities based on high-dimensional vector autoregressions (HD-VARs). The econometric technique we adopt is introduced by Hecq et al. (2023). They propose an LM test for Granger causality in HD-VAR models based on penalized least squares estimations. By applying HD-VARs, we aim to overcome the dimensionality curse, a typical drawback of VAR estimation with multiple variables and relatively short time series. The method we opt for to derive Granger causalities appears a good fit for our data, since even in case of the VAR(1) model there are 72 coefficients to be estimated vs. 222 observations. If the VARs are of a higher order, the coefficients estimated in the conventional VAR framework are likely to be biased.

We implement the above method by running a code in R[1]. It applies to the risk measures "as is" and those which account for the high and low-risk regimes. We also exploit this methodology when splitting the whole observation period into two sub-periods, January 2005-December 2015 and January 2016-June 2023, to examine if signing the Paris Agreement affects the pattern of causal linkages among the risk measures or not. We assume that this event may constitute a major breakpoint. Once surpassed, the international perception of climate agenda as a whole and climate risk, in particular, may have changed.

We consider all Granger causalities which are statistically significant at 5%. They are visualized as directional networks. We determine the most influential risk measures based on the difference between outgoing and incoming causal linkages as well as the the total number of Granger causalities into which this or that risk measure is involved. A greater total number of Granger causalities coupled with the excess of outgoing linkages over incoming ones indicate that a particular climate risk measure plays a notable role within our set of indicators.

[1] See https://github.com/Marga8/HDGCvar .

4 Results

4.1 Clearing the international climate risk measures of the effect of confounding factors

We begin by reporting OLS regressions characterizing the dependence of the international climate risk measures on global economic activity, volatility and policy uncertainty. Table 3 reveals that these confounding factors account for a moderate share in the variation of the risk measures, with coefficients of determination ranging from 0.02 to 0.45. However, in case of the New York Times Climate News Index and marginal expected capital shortfall of world financial firms under a climate stress scenario, the dependence appears the most tangible. Also, based on Table 3, the confounding factors contribute more to the variation of the measures capturing transition rather than physical risk. The average of the coefficients of determination in the regressions where the dependent variables proxy transition risk (CLPOL, MCRISK, INTSUM, TRI) totals 0.18, whereas the average for the regressions where the dependent variables are proxies of physical risk (GLOBWARM, NATDIS and PRI) is only about 0.04.

Table 3. Regressions of the international climate risk measures on global economic activity, volatility and policy uncertainty

	R^2 adj	β_{VIX}	β_{EPU}	β_{IP}
		t-stat	t-stat	t-stat
CLPOL	0.14	**0.23**	0.09	**0,23**
		(2.98)	(0.83)	**(2.18)**
MCRISK	0.28	-0.03	**0.36**	**0.21**
		(-0.45)	**(3.54)**	**(2.15)**
GLOBWARM	0.02	**0.20**	-0.18	**0.23**
		(2.52)	(-1.48)	**(1.99)**
INTSUM	0.15	**0.19**	**-0.23**	-0.19
		(2.50)	**(-2.03)**	(-1.75)
NATDIS	0.04	**0.26**	-0.20	**0.28**
		(3.21)	(-1.71)	**(2.49)**
NYTCR	0.45	-0.02	**0.29**	**0.43**
		(-0.36)	**(3.29)**	**(3.29)**
PRI	0.05	0.06	-0.09	-0.18
		(0.72)	(-0.75)	(-1.59)
TRI	0.16	**0.31**	-0.20	-0.14
		(4.06)	(-1.81)	(-1.35)

Notes: coefficients significant at the 5% level and respective t-statistics are in bold.

The dynamics of the residuals from the above regressions which account for the "pure" climate risk cleared of the effect of the confounding factors is represented in Figure 1. There is no much commonality in their dynamics, especially in the post-2020 period: while some risk measures clearly exhibit a hike during this time span, e.g. NATDIS, NYTCR, MCRISK, CLPOL, GLOBWARM, other metrics do not showcase any clear-cut trend.

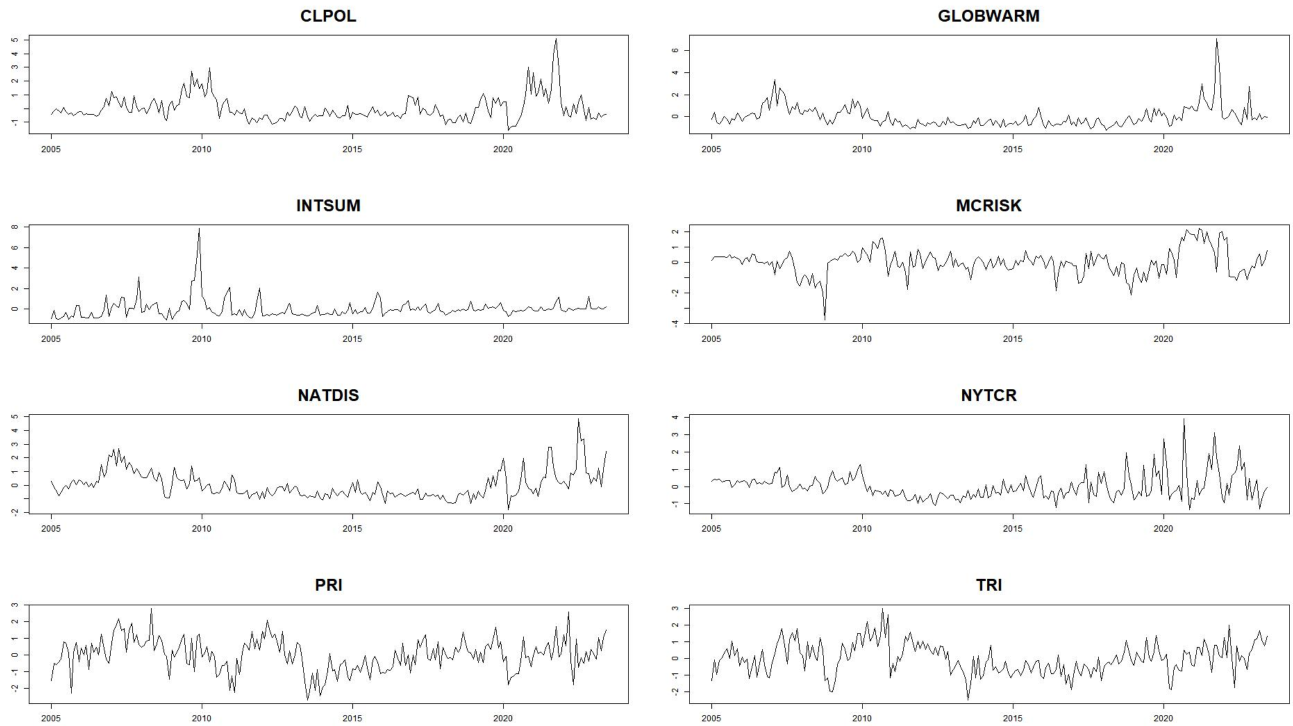

Figure 1. Dynamics of the international climate risk measures cleared of the effect of world industrial production, global volatility and global economic policy uncertainty, January 2005-June 2023.

4.1 Deriving causal linkages under three regimes of climate risk

We proceed by estimating the HD-VAR models and sequentially present the corresponding causal linkages among these international measures under the three regimes of climate risk.

Figure 2 describes the relationships in case of the measures considered "as is"[2].

[2] The results of the underlying Granger causality tests are provided in Tables A1-A3 of the Appendix.

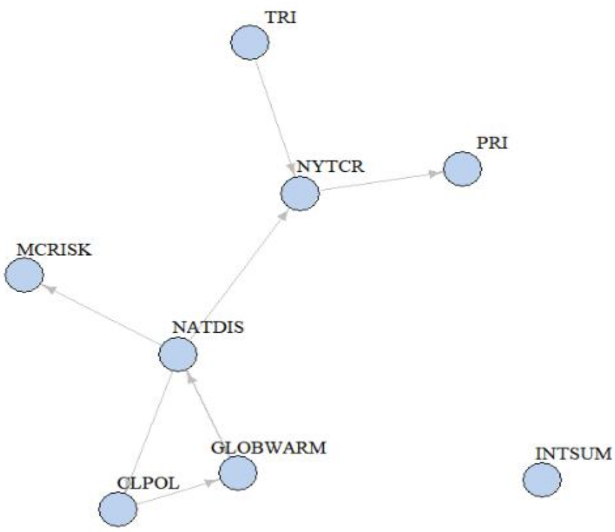

Figure 2. Granger causalities among the international climate risk measures (median estimation).

Overall, the density of causal linkages is low, suggesting that the information flow among the risk measures is not intense. The limited information spillover across the measures can further be corroborated by the first principal component accounting for only 38% of the variance of all the eight measures.

Against this backdrop, the NATDIS measure capturing public sentiment about natural disasters plays a central role in this causal network, as it has the biggest number of linkages with its peer measures. Moreover, in case of NATDIS, the number of outgoing linkages (three) exceeds that of incoming ones (one). Interestingly, the NATDIS Granger causes three measures gauging transition risk (MCRISK, CLPOL, NYTCR), while being driven by GLOBWARM, another physical risk measure. The latter has a neutral balance of outgoing and incoming linkages, so does CLPOL. PRI, MCRISK, NYTCR receive more linkages than generate themselves within this causal network. TRI Granger causes only NYTCR without any feedback from other measures, while INTSUM appears totally isolated from the rest.

The findings suggest that, while monitoring the build-up of climate risk internationally, policymakers and investors need to be first and foremost vigilant on its physical dimension proxied by the public sentiment about the exposure to natural disasters. This risk measure appears the most valuable in detecting “green swans”, i.e. disruptive climate-related events potentially entailing financial crises (Bolton et al., 2020). By tracking public sentiment about natural disasters policymakers can avoid or at least mitigate their consequences by adopting ex ante stringent macroprudential policy (Avril et al., 2022; Liu et al., 2024). The overwhelming importance of public sentiment about natural disasters is consistent with the ample cross-country evidence of natural disasters undermining financial stability through higher NPL ratios, lower profitability ratios (ROA and ROE) and decreased capital (Klomp, 2014; Gramlich et al., 2023; Peters, 2024), influencing the conduct of monetary policy (Klomp, 2020; Cantelmo et al., 2024) and even behavioral patterns of central bankers as to how to curb inflation in the post-disaster periods (Aslam et al., 2021). Against this backdrop, Hansen (2022) concludes that natural disasters now pose a daunting challenge for central bankers alongside uncertain climate changes. However, apart from such challenge, the leading role of public sentiment about natural disasters also comports with the view that their occurrence can engender transition risk, e.g. by hindering energy innovation (Zhao et al., 2022), renewable energy consumption (Lee et al., 2021) and green technology adoption (Hao et al., 2024).

Now we turn to the analysis of the causal network in terms of the high-risk regime (Fig.3). Compared to the median estimation, the sparsity of the network increases, as already three measures (INTSUM, MCRISK and TRI) have no connections with their peers.

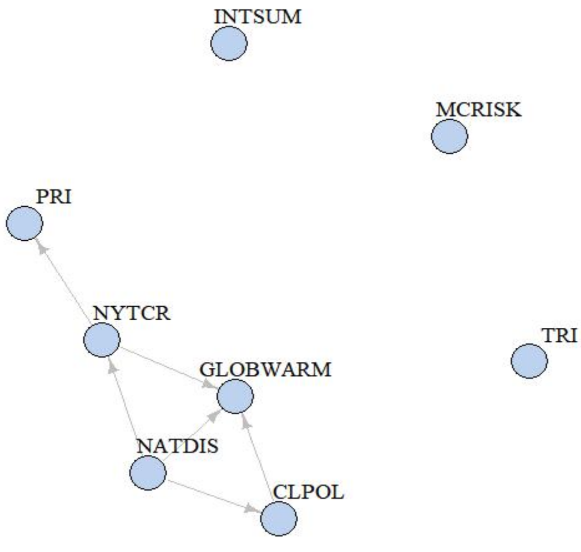

Figure 3. Granger causalities among the international climate risk measures (high-risk regime).

The NATDIS measure remains the most influential, having three outgoing linkages and zero incoming ones. Under this regime, the relevance of NYTCR rises, as it now has a positive balance of outgoing and incoming linkages. Meanwhile, the role of GLOBWARM notably declines, as it is driven by three peer measures, NATDIS, CLPOL and NYTCR. The CLPOL and PRI measures follow the same pattern of connections as under the median estimation. All in all, the findings indicate that the physical dimension of climate risk embodied in the NATDIS measure is still of primary importance when all the international climate risk measures are at an elevated level.

Under the low-risk regime, the density of the causal network slightly increases (Fig. 4).

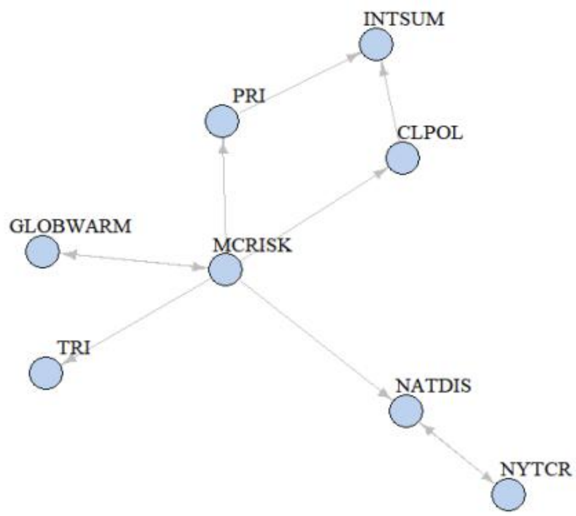

Figure 4. Granger causalities among the international climate risk measures (low-risk regime).

The MCRISK capturing the aggregate undercapitalization of financial firms worldwide under a climate stress scenario is found the most influential risk measure. It unidirectionally Granger causes four peer measures (NATDIS, TRI, PRI, CLPOL) and has a bidirectional relationship with one (GLOBWARM). The relevance of the NATDIS measure shrinks in comparison with the median and above-the-median estimations. Thus, when international climate risk is below its median, policymakers and investors need to pay more attention to its transition component embodied in the MCRISK measure. The result implicitly indicates that the degree of aggregate undercapitalization of world financials under a climate stress scenario may be a crucial factor to shape public sentiment about physical and transition risks when these risks are not acute. Better capitalized financial institutions can mitigate public concerns about climate risk, e.g. by providing more green finance, thereby prolonging the low-risk regime and generally facilitating the transition to the low-carbon economy. Conversely, the equity shortage of financial institutions under the low climate risk regime is detrimental as it leads to the erosion of such regime, entailing higher levels of physical and transition risks. These conjectures are consistent with the empirical evidence of the positive impact of green finance, including its digital instruments, on climate change mitigation and sustainable development on the global scale, e.g. Wang et al. (2022), Yu et al. (2022), Zhang et al. (2022).

Overall, the analysis confirms our conjecture that the importance of the international climate risk measures is conditional on the risk regime. Of the eight risk measures we have examined, public sentiment about natural disasters, NATDIS, appears the most influential during the median and above-the-median risk regime, while marginal capital shortfall of world financials under a climate stress scenario, MCRISK, is the most informative under the low-risk regime.

4.3 Deriving causal linkages among the international climate risk measures before and after signing the 2015 Paris Agreement

In our final empirical exercise, we investigate if the pattern of causal linkages among the risk measures changes when the Paris Agreement is adopted. Figures 5 and 6 present the causal networks before and in the aftermath of the event, respectively.

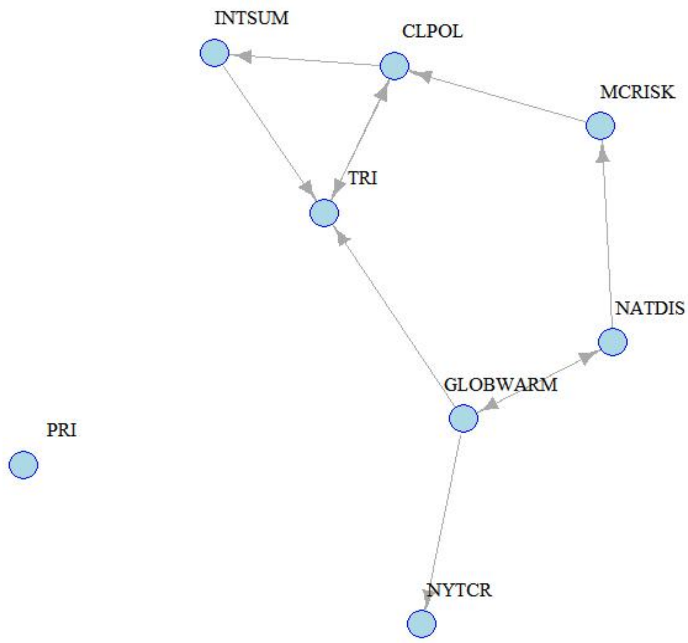

Figure 5. Granger causalities among the international climate risk measures before the Paris Agreement, January 2005-December 2015.

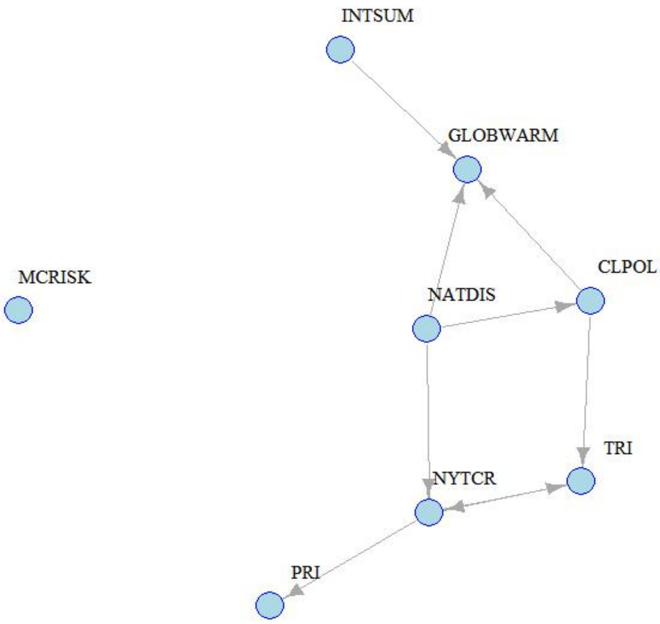

Figure 6. Granger causalities among the international climate risk measures in the aftermath of the Paris Agreement, January 2016-June 2023.

The figures indeed reveal that the patterns of causal linkages are different during the two sub-periods[3]. Before signing the Paris Agreement public sentiment about global warming, GLOBWARM, is found the most influential risk measure, having three outgoing linkages vs. one incoming. It is followed by the measures capturing public sentiment about natural disasters, NATDIS, and US climate policy, CLPOL. In the aftermath of signing the treaty, the importance of the GLOBWARM measure notably decays, whereas NATDIS turns into the pivotal risk measure followed by CLPOL. The leading role of NATDIS is in line with the intuition provided that this risk measure has witnessed a notable hike in the recent years, as shown in Figure 1, and has proved the most significant under two of the three climate risk regimes. The decline in the importance of GLOBWARM is likely to arise from the relative stabilization of the media attention to the topic of global warming in the international media in the 2010s. (Hase et al., 2021). Meanwhile, the attention to its impacts, first and foremost, natural disasters is still on the rise, especially in developing and emerging market economies (Hase et al., 2021; Otto and Raju, 2023). Furthermore, Eikelboom et al. (2024) find that in the media coverage specific terms related to climate agenda, e.g. “global warming”, “green house emissions” tend to be crowded out by more general ones, such as “carbon footprint” and “climate crisis”.

[3] The results of the underlying Granger causality tests are provided in Tables A4-A5 of the Appendix.

5 Robustness checks

Our baseline results are validated by means of two robustness checks.

First, as regards disentangling between above- and below-the-median components of the international risk measures with the aid of the HP filter, we have tried alternative values of the smoothing parameter: λ = 10000 and 5000. As an alternative to the HP filter, the Hamilton filter (Hamilton, 2018) applies to our data. Second, we consider Granger causalities significant at the 10% rather than 5% level, which increases the density of all the causal networks.

However, all these alterations haven't affected qualitatively the results of our baseline estimations reported in Section 4. Namely, the prevailing importance of the physical dimension of climate risk holds, with public sentiment about natural disasters, NATDIS, retaining its pivotal role under the median, high-risk regimes as well as in the aftermath of the Paris Agreement. Similarly, our robustness checks confirm that MCRISK is the most influential measure in terms of the low-risk regime. The results of the robustness checks are available from the authors upon request.

6 Conclusion

The paper underscores causal linkages within a tangle of eight international climate risk measures from January 2005 to June 2023. The analysis builds on Granger causality tests derived from high-dimensional VAR models (HD-VARs). We account for three regimes of climate risk (median, high and low) and conduct the analysis for two sub-periods, conditional on the signing of the Paris Agreement (January 2005-December 2015, January 2016-June 2023).

We find that the measures capturing public sentiment about the physical dimension of climate risk tend to have more outgoing and fewer incoming causal linkages compared to the measures accounting for the transition climate risk. The most influential measure within our tangle of indicators is public sentiment about natural disasters, NATDIS. It plays the pivotal role in the median and above-the-median risk setting. Also, it appears the most influential in the aftermath of signing the Paris Agreement. It is only under the low-risk regime that a measure capturing the transition dimension of climate risk, marginal expected capital shortfall of world financial firms (MCRISK), is found the most significant in the respective causal network.

The findings are useful from the standpoint of monitoring climate risk at the international level. By pinpointing the most salient climate risk measures, policymakers can elaborate policies aimed at preventing "green swans" in a more timely and precise manner. Also, investors may be interested in the leading risk measures revealed by our empirical horse race to try them as potentially relevant factors in asset pricing models and hedging strategies.

A natural extension to our study consists in incorporating new international climate risk measures once they are introduced as well as applying alternative quantitative techniques to infer about their connectedness in the time and time-frequency domains.

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Appendix

Table A1. Results of Granger causality tests among the international climate risk measures (median estimation)

Granger causality tests		
Null hypotheses	χ^2	**p-value**
CLPOL → CRISK	4.61	0.10
CLPOL → GLOBWARM	**12.84**	**0.00**
CLPOL → INTSUM	2.69	0.26
CLPOL → NATDIS	1.09	0.58
CLPOL → NYTCR	2.30	0.32
CLPOL → PRI	1.65	0.44
CLPOL → TRI	0.65	0.72
CRISK → CLPOL	5.74	0.06
CRISK → GLOBWARM	0.86	0.65
CRISK → INTSUM	0.45	0.80
CRISK → NATDIS	1.27	0.53
CRISK → NYTCR	0.10	0.95
CRISK → PRI	1.75	0.42
CRISK → TRI	4.89	0.09
GLOBWARM → CRISK	1.02	0.60
GLOBWARM → CLPOL	5.93	0.05
GLOBWARM → INTSUM	2.59	0.27
GLOBWARM → NATDIS	**8.22**	**0.02**

GLOBWARM → NYTCR	1.70	0.43
GLOBWARM → PRI	0.42	0.81
GLOBWARM → TRI	2.37	0.31
INTSUM → CRISK	2.13	0.34
INTSUM → CLPOL	0.79	0.67
INTSUM → GLOBWARM	4.38	0.11
INTSUM → NATDIS	3.13	0.21
INTSUM → NYTCR	2.72	0.26
INTSUM → PRI	3.07	0.22
INTSUM → TRI	3.19	0.20
NATDIS → CRISK	**9.68**	**0.01**
NATDIS → CLPOL	**6.25**	**0.04**
NATDIS → GLOBWARM	**29.27**	**0.00**
NATDIS → INTSUM	1.23	0.54
NATDIS → NYTCR	**18.93**	**0.00**
NATDIS → PRI	3.05	0.22
NATDIS → TRI	0.64	0.73
NYTCR → CRISK	2.61	0.27
NYTCR → CLPOL	2.17	0.34
NYTCR → GLOBWARM	1.78	0.41
NYTCR → INTSUM	0.21	0.90
NYTCR → NATDIS	1.16	0.56
NYTCR → PRI	**6.60**	**0.04**
NYTCR → TRI	3.06	0.22
PRI → CRISK	1.66	0.44
PRI → CLPOL	0.61	0.74
PRI → GLOBWARM	1.57	0.46
PRI → INTSUM	0.91	0.63
PRI → NATDIS	1.10	0.58
PRI → NYT	3.97	0.14
PRI → TRI	1.91	0.38
TRI → CRISK	2.94	0.23
TRI → CLPOL	0.32	0.85
TRI → GLOBWARM	4.13	0.13
TRI → INTSUM	4.07	0.13

TRI → NATDIS	1.97	0.37
TRI → NYT	**8.52**	**0.01**
TRI → PRI	0.08	0.96

Note: Granger causalities significant at 5% are in bold.

Table A2. Results of Granger causality tests among the international climate risk measures (high-risk regime)

Granger causality tests		
Null hypotheses	χ^2	**p-value**
CLPOL → CRISK	2.59	0.27
CLPOL → GLOBWARM	**20.30**	**0.00**
CLPOL → INTSUM	0.61	0.74
CLPOL → NATDIS	0.09	0.96
CLPOL → NYTCR	1.02	0.60
CLPOL → PRI	4.32	0.12
CLPOL → TRI	1.72	0.42
CRISK → CLPOL	0.70	0.70
CRISK → GLOBWARM	2.01	0.37
CRISK → INTSUM	1.97	0.37
CRISK → NATDIS	4.26	0.12
CRISK → NYTCR	1.35	0.51
CRISK → PRI	2.96	0.23
CRISK → TRI	3.69	0.16
GLOBWARM → CLPOL	2.25	0.32
GLOBWARM → GRISK	2.57	0.28
GLOBWARM → INTSUM	5.58	0.06
GLOBWARM → NATDIS	3.18	0.20
GLOBWARM → NYTCR	1.43	0.49
GLOBWARM → PRI	1.55	0.46
GLOBWARM → TRI	0.82	0.66
INTSUM → CLPOL	0.34	0.85
INTSUM → CRISK	1.39	0.50
INTSUM → GLOBWARM	1.91	0.39
INTSUM → NATDIS	1.93	0.38
INTSUM → NYTCR	1.80	0.41
INTSUM → PRI	1.37	0.50
INTSUM → TRI	3.73	0.16

NATDIS → CLPOL	**13.25**	**0.00**
NATDIS → CRISK	4.40	0.11
NATDIS → GLOBWARM	**32.10**	**0.00**
NATDIS → INTSUM	1.94	0.38
NATDIS → NYTCR	**19.94**	**0.00**
NATDIS → PRI	4.54	0.10
NATDIS → TRI	1.81	0.41
NYTCR → CLPOL	4.31	0.12
NYTCR → CRISK	3.38	0.18
NYTCR → GLOBWARM	**14.94**	**0.00**
NYTCR → INTSUM	1.64	0.44
NYTCR → NATDIS	0.28	0.87
NYTCR → PRI	**7.21**	**0.03**
NYTCR → TRI	2.48	0.29
PRI → CLPOL	1.18	0.55
PRI → CRISK	0.13	0.94
PRI → GLOBWARM	0.64	0.72
PRI → INTSUM	1.40	0.50
PRI → NATDIS	0.90	0.64
PRI → NYT	4.39	0.11
PRI → TRI	0.65	0.72
TRI → CLPOL	2.07	0.36
TRI → CRISK	0.79	0.67
TRI → GLOBWARM	1.81	0.40
TRI → INTSUM	5.55	0.06
TRI → NATDIS	0.24	0.89
TRI → NYT	4.03	0.13
TRI → PRI	0.65	0.72

Note: Granger causalities significant at 5% are in bold.

Table A3. Results of Granger causality tests among the international climate risk measures (low-risk regime)

Granger causality tests		
Null hypotheses	χ^2	**p-value**
CLPOL → CRISK	0.59	0.74
CLPOL → GLOBWARM	0.22	0.90
CLPOL → INTSUM	**6.24**	**0.04**

CLPOL → NATDIS	0.52	0.77
CLPOL → NYTCR	0.95	0.62
CLPOL → PRI	2.69	0.26
CLPOL → TRI	1.14	0.57
CRISK → CLPOL	**12.87**	**0.00**
CRISK → GLOBWARM	**12.17**	**0.00**
CRISK → INTSUM	4.91	0.09
CRISK → NATDIS	**12.72**	**0.00**
CRISK → NYTCR	1.99	0.37
CRISK → PRI	**6.18**	**0.05**
CRISK → TRI	**8.70**	**0.01**
GLOBWARM → CLPOL	3.20	0.20
GLOBWARM → GRISK	**9.65**	**0.01**
GLOBWARM → INTSUM	0.29	0.86
GLOBWARM → NATDIS	3.09	0.21
GLOBWARM → NYTCR	1.34	0.51
GLOBWARM → PRI	0.16	0.92
GLOBWARM → TRI	3.72	0.16
INTSUM → CLPOL	1.30	0.52
INTSUM → CRISK	0.53	0.77
INTSUM → GLOBWARM	0.56	0.76
INTSUM → NATDIS	5.40	0.07
INTSUM → NYTCR	0.25	0.88
INTSUM → PRI	1.78	0.41
INTSUM → TRI	2.73	0.25
NATDIS → CLPOL	4.40	0.11
NATDIS → CRISK	3.97	0.14
NATDIS → GLOBWARM	4.07	0.13
NATDIS → INTSUM	1.55	0.46
NATDIS → NYTCR	**6.08**	**0.05**
NATDIS → PRI	2.02	0.36
NATDIS → TRI	2.80	0.25
NYTCR → CLPOL	1.68	0.43
NYTCR → CRISK	0.00	1.00
NYTCR → GLOBWARM	0.18	0.91

NYTCR → INTSUM	0.39	0.82
NYTCR → NATDIS	**9.56**	**0.01**
NYTCR → PRI	1.51	0.47
NYTCR → TRI	2.05	0.36
PRI → CLPOL	1.00	0.61
PRI → CRISK	0.81	0.67
PRI → GLOBWARM	2.01	0.37
PRI → INTSUM	**7.11**	**0.03**
PRI → NATDIS	2.12	0.35
PRI → NYT	2.93	0.23
PRI → TRI	0.63	0.73
TRI → CLPOL	0.84	0.66
TRI → CRISK	0.44	0.80
TRI → GLOBWARM	1.96	0.38
TRI → INTSUM	4.55	0.10
TRI → NATDIS	0.02	0.99
TRI → NYT	5.33	0.07
TRI → PRI	1.80	0.41

Note: Granger causalities significant at 5% are in bold.

Table A4. Results of Granger causality tests among the international climate risk measures before the Paris Agreement

Granger causality tests		
Null hypotheses	χ^2	**p-value**
CLPOL → CRISK	5.45	0.07
CLPOL → GLOBWARM	2.87	0.24
CLPOL → INTSUM	**6.55**	**0.04**
CLPOL → NATDIS	1.42	0.49
CLPOL → NYTCR	1.92	0.38
CLPOL → PRI	0.35	0.84
CLPOL → TRI	**9.28**	**0.01**
CRISK → CLPOL	**6.94**	**0.03**
CRISK → GLOBWARM	5.47	0.06
CRISK → INTSUM	0.12	0.94
CRISK → NATDIS	4.14	0.13
CRISK → NYTCR	0.78	0.68
CRISK → PRI	0.09	0.95
CRISK → TRI	2.34	0.31

GLOBWARM → CLPOL	2.95	0.23
GLOBWARM → CRISK	3.34	0.19
GLOBWARM → INTSUM	3.39	0.18
GLOBWARM → NATDIS	**8.64**	**0.01**
GLOBWARM → NYTCR	**11.28**	**0.00**
GLOBWARM → PRI	1.02	0.60
GLOBWARM → TRI	**6.32**	**0.04**
INTSUM → CLPOL	1.06	0.59
INTSUM → CRISK	1.36	0.51
INTSUM → GLOBWARM	5.32	0.07
INTSUM → NATDIS	5.72	0.06
INTSUM → NYTCR	1.73	0.42
INTSUM → PRI	2.95	0.23
INTSUM → TRI	**7.04**	**0.03**
NATDIS → CLPOL	0.33	0.85
NATDIS → CRISK	**7.57**	**0.02**
NATDIS → GLOBWARM	**16.82**	**0.00**
NATDIS → INTSUM	0.92	0.63
NATDIS → NYTCR	3.43	0.18
NATDIS → PRI	3.04	0.22
NATDIS → TRI	3.93	0.14
NYTCR → CLPOL	2.02	0.36
NYTCR → CRISK	0.48	0.78
NYTCR → GLOBWARM	0.45	0.80
NYTCR → INTSUM	0.57	0.75
NYTCR → NATDIS	4.20	0.12
NYTCR → PRI	0.91	0.63
NYTCR → TRI	0.74	0.69
PRI → CLPOL	0.36	0.83
PRI → CRISK	0.40	0.82
PRI → GLOBWARM	0.11	0.95
PRI → INTSUM	2.24	0.33
PRI → NATDIS	3.34	0.19
PRI → NYT	1.61	0.45
PRI → TRI	1.40	0.50
TRI → CLPOL	**6.62**	**0.04**
TRI → CRISK	1.68	0.43

TRI → GLOBWARM	2.12	0.35
TRI → INTSUM	2.41	0.30
TRI → NATDIS	5.38	0.07
TRI → NYT	2.20	0.33
TRI → PRI	1.17	0.56

Note: Granger causalities significant at 5% are in bold.

Table A5. Results of Granger causality tests among the international climate risk measures in the aftermath of the Paris Agreement

Granger causality tests		
Null hypotheses	χ^2	**p-value**
CLPOL → CRISK	1.31	0.52
CLPOL → GLOBWARM	**8.41**	**0.01**
CLPOL → INTSUM	1.69	0.43
CLPOL → NATDIS	0.55	0.76
CLPOL → NYTCR	1.49	0.47
CLPOL → PRI	4.80	0.09
CLPOL → TRI	**9.33**	**0.01**
CRISK → CLPOL	1.02	0.60
CRISK → GLOBWARM	1.50	0.47
CRISK → INTSUM	2.76	0.25
CRISK → NATDIS	1.12	0.57
CRISK → NYTCR	0.04	0.98
CRISK → PRI	4.45	0.11
CRISK → TRI	4.20	0.12
GLOBWARM → CLPOL	1.74	0.42
GLOBWARM → CRISK	5.76	0.06
GLOBWARM → INTSUM	1.65	0.44
GLOBWARM → NATDIS	4.73	0.09
GLOBWARM → NYTCR	2.47	0.29
GLOBWARM → PRI	0.42	0.81
GLOBWARM → TRI	4.48	0.11
INTSUM → CLPOL	0.39	0.82
INTSUM → CRISK	0.44	0.80
INTSUM → GLOBWARM	**7.00**	**0.03**
INTSUM → NATDIS	1.57	0.46
INTSUM → NYTCR	0.75	0.69
INTSUM → PRI	2.70	0.26
INTSUM → TRI	2.82	0.24

NATDIS → CLPOL	**8.68**	**0.01**
NATDIS → CRISK	0.72	0.70
NATDIS → GLOBWARM	**14.69**	**0.00**
NATDIS → INTSUM	1.51	0.47
NATDIS → NYTCR	**16.16**	**0.00**
NATDIS → PRI	1.87	0.39
NATDIS → TRI	2.47	0.29
NYTCR → CLPOL	0.10	0.95
NYTCR → CRISK	1.88	0.39
NYTCR → GLOBWARM	3.37	0.19
NYTCR → INTSUM	1.02	0.60
NYTCR → NATDIS	2.21	0.33
NYTCR → PRI	**7.24**	**0.03**
NYTCR → TRI	**8.10**	**0.02**
PRI → CLPOL	1.67	0.43
PRI → CRISK	0.43	0.81
PRI → GLOBWARM	0.02	0.99
PRI → INTSUM	4.55	0.10
PRI → NATDIS	2.55	0.28
PRI → NYT	4.72	0.09
PRI → TRI	1.13	0.57
TRI → CLPOL	1.23	0.54
TRI → CRISK	0.14	0.93
TRI → GLOBWARM	0.68	0.71
TRI → INTSUM	3.58	0.17
TRI → NATDIS	1.12	0.57
TRI → NYT	**7.56**	**0.02**
TRI → PRI	0.41	0.82

Note: Granger causalities significant at 5% are in bold.