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Book

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Predicting the Conditional Distribution of US Stock Market Systemic Stress: The Role of Climate Risks[♣]

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Abstract

This paper explores how climate risks impact the overall systemic stress levels in the United States (US). We initially apply the TrAffic Light System for Systemic Stress (*TALIS³*) approach that classifies the stock markets across all 50 states based on their stress levels, to create an aggregate stress measure called *ATALIS³*. Then, we utilize a nonparametric causality-in-quantiles approach to thoroughly assess the predictive power of climate risks across the entire conditional distribution of *ATALIS³*, accounting for any data nonlinearity and structural changes. Our analysis covers daily data from July 1996 to March 2023, revealing that various climate risk indicators can predict the entire conditional distribution of *ATALIS³*, particularly around its median. The full-sample result also carries over time, when the nonparametric causality-in-quantiles test is conducted based on a rolling-window. Our findings, showing that climate risks are positively associated with *ATALIS³* over its entire conditional distribution, provide crucial insights for investors and policymakers regarding the economic impact of environmental changes.

Keywords: State stock markets; Systemic stress; Climate risks; Quantile predictions

JEL Codes: C21, C32, C53, G10, Q54.

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1. Introduction

A recent line of research has associated climate change-related risks to financial stress (Battiston et al., 2021; Flori et al., 2021; Del Fava et al., 2024), since extreme weather conditions pose a large aggregate risk to the financial system due to occurrences of rare disaster events impacting far out-in-the-left-tail realizations of the underlying states of the economy (Giglio et al., 2021; Stroebel and Wurgler, 2021; van Benthem et al., 2022). Theoretically speaking, the key assumption underlying rare-disaster models used to explain this nexus is that, the entire universe of assets in an economy is exposed to an aggregate jump-risk factor (Rietz, 1988; Barro, 2006, 2009). It follows that, even though in the cross section, some assets are more exposed to such a tail event than others: for instance, a jump-risk factor should be an important driver of the time-series variation in the tails of individual asset returns (Balcilar et al., 2023; Bonato et al., 2023; Salisu et al., 2023), due to reduction in productivity and/or the increase in the stochastic depreciation rate of capital to produce adverse impact on equity valuations (Donadelli, 2017, 2021a, b, 2022). In other words, one can hypothesize that the jump-risk factor associated with the climate risks, has predictive power for movements in the stress-levels of the aggregate stock market.

Against this backdrop, as our first objective, we compute, for the first time, a measure of aggregate systemic risk of the United States (US) economy based on state-level stock market data, by utilizing the TrAffic LIght System for Systemic Stress ($TALIS^3$), recently developed by Caporin et al. (2021). $TALIS^3$ combines the information contained in the Delta Conditional Value-at-Risk ($\Delta CoVaR$)) and the US state-level shortfalls (i.e., the realized losses of a state stock market are larger than the expected Value-at-Risk – VaR) to provide accurate systemic risk rankings. Therefore, $TALIS^3$ identifies the contribution of each US state for the systemic risk of the aggregate US stock market by combining signals from two different sources. The decision to employ the TALIS3 methodology over other stress indicators, as outlined by Benoit et al. (2017) and Silva et al. (2017), is driven by multiple factors. Firstly, $TALIS^3$ uses appropriate and well-known loss functions to quantify the level of stress of a particular state (i.e., squared deviations between the equity returns of a state and the corresponding VaR) and the system stress (i.e., the $\Delta CoVaR$ measure of Girardi and Ergün (2013)). Secondly, to analyse the severity of such stress regimes, these loss functions are dynamically analysed, leading to a colour-based classification of the states that includes four possible regimes. Lastly, $TALIS^3$ also allows the derivation of an aggregated index ($ATALIS^3$) based on the risk classification of each of the states, which provides a way to move beyond the isolated state-level categorization and gain a complete understanding of the dynamics of the equity market system.

The rationale behind our regional assessment of stock market stress to develop the *ATALIS³* index stems from research indicating that companies' main operations often cluster around their headquarters, affecting investment patterns as investors tend to prefer local companies (Pirinsky and Wang, 2006; Chaney et al., 2012). This local bias in investments (Coval and Moskowitz, 1999, 2001; Korniotis and Kumar, 2013) underlines the relevance of our regional stress analysis. By identifying and measuring stress levels across different states, we provide a nuanced picture of systemic stress in the equity market, invaluable for investors' portfolio strategies.

Moreover, we analyse, again for the first time, the predictive ability of climate anomalies—such as unusual temperature patterns, precipitation levels, and variations in heating and cooling days—on the entire conditional distribution of the *ATALIS³* indicator, using the nonparametric causality-in-quantiles test of Jeong et al. (2012), both for the full-sample, and in a time-varying (rolling-window) set-up (as in Bonaccolto et al. (2018)). This method is particularly effective as it enables us to detect predictability across the entire conditional distribution of *ATALIS³*, resulting from climate risks, while addressing the challenges posed by nonlinearities and structural breaks in the data. Moreover, given the presence of a fat tail in the unconditional distribution of the *ATALIS³*, a quantiles-based nonparametric predictive approach is more relevant in our context, rather than conditional mean-based nonlinear/nonparametric causality tests (as in, Hiemstra and Jones (1994), and Diks and Panchenko (2005, 2006), Nishiyama et al. (2011)), which may overlook significant influences on different segments of the systemic stress distribution. In addition to our focus on the aggregate level of equity market stress, we also briefly discuss findings from a pooled state-level multinomial logistic approach-based analysis of the effect of climate risks on the indicators of ordered regimes of stress.

Financial markets react swiftly to extreme events, integrating and transmitting new information rapidly into the broader economy, as highlighted by Caporin et al. (2022). Therefore, by studying the role of climate risks in predicting the time-varying stress in the financial system at a high frequency is likely to provide early relevant insights to policymakers in terms of its impact on the macroeconomy, for instance through MIxed DAta Sampling (MIDAS) models (Bańbura et al., 2011). Furthermore, the indirect impacts of climate risks on the macroeconomy, through financial stress, supplement their direct consequences on the U.S.

economy, as noted by Colacito et al. (2019), Sheng et al. (2022), and Cepni et al. (2024). This potentially leads to a more sustained effect on the real economy, necessitating that policymakers adjust the intensity of their monetary and fiscal strategies accordingly. Hence, our findings regarding the predictive power of climate risks on systemic stress in the U.S. stock market underline a significant intertwining of environmental factors with financial stability. The fact that climate risk indicators, such as abnormal weather patterns and temperature anomalies, exhibit a tangible influence on the distribution of systemic stress levels across the U.S. equity markets suggests that climate change is not merely an environmental or social issue but a core financial one. The identified relationships between climate risks and market stress underscore the pressing need for the financial industry and regulators to integrate climate-related data into their risk assessment models and investment strategies more comprehensively.

The remainder of the paper is organized as follows: Section 2 outlines the data, involving the construction of $ATALIS^3$ and (two) climate risks metrics, and presents the basics of the nonparametric causality-in-quantiles test. Section 3 discusses our empirical findings, with Section 4 concluding the paper.

2. Data and Methodology

2.1. Construction of the variables of interest

We employ daily stock log-returns returns, which start on the 2nd of February, 1994, for the 50 states of the US to compute the $TALIS^3$ for each of the states, and then the $ATALIS^3$ for the overall US. The state-level stock market indexes are derived from the Bloomberg terminal, which in turn, creates these indexes by taking the capitalization-weighted index of equities for companies domiciled in each US state. $TALIS^3$ can be used to monitor and process signals related to market shortfalls for the purpose of building systemic risk rankings, and is a system providing a classification of the underlying states into four categorizations of increasing stress: green, yellow, orange, and red. This stratification aids in the clear identification and understanding of varying degrees of financial stress within individual states.

As discussed earlier, our classification system, which utilizes two distinct loss functions calculated on a daily basis for this analysis: the first evaluates systemic risk using the $\Delta CoVaR$ measure, while the secondary function assesses risk at the state level by calculating the squared difference between the state's VaR and the aggregate equity market returns, based on the Center for Research in Security Prices (CRSP) composite index, obtained from Professor Kenneth R.

French's data library.[1] Then, conditional expectations to a distress regime (for the market and states, respectively) are computed for both loss functions. Contrasting the sample expectations to local thresholds (median loss functions over a rolling-window), states are ranked into the four stress classes, leading to $TALIS^3$. Furthermore, using the collections of all the stress indexes of the states, an aggregated indicator is also derived: the stress level is used as a weight for the aggregation of $\Delta CoVaR$ the state in a weighted geometric mean. The state- specific stress and the aggregated index provide relevant information for the analysis of the market conditions during turmoil.[2]

Using the US state level equity market indexes and the aggregated market index, we proceed to the computation of the state-specific $TALIS^3$ and to the country-wide $ATALIS^3$ index, with Figure 1(a) plotting the latter, over the period of 16th July, 1996 to 31st March, 2023. Note the length of the sample period is driven by data availability, and underlying estimations requirement at the time of writing this paper.[3] The state-level $TALIS^3$, reported with a specific colour shade, is plotted in Figure A1 in the Appendix of the paper separately for the days of each year (1996-2023), with the stress-level of the 50 states (ordered alphabetically[4]) represented in each row. Notably, the $ATALIS^3$ spikes moderately during the Asian financial crisis of 1997, the Dot-com bubble burst of 2000, the European sovereign debt crisis of 2009 to 2010, the Brexit and the sell-off in 2016, and the start of the Russia-Ukraine War in 2022. But the highest peaks are unsurprisingly associated with the Global Financial Crisis (GFC) of 2007-2009, and the outbreak of the COVID-19 pandemic in 2020, with the lowest level of the index observed over 2003 to 2006 during the tranquil market phase in the US. Though the stress levels of each state depicts quite a bit of heterogeneity, as seen from in Figure A1, all the states are virtually in red, i.e., highest class of stress, during the latter part of 2008 and early part of 2020, corresponding to the peaks of the GFC and the coronavirus outbreak.

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[2] For additional details on the methodology, we refer the reader to Caporin et al. (2021).
[3] We lose several data points due to the evaluation of $TALIS^3$: 500 observations for the estimation of a GARCH model in the evaluations of $\Delta CoVaR$ and VaR, 60 additional data to define the threshold for loss functions evaluation, and finally 60 more daily periods for the determination of the losses.
[4] Alabama (AL), Alaska (AK), Arizona (AZ), Arkansas (AR), California (CA), Colorado (CO), Connecticut (CT), Delaware (DE), Florida (FL), Georgia (GA), Hawaii (HI), Idaho (ID), Illinois (IL), Indiana (IN), Iowa (IA), Kansas (KS), Kentucky (KY), Louisiana (LA), Maine (ME), Maryland (MD), Massachusetts (MA), Michigan (MI), Minnesota (MN), Mississippi (MS), Missouri (MO), Montana (MT), Nebraska (NE), Nevada (NV), New Hampshire (NH), New Jersey (NJ), New Mexico (NM), New York (NY), North Carolina (NC), North Dakota (ND), Ohio (OH), Oklahoma (OK), Oregon (OR), Pennsylvania (PA), Rhode Island (RI), South Carolina(SC), South Dakota (SD), Tennessee (TN), Texas (TX), Utah (UT), Vermont (VT), Virginia (VA), Washington (WA), West Virginia (WV), Wisconsin (WI), and Wyoming (WY).

At the same time, we collect daily weather data also from the Bloomberg terminal, as compiled by the National Climatic Data Center (NCDC), for the US, as well as for the 50 states, with the former being the cross-sectional average of the weather variables across the latter over time. The weather data captures meteorological phenomena along several dimensions, including temperature, precipitation, number of heating degree days (HDD), number of cooling degree days (CDD), and wind speed as described below:

• Temperature ($temp_t$): The average temperature (usually of the high and low) that was observed between 7am and 7pm local time, expressed in Fahrenheit.

• HDD (H_t): The number of degrees that the day's average temperature is below 65 degrees Fahrenheit. It's used to calculate the heating requirements of a building.

• CDD (C_t): The number of degrees the day's average temperature is above 65 degrees Fahrenheit, aiding in estimating a building's cooling needs.

• Precipitation ($prec_t$): The amount of rain, snow, sleet, or hail that falls in a specific location.

• Wind speed ($wind_t$): The average speed of the wind, not accounting for gusts, represented in knots.

As in Choi et al., (2020), we decompose the weather-related variables into three components that account for seasonal, predictable, and abnormal patterns. In particular, for each day, *t*, we compute the daily weather measure (W_t) for the overall US, using the following formula:

$$W_t = W_t^M + W_t^D + W_t^A \quad (1)$$

where W_t = {$temperature_t$ ($temp_t$), HDD_t, CDD_t, $precipitation_t$ ($precip_t$), $wind\ speed_t$ ($wind_t$)}, and the term W_t^M denotes the mean of W_t for the overall US spanning the 120 months prior to *t*. Moreover, the variable W_t^D denotes the difference of the mean of the deviation of the W_t from the daily average temperature for the US in the same calendar day over the last ten years and W_t^M. Finally, the variable W_t^A is the remainder (i.e., the abnormal deviation of weather conditions) and, hence, captures extreme departures from normal weather conditions. For this reason, we focus on this variable in our analysis. We standardize the abnormal deviations, commonly known as the standardized anomaly, to obtain the following two comprehensive climate risks (*CR*) measures:

$$CR1_t = \frac{std(temp_t^A) + std(precip_t^A) + std(CDD_t^A) + std(HDD_t^A) + std(wind_t^A)}{5} \quad (2)$$

$$CR2_t = \frac{std(temp_t^A) + std(precip_t^A) + std(CDD_t^A) - std(HDD_t^A) + std(wind_t^A)}{5} \quad (3)$$

Note that in $CR2_t$ the standardized HDD_t^A enters with negative sign. HDD is a measure used to estimate the demand for energy needed to heat a building. Hence, high HDD indicates that more energy is needed to heat buildings due to lower temperatures, which implies less risk of global warming. We plot *CR1* and *CR2* in Figure 1(b), showing consistent fluctuations over the entire sample period. It must be noted that, the same approach as above is used to derive the two metrics of climate risks ($CR1_{it}$ and $CR2_{it}$) at the state-level by focussing on the underlying climate variables for each state *i.*

Table 1 summarizes $ATALIS^3$, *CR1* and *CR2*. Notably, *CR1* exhibits a higher standard deviation compared to *CR2*, as illustrated in Figure 1(b). All the three variables of interest being non-normal as confirmed by the strong rejection of the null of normality under the Jarque-Bera test. Importantly, the heavy tail of $ATALIS^3$ (due to positive skewness and excess kurtosis) provides an initial motivation to rely on a quantiles-based test of its predictability due to *CR1* and *CR2*, rather than conditional mean-reliant methods.

[INSERT FIGURE 1 AND TABLE 1]

To gain an initial understanding of the correlation between $ATALIS^3$ and *CR1* or *CR2*, we refer to Figure 2, which displays the conditional quantiles-based response of the former, stemming from various quantiles of the latter. This is derived using the Quantiles-on-Quantiles (QQ) regression method Sim and Zhou (2015).[5] In general, the variables of interest are positively correlated across their respective quantiles, with the sign and magnitude virtually being invariant over the quantiles of the climate risks metrics. This latter finding provides a motivation to consider a predictive approach, which we discuss in the next sub-section, that basically concentrates on the conditional distribution of only $ATALIS^3$ rather than also those of *CR1* and *CR2* simultaneously.

[INSERT FIGURE 2]

[5] The interested reader is referred to the original paper for complete technical details of the QQ approach.

2.2. Nonparametric causality-in-quantiles test

In this sub-section, we briefly present the methodology for testing nonlinear causality based on the framework of Jeong et al. (2012). Let y_t denote the *ATALIS*[3] and x_t either *CR1* or *CR2*. Further, let $Y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \ldots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t| \bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. The (non)causality in the θ-th quantile hypotheses to be tested are:

$$H_0:\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{4}$$

$$H_1:\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{5}$$

Jeong et al. (2012) show that the feasible kernel-based (standard normal) test statistic has the following format:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{6}$$

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{7}$$

with $L(\bullet)$ denoting the kernel function.

The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use a lag order of one based on the Schwarz Information Criterion (SIC). We determine h by the leave-one-out least-squares cross validation. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

3. Empirical Findings

Before we discuss the results from the causality-in-quantiles test, for the sake of completeness and comparability, we conduct the standard linear Granger causality test, with a lag-length of one. The resulting $\chi^2(1)$ test statistic associated with the causality running from *CR1* and *CR2* to *ATALIS*[3] are 0.024 and 0.667 with associated p-values of 0.878 and 0.414, respectively. In other words, the null hypothesis that climate risks does not Granger cause systemic equity market stress for the overall US, cannot be rejected even at the 10% level of significance. Nevertheless, this linear approach falls short of capturing the detailed, quantile-specific predictability nuances. Consequently, we proceed to the more nuanced nonparametric causality-in-quantiles examination. However, to set the stage for this sophisticated analysis, we first explore potential nonlinearity and structural shifts within the relationships between *CR1* or *CR2* and $ATALIS^3$. The presence of such complexities would validate the necessity for the nuanced nonparametric quantiles-based causality approach, as it adeptly addresses nonlinearity and structural breaks within the data, issues that are not accommodated by standard linear analyses.

For this purpose, we first apply the Brock et al. (1996, BDS) test on the residual derived from the $ATALIS^3$ equations involving one lag each of $ATALIS^3$ and *CR1,* and $ATALIS^3$ and *CR2*. Table 2 presents the results of the BDS test of nonlinearity. As the table shows, we find strong evidence, at the highest level of significance, for the rejection of the null hypothesis of *i.i.d.* residuals at various embedded dimensions (*m*), which, in turn, is indicative of nonlinearity in the relationship between climate risks and US systemic stress. To further motivate the causality-in-quantiles approach, we next use the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), to detect 1 to *M* structural breaks in the relationship between $ATALIS^3$ and *CR1,* and $ATALIS^3$ and *CR2*, allowing for heterogeneous error distributions across the breaks. When we apply these tests again to the one-lag-based $ATALIS^3$ equations, we detect three breaks at: 29th May, 2003; 3rd December, 2008, and; 29th January, 2018 under *CR1*, and 18th June, 2003; 3rd December, 2008, and; 12th October, 2018 when using *CR2* as the predictor. While the second break point is virtually in line with the peak of the GFC following the bankruptcy of Lehman Brothers, these dates also fall in and around major weather or climate disaster events with losses exceeding $1 billion each (specifically, $37. 5 billion in 2003, $91.4 billion in 2008, and $113 billion in 2018) to affect the US over our sample period.[6]

[INSERT TABLE 2]

Given the strong evidence of nonlinearity and structural breaks in the relationship between $ATALIS^3$ and *CR1,* and $ATALIS^3$ and *CR2*, we now turn our attention to the causality-in-quantiles test, which is robust to misspecification in the linear model due to its nonparametric nature, besides allowing us to test for predictability over the entire conditional distribution of

[6] https://www.ncei.noaa.gov/access/billions/state-summary/US.

the aggregate US stock market systemic stress indicator. The results are reported in Table 3, whereby we test the regime-specific null hypothesis of no-Granger causality running from *CR1* or *CR2* to and $ATALIS^3$ over the quantile range of 0.10 to 0.90 based on the standard normal test statistic. As can be seen from the table, predictability for $ATALIS^3$ from *CR1* and *CR2* holds over the entire quantile range considered of the aggregate systemic stress indicator at the 1% level of significance, with the strongest causal influence observed at the conditional median. In fact, the values of the standard normal test statistics under the two climate risks measures exceptionally close to each other, which is perhaps not surprising given a strong statistically significant correlation of 0.777 (with a *p*-value of 0.00) between *CR1* and *CR2*. The stronger predictability of median levels of equity market stress, which represent typical stress conditions, by climate risks as compared to extreme values (tails) can be rationalized. While heightened stress levels might correlate with broader macroeconomic factors, as noted by Koop and Korobilis (2014) and Kim and Shi (2021), the influence of climate risks and other variables on market expectations may be less pronounced under lower stress conditions. In contrast to the assumptions made by linear models, our application of a nonparametric model, which is designed to handle misalignments due to nonlinearity and structural breaks, demonstrates a marked but varied degree of predictability across different quantiles of the conditional distribution of $ATALIS^3$ as influenced by *CR1* and *CR2*.[7]

[INSERT TABLE 3]

Although robust predictive inference is derived based on the nonparametric causality-in-quantiles test, it is also interesting to estimate the sign of the effect of *CR1* and *CR2* on $ATALIS^3$ at various quantiles, especially to validate the theoretical positive relationship outlined in the introduction. But, in a nonparametric framework, this is not straightforward, as we need to employ the first-order partial derivatives. Estimation of the partial derivatives for nonparametric models can give rise to complications, because nonparametric methods exhibit slow convergence rates, due to the dimensionality and smoothness of the underlying

[7] We also utilize an alternative systemic risk measure, as proposed by Mihoci et al. (2020), which accounts for links and mutual dependencies between the US state-level stock markets by utilizing tail event information. This metric, known as the Financial Risk Meter (*FRM*), is based on least absolute shrinkage and selection operator (LASSO) quantile regression designed to capture tail event co-movements of asset (stock) returns. The results from the nonparametric causality-in-quantiles test from *CR1* and *CR2* to *FRM* is reported in Table A1 in the Appendix of the paper. In line with the findings of $ATALIS^3$, we find that the two climate risks metrics continue to predict (with similar strength) the entire conditional distribution of the (rolling-window-based) *FRM* (over 16th July, 1996 to 31st March, 2023), and again, the strongest impact is observed at the conditional median. These results ensure the robustness of our empirical conclusions involving climate risks on alternative measures of the aggregate US systemic stress based on state-level stock returns.

conditional expectation function. However, one can look at a statistic that summarizes the overall effect or the global curvature (i.e., the global sign and magnitude), but not the entire derivative curve. In this regard, a natural measure of the global curvature is the average derivative (AD) using the conditional pivotal quantile, based on approximation or the coupling approach of Belloni et al. (2019), which allows us to estimate the partial ADs. Based on the ADs reported in Table 4, we find consistent evidence of a positive predictive effect of both *CR1* and *CR2* on $ATALIS^3$, in line with the QQ regression results reported in Figure 2.

[INSERT TABLE 4]

Next, we briefly discuss the state-level findings. The state-level stress indicators are treated as ordered discrete variables, namely, 0 (green), 1 (yellow), 2 (orange), and 3 (red), which correspond to increasing levels of stock market stress. We apply multinomial logistic regressions using a lag of $CR1_i$ and $CR2_i$ as predictors. During the estimation process, $TALIS^3$ is consolidated from the original four regimes (0 to 3) into three, due to the infrequent appearance of regime 1 in the data; therefore, it is combined with regime 0. This results in three groups: 0-1 (green and yellow), 2 (orange), and 3 (red). We set state 2 as the baseline outcome and estimate both pooled and random-effects multinomial logit models. Analysing $CR1_i$ and $CR2_i$, we find that the estimates of the probability of moving from regime 2 to regime 1, and from regime 2 to regime 3, are statistically significant, with the first climate risk metric showing a stronger effect than the second. Specifically, as $CR1_i$ increases, the likelihood of moving to a lower stress regime, i.e., from 2 to 0-1, significantly decreases, whereas the probability of escalating to a higher stress regime, i.e., from 2 to 3, increases significantly. For $CR2_i$, these effects are statistically significant only when transitioning from regime 2 to regime 0-1. [8] In essence, climate risks are generally linked to higher, rather than lower, levels of stress across states, aligning with the theoretically expected positive relationship and the empirical findings observed for the overall US, as illustrated in Table 4.

Returning to the predictability of $ATALIS^3$ due to *CR1* and *CR2*, an interesting analysis is to provide a time-varying picture instead of the full-sample, by relying on a rolling-window of 500 observations (with weekly re-estimations to reduce computational burden). This will allow us to check if the full-sample result is driven by specific periods. As seen from Figures 3(a)

[8] The four-sets of estimate (p-value) from the pooled and random-effects multinomial logit model capturing movement out of regime 2 to regime 0-1, and regime 2 to regime 3 for $CR1_i$ and $CR2_i$ respectively are found to be as follows: -0.1150 (0.0000), 0.0323 (0.0070), -0.1306 (0.0000), 0.0317 (0.0080); -0.0228 (0.0040), -0.0097 (0.2560), -0.0168 (0.0540), -0.0084 (0.3240). Complete details of the results are available upon request from the authors.

and 3(b), in general, the predictability of the entire conditional distribution of *ATALIS³* from both *CR1* and *CR2* tends to hold consistently over July, 1997 to March, 2023, with strongest impact around the median, and relatively weaker conditional tails predictability. In other words, time-varying quantile causality results are in line with the full-sample evidence, though it must be said that conditional mean predictability is relatively stronger during the regimes of presidents Barack H. Obama II and Joseph R. Biden Jr, which is, perhaps, understandable in light of the strong emphasis on environmental policies by the Democratic Party, notwithstanding the fact that these terms also partially included the GFC and the COVID-19.

[INSERT FIGURE 3]

It is important to recognize that climate change encompasses both direct physical risks, as indicated by our CR1 and CR2 metrics, and indirect transition risks. These transition risks stem from shifts towards a low-carbon economy, driven by changes in climate policies, the rise of green technologies, and evolving consumer behaviours. Given this, as a robustness check, we report the results in Table 5 from the nonparametric causality-in-quantiles test on *ATALIS³* due to metrics of both physical and transition risks for the US, as developed by Faccini et al. (2023), using textual and narrative analysis of Reuters climate-change news.[9] Based on a sample period of 1st January, 2000 to 31st March, 2023, and utilizing news on "US climate policy", "International summits", "Global warming", and "Natural disasters", we again find strong evidence of predictability (primarily at the 1% level of significance) over the entire conditional distribution of *ATALIS³*. As with *CR1* and *CR2*, influence peaks around the median, and is relatively weaker at the tails.[10] Recognizing that news about US climate policy and international summits reflects short- and long-term transition risks, respectively, while articles on global warming and natural disasters highlight long-term physical risks, our results suggest that both types of risks carry predictable information across various conditional regimes of US-wide stock market stress. Essentially, our findings derived from *CR1* and *CR2*, which primarily represent physical risks, continue to be valid as we broaden the scope to include the transition dimension associated with climate change.[11]

[9] The data is available for download from: https://sites.google.com/site/econrenatofaccini/home/research?authuser=0.

[10] In fact, there is no evidence of causality, even at the 10% level of significance, from *CR4* at the quantile of 0.90 for *ATALIS³*.

[11] In Table A2 in the Appendix of the paper, the strong predictability of the entire conditional distribution of the *ATALIS³* due to physical and transition risks of climate change is further robustly verified by using the aggregate and 34 disaggregated Media Climate Change Concerns (MCC) indexes, as developed by Ardia et al. (2023) based on news about climate change published by major US newspapers and newswires over the period of 1st January,

Furthermore, this examination sheds light on how different sources of climate news—ranging from policy announcements and international agreements to reports of natural disasters and global warming trends—reflect varying timelines and aspects of risk, from immediate to long-term impacts. This nuanced understanding reinforces the notion that the stock market's response to climate change is multifaceted, reflecting a blend of reactions to immediate physical dangers and to the longer-term structural shifts in the economy.

[INSERT TABLE 5]

4. Conclusion

Climate change is, perhaps, the most important of challenges currently, by imposing large aggregate (physical and transition) risks to not only the macroeconomy, but the entire financial system. Given this, in this paper, we utilize a new colour-based systemic stress indicator namely, the TrAffic LIght System for Systemic Stress ($TALIS^3$) for the state-level stock markets of the US. These regional indicators is inspired by the loss functions frequently adopted in backtesting analyses of financial markets and systemic risk. Thus, allowing us to identify more precisely the equity markets and periods under distress. This new indicator provides a state-level ranking system that identifies various levels of systemic risk and provides a color-based code similar to the Basel Committee's TrAffic Light approach adopted to classify market risk violations of financial institution. Once we obtain the state-level $TALIS^3$ indicators, a weighted measure of aggregate systemic risk ($ATALIS^3$) is derived for the overall US equity market. The entire conditional distribution of $ATALIS^3$ is then predicted based on metrics of climate risks due to extreme weather conditions, in a nonparametric quantiles-based framework. This testing approach allows us to control for misspecification due to uncaptured nonlinearity and regime changes in the relationship between aggregate systemic stress and climate risks, which we statistically show to exist in our dataset over the daily period of 16th July, 1996 to 31st March, 2023.

We show that while climate risks fail to predict aggregate US systemic stress under the misspecified linear Granger causality model, strong evidence of causal influence from extreme

2003 to 31st August, 2022. In the same table, when we use the New York Times news-based aggregate measure of physical and regulatory risks related to biodiversity loss of Giglio et al. (2023), predictability of $ATALIS^3$ covers the quantile range of 0.10 to 0.70. Hence, extreme high-levels of conditional stock market stress of the US cannot be associated with biodiversity risks over the period of 1st January, 2000 to 18th December, 2022, but indeed such risks predict low to moderate segment of the conditional distribution of $ATALIS^3$, as did the associated measure of aggregate climate risks, with results also presented in Table A2, developed by Giglio et al. (2023). Note that, the data sets of Ardia et al. (2023) and Giglio et al. (2023) are, respectively, available for download from: https://sentometrics-research.com/download/mccc/ and https://www.biodiversityrisk.org/download/.

weather shocks on the entire conditional distribution of the *ATALIS*^{3} holds under the robust nonparametric causality-in-quantiles, with strongest impact registered around the median. Moreover, in line with theoretical predictions defining the climate risks-systemic risks nexus, the detected impact of the latter on the entire conditional distribution of the former is positive. A brief state-level analysis also confirms that higher climate risks raises the probability of moving into higher-regimes of the *TALIS*^{3}. In addition, our results involving the predictability of *ATALIS*^{3} continue to be robust, when we utilize news-based measures of not only physical risks, but also transition risks, involving climate change.

Expanding on these insights, it is evident that the integration of climate risk into investment strategies not only enhances financial decision-making but also promotes a more sustainable market environment. By adopting quantile-based models, investors can navigate through varying degrees of market stress with greater precision, tailoring their strategies to withstand environmental uncertainties. This approach facilitates a more nuanced understanding of risk, enabling investors to identify opportunities even in volatile market conditions, thus contributing to the resilience and sustainability of their portfolios.

Moreover, the predictive power of climate risk indicators in determining financial stress levels underscores the importance of environmental considerations in economic planning and regulation. Policymakers equipped with this knowledge can design more effective interventions, ranging from regulatory adjustments to fiscal incentives, aimed at mitigating the adverse effects of climate change on financial markets. By implementing forward-looking policies that reflect the intricate relationship between climate risks and market dynamics, governments can enhance economic stability, foster green investments, and support the transition towards a low-carbon economy. Additionally, the implications of our research extend beyond traditional financial markets. The methodologies and findings presented can inform risk assessment and investment decisions in sectors directly impacted by climate change, such as agriculture, energy, and insurance. By understanding the specific vulnerabilities and opportunities within these industries, businesses and investors can better prepare for future scenarios, leading to more resilient and adaptive economic systems.

In essence, our research emphasizes the necessity for an adaptive financial sector that proactively addresses the multifaceted impacts of climate risks. As climate change continues to shape the global economic landscape, the ability to anticipate and respond to its financial implications becomes increasingly critical. This study lays the groundwork for future research aimed at uncovering the complex dynamics between environmental risks and financial systems, encouraging further exploration into how different sectors and asset classes are affected by and can adapt to the realities of climate change.

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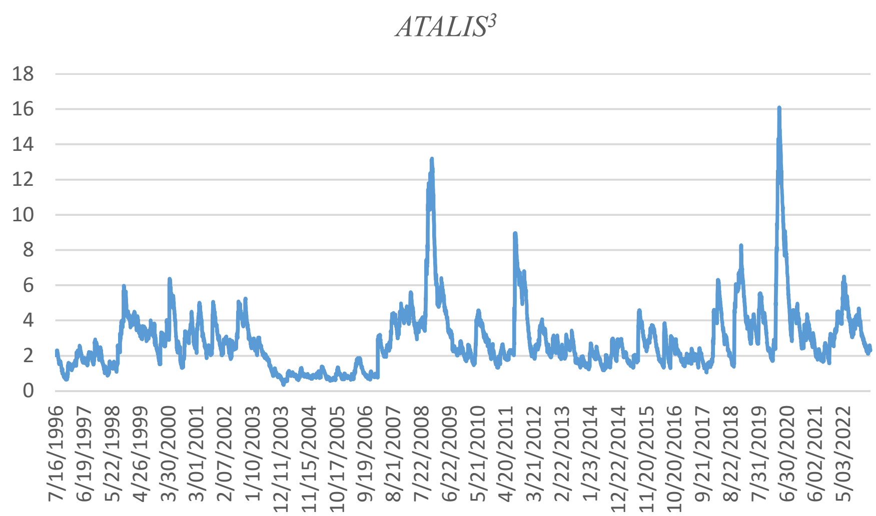
FIGURES AND TABLES:

Figure 1. Data Plots

1(a). Aggregate US Systemic Stress (ATALIS³)



1(b). Aggregate US Climate Risks (CR1 and *CR2)*

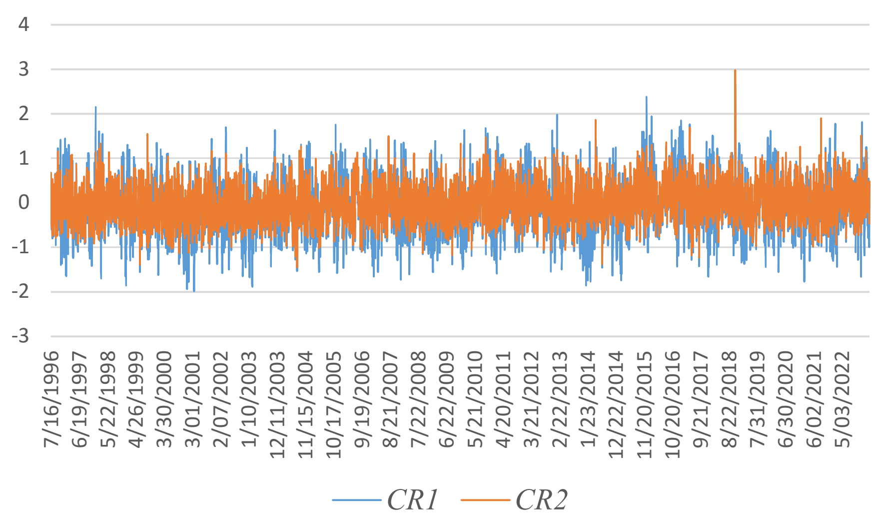
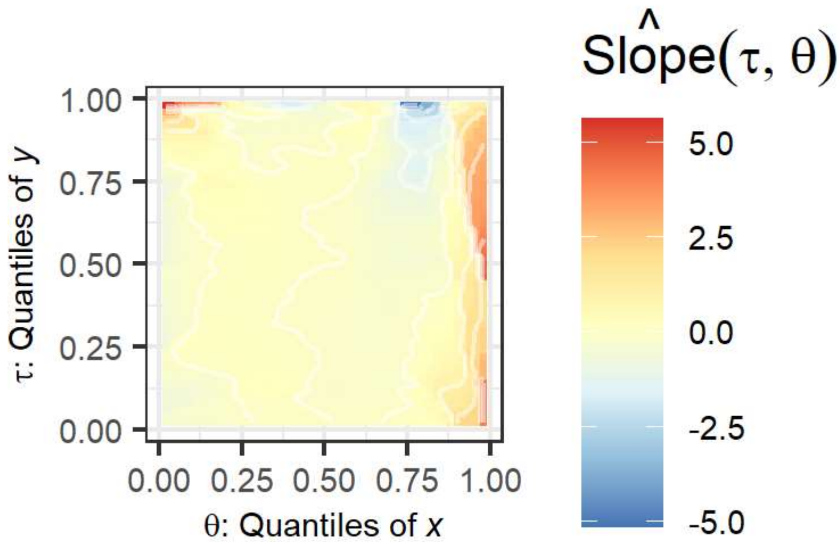
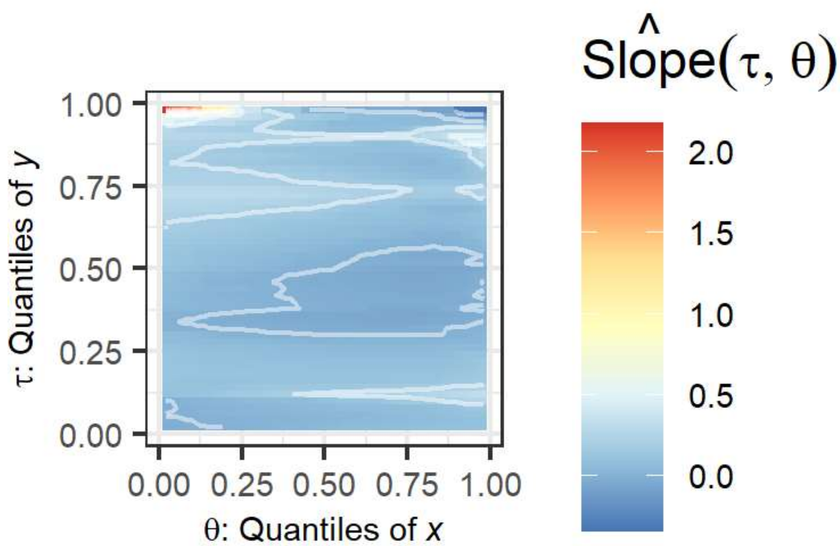


Figure 2. QQ Plot of the Climate Risks on the Aggregate US Systemic Stress

2(a). Effect on ATALIS³ from CR1



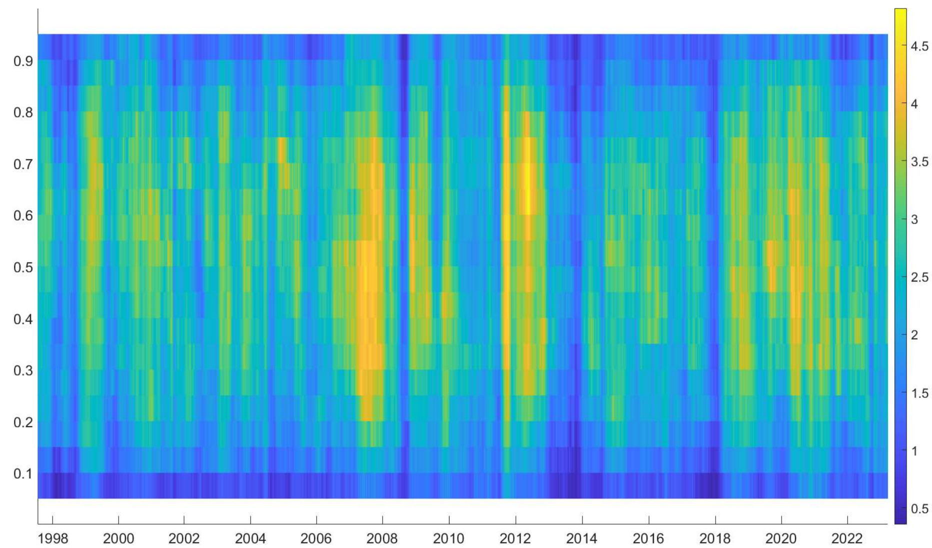
2(b). Effect on ATALIS³ from CR2



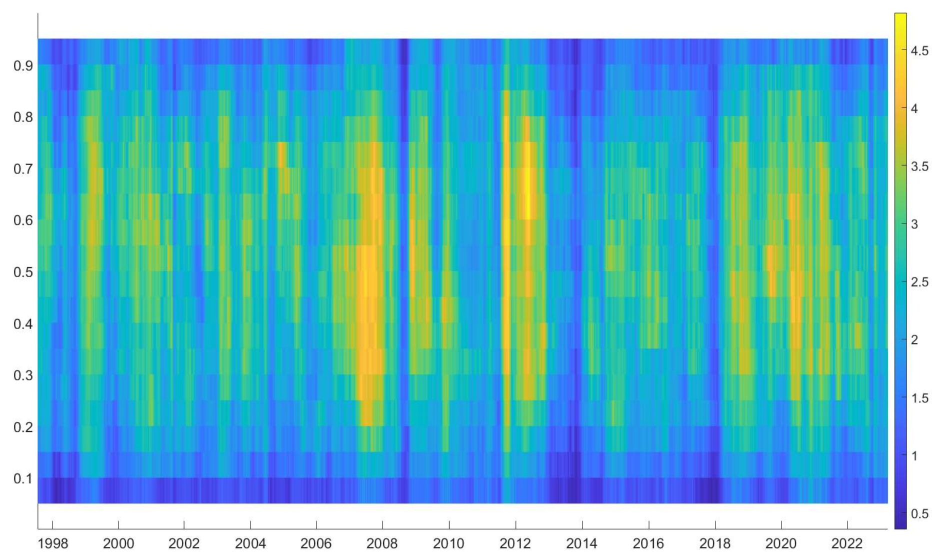
Note: *y* corresponds to *ATALIS³*, while *x* is *CR1* or *CR2*.

Figure 3. Time-Varying (Rolling-Window) Nonparametric Causality-in-Quantiles Test Results for Aggregate US Systemic Stress due to Climate Risks

3(a). Causality of ATALIS³ from CR1



3(b). Causality of ATALIS³ from CR2



Note: Horizontal axis represents the date, while the vertical axis captures the conditional quantiles of *ATALIS³*, with the heat-map representing the time-varying standard normal test statistics corresponding to the hypothesis that there is no Granger causality for a particular quantile running from *CR1* or *CR2* to *ATALIS³*; 1.645, 1.96, and 2.575 represents the critical values at the significance level of 10%, 5% and 1%, respectively.

Table 1. Summary Statistics

	Variable		
Statistic	*ATALIS*^{3}	*CR1*	*CR2*
Mean	2.8593	-0.0831	-0.0316
Median	2.4631	-0.0979	-0.0596
Maximum	16.1024	2.6543	2.9789
Minimum	0.3350	-1.9844	-1.4524
Std. Dev.	1.8593	0.5933	0.4168
Skewness	2.3957	0.0972	0.3870
Kurtosis	12.3755	3.0637	3.5199
Jarque-Bera	30665.7800***	11.5822***	240.4740***
Observations	6639		

Note: Std. Dev: stands for standard deviation; The null hypotheses of the Jarque-Bera test correspond to normality; *** indicates rejection of the null hypothesis at the 1% level of significance.

Table 2. Brock *et al.* (1996, BDS) Test of Nonlinearity

Independent Variable	Dimension (*m*)				
	2	3	4	5	6
CR1	15.2700***	18.8253***	21.0609***	22.7954***	24.4877***
CR2	15.3108***	18.8850***	21.1254***	22.8558***	24.5357***

Note: Entries correspond to the *z*-statistic of the BDS test with the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the *ATALIS*^{3} equation with one lag each of *ATALIS*^{3} and *CR1* or *CR2*; *** indicates rejection of the null hypothesis at 1% level of significance.

Table 3. Nonparametric Causality-in-Quantiles Test Results for Aggregate US Systemic Stress due to Climate Risks

Quantile	*CR1*	*CR2*
0.10	5.9031***	6.3116***
0.20	8.4778***	8.5217***
0.30	9.4221***	9.0749***
0.40	9.7952***	10.1142***
0.50	10.2621***	10.6016***
0.60	10.1990***	10.1362***
0.70	9.7817***	9.0834***
0.80	8.4769***	8.0777***
0.90	5.7272***	5.6254***

Note: Entries report the standard normal test statistic for the hypothesis that there is no Granger causality for a particular quantile running from *CR1* or *CR2* to *ATALIS*^{3}; *** indicates rejection of the null hypothesis at 1% level of significance (Critical value: 2.575).

Table 4. Average Derivative Estimates for the Effect of Climate Risks on Aggregate US Systemic Stress

Quantile	*CR1*	*CR2*
0.10	0.0377	0.0546
0.20	0.0378	0.0987
0.30	0.0020	0.0350
0.40	0.0027	0.0175
0.50	0.0341	0.0440
0.60	0.0074	0.1054
0.70	0.0454	0.2546
0.80	0.0051	0.1988
0.90	0.0007	0.2398

Note: Entries correspond to average derivative (AD) estimates of the sign of the effect of climate risks: *CR1* and *CR2* on $ATALIS^3$ at a particular quantile.

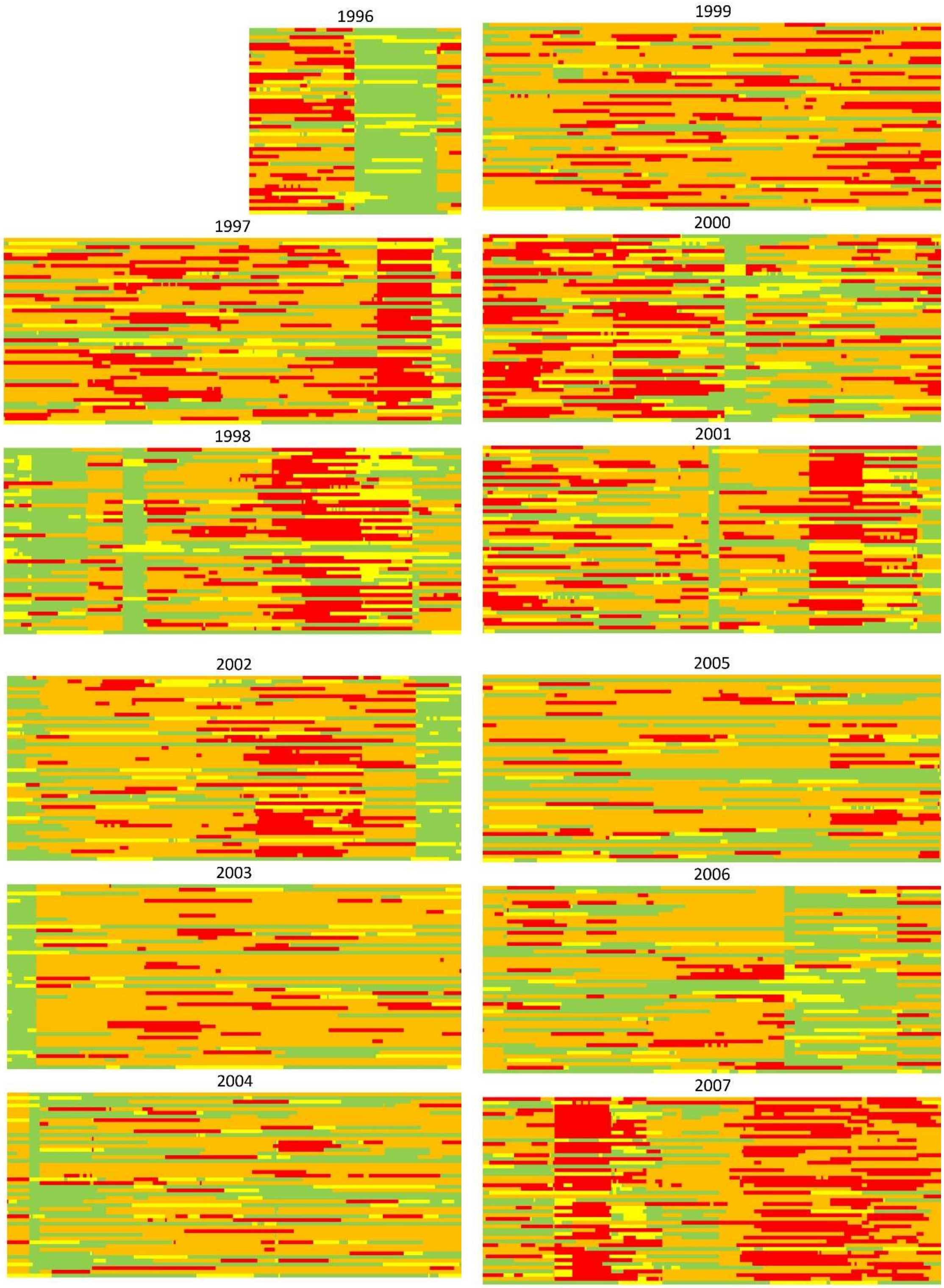
Table 5. Nonparametric Causality-in-Quantiles Test Results for Aggregate US Systemic Stress due to Climate Risks based on Reuters Climate-Change News

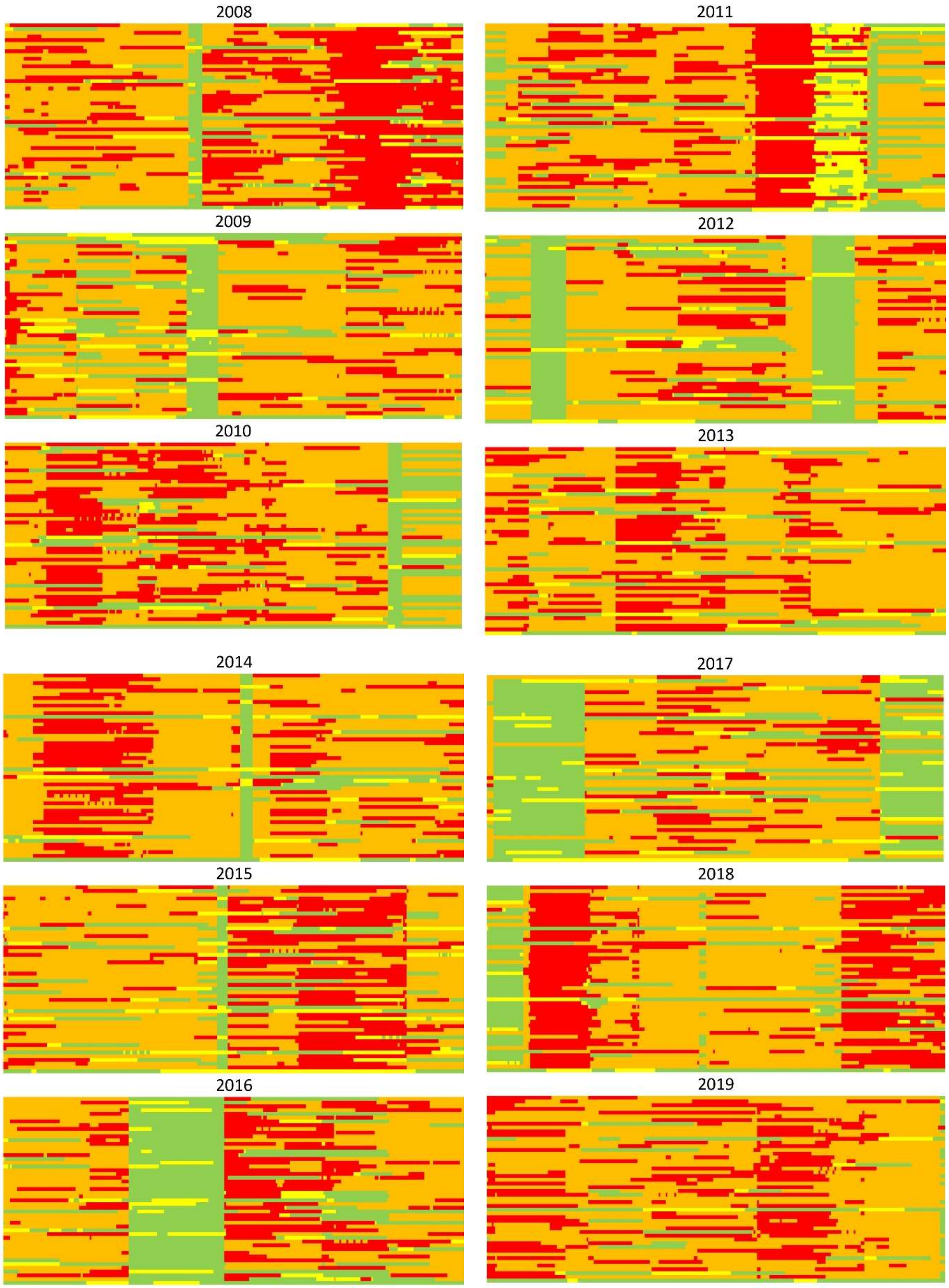
Quantile	US Climate Policy	International Summits	Global Warming	Natural Disasters
0.10	4.2628***	2.7627***	4.5446***	4.1973***
0.20	4.7565***	3.6803***	6.2187***	5.0017***
0.30	4.6441***	3.5589***	5.1757***	6.1664***
0.40	4.8520***	3.4781***	4.6347***	5.4626***
0.50	5.2815***	3.5528***	4.7213***	5.5177***
0.60	5.4953***	3.3856***	4.8027***	5.3232***
0.70	5.0432***	3.2653***	4.3666***	4.7862***
0.80	3.9397***	2.6668***	4.1682***	4.4742***
0.90	2.4743**	1.5532	2.8176***	3.0906***

Note: Entries report the standard normal test statistic for the hypothesis that there is no Granger causality for a particular quantile running from a particular news-based metric of climate risks to $ATALIS^3$; *** and ** indicates rejection of the null hypothesis at 1% (Critical value: 2.5750) and 5% (Critical value: 1.96) levels of significance, respectively.

APPENDIX:

Figure A1. Time-Series of State-Level Systemic Stress Indexes (*TALIS*^{3}): July 1996-March, 2023

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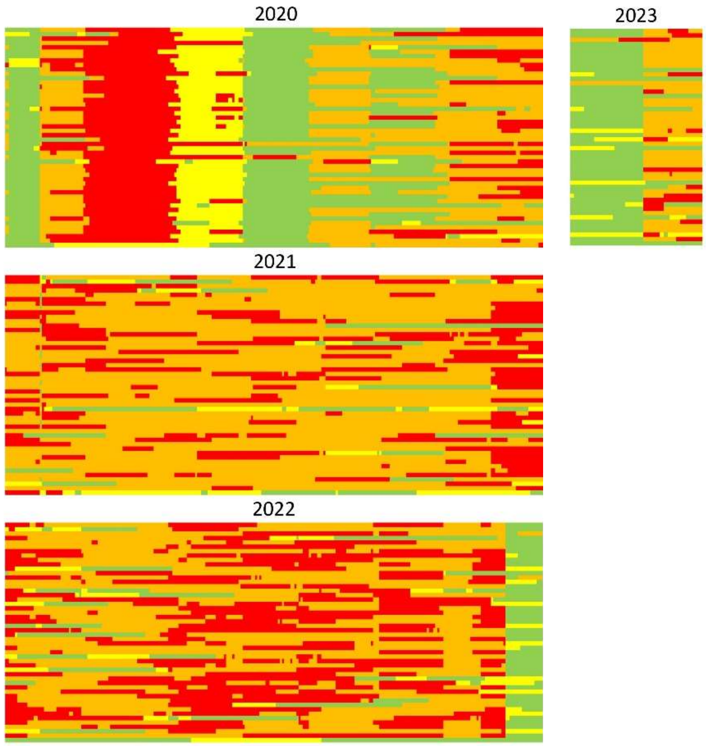

Note: Each row of the figures correspond to the 50 US states ordered alphabetically as follows: Alabama (AL), Alaska (AK), Arizona (AZ), Arkansas (AR), California (CA), Colorado (CO), Connecticut (CT), Delaware (DE), Florida (FL), Georgia (GA), Hawaii (HI), Idaho (ID), Illinois (IL), Indiana (IN), Iowa (IA), Kansas (KS), Kentucky (KY), Louisiana (LA), Maine (ME), Maryland (MD), Massachusetts (MA), Michigan (MI), Minnesota (MN), Mississippi (MS), Missouri (MO), Montana (MT), Nebraska (NE), Nevada (NV), New Hampshire (NH), New Jersey (NJ), New Mexico (NM), New York (NY), North Carolina (NC), North Dakota (ND), Ohio (OH), Oklahoma (OK), Oregon (OR), Pennsylvania (PA), Rhode Island (RI), South Carolina (SC), South Dakota (SD), Tennessee (TN), Texas (TX), Utah (UT), Vermont (VT), Virginia (VA), Washington (WA), West Virginia (WV), Wisconsin (WI), and Wyoming (WY); The colors correspond green, yellow, orange and red, corresponds to the lowest- to the highest-level of stock market stress in each states at a particular date of a specific year.

Table A1. Nonparametric Causality-in-Quantiles Test Results for an Alternative Measure of Aggregate US Systemic Stress (Financial Risk Meter (*FRM*)) due to Climate Risks

Quantile	*CR1*	*CR2*
0.10	10.4534***	10.6080***
0.20	14.4006***	14.6364***
0.30	16.8923***	16.3486***
0.40	17.9692***	17.7272***
0.50	18.0771***	17.8905***
0.60	17.7964***	17.1962***
0.70	16.6515***	16.0349***
0.80	13.8949***	14.1704***
0.90	10.1776***	10.2429***

Note: Entries report the standard normal test statistic for the hypothesis that there is no Granger causality for a particular quantile running from *CR1* or *CR2* to *FRM*; *** indicates rejection of the null hypothesis at 1% level of significance (Critical value: 2.575).

Table A2. Nonparametric Causality-in-Quantiles Test Results for Aggregate US Systemic Stress due to Climate Risks based on Climate Change Related Topics from Newspapers

	Quantile								
Predictor	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Aggregate	6.7022***	8.5988***	9.1940***	9.6542***	9.6286***	9.2941***	8.6321***	7.1845***	5.3504***
Cluster Business Impact	7.0519***	8.6009	9.3371***	9.4977***	10.3022***	10.1211***	9.5130***	7.9678***	4.8906***
Cluster Environmental Impact	6.5022***	8.4369	8.5289***	8.8041***	9.45***81	9.1377***	8.1560***	6.7643***	5.2784***
Cluster Research	6.3597***	8.6236	8.8227***	9.4877***	9.955***8	9.6173***	8.7806***	7.4601***	5.7057***
Cluster Societal Debate	6.5199***	8.0873	8.5356***	9.0489***	9.1546***	9.0986***	8.0285***	6.7409***	5.0701***
Agreements/Actions	6.2776***	8.2306	9.3209***	9.3017***	9.4515***	9.8014***	9.5501***	7.8907***	5.4572***
Agriculture Shifts	6.7132***	7.0483	7.4303***	7.7336***	7.7692***	7.7422***	7.6347***	5.7009***	4.2210***
Airline Industry	6.1414***	7.3829	7.3405***	7.3058***	7.6482***	7.7626***	7.6447***	6.0101***	4.4061***
Arctic Wildlife	5.2763***	5.8774	5.5070***	5.7006***	5.9017***	5.7682***	5.4079***	4.0559***	3.1075***
Car Industry	6.0648***	7.1156	7.5269***	8.6715***	9.3113***	8.3467***	7.7159***	5.9401***	4.5084***
Carbon Credits Market	5.6387***	7.1911	8.2533***	8.5336***	8.4004***	8.2704***	7.3693***	5.9346***	4.3898***
Carbon Reduction Technologies	6.5770***	7.9249	8.4209***	8.2654***	8.8321***	8.3656***	8.5174***	6.9872***	4.6937***
Carbon Tax	6.2973***	8.0794	9.4758***	9.7775***	9.6834***	8.7436***	8.2559***	6.8059***	4.8722***
Cities	6.2360***	7.4734	7.5790***	7.7531***	7.7649***	8.0702***	7.8163***	5.7297***	4.2630***
Climate Legislation/Regulations	5.9903***	7.2252	7.8863***	8.2120***	8.9996***	8.7268***	8.0722***	6.3968***	4.7304***
Climate Summits	5.5815***	7.6801	8.2079***	8.5898***	8.8860***	9.1717***	8.0142***	6.5097***	4.5671***
Controversies	6.6257***	8.8292	9.0266***	9.3340***	10.0929***	9.8341***	8.5609***	6.5286***	4.8188***
Corporations/Investments	5.8496***	7.0563	7.3282***	7.6481***	8.1911***	7.7647***	7.1523***	5.9838***	4.4834***
Ecosystems	5.8857***	6.9363	7.4339***	8.2813***	8.2243***	7.5958***	7.5133***	5.7932***	3.9616***
Extreme Temperatures	6.2225***	7.9997	8.5914***	8.5510***	9.2876***	8.4826***	7.6737***	6.3955***	4.6882***
Food Shortage/Poverty	5.8551***	7.7213	7.6889***	8.7209***	8.0530***	7.5923***	7.2606***	5.9160***	4.0997***
Forests	5.7788***	7.2531	6.9272***	6.4122***	7.1514***	6.8488***	7.1195***	5.7647***	4.2054***
Glaciers/Ice Sheets	5.5436***	7.0149	7.0776***	7.4493***	7.5055***	7.7622***	7.2580***	5.5825***	4.2629***
Global Warming Sentiments	6.1927***	7.8416	8.7254***	9.1427***	9.7472***	9.4459***	8.9862***	7.6357***	5.6058***
Government Programs	6.2209***	8.2218	8.4974***	8.8787***	8.9030***	8.2844***	8.0255***	6.5339***	4.7481***
Hurricanes/Floods	5.9395	7.5025	6.8736***	6.8477***	6.9724	6.7375***	6.6679***	5.2759***	3.6039***

Legal Actions	5.6974***	7.8411***	7.7398***	8.3820***	8.6556***	8.5897***	8.3117***	6.3541***	4.5742***
Marine Wildlife	5.6013***	6.7522***	6.3569***	7.3543***	7.2392***	6.4886***	7.0439***	5.9740***	4.1507***
Political Campaign	5.6904***	7.6156***	8.2239***	8.8140***	8.6859***	8.4890***	7.3975***	5.9431***	4.4358***
Renewable Energy	6.2072***	8.0293***	8.2069***	8.1886***	8.9063***	8.6154***	8.6164***	6.6972***	4.6741***
Scientific Studies	6.5128***	7.8317***	8.7285***	9.1166***	9.7669***	9.1992***	8.8351***	7.1924***	4.8077***
Social Events	6.1882***	8.4583***	8.3018***	9.0680***	9.3321***	9.3179***	8.2399***	6.4692***	4.2783***
Tourism	6.3251***	7.5743***	7.8591***	7.6887***	8.7464***	8.6950***	8.6735***	6.2420***	4.5598***
UN/IPCC Reports	6.1854***	7.8403***	8.0576***	8.4710***	8.6903***	8.5866***	8.0008***	6.5041***	4.8343***
Water/Drought	6.2577***	7.8323***	7.5892***	7.8566***	7.5711***	7.7080***	7.5602***	6.1439***	4.1021***
Biodiversity Risks	2.0234**	2.8073***	2.8715***	2.5800***	2.5497**	2.0737**	2.1937**	1.4013	1.0476
Climate Risks	2.6171***	3.2686***	2.6876***	1.8953*	2.0754**	2.2527**	2.3879**	1.5380	0.8719

Note: Entries refer to standard normal test statistics for the hypothesis that there is no Granger causality for a particular quantile running from newspapers-based (New York Times, Washington Post, Los Angeles Times, Wall Street Journal, Houston Chronicle, Chicago Tribune, Arizona Republic, USA Today, New York Daily News, and New York Post) climate risks to *ATALIS*^{3}, with the first 35 indexes (see, Table 3 for complete details on the themes of business impact, environmental impact and societal debate) from Ardia et al. (2023), and the final two from Giglio et al. (2023); ***, **, and * represents significance level of 1%, 5% and 10%, respectively, with corresponding critical values of 2.575, 1.96 and 1.645.