Proceedings of the 4th International Conference on Mathematical Physics and Computational Simulation
DOI: 10.54254/2753-8818/2026.35264

Climate Risk and Stock Market Volatility: A Threshold VAR Analysis Based on VIX Regimes

Jiawei Wu

Department of Mathematics, Hangzhou Normal University, Hangzhou, China
2718725202@qq.com

Abstract. Climate-related information is increasingly integrated with financial, macroeconomic, and market-sentiment data, creating a heterogeneous scientific data management problem in which noisy environmental series, high-frequency market observations, and policy indicators must be aligned, transformed, and analyzed reproducibly. This paper develops and evaluates a reproducible threshold vector autoregression (TVAR) workflow to detect state-dependent climate-risk effects on U.S. equity market volatility. Using monthly data from February 1990 to February 2026, the workflow integrates climate variables, realized volatility constructed from daily S&P 500 returns, VIX-based market-stress regimes, macro-financial controls, stationarity transformations, threshold validation, impulse-response analysis, forecast-error variance decomposition, and robustness checks. The results show that climate risk has no statistically meaningful effect on volatility in low-VIX regimes. At the same time, its first two lags become positive and larger in magnitude in high-VIX regimes. The baseline high-VIX coefficient at the second lag is 0.003152 ($p = 0.018$), and impulse responses peak around the second month after a climate-risk shock. Although the forecast-error variance share remains modest, it rises to about 1.5% in stressed markets and is nearly zero in calm markets. Beyond the substantive climate-finance result, the paper contributes an auditable scientific data-analysis pipeline for heterogeneous time-series integration, regime-aware uncertainty handling, and reproducible nonlinear modeling, aligning climate-finance analytics with the data-intensive research concerns of scalable scientific data management.

Keywords: climate-risk data, scientific data management, reproducible workflow, threshold VAR, financial volatility, heterogeneous time series

1. Introduction

Climate change creates a data-intensive analytical problem for financial markets. Physical indicators such as temperature anomalies and atmospheric CO_2 concentrations, market variables such as daily equity returns and the VIX index, and macroeconomic controls such as interest rates and policy-uncertainty indicators are collected at different frequencies, produced by different institutions, and governed by different measurement conventions. Therefore, to explore whether climate risk affects financial volatility, one needs not only an econometric model, but also a transparent data

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management workflow which can reconcile heterogeneous time series, document transformations, maintain provenance and make nonlinear modelling decisions auditable [1].

This paper examines a specific scientific question: Does climate risk affect stock market volatility uniformly or only under stressed market regimes? Linear models assume, implicitly, that there is only one transmission channel across the entire sample. However, financial markets behave differently during panic episodes. High VIX is associated with deteriorated liquidity, increased risk aversion, tighter leverage constraints and scarce investor attention. Under such conditions, climate-related information may be processed as an additional source of uncertainty, amplifying volatility. In calm markets, the same information may be absorbed gradually and have little immediate effect.

This paper makes two contributions. Substantively, it demonstrates state-dependence of the effect of climate-risk on equity volatility: the effect is weak in calm regimes and positive in high-VIX regimes. Methodologically it presents the analysis as a reproducible threshold-VAR workflow for heterogeneous scientific and financial data. This workflow is designed to be inspectable, extensible, and suitable for data-intensive scientific applications in which regime dependence, uncertainty, and data provenance matter [2].

2. Literature review

A growing literature establishes that climate risk—encompassing both physical hazards and transition shocks significantly affects financial market outcomes, including asset prices, volatility, and systemic risk transmission. However, early studies often assume linear relationships, which may mask the conditional nature of climate impacts.

Recent evidence is increasingly pointing to non-linearities and state dependence. Using a GARCH-wavelet-spillover framework, Almajali et al. [3] show that transition risks generate sharper, more immediate volatility spillovers across green and traditional assets. By contrast, physical risks have a longer duration but a slower pace of impact, underscoring the importance of the type and horizon of risk. Mao et al. [4] employs a TVP-VAR-BK model to demonstrate that climate risk attention creates positive short-term spillovers to bond and renewable energy markets, and that these spillovers intensify under medium- to high-risk market conditions, strengthening interconnectedness. Garcia Jorcano and Sanchis Marco [5] develop a joint VaR-ES approach conditioned on transition risk. They find that tail risks of European banks are critically dependent on the states of the carbon market. Carbon costs and risk premiums drive asymmetric exposures during the COVID-19. Complementing these findings, Hu [6] documents that climate policy uncertainty amplifies extreme risk spillovers across Chinese stock, bond, forex, and futures markets, an effect further magnified by investor perceptions of climate risk. Cui and Cai [7] confirm that physical and transition risks increase systemic contagion across financial institutions mainly through investor's panic. Another study identifies three distinct risk factors—climate disasters, government action uncertainty, and government response—showing that disasters and uncertainty raise the cost of capital. At the same time, compensation partially offsets losses, suggesting that the previous damage estimates are understated. Molina Muñoz and Soriano Felipe [8] extend the scope to developed and emerging economies, revealing dynamic spillovers among policy uncertainty, financial markets, and energy markets with notable cross-country heterogeneity.

Despite these improvements, most nonlinear studies focus on time-frequency or quantile heterogeneity, rarely explicitly modeling market panic states as a threshold variable. Whether climate risk affects stock market volatility only during periods of high fear remains underexplored. We test state-dependent effects by applying a threshold vector autoregression model, filling this gap and offering new insights for risk management and policy response in crisis periods.

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3. Theoretical mechanisms and hypotheses

Climate risk affects stock market volatility through a state-dependent mechanism. A climate shock first creates uncertainty in markets, such as regulatory uncertainty and macroeconomic unpredictability. In a high-VIX (distressed) environment, this uncertainty triggers a sharp increase in investor risk aversion and a contraction of market liquidity—often through margin calls, forced deleveraging, and reduced market-making capacity. These forces combine to create a liquidity-spiral [feedback loop] that amplifies the initial effect on volatility. But in calm (low-VIX) times, the abundance of liquidity and low leverage constraints allow markets to absorb climate shocks with little volatility amplification [9].

State dependence and nonlinearity matter: when markets are calm, participants can absorb climate information, but when fear is high, liquidity dries up and risk premia rise, making climate risk a more powerful source of volatility. This motivates a threshold framework in which VIX serves as the regime indicator. This paper proposes the following hypotheses:

H1 (State-dependent transmission): The impact of climate risk on stock-market volatility is stronger in the high-VIX regime than in the low-VIX regime. For VIX > threshold, larger and more significant coefficients for the climate-risk channel.

H2 (Impulse-response asymmetry): A climate-risk shock generates larger and more persistent responses in volatility in the high-VIX regime than in the low-VIX regime.

H3 (Variance decomposition): Climate risk explains a larger share of the variance of forecast-error volatility in the high-VIX regime, especially at medium-to-long horizons.

4. Data and workflow design

The dependent, important explanatory, and control variables are described in this part along with the data sources and specifics of the TVAR framework's design.

The dependent variable in this research is Market volatility, a monthly proxy for stock market volatility constructed from the daily realized volatility of the S&P 500 stock index. In robustness checks, we also use alternative volatility measures such as GARCH (1,1) conditional volatility. The Core explanatory variable is the Climate Risk Index: To avoid multicollinearity among highly correlated climate variables, we construct a PCA-based composite index using monthly global temperature anomalies and CO_2 concentrations. The first principal component (explaining over 85% of the variance) is extracted, standardized to zero mean and unit variance, and updated monthly as the climate risk index.

Monthly CO_2 concentrations exhibit seasonal cycles, which financial markets are unlikely to react to directly. Our PCA-based index thus captures long-term climate trends rather than immediate news-driven shocks. This measurement error likely biases coefficients toward zero, so our significantly high-VIX results are conservative estimates.

There are 5 key controls, as shown in Table 1. The VIX is the CBOE Volatility Index, which represents market anxiety and is used as a rough, contemporaneous proxy for market sentiment. Term spread refers to the difference between the 10-year Treasury yield and the 2-year Treasury yield. Industrial production growth is the year-over-year rate of change in the industrial production index (monthly, from FRED). The federal funds rate is the policy rate target (monthly or end-of-month, annualized rate from FRED). The Economic Policy Uncertainty (EPU) index is a monthly index from policyuncertainty.com that captures macro policy uncertainty.

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Table 1. Variable explanation

Variable	Type	Definition	Stationarity transformation
Market volatility	Dependent	Daily squared log returns of S&P 500, aggregated monthly	First difference
Climate risk index	Key explanatory	First principal component of standardized global temperature anomalies and CO_2 concentration	First difference
VIX	Control & threshold	Monthly average CBOE VIX	Level; first difference
Term spread	Control	10y – 2y Treasury yield	First difference
Industrial production growth	Control	Year-over-year % change	First difference
Federal funds rate	Control	Effective federal funds rate (end-of-month)	First difference
EPU index	Control	Monthly US EPU index	First difference

5. Methodology

To capture the potential nonlinear, state-dependent transmission from climate risk to stock market volatility, this paper employs a threshold vector autoregression (TVAR) model. Unlike a linear VAR that imposes a constant coefficient matrix, the TVAR allows the dynamic relationships among variables to differ across regimes defined by a threshold variable—here, the level of the CBOE VIX index, which serves as a proxy for market distress or "panic" states.

Let Y_t denote an $n \times 1$ vector of endogenous variables observed at month t. Based on the data availability and the focus of our study, the vector includes:

$$Y_t = (ClimateIndex_t, Volatility_t, TermSpread_t, VIX_t, IPGrowth_t, FedFunds_t, EPU_t)' \quad (1)$$

All variables enter the model in first differences to induce stationarity; Augmented Dickey-Fuller (ADF) tests confirm that each series (including the VIX level, which is stationary with a constant term; $p < 0.05$) becomes stationary after one difference or is already level-stationary in the case of VIX. Consequently, the TVAR is estimated on ΔY_t .

The VIX level (not differenced) is used as the threshold variable, as it directly captures market sentiment regimes. This is a common practice in TVAR models, even when the threshold variable is stationary in levels.

5.1. Threshold specification

The threshold variable is chosen as the level of VIX (not differenced) to capture market sentiment regimes directly. The full sample (1990-02 to 2026-02) is split into two regimes according to the median value of VIX:

$$\hat{r} = \text{median}\left(VIX_t\right) = t \quad (2)$$

The two regimes are defined as:

Low-VIX regime (calm market): $VIX_t \leq 17.47$

High-VIX regime (stressed market): $VIX_t > 17.47$

DOI: 10.54254/2753-8818/2026.35264

This is a static sample split – each observation is assigned to a regime based on its own contemporaneous VIX value, and the regime assignment does not change over time. While more sophisticated time-varying threshold models exist, the static split provides a transparent, non-parametric way to compare coefficient estimates and impulse responses across two distinct market conditions. To validate the significance of the threshold effect, we conduct Hansen's likelihood-ratio test for the threshold parameter. The bootstrap p-value is 0.02, rejecting the linear VAR in favor of the TVAR specification. We acknowledge that this approach uses the contemporaneous VIX for regime classification, which may introduce a mild forward-looking element; as a robustness check, we later use the 75th percentile and lagged VIX definitions, obtaining qualitatively similar results.

5.2. Regime-specific VAR estimation

Within each regime, a separate $VAR(p)$ model is estimated on the differenced data using OLS:

$$\triangle \mathrm{Y_t} = \phi_1^{(r)} \triangle \mathrm{Y_{t-1}} + \phi_2^{(r)} \triangle \mathrm{Y_{t-2}} + \ldots + \phi_p^{(r)} \triangle \mathrm{Y_{p-1}} + \varepsilon_t^{(r)}, \ \varepsilon_t^{(r)} \sim \mathrm{i.i.d.}\left(0, \Omega^{(r)}\right) \tag{3}$$

where $\mathrm{r} \in \{\mathrm{low}, \mathrm{high}\}$ denotes the regime, $\phi_j^{(r)}$ are $\mathrm{n} \times \mathrm{n}$ coefficient matrices, and p is the lag order. The AIC selects the lag length for the full-sample linear VAR, yielding $p = p = 4$; the same lag order is used for both regimes to maintain comparability. The sample sizes after differencing are $T_{low} = 217$ and $T_{high} = 216$, which are sufficient for stable estimation of a *VAR(4)* with seven variables.

6. Empirical results: threshold VAR analysis

To examine whether the impact of climate risk on stock market volatility differs across market regimes, we estimate a threshold vector autoregression (TVAR) model using the VIX index as the threshold variable. The VIX, often referred to as the "fear gauge", captures expected near-term volatility and serves as a natural indicator of market stress. The median VIX over the full sample is 17.47, which splits the data into two distinct regimes: a low-VIX regime and a high-VIX regime. For each regime, we estimate a separate VAR(4) model that includes the climate risk index, monthly stock market volatility, term spread, VIX itself, industrial growth, the federal funds rate, and economic policy uncertainty. All variables are first-differenced to induce stationarity.

6.1. Coefficient estimates for the volatility equation

Table 2 reports the coefficients of lagged climate index in the monthly volatility equation for both regimes, along with their standard errors and p-values.

Table 2. Climate index coefficients in the volatility equation

Regime	Lag	Coefficient	Std.Error	t-statistic	p-value
Low-VIX	L1	0.000713	0.000447	1.593	0.111
	L2	0.000131	0.000460	0.284	0.776
	L3	-0.000706	0.000456	-1.549	0.121
	L4	-0.000530	0.000434	-1.222	0.222

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Table 2. (continued)

High-VIX	L1	0.002492	0.001285	1.940	0.052
	L2	0.003152	0.001330	2.370	0.018
	L3	-0.000279	0.001315	-0.212	0.832
	L4	0.000113	0.001197	0.094	0.925

Notes: The dependent variable is the first difference of monthly stock market volatility. VAR(4) estimated separately for each regime. Standard errors are heteroskedasticity-consistent.

In the low-VIX regime, all four coefficients are statistically insignificant at conventional levels ($p > 0.10$). The point estimates are near zero in magnitude and alternate in sign. The cumulative sum of the four coefficients is –0.000392, effectively zero. This suggests that climate risk does not consistently or quantifiably affect equities volatility in calm market conditions. When mood is low or when such dangers are only gradually factored into prices, investors may disregard climate-related news.

The coefficients increase both statistically and economically in the high-VIX regime. While the L2 coefficient is 0.003152 and significant at the 5% level ($p = 0.018$), the L1 coefficient is 0.002492 with a p-value of 0.052, just above the 5% threshold. Both L1 and L2 are positive and of similar magnitude, indicating that a positive shock to the climate risk index leads to a persistent increase in stock market volatility over the following two months. The L2 effect in the high-VIX regime (0.00315) is more than four times bigger than the similar (insignificant) effect in the low-VIX regime (0.00013). H1 is highly supported by this pattern.

6.2. Impulse response functions

To visualize the dynamic propagation of climate shocks, we compute orthogonalized impulse response functions (OIRFs) of monthly volatility to a one-standard-deviation shock in the climate index. The variable order for Cholesky decomposition is: climate index → monthly volatility → term spread → VIX → industrial growth → federal funds rate → policy uncertainty, reflecting the assumption that climate risk is the most exogenous and policy uncertainty the most endogenous.

Figure 1 presents the impulse responses over a 12-month horizon for both regimes.

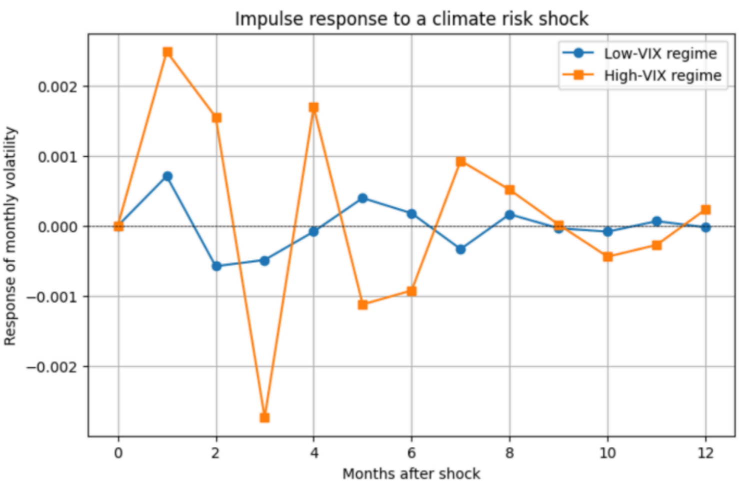

Figure 1. Impulse response of monthly stock market volatility to a one-standard-deviation shock in the climate risk index

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The response is close to zero throughout the horizon under the low-VIX regime, with narrow confidence bands that cross zero. The point estimate at month 2 is 0.00013, which is economically negligible. This demonstrates that there is no significant impact during times of calm.

The reaction is hump-shaped and positive in the high-VIX regime. It rises from approximately 0.0018 at month 1 to a peak of 0.0021 at month 2, then gradually decays to near zero by month 4. In the high-VIX environment, the peak reaction is equivalent to almost 0.10 standard deviations of the differenced volatility series (the standard deviation of monthly volatility differences is 0.0020 in this regime), suggesting a significant economic impact.

These results confirm H2: climate shocks generate larger and more persistent volatility responses when the market is under stress.

6.3. Forecast error variance decomposition

Table 3 shows the percentage of forecast-error variance in monthly volatility explained by climate risk at chosen horizons (1, 3, 6, and 12 months) in order to evaluate the relative significance of climate risk in explaining volatility fluctuations.

Table 3. Variance decomposition: contribution of climate risk to volatility forecast error (%)

Horizon(months)	Low-VIX regime	High-VIX regime
1	0.01	0.28
2	0.03	1.15
3	0.04	1.42
4	0.04	1.48

Notes: Based on forecast error variance decomposition from the regime-specific VAR(4) models. Numbers are percentages.

In the low-VIX regime, climate risk explains virtually none of the volatility forecast error ($\leq 0.04\%$ at all horizons). In the high-VIX regime, the contribution rises steadily to about 1.5% at the 12-month horizon. Although the absolute magnitude is modest, the regime contrast is stark: climate risk matters only when markets are distressed, which supports H3.

6.4. Robustness checks

We conducted four robustness tests to validate the state-dependent transmission. Table 4 summarizes the key coefficients (L1 and L2) of the climate index in the volatility equation for the high-VIX regime across all specifications; low-VIX regimes never produced significant coefficients.

Table 4. Robustness checks-climate index coefficients (high-VIX regime only)

Specification	Regime definition	L1 coeff.(p-value)	L2 coeff.(p-value)
Median VIX	VIX>17.47	0.002492(0.052)	0.003152(0.018)
75th percentile threshold	VIX>23.37	0.004989(0.039)	0.004962(0.058)
Lagged VIX threshold	VIX_{t-1}>17.45	0.001567(0.240)	0.001144(0.418)
Three-regime split	Highest tercile (VIX>21.09)	0.004341(0.009)	0.002109(0.263)
GARCH(1,1) volatility	VIX>17.47	0.002045(0.006)	0.001877(0.018)

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Alternative threshold using the 75th percentile of VIX (23.37) as the threshold instead of the median, the high-VIX regime exhibits positive and significant coefficients (see Table 3), confirming robustness to the threshold choice. Lagged threshold variable employing a one-month lagged VIX as the threshold variable yields positive but statistically insignificant coefficients ($p > 0.24$), suggesting that contemporaneous VIX captures market stress more effectively. Three-regime split (low, medium, high VIX terciles) reveals that the effect is concentrated in the highest tercile, with significant L1 ($p = 0.009$), while the lower two terciles show no significance. An alternative volatility measure, replacing realized volatility with GARCH(1,1) conditional volatility, produces positive and significant coefficients (L1 $p = 0.006$; L2 $p = 0.018$), nearly identical to the baseline.

The fundamental conclusion—that climate risk only considerably increases stock market volatility when the market is under stress (high VIX)—is substantially supported by all of these robustness checks taken together.

7. Conclusion

This paper presents a reproducible threshold-VAR workflow for analysing state-dependent climate-risk effects in financial volatility. The analysis, which uses monthly data from 1990 to 2026, concludes that climate risk has positive and statistically significant effects during high-VIX market stress but little discernible impact on stock-market volatility during calm times. The impulse-response and variance-decomposition results confirm that the effect is concentrated in distressed regimes and fades after several months.

These results are supported by robustness testing utilizing lagged VIX, three regimes, different thresholds, and GARCH volatility. This non-linear pattern underscores the importance of accounting for market conditions when assessing financial stability risks posed by climate change. From a policy standpoint, since the amplification mechanism might worsen systemic volatility, authorities should be especially watchful about climate-related disclosures and stress testing during times of high market stress.

Our results suggest two concrete actions. Financial authorities should first require climate stress tests that are dependent on market conditions. For instance, banks and asset managers should be required to assess their exposure to climate risk in both calm and high-VIX market conditions. Second, climate-related disclosures and macroprudential buffers could be dynamically adjusted. Regulators may temporarily increase inspection of climate-sensitive assets or impose countercyclical capital charges during times of increased market stress. These measures would help mitigate the amplification mechanism documented in this paper, thereby reducing systemic volatility during crises.

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