

Peer-reviewed research

The Role of Climate Awareness and Extreme Events in Shaping the Correlation Between Clean and Dirty Energy Stocks

Hela Ben Hamida¹ ¹ Department of Finance, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Saudi Arabia

Keywords: Clean energy stocks, Dirty stocks, Comovements, Multivariate GJR-GARCH-DCC, GARCH-X, Extreme events

JEL Classifications: C32 Time-Series Models - Dynamic Quantile Regressions - Dynamic Treatment Effect Models - Diffusion Processes - State Space Models, C58 Financial Econometrics, G11 Portfolio Choice - Investment Decisions, G32 Financing Policy - Financial Risk and Risk Management - Capital and Ownership Structure - Value of Firms - Goodwill

<https://doi.org/10.46557/001c.156395>

Energy RESEARCH LETTERS

Vol. 7, Issue Early View, 2026

This paper examines the impact of climate change awareness and extreme events on the dynamic correlations between clean and dirty energy stocks. The findings indicate that increasing climate concerns weaken the strength of these correlations, while extreme events—such as the European energy crisis, the COVID-19 pandemic, and the Russo-Ukrainian war—reduce the volatility of the correlation. These results have important implications for both green and dirty investments.

I. Introduction

Over the last decade, public concern about climate change has increased significantly, largely driven by rising carbon dioxide emissions. This growing awareness has led to greater demand for clean energy sources, such as wind, solar, and geothermal power (D. Li et al., 2024). In contrast, fossil fuels—including coal, crude oil, and natural gas—are increasingly being classified as sources of “dirty energy.”

The importance of clean energy is evident in climate finance. The United Nations Framework Convention on Climate Change (UNFCCC) defines climate finance as local, national, or transnational funding from public, private, and alternative sources aimed at mitigating the adverse effects of climate change, as outlined in agreements like the Kyoto Protocol and the Paris Agreement (D. Li et al., 2024). Extreme climate changes have a detrimental impact on industrial sectors, with measurable spillover effects on financial markets (e.g., Saqib et al., 2023; Wu, 2025). This heightened risk may prompt investors to divest from carbon-intensive firms, which in turn can influence the relationship between clean and dirty stock prices. Despite its importance, few studies have explored climate change awareness as a potential factor driving the dynamic relationships between clean and dirty stocks.

Investment trends underscore the increasing significance of this nexus in both industry and academia. According to the IEA report (2025)¹, investments in clean technologies are expected to soar to \$2.2 trillion by the end of 2025, reflecting global efforts to reduce greenhouse gas

emissions. Conversely, investments in traditional energy sources are projected to reach only \$1.1 trillion. Academic research has shifted toward analyzing the clean-dirty nexus, covering volatility spillovers (e.g., Huang et al., 2025), time-varying correlations (e.g., Bouri et al., 2025), connectedness structure (e.g., A. Li & Zhong, 2025), dependence structure (e.g., Chen et al., 2025), time-frequency coherences (e.g., Tiwari et al., 2023), hedging effectiveness (e.g., Kanjilal et al., 2025), and the identification of key macroeconomic drivers (e.g., Ahmed, 2024). However, the drivers of the clean-dirty nexus have received far less attention, and the role of climate change and extreme events remains insufficiently understood.

This research makes three contributions. First, it is the first to apply a multivariate GJR-GARCH model with dynamic conditional correlation (DCC) to capture clean-dirty correlations. Second, it builds on the work of Santi (2023) by employing the Google Search Trend (GST) approach to create a Climate Change Attention Index (CCAI). Lastly, it introduces a GARCH-X specification (e.g., Caporin & McAleer, 2012) that incorporates the CCAI and extreme events as exogenous variables into both the DCC conditional mean and variance. Together, these contributions advance the literature by revealing how climate attention and extreme events influence the strength and volatility of correlations between clean and dirty stocks.

a Corresponding author email: hmbenhamida@imamu.edu.sa

1 <https://www.iea.org/reports/world-energy-outlook-2025>.

Table 1. Descriptive statistics

Statistics	GOEI	GCEI	CCAI
Mean	0.000438	0.0001635	-0.000491
S. D	0.1159	0.22497	0.18707
Skewness	0.0196***	-0.1188***	0.10641***
Ex. Kurtosis	11.635***	16.251***	10.03***
J-B	189.04***	368.01***	6921.01***
KPSS	0.1838***	0.092***	0.102***
ADF	-10.03	-8.46	-12.24
ADF-p value	(<0.0001)	(<0.0001)	(<0.0001)
LM ARCH test	171.9	145.06	165.03
LM ARCH test p-value	(<0.0001)	(<0.0001)	(<0.0001)

Notes: J-B refers to the Jarque-Bera normality test. ADF and KPSS are stationarity tests. The LM ARCH statistic tests for conditional heteroscedasticity. All p-values are shown in parentheses.

II. Data and Methodology

A. Data

We use daily data for clean energy and dirty stocks. Clean energy stocks are represented by the S&P global clean energy index (GCEI), which is designed to track the performance of companies worldwide that are involved in the clean energy sector. Dirty stocks are approximated by GOEI, which tracks the performance of the 120 largest companies within the S&P Global Index that are engaged in various aspects of the oil and gas industries. The GOEI is weighted by total market capitalization and was sourced from the S&P Dow Jones Indices database.

The climate change attention index (CCAI) measures the level of public attention devoted to climate change at a given time, with the primary aim of capturing shifts in awareness, sentiment, and concern (e.g., Baur & Oll, 2016). To construct the index, we use Google search trend (GST) data, collected daily for selected climate-related keywords using the Trendecon R package. These keywords are aggregated into the CCAI using principal component analysis (PCA), which reduces dimensionality, filters noise, and produces a robust and interpretable composite indicator (e.g., Da et al., 2011). The resulting index is normalized on a scale from 1 to 100, where lower values indicate reduced public attention to climate risk and higher values denote heightened attention.

The data span from January 30, 2015, to April 4, 2024. The time series were synchronized daily to avoid any lag between the CCAI and the stock indexes. All the time series were converted into logarithmic changes. Both clean and dirty returns exhibit significant deviations from normality,

as well as evidence of nonlinearity and heteroscedasticity, thereby confirming the suitability of the GJR-GARCH model (see [Table 1](#)).

B. Methodology

We proceed in two steps. In the first step, we employ the multivariate GJR-GARCH (M-GJR-GARCH)² model of Glosten, Jagannathan, and Runkle (1993) under dynamic conditional correlation (DCC) to model the dynamic correlations between clean and dirty stocks. The GJR-GARCH model³ can account for the main stylized facts of return volatility, such as volatility clustering, nonlinearity, and asymmetry. The model has been shown to outperform several other GARCH-class models (e.g., Vijayalakshmi, 2024). Model lag lengths are selected using the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC).

In the second step, the CCAI is incorporated into the conditional mean equation of the DCC-GARCH specification to quantify the impact of climate attention on the strength of clean-dirty correlations. Dummy variables are additionally introduced to capture the effect of extreme events, such as the COVID-19 pandemic (February 11, 2020 – December 31, 2022), the Russo-Ukrainian war (RUW) (February 24, 2022 – April 4, 2024), and the related energy crisis in Europe (EUEC) (February 2022 – December 2022).⁴ This approach enables us to assess the impact of these events on the stability of the correlations. The DCC mean and variance are specified as follows:

$$DCC_t = \alpha_0 + \beta_1 CCAI_t + \beta_2 CCAI_{t-1} + e_{i,t} \quad (1)$$

$$h_{ij,t} = c + ae_{ij,t}^2 + bh_{ij,t} + \sum_{k=1}^m d_k dum_{k,t} \quad (2)$$

² The journal's readers can refer to Glosten, Jagannathan, and Runkle (1993) for a detailed description.

³ We estimate various GARCH-class models, including the GARCH, EGARCH, TGARCH, FIGARCH, and ADCC GARCH. The GJR-GARCH model shows the best fit of the data. Estimations of the GARCH-class models and their fitting performance are available upon request addressed to the corresponding author.

⁴ A dummy variable is assigned a value of 1 during an extreme event and 0 otherwise.

Table 2. Estimation results of the AR(1)-GJR-GARCH(1,1)

	Dirty stocks	Clean stocks
Panel A: GJR-GARCH estimates		
<i>Cst. (m)</i>	0.0010 (0.78)	0.003 (0.95)
<i>AR(1)</i>	-0.2368*** (-11.27)	-0.1706*** (-8.57)
<i>Cst. (v)</i>	0.22155* (1.67)	0.005** (2.03)
<i>Arch(1)</i>	0.0356*** (3.64)	0.058*** (4.10)
<i>Garch(1)</i>	0.9693*** (12.04)	0.9335*** (10.5)
<i>GJR(γ)</i>	0.010*** (7.82)	0.035** (1.82)
Panel B: DCC estimates		
<i>DCC average</i>		0.029** (1.91)
<i>a</i>		0.0655** (1.90)
<i>b</i>		0.9258*** (21.53)
Panel C: Test diagnostics		
<i>Q²(20)</i>		10.23 [0.96]
<i>Hosking (20)</i>		53.33 [0.97]
<i>Li – McLeod</i>		102.36 [0.93]

Note: The Ljung-Box test statistic of the 2nd squared residuals is Q(20). Hosking (20) and Li–McLeod (20) are the multivariate Portmanteau serial correlation tests, respectively. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively. Values reported in parentheses are *t*-statistics, while those in brackets are *p*-values.

where DCC_t is the DCC at time (*t*), $CCAI_t$ and $CCAI_{t-1}$ are the current and the one-period lagged values of CCAI, and $dum_{k,t}$ is a dummy variable indicating a turbulent period.

III. Empirical results

Table 2 confirms the suitability of the M-GJR-GARCH-DCC model for clean–dirty stock correlations, as indicated by the diagnostic tests (Panel C). The ARCH and GARCH components are statistically significant, while the GJR component (γ) is negative and significant, capturing the asymmetric effects of positive and negative shocks (Panel B). The average DCC is weakly positive (0.029), suggesting a low but positive correlation between dirty and clean energy stocks. The DCC series also shows substantial volatility, ranging from -0.899 to 0.8014 , and strong heteroscedasticity, which justifies the use of a GARCH-X framework.

Figure 1 reports the fluctuating path of the DCCs. During the EUEC and RUW periods, correlations surged, reflecting heightened correlation under stress conditions, while their volatility decreased. In contrast, the COVID-19 period is marked by a notable decline in correlations, suggesting a temporary dissociation between clean and dirty assets. Overall, the results indicate that extreme events have a sig-

nificant influence on the strength, direction, and volatility of correlations between clean and dirty assets.

To assess the impact of CCAI on clean–dirty DCCs, we include its contemporaneous and lagged values in the GARCH-X mean equation (see Equation (1)). Equation (2) additionally incorporates dummy variables for the selected extreme events. The results of mean equation show that $\beta_1 = -0.0168$, indicating that an increase in CCAI reduces the contemporaneous clean–dirty correlation by 1.68%. Equation (2) produces a consistent estimate of $\beta^1 = -0.0210$. These findings are consistent with those of Li et al. (2024), who also document an adverse effect of CCAI on clean–dirty correlations. This may reflect the tendency of clean energy stocks to benefit from heightened climate awareness, while dirty stocks underperform due to regulatory pressure and shifts in consumer preferences. The conditional variance estimates further show that all three dummy variables are negative and statistically significant at the 1% level, suggesting that extreme episodes reduce DCC volatility. This implies that under stress conditions, investors may engage in indiscriminate selling to mitigate portfolio risk, thereby narrowing the divergence between sustainable and non-sustainable assets. Finally, the Ljung-Box diagnostic indicates no significant autocorrelation in the residuals, confirming that the GARCH-X model effectively captures conditional heteroscedasticity.

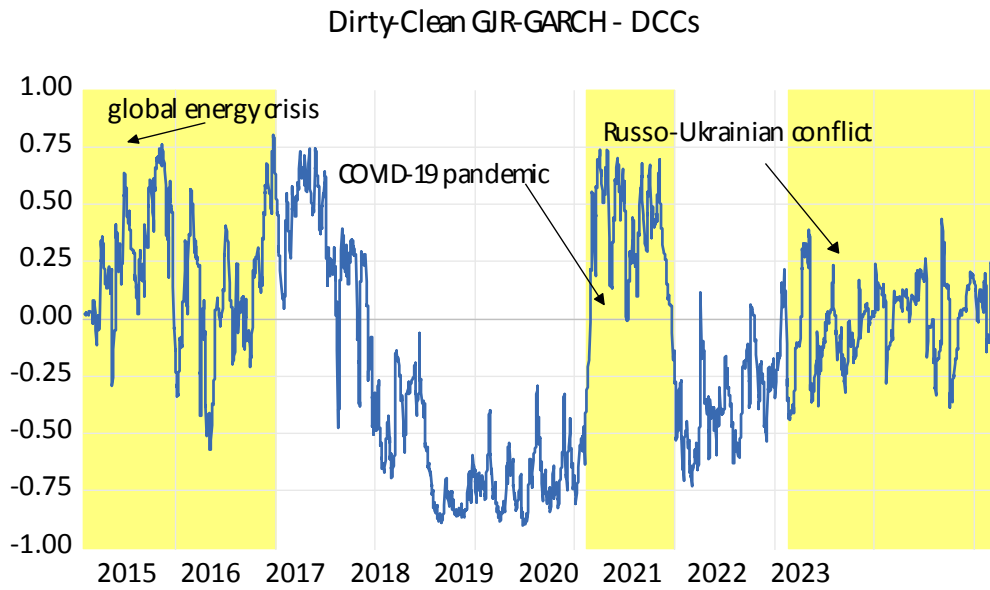


Figure 1. The time-path of the clean-dirty dynamic correlations

Table 3. The GARCH-X model for the DCC with CCAI and extreme events

	Model (1)	Model (2)
Panel A: Results from Equation (1)		
α_0	-0.0043*** (-3.32)	-0.0044*** (-4.03)
β_1	-0.0168*** (-2.53)	-0.0210*** (-2.97)
β_2	-0.0021 (-0.24)	-0.00752 (-0.81)
Panel B: the conditionnal variance model (Equation 2)		
Cst	0.0033*** (16.07)	0.0061*** (10.25)
a	1.0187*** (14.91)	1.0161*** (13.72)
b	-0.0211*** (-3.29)	-0.0322** (-1.90)
$dum_1(EUEC)$	-	-0.00287*** (-4.10)
$dum_2(COVID - 10)$	-	-0.001135*** (-3.60)
$dum_3(RUW)$	-	-0.00337*** (-5.93)
$LB(20)$	8.88 [0.98]	8.91 [0.99]

Note: Values reported in parentheses are the t -statistics. $LB(20)$ is the Ljung-Box statistic for the 20th squared residuals. Values reported in brackets are the corresponding p -values. The DCCs are expressed in their logarithmic changes when included in the GARCH mean equation.

IV. Conclusion

This paper investigates how public attention to climate change and extreme events shapes the dynamic correlation between clean and dirty stocks. By implementing a multivariate GJR-GARCH-DCC and a GARCH-X method on recent data, we find that these assets are generally weakly and positively correlated. Climate change attention tends to at-

tenuate the strength of their comovements, while periods of systemic stress reduce the volatility of these correlations.

Our findings suggest a form of decoupling, defined here as the temporary or structural weakening of clean-dirty stock correlations. Temporary decoupling occurs during crisis episodes when uncertainty dominates, while persistent public climate concerns and ESG-driven investment trends may drive more structural decoupling. This distinction refines prior evidence on financial asset comovements and

extends the literature on ESG dynamics by identifying climate awareness as a determinant of correlation risk.

For policymakers, these results underscore the importance of managing correlation volatility during periods of heightened uncertainty. Regulatory bodies and policymakers can use such evidence to design climate-resilient financial systems and ESG investment guidelines, ensuring that clean energy markets remain potential diversifiers even during turbulent periods. For investors, the findings indicate that the benefits of hedging between clean and dirty stocks diminish during crises, requiring more adaptive portfolio management strategies.

Future research could further distinguish between structural and transitory drivers of decoupling by incorporating other proxies for climate attention, such as physical risk or transition risk. Extending the study to other asset classes, including green and brown bonds, cryptocurrencies, and tokens, would enhance our understanding of how climate-related dynamics shape financial interconnectedness.

Submitted: February 25, 2025 AEDT. Accepted: October 16, 2025 AEDT. Published: March 20, 2026 AEDT.



This is an open-access article distributed under the terms of the Creative Commons Attribution-ShareAlike 4.0 International License (CCBY-SA-4.0). View this license's legal deed at <https://creativecommons.org/licenses/by-sa/4.0> and legal code at <https://creativecommons.org/licenses/by-sa/4.0/legalcode> for more information.

References

- Ahmed, W. M. A. (2024). Climate change attention and eco-friendly investments: Evidence from quantile ARDL analysis. *Energy Economics*, 135, 107051. <https://doi.org/10.1016/j.eneco.2024.107051>
- Baur, D. G., & Oll, J. (2016). Using Google Trends to measure issues in finance: The case of climate change. *Journal of International Financial Markets, Institutions and Money*, 44, 150–163. <https://doi.org/10.1016/j.intfin.2016.05.006>
- Bouri, E., Dudda, T. L., & Rognone, L. (2025). Climate risk and the nexus of clean energy and technology stocks. *Annals of Operational Research*, 347, 445–469. <https://doi.org/10.1007/s10479-023-05487-z>
- Caporin, M., & McAleer, M. (2012). Ten things you should know about the conditional correlation model. *Empirical Economics*, 43(1), 1–23. <https://doi.org/10.1007/s00181-012-0586-6>
- Chen, Y., Zhu, H., & Liu, Y. (2025). Measuring multi-scale risk contagion between crude oil, clean energy, and stock market: A MODWT-Vine-copula method. *Research in International Business and Finance*, 75, 102790. <https://doi.org/10.1016/j.ribaf.2025.102790>
- Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5), 1461–1499. <https://doi.org/10.1111/j.1540-6261.2011.01679.x>
- Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relationship between the expected value and the volatility of nominal excess return on stocks. *The Journal of Finance*, 48(5), 1779–1801. <https://doi.org/10.1111/j.1540-6261.1993.tb05128.x>
- Huang, J., Liu, Z., & Guo, K. (2025). Climate risks and the connectedness between clean and dirty energy markets. *Finance Research Letters*, 74, 106799. <https://doi.org/10.1016/j.frl.2025.106799>
- Kanjilal, K., Paul, M., & Ghosh, S. (2025). Hedging dynamics between oil and clean energy stock indices amid the Russia-Ukraine war and geopolitical turmoil. *Finance Research Letters*, 84, 107753. <https://doi.org/10.1016/j.frl.2025.107753>
- Li, A., & Zhong, B. (2025). Asymmetric spillover connectedness between clean energy markets and industrial stock markets: How uncertainties affect it. *PLOS ONE*, 20(3), e0316171. <https://doi.org/10.1371/journal.pone.0316171>
- Li, D., Wu, Z., & Tang, Y. (2024). Do climate risks affect dirty–clean energy stock price dynamic correlations? *Energy Economics*, 136, 107713. <https://doi.org/10.1016/j.eneco.2024.107713>
- Santi, C. (2023). Investor climate sentiment and financial markets. *International Review of Financial Analysis*, 86, 102490. <https://doi.org/10.1016/j.irfa.2023.102490>
- Saqib, F., Karim, S., Naeem, M. A., Nepal, R., & Jamasb, T. (2023). Co-movement between dirty and clean energy: A time-frequency perspective. *Energy Economics*, 119, 106565. <https://doi.org/10.1016/j.eneco.2023.106565>
- Tiwari, A. K., Trabelsi, N., Abakah, E. J. A., Nasreen, S., & Lee, C. (2023). An empirical analysis of the dynamic relationship between clean and dirty energy markets. *Energy Economics*, 124, 106766. <https://doi.org/10.1016/j.eneco.2023.106766>
- Vijayalakshmi, V. (2024). Implementation of sentiment analysis in stock market prediction using variants of GARCH models. In D. Jude Hemanth (Ed.), *Computational Intelligence Methods for Sentiment Analysis in Natural Language Processing Applications* (pp. 227–249). Morgan Kaufmann. <https://doi.org/10.1016/B978-0-443-22009-8.00002-1>
- Wu, B. (2025). Climate Risk and Corporate Value: Evidence from Temperature Bins and Panel Regression. *ArXiv*. <https://arxiv.org/abs/2503.14233>