

Peer-reviewed research

Dynamics of Brown and Green Energy Stocks Under Climate-Related Risk: Statistical Evidence From the United States

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Keywords: Climate risk, Brown energy, Green energy, United States, Time series

JEL Classifications: C22 Time-Series Models - Dynamic Quantile Regressions - Dynamic Treatment Effect Models - Diffusion Processes, G10 General, Q54 Climate - Natural Disasters and Their Management - Global Warming

<https://doi.org/10.46557/001c.126024>

Energy RESEARCH LETTERS

Vol. 7, Issue 4, 2026

Climate change poses challenges to economies and financial markets, particularly energy sectors transitioning to low-carbon alternatives. This study explores the relationship between climate-related transition risks and the performance of brown and green energy stocks in the U.S. from February 2009 to December 2023, using the transition risk index by Bua et al. (2024). Advanced econometric methods, including transfer entropy and nonparametric causality-in-quantiles, reveal significant information flows from transition risk growth to energy stock returns and volatility. Robustness checks confirm these findings. The results emphasize the importance of transition risks in energy markets, recommending enhanced monitoring, clean energy investment support for brown energy firms, risk disclosure mandates, and flexible policies.

I. Introduction

Climate change poses significant challenges to economies and financial markets, particularly in transitioning to a low-carbon economy, which requires costly adjustments for fossil fuel-dependent firms (Akadiri & Adebayo, 2022). This study examines the relationship between climate-related transition risks and the performance of brown and green energy stocks in the United States from February 2009 to December 2023, leveraging the transition risk index developed by Bua et al. (2024). This index is crucial as it encapsulates the essence of transition risks, especially for firms reliant on traditional energy sources.

The study is motivated by the urgent need to address climate change and its financial implications for energy markets. Traditional energy firms, represented by the S&P 500 Energy Index, face significant risks with the global shift towards cleaner energy alternatives. Conversely, firms involved in clean energy technologies, tracked by the NASDAQ Clean Edge Green Energy Index, may benefit from this transition. Understanding these dynamics is vital for investors, policymakers, and stakeholders navigating the complexities of the energy market in the context of climate change. While previous studies have highlighted the financial risks associated with climate change (Awowusi et al., 2022; Akadiri & Adebayo, 2022; Battiston et al., 2021; Ranger et al., 2021), a gap exists in understanding the spe-

cific impacts on brown and green energy stocks over an extended period.

The primary objective of this study is to analyze the relationship between climate-related transition risks and the performance of brown and green energy stocks. Employing various econometric methodologies, including transfer entropy, nonparametric causality-in-quantiles, and time-varying causality in the presence of instabilities, the study uncovers causal relationships and dynamic interactions between these variables. Transfer entropy detects linear and nonlinear directional relationships, providing a comprehensive understanding of dynamic interactions. Nonparametric causality-in-quantiles examines causal relationships across different points in the conditional distribution, capturing heterogeneous effects missed by conventional mean-based methods. The time-varying causality approach addresses potential instabilities and structural breaks over time, ensuring robust analysis despite evolving market conditions. This methodological rigor is essential for understanding the complexities of the energy market and the evolving nature of climate-related risks.

This study's contributions are three-fold. First, it provides empirical evidence on the impact of transition risks on energy stocks, enhancing the understanding of climate finance. Second, by utilizing the transition risk index of Bua et al. (2024), it offers a novel approach to measuring climate-related risks, which future research can adopt. Lastly,

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the insights gained can inform investment strategies, policy decisions, and corporate planning, enabling stakeholders to make informed decisions amid climate-related uncertainties. This research fills a literature gap and has practical implications for managing the financial risks associated with the transition to a low-carbon economy.

II. Data and Methodology

A. Data

This study examines monthly data for the U.S. climate-related risks and brown and green energy stocks from February 2009 to December 2023, utilizing the transition risk index of Bua et al. (2024). Transition risk arises from costly adjustments needed for a low-carbon economy due to changes in policies, technology, and public preferences. This index is crucial for firms reliant on fossil fuels (Bua et al., 2024).¹ Brown energy stocks are represented by the S&P 500 Energy Index, which includes firms involved in oil, gas, coal, and consumable fuels.² Green energy stocks are tracked by the NASDAQ Clean Edge Green Energy Index³, covering firms in clean energy technologies. To ensure data stationarity, nonstationary data sequences are transformed, and growth rates of the transition risk index and return series of brown and green stocks are calculated using appropriate equations.

$$\ln \left(\frac{V_t}{V_{t-1}} \right) \times 100 \quad (1)$$

Where V_t refers to the variable under consideration at time t , V_{t-1} represents the variable under consideration at time $t - 1$, and $\ln$ stands for the natural logarithm. These new data sequences (transition risk growth rate [TRG], brown energy returns [BER] and green energy returns [GER]) are used for empirical analyses.

B. Methodology

B.I. Transfer entropy

The empirical analysis starts with an overall assessment of information flows between the growth rate of the transition risk and stock returns (brown and green). This is achieved via the Shannon transfer entropy approach. According to Mao & Shang (2017), accurately modeling cause-and-effect dynamics in complex systems can be challenging. The transfer entropy method is particularly influential among the various techniques developed to address this problem (Olasehinde-Williams, 2024). For this reason, this method is chosen to determine information flows between the variables of interest (growth rate of transition risk,

brown energy stock returns, and green energy stock returns).

Following Shannon (1948), the transfer entropy equation is as follows:

$$H_J = - \sum_j p(j) \cdot \log(p(j)) \quad (2)$$

Where $\log$ is logarithm to base 2, J represents a random variable, $j_1, j_2, \dots, j_n$ are potential outcomes. $p(j_1), p(j_2), \dots, p(j_n)$ are probabilities of outcomes.

B.II. Nonparametric causality-in-quantiles

After determining the nature of information flows between the variables, we proceed to determining the direction of causal flows between the growth rate of transition risk and the returns of brown and green stocks through the nonparametric causality-in-quantiles test of Balcilar et al. (2018). In financial analysis, causality is conventionally assessed using the Granger (1969) causality test, which typically identifies whether one variable can predict another. However, this method is limited because it only considers the conditional mean, which may not be informative if the variables involved have non-elliptical or fat-tailed distributions, as is common in many financial datasets (Balcilar et al., 2018). Additionally, causal relationships in the tails of the distribution may differ significantly from those at the center (Lee & Yang, 2012). Consequently, relying on Granger causality might lead to incorrect conclusions if causal relationships are only present in specific areas of the conditional joint distribution. To address this issue, we use the nonparametric causality-in-quantiles test of Balcilar et al. (2018). Being a combination of the k^{th} order nonlinear causality test by Nishiyama et al. (2011) and the causality-in-quantiles test of Jeong et al. (2012), this method effectively identifies nonlinear causality, especially in datasets with extreme values (see Olasehinde-Williams et al., 2023). The nonparametric causality-in-quantiles test allows for the investigation of causality, or the absence of it, in the θ -th quantile considering both mean (first moment) and variance (second moment). This test can thus simultaneously analyze causality in mean and variance.

The null hypothesis that TRG_t does not Granger cause BER_t in the θ -th quantile up to M -th moment can be tested as follows⁴:

$$H_0 : P \{ F_{BER_t^m | X_{t-1}} \{ Q_\theta(BER_{t-1}) | X_{t-1} \} = \theta \} = 1, \quad (3)$$

$$m = 1, 2, \dots, M$$

$$H_1 : P \{ F_{BER_t^m | X_{t-1}} \{ Q_\theta(BER_{t-1}) | X_{t-1} \} = \theta \} < 1, \quad (4)$$

$$m = 1, 2, \dots, M$$

The kernel-based test statistics are given as follows:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^T \sum_{s=p+1, s \neq t}^T K \left(\frac{X_{t-1} - X_{s-1}}{h} \right) \hat{\varepsilon}_t \hat{\varepsilon}_s \quad (5)$$

¹ https://www.policyuncertainty.com/Climate_Risk_Indexes.html

² <https://www.spglobal.com/spdji/en/indices/equity/sp-500-energy-sector/#data>

³ <https://indexes.nasdaqomx.com/Index/History/CELS>

⁴ Equations (3) and (4) are repeated to test for causal relationship between TRG & GER.

Table 1. Shannon transfer entropy results

Direction	Eff. TE	Bootstrapped TE quantiles				
		0%	25%	50%	75%	100%
TRG→BER	0.0167*** (0.051)	0.0060	0.0131	0.0182	0.0267	0.0784
BER→TRG	0.0000 (0.663)	0.0036	0.0142	0.0203	0.0298	0.0711

The effective transfer entropy (Eff. TE) and other statistical values are calculated with 300 replications for the bootstrapped TE quantiles, and the weighting parameter is set at $q=3$. Statistical significance is determined through the Markov block bootstrap method. *** represents statistical significance at 10% level.

Where $K(\bullet)$ is the kernel function with bandwidth. T represents sample size. p is the lag order, and $\hat{\varepsilon}_t = 1 \{r_t \leq \hat{Q}_\theta(R_{t-1})\} - \theta$ is the regression error, with $\hat{Q}_\theta(R_{t-1})$ as the estimate of the θ -th conditional quantile and $1 \{\bullet\}$ is the indicator function.

B.III. Time-varying causality in the presence of instabilities

Issues such as regime shifts and structural breaks cause errors in causality tests based on time-invariant techniques (Fromentin, 2023). Moreover, it is essential to account for temporal changes in these statistical analyses (Fromentin, 2023). Therefore, to ensure robustness in the empirical analysis, this study also employs the causality test of Rossi & Wang (2019) as a final step to examine the relationship between the growth rate of transition risk and returns of brown and green stocks. This approach is resilient to instabilities and accommodates time-varying characteristics.

Following Rossi & Wang (2019), the time-varying causality test is based on a reduced-form VAR model with time-varying parameters specified as follows:

$$A_t(L)y_t = u_t \quad (6)$$

$$A_t(L) = I - A_{1t}L - A_{2t}L^2 - \dots - A_{pt}L^p \quad (7)$$

Where $y_t = [y_{1t}, y_{2t}, \dots, y_{nt}]'$ refers to an $(n \times 1)$ vector of endogenous variables, $A_{jt} = (n \times n)$ coefficient matrices with time-varying characteristics, and ε_{U_t} is the error term.

III. Results

A. Shannon transfer entropy results

The Shannon transfer entropy and effective transfer entropy analyses presented in Tables 1 and 2 reveal significant information flows from transition risk growth to brown and green energy returns, but not vice versa. This indicates that knowledge of transition risk is crucial for understanding and reducing uncertainty in brown and green energy markets.

B. Nonparametric causality-in-quantiles and quantile-on-quantile Granger causality results

This study evaluates the predictive power of transition risk on the returns and volatility of brown and green energy stocks using the nonparametric causality-in-quantiles method. This technique, being model-free, identifies causal

effects and volatility spillovers, highlighting higher-order dependencies that might be missed in conditional means. The result reveals that the null hypothesis of no causal effects in mean from transition risk growth to brown energy returns can be rejected at a 10% significance level for quantiles between 0.13 and 0.75, and that the null hypothesis of no causal effects in variance can be rejected across nearly all quantiles at the same significance level. For clean energy returns, the result indicates that the null hypothesis of no causal effect in mean can be rejected in the middle quantiles (0.38–0.77), while the null hypothesis of no causal effects in variance can be rejected at low to high quantiles (0.13–0.88). These findings suggest that transition risk has predictive power over the returns and volatility of both brown and green energy stocks, underlining its significance in forecasting energy market dynamics and volatility spillovers.

C. Results of time-varying causality in the presence of instabilities

A time-varying Granger causality test was used to examine links between transition risk and energy returns. Table 3 shows that transition risk growth affected brown energy returns from 2017 to 2020, including during the 2018 oil crash and COVID-19, with reverse effects around the 2014 oil price plunge. For green energy returns, significant effects were observed around 2011 and post-2019 during “Black Monday” and COVID-19, with reverse causality noted from 2011 to 2019.

IV. Conclusion

This study analyzes the complex relationships between climate-related transition risks and the performance of brown and green energy stocks in the United States from February 2009 to December 2023, using a variety of econometric methods. Based on the findings, several policy recommendations are proposed to manage the financial impacts of climate-related transition risks on energy markets. Policymakers should enhance the monitoring and reporting of transition risks by developing thorough frameworks to track policy changes, technological advancements, and public preference shifts. Increasing support and incentives for investments in clean energy technologies, such as tax breaks, subsidies, and favorable financing options, will promote green energy investments. Additionally, targeted sup-

Table 2. Shannon transfer entropy results

Direction	Eff. TE	Bootstrapped TE quantiles				
		0%	25%	50%	75%	100%
TRG→GER	0.0201*** (0.0967)	0.0036	0.0131	0.0188	0.0284	0.0768
GER→TRG	0.0000 (0.643)	0.0034	0.0129	0.0189	0.0276	0.0631

The effective transfer entropy (Eff. TE) and other statistical values are calculated with 300 replications for the bootstrapped TE quantiles, and the weighting parameter is set at $q=3$. Statistical significance is determined through the Markov block bootstrap method. *** represents statistical significance at 10% level.

Table 3. Time-varying parameter Granger causality test results

Statistics	Exp	MeanW	Nyblom	SupLR
TRG→BER	75.565*** (0.000)	51.477*** (0.000)	6.298 (0.743)	160.617*** (0.000)
BER→TRG	21.932*** (0.000)	31.990* (0.064)	3.404 (0.868)	49.917*** (0.000)
TRG→GER	18.901** (0.038)	33.817** (0.040)	4.997 (0.555)	43.770** (0.035)
GER→TRG	28.351*** (0.000)	47.473*** (0.000)	5.566 (0.438)	64.059*** (0.000)

The four alternative test statistics, namely exponential Wald, mean Wald, Nyblom, and Quandt Likelihood Ratio tests, are reported. p -values are reported in parentheses. The arrow depicts the direction of causality. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

port for brown energy firms is crucial to help them adapt to a low-carbon economy through funding for cleaner technologies, retraining programs for workers, and transitional financial assistance. Financial regulators should mandate the disclosure of transition risk exposures, enhancing transparency and enabling informed investment decisions. Lastly, policymakers should adopt flexible and adaptive strategies, including periodic reviews of climate policies

and regulatory frameworks, to effectively respond to emerging trends and market conditions.

The content of this paper are authors' sole responsibility. They do not represent the views of any of the institutions.

Submitted: July 24, 2024 AEDT. Accepted: September 10, 2024 AEDT. Published: January 31, 2025 AEDT.



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