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Comparative Analysis of Climate Change Financing Potential of Renewable and Non-Renewable Energy Stocks: A Predictive Approach

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With the pressing need for green finances to combat climate change, there has been a growing advocacy for investing in renewable energy stocks. However, the investment landscape continues to favor non-renewable energy stocks. To understand this financial decision, which seems to contradict the global push for sustainability, we employ the GARCH-MIDAS model to compare the resilience of renewable and non-renewable energy stocks to climate-related risks. Our findings indicate that both RE and NRE are vulnerable to the effects of climate change. However, our results suggest that investors may perceive RE stocks as more resilient and stable considering climate-induced shocks.

I. Introduction

The concept of 'climate finance' has gained significant attention in global discourse, underscoring the critical need for substantial financial resources to adapt to and mitigate the impact of climate change. Traditionally, investors have focused primarily on maximizing profits and managing portfolio strategies to minimize risks. However, with the growing threat of climate-related risks, market participants are increasingly turning toward investments in environmentally friendly stocks, particularly those in the renewable energy sector. Renewable energy stocks have been widely acknowledged to address rising climate change through committed and adequate investment in renewable energy (Murray-West, 2023). Though renewable energy stocks have been added to existing energy portfolios, they remain distinct due to their climate compliance characteristics (Ngwakwe, 2023).

Despite the increasing advocacy for investment in renewable energy stocks to provide green financing to mitigate climate change, the annual investment of over \$850 billion in high-emission sectors, such as fossil fuels, indicates a continued preference for non-renewable energy stocks (Adediran et al., 2023). This financial decision, which seems to contradict the global push for sustainability, is the focus of our study. Our goal is to examine the comparative resilience of renewable and non-renewable energy stocks to climate-related risks, assessing whether risk-averse investors seeking adaptation to climate change can achieve

higher returns through renewable energy stocks than through non-renewable energy stocks.

Empirically, there has been a proliferation of literature on climate change and stock market behaviour (Adediran et al., 2023; Amighini et al., 2022; Apergis, 2023; Dutta et al., 2023; Zhang et al., 2022). Related to our study, Oloko et al. (2023) was the first to address whether stocks can finance climate change. However, the likelihood that the climate change financing potential of stocks is sensitive to sectoral dynamics remains largely unexplored. Hence, this study's first contribution is to provide insight into which of the two options—renewable or non-renewable energy stocks—is less vulnerable to climate-related risks.

There is empirical evidence showing that renewable and non-renewable energy sources contribute differently to climate change (Acaroğlu & Güllü, 2022; Hussain et al., 2022), but none, to the best of our knowledge, has considered the relative resilience of these stocks to climate-related risks. Our study's innovation is that the energy stock that remains resilient and relatively stable after climate change-related shocks will be considered capable of financing climate change, as stability can help minimize investors' losses amid changing climate conditions.

Methodologically, while it is intuitively reasonable to assume climate change explains the long-run volatility dynamics of renewable and non-renewable stocks, it might be empirically challenging to link high-frequency stock market price movements to slow-moving climate trends. To ad-

dress this gap, we propose using the Generalized Autoregressive Conditional Heteroskedasticity variant of mixed data sampling (GARCH-MIDAS) model. This model is well-suited for examining both price and return dynamics, as well as long-run market volatility. The GARCH-MIDAS approach is advantageous because it allows high-frequency fluctuations in the energy stock market to coexist with slow-moving climate change dynamics without losing relevant information (Engle et al., 2013).

II. Data and Methodology

A. Data

The daily data for renewable energy (*RE*) and non-renewable energy (*NRE*) stocks used in this study are measured through the S&P Global Clean Energy Index (SPGT-CLEN) for *RE* and the FTSE 350 Oil & Gas Index (FTNMX601010) for *NRE*. Both data sets were obtained from [Investing.com](https://www.investing.com). Monthly climate change data, represented by temperature (*TEMP*) anomalies, were sourced from the National Aeronautics and Space Administration (NASA) and the Goddard Institute for Space Studies (GISS). The study covers the period from February 2012 to July 2024.

To address the unit root problem in the series, we take the first difference of the natural logarithm of each series. More importantly, we prefer an estimation technique that accommodates the inherent statistical features often found in high-frequency series, such as the ARCH effect, serial correlation, and persistence.

B. Methodology

Given that the variables under consideration are sampled at different frequencies—daily and monthly—the GARCH-MIDAS model by Engle et al. (2013), which utilizes data at their natural frequencies, is considered the most appropriate for this study. The GARCH-MIDAS framework helps avoid the loss of information that might occur if we followed the common practice of disaggregating data into a uniform frequency. Equation (1) presents the generic representation of the GARCH-MIDAS model (see Engle et al., 2013):

$$z_{i,t} = \mu + \sqrt{\tau_t} \times h_{i,t} \varepsilon_{i,t}, \varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0,1), \quad \forall i = 1, \dots, N_t \quad (1)$$

$$h_{i,t} = (1 - \alpha - \beta) + \frac{(z_{i-1,t} - \mu)^2}{\tau_i} + \beta h_{i-1,t} \quad (2)$$

$$\tau_i^{(r\omega)} = m^{(r\omega)} + \theta^{(r\omega)} \sum_{k=1}^K \phi_k(\omega_1, \omega_1) X_{i-k}^{(r\omega)} \quad (3)$$

Starting with Equation (1), which defines our mean equation, the parameter of interest, denoted by (μ), measures the unconditional average returns which are captured separately for renewable and non-renewable energy stocks. Equations (2) and (3) present the short-run and long-run components of the conditional variance in the GARCH-MIDAS model. The short-run component involves measuring the ARCH and GARCH effects, denoting the short-run segment of the conditional variance following a GARCH (1,1)

process. The long-run component of the conditional variance is captured by (τ_t) in Equation (3), which helps accommodate the exogenous or realized volatility, with or without an exogenous factor. Other parameters of interest, particularly in Equation (3), are ($r\omega$) and (m). The former reflects the outcome of implementing a rolling-window approach, allowing the secular long-run component to vary monthly, while the latter measures the intercept of the long-run component of the conditional variance. Of particular interest in this study is the slope coefficient (θ), which measures the effect of climate on the volatility of the energy stocks under consideration.

III. Empirical Results

Our analysis focuses on determining the comparative climate change financing potential of renewable and non-renewable energy stocks. Key parameters of interest include the sum of ($\alpha + \beta$), and most importantly, the slope coefficient (θ). A model with the lowest sum ($\alpha + \beta$) and the lowest positive slope coefficient (θ), will indicate the stock with the least volatility, making it more attractive to investors concerned with minimizing losses due to climate-related risks.

Our findings in [Table 1](#) show that the slope coefficient is consistently positive and statistically significant, whether the energy stock is renewable or non-renewable. This suggests that the null hypothesis of no predictability is rejected for both stock categories. However, the volatility in renewable energy stocks appears to be more influenced by climate change than non-renewable energy stocks. This aligns with the findings of Adediran et al. (2023), which report that investors continue to favor high-emission sectors like fossil fuels. Nevertheless, the sum of ($\alpha + \beta$) for renewable energy stocks is 0.95, compared to 0.99 for non-renewable stocks, indicating that shocks to non-renewable energy stocks, including those caused by climate change, are more likely to be permanent, while renewable energy stocks experience less persistent volatility. What this suggests is that the shocks inducing volatility, including those attributed to climate change, are likely to be permanent in the case of non-renewable energy stocks but less persistent for renewable energy stocks, at least relatively speaking. Thus, while the out-of-sample forecast results in [Table 2](#) show that climate change is significant in predicting the volatility dynamics of both renewable and non-renewable energy stocks, investors may find renewable energy stocks to be a more resilient investment in the face of climate change-induced shocks compared to non-renewable stocks.

IV. Conclusion

Using the GARCH-MIDAS model, we conducted an in-depth analysis of the volatility of renewable (*RE*) and non-renewable (*NRE*) energy stocks within the framework of climate-related risks. Our comprehensive findings reveal that both *RE* and *NRE* stocks are susceptible to the impacts of climate change, with *RE* stocks exhibiting more significant volatility attributed to climate change. Furthermore, our meticulous analysis indicates that while climate change in-

Table 1. GARCH-MIDAS estimates

	Renewable Energy-based Model		Non-Renewable Energy-based Model	
	GARCH-MIDAS-RV	GARCH-MIDAS-X	GARCH-MIDAS-RV	GARCH-MIDAS-X
μ	0.0004 ** (0.0002)	-0.0001 (0.0004)	0.0003 (0.0002)	0.0002 (0.0002)
α	0.1472*** (0.0128)	0.0502*** (0.0128)	0.1545*** (0.0104)	0.0707*** (0.0037)
β	0.7635*** (0.0196)	0.9004*** (0.0270)	0.6875*** (0.0265)	0.9196*** (0.0049)
θ	0.1994*** (0.0094)	0.0272*** (0.0035)	0.1988*** (0.0070)	0.0007*** (0.0003)
w	5.0081*** (1.2516)	4.9998*** (0.0487)	20.0990*** (0.33896)	17.2290* (10.3200)
m	0.0056*** (0.0009)	0.0010*** (0.0001)	0.0071*** (0.0007)	0.0003*** (0.0000)

Note: The term *RV* denotes realized volatility while *X* represents exogenous factor μ is the unconditional mean parameter, while α and β are the ARCH and GARCH terms, respectively. The parameter θ is the slope coefficient, and w and m are the adjusted beta polynomial weight and long-run constant terms. The values in parentheses are the standard errors of the parameter estimates, while ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 2. Out-of-sample forecast evaluation

	75% Sub-sample			90% Sub-sample		
	h=10	h=20	h=30	h=10	h=20	h=30
Renewable Energy-based Model						
<i>RV</i> vs <i>TEMP</i>	-4.3779*** [0.0001]	-2.8340** [0.0196]	-5.2904*** [0.0000]	-4.3849*** [0.0003]	-2.8665** [0.0186]	-5.3028*** [0.0000]
Non-Renewable Energy-based Model						
<i>RV</i> vs <i>TEMP</i>	-4.3628*** [0.0000]	-4.0709*** [0.0000]	-5.2904*** [0.0000]	-4.4004*** [0.0000]	-3.4287*** [0.0075]	-3.8933*** [0.0000]

Note: The term *RV* denotes Realized Volatility. The out-of-sample forecast result is based on Harvey et al. (1997). If the statistic is negative and statistically significant, GARCH-MIDAS-X is deemed the most accurate for predicting energy stock return volatility. If the statistic is not significant, it implies that the null hypothesis is not rejected, and the two competing models are the same. The values in square brackets are the probability values, while the syntax ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

fluences the volatility of both *RE* and *NRE* stocks, investors may discern *RE* stocks as displaying greater resilience and stability in the face of climate change-induced shocks. As a result, *RE* stocks can help fund climate change initiatives, given their potential stability amid climate-related risks. Thus, compared to *NRE* stocks, investors are likely to be bi-

ased towards holding their capital in *RE* stocks because they are more resilient to climate-related shocks.

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