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Effects of Temperature Rise on Clean Energy-Based Capital Market Investments: Neural Network-Based Granger Causality Analysis

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Abstract: During the past 20 years, due to climate change, the government and the private sector have significantly focused on relying on non-fossil fuel-based methods for their energy needs. Climate change-related events, such as unusual weather conditions, abnormal temperature spikes, etc., have an adverse influence on clean energy-based investments. In the given study, we intend to focus on how an incremental temperature rise could affect investors' perceptions of clean energy assets. To understand the investor-based sentiment on climate change, we utilize prominent clean energy ETFs (exchange traded funds) and consider the temperature's effect on them. The daily average temperatures of the three most dynamic international financial centers: New York, London and Tokyo, are taken as predictors. Deep learning-based neural networks are applied to understand both the linear and non-linear relationships between the desired variables and identify the causal effects. The results indicate that in almost all the cases with desired lags, there is some sort of non-linear causality, irrespective of linear causality effects. We hope this occurrence can help portfolio managers and environmental professionals in identifying novel climate change-related factors when considering the temperature-related risks.

Keywords: clean energy prices; extreme temperatures; climate mitigation; capital markets; causality

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1. Introduction

A substantial amount of evidence validates climate change. Earth's climate is stochastic, and intense weather and climate events are becoming increasingly prevalent. The alarming insights concerning climate change have attracted the attention of global environmental experts, scientists and economists alike in the past few decades. Climate change also exacerbates rising temperatures and raises potential risks to humankind and natural systems, resulting in catastrophic biodiversity loss 2010 [1]. There have been studies which corroborate the fact that a single degree temperature rise could have an overall impact on the economic prosperity of nations. Rising temperatures have undesirable effects on a nation's industrial and agricultural output, resulting in political instability Dell et al. [2]. The case is even worse for poorer countries. Temperature rise effects have also been shown to have significant impacts in areas such as labor productivity (Hsiang [3]), crop yields (Schlenker et al. [4]), legal decision-making (Heyes and Saberian [5]), etc., to name a few. Apart from these, temperature escalations could also profoundly influence the demand and capacity utilization of utility-based electric power, further impacting other vital sectors such as transportation Khan et al. [6]. Likewise, (Fisher et al. [7]) showed a negative link between temperature rise and agriculture output in the US. Temperature fluctuations also drastically affect stock markets globally. Most of these studies were inclined toward high climate risks impacting a broader set of asset prices. Moreover, international institutions such as the World Bank and Asian Development Bank (ADB) provide fixed-income securities, such as green bonds and eco notes Reichelt [8]. However, they are accessible to only a narrow range of investors, and individual retail investors have limited awareness of them. Henceforth in the given study, we intended to focus on the equity markets through ETF-based clean energy instruments.

According to our literature review, there were not enough studies focused explicitly on finding the consequences of temperature rise on the stock prices in the renewable energy sector. Hence with the given study, we intended to focus on how the incremental temperature growth over the past decade has impacted investments in renewable energy-based capital market assets through a unique non-linear approach. The study's key objective was to comprehend how the incremental temperature growth over the past decade has impacted investments in renewable energy-based capital market assets through a unique non-linear approach. This study is unique in three different ways:

Firstly, the study was the first to employ an artificial neural network (ANN)-based causality analysis of climatic variables such as temperature rise on stock prices. Utilizing the ANN-based approach helped in discovering the existence of the non-linear association.

Secondly, the study's scope was narrowed down by focusing on the clean energy sector, instead of the existing studies dedicated to recognizing the bearings of temperature rise on capital markets at a broader level. Finally, an extensive analysis of the non-linear causality relationship was conducted, and its result was compared to traditional linear causality models for both the prices and volumes data.

The given paper is structured as follows. Section 2 provides a brief literature review of recent studies related to temperature effects on capital markets, such as investor's sentiments and their risk appetite for financial assets in general. Section 3 describes the data used for the study, such as clean energy ETF datasets and the various predictors of temperatures of global financial centers, along with the explanation of the neural network-based non-linear causality methodology. Section 4 presents the empirical results describing how incremental temperature growth impacts the investors' responses to clean energy stocks through non-linear GC (Granger causality) methods. Section 5 summarizes and concludes the study with discussion related to its impact on policy decisions.

2. Literature Review

The clean energy industry is growing, and its consumption has turned more imperative in response to serious environmental problems. Thus, more and more investors are beginning to target clean energy firms in their portfolios Liu and Zeng [9].

Consequently, recent events, such as the Paris Agreement in 2015, climate protests following it and various prominent IPCC (Intergovernmental Panel on Climate Change)-led COP (Conference of the Parties) meetings over the years have brought investors' attentions to climate risks Krueger et al. [10]. Chen et al. [11], in their study, indicated that in nations where clean energy investment was higher, low carbon activity was more likely to be pursued. These awareness levels have forced investors to focus more on investing in equities related to renewable energy technologies. Fahmy [12] corroborated this fact. Their investigations of investor sentiment during the Paris Agreement in 2015, using Google search results, showed that the search for clean energy-related investments increased significantly after the deal. It also showed that public attention to climate investing rises during extreme weather events.

Prior research has shown that climate change impacts clean energy usage. Still, a lack of literature thoroughly explores how climate change affects clean energy investment.

Hansen et al. [13] identified three reasons for clean energy investments: GHG (green-house gas) emissions, severe temperatures and extreme weather events. A heat wave may increase energy demand owing to air conditioning while simultaneously putting the electrical generation infrastructure under strain, potentially resulting in outages. Moreover, excessive temperatures harm electricity production and impact energy production, resulting in supply cuts of various magnitudes that affect other infrastructures (Pryor et al. [14]). Moreover, Xu et al. [15] elucidated that factors such as temperature, humidity and type of day have an undeviating effect on energy consumption levels. Şenhaz et al. [16] also stated that high levels of carbon emissions result in higher returns for clean energy companies. Apart from this, there have been other recent studies specifically focused on other environmental factors such as air pollution, humidity levels and sunshine exposure effects on investment returns Tufan and Hamarat [17]; Levy and Yagil [18]; Teng and He [19]. These results also corroborate with the findings of Howarth and Hoffman [20], suggesting three factors, namely humidity, temperature and sunshine time, have the most significant impact on an investor's mood. However, in the given study, we mainly intended to focus on temperature rise as humidity and sunshine are not uniformly distributed across the regions throughout annual weather cycles.

The impact of temperature variations on various economic variables has been extensively studied. Addoum et al. [21] used the daily temperature data across the United States to study how it affected the sales and productivity of various business establishments. Similarly, Burke et al. [22] determined a non-linear relationship between temperature rise and economic productivity, resulting in reduced global incomes. Colacito et al. [23] used panel data of various economic sectors in the United States to infer that increasing temperatures could significantly shrink economic growth in the coming years. There have been studies focused on temperature on stock market performance. For example, Cao and Wei [24] stated that due to apathy and aggression in high-temperature environs, investors may hinder risk-taking, ultimately resulting in negative stock returns. Similarly, Balvers [25] stated that a rise in temperature results in a rising cost of equity for listed companies. Bansal et al. [26] stated that temperature-related disasters significantly affect stock returns. Baker and Wurgler [27] were the first to study the effect of an investor's mood on temperature. Their results implied that investor mood impacts the extreme temperature effect. These effects endured even after addressing several issues.

On the other hand, according to He and Ma [28], in smaller, younger, more volatile and less lucrative enterprises with a higher proportion of intangible assets, extreme temperatures significantly impact abnormal stock returns. Their data also implied that investor sentiments influence the severe temperature effect, which overall impacts the market. Moreover, Yan et al. [29] concluded with China as an example that temperature rise results in a decrease in stock price returns.

According to our findings, not many papers have focused explicitly on the clean energy sector. Regarding sector-specific studies, He and Ma [28] demonstrated that for steel and construction companies' temperature-induced disasters, mood plays a role in abnormal stock returns, especially on the higher side. For clean energy stocks, experts are inclined to be more optimistic, resulting in higher returns than average market returns Lohrmann and Lohrmann [30].

Hence in the given study, the temperature effects were studied on the stock market performance particularly for the clean energy companies.

Exchange traded funds (ETFs) are securities directly traded on stock exchanges to track a specific index or sector. One of the other significant benefits of ETFs is their low transaction costs and liquidity Ben-David et al. [31]; Kosev and Williams [32]. Clean energy-based ETFs are a unique instrument that tracks companies dealing with non-conventional sources of energy, hence, in this study, we took it to be a proxy for clean energy stocks.

As shown in Figure 1, the price dynamics of the most actively traded renewable energy-based ETFs, namely First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN), iShares Global Clean Energy ETF (ICLN), Invesco WilderHill Clean Energy ETF (PBW) and Invesco Solar ETF (TAN), has been quite varied for the last 10–12 years. A graphic review of Figure 1 reveals some interesting features, such as the fact that during the years starting from 2010 to the end of 2012, there was a sheer decrease in the prices. This was primarily the product of government subsidies and incentive plans, leading to a more significant number of renewable projects and, in turn, bringing down electricity generation prices worldwide Mendelsohn and Feldman [33]. Then, from 2013 onwards until 2017, there was a slight upward trend in prices attributed to climate change, such as in the Paris Agreement in 2015 (Agreement, P. [34]) which gained more attractiveness during 2014 as interest rates approached historic lows and investors looked for alternative means of generating consistent, low-risk incomes La Monaca. et al. [35]. This continued until the subsequent announcement of the US withdrawal from it Fahmy [12], and even outperformed other conventional energy peers Ibikunle et al. [36]. From 2017 until the beginning of the pandemic, the prices were pretty stable. Subsequently, after the pandemic, there was an enormous spike, which was a result of a commitment to investments by private investors Pavlova and de Boyrie [37]; Fahmy [12].

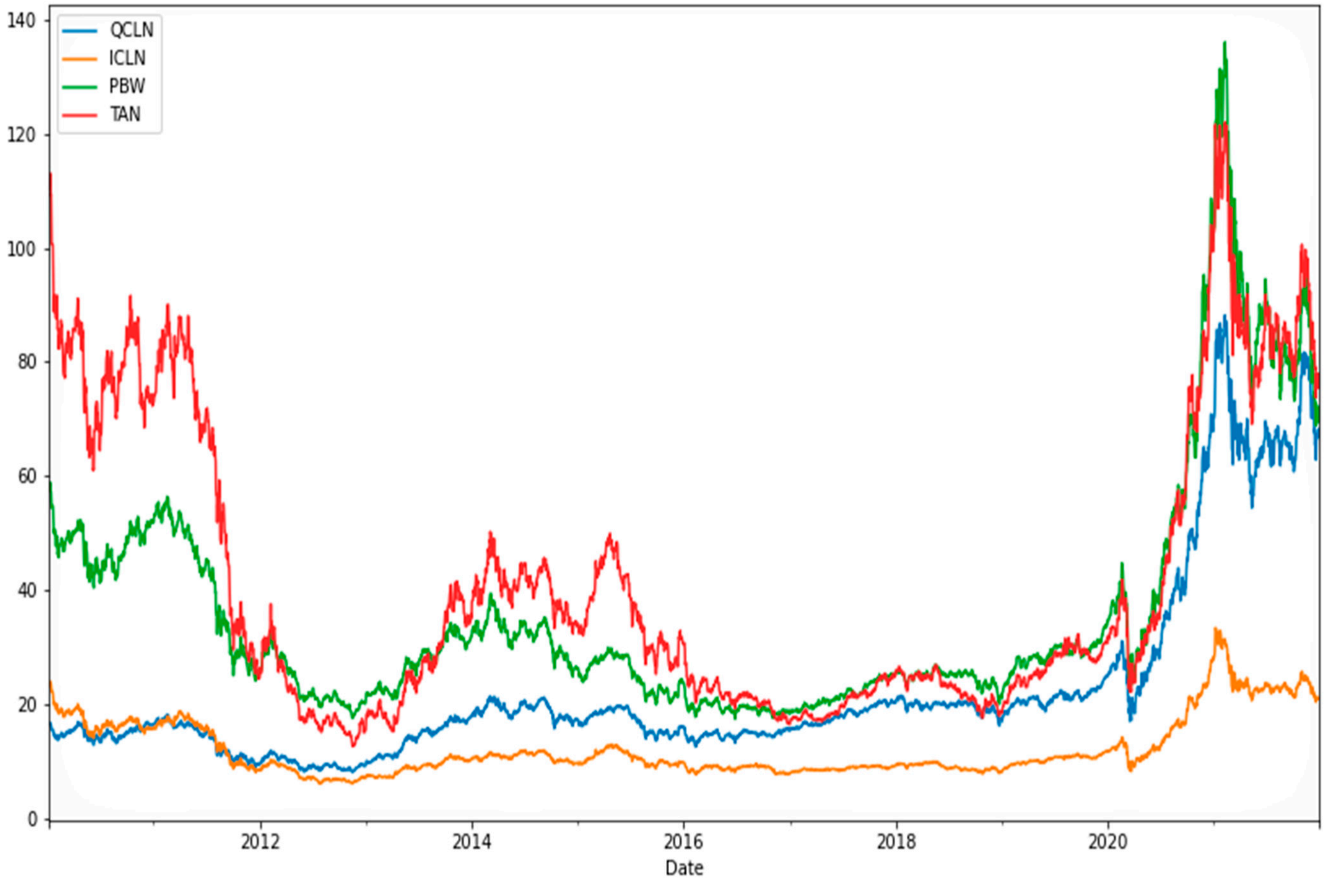

Figure 1. Major clean energy ETF prices (in US dollars) between January 2010 and December 2021.

Apart from this, some studies have focused on other areas of interest that could significantly influence clean energy stock prices. There are examples of sectoral companies in the technology and oil sectors which have shown causal effects on clean energy, such as Kumar et al. [38], Broadstock et al. [39], Kocaarslan and Soytas [40] and Dutta et al. [41]. On the contrary, others, such as Nasreen et al. [42], Ferrer et al. [43] and Elie et al. [44], did not find any substantial causal linkages. Examples such as Kocaarslan and Soytas [40], Sadorsky [45] and Wang et al. [46] have used ETFs to study market uncertainty surrounding clean energy stocks.

3. Data and Methodology

Daily average temperature data of the three most significant economic hotspots, namely New York, London and Tokyo, was obtained from the National Centers for Environmental Information (NCEI) as of June 2022. The data was obtained from monitoring stations nearest to each city's international airport. Similarly, for the dependent variable, daily ETF price data was considered for the two most traded clean energy ETF scrips on the NASDAQ stock exchange using the Thomson Reuters Eikon platform. The most active clean energy-based ETFs by volume, namely First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN) and iShares Global Clean Energy ETF (ICLN), were taken to account for the daily prices of clean energy stocks. The reasons for choosing these two ETFs were that they (i) track companies dealing with a broad spectrum of clean energy sources, including but not limited to solar, wind, geothermal, nuclear and biomass, etc., and (ii) they take into account companies from an extensive geographical area covering both developed and the developing world.

The drawback of using the traditional linear Granger causality method is that it is based upon linear constraints and must follow a normal distribution. To address these issues, Baek and Brock [47] suggested a non-linear Granger causality test by using Monte Carlo simulations on non-linear models to test their forecasting performance. According to their findings, the performance decreased in the presence of non-linearity; hence, non-linear models have an enhanced predictive ability compared to their linear counterparts. This is also confirmed by others, such as Lusch et al. [48]. According to them, Granger causality-based non-linear models could deliver improved causality results. Since then, non-linear GC models have been used in a variety of fields, namely finance (Hiemstra and Jones [49]), neuroscience (Bergmann and Hartwigsen [50]) and ecology (Cox Jr and Popken [51]). Studies such as Henderson and Michailidis [52] have used non-parametric processes to account for non-linear effects. However, non-linear methods could add some additive impact on the model, influencing its overall accuracy. These non-linear additive effects might be triggered by various circumstances Hastie [53]. To address these issues, neural network-based control mechanisms were added to the given model, as they have already been shown to improve causality estimations in studies related to stock indices Tabari et al. [54]. Technically, neural networks can be considered a novel methodology within the field of econometrics. They have certain advantages over traditional methods, such as (i) they are self-adaptive, data-driven methods that do not require distributional assumptions and (ii) they are non-linear. The use of artificial neural networks (ANNs) for modeling non-linear time series has become increasingly popular; pioneering works in this area include Zhang [55], Zhang and Qi [56], Chen et al. [11] and Khashei and Bijari [57].

On the one hand, there are examples, such as Tank et al. [58], who have used sparsity-inducing methods to reduce some sets of weights to zero for capturing Granger casual structure; others such as Marcinkevičs and Vogt [59] have used distinct self-explaining neural networks to enhance the overall performance of these models. However, our interest was in determining Granger causality through neural networks, which allowed us to contrast the existence of non-linear causality. For this purpose and the appropriateness of the data used in the study, we closely followed the work of Maciej et al. [60], which developed an algorithm to determine the existence of non-linear causality using neural networks based on the multi-layer perceptron (MLP), long short-term memory (LSTM) and gated recurrent unit (GRU). All of the standard RNN models that deal with gradient descent issues, including LSTM and GRUs, are adaptations of MLPs. LSTM can accommodate deep learning problems requiring long-term recollection of events. It has recurrent gates, frequently called input, output and forgets gates. Additionally, it weakens signals that contain both low- and high-frequency elements Gers et al. [61].

According to our analysis, this was probably the first study to employ neural network-based Granger causality to understand the relation of temperature rise with clean energy stock prices.

Based on the work of Zhang [55] and Khashei and Bijari [57], for the case of a time series $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})$, the representative ANN for the case of a single hidden layer has the following mathematical representation

$$y_t = w_0 + \sum_{j=1}^{q} w_j g\left(w_{0j} + \sum_{i=1}^{p} w_{ij} y_{t-i}\right) + \varepsilon_t \quad (1)$$

where w_{ij} ($i = 0, 1, 2, \ldots, p$; $j = 1, 2, \ldots, q$) and w_j ($j = 0, 1, 2, \ldots, q$) are the parameters or weights of the model, p is the number of input nodes and q is the number of hidden layer nodes. In general terms, the above expression can be generalized to the following formulation

$$y_t = f\left(y_{t-1}, y_{t-2}, \ldots, y_{t-p}; w\right) \quad (2)$$

where the neural network is equivalent to a non-linear auto-regressive model in which the function $f(\,)$ is determined by the structure of the network.

4. Results

Initially, we present the descriptive statistics of the variables considered in the study. Table 1 shows these statistics for the variables return_qcln, return_icln, vol_qcln, vol_icln, temp_NY, temp_L and temp_T.

Table 1. Descriptive statistics.

	Return_Qcln	**Return_Icln**	**Vol_Qcln**	**Vol_Icln**	**Temp_NY**	**Temp_L**	**Temp_T**
N	4376	4376	4376	4376	4376	4376	4376
Mean	0.0317	−0.0176	70,662.3	72,002.6	55.6	51.4	62.3
Median	0.1389	0.0000	14,830	25,445	55.5	51.3	63
Std	1.7893	1.6175	145,349.6	139,501.2	16.5	11.3	13.9
Min	−13.9	−13.7	100	1010	8.5	11.4	34.1
Max	13.6	10.8	999,810	991,680	90.1	83.4	90.3
Skew	−0.4139	−0.5235	3.3958	3.7514	−0.1744	−0.1980	−0.0133
Kurtosis	4.4585	5.5627	12.6491	15.4445	−0.9641	−0.2615	−1.1707

The sample consisted of 4376 observations from January 2010 to December 2021. In evaluating the returns of the QCLN and ICLN assets, we observed that the former maintained positive average returns of 0.0317%. In comparison, the latter held negative average returns of −0.0176%. Concerning the median, 50% of the QCLN returns were below 0.1389% and for ICLN, 50% of the returns were below 0%. The dispersion between QCLN and ICLN was relatively similar since the standard deviations were 1.7893 and 1.6175, respectively. The minimum returns were −13.9% for QCLN and −13.7% for ICLN, while the maximum returns were 13.6% for QCLN and 10.8% for ICLN.

Both assets presented negative skewness of −0.4139 and −0.5235 for QCLN and ICLN, respectively. The kurtosis of QCLN was 4.4585 and that of ICLN was 5.5627, both greater than three and indicating moderately leptokurtic distributions. As for the traded volumes of these assets during the historical period considered, on average, approximately 70,662 QCLN securities and 72,002 ICLN securities were traded. On the other hand, 50% of the QCLN trading volume was below 14,830 transactions, and 50% of the ICLN trading volume was below 25,445 transactions. The dispersion of QCLN trading volume was greater than that of ICLN, with values of approximately 145,349 and 139,501, respectively. The minimum traded volume in the period was 100 for QCLN and 1010 for ICLN, while the maximum traded volumes of QCLN and ICLN were 999,810 and 991,680, respectively. Both variables presented positive skewness in the order of 3.3958 and 3.7514 for QCLN and ICLN, respectively. Moreover, both variables presented a high typical kurtosis of the financial variables in the order of 12.6491 for QCLN and 15.4445 for ICLN, which indicated that the distribution of the traded volume of these securities was subject to many more extreme values than those of a normal distribution, therefore, the normality assumption was a very inadequate approximation for these variables.

For the variables that measured the average temperature in the cities of New York, London and Tokyo, the average temperature in these cities during the study period was approximately 55.6 °C, 51.4 °C and 62.3 °C for New York, London and Tokyo, respectively, while the median values of the temperatures among these cities were very similar to the previous averages. Temperature variability was highest in New York with a standard deviation of 16.5, followed by Tokyo with a standard deviation of 13.9, and finally, London exhibited the lowest temperature variability with a standard deviation of 11.3. The minimum temperatures during the period for New York, London and Tokyo were 8.5 °C, 11.4 °C and 34.1 °C, respectively, while the maximum temperatures of New York and Tokyo were very similar in the order of 90.1 °C and 90.3 °C, respectively, and the maximum temperature of London during the period was 83.4 °C. The temperatures of the three cities presented positive asymmetry during the period, with a greater concentration towards the upper tail, with asymmetry values of −0.1744, −0.198 and −0.0133 for New York, London and Tokyo, respectively. Likewise, all three cities presented Kurtosis of less than three, indicating a mesokurtic distribution, that is, with greater dispersion than that of a normal distribution. More specifically, the kurtosis values for New York, London and Tokyo were −0.9641, −0.2615 and −1.1707, respectively.

In the application of the algorithm, the three neural network architectures, namely MLP, LSTM and GRU, were evaluated, and the linear Granger causality (AR) test was applied to establish comparisons. Of the three types of neural networks, only MLP proved to be valid; for LSTM and GRU, the algorithm did not produce decent results. As for the MLP design, the calculations were performed for 30 and 60 lags, respectively, and two hidden layers were used, each with 100 neurons, respectively. The training sample consisted of 70% of the data and the test sample consisted of 30%. To determine the presence of non-linear causality of X to Y, (Maciej et al., 2021) suggested using the Wilcoxon signed-rank test, a non-parametric test that allows testing whether the prediction errors obtained on the test set from the past-based model of X and the past-based model of both X and Y have the same distribution (No assumption of normality is required). These data were normalized to optimize the performance of the neural network algorithms.

Table 2 shows the results for the case of non-linear Granger causality between temperature and returns. When considering 30 lags, except for the London temperature case, in all remaining cases the null hypothesis of no non-linear Granger causality was rejected, indicating that temperature history was a good predictor of QCLN and ICLN returns, the same was true when considering 60 lags. Comparatively, for both lags, the null hypothesis of no non-linear Granger causality (AR) was rejected, indicating the inability of these methods to capture non-linear causality and the inherent bias they could lead to.

Table 2. *p*-values for each model and each tested lag obtained from the Wilcoxon signed-rank test in case where Y → X. AR describes linear Granger causality. Cases where a causal relationship was detected are shown in bold.

Lag Value	Granger Causality	MLP	AR
30	**temp_NY ↛ return_qcln**	**3.300×10^{-85} ****	0.9586
	temp_L ↛ return_qcln	0.1558	0.7259
	temp_T ↛ return_qcln	**0.00181 ****	0.3639
	temp_NY ↛ return_icln	**0.0004598 ****	0.9693
	temp_L ↛ return_icln	**3.02839×10^{-52} ****	0.6994
	temp_T ↛ return_icln	**0.02819 ***	0.2961
60	**temp_NY ↛ return_qcln**	**1.189715×10^{-28} ****	0.8919
	temp_L ↛ return_qcln	**6.802304×10^{-13} ****	0.5499
	temp_T ↛ return_qcln	**1.066786×10^{-13} ****	0.5741
	temp_NY ↛ return_icln	**3.579381×10^{-05} ****	0.9281
	temp_L ↛ return_icln	**2.161692×10^{-49} ****	0.3977
	temp_T ↛ return_icln	**1.197499×10^{-40} ****	0.3111

Notes: * $p < 0.05$, ** $p < 0.01$.

Table 3 shows the results of the non-linear and linear Granger causality testing of temperature concerning QCLN and ICLN traded volumes in the stock market. As can be seen in the table, we had mixed results; when 30 lags were considered, in effect, the historical past of the average temperature of the cities of New York, London and Tokyo were a good predictor of QCLN and ICLN traded volumes.

Table 3. *p*-values for each model and each tested lag obtained from the Wilcoxon signed-rank test in case where Y → X. AR describes linear Granger causality. Cases where a causal relationship was detected are shown in bold.

Lag Value	Granger Causality	MLP	AR
30	**temp_NY ↛ vol_qcln**	**2.073000×10^{-36} ****	**0.0507 ***
	temp_L ↛ vol_qcln	**4.015626×10^{-09} ****	**0.0383 ***
	temp_T ↛ vol_qcln	**$3.122777 \times 10^{-108}$ ****	0.6730
	temp_NY ↛ vol_icln	**4.050622×10^{-49} ****	0.3861
	temp_L ↛ vol_icln	**1.890867×10^{-68} ****	0.9022
	temp_T ↛ vol_icln	**2.989957×10^{-77} ****	**0.0974 ***
60	**temp_NY ↛ vol_qcln**	**6.542931×10^{-16} ****	**0.0452 ****
	temp_L ↛ vol_qcln	**2.369952×10^{-13} ****	**0.0668 ***
	temp_T ↛ vol_qcln	**1.797172×10^{-50} ****	0.1938
	temp_NY ↛ vol_icln	**6.052480×10^{-62} ****	0.6370
	temp_L ↛ vol_icln	**1.858961×10^{-68} ****	0.1864
	temp_T ↛ vol_icln	0.630244	**0.0703 ***

Notes: * $p < 0.05$, ** $p < 0.01$.

According to the AR column containing the results of the linear Granger causality test, the average temperature history of New York and London caused in the Granger sense, the traded volumes of QCLN and ICLN at the 5% significance level. The given phenomenon indicated that the neural network captured temperature-driven non-linear causality, and some of the linear causality was captured with linear methods. It suggested the desirability of using both methodologies conjointly. When considering 60 lags, we also observed the complementary effect of both approaches concerning the predictive power of historical past average temperatures in New York and London on the QCLN traded volume. Likewise, the past average temperatures of the cities of New York, London and Tokyo had a non-linear impact on the QCLN and ICLN volumes. At the same time, their respective linear counterpart did not reject the hypothesis of Granger non-causality. Finally, it was noted that Tokyo's history of average temperatures linearly caused ICLN traded volume at the 5% level; the respective non-linear Granger causality hypothesis was not rejected. This also corroborated that Tokyo is in an entirely different time zone and, hence, has non-drastic effects on the volumes of the traded ETFs Kao and Fung [62].

This paper aimed to determine whether the average daily temperatures Granger caused clean energy stock prices, through daily volumes and returns of exchange traded funds (ETFs), for the period from January 2010 to December 2021. There is abundant econometric literature on the determination of Granger causality through univariate regression techniques and vector auto-regressive models; the common factor among these techniques is the verification of linear causality. The work intended to focus on linear and non-linear causality between temperature and clean energy stock prices and trading volumes. In more than 90% of scenarios, i.e., 11 of 12 cases, concerning temperature and trading volume relationship, the non-linear causal effect was found. In approximately 50% of scenarios, linear and non-linear effects were seen. Similarly, in almost all the cases, there were non-linear effects between daily temperature rise and daily prices; however, the presence of a linear effect was weak. The existence of non-linear behavior implied there is a need also to increase attention on other factors apart from looking at investors' moods, as conducted by previous studies (Cao and Wei [24]; He and Ma [28]).

In general, real-world phenomena are mixtures of linear and non-linear behaviors. Trying to evaluate hypotheses of interest while omitting the non-linear nature of these phenomena has the fundamental consequence of incurring what the statistical literature calls a type I error, i.e., rejecting the hypothesis being true. This can be clearly illustrated through the results of our work; in Table 2, we observed that when contrasting Granger non-causality between temperatures and returns—in the cases of New York and Tokyo temperatures—using a linear approximation (RA), it was not possible to reject the hypothesis of non-causality. Still, when using the non-linear approximation (MLP), it was possible to reject the hypothesis of non-causality. In other words, had we conformed to the linear approximation (RA), discarding the possible existence of non-linearity, we would have committed a type I error; therefore, the way to minimize the possibility of committing a type I error in the context of Granger causality is to use both the linear and the non-linear approximation, because we do not know ex ante which component—linear or non-linear—determines the phenomenon.

5. Discussions and Policy Implications

Furthermore, the findings could also be integrated into studies on analyzing various climate-related risks to green sector-specific stock prices and how they could affect the overall cost of equity due to magnified risk premiums (Balvers [25]). The non-linear linkages between temperature rise and price could be incorporated for policy-level analysis at various government institutions, while meeting the needs of their sustainability goals. On the other hand, it could be utilized by various sovereign wealth and pension funds while it accessed risk-adjusted returns for their clean energy investments. Moreover, the given non-linearity opens up the necessity for further inquiries into the occurrence of structural breaks in the given relationship. The level of complexity involved with non-linear deep learning approaches makes it difficult to find the degree of symmetry and asymmetry in a given time series. Hence, future extensions could be performed using integrating models such as asymmetric generalized auto-regressive conditional heteroscedasticity (GARCH) or AGARCH to focus on this aspect. To conclude, the study approves that global climate warming has broad economic implications not just confined to productivity and wealth creation but also financial markets. Finally, the given work has shown the usefulness of neural network-based methods to capture the non-linear causality of environmental variables concerning stock market-specific variables.

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Abbreviations

The following abbreviations are used in this manuscript:

ETF	Exchange Traded Funds
ANN	Artificial Neural Network
MLP	Multi-Layer Perceptron
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
QCLN	First Trust NASDAQ Clean Edge Green Energy Index Fund
ICLN	iShares Global Clean Energy
PBW	Invesco WilderHill Clean Energy ETF
TAN	Invesco Solar ETF
NCEI	National Centre for Environmental Information
IPCC	Intergovernmental Panel on Climate Change
COP	Conference of the Parties
ADB	Asian Development Bank
GARCH	Generalized Auto-Regressive Conditional Heteroscedasticity

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