Financial Internet Quarterly 2025, vol. 21 / no. 3, p. 62-76
10.2478/fiqf-2025-0019

Financial Internet Quarterly

DOES CLIMATE POLICY UNCERTAINTY MOVE WITH STOCK MARKETS? EVIDENCE FROM ADVANCED ECONOMIES WITH THE BEST CLIMATE CHANGE PERFORMANCE

Muge Saglam Bezgin[1], Selim Gungor[2]

Abstract

This study aims to understand how climate policy uncertainty affects investor behavior and whether it moves with stock markets in advanced economies. Accordingly, we examine data for January 2000-2023 for the stock market indices of Sweden, the United Kingdom, Germany, Norway, the Netherlands, and Finland, which have a 'good' CCP rating according to the MSCI classification and the climate policy uncertainty index. Furthermore, we apply two main methodologies: Wavelet Coherence Analysis and the Breitung and Candelon Frequency Causality Test. WCA shows the time-based co-movements between CPU and stock market indices and their effects on each other. We also consider the causality test to examine causality at various frequencies. The WCA results reveal a relationship between the CPU index and all markets except the Norwegian market. As a result of the causality, we conclude that there is a strong causality between the CPU index and the Finnish and Swedish stock markets in the short run, a strong causality between the CPU index and the Dutch market in the long run, and a weak causality between the CPU index and the German stock market in the short, medium and long run. Investors can develop strategies to mitigate risks and hedge volatility by monitoring exogenous factors such as CPU. Strategies such as quick-action stop-loss orders are recommended, especially for short-term CPU-affected markets such as the Swedish and Finnish stock markets.

JEL classification: G11, G32, Q54
Keywords: Climate Policy Uncertainty, Stock Market, Wavelet Coherence, Frequency Causality

Received: 23.11.2024 Accepted: 20.06.2025

Cite this:
Bezgin, S.M. & Gungor, S. (2025). Does climate policy uncertainty move with stock markets? Evidence from advanced economies with the best climate change performance. Financial Internet Quarterly 21(3), pp. 62-76.

[1] Karamanoglu Mehmetbey University, Türkiye, e-mail: mugesaglam@kmu.edu.tr, ORCID: https://orcid.org/0000-0001-8674-2707.
[2] Tokat Gaziosmanpasa University, Türkiye, e-mail: selim.gungor@gop.edu.tr, ORCID: https://orcid.org/0000-0002-2997-1113.

Introduction

In the 21st century, climate-related events such as fires, typhoons, floods, and droughts have become more frequent, making climate change one of the most significant challenges for humanity and a complex problem for governments to solve (Raza et al., 2024). According to the UN (2022) and IPCC (2023), global temperatures are projected to rise by 1.1 to 1.7°C by 2026, with a 48% chance of exceeding 1.5°C. Human-induced climate change already impacts weather patterns, water and food security, health, economies, and ecosystems, causing losses in agriculture, renewable energy use, and employment (Dafermos et al., 2018; Yang, 2019; Boulange et al., 2021). Globalization has increased connectivity between countries in trade, investment, production, and finance, leading to interdependence across systems. The impacts of climate change can reverberate in the financial sector, so financial institutions and governments should incorporate climate and environmental risks into their financial risk assessments (Battiston et al., 2017). Uncertainties in climate change policies may cause entrepreneurs to reduce their long-term investments and take a wait-and-see approach (Landis et al., 2012; Bardoscia et al., 2017; Paroussos et al., 2019).

CPU reflects uncertainty in climate policies, influencing market trends, investor behavior, and financial market volatility. Its effects vary by country, and understanding its spillover impact on international equity markets requires assessing dynamic correlations (Xu et al., 2023). Portfolio diversification, vital for minimizing losses during uncertainty, hinges on understanding market return correlations (Markowitz, 1959). Monitoring the CPU index can guide investors by revealing the impacts of policy uncertainty on sustainable development and economic growth.

While there is a growing interest in the relationship between climate risk and finance in the existing literature, empirical studies addressing the direct and dynamic relationship between climate policy uncertainty and stock markets using high-frequency, multi-scale analyses are limited. Furthermore, existing studies in the literature are mainly limited to single-country analyses or approaches to the macroeconomic effects of the CPU from a general framework and do not sufficiently reveal time-scale changes and the spillover effects of uncertainty across markets. This paper aims to fill this gap and analyze the causality relationship between climate policy uncertainty and the stock markets of six developed and environmentally sensitive economies (Sweden, the UK, Germany, Norway, the Netherlands and Finland). The main research questions that this study attempts to answer are as follows:

1. Does climate policy uncertainty have a causal effect on the stock returns of advanced economies?
2. Are CPU effects consistent across different periods and market conditions?
3. What are the implications of the CPU for international portfolio diversification and financial stability?

This paper makes innovative contributions to the literature in three main aspects. First, using Gavriilidis' (2021) CPU index, it explores the impact of climate policy uncertainty on decisions, innovation, and economic performance. Second, the frequency causality test and wavelet coherence analysis help to capture different investor time horizons and reveal information across different time scales, supporting the study's motivation. Third, we analyze CPU effects in developed economies with high peripheral performance, often overlooked and presenting unique implications for regional differences. Lastly, this research guides policymakers and financial institutions in developing resilient strategies that incorporate environmental risks and contribute to green finance and sustainable investment by revealing the effects of climate policy uncertainty on investor behavior, risk perception, and market volatility.

The rest of the paper is organized as follows: Section 2 reviews the literature, Section 3 details the dataset and methodology, Section 4 discusses findings, and Section 5 concludes with implications and policy recommendations.

Literature review

Uncertainty, particularly regarding climate policy, can lead firms to delay investments. However, it can also have the opposite effect, encouraging investment. As a result, examining CPU and its impact on various factors has become a global priority in recent years.

Recent studies in the literature construct a climate policy uncertainty index. Some of these are the studies of Gavriilidis (2021), Huo et al. (2023), and Lin and Zhao (2021). This research considers the index of Gavriilidis (2021) for the CPU variable. Gavriilidis (2021) compiled and analyzed news and articles from 8 leading US newspapers and created a CPU index. Numerous studies also have examined the effects of the CPU on the market, especially in the context of the stock market and investment decisions. Bouri et al. (2022), Khalfaoui et al. (2022), Banerjee et al. (2024), Iqbal et al. (2024), Sarker (2024), Shuaibu et al. (2024) and Nga and Hung (2025) discussed the general effects of CPU on the stock market. Chan and Malik (2022) examined the effect of CPU on stock returns on 3589 individual stocks traded in the US market, while Treepongkaruna et al. (2023) evaluated the effect of CPU on 3647 individual stocks. The results suggested a statistically and economically significant negative relationship between a firm's exposure to CPU and the cross-sectional pricing of CPU in individual stocks. Hoque et al. (2023) determined that the US CPU influences global and alternative energy stocks, with the CPU being an information source and global energy stocks as receivers. Tedeschi et al. (2024) confirmed that CPU shocks positively impact European markets using Bayesian TVP-VAR models. Xu et al. (2023) observed that changes in the Chinese CPU initially affect returns and volatility differently but eventually create stronger links between Chinese and US markets. Applying new wavelet approaches, Athari and Kirikkaleli (2025) concluded that while renewable energy and clean technology (RECT) stocks caused CPU to suffer a significant disruption between 2014 and 2018 after 2019, CPU started to cause RECT stocks.

In addition, some studies have focused on the effects of CPU on market volatility. Lasisi et al. (2022) investigated the impact of CPU on US and UK stock market volatility, while Chen et al. (2023) examined the impact of CPU on Chinese stock market volatility. The results proved that stock market volatility responds significantly to CPU. Raza et al. (2024) used GARCH-MIDAS models to show that CPU raises volatility in green and sustainable markets, including S&P Green Bond and Clean Energy indices.

Finally, several studies have addressed the effects of CPU on specific sectors or groups of companies. He and Zhang (2022) analyzed the impact of CPU on the predictability of stock returns in the oil sector using predictive regression models. They showed that CPU exhibits predictive solid power for both in-sample and out-of-sample stock returns in the oil sector. Alqaralleh (2023) found that CPU reduces investment in China's sectors during stable periods and shifts the lead-lag dynamics during turbulent periods. Lee and Cho (2023) argued that CPU negatively predicts stock returns for small companies in China. Pijourlet (2024) indicated that CPU negatively affects US consumer and industrial stocks while boosting technology and consumer discretionary stocks. Yao et al. (2023) also reported that CPU shocks have a more substantial impact on the long-run stock returns of China and its major trading partners. Zhang et al. (2023) demonstrated that companies with lower CPU betas have higher future returns in China.

However, limited literature analyses the multidimensional frequency-based causality relationship between the CPU and European markets. Therefore, this research is innovative in terms of its methodological contribution to the literature and its use of wavelet and frequency domain causality techniques.

Data set and methodology

Data set

In this study, we analyze the data of 6 countries among the 15 countries with the highest score according to CCPI. The countries included in the analysis are developed markets according to MSCI and the data range is January 2000 - May 2023. The CPU variable is the index developed by Gavriilidis (2021). We also display the scores of countries according to their climate change policy in Appendinx 1.

As can be seen in Figure 1, there are no countries with a score of 80 and above as of 2023. 15 countries with scores between 60 and 80 are classified as ‘good’, including leading fossil fuel producers such as India, Norway, the UK and Germany. Of the 63 countries whose climate policy performance was assessed, 45 countries scored in the middle or below, meaning that 79% of the countries analyzed have inadequate climate policies. In our study, we selected countries with active climate policies and developed stock markets for analysis. According to the MSCI classification, 6 of the 15 countries with a 'good' CCP rating are developed markets: Sweden, the UK, Germany, Norway, the Netherlands and Finland. Table 1 shows the descriptive statistics of the main stock indices and CPU indices of these countries.

Table 1: Descriptive statistics

Variables	AEX	CPU	DAX	FTSE	OBX	OMXH25	OMXSPI
Median	2.65558	2.00345	3.86869	3.78883	2.61108	3.43254	2.56330
Std. Dev.	0.12720	0.21663	0.19574	0.07982	0.29133	0.17461	0.20573
Skewness	-0.02557	0.23963	-0.24711	-0.70398	-0.30885	-0.14048	0.02553
Kurtosis	2.24277	2.71430	2.17869	2.76491	2.15801	2.08573	2.29733
J-B	6.72001**	3.63201	1.07194***	2.37725***	1.27226***	1.06729***	5.79072**

Source: Authors’ own work.

As can be seen in Table 1, the DAX variable has the highest mean, but the FTSE has the highest standard deviation, indicating that the FTSE is riskier than the other variables. According to the skewness values, the AEX index is close to symmetry, with negative skewness indicating a slight shift to the left. The kurtosis of the AEX indicates a blunt peak, i.e. extreme values are not expected. The Jarque-Bera test shows that the AEX tends to deviate from a normal distribution, while the CPU index is closer to a normal distribution as the p-value is greater than 0.05. The negative skewness of the DAX, OBX and OMXH25 indices indicates a leftward skewness, while the positive skewness of the OMXSPI indicates a rightward skewness. High kurtosis values generally indicate the presence of outliers, with the FTSE containing more frequent extreme events than the other variables. In general, all variables in the analysis have high frequency financial time series characteristics and are suitable for complex modelling. Table 2 shows the levels of stationarity of the variables according to the Lee-Strazicich LM unit root test.

Table 2: Results of Lee-Strazicich LM unit root test

Variables	Tau	Break point	lag	Test critical values	S(t-1)	Constant	B1(t)
AEX	-2.60729	31	8	-4.24756	-0.0420 [-26072]	-0.0047 [-1.8734]	-0.083500 [-3.694280]
D(AEX)	-8.35313		2	-3.85176	-0.8115 [-83531]	0.0004 [0.3430]	-0.048320 [-2.055310]
CPU	-6.40870	194	2	-3.85230	-0.4495 [-64087]	-0.0094 [-11546]	0.023298 [0.174450]
DAX	-2.30095	31	1	-3.85230	-0.0339 [-23009]	-0.0020 [-0.9334]	-0.137650 [-554160]
D(DAX)	-9.15495		2	-3.85170	-0.9547 [-91549]	0.0017 [11288]	-0.014640 [-0.561240]
FTSE	-2.89757	31	7	-3.85230	-0.0514 [-28975]	-0.0019 [-15282]	-0.063470 [-373696]
D(FTSE)	-7.58473		3	-3.85170	-0.8883 [-75847]	0.0206 [71347]	-0.044230 [-257614]
OBX	-3.08306	111	8	-3.85230	-0.0523 [-30830]	0.0015 [10216]	0.078670 [28807]
D(OBX)	-1.39318		0	-3.85170	-0.8222 [-13931]	0.0048 [30744]	-0.039800 [-153130]
OMXH25	-1.77936	31	3	-3.85230 -2.92260	-0.0190 [-17793]	-0.0017 [-0.8589]	-0.059520 [-247637]
D(OMXH25)	-7.99034		2	-3.85170	-0.6986 [-79903]	0.0103 [53179]	-0.024960 [-100589]
OMXSPI	-1.95227	36	3	-3.85200	-0.0217 [-19522]	-0.0022 [-0.9872]	-0.028700 [-122278]
D(OMXSPI)	-8.46845		2	-3.85100	-0.8673 [-84684]	0.0124 [62307]	-0.018380 [-0.795010]

Note: Values in brackets represent t-statistics

Source: Authors' own work.

The LM unit root test assesses the stationarity of the series based on structural breaks. The t-statistic of the AEX series is above the critical value, indicating that the series is non-stationary with the structural break at the 31st observation; however, its first difference is stationary. The t-statistic of the CPU series is below the critical value, indicating that the series is stationary with the break at the 194th observation. The DAX series is also non-stationary with a structural break at the 31st observation, but its difference is stationary. The FTSE, OBX and OMXH25 series are also stationary at the first difference, while the OMXSPI series is non-stationary with a break at the 36th observation. In summary, while the levels of the AEX, DAX, FTSE, OBX, OMXH25 and OMXSPI series are non-stationary, their differences are stationary.

Wavelet analysis

Wavelet analysis, which examines time series in both time and frequency domains, is effective for non-stationary series (Aguiar-Conraria & Soares, 2011). It is commonly used to detect leading indicators and estimate causality or co-movement between variables (Chen et al., 2017). By analyzing similarities and differences in various frequency regions, wavelet transforms help identify correlations between signals. This method also estimates wavelet cross-spectrum, phase coherence, and wavelet coherence (Polanco et al., 2011). Wavelet functions are based on father and mother wavelets, with the former handling low-frequency components and the latter focusing on high-frequency details.

The wavelet transform is based on the assumption of two basic wavelet phenomena: father wavelets, which work with mother wavelets and low-frequency trend components, which use high-frequency detail components. Wavelet functions are generated based on scale parameters, mother wavelet function and location. A mother wavelet function defined as $\Psi \in L^2(R)$ can be constructed as follows (Cai et al., 2017):

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), s, \tau \in R, s \neq 0 \quad (1)$$

Where:

$$\frac{1}{\sqrt{|s|}}$$

is the normalization factor that provides the unit variance of the wavelet,

s = is the scaling factor that controls the width of the wavelet. Scale and frequency are inversely related. Therefore, a high scale implies an extended wavelet suitable for detecting a lower frequency,

τ = is a translation parameter that controls the position of the wavelet (Cai et al., 2017).

The Morlet wavelet, commonly used in time-series analysis, is particularly effective for non-stationary data (Cohen, 2019). In financial markets, it provides time-frequency localization, helping analysts uncover patterns, trends, and relationships in asset prices and volatility. Its ability to capture frequency changes aids in detecting market shifts, predicting price movements, and assessing external impacts. Based on all this, we utilize the Morlet wavelet in this research. Morlet wavelet can be stated as in Equation (2) (Aloui & Hkiri, 2014):

$$\psi^M(t) = \frac{1}{\pi^{1/4}} e^{i\omega_0 t} e^{\frac{-t^2}{2}} \quad (2)$$

Where:

ω_0 = is the centre parameter of the wavelet.

Cross-wavelet power between two-time series can be described as the local covariance between time series at any scale (frequency band) and at any time. The cross-wavelet power between two-time series, x(t) and y(t), as characterized by Hudgins et al. (1993), is as in Equation (3):

$$W_{xy}(a,b) = W_x(a,b)\overline{W_y(a,b)} \quad (3)$$

According to Equation (3), cross wavelet transforms show areas of high joint power representing the local covariance between time series and at each scale (Vacha & Barunik, 2012, Kuşkaya et al., 2021). Finally, wavelet coherency is defined as follows (Aguiar-Conraria et al., 2013; Kuşkaya et al., 2021):

$$R_{xy}(a,b) = \frac{\left|S\left(\left|W_{xy}(a,b)\right|\right)\right|}{\left|S\left(\left|W_{xx}(a,b)\right|\right)\right|^{1/2}\left|S\left(\left|W_{yy}(a,b)\right|\right)\right|^{1/2}} \quad (4)$$

In Equation (4), represents the correlation, R_{xy} is the smoothing parameter.

Breitung and Candelon causality test

Breitung and Candelon's causality test identifies causality at short, medium, and long horizons, revealing information flow between variables across frequencies (Rjoub et al., 2021, Chekouri et al., 2021, Nasreen et al., 2022). The test equation is generally expressed as follows (Nasreen et al., 2022):

$$y_t = \alpha_1 y_{t-1} + \ldots + \alpha_p y_{t-p} + \beta_1 z_{t-1} + \ldots + \beta_p z_{t-p} + \mu_t \quad (5)$$

Where α_p and β_p = are coefficients and μ_t is an error term.

The null hypothesis of Granger causality from z_t to y_t at frequency (ω) is tested by $M_{z\to y}(\omega) = 0$, which is equivalent to the null linear restriction:

$$H_0 = R(\omega)\beta = 0 \quad (6)$$

Where $\beta = |\beta_1 \ldots \beta_p|'$ is the vector of the coefficients and:

$$R(\omega) = \begin{bmatrix} cos(\omega)cos(2\omega)...cos(p\omega) \\ sin(\omega)sin(2\omega)...sin(p\omega) \end{bmatrix} \quad (7)$$

F-statistics are used to the null hypothesis in the frequency interval, $\omega \in (0,\pi)$.

The hypothesis regarding causality to be tested in this research can be stated as follows:

H_0: There is no causality between CPU and stock exchange.

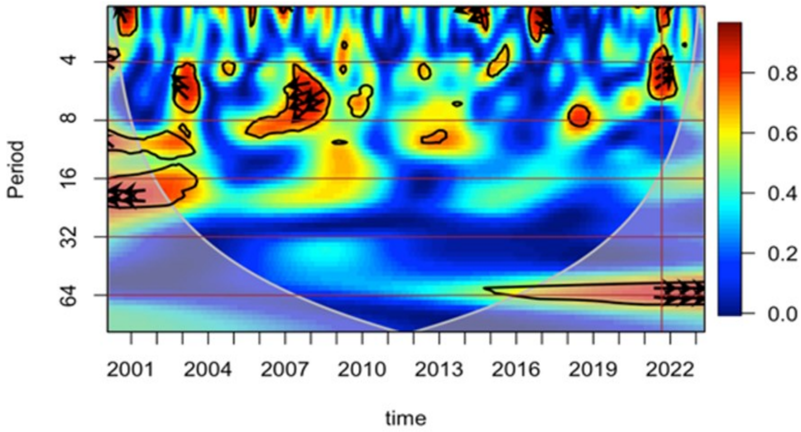
H_1: There is causality between CPU and stock exchange.

Results

Results of wavelet coherence analysis

In wavelet coherence analysis we use periods of 4, 8, 16, 32 and 64. Values between 0 and 1 indicate the correlation between two series. Blue indicates low correlation, while red indicates high correlation. Arrows indicate the direction of the relationship. Arrows pointing to the right indicate a positive relationship, while arrows pointing to the left indicate a negative relationship. Upward arrows indicate that the first series influences the second, and downward arrows indicate that the second series influences the first.

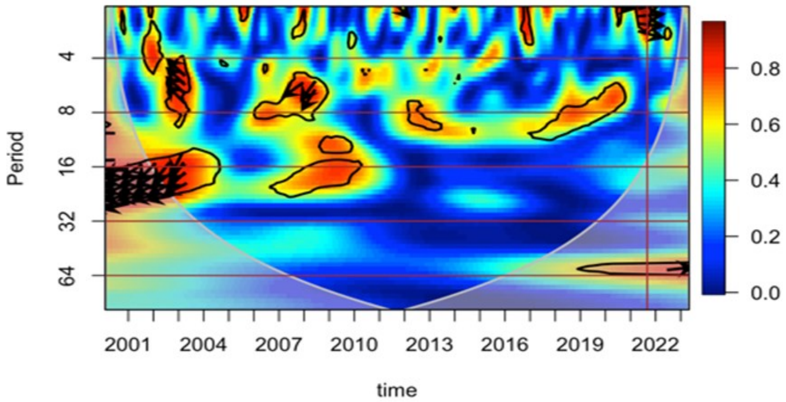
Figure 2: Wavelet coherence result of CPU vs OMXH25



Source: Authors' own work.

Figure 2 shows a statistically significant relationship between the CPU and OMXH25 indices, which is stronger in periods 4-8. In 2001, this correlation is strong, with the CPU index influencing the OMXH25. Between 2007 and 2010 there is a negative interaction, while in 2022 - 2023 the relationship becomes positive, with a high correlation coefficient (close to 1), indicating a strong influence of the CPU on the OMXH25.

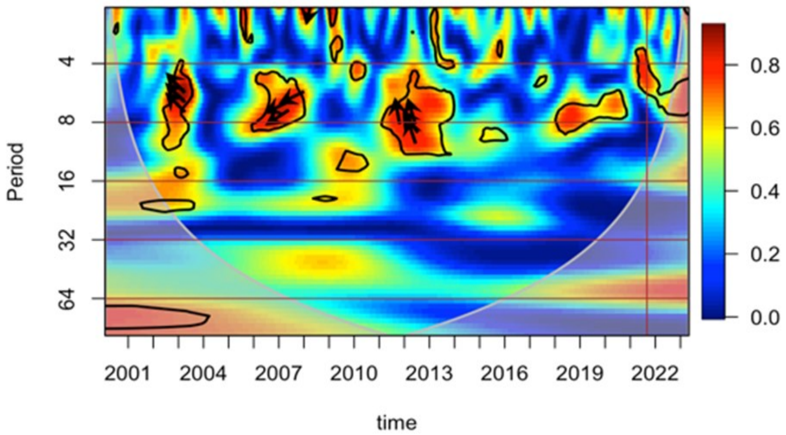
Figure 3: Wavelet coherence result of CPU vs AEX



Source: Authors' own work.

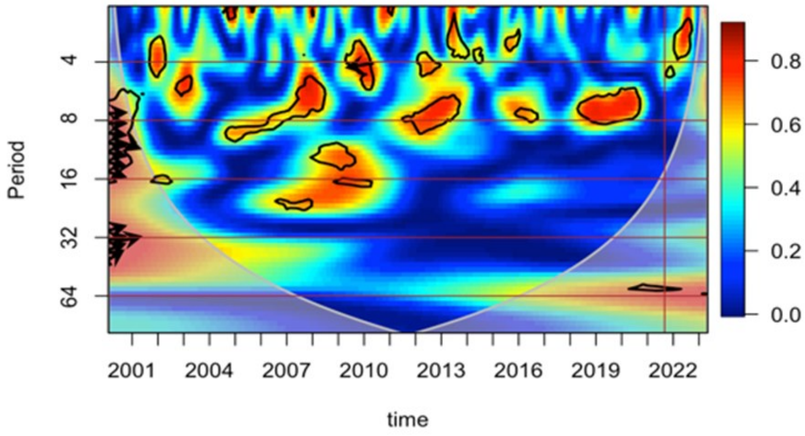
Figure 3 shows a strong relationship between the CPU and AEX indices in the 16-32 period from 2001-2004, with a generally negative direction, except in 2022 and in the 4-period. In 2004, the arrows indicate that the CPU influences the AEX, while in 2007, in the 4-8 period, the strength of the relationship is close to 1, suggesting that the AEX influences the CPU. In 2022-2023, CPU has a positive short-term effect on AEX.

Figure 4. Wavelet coherence result of CPU vs OMXSPI



Source: Authors' own work.

Figure 5: Wavelet coherence result of CPU vs OBX

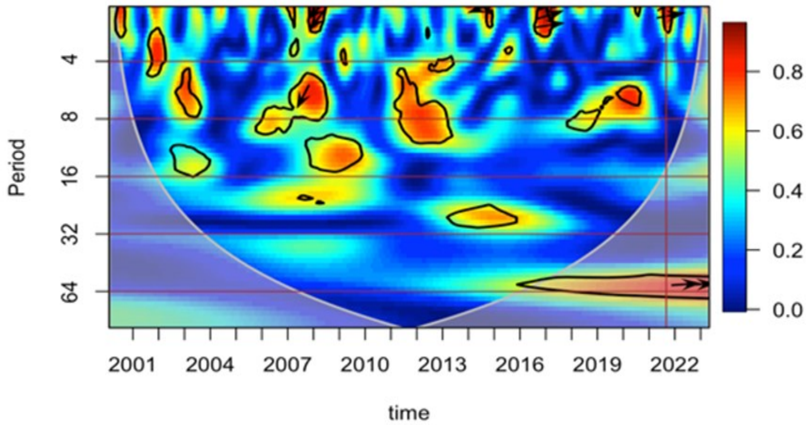


Source: Authors' own work.

According to the results in Figure 4, the correlation between the variables was quite strong in 2004, 2007, and 2013 in the 4-8 period. In addition, regarding the direction of the relationship, CPU hurt OMXSPI in 2004 and had a positive effect in 2007 and 2023. However, we cannot argue a statistically significant relationship between the variables except for these periods.

As shown in Figure 5, we cannot declare a significant relationship between CPU and OBX variables.

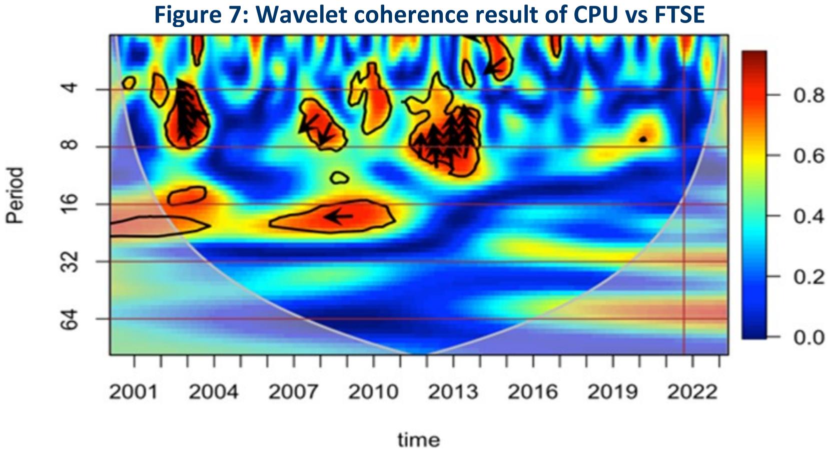
Figure 6: Wavelet coherence result of CPU vs DAX



Source: Authors' own work.

The results in Figure 6 show that the short-run relationship between CPU and DAX is quite strong in 2007, 2013, 2016 and 2022. Regarding the direction of the relationship, we conclude that in 2007 and 2013, there was an inverse effect from DAX to CPU, while in 2016 and 2022, there was a positive effect from CPU to DAX.

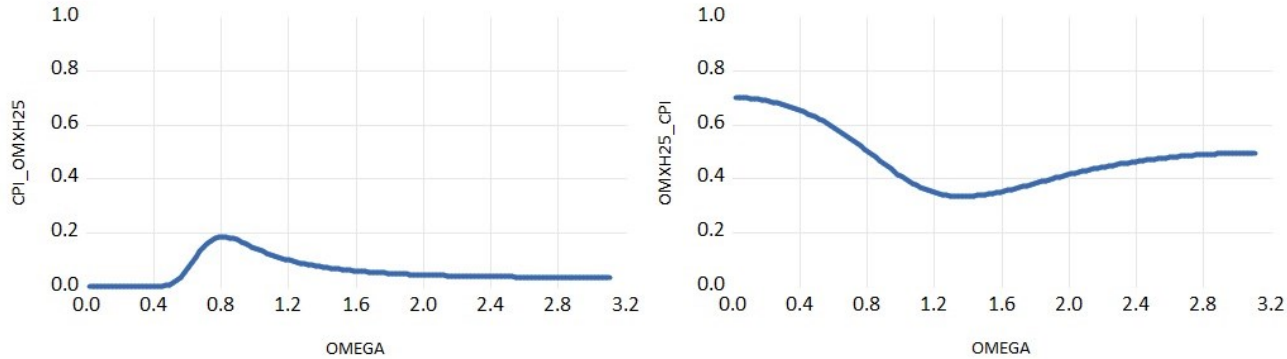
Figure 7: Wavelet coherence result of CPU vs FTSE



Source: Authors' own work.

Figure 7 presents the wavelet coherence results for CPU and FTSE. Accordingly, the relationship between the variables is quite strong, and the CPU negatively affected the FTSE over the 4-8 period in 2004 and 2013.

Figure 8: CPU and OMXH25 frequence domain causality



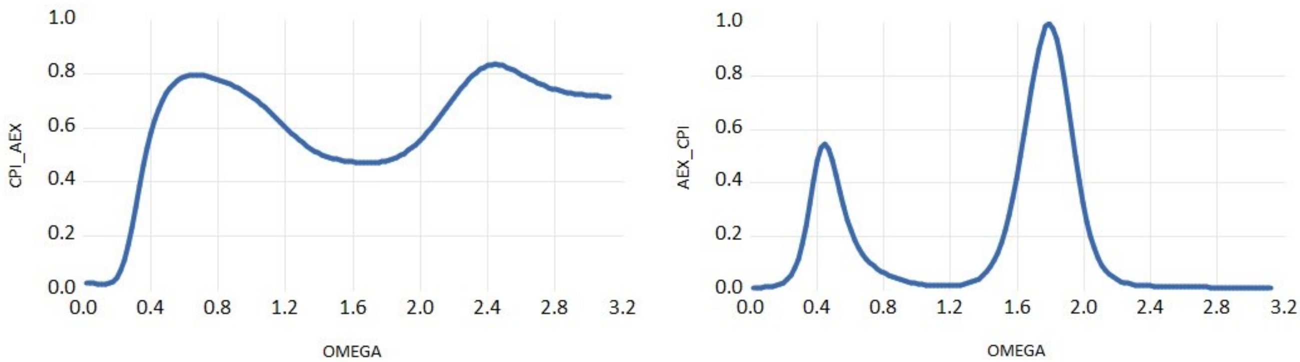
Note: Causality in the frequency domain | H_0: There is not causality at frequency Omega | p-value D.F. (2.271) | Selected lag: 3 | Exogenous variables: C. CPU-OMXH25 F-Stat: 205.0034947, H_0: reject. OMXH25-CPU F-Stat: 2.289961, H_0: cannot reject

Source: Authors' own work.

Robustness checks with Breitung and Candelon causality test

Figure 8 displays the causality relationship at different frequencies. According to the causality test results, we cannot accept the null hypothesis that there is no causality from CPU to OMXH25. Moreover, the graph analysis shows the most robust causal relationship in the frequency range of 0.4-1.2. This result supports the results of the wavelet coherence analysis. However, there is no causality from the OMXH25 variable to the CPU variable.

Figure 9: CPU and AEX frequence domain causality

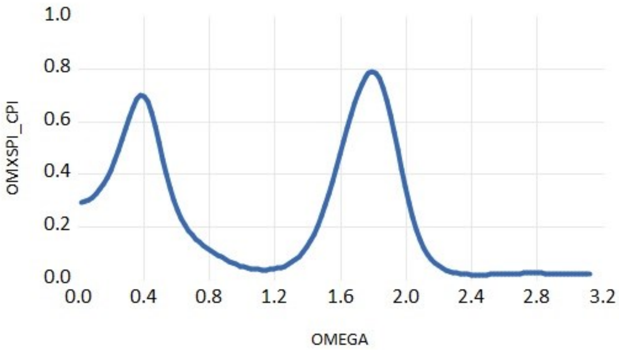


Note: Causality in the frequency domain | H_0: There is not causality at frequency Omega | p-value D.F. (2.259) | Selected lag: 7 | Exogenous variables: C. CPU-DAX F-stat: 92.53826152, DAX-CPU F-Stat: 14.389309, H_0: reject

Source: Authors' own work.

Figure 9 indicates a causal relationship from CPU to AEX, aligning with the wavelet coherence results. The relationship is strongest in the 0.4-1.2 and 2-3.2 frequency ranges, showing CPU's significant influence on AEX in both the short and long term.

Figure 10: CPU and OMXSPI frequence domain causality

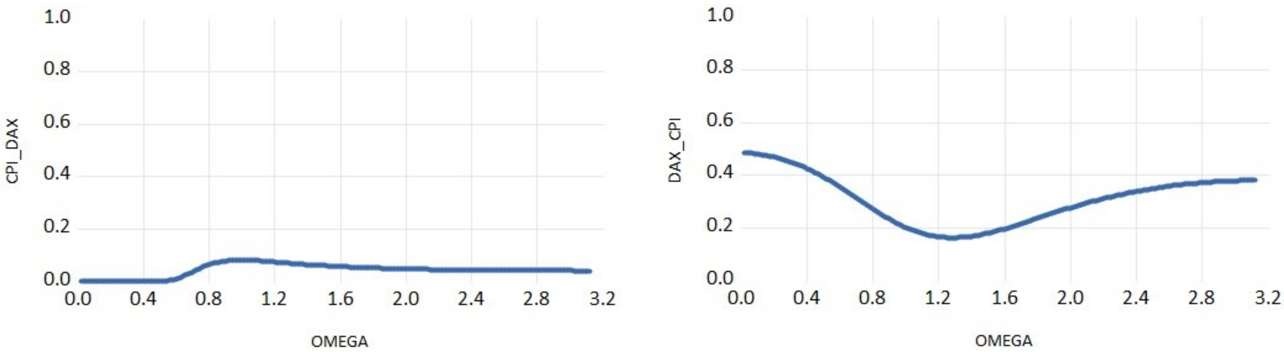


Note: Causality in the frequency domain | H_0: There is not causality at frequency Omega | p-value D.F. (2.259) | Selected lag: 7 | CPU-OMXSPI F-Stat: 247.7163093, H_0: reject, OMXSPI-CPU F-Stat: 25.26559, H_0: reject

Source: Authors' own work.

Figure 10 shows that CPU's causality on OMXSPI is weak at low frequencies (0-0.5) but strengthens near a frequency of 1, peaking around 2-2.5 before declining. These findings support the wavelet coherence analysis, confirming a causal relationship from CPU to OMXSPI. Additionally, OMXSPI has a significant causal effect on CPU at low frequencies, which decreases after 0.5, slightly rises around 1, and then falls again near frequency 2.

Figure 11: CPU and DAX frequence domain causality

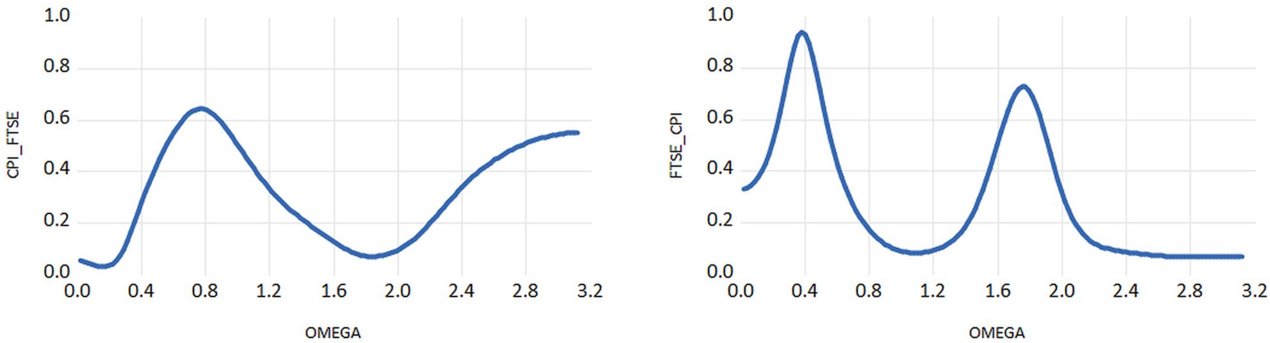


Note: Causality in the frequency domain | H_0: There is not causality at frequency Omega | p-value D.F. (2.271) | Selected lag: 3 | PU-DAX F-Stat: 92.53826152, H_0: reject, DAX-CPU F-Stat: 14.389309, H_0: reject

Source: Authors' own work.

Figure 11 shows a weak causality from CPU to DAX at low frequencies (0-0.5), with a slight increase at medium frequencies (0.5-1.5), which remains low overall. At high frequencies (1.5+) the causality levels off at very low levels. Conversely, DAX has a moderate causal effect on CPU at low frequencies, decreases at medium frequencies, increases slightly after 1.5 and remains moderate at high frequencies.

Figure 12: CPU and FTSE frequence domain causality



Note: Causality in the frequency domain | H_0: There is not causality at frequency Omega | p-value D.F. (2.259) | Selected lag: 7 | CPU-FTSE F-Stat: 68.4941027, H_0: reject, FTSE-CPU F-Stat: 4.3079520, H_0: reject

Source: Authors' own work.

Figure 12 demonstrates a causality relationship between CPU and FTSE. At low frequencies (0-0.5), CPU's causal effect on FTSE peaks around 0.6, decreases at medium frequencies (0.5-1.5), and peaks again at high frequencies (1.5+), around 2.5. Conversely, FTSE's influence on CPU shows similar behavior, peaking at low and high frequencies. These findings align with the wavelet coherence analysis.

Conclusions

This research examines the causality between CPU and selected developed markets from January 2000 to May 2023. Accordingly, we investigate whether there is a causality relationship between the CPU index and the major stock indices of Finland (OMXH25), Germany (DAX), Netherlands (AEX), Norway (OBX), Sweden (OMXSPI), and the UK (FTSE) by considering wavelet coherence and the Breitung and Candelon causality methods. As a result of the analysis, we cannot observe any causal relationship between the CPU index and the OBX. However, we conclude that there is a causal relationship between CPU and all other indices analyzed at different times and frequencies. The causality test is crucial for assessing the strength and timing of relationships between variables, which helps investors in their decision-making and risk management. The frequency causality test, which supports the wavelet coherence analysis, shows a causal relationship between all indices except the Norwegian market and the CPU index at different periods. It shows short-term causality from the CPU to the OMXH25 and OMXSPI, guiding investors to take positions during short-term shocks to the CPU. The AEX index also shows short-run and long-run causality with CPU, suggesting a medium-term position for risk-averse investors in hedging strategies. The results suggest that investors adopt different market strategies based on CPU dynamics. However, the Norwegian market is independent of CPU so that investors can construct CPU-independent portfolios. Uncertainty in climate policy affects risk perception and market volatility, and investors can mitigate risks with adaptive strategies such as stop-loss orders. Modern portfolio theory (MPT) assumes fixed correlations in portfolio optimization, but wavelet coherence analysis shows that correlations between CPU and stock indices vary over time. Thus, dynamic portfolio diversification and adaptive risk management are more appropriate than traditional fixed correlation models, highlighting the need for adaptive models in financial theories. The results obtained are also consistent with the literature. In other words, in terms of the relationship between indices and uncertainty index, the results of this research are in line with Lasisi et al. (2022), Chen et al. (2023), Hoque et al. (2023), Lee and Cho (2023), Xu et al. (2023), Yao et al. (2023), Zhang et al. (2023), Pijourlet (2024), Raza et al. (2024), Shuaibu et al. (2024), Tedeschi et al. (2024) as well as Athari and Kirikkaleli (2025).

The time- and frequency-dependent causality relationship between CPU and market indices has important implications for policymakers. Especially considering that the CPU increases short-term volatility in some markets, climate policies must be designed to be more predictable, stable, and transparent. Moreover, it would benefit regulatory authorities to fulfill their information and guidance functions for investors more effectively to reduce market volatility due to uncertainty.

The results of our study suggest that Climate Policy Uncertainty (CPU) has significant effects on the stock markets of the advanced economies analyzed. This has several important implications for policymakers. First, given that CPU can contribute to market volatility, governments and regulators should focus on reducing this uncertainty through coherent and long-term climate the Finnish and Swedish markets suggests that policy changes in these countries can have a rapid and significant impact on markets. Therefore, the impact of policy changes should be carefully assessed and effectively communicated to stakeholders. In the long run, the strong causality observed in the Dutch market highlights the potential impact of climate policies on long-term investment decisions. This increases the importance of policies that promote sustainable investments and are aligned with long-term climate goals.

This study has several limitations. First, our analysis is limited to advanced economies with a 'good' CCP rating according to the MSCI classification. Future research could examine the generalizability of these findings by including countries with different levels of climate performance and emerging economies. Second, the CPU index used in our study is a single measure of climate policy uncertainty. Robustness analyses can be conducted using other measures of uncertainty. Finally, our study focuses on stock markets in general. Investigating the heterogeneous effects of climate policy uncertainty on different sectors could be an important area of research to develop more detailed policy recommendations.

In future research, the effects of CPU on the market can be addressed at a micro level on a sectoral basis. Studies to be conducted, especially in sectors with high sensitivity to climate policies such as energy, automotive, and pharmaceuticals, will provide more targeted results in terms of both investment decisions and policy design. Moreover, analyzing how markets in emerging economies respond to the CPU is important to understand the impact of economic structures and policy regimes on this relationship. Finally, using artificial intelligence and machine learning techniques to predict the relationship between CPU and stock markets can make methodologically innovative contributions to the field.

References

Aguiar-Conraria, L. & Soares, M.J. (2011). Oil And The Macroeconomy: Using Wavelets to Analyze Old Issues. Empirical Economics, 40(3), 645-655, https://dx.doi.org/10.1007/s00181-010-0371-x.

Aloui, C. & Hkiri, B. (2014). Co-Movements Of GCC Emerging Stock Markets: New Evidence from Wavelet Coherence Analysis. Economic Modelling, 36, 421-431.

Alqaralleh, H.S. (2023). The Extreme Spillover From Climate Policy Uncertainty to the Chinese Sector Stock Market: Wavelet Time-Varying Approach. Letters in Spatial and Resource Sciences, 16(1), 117-131, https://dx.doi.org/10.1007/s12076-023-00352-w.

Athari, S.A. & Kirikkaleli, D. (2025). How Do Climate Policy Uncertainty and Renewable Energy and Clean Technology Stock Prices Co-Move? Evidence from Canada. Empirical Economics, 68(1), 353-371, https://dx.doi.org/10.1007/s00181-024-02643-7.

Banerjee, A.K., Özer, Z.S., Rahman, M.R. & Sensoy, A. (2024). How Does the Time-Varying Dynamics of Spillover Between Clean and Brown Energy ETFs Change with the Intervention of Climate Risk and Climate Policy Uncertainty? International Review of Economics & Finance, 93, 442-468, https://dx.doi.org/10.1016/j.iref.2024.03.046.

Bardoscia, M., Battiston, S., Caccioli, F. & Caldarelli, G. (2017). Pathways Towards Instability in Financial Networks. Nature Communications, 8(1), 116-144, https://dx.doi.org/10.1038/ncomms14416.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F. & Visentin, G. (2017). A Climate Stress-Test of the Financial System. Nature Climate Change, 7(4), 283-288, https://dx.doi.org/10.1038/nclimate3255.

Boulange, J., Hanasaki, N., Yamazaki, D. & Pokhrel, Y. (2021). Role of Dams in Reducing Global Flood Exposure under Climate Change. Nature Communications, 12(1), 417-435, https://dx.doi.org/10.1038/s41467-020-20704-0.

Bouri, E., Iqbal, N. & Klein, T. (2022). Climate Policy Uncertainty and the Price Dynamics of Green and Brown Energy Stocks. Finance Research Letters, 47, 1-5, https://dx.doi.org/10.1016/j.frl.2022.102740.

Cai, X.J., Tian, S., Yuan, N. & Hamori, S. (2017). Interdependence Between Oil and East Asian Stock Markets: Evidence from Wavelet Coherence Analysis. Journal of International Financial Markets, Institutions and Money, 48, 206-223, https://dx.doi.org/10.1016/j.intfin.2017.02.001.

Chan, K.F. & Malik, I. (2022). Climate Policy Uncertainty and the Cross-Section of Stock Returns. SSRN Electronic Journal, 1-46, https://dx.doi.org/10.2139/ssrn.4075528.

Chekouri, S., Chibi, A. & Benbouziane, M. (2021). Economic Growth, Carbon Dioxide Emissions and Energy Consumption in Algeria: A Wavelet Coherence Approach. World Journal of Science, Technology and Sustainable Development, 18(2), 172-189, https://dx.doi.org/10.1108/wjstsd-12-2020-0097.

Chen, K., Zhang, Y. & Zhong, Q. (2019). Wavelet Coherency Structure in Open Channel Flow. Water, 11(8), 1664-1697, https://dx.doi.org/10.3390/w11081664.

Chen, M.P., Chen, W.Y. & Tseng, T.C. (2017). Co-Movements of Returns in the Health Care Sectors from the US, UK, And Germany Stock Markets: Evidence from The Continuous Wavelet Analyses. International Review of Economics & Finance, 49, 484-498, https://dx.doi.org/10.1016/j.iref.2017.02.009.

Chen, Z., Zhang, L. & Weng, C. (2023). Does Climate Policy Uncertainty Affect Chinese Stock Market Volatility? International Review of Economics & Finance, 84, 369-381, https://dx.doi.org/10.1016/j.iref.2022.11.030.

Cohen, M.X. (2019). A Better Way to Define And Describe Morlet Wavelets for Time-Frequency Analysis. NeuroImage, 199, 81-86.

Dafermos, Y., Nikolaidi, M. & Galanis, G. (2018). Climate Change, Financial Stability and Monetary Policy. Ecological Economics, 152, 219-234, https://dx.doi.org/10.1016/j.ecolecon.2018.05.011.

Dicle, M.F. & Levendis, J. (2013). Estimating Geweke's (1982) Measure of Instantaneous Feedback. The Stata Journal, 13(1), 136-140, https://dx.doi.org/10.1177/1536867X1301300110.

Economic Policy Uncertainty. (2024). Categorical EPU: Climate policy uncertainty data. Economic Policy Uncertainty. https://www.policyuncertainty.com/climate_uncertainty.html (Accessed: 26.06.2024).

Gavriilidis, K. (2021). Measuring Climate Policy Uncertainty. SSRN Electronic Journal, 1-9, https://dx.doi.org/10.2139/ssrn.3847388.

He, M. & Zhang, Y. (2022). Climate Policy Uncertainty and the Stock Return Predictability of the Oil Industry. Journal of International Financial Markets, Institutions and Money, 81, 1-21, https://dx.doi.org/10.1016/j.intfin.2022.101675.

Hoque, M. E., Soo-Wah, L., Bilgili, F. & Ali, M.H. (2023). Connectedness And Spillover Effects Of US Climate Policy Uncertainty On Energy Stock, Alternative Energy Stock, and Carbon Futures. Environmental Science and Pollution Research, 30(7), 18956-18972, https://dx.doi.org/10.1007/s11356-022-23464-0.

Huo, M., Li, C. & Liu, R. (2023). Climate Policy Uncertainty and Corporate Green Innovation Performance: From the Perspectives of Organizational Inertia and Management Internal Characteristics. Managerial and Decision Economics, 45(1), 34-53, https://dx.doi.org/10.1002/mde.3981.

IPCC. (2023). Climate Change 2023 Synthesis Report. https://www.ipcc.ch/report/ar6/syr/ (Accessed: 26.06.2024).

Iqbal, N., Bouri, E., Shahzad, S.J.H. & Alsagr, N. (2024). Asymmetric Impacts of Chinese Climate Policy Uncertainty on Chinese Asset Prices. Energy Economics, 133, 1-12, https://dx.doi.org/10.1016/j.eneco.2024.107518.

Jemai, S., Ellouze, M. & Abida, H. (2017). Variability of Precipitation in Arid Climates Using The Wavelet Approach: Case Study of Watershed Of Gabes in South-East Tunisia. Atmosphere, 8(9), 178-191, https://dx.doi.org/10.3390/atmos8090178.

Khalfaoui, R., Mefteh-Wali, S., Viviani, J.L., Jabeur, S.B., Abedin, M.Z. & Lucey, B.M. (2022). How Do Climate Risk And Clean Energy Spillovers, and Uncertainty Affect US Stock Markets? Technological Forecasting and Social Change, 185, 1-20, https://dx.doi.org/10.1016/j.techfore.2022.122083.

Kuşkaya, S., Ünlü, F. & Gençoğlu, P. (2021). The Analysis of the Relationship Between Exchange Rate and Producer Price Index With Continuous Wavelet Coherence Model: Empirical Findings on Turkey. İzmir Journal of Economics, 36(2), 365-378, https://dx.doi.org/10.24988/ije.202136208.

Landis, F. & Bernauer, T. (2012). Transfer Payments in Global Climate Policy. Nature Climate Change, 2(8), 628-633.

Lasisi, L., Omoke, P.C. & Salisu, A.A. (2022). Climate Policy Uncertainty and Stock Market Volatility. Asian Economics Letters, 4, 1-6, https://dx.doi.org/10.46557/001c.37246.

Lee, K. & Cho, J. (2023). Measuring Chinese Climate Uncertainty. International Review Of Economics & Finance, 88, 890-891, https://dx.doi.org/10.1016/j.iref.2023.07.004.

Lin, B. & Zhao, H. (2021). Measuring Policy Uncertainty under Climate Change. Energy Proceedings, 83, 1-9, https://dx.doi.org/10.46855/energy-proceedings-8490.

Markowitz, H. (1959). Portfolio Selection: Efficient Diversification of Investments. John Wiley & Sons, Inc, Hoboken.

Nga, P.T.H. & Hung, N.T. (2025). Does Climate Policy Uncertainty Affect Asian Financial Markets? Evidence from A Wavelet-Quantile-Based Approach. International Journal of Islamic and Middle Eastern Finance and Management, http://dx.doi.org/10.1108/IMEFM-07-2024-0347.

Nasreen, S., Tiwari, A., Jiang, Z. & Yoon, S. (2022). Dependence Structure between Bitcoin and Economic Policy Uncertainty: Evidence from Time–Frequency Quantile-Dependence Methods. International Journal of Financial Studies, 10(3), 49-64, https://dx.doi.org/10.3390/ijfs10030049.

Paroussos, L., Mandel, A., Fragkiadakis, K., Fragkos, P., Hinkel, J. & Vrontisi, Z. (2019). Climate Clubs and the Macro-Economic Benefits Of International Cooperation on Climate Policy. Nature Climate Change, 9(7), 542-546, https://dx.doi.org/10.1038/s41558-019-0501-1.

Pijourlet, G. (2024). Climate Policy Uncertainty and US Industry Stock Returns: A Quantile Regression Approach. Economics Bulletin, 44(1), 182-189.

Polanco, J., Ganzedo, U., Sáenz, J., Caballero-Alfonso, A.M. & Castro-Hernández, J.J. (2011). Wavelet Analysis of Correlation among Canary Islands Octopus Captures Per Unit Effort, Sea-Surface Temperatures and the North Atlantic Oscillation. Fisheries Research, 107(3), 177-183.

Rahmati, M., Groh, J., Graf, A., Pütz, T., Vanderborght, J. & Vereecken, H. (2020). On the Impact of Increasing Drought on the Relationship Between Soil Water Content and Evapotranspiration of a Grassland. Vadose Zone Journal, 19(1), 1-20, https://dx.doi.org/10.1002/vzj2.20029.

Raza, S.A., Khan, K.A., Benkraiem, R. & Guesmi, K. (2024). The Importance of Climate Policy Uncertainty in Forecasting the Green, Clean, and Sustainable Financial Markets Volatility. International Review of Financial Analysis, 91, 1-12, https://dx.doi.org/10.1016/j.irfa.2023.102984.

Rjoub, H., Odugbesan, J., Adebayo, T. & Wong, W. (2021). Investigating the Causal Relationships among Carbon Emissions, Economic Growth, and Life Expectancy in Turkey: Evidence from Time and Frequency Domain Causality Techniques. Sustainability, 13(5), 2924-2935, https://dx.doi.org/10.3390/su13052924.

Sarker, P. (2024). Nonlinear Effects Of Climate Policy Uncertainty on Carbon Allowance and ESG Prices: Evidence from the US. SSRN Electronic Journal, 1-12, https://dx.doi.org/10.2139/ssrn.4753329.

Schaefli, B., Maraun, D. & Holschneider, M. (2007). What Drives High Flow Events in the Swiss Alps? Recent Developments in Wavelet Spectral Analysis and Their Application to Hydrology. Advances in Water Resources, 30(12), 2511-2525, https://dx.doi.org/10.1016/j.advwatres.2007.06.004.

Shuaibu, M.I., Mamman, S.O., Iliyasu, J. & Zhanqin, W. (2024). Asymmetric Pricing of Climate Policy Uncertainty under Heterogeneous Stocks Market Conditions in China: Evidence from GARCH and Quantile Models. Letters in Spatial and Resource Sciences, 17(1), 10-25, https://dx.doi.org/10.1007/s12076-024-00372-0.

Tedeschi, M., Foglia, M., Bouri, E. & Dai, P.F. (2024). How Does Climate Policy Uncertainty Affect Financial Markets? Evidence from Europe. Economics Letters, 234, 1-5, https://dx.doi.org/10.1016/j.econlet.2023.111443

Treepongkaruna, S., Chan, K.F. & Malik, I. (2023). Climate Policy Uncertainty and the Cross-Section of Stock Returns. Financial Research Letters, 55, 1-8, https://dx.doi.org/10.1016/j.frl.2023.103837.

UNCC. (2022). United İn Science: We Are Heading in the Wrong Direction. https://unfccc.int/news/united-in-science-we-are-heading-in-the-wrong-direction (Accessed: 26.06.2024).

Vacha, L. & Barunik, J. (2012). Co-Movement of Energy Commodities Revisited: Evidence from Wavelet Coherence Analysis. Energy Economics, 34(1), 241-247.

Xu, X., Huang, S., Lucey, B.M. & An, H. (2023). The Impacts of Climate Policy Uncertainty on Stock Markets: Comparison between China and the US. International Review of Financial Analysis, 88, 1-16, https://dx.doi.org/10.1016/j.irfa.2023.102671.

Yang, Z. (2019). Increasing Returns to Scale in Energy-Intensive Sectors and Its Implications on Climate Change Modeling. Energy Economics, 83, 208-216, https://dx.doi.org/10.1016/j.eneco.2019.06.011.

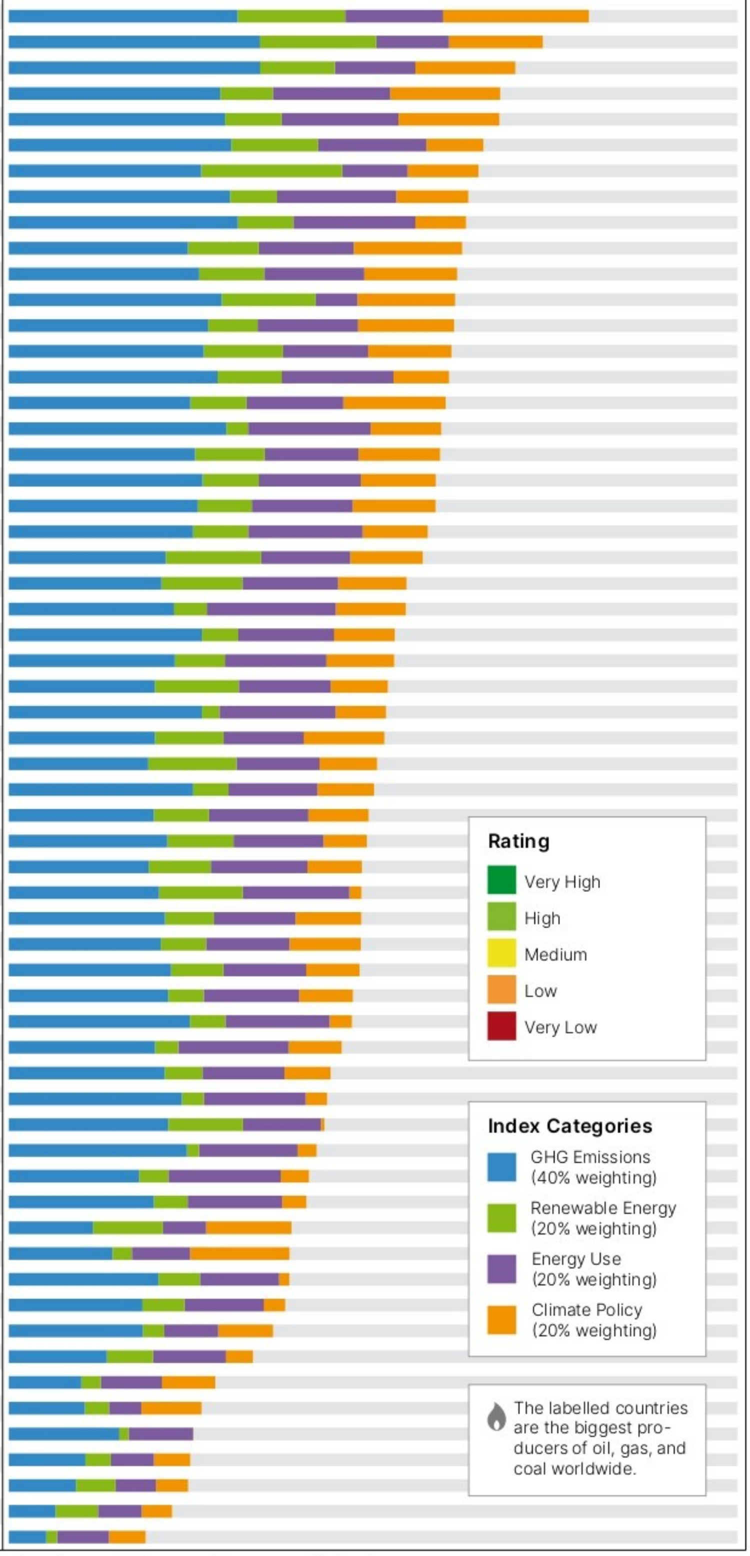
Yao, X., He, W., Li, J. & Le, W. (2023). Climate Policy Uncertainty through Production Networks: Evidence from the Stock Market. Economics Letters, 233, 1-3, https://dx.doi.org/10.1016/j.econlet.2023.111405.

Zhang, Y., He, M., Liao, C. & Wang, Y. (2023). Climate Risk Exposure and the Cross-Section of Chinese Stock Returns. Financial Research Letters, 55, 1-7, https://dx.doi.org/10.1016/j.frl.2023.103.

Appendinx 1: Climate change performance rating of the countries

Rank	Rank change	Country	Score**
1.*	–	–	–
2.	–	–	–
3.	–	–	–
4.	0 –	Denmark	79.61
5.	0 –	Sweden	73.28
6.	3 ▲	Chile	69.54
7.	1 ▲	Morocco	67.44
8.	2 ▲	India	67.35
9.	23 ▲	Estonia	65.14
10.	-4 ▼	Norway	64.47
11.	-4 ▼	United Kingdom	63.07
12.	11 ▲	Philippines	62.75
13.	6 ▲	Netherlands	62.24
14.	2 ▲	Portugal	61.55
15.	-1 ▼	Finland	61.24
16.	-3 ▼	Germany	61.11
17.	1 ▲	Luxembourg	60.76
18.	-6 ▼	Malta	60.42
19.	3 ▲	European Union (27)	59.96
20.	1 ▲	Egypt	59.37
21.	-10 ▼	Lithuania	59.21
22.	-7 ▼	Switzerland	58.61
23.	11 ▲	Spain	58.59
24.	0 –	Greece	57.52
25.	1 ▲	Latvia	56.81
26.	1 ▲	Indonesia	54.59
27.	-2 ▼	Colombia	54.50
28.	-11 ▼	France	52.97
29.	1 ▲	Italy	52.90
30.	-1 ▼	Croatia	52.04
31.	-3 ▼	Mexico	51.77
32.	5 ▲	Austria	51.56
33.	2 ▲	New Zealand	50.55
34.	6 ▲	Slovak Republic	50.12
35.	7 ▲	Cyprus	49.39
36.	8 ▲	Bulgaria	49.15
37.	9 ▲	Ireland	48.47
38.	-5 ▼	Brazil	48.39
39.	10 ▲	Belgium	48.38
40.	3 ▲	Vietnam	48.31
41.	9 ▲	Slovenia	48.16
42.	-11 ▼	Thailand	47.23
43.	-7 ▼	Romania	47.09
44.	-5 ▼	South Africa	45.69
45.	6 ▲	Czech Republic	44.16
46.	2 ▲	Belarus	43.69
47.	-6 ▼	Turkey	43.32
48.	6 ▲	Algeria	42.26
49.	-2 ▼	Argentina	41.19
50.	-5 ▼	Japan	40.85
51.	-13 ▼	China	38.80
52.	3 ▲	United States	38.53
53.	0 –	Hungary	38.51
54.	-2 ▼	Poland	37.94
55.	4 ▲	Australia	36.26
56.	1 ▲	Malaysia	33.51
57.	1 ▲	Chinese Taipei	28.35
58.	3 ▲	Canada	26.47
59.	-3 ▼	Russian Federation	25.28
60.	0 –	Korea	24.91
61.	3 ▲	Kazakhstan	24.61
62.	1 ▲	Saudi Arabia	22.41
63.	-1 ▼	Islamic Republic of Iran	18.77

Categories



Source: IPCC. (2023). Climate Change 2023 Synthesis Report. https://www.ipcc.ch/report/ar6/syr/ (Accessed: 26.06.2024).