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# Carbon exchange-traded funds market and economic policy uncertainty

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A R T I C L E I N F O

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A B S T R A C T

This study empirically analyses the relationship between economic policy uncertainty (EPU) and three carbon exchange-traded funds (ETFs) using wavelet coherence analysis as well as dynamic conditional correlation (DCC) from a multivariate GARCH model. The analysis techniques employed allow us to analyze the nature of the relationship which may depend on time and frequency. Our findings indicate that there exists a significant negative correlation between EPU and the ETFs for almost all times and frequencies. However, for some times and frequencies, the identified negative relationship is not significant. Interestingly, we also find that for some times and frequencies, EPU leads the ETFs and for some other times and frequencies ETFs lead the EPU.

## 1. Introduction and background

Emission Trading Systems (ETSs) have been reported to be an effective tool to mitigate the adverse effects of climate change, mainly caused by greenhouse gas emissions (GHGs), and subsequently achieve the objectives of global initiatives such as the Kyoto Protocol and the Paris Agreement. They are designed to put a cap on either emission or emission intensity of all or selected GHGs such as CO2. The credit and allowance issued by the government can be traded among entities in a market known as the carbon market whose environmental and economic benefits are documented in the literature. The development of Emission Trading Systems (ETSs) in general, and the carbon market specifically, represents a critical step in addressing climate change challenges. Assigning a monetary value to carbon emissions has shown to be a successful strategy for reducing both emissions and the ensuing costs. These costs ultimately affect a broad range of stakeholders, from businesses to individuals, through various negative consequences associated with climate change. Within the carbon credit financial landscape, exchange-traded funds (ETFs) have garnered attention for their multiple benefits, including diversification options, tax advantages, immediate liquidity, and lower associated costs (Henriques et al., 2022; Shrestha et al., 2020). What began as niche instruments for mimicking market indices has evolved into some of the most widely used financial securities available. In addition to ETSs, a reduction in carbon emissions can also be achieved through a free-market mechanism where investors can invest in firms operating in low-carbon and renewable energy industries. Rather than investing in individual firms, investors can diversify by investing in carbon exchange-traded funds (ETFs). Therefore, carbon ETF markets can play a critical role in reducing CO2 emissions (Shrestha et al., 2023).

Economic policy uncertainty[1] (EPU) is a widely used measure of uncertainty that has reported implications for the financial markets including: i) influencing and potentially postponing crucial decisions (including investment and consumption) made by firms and other economic agents (Gulen and Ion, 2016); ii) the potential to raise financing and production costs by impacting both the supply and demand channels, thereby exacerbating disinvestment and economic contraction (Pastor and Veronesi, 2013); iii) heightening risks in financial markets, particularly by diminishing the value of government protection for markets; iv) and finally, impacting inflation, interest rates, and expected risk premiums (Pastor and Veronesi, 2012).

The effects of EPU on some classes of ETSs have been well

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[1] Defined as the presence of a non-zero probability of changes in the current economic policies that establish the framework and rules by which economic agents operate (Baker et al., 2016). Baker, Bloom, and Davis (2016) provided one of the most comprehensive measures of economic policy uncertainty, encompassing variables like news media references, tax code provisions, and disagreement among forecasters. Their work serves as a foundational basis for studying the impact of economic policy uncertainty on various financial markets.

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documented in the literature by Liu et al. (2023) and Wang et al. (2022) (for China's emission trading scheme) and Ye et al. (2021); Dai et al. (2022) and Gao et al. (2023) (for European emission trading system). Additionally, EPU was found to have large, market-wide economic effects that are mostly non-diversifiable. In particular, it negatively impacts market returns and discount rates (Brogaard and Detzel, 2015). Rising EPU also exacerbates the divergence in investor expectations about the future exchange rate movement (Wang et al., 2022). Benlagha and Hermit (2022) found that EPU can elicit significant reactions from the sovereign bond markets in the short-term in G7 countries and finally Gupta et al. (2022) assert that EPU increases investment cash flow sensitivity and subsequently reduces corporate investment.

Despite the growing importance of carbon ETFs, there is limited empirical evidence on how EPU affects the performance, volatility, and investment flows in the carbon ETF market. Understanding the relationship between these two variables is crucial for investors, policymakers, and stakeholders interested in sustainable investment and climate change mitigation. Considering this research gap, this study aims to comprehensively investigate the relationship between EPU and the performance of ETFs. We seek to understand how fluctuations in EPU influence the performance and volatility of three specific carbon ETFs: the VanEck Low Carbon Energy ETF, the iShares MSCI ACWI Low Carbon Target ETF, and the SPDR MSCI ACWI Climate Paris Aligned ETF. To achieve this, we use a novel approach suggested by Vacha and Barunik (2012) to follow a model-free way of estimating correlations that vary with time and frequency. Utilizing wavelet coherence analysis and DCC GARCH model, we aim to capture the time-varying and frequency-dependent correlations between EPU and the selected carbon ETFs. This approach allows us to identify periods and frequencies where the relationship is particularly strong or weak. More specifically, we intend to determine whether EPU leads changes in the performance of carbon ETFs, or vice versa, and how this directional influence varies over time and across different frequencies. Understanding these directional dynamics can provide deeper insights into the causal relationships between policy uncertainty and carbon market performance. By addressing the limited empirical evidence on the EPU-carbon ETF nexus, this study aims to fill a significant gap in the existing literature.

This study makes several notable contributions to the literature on the nexus between EPU and carbon ETFs. We innovate by applying wavelet coherence analysis to explore this relationship within the time-frequency domain. This approach allows for a more nuanced examination of their interconnections, uncovering significant correlations across various periods and frequencies. This methodology stands in contrast to traditional econometric techniques, offering a deeper understanding of the temporal and frequency-dependent nature of these relationships. Our research elucidates the complex directional interactions between EPU and carbon ETF indices, identifying periods during which each sector leads or lags the other. This bidirectional relationship enhances our understanding of the causality and timing of their interactions, providing insights into turbulences in economic policies and carbon ETFs influence each other over time. By employing DCC GARCH models, we contribute to the literature on financial market dynamics through the lens of mean-reverting processes. Our findings on the time-varying correlations and their mean-reverting nature add to the discourse on the predictability and stability of the relationship between EPU and carbon ETFs.

Understanding the interplay between EPU and the performance of ETFs is crucial for several reasons, particularly given the current economic and environmental challenges. Despite the growing importance of carbon ETFs in sustainable finance, there is limited empirical evidence on how EPU affects these financial instruments. Previous studies have extensively examined the impact of EPU on traditional financial markets and some classes of ETSs. However, the specific relationship between EPU and carbon ETFs remains underexplored. EPU has been shown to have wide-ranging effects on financial markets, including increased risks, delayed investments, and economic contractions. Understanding its impact on carbon ETFs is particularly relevant in today's volatile economic climate, where policy shifts can have immediate and profound effects on financial markets. By analyzing how EPU affects carbon ETFs, this research provides valuable insights for investors and financial advisors who need to navigate these uncertainties. Additionally, carbon ETFs play a pivotal role in promoting low-carbon investments and supporting the transition to a more sustainable economy. By diversifying investments across firms that are committed to reducing carbon emissions, these ETFs contribute to global efforts to combat climate change. Understanding the impact of EPU on carbon ETFs helps stakeholders better manage risks and make informed decisions that support environmental sustainability. This is especially relevant in the context of global initiatives such as the Paris Agreement, which aims to limit global warming by reducing greenhouse gas emissions. For policymakers, this research provides empirical evidence on how economic policy decisions impact a critical financial tool aimed at mitigating climate change. By understanding the relationship between EPU and carbon ETFs, policymakers can design more effective strategies to stabilize these markets and encourage sustainable investment. This is particularly important as governments worldwide grapple with the dual challenges of fostering economic growth and addressing climate change. The findings of this study have practical applications for a wide range of stakeholders. Investors can use the insights to make more informed decisions about their portfolios, financial advisors can better guide their clients, and policymakers can develop strategies that mitigate the adverse effects of policy uncertainty on sustainable investments. By bridging the gap between academic research and real-world applications, this study aims to contribute to both the theoretical understanding and practical management of EPU's impact on the carbon ETF market.

The organization of this paper is as follows: Section 2 covers the methodologies used in the study. Moving forward, Section 3 discusses the empirical results. Finally, in Section 4, we conclude by highlighting our primary findings and their implications.

## 2. Method

### 2.1. Wavelet analysis

In this subsection, we first briefly describe wavelet coherence analysis (Grinsted et al. (2004) and Torrence and Compo (1998)). The continuous wavelet transform (CWT, $W_n^X(s)$) for a discrete time series $x_n$, $n = 1, \ldots, N$ with uniform time steps $\delta t$ is defined as:

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{m=1}^{N} x_m \psi_0 \left[ \frac{(m-n)\delta t}{s} \right] \tag{1}$$

where $\psi_0()$ represents a particular mother wavelet, $s > 0$ is the scaling factor (that stretches the wavelet) and $n$ is the translation parameter (that represents the location of the wavelet). Then, we can define the cross wavelet transform ($W_n^{XY}(s)$) of two time series $x_n$ and $y_n$ as follows:

$$W_n^{XY}(s) = W_n^X(s) W_n^{Y*}(s) \tag{2}$$

where the superscript '* ' represents the complex conjugate. Now, the wavelet coherence ($R_n^2(s)$) of the two time series can be defined as:

$$R_n^2(s) = \frac{\left|S(s^{-1} W_n^{XY}(s))\right|^2}{S(s^{-1}\left|W_n^X(s)\right|^2) S(s^{-1}\left|W_n^Y(s)\right|^2)} \tag{3}$$

where $S()$ is a smoothing function. In this case, the phase difference is given by

$$\phi_n^{XY}(s) = \tan^{-1}\left( \frac{\mathrm{Im}(W_n^{XY}(s))}{\mathrm{Re}(W_n^{XY}(s))} \right) \tag{4}$$

Where Re() and Im() represent the real and imaginary parts of the complex cross wavelet transform. In the coherence diagram, the phase is plotted using arrows. When the two series are in phase or positively correlated, the arrow will be pointing to the right and vice versa. When the first series leads the second, the arrow would be pointing right-up or left-down. Similarly, when the second series leads the first, the arrow would be pointing right-down or left-up.

### 2.2. DCC GARCH analysis

The Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC GARCH) model suggested by Engle (2002) is the extension of the standard GARCH model where $Y_t$ is a $m \times 1$ vector representing $m$ time series.[2] The DCC GARCH model is described by the following system of equations:

$$Y_t = \mu + \varepsilon_t, \quad \varepsilon_t = H_t^{1/2}\eta_t \tag{5}$$

where $\eta_t$is a vector of iid standard normal random variables.

$$H_t = D_t R_t D_t, \quad D_t = diag\left(\sqrt{h_{1t}}, \dots \sqrt{h_{Nt}}\right) \tag{6}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \quad Q_t^* = diag\left(\sqrt{q_{11t}}, \dots \sqrt{q_{mmt}}\right) \tag{7}$$

$$Q_t = S(1 - \alpha - \beta) + \alpha\left(\epsilon_{t-1}\epsilon_{t-1}'\right) + \beta Q_{t-1} \tag{8}$$

$Q_t$ and $R_t$ are the covariance and correlation matrices respectively, and $S$ is the unconditional covariance matrix of the $\epsilon_t = D_t^{-1}\varepsilon_t$. It is required that $\alpha > 0$ and $\beta > 0$ for the covariance matrix to be positive definite. When $\alpha + \beta < 1$, the model is so-called mean reverting.

## 3. Empirical results

### 3.1. Data description

This study uses the daily prices ($P_t$) for the three carbon ETFs, (i) *VanEck Low Carbon Energy ETF, (ii) iShares MCSI ACWI Low Carbon Target ETF, and (iii) SPDR MCSI ACWI Climate Paris Aligned ETF*[3] covering the period of Dec 9, 2014 to Aug 1, 2023.[4] The sample size consists of 2255 observations. Following prior studies, the logarithmic return is computed as follows:

$$r_t = [\ln(P_t) - \ln(P_{t-1})] \times 100\# \tag{9}$$

For EPU, we use the index constructed by Baker et al. (2016) for the same sample period. Graphical illustrations and calculations are performed using R programming software. Table 1 shows the summary statistics and the stationarity tests where VanEck has the highest mean return and SPDR has the lowest mean return. Carbon ETF indices all have negative skewness and significantly higher kurtosis compared to the standard normal distribution. Finally, all Jarque-Berra statistics are significant.

**Table 1**
Descriptive statistics of the daily logarithmic returns.

| | iShare | SPDR | VanEck | EPU |
|---|---|---|---|---|
| Observations | 2255 | 2255 | 2255 | 2255 |
| Min. | −0.11756 | −0.10747 | −0.11441 | −1.91032 |
| Max. | 0.07708 | 0.08803 | 0.11702 | 3.21562 |
| Mean | 0.00023 | 0.00022 | 0.00037 | 0.00043 |
| Std. Dev | 0.01073 | 0.01088 | 0.01632 | 0.50517 |
| Skewness | −1.10318 | −0.89017 | −0.34665 | 0.23527 |
| Kurtosis | 18.2709 | 17.94473 | 8.9553 | 4.44322 |
| Jarque-Berra | 22,368.51 | 21,282.94 | 3377.45 | 216.51 |

As shown in Fig. 1, the VanEck Low Carbon Energy ETF experienced stable prices until 2018, rapid growth peaking in early 2021, followed by volatility, and stabilized above 100 by 2023. The iShares MSCI ACWI Low Carbon Target ETF showed steady growth with fluctuations until 2020, peaked in early 2021, experienced volatility, and recovered steadily above 160 by 2023. The Economic Policy Uncertainty Index had low and stable values until late 2019, peaked sharply in 2020, then declined with intermittent volatility through 2023. The log returns for the Economic Policy Uncertainty Index, SPDR MSCI ACWI Climate Paris Aligned ETF, iShares MSCI ACWI Low Carbon Target ETF, and VanEck Low Carbon Energy ETF all show fluctuations around zero from late 2014 to 2023, with notable spikes and increased volatility during early 2020.

### 3.2. Evidence from the wavelet coherence

Fig. 2 shows the estimated wavelet coherence and phase for all three pairs with one of the three carbon ETF indices and EPU. The figures reveal some interesting results. There are more significant regions or areas between the two carbon ETF (iShare and SPDR) indices and the EPU index, indicating significant correlation over some periods and at certain frequencies. However, when it comes to the significant regions between the VanEck index and EPU, the total area is less compared to the previous two indices.

Furthermore, almost all arrows are pointing to the left indicating a strong negative correlation between the carbon ETF indices and the EPU index. Finally, there are a significant number of arrows pointing upward and a significant number of arrows pointing downward. This indicates that for some dates and some frequencies the carbon ETF indices lead the EPU. However, for other dates and frequencies, the opposite is true. The results clearly show that the extent and nature of the relationship between EPU and ETFs depends on time and frequency.

### 3.3. Evidence from DCC GARCH

The estimates of the parameters for the DCC GARCH model are summarized in Table 2. All the parameters are highly significant. All the estimates of $\alpha$ and $\beta$ are positive as required by the model because these are the parameters of the model describing the data-generating process for the covariance matrices whose diagonal terms cannot be negative. Finally, the estimates of the sum of these parameters (i.e., $\alpha + \beta$) are all less than 1, indicating that the covariance-generating process is a mean reverting process. The main reason we estimated the DCC GARCH model is to get the time series estimate of the dynamic correlation between the carbon ETF indices and the EPU index. We will discuss the behavior of the dynamic correlation in the next subsection.

[2] In this study, $m = 2$ because we are considering two series at a time.

[3] Since high carbon emissions are a global issue, we use these ETFs representing firms operating globally. However, these carbon ETFs differ from one another in some specific respects. For example, the first ETF, VanEck, represents the largest and most liquid companies in the global low-carbon energy industry. Here the low-carbon energy industry includes wind, solar, hydro, hydrogen, bio-fuel, geothermal technology, lithium-ion batteries, electric vehicles, waste-to-energy production, smart grid technologies, etc. The iShares ETF represents large and mid-capitalization companies from developed and emerging markets with lower carbon exposure than the broad market. The third ETF, SPDR ETF, represents large and mid-capitalization securities across 23 Developed Markets and 24 Emerging Markets. Therefore, these ETFs may represent different aspects of the low-carbon industry. The inclusion of these ETFs is also based on having sufficient observations for the analysis.

[4] In our analysis, the sample period includes the duration of the Covid-19 pandemic. This likely caused significant structural changes across various sectors including EPU and carbon ETF markets, potentially affecting the trends and patterns in our data. Therefore, it is crucial to recognize the possibility of a structural break within this period. This may impact the estimation of the DCC-GARCH model. However, it will not affect the wavelet coherence analysis as this allows the relationship between series over time and frequency.

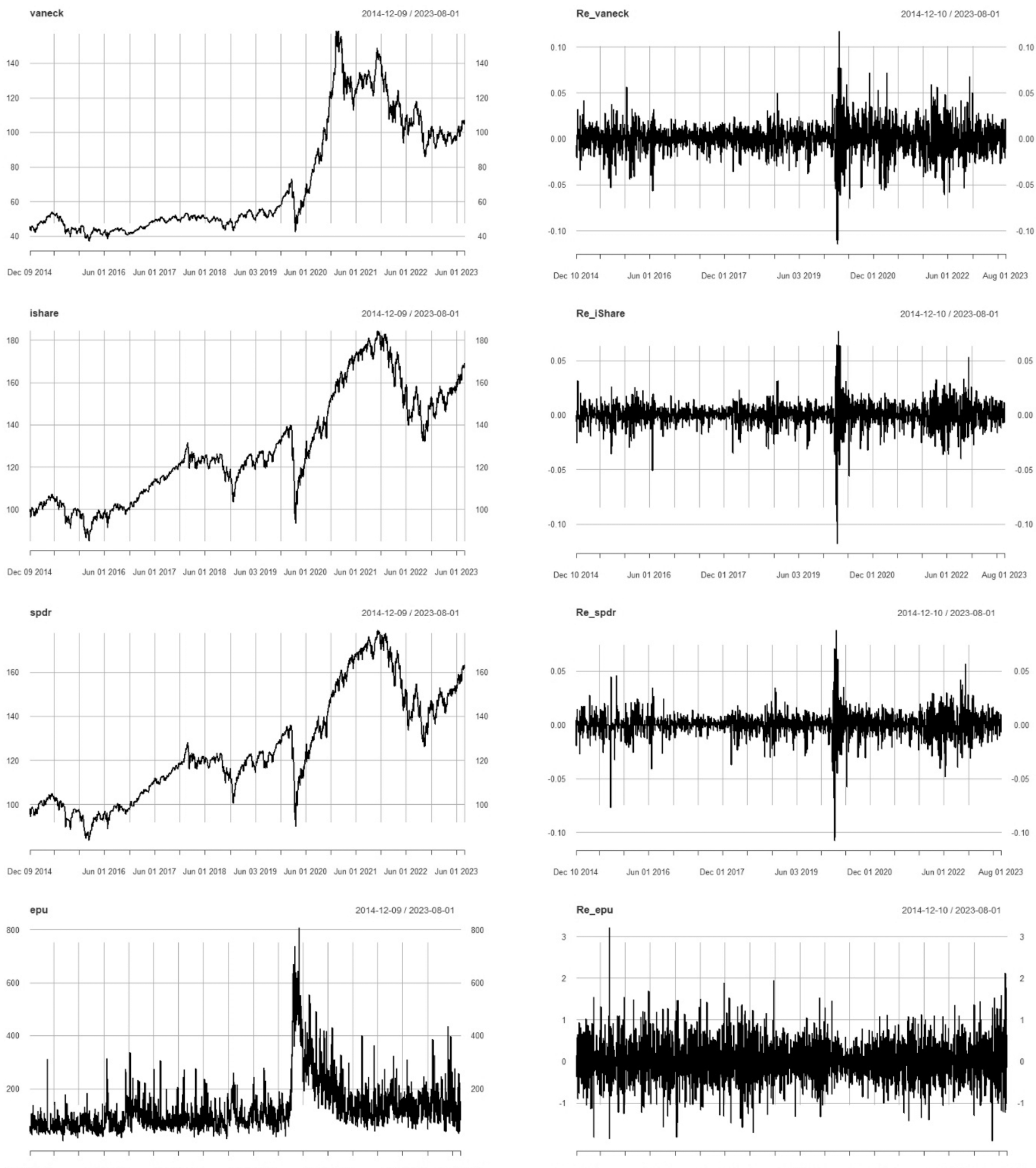


**Fig. 1.** The price levels (shown on the left) and logarithmic returns (shown on the right).

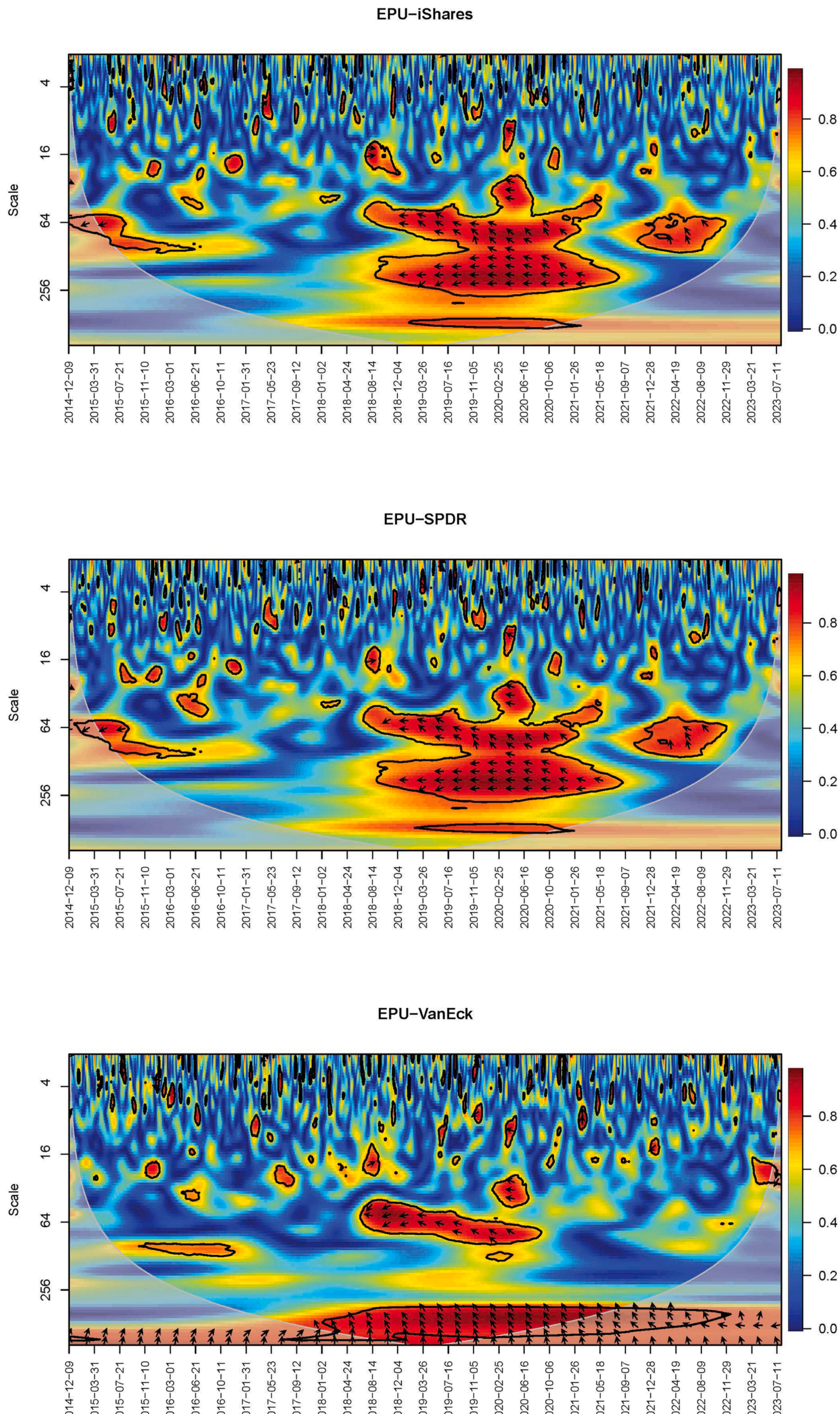


**Fig. 2.** Wavelet coherence output. The horizontal axis shows time, while the vertical axis shows the period in days.

### 3.4. *Time series dynamics of the co-movement*

Using both the wavelet coherence and DCC GARCH, we can get the time series estimate of the dynamic correlation between one of the

**Table 2**
Coefficient estimates of multivariate DCC GARCH.

| | | EPU | | |
|---|---|---|---|---|
| | | Coefficient | St. Deviation | $\alpha+\beta$ |
| iShares | $\alpha_{DCC}$ | 0.015939 | 0.015216 | |
| | $\beta_{DCC}$ | 0.768713 | 0.174153 | 0.784652 |
| | Log. Likelihood | 5947.785 | | |
| SPDR | $\alpha_{DCC}$ | 0.044502 | 0.045100 | |
| | $\beta_{DCC}$ | 0.000001 | 0.657700 | 0.044503 |
| | Log. Likelihood | 5889.96 | | |
| VanEck | $\alpha_{DCC}$ | 0.000000 | 0.000031 | |
| | $\beta_{DCC}$ | 0.917863 | 0.080201 | 0.917863 |
| | Log. Likelihood | 4843.10 | | |

carbon ETF indices and the EPU index.[5] The time series of the dynamic correlations are shown in Fig. 3. The unconditional correlations as well as the average value of the dynamic correlation from wavelet coherence and DCC GARCH are summarized in Table 3. The unconditional correlations are higher than the average conditional correlations from both wavelet coherence and DCC GARCH for all pairs considered. Furthermore, the average dynamic (i.e., conditional) correlations are higher for the DCC GARCH model compared to the wavelet coherence. This is also clear from Fig. 3 where both dynamic correlation series fluctuate but the one from the DCC GARCH is higher than that from the wavelet coherence on the average.

### 3.5. Robustness analysis

Table 4 represent the results of a volatility spillover analysis among four indices in our study: iShares, SPDR, VanEck, and EPU. This analysis is used to understand how fluctuations (volatility) in one market or asset can influence others. It is employed in present research as robustness check and complementary analysis to our Wavelet coherence and DCC GARCH results.

Diagonal values (41.89 for iShares, 42.8 for SPDR, 47.37 for VanEck, and 91.57 for EPU) represent the percentage of volatility that is self-attributed or the contribution of each index to its own volatility. For example, EPU has the highest self-contribution at 91.57%, meaning its volatility is mostly generated internally. The off-diagonal elements show the directional spillover effects from one index to another. For example, iShares contributes 31.44% to SPDR's volatility and 25.22% to VanEck's. Similarly, SPDR contributes 33.66% to iShares's volatility. The "FROM" row shows the total contribution of each index to the others. For instance, iShares has a total outwards spillover of 58.11%, indicating it influences the other indices' volatility by this proportion. The "TO" column represents the total incoming spillover to each index from the others. For example, the total incoming volatility spillover to iShares is 64.82%. "Inc.Own" refers to the total connectedness index (TCI) or the sum of inward and self-contributions to volatility. It essentially shows how much of the volatility is accounted for within this network for each index. The "NET" row shows the net spillovers, calculated as the difference between the "TO" and "FROM" values. Positive values indicate a net receiver of volatility, while negative values suggest a net contributor. For example, iShares is a net receiver with a value of 6.7, while VanEck is a net contributor with −2.21.

Fig. 4 shows the "TO" values from the spillover connectedness analysis across four indices in our study over a period stretching from September 9, 2015, to August 1, 2023. These "TO" values represent the total incoming volatility spillover that each of these indices receives from the others. The "TO" values change over time for each index, indicating that the interconnectedness and the impact of volatility spillovers among these indices vary across the observed period. iShares and VanEck seem to exhibit higher "TO" values on average, suggesting that they are more influenced by or more receptive to volatility spillovers from the other entities. This could imply that their market behaviors or performances are more significantly affected by external factors within this network. SPDR, while also receiving a considerable amount of spillover, tends to have lower "TO" values compared to iShares and VanEck, indicating a relatively lesser degree of incoming volatility from the others. EPU shows significantly lower "TO" values throughout the period, highlighting its minimal incoming spillover from the others.

Fig. 5 shows the "FROM" values from the connectedness analysis. These values represent the total outgoing volatility spillover that each index contributes to the others. iShares, SPDR, and VanEck have relatively high "FROM" values throughout the period, indicating that they are significant contributors to the volatility experienced by the other indices. Their contributions to the network's volatility suggest that fluctuations in their markets or performances can have notable impacts on the others. EPU shows consistently lower "FROM" values compared to the other three indices. This indicates that EPU contributes less to the volatility of the others, which aligns with its earlier observed lower receptiveness to incoming spillovers ("TO" values).

Fig. 6 from our spillover connectedness analysis, indicate the net effect of volatility spillovers for each index—essentially, the difference between the total incoming (TO) and outgoing (FROM) spillover effects. An index with a positive NET value is a net receiver of volatility spillover, meaning it is more influenced by the volatility of other indices than it influences them. This could be interpreted as the index being more vulnerable to external shocks or market movements. An index with a negative NET value is a net contributor of volatility spillover, indicating it influences the volatility of other indices more than it is influenced by them. This might suggest that the index is a key driver of market dynamics within this network.

iShares mostly shows positive NET values, indicating it often acts as a net receiver of volatility. This suggests that iShares' volatility is significantly influenced by the spillovers from other entities in the network. SPDR experiences fluctuations between positive and negative NET values over time, indicating its role as both a net receiver and a net contributor of volatility varies across the observed period. VanEck also fluctuates between being a net receiver and a net contributor, similar to SPDR, but with a tendency to have positive NET values, especially towards the latter part of the dataset, suggesting a shift towards being more influenced by others' volatility. EPU consistently shows negative NET values, clearly identifying it as a net contributor of volatility spillover. Despite its overall lower connectedness (as inferred from TO and FROM values), when EPU does influence others, it tends to contribute more volatility than it receives.

The "NPDC" values from spillover connectedness analysis are presented in Fig. 7 and shows pairwise net directional spillovers among four indices. These values represent the net effect of volatility spillovers from one index to another, subtracting the influence they receive in return. A positive value indicates a net spillover from the first index to the second index, while a negative value indicates the opposite. Values close to zero indicate a balanced exchange of volatility between the entities on that date. The fluctuating positive and negative values across different dates highlight the dynamic nature of volatility spillover among these indices. Their roles as net receivers or contributors of volatility can change over time due to varying market conditions, economic events, or changes in investor behavior.

## 4. Discussions

The application of wavelet coherence reveals nuanced correlations between the carbon ETFs and EPU, varying over time and frequency.

[5] In fact, the wavelet coherence allows us to estimate the correlation over time as well as over different frequencies (i.e., scales). Therefore, to get the estimate of correlation over time, we average the correlations over different frequencies. This allows us to compare the dynamic correlation from wavelet coherence with that from the DCC GARCH.

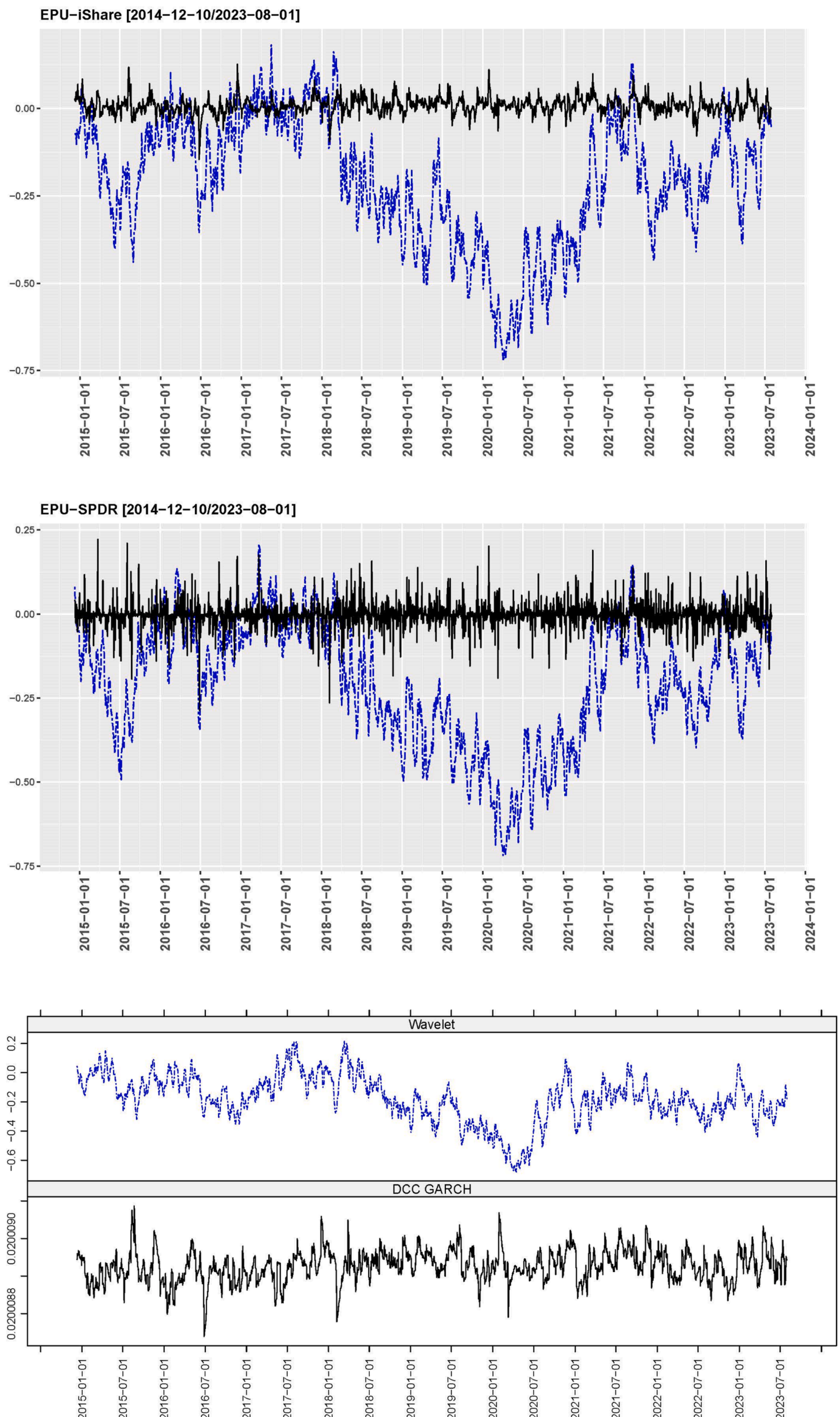


**Fig. 3.** Comparison of correlations between the DCC GARCH (black line) and dynamic correlations from the wavelet coherence (blue line).

This method, grounded in the work of Vacha and Barunik (2012), showcases how correlations between financial time series evolve, providing a richer understanding of market dynamics than traditional methods. Particularly, the distinct correlation patterns between iShares, SPDR, and EPU, as opposed to VanEck, highlight differential sensitivities to economic policy uncertainty, suggesting varying investor perceptions and reactions within the low-carbon investment sphere. Our results are in line with the work of Ren et al. (2022) who quantified the

**Table 3**
Comparison of correlation coefficients by DCC GARCH and mean value of correlations obtained from Wavelet coherence analysis.

| | | EPU |
|---|---|---|
| iShare | Unconditional | -0.001825 |
| | DCC | 0.008446 |
| | WTC | −0.208743 |
| SPDR | Unconditional | −0.007050 |
| | DCC | −0.002113 |
| | WTC | −0.212375 |
| VanEck | Unconditional | 0.010822 |
| | DCC | 0.020009 |
| | WTC | −0.177656 |

**Table 4**
Volatility spillover results of connectedness analysis.

| | iShares | SPDR | VanEck | EPU | FROM |
|---|---|---|---|---|---|
| iShares | 41.89 | 31.44 | 25.22 | 1.46 | 58.11 |
| SPDR | 33.66 | 42.8 | 22.11 | 1.42 | 57.2 |
| VanEck | 28.14 | 22.99 | 47.37 | 1.5 | 52.63 |
| EPU | 3.02 | 2.33 | 3.09 | 91.57 | 8.43 |
| TO | 64.82 | 56.76 | 50.42 | 4.38 | 176.37 |
| Inc.Own | 106.7 | 99.56 | 97.79 | 95.95 | cTCI/TCI |
| NET | 6.7 | −0.44 | −2.21 | −4.05 | 58.79/44.09 |
| NPT | 3 | 2 | 1 | 0 | |

interrelationship between the carbon futures and green bond markets and Cao and Xu (2016) investigate the nonlinear structure between carbon and energy markets by employing the wavelet transform.

The DCC GARCH model results reveal a mean-reverting dynamic correlation, indicating that despite short-term fluctuations, correlations between the ETFs and EPU tend to stabilize over the long term. This finding supports Engle's (2002) discussion on the mean-reverting nature of financial time series correlations and enriches our understanding of how economic policy uncertainty impacts market behaviors over different time horizons. The results also support the studies by Zhang et al. (2022) and Balcılar et al. (2016) who used DCC GARCH to analyze the volatility spillover between Carbon market and other financial markets.

Our findings from the volatility spillover analysis, employing methodologies akin to Diebold and Yilmaz (2012), highlight iShares as a predominant net receiver of volatility. This indicates its higher susceptibility to market-wide shocks, a phenomenon well-documented in the literature on financial market reactions to information flow and policy changes (Baker et al., 2016). Conversely, EPU's role as a net contributor reinforces the significant impact of policy uncertainty on market dynamics, echoing the broader implications of economic policy on financial markets (Bekaert et al., 2013). Connectedness analysis is recently used by Çelik et al. (2022) on clean energy ETFs who indicate this estimator based on the range is much less noisy than squared returns.

By juxtaposing the outcomes from DCC GARCH and wavelet coherence with those from the volatility spillover analysis, our study presents a comprehensive view of the interactions between economic policy uncertainty and low-carbon ETFs. This comparative approach not only underscores the dynamic and multifaceted nature of these relationships but also bridges our empirical findings with the theoretical frameworks proposed by Pastor and Veronesi (2012) on policy uncertainty and asset prices. Our research extends the narrative on the influence of economic policy uncertainty on financial markets, situating low-carbon ETFs within the ongoing discourse on sustainable investing and climate risk (Krueger et al., 2018). The nuanced insights into volatility transmission and correlation dynamics contribute to a deeper understanding of how policy-driven uncertainty shapes the evolving landscape of sustainable finance.

## 5. Conclusion

The study conducted a comprehensive analysis of the relationship between economic policy uncertainty (EPU) and the carbon exchange-traded funds (ETF) market. Utilizing a novel approach that combines wavelet coherence and dynamic conditional correlation (DCC) from a multivariate GARCH model, we gained insights into the time-varying correlations between these two variables.

Our findings indicate a significant negative correlation between EPU and carbon ETFs across most times and frequencies. However, this relationship varies, becoming insignificant at certain times and

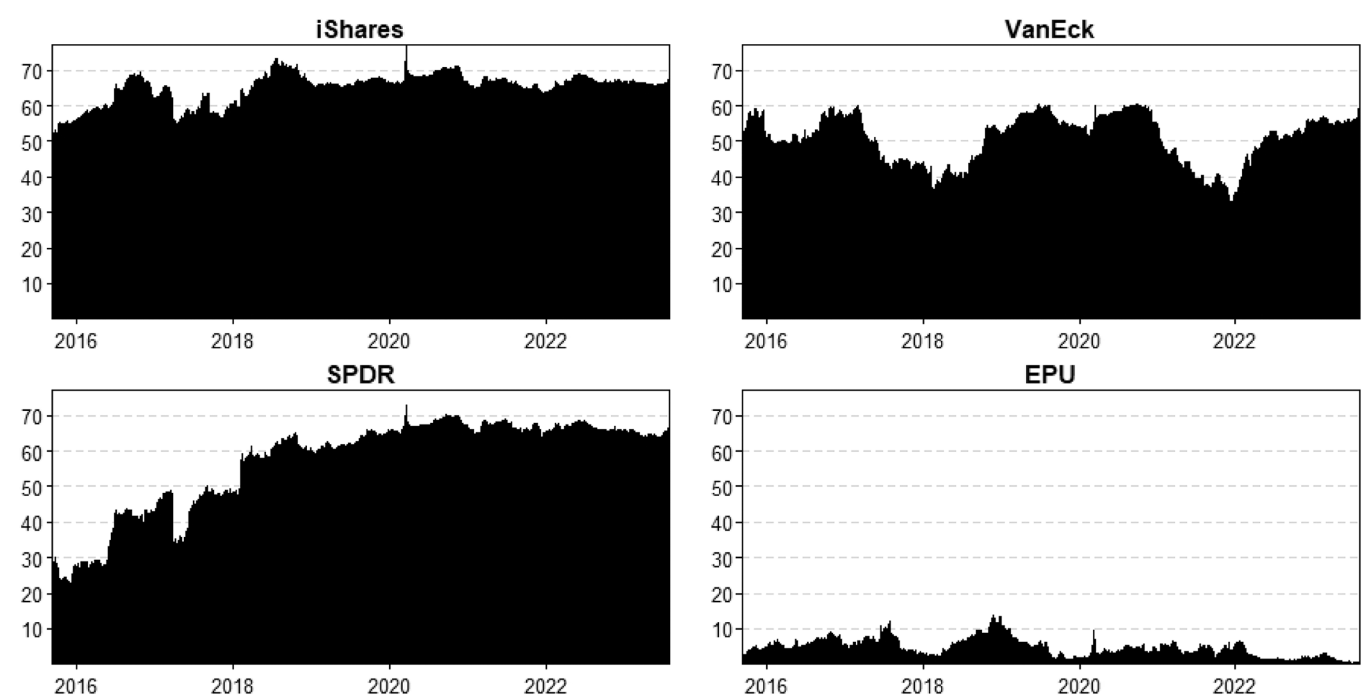


**Fig. 4.** Directional volatility spillovers, TO indices.

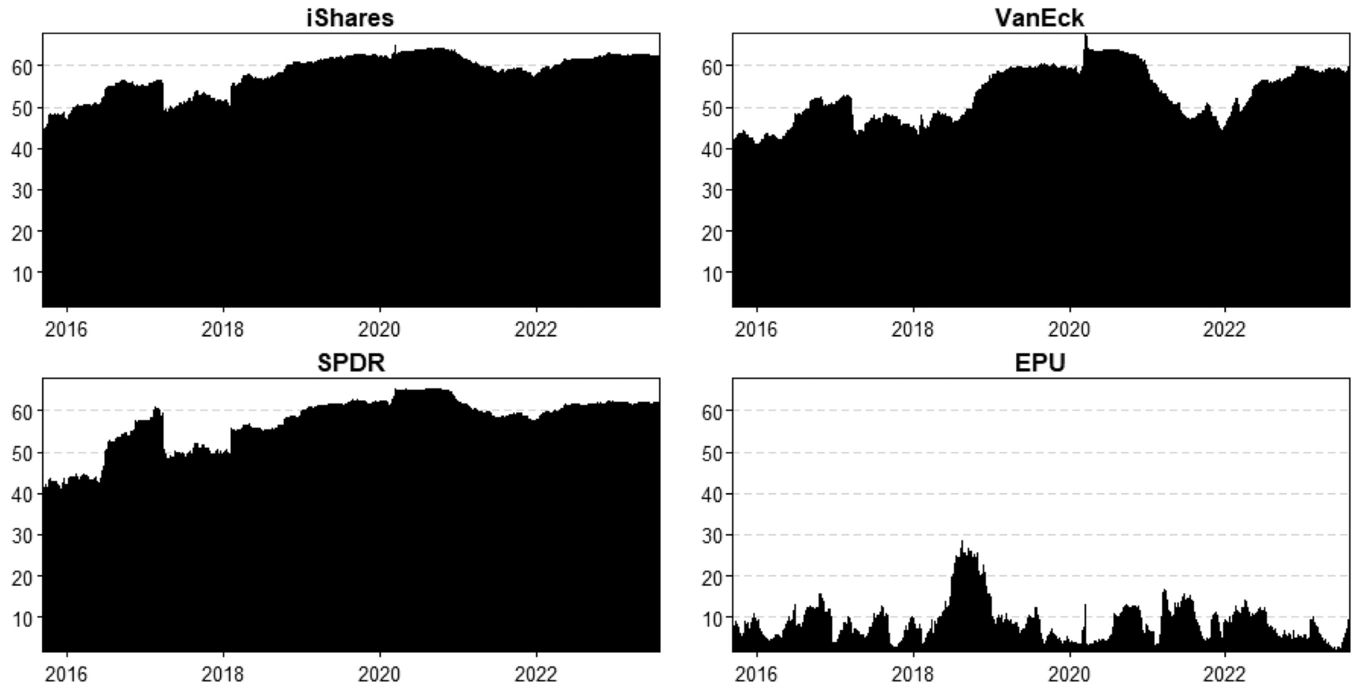


**Fig. 5.** Directional volatility spillovers, FROM indices.

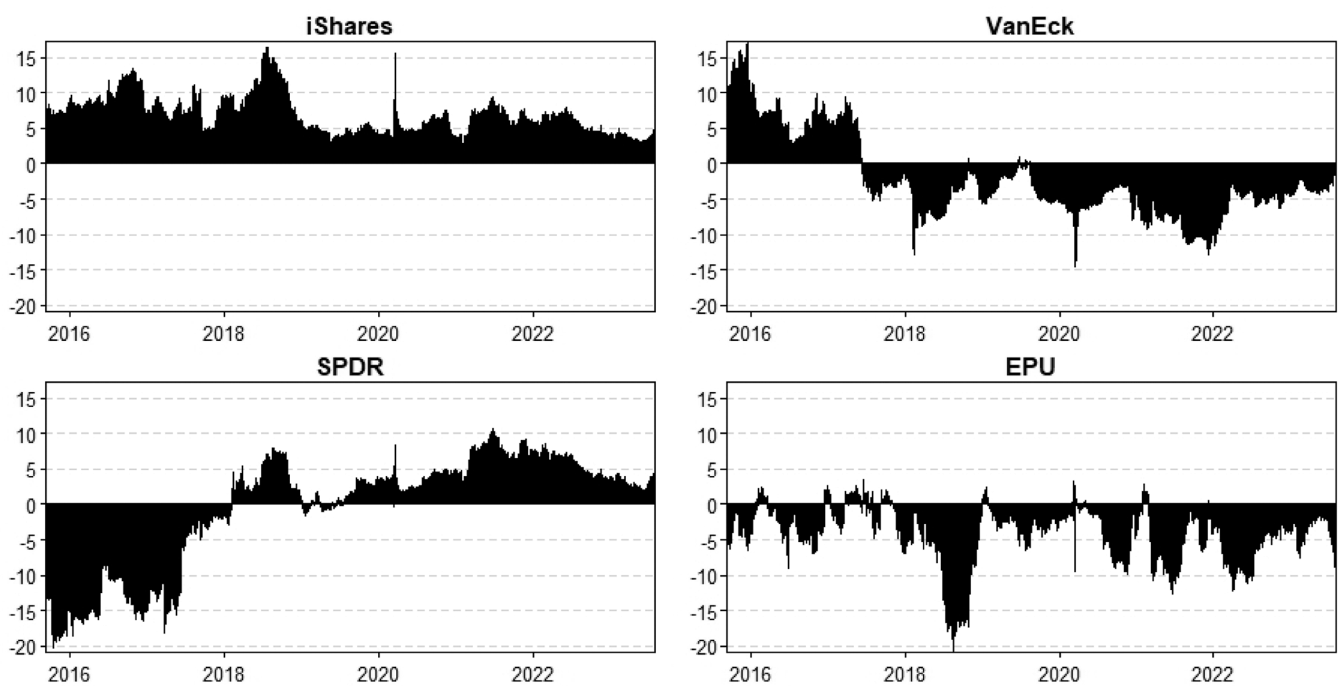


**Fig. 6.** Net volatility spillovers.

frequencies. Notably, our analysis reveals that EPU sometimes leads the ETFs, and at other times, ETFs lead the EPU. These dynamics are essential for stakeholders involved in sustainable investment and climate change mitigation.

This study contributes to the literature by illuminating the complex and dynamic relationship between economic policy uncertainty and the carbon ETF market. By employing advanced econometric techniques, we offer a nuanced understanding of how these variables interact over time and across different frequencies, thus filling a gap in existing research. Investors can use the insights from this study to better manage risks associated with economic policy changes. Understanding the times and frequencies where EPU significantly impacts carbon ETFs can inform investment strategies, such as hedging or adjusting portfolio allocations to mitigate potential losses. By recognizing periods when EPU leads the market, investors can anticipate market movements and adjust their strategies accordingly. This proactive approach can enhance investment returns and contribute to more stable portfolio performance.

The findings suggest that economic policy uncertainty significantly affects the carbon ETF market. Policymakers should consider the market implications of their decisions and strive for clearer, more predictable

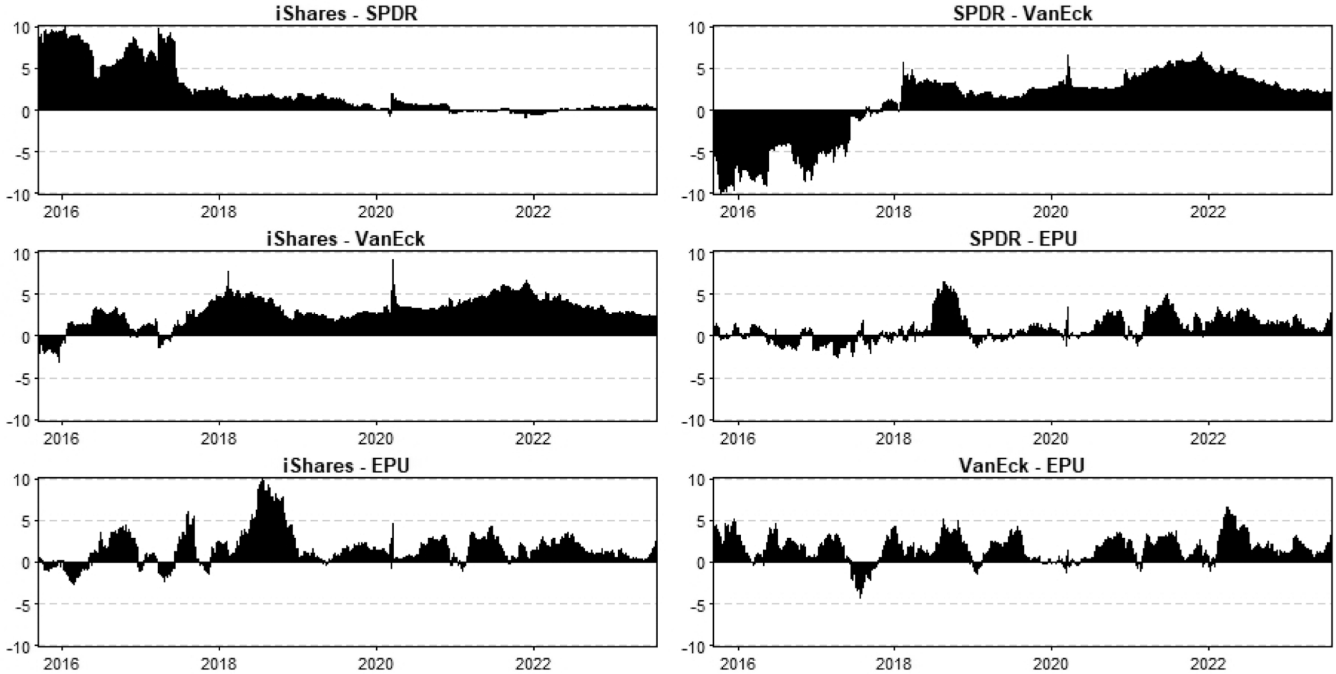


**Fig. 7.** Net pairwise volatility spillovers.

policy frameworks to reduce uncertainty and foster a more stable investment environment. By understanding the relationship between policy uncertainty and market performance, policymakers can design regulations and incentives that promote investment in carbon ETFs, thereby supporting sustainable finance initiatives and climate change mitigation efforts. Regulators can use these insights to monitor the impact of economic policies on the carbon ETF market and implement measures to enhance market stability. This might include creating safeguards against market volatility induced by policy uncertainty. Clear communication and guidance regarding policy changes can help mitigate the adverse effects of uncertainty on the market. Regulators can work towards improving transparency and predictability in economic policy to support investor confidence.

The study acknowledges several limitations. Firstly, data availability was restricted, potentially impacting the comprehensiveness of the analysis. Secondly, the fast-changing nature of economic policies poses challenges for accurately predicting future trends based on historical data. Lastly, the carbon ETF market is relatively new, meaning the findings may not fully capture its complexities and evolving nature.

For future research, it is recommended to extend the study to include a broader dataset, encompassing different regions and time frames, to validate and enhance the current findings. Future studies could also explore the impact of specific policy changes on the carbon ETF market, providing more nuanced insights into the relationship between policy decisions and market dynamics. As the carbon ETF market matures, revisiting this study will be beneficial to understand how the market dynamics evolve over time and in response to global economic and environmental changes, particularly considering factors such as climate policy uncertainty as indicated in recent studies (Siddique et al., 2023).

## CRediT authorship contribution statement

**Keshab Shrestha:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Data curation. **Babak Naysary:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

## Declaration of Competing Interest

Authors have no competing interests to declare.

## Data availability

Data will be made available on request.

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