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Volatility spillovers and conditional correlations between oil, renewables and stock markets: A multivariate GARCH-in-mean analysis

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ABSTRACT

We investigate linkages between three different markets: renewable energy (represented by a range of renewable energy ETFs); traditional energy (represented by crude oil ETF); and common stocks (represented by the S&P 500 Index ETF). We use daily data from 2008 to 2021. The econometric framework adopted is the VARMA-DCC-GARCH-in-mean model. We find that this framework is ideal because it allows us to identify the impact of uncertainty in one market on returns in another market, and also volatility spillovers, that is, the phenomenon of high uncertainty in one market spreading to other markets. Our key findings are as follows. Stock-market uncertainty influences traditional energy (negatively) and renewable energy (positively) at the mean level. Stock market volatility has a positive spillover effect on both conventional and renewable energies in the short-run, but these spillover effects are negative in the long-run. Our estimates of the time-paths of dynamic conditional correlations provide evidence that the renewable market is more heavily "financialized" than the traditional energy market, and moreover that the strong financialization of renewables is robust to financial crises.

1. Introduction

Over the coming decades, climate change has progressively influenced the human living environment and significantly impacted activities in financial markets. Energy transition plays a significant role as an effective strategy for mitigating climate change by decarbonizing the energy sector. Renewable energy sources, including water, wind, solar, and nuclear power, have been altering the dominance of fossil fuel-based energy sources in the overall economy. The energy sector is undergoing a significant transformation with the increasing integration of renewable energy sources. This shift is reshaping financial markets, particularly the interactions between renewable energy assets, traditional energy assets, and common stock markets. Understanding these linkages is vital for investors, policymakers, and stakeholders to navigate the evolving energy landscape.

Energy markets have a profoundly significant impact on the global economy. Energy prices, particularly oil prices, significantly influence economic performance, individual industries, and consequently, stock markets. While previous studies have examined the connections between energy markets and stock markets [1–3], there is a paucity of research addressing the dynamics between the stock market and traditional energy differ from those in renewable energy. This paper aims to fill this gap by investigating volatility spillovers and conditional correlations between the renewable energy ETF, crude oil ETF, and the S&P 500 Index ETF. Specifically, we aim to analyse the extent of volatility transmission among these markets, determine the impact of stock market uncertainty on traditional and renewable energy sectors, and assess the financialization robustness of renewable energy in different market conditions, including financial crises.

This paper is motivated by an important recent change to the energy mix: the rapid growth of renewable energy sources. This change is mainly driven by rising prices of traditional energy, and also as a response to the growing threat of climate change. According to the US Energy Information Administration (EIA) reports, the supply of renewable energy has increased by 90% since 2000 and by 42% since 2010, making it the fastest-growing energy source in the United States. International investment in renewable energy sources increased to US$755 billion in 2021, more than 23 times the US$32.2 billion seen in 2004. The consumption of renewable energy in the USA has doubled between 2000 and 2017, and in 2017 renewable energy accounted for 11% of total energy consumption in the U.S..[1]

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Given the growing importance of renewables, it is natural to consider whether the linkages found between traditional energy and stocks, surveyed briefly in the next section, also appear between renewables and stocks. There is a large number of researchers who find evidence of the impact of the oil price on the stock prices of alternative energies, such as, Henriques and Sadorsky [4], Sadorsky [5], Bondia et al. [6]. As previously discussed, the growing importance of new energy sources prompts us to ask what is the relationship between stocks and them.

To give a complete and detailed answer, we break new ground by separately considering the following different types of renewable energy: water; wind; solar; nuclear; and "benchmark". Each market will be represented by daily returns on appropriately chosen Exchange Traded Funds (ETFs). The renewable energy market will be represented by one of the renewable energy ETF returns, the traditional energy market by the crude oil ETF return, and the stock market by the S&P 500 Index ETF return. We will use daily data on these ETF returns from 2008 to 2021. Our principal reason for using ETFs is that they provide a source of data on renewable energy prices, separately for the range of renewable energy sources listed above. This enables us to extend previous work by considering these energy sources separately, rather than using a single measure representing the entire renewable energy market.[2] Another feature of ETFs that makes them desirable for this sort of analysis is that they are highly liquid, as a consequence of their ease of trading, low management fees, and tax efficiency. Hence ETF prices are highly responsive to market conditions and therefore ideal for this sort of modelling. Further, ETFs are applicable tools to construct optimal portfolios by applying the empirical results from this paper.

We set out to identify the linkages at broadly two different levels: the impact of uncertainty in one market on returns in another market; and the impact of uncertainty in the first market on uncertainty in the second. We will refer to the former type of linkage as the "GARCH-in-mean effect", and the latter as a "volatility spillover" [8]. As an econometric framework, we adopt the VARMA-DCC-GARCH-in-mean model, because it captures both types of linkage. Another advantage of this approach is that it makes no prior assumptions regarding directions of causality: shocks can take effect in either direction or in both directions. Bauwens et al. [9] provides a useful survey of this and related models. Based on this analysis, useful insights are provided, such as portfolio strategies for investors and policy suggestions for authorities. In addition to the DCC-GARCH family model, other approaches, such as the volatility spillover methodology proposed by Diebold and Yilmaz [10], have been widely used in the literature. This framework uses forecast-error variance decomposition to measure total and directional spillovers and has been applied in various contexts (e.g., [11]). Compared with those models, the DCC-GARCH family model offers time-varying conditional correlations, allowing for a more granular analysis of how spillovers evolve over time, particularly during periods of market turbulence. Additionally, the DCC framework directly informs portfolio construction through optimal hedge ratios, an essential component of our study.

Another important question that can be addressed in our framework is how renewable energy stocks are perceived by investors. The results of both Henriques and Sadorsky [4] and Bondia et al. [6] indicate that investors perceive renewable energy companies similarly to high-technology companies, and this is explained in terms of the development of renewable energy being heavily reliant on scientific advances. This concept of investor perception relates closely to the more general phenomenon of financialization [12]. Financialization of a commodity is said to occur when a commodity gains the exposure of a wide set of financial players with no physical interest in the commodity, such as hedge funds, pension funds, insurance companies and retail investors. There is evidence that the financialization of oil has increased in recent years [13]. This paper is the first to expose renewable energies showing strong financialization characteristics. A further advantage of the VARMA-DCC-GARCH-in-mean framework adopted in this paper is that it not only provides an estimate of the degree of financialization but also shows how the degree of financialization has evolved over time.

Due to the innovative introduction of volatility in the return equations, the first contribution of this paper is that: this research employs multivariate GARCH class models to reveal time-varying relationships and volatility dynamics, offering a more nuanced understanding of market interdependencies compared to static analyses. The use of the CCC-VARMA-GARCH-in-mean and DCC-VARMA-GARCH-in-mean models allows us to explore GARCH-in-mean effects and volatility spillovers simultaneously, and also, in the DCC case, the dynamic conditional correlations. Estimation of the dynamic conditional correlation is useful in many ways, notably that it provides a formula for optimal hedge ratios, and informs optimal portfolio construction [14,15]. This paper provides clues for portfolio construction using a blend of non-renewable and renewable energies. So, the findings of this paper offer guidance on portfolio construction and hedging strategies involving traditional and renewable energy assets.

We also contribute to the literature by considering several different types of renewable energy (water, wind, solar, nuclear, and a benchmark) and the use of ETFs to represent those renewable energy sources provides granular insights into how specific types of renewable energy interact with traditional energy and stock markets. Finally, the results provide valuable insights for policymakers on the interconnectedness of energy markets and stock markets, especially under different market conditions and during crises.

Within our chosen econometric framework to serve investors and policymakers, we set out to address the following research questions. It provides useful insights for practitioners and academics.

Q1: What are the linkages between energy prices (both traditional energy and different types of renewable energy) and stock prices?

Q2: Which of traditional and renewable energy is more closely linked to the stock market?

Q3: Are the linkages different at times of financial crisis or other types of crisis?

Q4: Has the linkage between oil and S&P 500 changed over the last decade in which the role of the U.S. has changed from oil importer to oil exporter?

The remainder of this article is organized as follows: Section 2 provides a brief survey of the literature covering empirical models of linkages between energy markets and stock markets. Section 3 describes the data set and variables used in the empirical analysis. Section 4 outlines the methodology, covering the three different multivariate GARCH-in-mean specifications that are applied. Section 5 presents the empirical results. Finally, some conclusions and suggestions for further research are provided in Section 6.

2. Literature review

As mentioned in the Introduction, there is already a large literature that explores the linkages between the energy market and stock markets [1–3]. However, there appears to be little consensus on the precise nature of these linkages. Some researchers have found a clear negative association between the oil price and stock prices [16,17]. Others find no association [18], and some even find a positive association [19].

Various reasons for the differences in results have been advanced. Kilian and Park [20] explain the differences in terms of the nature of the oil shock in question. A positive demand shock is likely to cause an increase in the oil price, but this kind of shock is likely to be associated with a favourable economic outlook, and hence is likely to have a positive effect on stock prices. In contrast, a negative supply

[2] Examples of studies using a single measure to represent the market for renewables are Sadorsky [5] and Henriques and Sadorsky [4] who use the WilderHill Clean Energy Index, Bondia et al. [6] who use WilderHill New Energy Global Index, and Wen et al. [7] who use China's New Energy index.

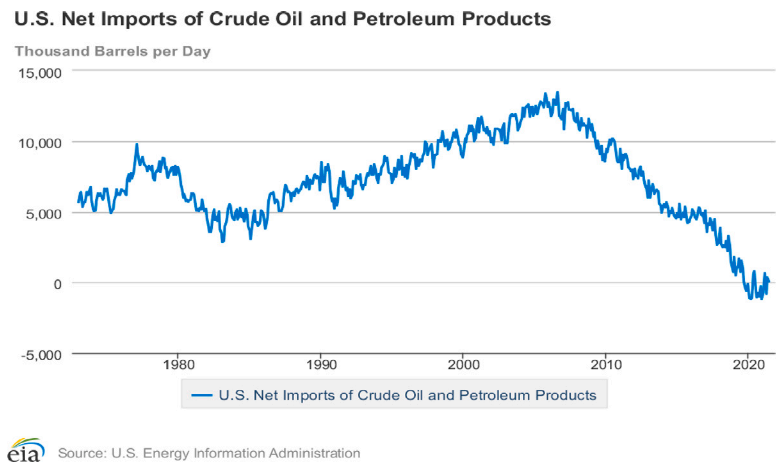

Fig. 1. U.S. net imports of crude oil and petroleum products.

shock, while also likely to cause an increase in the oil price, is likely to bring about a dampening of company cash flows and hence a fall in stock prices. Moreover, the relative importance of demand and supply shocks evolves over time, so any relationship estimated in a regression framework is likely to be unstable over time [17].

Another possible reason why results are mixed is that the measure of stock prices typically used is a stock market index. This clearly conceals any between-sector differences in responses to oil shocks. Oberndorfer [19] and Arouri and Nguyen [21] both find that sectors such as Oil and Gas react positively to oil price increases, while sectors such as Food and Beverages react negatively.

Park and Ratti [22] explain differences in terms of whether the economy in question is a net exporter or a net importer of oil, finding in particular that Norway, as a net oil exporter, is alone among European countries in showing a significantly positive response of stock returns to an oil price increase. This is important in the US context because in 2018 the USA changed from being a net importer to a net exporter of oil (see Fig. 1).

Yet another reason for differences in findings is that linkages have been analysed at different levels. For example, it is possible to analyse the impact of oil price uncertainty, rather than the impact of the oil price itself, on stock prices. Alsalman [23] pursued this objective using the bivariate GARCH-in-mean VAR model. Her main finding is that oil price uncertainty has no significant effect on stock prices and she interprets this in terms of companies being able to transfer higher costs to customers and also being able to hedge against fluctuations in oil prices. In contrast, Rahman and Serletis [24] use a similar specification to find evidence that oil price uncertainty is associated with a lower growth rate in the Canadian economy. Another level at which linkages have been found is that of volatility spillovers. Chang et al. [25] examine and confirm significant spillover effects in the natural gas spot, futures, and Exchange-Traded Fund (ETF) markets for both the USA and the UK. Interestingly, negative volatility spillovers between oil and stocks have been found by Arouri and Nguyen [21],Malik and Ewing [26],Chiou and Lee [27].

Another key feature of spillover effects is that they tend to change over time. In particular, the spillovers appear to grow in periods after crises. For example, Luo and Qin [28] find that crude oil volatility index (OVX) shocks have a significant and negative effect on Chinese stock returns, and that this effect became stronger after the global financial crisis. Awartani and Maghyereh [29] also find that dynamic spillover transmissions intensified following the financial turmoil of 2008. Zhu et al. [30] find weak dynamic dependence between crude oil prices and stock market returns, with the dependence rising markedly in the post-crisis period. Hassan et al. [31] find that the dynamic correlation between Islamic stocks and crude oil increased during the global financial crisis. Filis et al. [32] find that oil prices only have a positive impact on stock prices, but only during the global financial crisis.

There is a large amount of evidence of the impact of the oil price on the stock prices of alternative energies. For example, Henriques and Sadorsky [4] find that stock prices of alternative energy companies are impacted both by oil prices and by the prices of technology stocks. Sadorsky [5] finds that the linkage to technology stock prices is stronger than that to oil prices. Bondia et al. [6] obtain similar results and make the important distinction between short-run and long-run linkages, reporting that these linkages apply in the short run but not in the long run. Consistent findings also are confirmed by Reboredo et al. [33],Reboredo [34], and Wen et al. [7]. There is some evidence relating to the volatility transmission mechanism between crude oil and alternative energies. Wen et al. [7] document significant volatility spillovers between renewable energy (represented by China's new energy, NE, Index) and fossil fuel companies (represented by the coal and oil, CO, index).

3. Preliminary analysis

Our analysis is performed on daily price data on seven ETFs, listed as active in the US stock market (see Table 1). The sample period is from 27th June 2008 to 23rd June 2021, covering a total of 22,883 daily observations. Specifically, the dataset includes daily data points for the following variables: Crude Oil ETF, S& P 500 ETF, Water ETF, Wind ETF Solar ETF, Nuclear ETF, and Renewable Energy Benchmark ETF. This period covered for each variable corresponds to the data availability within this overall sample period. The choice of June 27, 2008, as the starting point for our research is motivated by its significance in global financial and energy markets. This period coincides with pivotal developments, including the continuous changes in market prices, returns and volatility due to the onset of the Global Financial Crisis, which had profound implications for stock markets, traditional energy markets, and the emerging renewable energy sector. By starting our analysis during this period, we aim to capture the dynamic relationships between these markets under conditions of heightened uncertainty and market stress. The data is extracted from Datastream, The seven price paths are presented in Fig. 2.

From each price series, p_t, continuously compounded daily return at time t is calculated by using formula (1):

$$y_t = ln\left(\frac{p_t}{p_{t-1}}\right) \tag{1}$$

Summary statistics of the return series are presented in Table 2. These provide evidence of both negative skewness and excess kurtosis. The excess kurtosis leads us to adopt the multivariate Student's t-distribution for the equation errors in the multivariate GARCH-in-mean model.

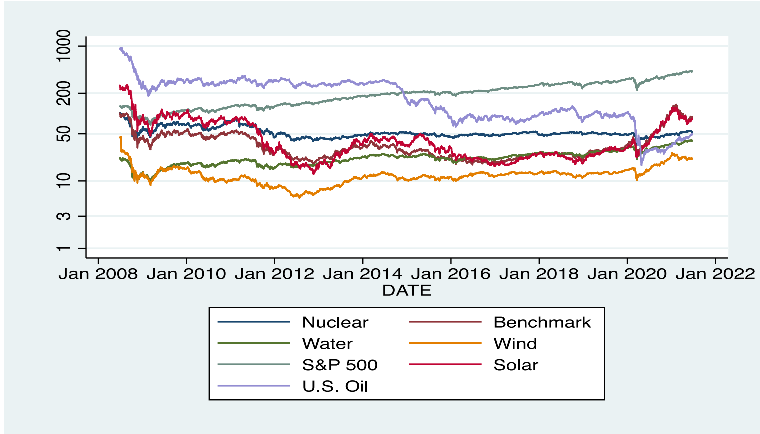

Fig. 2. ETF Price Plot ($); log-scale.

Table 1
ETF information.

Symbol	ETF name	ETF category	Asset class	Timespan begin	End	Frequency	Market	Currency
USO	United States Oil Fund	Crude Oil	Equity	27/06/2008	23/06/2021	Daily	United States	Dollar
SPY	SPDR S&P 500	S&P 500	Equity	27/06/2008	23/06/2021	Daily	United States	Dollar
PIO	Invesco Global Water	Water	Equity	27/06/2008	23/06/2021	Daily	United States	Dollar
FAN	First Trust Global Wind Energy	Wind	Equity	27/06/2008	23/06/2021	Daily	United States	Dollar
TAN	Invesco Solar	Solar	Equity	27/06/2008	23/06/2021	Daily	United States	Dollar
NLR	Vanv Uranium + Nuclear Energy	Nuclear	Equity	27/06/2008	23/06/2021	Daily	United States	Dollar
PBW	Wilderhill Clean Energy	Renewable Energy						
Benchmark	Equity	27/06/2008	23/06/2021	Daily	United States	Dollar		

Table 2
Summary statistics of return series.

	Nuclear	Benchmark	Water	Wind	S&P500	Solar	Oil
Mean	−0.0002	−0.00003	0.0002	−0.0002	0.0003	−0.0003	−0.0008
Min	−0.1407	−0.1563	−0.1151	−0.4917	−0.1158	−0.2077	−0.2918
Max	0.1211	0.1582	0.1754	0.1774	0.1355	0.1976	0.1541
S.D.	0.0154	0.0228	0.0147	0.0198	0.0131	0.0293	0.0245
Skewness	−1.0393	−0.4902	−0.2766	−4.9946	−0.4010	−0.4104	−1.2592
Kurtosis	16.2452	9.2094	16.9632	125.9921	17.9689	9.5386	18.9639
Observations	3,269	3,269	3,269	3,269	3,269	3,269	3,269

Fig. 3 shows the time paths of daily returns. Here, we see strong evidence of volatility clustering in all return series. Moreover, volatility clusters tend to occur contemporaneously for all series, notably between 2008 and 2009 (global financial crisis), between 2010 and 2012 (European debt crisis), and from 2020 onward (Covid-19 crisis). This provides a clear motivation for the adoption of the multivariate GARCH framework.

4. Methodology

In this section, we outline the three multivariate GARCH specifications: BEKK-GARCH; CCC-VARMA-GARCH; and DCC-VARMA-GARCH. Multivariate GARCH specifications typically consist of two components. One is for modelling the returns themselves, while the other models the variances and covariances of returns. This structure allows us to capture the dynamic relationships between multiple time series. In introducing the models it is therefore useful to consider these two components separately.

4.1. Specification of conditional mean

We first consider how volatility in one market might impact the return in the same market and other markets, known as GARCH-in-mean effects. Engle et al. [35] extended the original ARCH framework to allow the mean of a sequence to depend on its conditional variance.Bollerslev et al. [36] further extended the model to allow time-varying conditional variances of asset returns and a time-varying risk premium, thereby enriching asset pricing theory.

Several studies have introduced GARCH-in-mean errors into the structural vector autoregression (SVAR) framework, using a zero restriction to allow oil uncertainty to affect the output mean level but not vice versa [23,37–39]. We follow other researchers by including the variances of all returns in each mean equation [23,24,40–42]. Formally, the specification is:

$$\boldsymbol{y}_t = \boldsymbol{c} + \boldsymbol{\Gamma}^1 \boldsymbol{y}_{t-1} + \boldsymbol{\Gamma}^2 \boldsymbol{y}_{t-2} + \boldsymbol{\Gamma}^3 \boldsymbol{y}_{t-3} + \boldsymbol{\Psi} \boldsymbol{\Sigma}_{ii,t} + \boldsymbol{u}_t \tag{2}$$

$$\boldsymbol{u}_t = \boldsymbol{\sigma}_t \boldsymbol{v}_t, \quad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{I}_{\boldsymbol{N}}) \tag{3}$$

$$\boldsymbol{u}_t | \boldsymbol{F}_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_{u,t}) \tag{4}$$

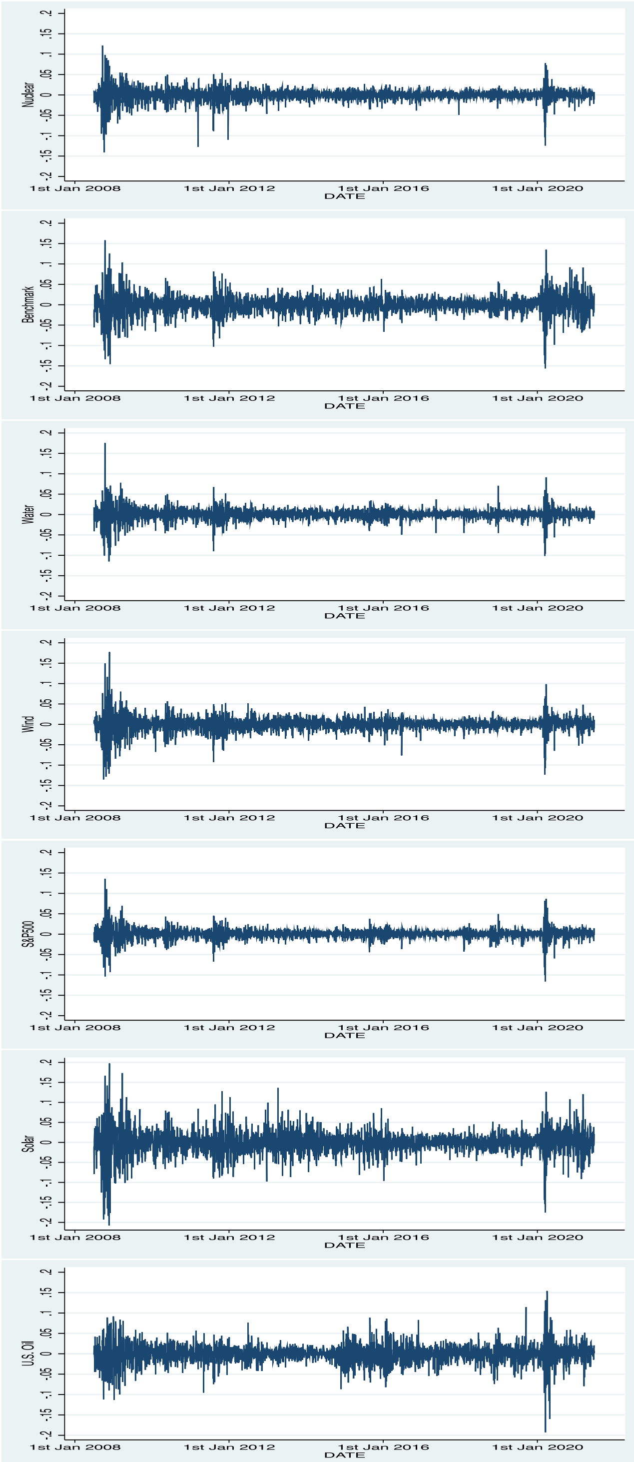

Fig. 3. Daily ETF Returns from 28th June 2008 to 23rd June 2021. From Top: Nuclear, Benchmark, Water, Wind, S&P 500, Solar, and U.S. Oil.

where, $\boldsymbol{F}_{t-1}$ denotes the available information set in period $t-1$, and $\mathbf{0}$ is a null vector. $\boldsymbol{I}_N$ is the identity matrix of order N.

Given the evidence from the Jarque–Bera normality test (see Table 2), we characterize the joint data generating process underlying returns as a trivariate GARCH-in-mean model within the errors from the multivariate Student's t-distribution. By assuming that the standardized errors $\boldsymbol{v}_t$ follow a multivariate Student's t-distribution with ν degrees of freedom, we are allowing for the fat tails seen in the data.

4.2. Specification of conditional variance

We use three different modelling approaches: the BEKK-GARCH model, the CCC-VARMA-GARCH model, and the DCC-VARMA-GARCH model.

The BEKK-GARCH model[3] was introduced by Engle and Kroner [44]. $\boldsymbol{C}^*$ is a lower-triangular $N \times N$ matrix. The ARCH and GARCH terms are formed by a sandwich product with the $N \times N$ matrices of coefficients $\boldsymbol{A}_i^*$ and $\boldsymbol{B}_j^*$ around the symmetric matrices $\boldsymbol{u}_{t-j}\boldsymbol{u}_{t-j}'$ and $\boldsymbol{\Sigma}_{u,t-j}$ respectively. In keeping with the literature, we define the premultiplying matrix as the transposed one:

$$\boldsymbol{\Sigma}_{u,t} = \boldsymbol{C}^*\boldsymbol{C}^{*\prime} + \sum_{j=1}^{p} \boldsymbol{A}_j^{*\prime}\boldsymbol{u}_{t-j}\boldsymbol{u}_{t-j}'\boldsymbol{A}_j^* + \sum_{j=1}^{q} \boldsymbol{B}_j^{*\prime}\boldsymbol{\Sigma}_{u,t-j}\boldsymbol{B}_j^* \tag{5}$$

The second and third of the models used here are variations on the VARMA-GARCH model proposed by Ling and McAleer [45]. In this framework, the conditional variances include not just their own lagged squared residuals and own variances, but all the other returns' lagged squared residuals and variances in each variance equation. The specification for the conditional variance is therefore:

$$\sigma_{ii,t}^2 = c_{ii} + \sum_{j=1}^{3} a_{ij}u_{j,t-1}^2 + \sum_{j=1}^{3} b_{ij}\sigma_{jj,t-1}^2 \tag{6}$$

where, a_{ij} (an ARCH term) is the parameter representing the effect of the lagged squared residual for variable j on the variance of variable i, while b_{ij} (a GARCH term) represents the effect of the lagged variance of variable j on the variance of variable i.

The CCC version of the VARMA-GARCH model, proposed by Bollerslev et al. [46], is the constant conditional correlation model. The DCC version of the model, proposed by Engle [47], is the dynamic conditional correlation model. As the names suggest, the DCC model is more flexible than the CCC model because the DCC form allows conditional correlations to be time-dependent. The capture of dynamic conditional correlations is essential for understanding the evolving relationships between these markets.

The CCC model may be defined in matrix notation as:

$$\boldsymbol{\Sigma}_{u,t} = \boldsymbol{D}_t\boldsymbol{R}\boldsymbol{D}_t, \quad \sigma_{ij,t}^2 = (\rho_{ij}\sigma_{ii,t}\sigma_{jj,t}) \tag{7}$$

$$\boldsymbol{D}_t = diag(\sigma_{11,t} \cdots \sigma_{NN,t}), \quad \boldsymbol{R} = \{\rho_{ij}\} \tag{8}$$

The DCC version of the VARMA-GARCH model, due to Engle (2002), is defined as:

$$\boldsymbol{\Sigma}_{u,t} = \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t \tag{9}$$

$$\boldsymbol{R}_t = diag(q_{11,t}^{-1/2} \cdots q_{NN,t}^{-1/2})\boldsymbol{Q}_t diag(q_{11,t}^{-1/2} \cdots q_{NN,t}^{-1/2}), \tag{10}$$

$$\boldsymbol{Q}_t = \{q_{ij,t}\} = (1-\alpha-\beta)\overline{\boldsymbol{Q}} + \alpha v_{t-1}v_{t-1}' + \beta\boldsymbol{Q}_{t-1} \tag{11}$$

$\boldsymbol{Q}_t$ is an $N \times N$ symmetric positive definite matrix. $\overline{\boldsymbol{Q}}$ is the $N \times N$ unconditional covariances matrix of v_t. α and β are nonnegative scalar parameter satisfying $\alpha + \beta < 1$.

The dynamic conditional correlation is given by:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{12}$$

The covariance $\sigma_{ij,t}^2$ is obtained using variances from the GARCH model and correlation ρ_{ij} given in (12). It is expressed as $\sigma_{ij,t}^2 = \frac{q_{ij,t}\sigma_{ii,t}\sigma_{jj,t}}{\sqrt{q_{ii,t}q_{jj,t}}}$.

We use four information criteria to select the best-fitting model: AIC, BIC, HQ, and FPE [48,49]. All criteria include penalty terms for the number of parameters in the estimated model (k). The four criteria are

[3] The acronym BEKK originates from Baba et al. [43], who developed an early version of this model.

Table 3
Information criteria.

	Water			Solar			Nuclear			Wind			Benchmark		
	BEKK	CCC	DCC	BEKK	CCC	DCC	BEKK	CCC	DCC	BEKK	CCC	DCC	BEKK	CCC	DCC
AIC	8.398	8.432	8.378	10.673	10.698	10.648	9.064	9.139	9.048	9.290	9.325	9.278	9.822	9.864	9.799
BIC	8.534	8.568	8.512	10.809	10.834	10.782	9.200	9.275	9.182	9.427	9.461	9.413	9.959	10.000	9.933
HQ	8.446	8.481	8.426	10.722	10.746	10.696	9.113	9.188	9.096	9.339	9.374	9.326	9.871	9.913	9.847
FPE	8.398	8.432	8.378	10.673	10.698	10.648	9.064	9.139	9.048	9.290	9.325	9.278	9.822	9.864	9.799

given by[4]:

$$AIC\ (Akaike\ Information\ Criterion) = -2logL + k \times 2 \tag{13}$$

$$BIC\ (Schwarz\ Bayesian\ Criterion) = -2logL + k \times logT \tag{14}$$

$$HQ\ (Hannan - Quinn) = -2logL + k \times 2log(logT) \tag{15}$$

$$FPE\ (log)\ (Final\ Prediction\ Error) = -2logL + Tlog(\frac{T+k}{T-k}) \tag{16}$$

where, k is the number of estimated parameters and T, is the number of observations. For any given criterion, the best model is the one for which the criterion is minimized.

The quasi-maximum likelihood method is applied in RATS[5] to estimate multivariate GARCH systems. The estimation for the CCC-GARCH and the DCC-GARCH adopted a two-stage approach. First, the parameters in the univariate GARCH model are estimated for each data series by replacing $\boldsymbol{R_t}$ with the identity matrix $\boldsymbol{I_n}$ in the likelihood function. In the second stage, the likelihood function above is applied to compute the rest parameters (ρij in CCC, α and β in DCC). When the errors are assumed to be Student's t-distributed, the first stage is the same as a normal distribution, which means assuming a univariate GARCH model following a normal distribution. Then in the second stage, ν, α, and β are estimated.

4.3. Methodology key points

To summarize the methodology of this study, it incorporates GARCH-in-mean effects in the conditional mean specification to capture how volatility impacts returns. For the conditional variance models, it employs BEKK-GARCH to ensure positive definiteness, CCC-VARMA-GARCH to assume constant correlations, and DCC-VARMA-GARCH to allow for time-varying correlations. A notable methodological innovation is the integration of multiple renewable energy types into the GARCH framework, which captures complex interdependencies among them.

5. Empirical results and discussion

In this section, we report the results from estimating the three models outlined in Section 4 using the data summarized in Section 3. Although we analyse return data from five different renewable energy types, we model the five series one at a time. Hence, each model contains three return variables: the return on *one* of the five renewable energy ETFs; the return on the S&P500 ETF; and the return on the oil ETF.

To compare the performance of the three models, we employ four different information criteria: AIC, BIC, HQ and FPE. These are reported for each estimated model in Table 3. By all criteria, the DCC-VARMA-GARCH-in-mean model outperforms the other models, followed by the BEKK-GARCH-in-mean model.

Table 4 shows, for each estimation, the empirical probability of a residual being in the left 0.05 tail. The values are all above 0.05, indicating that the model fits substantially better when applying the multivariate Student's t-distribution to model the errors compared with the Normally distributed errors. The shape parameter ν for the degree of the Student's t-distribution, listed in Table 4, suggests that the S&P 500 ETF has the fattest tail, similar to the WTI ETF, providing strong evidence to support the Student-t distribution as the optimal choice.

5.1. GARCH-in-mean effects

In Table 5 we report the GARCH-in-mean estimates. In the GARCH-in-mean specification, we allow the variances of three returns to enter each mean level. The three elements of Ψ represent the GARCH-in-mean effect of renewable energy, S&P 500, and oil. These parameters therefore capture the effects of uncertainty on returns. The purpose of the arrows appearing in the first column of Table 5 is to make it clear which variable's volatility is affecting which variable's return. For example, "Ren←Stock" represents the effect of S&P 500 volatility on the return on the renewable under consideration.

From Table 5, we see that the coefficient on the conditional variance of the S&P 500 in its return equation, ψ_{22}, estimated using the DCC-GARCH-in-mean model when the renewable is wind, is +0.0708 with a p-value of 0.012. This simply indicates that the S&P 500 volatility has a significant and positive effect on its return. Similarly positive and significant estimates of ψ_{22} are seen when the renewable is water and nuclear. These findings confirm the basic assumption underlying the Capital Asset Pricing Model (CAPM), which was introduced by Sharpe [50],Lintner [51]. The CAPM describes the relationship between risk and return. The positive estimates seen here confirm that investors, who are assumed to be risk averse, require a high return as compensation for bearing extra risk.

In Table 5, we also see that the coefficient on the conditional variance of the S&P 500 in the oil return equation, ψ_{32}, estimated using the DCC-GARCH-in-mean model when the renewable is Benchmark, is −0.1071 with a p-value of 0.003. Similar, negative GARCH-in-mean effects are seen when the renewable is solar or nuclear. These results are consistent with some previous literature (Arouri and Nguyen [21], Malik and Ewing [26],Chiou and Lee [27]) which finds that stock uncertainty has a significant and negative effect on oil derivative market performance.

The effect of stock uncertainty on nuclear and wind renewable energy returns (ψ_{12} in Table 5) is positive. Thus we arrive at the interesting result that stock uncertainty influences traditional energy and renewable energy in opposite directions. What we observed is that stock market uncertainty negatively affects traditional energy markets while positively influencing renewable energy markets, suggesting a differential impact based on energy type.

From the estimate of ψ_{21}, we see that the uncertainty of benchmark renewable energy has a significantly positive effect on stock return. However, there is no similar result for any of the other renewable energies. It is plausible the renewable energy benchmark ETF (symbol: PBW) takes the dominant role among renewable energy sources because PBW tracks an index (ECO) of a highly diverse range of underlying assets including wind, solar, biofuels, and geothermal energy-related companies.

[4] The Schwarz Bayesian Criterion is also called the Bayesian Information Criterion, BIC.

[5] Estima, 2022, Evanston, USA.

Table 4
Probability of a residual being in the left 0.05 tail.

	Water			Solar			Nuclear			Wind			Benchmark		
	BEKK	CCC	DCC	BEKK	CCC	DCC	BEKK	CCC	DCC	BEKK	CCC	DCC	BEKK	CCC	DCC
Renewable energy	0.064	0.065	0.060	0.059	0.060	0.056	0.061	0.067	0.061	0.063	0.067	0.058	0.066	0.069	0.062
Stock	0.068	0.071	0.065	0.066	0.070	0.064	0.066	0.071	0.631	0.066	0.072	0.062	0.069	0.070	0.065
WTI	0.068	0.071	0.065	0.065	0.070	0.064	0.066	0.071	0.631	0.066	0.072	0.062	0.069	0.070	0.065

Table 5
GARCH-in-mean coefficients Ψ estimation result.

	Water			Solar			Nuclear			Wind			Benchmark		
	BEKK	CCC	DCC	BEKK	CCC	DCC	BEKK	CCC	DCC	BEKK	CCC	DCC	BEKK	CCC	DCC
Ren←Ren(Ψ_{11})	0.0002	−0.0134	−0.0078	0.0002	−0.0119	−0.0039	0.0075	−0.0091	0.0085	−0.0180	−0.0371	−0.0169	0.0138	0.0193	0.0173
	(0.994)	(0.810)	(0.867)	(0.987)	(0.229)	(0.703)	(0.613)	(0.788)	(0.782)	(0.401)	(0.135)	(0.425)	(0.346)	(0.325)	(0.312)
Ren←Stock(Ψ_{12})	0.0285	0.0594	0.0419	0.0370	0.0637	0.0443	**0.0449**	0.0469	0.0307	**0.0565**	**0.0851**	0.0550	0.0274	0.0104	0.0107
	(0.520)	(0.366)	(0.448)	(0.308)	(0.126)	(0.314)	**(0.023)**	(0.194)	(0.369)	**(0.076)**	**(0.041)**	(0.121)	(0.481)	(0.825)	(0.806)
Ren←Oil(Ψ_{13})	−0.0144	−0.0002	−0.0015	0.0001	0.0022	−0.0002	−0.0051	−0.0028	−0.0047	−0.0015	−0.0004	−0.0020	−0.0035	−0.0004	−0.0019
	(0.698)	(0.960)	(0.627)	(0.980)	(0.765)	(0.979)	(0.101)	(0.401)	(0.261)	(0.741)	(0.920)	(0.599)	(0.527)	(0.940)	(0.807)
Stock←Ren(Ψ_{21})	−0.0255	−0.0510	−0.0357	0.0038	0.0014	0.0021	0.0024	−0.0049	0.0127	−0.0229	−0.0227	−0.0187	**0.0116**	**0.0136**	**0.0130**
	(0.491)	(0.316)	(0.401)	(0.322)	(0.722)	(0.625)	(0.839)	(0.831)	(0.547)	(0.147)	(0.217)	(0.259)	**(0.064)**	**(0.065)**	**(0.070)**
Stock←Stock(Ψ_{22})	**0.0730**	**0.1194**	**0.0899**	0.0245	0.0371	0.0304	**0.0396**	**0.0549**	0.0233	**0.0751**	**0.0833**	**0.0708**	0.0163	0.0124	0.0103
	(0.078)	**(0.053)**	**(0.078)**	(0.203)	(0.123)	(0.205)	**(0.045)**	**(0.067)**	(0.408)	**(0.006)**	**(0.008)**	**(0.012)**	(0.393)	(0.576)	(0.655)
Stock←Oil(Ψ_{23})	−0.0031	−0.0030	−0.0035	−0.0015	−0.0017	−0.0025	−0.0024	−0.0032	−0.0033	−0.0036	−0.0033	−0.0048	−0.0035	−0.0018	−0.0031
	(0.386)	(0.478)	(0.212)	(0.482)	(0.671)	(0.527)	(0.375)	(0.237)	(0.432)	(0.353)	(0.358)	(0.139)	(0.233)	(0.574)	(0.442)
Oil←Ren(Ψ_{31})	0.0708	−0.0035	0.0573	**0.0105**	0.0088	0.0093	**0.0634**	−0.0045	0.0425	0.0064	−0.0174	−0.0042	**0.0441**	**0.0483**	**0.0440**
	(0.113)	(0.971)	(0.443)	**(0.051)**	(0.152)	(0.142)	**(0.031)**	(0.929)	(0.348)	(0.833)	(0.618)	(0.895)	**(0.002)**	**(0.003)**	**(0.002)**
Oil←Stock(Ψ_{32})	−0.0857	−0.0216	−0.0811	**−0.0529**	**−0.0639**	**−0.0553**	**−0.0816**	−0.0349	−0.0730	−0.0205	−0.0058	−0.0082	**−0.0989**	**−0.1234**	**−0.1071**
	(0.116)	(0.861)	(0.395)	**(0.053)**	**(0.039)**	**(0.063)**	**(0.012)**	(0.550)	(0.160)	(0.642)	(0.926)	(0.881)	**(0.000)**	**(0.004)**	**(0.003)**
Oil←Oil(Ψ_{33})	0.0036	0.0080	0.0058	**0.0116**	0.0109	0.0102	0.0034	0.0079	0.0059	0.0028	0.0063	0.0033	0.0034	0.0056	0.0044
	(0.521)	(0.480)	(0.589)	**(0.028)**	(0.122)	(0.147)	(0.686)	(0.383)	(0.533)	(0.764)	(0.450)	(0.691)	(0.555)	(0.489)	(0.634)

GARCH-in-mean coefficients (estimates of Ψ in Equation(7)) with p-values in parentheses: The coefficients Ψ_{ij} represent the impact of the variable j's volatility on the variable i's mean. See Section 4.1 above for further details. The horizontal arrows appearing in the left-most column indicate the direction of each effect. "ren" (for "renewable") stands for the relevant renewable ETFs in each estimation, and this variable is shown in the top row. The boldface entries represent significant effects (p-value <0.1).

The estimates of ψ_{31} appearing in the benchmark column show that the benchmark renewable's volatility has a positive effect on the oil return. This result underscores the substitutive relationship between renewables and traditional energy sources. Our results align with Alsalman [23], who found that coal industry stock returns respond positively to oil price uncertainty.

5.2. Volatility spillovers

We present the volatility spillover results from the BEKK-GARCH model in Table 6 and those from the CCC and DCC models in Table 7. The reason why two different tables are required is that, as explained in the paragraph following 6 above, while in the BEKK-GARCH model the parameters a_{ij} and b_{ij} represent the volatility spillover from variable i to variable j, in the other two models these parameters represent the volatility spillover from j to i.

In line with standard GARCH models, the a parameters are interpreted in terms of the impact of new information on volatility, and the b parameters in terms of the persistence of volatility clusters. We first note that the diagonal terms a_{ii} and b_{ii} are interpreted in the same way as the ARCH and GARCH parameters, respectively, in a univariate GARCH model. Needless to say, these parameters are always estimated as positive and strongly significant. One point of note is that the BEKK-GARCH model tends to produce larger estimates of the a_{ii} parameters, and smaller estimates of the b_{ii} parameters, than the other two models.

Turning to the off-diagonal terms, we first note that the difference between the a_{ij} terms and the b_{ij} terms is that the former may be interpreted as short-run volatility spillovers, and the latter as long-run volatility spillovers. As with the interpretation of the GARCH-in-mean effects in Table 5 , we employ arrows in Tables 6 and 7 to make clear the direction of each volatility spillover.

Interestingly, we find that the long-run spillovers are sometimes of the opposite sign to the corresponding short-run spillover. Most obviously, the volatility spillover from S&P 500 to each renewable energy is strongly positive in the short-run, but strongly negative in the long-run. We further note that a similar pattern is seen in the volatility spillovers from S&P 500 to oil, although these spillovers are smaller in magnitude and sometimes insignificant. This difference provides evidence that the renewable ETFs are "financialized" to a greater extent than the oil ETF.

The positive short-run spillovers from the S&P 500 to renewable energy ETFs indicate that market-wide shocks are quickly transmitted to the renewable energy sector, suggesting a high degree of financial integration. This finding is critical for investors seeking diversification benefits, as it implies that renewable energy investments may not provide the desired insulation during periods of market stress. The observed long-run negative spillovers from the S&P 500 to renewable energy ETFs could be attributed to investor reallocation strategies, where market downturns prompt a shift from riskier renewable investments to more stable assets. This behaviour underscores the importance of understanding investor psychology in response to market fluctuations. The finding that volatility spillovers from the S&P 500 to renewable energy ETFs are stronger than to oil ETFs suggests that renewable energy markets are more susceptible to broader financial market conditions. This underscores the need for supportive policies that can mitigate the impact of financial market volatility on renewable energy investments.

5.3. Conditional correlations

Finally, we turn to the conditional correlation estimates. As explained in Section 4.2, the CCC model produces a single matrix of constant conditional correlations. These are reported in Table 8. All of the conditional correlations are positive and strongly significant. By far the highest conditional correlations are those between renewable energies and the S&P 500 (ρ_{21}). Of the renewables, the one with the highest conditional correlation to the S&P 500 is water (+0.8274). The conditional correlation coefficient of 0.8274 between the Water ETF and the S&P 500 indicates a strong co-movement, suggesting that a 1% increase in the S&P 500 is associated with an approximately 0.83% increase in the Water ETF. This high correlation suggests that investments in water-related renewable energy are closely tied to overall market

Table 6
BEKK-GARCH model volatility spillover coefficients estimation result.

	Water	Solar	Nuclear	Wind	Benchmark
Ren→Ren(a_{11})	**0.1617**	**0.1779**	**0.1516**	**0.1820**	**0.2039**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Ren→Stock(a_{12})	−0.0172	0.0091	−0.0179	0.0229	**0.0247**
	(0.504)	(0.276)	(0.111)	(0.200)	**(0.042)**
Ren→Oil(a_{13})	**−0.0953**	0.0054	**−0.0457**	−0.0294	0.0173
	(0.036)	(0.637)	**(0.071)**	(0.271)	(0.336)
Stock→Ren(a_{21})	**0.1821**	**0.2396**	**0.1297**	**0.1480**	**0.2008**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Stock→Stock(a_{22})	**0.3861**	**0.3787**	**0.3524**	**0.3487**	**0.3561**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Stock→Oil(a_{23})	**0.1381**	0.0243	0.0368	0.0689	0.0612
	(0.029)	(0.515)	(0.338)	(0.149)	(0.140)
Oil→Ren(a_{31})	−0.0128	**−0.0271**	**−0.0118**	−0.0146	−0.0140
	(0.128)	**(0.065)**	**(0.072)**	(0.119)	(0.283)
Oil→Stock(a_{32})	**−0.0175**	**−0.0148**	**−0.0152**	**−0.0196**	−0.0108
	(0.049)	**(0.057)**	**(0.045)**	**(0.032)**	(0.198)
Oil→Oil(a_{33})	**0.2470**	**0.2577**	**0.2566**	**0.2417**	**0.2565**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Ren→Ren(b_{11})	**0.9897**	**0.9863**	**0.9925**	**0.9968**	**0.9773**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Ren→Stock(b_{12})	0.0155	0.0027	**0.0212**	**0.0157**	−0.0031
	(0.132)	(0.210)	**(0.000)**	**(0.000)**	(0.321)
Ren→Oil(b_{13})	0.0244	−0.0012	**0.0180**	0.0124	−0.0014
	(0.169)	(0.650)	**(0.061)**	(0.109)	(0.745)
Stock→Ren(b_{21})	**−0.0600**	**−0.0805**	**−0.0407**	**−0.0667**	**−0.0647**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Stock→Stock(b_{22})	**0.9053**	**0.9093**	**0.9151**	**0.9038**	**0.9172**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Stock→Oil(b_{23})	−0.0294	0.0024	−0.0068	−0.0186	−0.0198
	(0.286)	(0.870)	(0.706)	(0.345)	(0.233)
Oil→Ren(b_{31})	**0.0063**	**0.0087**	**0.0049**	**0.0061**	0.0055
	(0.017)	**(0.074)**	**(0.005)**	**(0.022)**	(0.217)
Oil→Stock(b_{32})	**0.0072**	**0.0060**	**0.0062**	**0.0068**	**0.0052**
	(0.013)	**(0.021)**	**(0.006)**	**(0.019)**	**(0.079)**
Oil→Oil(b_{33})	**0.9629**	**0.9602**	**0.9602**	**0.9652**	**0.9608**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**

Estimates of a_{ij} and b_{ij}, with p-values in parentheses. The parameters a_{ij} and b_{ij} represent the volatility spillover effect in the direction from the variable i to the variable j (for further detail see Section 4.2 above). The horizontal arrows appearing in the leftmost column indicate the direction of each effect. "Ren" (for "renewable") stands for a different renewable ETF in each estimation, and this variable is shown in the top row. The boldface entries represent significant effects (p-value <0.1).

performance.

It was also explained in Section 4.2 that the DCC model produces a time path of the dynamic conditional correlation, which is defined in (12) above. These dynamic conditional correlations are presented in Fig. 4. We first note that these time paths are broadly consistent with the results from the CCC model (Table 8): the dynamic conditional correlation between each renewable and the S&P 500 tends to be higher than those of other pairings; also, the dynamic conditional correlation between water and the S&P 500 is the highest of all.

The time paths in Fig. 4 also show considerable variation over time. There are several interesting features to note. Firstly, the dynamic correlation between oil and S&P 500 exhibits a downward trend over time. This could be related to the gradual decrease in US net imports of crude oil and petroleum products over the same period (see Fig. 1), with the USA becoming a net exporter of oil in 2018. This is also consistent with the results reported by Wang and Liu [52].

The second feature of interest in Fig. 4 is that the dynamic conditional correlations between renewable and oil, and that between S&P 500 and oil, appear to reduce steeply, and sometimes become negative, at the *start* of a crisis — namely September 2008 (the beginning of the global financial crisis) and February 2011 (the beginning of the debt ceiling crisis). However, following the steep fall, there is a quick recovery to values that are perhaps higher than pre-crisis. This is interesting because it suggests that a sudden, temporary, fall in the dynamic conditional correlation between S&P 500 and oil may be perceived as a precursor to a crisis.

Finally, we note that the dynamic conditional correlation between renewable and S&P 500 does not react in the same way to crises — it tends to remain high even in crisis periods. This may be interpreted as further evidence of the strong financialization of renewables.

6. Conclusion

A substantial amount of literature investigates the linkages between oil prices and financial market prices. Additionally, there is a growing body of research that includes renewable energy prices in this analysis. Most of these studies rely on a single variable to represent the renewable energy market. For example, Sadorsky [5] and Henriques and Sadorsky [4] use the WilderHill Clean Energy Index. We have contributed to this literature by considering several different types of renewable energy: water, wind, solar, nuclear, and "benchmark" renewable energy. We have used ETF prices for each of these.

We have applied three state-of-the-art econometric models to this problem: BEKK-GARCH-in-mean; CCC-VARMA-GARCH-in-mean; and DCC-VARMA-GARCH-in-mean. To further improve the fit to the data, each model assumes that errors follow a multivariate Student's t-distribution. Using a range of model selection criteria, we have established that the DCC-VARMA-GARCH-in-mean is superior when applied

Table 7
CCC-VARMA-GARCH model and DCC-VARMA-GARCH model volatility spillover coefficients estimation result.

	Water		Solar		Nuclear		Wind		Benchmark	
	CCC	DCC	CCC	DCC	CCC	DCC	CCC	DCC	CCC	DCC
Ren→Ren(a_{11})	**0.0503**	**0.0649**	**0.0401**	**0.0390**	**0.0060**	0.0043	**0.0554**	**0.0513**	**0.0444**	**0.0477**
	(0.001)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.078)**	(0.198)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Stock→Ren(a_{12})	**0.0652**	**0.0828**	**0.1121**	**0.1695**	**0.0726**	**0.0840**	**0.0497**	**0.0771**	**0.1044**	**0.1508**
	(0.000)	**(0.000)**	**(0.001)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.003)**	**(0.000)**	**(0.000)**	**(0.000)**
Oil→Ren(a_{13})	0.0010	0.0000	0.0010	0.0025	**0.0029**	0.0020	0.0004	−0.0001	0.0037	0.0025
	(0.535)	(0.993)	(0.804)	(0.578)	**(0.032)**	(0.113)	(0.826)	(0.947)	(0.286)	(0.501)
Ren→Stock(a_{21})	0.0125	0.0127	**0.0026**	0.0016	−0.0025	−0.0031	**0.0087**	0.0057	0.0036	0.0024
	(0.186)	(0.190)	**(0.006)**	(0.138)	(0.290)	(0.221)	**(0.094)**	(0.294)	(0.163)	(0.322)
Stock→Stock(a_{22})	**0.0993**	**0.1285**	**0.1238**	**0.1444**	**0.1148**	**0.1217**	**0.1106**	**0.1349**	**0.1258**	**0.1470**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Oil→Stock(a_{23})	0.0014	0.0010	**0.0043**	**0.0034**	**0.0037**	**0.0028**	**0.0026**	0.0023	0.0027	0.0017
	(0.315)	(0.461)	**(0.003)**	**(0.047)**	**(0.022)**	**(0.055)**	**(0.087)**	(0.127)	(0.127)	(0.316)
Ren→Oil(a_{31})	−0.0335	−0.0390	0.0025	0.0024	−0.0089	**−0.0115**	−0.0053	−0.0045	0.0093	0.0102
	(0.154)	(0.121)	(0.262)	(0.435)	(0.109)	**(0.034)**	(0.706)	(0.750)	(0.217)	(0.170)
Stock→Oil(a_{32})	**0.1052**	**0.1338**	**0.0581**	**0.0810**	**0.0669**	**0.0776**	**0.0766**	**0.0958**	**0.0577**	**0.0784**
	(0.003)	**(0.000)**	**(0.044)**	**(0.009)**	**(0.017)**	**(0.004)**	**(0.018)**	**(0.006)**	**(0.079)**	**(0.020)**
Oil→Oil(a_{33})	**0.0726**	**0.0711**	**0.0771**	**0.0770**	**0.0773**	**0.0762**	**0.0755**	**0.0743**	**0.0753**	**0.0743**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Ren→Ren(b_{11})	**0.9203**	**0.9176**	**0.9605**	**0.9586**	**0.9882**	**1.0031**	**0.9294**	**0.9485**	**0.9607**	**0.9505**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Stock→Ren(b_{12})	**−0.1016**	**−0.0876**	**−0.1766**	**−0.1727**	**−0.1079**	**−0.1034**	**−0.0868**	**−0.0862**	**−0.1858**	**−0.1581**
	(0.000)	**(0.001)**	**(0.000)**	**(0.001)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Oil→Ren(b_{13})	0.0028	0.0032	0.0030	0.0007	**0.0003**	0.0002	0.0014	0.0012	−0.0016	−0.0014
	(0.171)	(0.115)	(0.553)	(0.901)	**(0.000)**	(0.897)	(0.512)	(0.534)	(0.708)	(0.749)
Ren→Stock(b_{21})	−0.0227	−0.0124	**0.0030**	0.0025	0.0021	**0.0186**	−0.0044	0.0054	**0.0054**	0.0032
	(0.169)	(0.392)	**(0.044)**	(0.104)	(0.691)	**(0.002)**	(0.562)	(0.439)	**(0.095)**	(0.322)
Stock→Stock(b_{22})	**0.8498**	**0.8491**	**0.8092**	**0.8252**	**0.8291**	**0.8465**	**0.8280**	**0.8381**	**0.8065**	**0.8314**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Oil→Stock(b_{23})	0.0016	0.0015	0.0010	0.0010	0.0008	0.0003	0.0006	0.0003	−0.0002	−0.0004
	(0.358)	(0.374)	(0.566)	(0.595)	(0.663)	(0.858)	(0.723)	(0.860)	(0.917)	(0.816)
Ren→Oil(b_{31})	0.0194	0.0331	−0.0044	−0.0050	−0.0108	0.0173	0.0035	0.0117	−0.0112	−0.0152
	(0.654)	(0.404)	(0.232)	(0.258)	(0.434)	(0.135)	(0.863)	(0.511)	(0.204)	(0.096)
Stock→Oil(b_{32})	**−0.1034**	**−0.1044**	−0.0515	−0.0435	−0.0629	**−0.0590**	**−0.0852**	**−0.0812**	−0.0582	−0.0366
	(0.087)	**(0.065)**	(0.261)	(0.287)	(0.159)	**(0.091)**	**(0.086)**	**(0.069)**	(0.223)	(0.364)
Oil→Oil(b_{33})	**0.9132**	**0.9148**	**0.9094**	**0.9098**	**0.9119**	**0.9128**	**0.9110**	**0.9142**	**0.9095**	**0.9113**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**

Estimates of a_{ij} and b_{ij}, with p-values in parentheses. The parameters a_{ij} and b_{ij} represent the volatility spillover effect in the direction from the variable j to the variable i (for further detail see Section 4.2 above). The horizontal arrows appearing in the leftmost column indicate the direction of each effect. "Ren" (for "renewable") stands for a different renewable ETF in each estimation, and this variable is shown in the top row. The boldface entries represent significant effects (p-value <0.1).

Table 8
CCC-GARCH conditional correlation estimates.

	Water	Solar	Nuclear	Wind	Benchmark
Stock-ren(ρ_{21})	**0.8274**	**0.6053**	**0.6273**	**0.6997**	**0.7273**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Oil-ren(ρ_{31})	**0.3846**	**0.3393**	**0.3372**	**0.3478**	**0.3788**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Oil-stock(ρ_{32})	**0.4093**	**0.4069**	**0.4082**	**0.4067**	**0.4044**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**

ρ_{ij} is defined in Eq. (7) in Section 4.2, and represents the (constant) conditional correlation between variables i and j.

to the data set we consider.

The results presented in this paper are not only of significant interest to academic researchers but also hold considerable value for practitioners, including policymakers, portfolio managers, investors, consumers, and producers. For example, estimation of the dynamic conditional correlation from the DCC-GARCH model is useful to portfolio managers, because it provides a formula for optimal hedge ratios, and informs optimal portfolio construction. Chang et al. [14] have used this strategy to devise a crude oil hedging strategy while Ahmad et al. [15] have pursued the same goal for clean energy equities.

To conclude the paper, we return to the questions posed in the Introduction. The first asked what are the linkages between energy prices (both conventional energy and different types of renewable energy) and stock prices. To answer this, we first considered the GARCH-in-mean effects. The most striking result here was that while S&P 500 volatility has a significant negative effect on the oil return, in line with previous literature, S&P 500 volatility has a significant positive effect on the renewable energy return. In other words, stock market uncertainty has opposite effects on traditional and renewable energy markets. Based on this, stockholders could use traditional energy derivatives for risk hedging. Renewable energy ETFs/stocks are the optimal choice for energy-related portfolio construction. Another striking result is that uncertainty in benchmark renewable energy affects both stock returns and oil returns positively. For the investment strategy, investors should

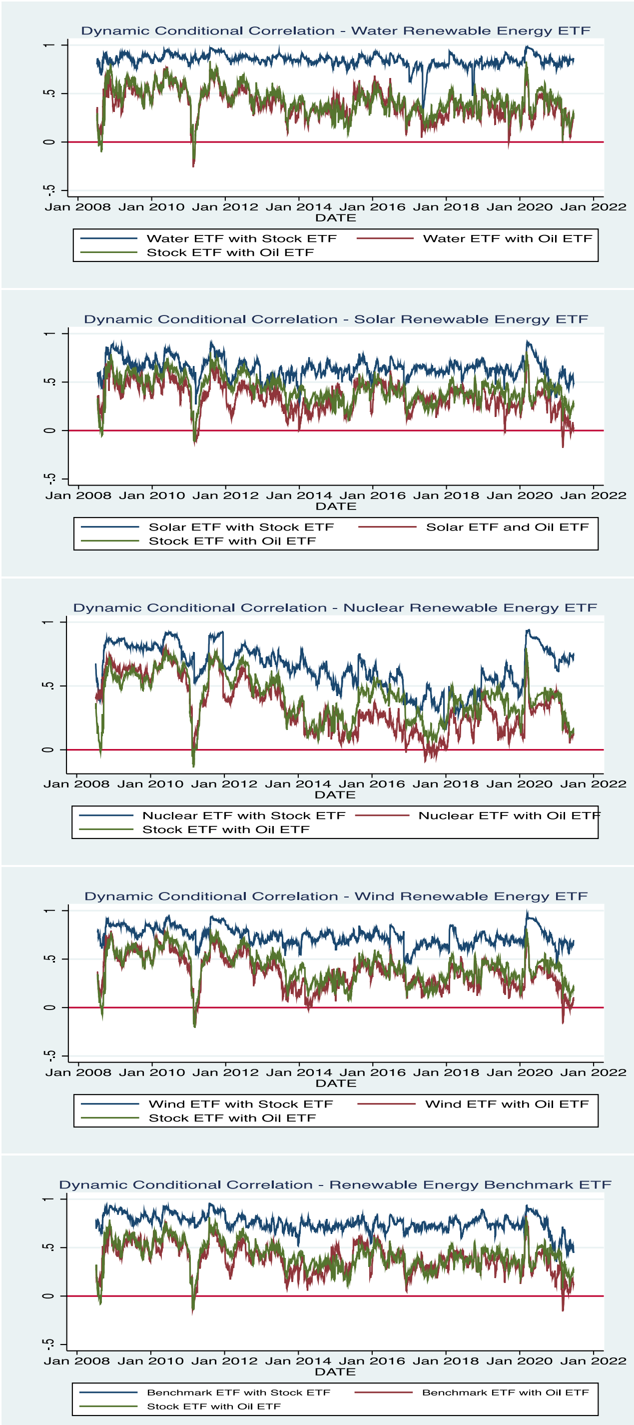

Fig. 4. Dynamic Conditional Correlations from the DCC model, defined in (12).

avoid using renewable energy benchmarks for stock/energy risk hedging. Investors who already position themselves the renewable energy benchmark investments should be aware of the financialization effect — financial market volatility spillovers. The positive aspect is that financialization contributes to long-run potential growth.

We also found evidence of volatility spillovers that were fairly consistent across the full suite of specifications (BEKK, CCC, and DCC). Here, results appear to differ between the short run and the long run. In the short run, stock market uncertainty appears to increase both renewable market uncertainty and oil market uncertainty. But in the long run, both of these volatility spillovers are negative. It advises that stockholders in short-run investments or long-run should apply different investment strategies, especially when stepping into the energy field. Moreover, policymakers should pay attention to the negative volatility spillovers from the stock market to the energy market (whether traditional or renewable energies).

The second question was which of traditional and renewable energy is more closely linked to the stock market. From the CCC model, we saw the correlation between renewable energy and S&P. This difference was confirmed using the DCC model, where we found the time path of the dynamic conditional correlation between renewable and S&P tended to be the highest of all variable combinations. The highest of all was seen when renewable water was being considered. This is interpreted in terms of financialization [12]. Based on our results, renewable energy does appear to be more highly financialized than traditional energy, with water being the most highly financialized renewable. Financialization means the co-movement exists in the pair of financial assets, and a high level indicates the strengthened links. On the one hand, policy should be instructed to reduce the negative impact of the financial market on the energy market. On the other hand, energy financialization should be considered in portfolio strategies.

The third question was whether the linkages changed in any way at times of financial crisis, or other types of crisis. Obviously, the best place to look for an answer to this is the time paths of dynamic conditional correlation resulting from the estimation of the DCC-VARMA-GARCH model and presented in Fig. 4 above. The most striking aspect of these graphs is that the two dynamic conditional correlations involving oil both appear to fall steeply at the beginning of a financial crisis (e.g. September 2008 and February 2011), essentially becoming zero or negative, but then recover quickly and to reach higher values than pre-crisis. In contrast, the dynamic conditional correlation between renewable and S&P does not react very much to crises. The interpretation of this result is that the aforementioned high financialization of renewables appears robust to financial crises. It implied that oil derivatives are ideal risk-hedging instruments in the economic turmoil period.

The fourth and final question concerned the linkage between oil and S&P 500. Here we refer once again to Fig. 4 and note that over the sample range 2008 to 2022, there is a clear downward trend in the dynamic conditional correlation between oil and S&P 500. This seems counter-intuitive when we recall that, over the same period, the USA has gradually reduced its net oil imports and recently became a net exporter (see Fig. 1). Since rising oil prices generate current account surpluses for oil exporters, we surely expect the positive association between oil and S&P 500 to increase over this period. We must therefore look elsewhere for an explanation for the decrease and this is an interesting topic for further research. Oil-relying countries are more independent from the financial market's influence on energy markets. In other words, it is crucial to observe and deal with the negative impact on energy markets in oil-imported countries.

While our study provides valuable insights into the volatility spillovers and conditional correlations between stock, traditional energy, and renewable energy markets, it is important to acknowledge several limitations. Although we have considered several different types of renewable energy, we have not considered them in the same model. It would be interesting to do this and to uncover linkages between different renewable energies. However, as remarked earlier, the multivariate GARCH models that we have used become hard to estimate when there are many equations in the model. One way of addressing this is to consider the sparse multivariate GARCH model due to Dhaene et al. [8]. This model allows for prior restrictions in terms of e.g. zero volatility spillovers for specific variable pairs. Apart from the advantage of making estimation possible, a further advantage of this type of model is that it is less likely to suffer from over-fitting than a full model, and would therefore be better if the objective is out-of-sample forecasting. This is clearly another exciting area for further research.

CRediT authorship contribution statement

Wenxue Wang: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization, Investigation, Formal analysis, Funding acquisition. **Peter G. Moffatt:** Conceptualization, Methodology, Visualization, Writing – Original draft , Writing – review & editing. **Zheng Zhang:** Conceptualization, Methodology, Software, Data curation, Visualization, Writing –review & editing, Formal analysis, Funding acquisition. **Muhammad Yousaf Raza:** Conceptualization, Methodology, Data curation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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