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"Portfolio selection from risk transfer mechanisms in a time of crisis for renewable energy markets"

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Portfolio selection from risk transfer mechanisms in a time of crisis for renewable energy markets

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Abstract

This study explores risk transmission in financial markets, focusing on investor hedging decisions. It examines risk movement between renewable and fossil fuel energy assets in energy ETFs during the Global Financial Crisis (GFC) and the COVID-19 pandemic. A novel test evaluates how an energy asset's volatility impacts the overall portfolio risk, offering insights for managing financial risk. The analysis covers three major renewable energy ETFs (solar, wind, and hydro) and three fossil fuel ETFs (oil, coal, and natural gas). During the COVID-19 crisis, effective combinations such as (solar, coal) and (wind, coal) are recommended for minimizing losses. Although not ideal for hedging solar-related risks, (solar, oil) is advantageous for oil-related shocks. The study found that combining solar with oil and wind with oil was effective in mitigating losses during the GFC and before COVID-19. In non-pandemic periods, combinations like (solar, oil) or (solar, coal) are valuable for risk management. This research highlights the interconnectedness of energy assets and provides actionable insights for investors and policymakers. Future research could examine other events, like the Russia-Ukraine war, impacting global energy markets

Keywords: Renewable energy, Volatility spillover, Risk Transfer, GFC, COVID-19.
JEL: C32, C58, G01, G11, G14, Q42, Q47

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1. Introduction

Recently, the focus on renewable energy sources has increased due to growing concerns about climate change, global warming and greenhouse gas emissions. The energy market has become an attractive way to raise funds as many countries are dependent on foreign energy sources and the supply of non-renewable energy sources such as oil, gas and coal is declining. However, investing in green or renewable energy is not without significant financial risks and economic downturns can be devastating for investors. It is therefore important for investors to have a good understanding of risk management when selecting portfolios to avoid prolonged financial difficulties and potential ruin. In financial markets, the selection of appropriate hedging instruments is essential to ensure negative covariance between asset cross-returns, i.e. to offset large losses in financial assets with positive returns in hedging instruments. To this end, Chang et al. (2018) [1] tested partial volatility spillovers of shocks in crops and renewable assets to determine the impact of bad news on markets. In this study, we propose a novel second-moment test of partial volatility spillovers to investigate the impact of volatility on energy financial markets.

Investors may adjust their portfolios in response to risk-reducing news, such as a financial crisis or a pandemic. In December 2009, the COVID-19 disease caused by the novel SARS-CoV-2 virus emerged in Wuhan, China, resulting in nearly 700 million infections and seven million deaths worldwide (see Coronavirus Cases - Worldwide, Worldometer, https://www.worldometers.info/coronavirus/). To control the spread of the disease, most countries introduced measures such as travel and work restrictions and quarantines. These changes have raised fears of a global credit crunch among financial market investors, as the pandemic has had a significant impact on both the fossil fuel and renewable energy sectors. While the energy stock index is commonly used to assess the performance of specific energy assets, it is not tradable and provides investors with limited information for practical risk management. Energy-related Exchange Traded Funds (ETFs), on the other hand, are tradable and marketable and can be directly incorporated into financial portfolios to analyses risk transmission in energy financial markets.

In this study, we aim to examine risk transmission during two crises: the Global Financial Crisis (GFC) from 25 June 2008 to 31 December 2009, and the COVID-19 pandemic caused by the virulent SARS-CoV-2 virus, which began on 30 January 2020 as the World Health Organization (WHO) belatedly declared a global public health emergency on 30 January 2020. While there is no general agreement for the starting time of the GFC and the COVID-19 crisis, for the GFC, which started at the middle of 2007 and affected a period of nearly 18 months until the end of 2009, we started the data from which the TAN(solar) and FAN(wind)began and ended at the end of the date of 2009, for COVID-19 pandemic, most countries began to take the coronavirus seriously after the WHO declared a global public health emergency on 30 January 2020, as which we define the starting date. To achieve this, we have selected three widely used renewable energy ETFs: solar (TAN), wind (FAN) and hydro (PHO), as well as three of the most popular fossil fuel energy ETFs: crude oil (USO), coal (KOL) and natural gas (UNG). Our research focuses on analyzing risk transmission in renewable and fossil fuel energy assets, as well as cross-risk transmission from renewable to fossil fuel energy assets and vice versa. Specifically, this investigation has two main objectives: (1) to test how shocks (good or bad news) in one energy asset can affect the risk of an energy portfolio through co-volatility spillovers, as developed by Chang et al. (2018) [1]; (2) to develop a novel test of risk volatility spillovers of one energy asset to the co-volatility of risk in an energy portfolio, as shown in figure 1. Our novel test of risk transmission in volatility aims to explain how changes in the bad news or risk happened of one energy asset can lead to changes in the risk of an energy portfolio, as shown in figure 2.

2. Literature Review

Numerous studies in the literature have utilized the Granger causality test to examine the impact of oil prices on renewable energy consumption, with the aim of providing guidance to policymakers on reducing dependence on finite fossil fuels. Troster et al. (2018) [2] employed monthly oil prices, the US industrial production index, and renewable energy consumption data from January 1989 to July 2016, and found bi-directional causality between renewable energy consumption and economic growth in the lower tails of the distribution. In contrast, at the extreme quantiles of the distribution, there was unidirectional causality from oil prices to economic growth. The authors concluded that there was unidirectional causality running from renewable energy consumption to economic growth at the highest quantiles of the distribution, while lower-tail causality was evident from oil price changes to renewable energy consumption.

Managi and Okimoto (2013) [3] examined the relationships between oil prices, clean energy stock prices, technology stock prices and interest rates using weekly data from 3 January 2001 to 24 February 2010. The authors found that US West Texas Intermediate crude oil futures prices and the Arca Technology stock price positively affected the WilderHill Clean Energy (TECH) price. Other empirical studies have focused on the hedging of crude oil and other energy products. Lin and Li (2015) [4] used the VEC-MGARCH model to investigate price and volatility spillover effects for crude oil and natural gas markets in the US, Europe and Japan. Their results showed that European and Japanese gas prices are cointegrated with Brent crude oil prices, but US gas prices are decoupled from oil due to the liberalization of the natural gas market and the expansion of shale gas. The authors found volatility spillovers from the oil market to the gas market in the three regions, but no spillovers in the opposite direction for both the US and Europe.

Reboredo (2015) [5] conducted a study on the co-movement and systemic risk between oil and clean energy stock prices. The authors used copulas to analyze the dependence structure between oil and renewable energy markets from 30 December 2005 to 12 December 2013. The study found that high oil prices can encourage the development of the renewable energy sector, as economic growth increases due to improvements in renewable energy projects. Conversely, low oil prices have the opposite effect.

Rizvi et al. (2022) [6] use Vector autoregression and Baba-Engle-Kraft-Kroner parameterization of multivariate GARCH models to examine the relative strength of return and volatility spillovers from green and gray energy markets and find that return shocks originating in green energy and transmitted to other markets are more pronounced. However, volatility spillovers originating in the gray energy market are still prominent and robust for some asset classes, such as bonds.

Gevorkyan (2017) [7] investigated the persistence of risk in renewable energy and non-renewable resources. The study used the GARCH (1,1) model to measure the volatility of futures prices for renewable and non-renewable resources. The non-linear Vector Smooth Transition Autoregressive (VSTAR) model was also used to compare the speed of transition from one regime to another for different resources. The results showed that some renewable resources, such as soya bean, maize, and coffee, have greater volatility in futures prices than the benchmark crude oil. However, certain products, including oil, natural gas, coffee, soya bean, and maize futures, not only have higher variances compared to other futures commodities but also exhibit the most abrupt transition functions from low to high volatility regimes.

Numerous multivariate conditional volatility models have been developed by econometricians to capture risk transmission effects between assets. These models include the CCC, VARMA-GARCH, VARMA-AGARCH and Full BEKK models. However, most of these models and tests in empirical finance still face theoretical problems. For example, models such as CCC, VARMA-GARCH and VARMA-AGARCH have static conditional covariances and correlations, which make it impossible to account for volatility and co-covariance spillovers. On the other hand, the Full BEKK model lacks an underlying stochastic process that can lead to its specification, has no regularity conditions, no likelihood function for parameter estimation and no asymptotic statistical properties. Therefore, the Diagonal BEKK version can only be considered if the intention is to measure volatility spillovers accurately, as it has appropriate regularity conditions, a likelihood function for parameter estimation, and estimates with valid asymptotic properties. Some of the papers that have examined these models include Baba et al., 1985 [8]; Engle and Kroner, 1995 [9]; Bollerslev, 1986 [10]; Bollerslev et al., 1988 [11]; Engle, 2002 [12]; Ling and McAleer, 2003 [13]; McAleer et al., 2009 [14]; McAleer and Hafner, 2014 [15] and Tse and Tsui, 2002 [16].

Chang et al. (2018) [1] proposed a new definition of co-volatility spillovers to measure the extent of co-risk transmission. They found that the futures prices of bioethanol and two agricultural commodities, corn and sugarcane, had stronger co-volatility spillovers than their spot price counterparts during the period from 31 October 2005 to 14 January 2015. Later, Chang et al. (2019) [17] examined volatility spillovers between crude oil and related financial markets in different countries, such as the United States, the United Kingdom and China, before, during and after the global financial crisis. The researchers observed significant negative co-volatility spillover effects for all crude oil and financial index pairs in the UK and the US during and after the GFC, suggesting opportunities for optimal dynamic hedging. In the Chinese market, there were numerous pairs of crude oil and financial indexes that experienced significant negative co-variation effects during the GFC, but positive and negative signs of co-variation spillovers in the post-GFC period, suggesting opportunities for optimal dynamic hedging across oil and financial markets as well as with the UK and the US.

Batten et al. (2021) [18] examined the practicality of hedging stocks with oil and showed that uncertainty during the Global Financial Crisis (GFC) could affect the effectiveness of hedging portfolio returns for stock-oil combinations.

This study extends the concept of Chang et al.'s co-volatility spillovers to develop a new risk transmission test for renewable and non-renewable energy assets, specifically during the GFC and COVID-19 pandemic, to gain a deeper understanding of risk transmission.

3. Model Specifications

We begin by considering a vector random coefficient autoregressive process for the shocks on returns, and use this to develop new tests for bivariate moment volatility causality based on the Diagonal BEKK (DBEKK) conditional volatility model. The DBEKK model meets appropriate regularity conditions and has valid asymptotic properties. Building on Chang et al.'s (2018) [1] definition of co-volatility spillovers, we extend the concept to include the effect of second-moment squared shocks on co-volatility spillovers, in addition to the impact of first-moment shocks. This allows us to better understand the delayed shocks in one asset on the subsequent co-volatility in another asset.

3.1 Full BEKK versus Diagonal BEKK model

The present study builds upon the work of McAleer et al. (2008) [19], who extended Tsay's (1987) [20] univariate random coefficient autoregressive (RCA) process to a multivariate setting. The multivariate extension is presented below:

$$R_t = E(R_t|I_{t-1}) + \varepsilon_t \qquad (1)$$

where R_t denotes returns on the asset, $R_t = (R_{1t}, \dots R_{mt})'$, ε_t denotes the shocks on returns, $\varepsilon_t = (\varepsilon_{1t}, \dots \varepsilon_{mt})'$, and I_{t-1} refers to the information set that is available at time $t-1$.

As shown in McAleer et al. (2008) [19], the shocks on returns (ε_t) are assumed to follow a vector random coefficient autoregressive (VRCAR) stochastic process, with $m \times 1$ vector components, where m denotes the number of financial assets, as given below:

$$\varepsilon_t = \Phi_t \varepsilon_{t-1} + \eta_t \tag{2}$$

where ε_t and η_t are $m \times 1$ vectors, η_t is a random standardized residual, $\eta_t \sim iid(0, \Omega)$, and Ω is an $m \times m$ matrix. Φ_t is a random coefficient autoregressive matrix, with an $m \times m$ matrix of random coefficients, $\Phi_t \sim iid(0, \Sigma)$, Σ is an $m \times m$ matrix if Φ_t is a diagonal matrix. From equation (2), the conditional volatility H_t is given as:

$$\begin{aligned} H_t = E(\varepsilon_t \varepsilon_t' | I_{t-1}) &= E(\Phi_t \varepsilon_t \varepsilon_t' \Phi_t' | I_{t-1}) + E(\eta_t \eta_t' | I_{t-1}) \\ &= E(\Phi_t \Phi_t') \times E(\varepsilon_t \varepsilon_t' | I_{t-1}) + E(\eta_t \eta_t' | I_{t-1}) \\ &= A' \varepsilon_{t-1} \varepsilon_{t-1}' A + C'C \end{aligned} \tag{3}$$

where $\Omega = C'C$, and $E(\Phi_t \Phi_t') = \Sigma = A'A$.

A lagged dependent variable matrix, H_{t-1}, is typically added to equation (3) to improve the sample fit, as given below (for more details, refer to Baba et al. (1985) [8] and Engle and Kroner (1995) [9]):

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \qquad (4)$$

where

$$C = \begin{bmatrix} c_{11} & \cdots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mm} \end{bmatrix},\ A = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mm} \end{bmatrix},\ B = \begin{bmatrix} b_{11} & \cdots & b_{1m} \\ \vdots & \ddots & \vdots \\ b_{m1} & \cdots & b_{mm} \end{bmatrix}$$

According to McAleer et al. (2008) [19], it is not possible to derive the Full BEKK model in equations (3) and (4) from any known underlying stochastic process. As a result, there are no regularity conditions, no likelihood function for estimating parameters, and no valid asymptotic properties of the QMLE of the parameters. Therefore, any statistical analysis of the estimated parameters is invalid. In contrast, McAleer et al. (2008) [19] have shown that DBEKK can be derived from a known underlying stochastic process, subject to appropriate regularity conditions, and the asymptotic properties of the QMLE can be established as consistent and asymptotically normal. Further information can be found in McAleer's (2019a, b) [21] [22] papers. The structural properties of DBEKK in equation (4) require the weighting matrix, A,, and the matrix that contributes to the long run properties, B, to be diagonal.

$$C = \begin{bmatrix} c_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mm} \end{bmatrix}, \quad A = \begin{bmatrix} a_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_{mm} \end{bmatrix}, \quad B = \begin{bmatrix} b_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & b_{mm} \end{bmatrix}$$

In order to conduct the empirical analysis, equation (4) can be presented as equations (5) - (7):

$$h_{i,t} = c_{ii} + {a_{ii}}^2 \varepsilon_{i,t-1}^2 + {b_{ii}}^2 h_{i,t-1} \tag{5}$$

$$h_{j,t} = c_{jj} + {a_{jj}}^2 \varepsilon_{j,t-1}^2 + {b_{jj}}^2 h_{j,t-1} \tag{6}$$

$$h_{ij,t} = c_{ij} + a_{ii} \times a_{jj} \times \varepsilon_{i,t-1} \times \varepsilon_{j,t-1} + b_{ii} \times b_{jj} \times h_{ij,t-1} \tag{7}$$

3.2 Extended Diagonal BEKK Model with Exogenous Unconditional Shocks

Granger (1969) [23] introduced the concept of first-moment causality based on predictability, where an asset *i* is said to Granger cause asset *j* if asset *j* can be forecast better using previous asset *i* and previous asset *j* than using previous asset *j* alone. Sims (1972) [24] showed that this criterion fails to Granger cause Y only if Y is econometrically exogenous in a dynamic regression of X on Y. To test the Volatility Causality from asset *j* to asset *i*, we incorporate exogenous unconditional shocks of return j, $\varepsilon_{j,t-1}^2$, into equation (5) as shown in equation (8). Similarly, we add exogenous unconditional shocks of return i, $\varepsilon_{i,t-1}^2$, to equation (6) and $\varepsilon_{j,t-1}^2$ to equation (7). Equations (9) and (10) then follow.

$$h_{i,\,t} = c_{ii} + a_{ii}^2 \varepsilon_{i,t-1}^2 + b_{ii}^2 h_{i,t-1} + e_{ii}^* \varepsilon_{j,t-1}^2 \tag{8}$$

$$h_{j,t} = c_{jj} + {a_{jj}}^2 \varepsilon_{j,t-1}^2 + {b_{jj}}^2 h_{j,t-1} + e_{jj}^* \varepsilon_{j,t-1}^2 \tag{9}$$

$$h_{ij,t} = c_{ij} + (a_{ii} \times a_{jj}) \varepsilon_{i,t-1} \times \varepsilon_{j,t-1} + (b_{ii} \times b_{jj}) h_{ij,t-1} + {e_{ij}}^* \varepsilon_{j,t-1}^2 \tag{10}$$

where $h_{i,t}$ is the conditional volatility of asset i at time t, $h_{j,t}$ is the conditional volatility of asset j at time t, $h_{ij,t}$ is the co-volatility of assets i and j at time t, $\varepsilon_{i,t-1}$

denotes the shocks of asset i at t-1, and $\varepsilon_{j,t-1}$ denotes the shocks of asset j at t-1.

3.3 Partial Volatility Spillovers and Risk Volatility Spillovers

As described in Chang et al. (2018) [1], the partial co-volatility spillovers could be derived from the DBEKK model as it provides consistent and asymptotically normal QMLEs of the estimated parameters, so we will focus on the partial co-volatility spillover effects.

The definition of partial co-volatility spillovers of return shocks in Chang et al. (2018) [1] is as follows:

$$\mathrm{H}_{ij,t}/\partial\varepsilon_{k,t-1},\ i \neq j,\ k = \text{either } i \text{ or } j.$$

Instead of partial volatility spillovers from negative shocks, equation (10) allows a further test of partial volatility spillovers from volatility. We extend the same idea to the partial co-volatility spillovers from the squared return shocks, which are given as:

$$\mathrm{H}_{ij,t}/\partial\varepsilon^2_{k,t-1},\ i \neq j,\ k = \text{either } i \text{ or } j.$$

Both partial co-volatility spillovers from the shocks and squared shocks of returns can be calculated from equation (10), which is given as:

$$\frac{\partial h_{ij,t}}{\partial \varepsilon_{j,t-1}} = (a_{ii} \times a_{jj}) \times \varepsilon_{i,t-1} + 2{e_{ij}}^* \times \varepsilon_{j,t-1},\ i \neq j$$

$$\frac{h_{ij,t}}{\partial \varepsilon^2_{j,t-1}} = {e_{ij}}^*, \qquad i \neq j.$$

A test of the null hypothesis for the return shocks j on the subsequent co-volatility of assets i and j is given by

$$H_0: a_{ii}a_{jj} = 0 \text{ and } e_{ij}{}^* = 0, \; i \neq j.$$

Similarly, the test of the null hypothesis for the squared shocks of return j on the subsequent co-volatility of assets i and j is given by:

$$H_0: e_{ij}{}^* = 0, \quad i \neq j$$

4. Data and Variables

4.1 Global Renewable Energy

Renewable energy is energy obtained from renewable resources such as solar, hydro, wind, wave, biomass and geothermal. As shown in Figure 3, the report from Bloomberg 2021 [25], the energy generation by sources in the US, renewable energy compared to fossil fuels, we can see that the capacity of renewable energy has been increasing since 2012, especially the generation of solar energy has increased rapidly since 2017. In addition, the increasing use of alternative energy has already established itself as a trend for the future.

Renewable energy provides energy in four main areas, namely electricity generation, air and water heating/cooling, transport and rural (off-grid) energy services. The International Energy Agency (IEA) 2021 [26] reports that renewable energy sources such as wind and solar PV have increased in recent years, driven by the large demand for electric vehicles. The share of electricity in the world's final energy consumption has risen steadily in recent decades and now stands at 20%. As demand for electricity has grown, so has its share of energy-related investment. Since 2016, global investment in the electricity sector has consistently been higher than in oil and gas supply. As the clean energy transition accelerates, this gap will widen, making electricity the central arena for energy-related financial transactions.

Investments in renewable energy have been steadily on the rise, as illustrated in Figure 4 of the 2020 IEA report [27]. This figure provides a clear depiction of the increasing capital allocated to solar, wind, hydro, and other renewable energy sources from 2012 to 2020. Notably, total investments in renewable energy have surged from $200 billion in 2012 to $300 billion in 2019. Furthermore, Figure 5 demonstrates a pronounced acceleration in global energy investments in renewable sources since 2017.

The IEA's 2022 [28] further indicated that the momentum in clean energy investments is expected to continue its upward trajectory. By 2022, investments in clean energy are projected to surpass a staggering $1.4 trillion, constituting nearly three-quarters of the overall growth in total energy investment, as shown in figure 6. This trend is underscored by consistent year-over-year increases in investments across renewables, energy efficiency, and electric vehicles. These trends collectively signal a global consensus on the growing significance of renewable energy sources.

4.2 Variables and Statistical Analysis

To test for risk spillovers in renewable energy and fossil fuel energy returns, we use three renewable energy as solar (TAN), wind (FAN), hydro (PHO), and three fuel energy as crude oil (USO), coal (KOL), and natural gas (UNG). The sample, which is current, covers the period from 25 June 2008 to 31 May 2022, except for the Coal ETF-KOL, which will cease trading on 22 December 2020. The length of the sample period is determined by the availability of data.

The return is obtained by taking the natural logarithm of the daily price data, subtracting the natural logarithm of the daily closing price for two consecutive days and multiplying by 100 (this is equivalent to using log differences in prices). The definitions of the variables are shown in Table 1.

As shown in Figure 7, there is a phenomenon of volatility clustering in ETF returns. Renewable energy ETFs, as well as solar, wind and hydro, show higher volatility than crude oil and natural gas during the 2008-2009 global financial crisis (GFC). Crude oil shows higher volatility than renewables in the 2014-2016 period, which may be due to the declining global demand for oil combined with a growing supply glut and the boom in shale oil production in the US.

In addition, the Covid-19 pandemic, which the World Health Organization (WHO) predicts will begin in 2020, has led many countries to implement a "lockdown" policy. The level of enforcement varies from light to strict. As a result of the restrictions, reduced economic activity caused significant disruption to economies around the world. There was also a significant reduction in energy consumption, with crude oil becoming much more volatile since the beginning of 2020. As shown in Figures 8 and 9, the high variability of ETF returns can be seen during the 2008-2009 Global Financial Crisis (GFC) and the 2010-2012 European debt crisis.

The descriptive statistics for ETF returns are shown in Table 2. The solar ETF (TAN) has the highest standard deviation in the ETF markets over the sample period, followed by the natural gas ETF (UNG). The returns have different degrees of skewness. Skewness is important in financial and investment analysis because most financial datasets have either positive or negative skewness, rather than following the normal distribution, which has zero skewness.

All ETF returns except Natural Gas are essentially skewed to the left, indicating that these ETF series have longer left tails (extreme losses) than right tails (extreme gains). In addition, all ETF returns have a kurtosis significantly higher than 3, indicating that there is a higher probability of extreme market movements in both tails of the distribution, i.e. extremely large gains and losses. The Jarque-Bera Lagrange multiplier test statistics for normality confirm the existence of non-normal distributions in all return series.

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests of the ETF return series are summarized in Table 3. The ADF test accounts for serial correlation by explicitly specifying the structure of serial correlation in the return shocks. The non-parametric PP test allows for relatively mild assumptions that do not require a specific type of serial correlation or heteroskedasticity in the disturbances and can have higher power than the ADF test in a wide range of circumstances.

The null hypothesis of the ADF and PP tests is that the series has a unit root (Dickey and Fuller, 1979 [29]; Said and Dickey, 1984 [30]; Phillips and Perron, 1988 [31]). Based on the results of the ADF and PP tests, the large negative values in all cases indicate rejection of the null hypothesis of unit roots at the 1% significance level. Therefore, all return series for the empirical analysis are found to be stationary.

5. Empirical Results

5.1 Partial Co-Volatility Spillovers from Negative Shocks

This section focuses on partial co-volatility spillovers. As explained in Section 3.3, the partial co-volatility spillover effects of shocks can be tested by $a_{ii}a_{jj} = 0$ and $e_{ij}{}^{*} = 0$ in equation (10).

For reasons of space, Tables 4 and 5 report the partial co-volatility spillover effects of negative shocks, while details of the estimates are presented in Appendices 1-4. Each table covers the GFC (from 25 June 2008 to 31 December 2009), pre COVID-19 (from 1 January 2010 to 29 January 2020) and the COVID-19 pandemic (from 30 January 2020 to date). Table 4 shows the partial co-volatility spillover effects of the bad news shocks between three renewable energy ETFs, namely Solar (TAN), Wind (FAN) and Hydro (PHO), three fossil fuel ETFs, namely Crude Oil (USO), Coal (KOL) and Natural Gas (UNG). Table 5 shows the cross-sector partial co-volatility spillovers between Solar (TAN), Wind (FAN), Hydro (PHO), Crude Oil (USO), Coal (KOL) and Natural Gas (UNG).

Table 4 first shows that during the time before COVID-19 and the time during COVID-19, the combination of Solar and Wind and Solar and Hydro can serve as assets within the investment portfolio in order to reduce investment risk through appropriate hedging. Bad news from the Solar ETF has negative spillover effects on the subsequent Solar with Wind ETFs, and this is also the case for Hydro and Solar ETFs. From the point of view of reducing investment risk, Solar and Wind and Hydro ETFs can be regarded as efficient investment portfolios.

Next, we focus on the partial co-volatility spillover effects of the negative shocks in the three fossil fuel energy ETFs, namely Crude Oil (USO), Coal (KOL) and Natural Gas (UNG). Not surprisingly, only a few of the three fossil fuel energy sources can be used in an efficient portfolio, particularly the combination of crude oil and coal. For example, during the GFC and pre-Covid-19 periods, when the bad news comes from coal, crude oil might be a good choice for an efficient portfolio with coal ETFs, while during the GFC and pre-Covid-19 periods, when the bad news comes from crude oil, coal might be a good choice for an efficient portfolio with crude oil ETFs.

Table 5 reports cross-sector partial co-volatility spillover effects between renewable energy ETFs, namely solar (TAN), wind (FAN), hydro (PHO), crude oil (USO), coal (KOL) and natural gas (UNG). For the GFC and pre-Covid-19 periods, regardless of whether the bad news comes from solar or crude oil ETFs, the combination of solar and crude oil ETFs has negative partial co-volatility spillover effects. Similar results are found for the efficient portfolio between solar and coal ETFs. For the GFC and pre-COVID-19 period, regardless of the bad news from Solar or Crude Oil ETFs, the combination between Solar ETF and Crude Oil ETF has a negative partial co-variability spillover effect, which does not occur during the COVID-19 period.

Furthermore, in the context of the COVID-19 period, when bad news hits coal ETFs, it is advisable to consider solar, wind, and hydro ETFs as potential components of an efficient portfolio. This strategic choice is driven by the fact that their partial co-covariance spill-over effects are significantly negatively correlated with the Coal ETFs during this specific period. Furthermore, in situations where the Hydro ETF sector experiences bad news during the COVID-19 era, it becomes worthwhile to consider including Oil and Gas ETFs in an efficient portfolio. It's important to note, however, that these observed relationships do not hold true for the periods encompassing the Global Financial Crisis (GFC) and the era prior to the COVID-19 pandemic.

5.2 Co-volatility Spillovers of Squared Shocks (Risk Volatility)

In section 5.1, we looked at the volatility spillover of shocks across assets. If the effect is negative, we can see that bad news in an energy market causes small changes in the risk of the portfolio, which can be selected as a good investment portfolio. Next, let us look at how "risk volatility" is transmitted. Under the negative partial co-covariance spillovers of the asset market, if there are positive co-covariance spillovers of squared shocks, this implies that the volatility of two energy markets will both change dramatically or only change a little for both markets, which means that the positive and negative returns between two assets in the portfolio can be offset.

Thus, this section presents the second-moment co-covariance spillover effects of the squared return shocks. As explained in Section 3.3, the partial co-volatility spillover effects from the squared shocks of returns can be tested by $e_{ij}{}^{*} = 0$in equation (10). Similarly, Tables 6 and 7 report the partial co-covariance spillover effects of negative shocks, while the corresponding estimates are presented in Appendices 5-8. Tables 6 and 7 cover the periods GFC (from 25 June 2008 to 31 December 2009), pre COVID-19 (from 1 January 2010 to 29 January 2020) and during COVID-19 (from 30 January 2020 to date).

Table 6 reports the second moment squared shock effects (or volatility) on the partial co-volatility spillovers in the three renewables, namely solar (TAN), wind (FAN) and hydro (PHO), and in the three fossil fuels, namely crude oil (USO), coal (KOL) and natural gas (UNG). Table 7 shows the cross-sectoral partial co-volatility spillover effects of the second moment squared shocks between Solar (TAN), Wind (FAN), Hydro (PHO), Crude Oil (USO), Coal (KOL) and Natural Gas (UNG).

As can be seen in the first column of Table 6, none of the combinations in the three renewable energy ETFs showed partial co-volatility risk spillover effects during the GFC. This result is consistent with the results for the GFC in Table 4, as the financial market was difficult for investors to construct efficient portfolios during the GFC. Prior to the COVID-19, the squared shocks (volatility) from the Solar ETF show negative partial co-volatility spillovers on the subsequent Wind ETF with Solar ETF. Moreover, the squared shocks (or volatility) from the Wind ETF have positive spillover effects on the subsequent Solar ETF with Wind ETF and the volatility from the Hydro ETF have positive spillover effects on the subsequent Hyrdo ETF with Solar ETF, respectively. This empirical result is consistent with the result during the GFC in Table 4, as in normal times without structural breaks, the Solar, Wind and Hydro ETFs could form efficient portfolios for financial investors. During COVID-19, the risk volatility of wind with solar and hydro with solar and wind ETFs causes positive partial co-volatility spillover effects for their counterpart combinations, indicating that the assets have different volatilities during COVID-19, which can lead to efficient portfolios.

The risk volatility of three fossil fuel energy ETFs, namely Crude Oil (USO), Coal (KOL) and Natural Gas (UNG), shows that during the GFC, the squared shocks of Crude Oil have significant positive partial co-covariance spillovers for Coal and Crude Oil ETFs, and the squared shocks of Coal have significant negative partial co-covariance spillovers for Coal and Crude Oil ETFs. These again confirm that the financial market order was disrupted during the GFC, making it difficult for investors to construct efficient portfolios, except for the combination of Crude Oil and Coal. Prior to COVID-19, only the squared shocks caused by coal had positive partial co-covariance spillover effects on coal and crude oil ETFs. During COVID-19, the volatility from crude oil to coal ETFs show positive partial co-variation spillover effects. The empirical results confirm, as previously observed, that Crude Oil ETFs and Coal ETFs have similar volatility patterns during COVID-19, such that they can yield efficient portfolios.

Table 7 focuses on the cross-sector partial co-movement spillover effects of the second moment squared shocks between renewable energy ETFs and fossil fuel energy ETFs. It is clear that both before COVID-19 and during the GFC period, the squared shocks caused by solar and crude oil have positive partial co-movement spillover effects on solar with crude oil ETFs, solar with coal ETFs, crude oil with solar ETFs and crude oil with wind ETFs. However, market conditions changed dramatically during COVID-19, as can be seen in the third column of Table 7, the volatility caused by hydro ETFs has negative partial co-volatility spillover effects with crude oil, coal and natural gas, while coal ETFs have positive partial co-volatility spillover effects with solar, wind and hydro, respectively. Based on these empirical results, which suggest that during the COVID-19 period, when risks from coal ETFs are high, investors could use the renewable energy ETFs as an efficient portfolio to reduce risk, while other combinations may not be as good to choose as an efficient portfolio.

6. Discussions

For the sake of clarity, in Tables 8 (which summarizes Tables 4 and 6) and 9 (which summarizes Tables 5 and 7) we have organized the results of the co-covariance spillover for both shocks and quadratic shocks (risks). Optimal investment portfolios are characterized by a negative spillover for shocks and a positive spillover for risks. When both are negative, this means that the volatility of the two assets moves in opposite directions in response to a shock or risk event. As far as risk is concerned, these changes in volatility offer little protection against losses.

During the COVID-19 pandemic, Table 8 suggests that investors should consider a combination of (solar, wind) and (solar, hydro) as an effective investment strategy. This combination is beneficial when the risks are from wind or hydro sources, as it leads to opposite movements in volatility, thereby reducing potential losses. However, the effectiveness of the hedge may be reduced if the risks are associated with solar energy. In the period prior to COVID-19, viable assets are (solar, wind), (solar, hydro) and (oil, coal). Particularly during the Global Financial Crisis (GFC), the most favorable renewable energy investment portfolio includes only oil and coal, making other options less attractive.

Table 9 shows findings for cross-market strategies. Over the COVID-19 period, the combination of (solar, coal) and (wind, coal) is effective in minimizing losses. In addition, a portfolio with (solar, oil) can mitigate losses in the case of shocks or risks related to oil. However, it may not provide a hedge against solar-related risks.

In contrast, for the GFC and preCOVID-19 periods, alternative proposals emerge. Robust investment portfolios that reduce losses during the GFC are created by combining solar with oil and wind with oil. However, prior to COVID-19 pandemic, asset combinations such as (solar, oil) or (solar, coal) are valuable for risk management in non-pandemic periods.

7. Conclusion

The drive towards net-zero emissions has led to an increasing number of companies and countries setting targets to become fully carbon neutral. Understanding the transmission of risk is critical for investors in financial markets seeking to select optimal hedging instruments. This paper examines the transmission of risk between renewable and fossil fuel energy assets in energy exchange traded funds (ETFs). Specifically, we analyze risk transmission during two crisis periods, the Global Financial Crisis (GFC) from 25 June 2008 to 31 December 2009 and the COVID-19 pandemic from 30 January 2020 to date.

Our study focuses on the three most common renewable energy ETFs: solar (TAN), wind (FAN) and hydro (PHO), and the three most common fossil fuel energy ETFs: crude oil (USO), coal (KOL) and natural gas (UNG). We examine the risk transfer between renewable and fossil fuel energy assets, as well as the cross-risk transfer from renewable energy assets to fossil fuel energy assets and vice versa. Our results show that a shock in one energy asset can cause changes in the risk of the entire energy portfolio. We show that when one commodity experiences bad news and its volatility changes significantly, the volatility of another commodity changes little, which can stabilize financial losses.

Overall, our study introduces a novel test of risk transmission from the volatility of an energy asset to the co-volatility of the energy portfolio. This test helps us understand how a shock, whether good or bad news, in an energy asset causes changes in the risk of an investment portfolio. And we provide insights into risk transmission in energy ETFs and can help investors understand how shocks or volatility in one market can affect a related market. Our empirical results provide useful guidance to policy makers, market investors and energy producers on how to manage the risk in financial portfolios in the best possible way. In addition, while we've studied the period of the GFC and the COVID-19 pandemic, there are still several events, such as the war between Russia and Ukraine, that can also affect global energy markets and cause volatility in energy assets and impact energy portfolios. These are worthy of further study in the future.

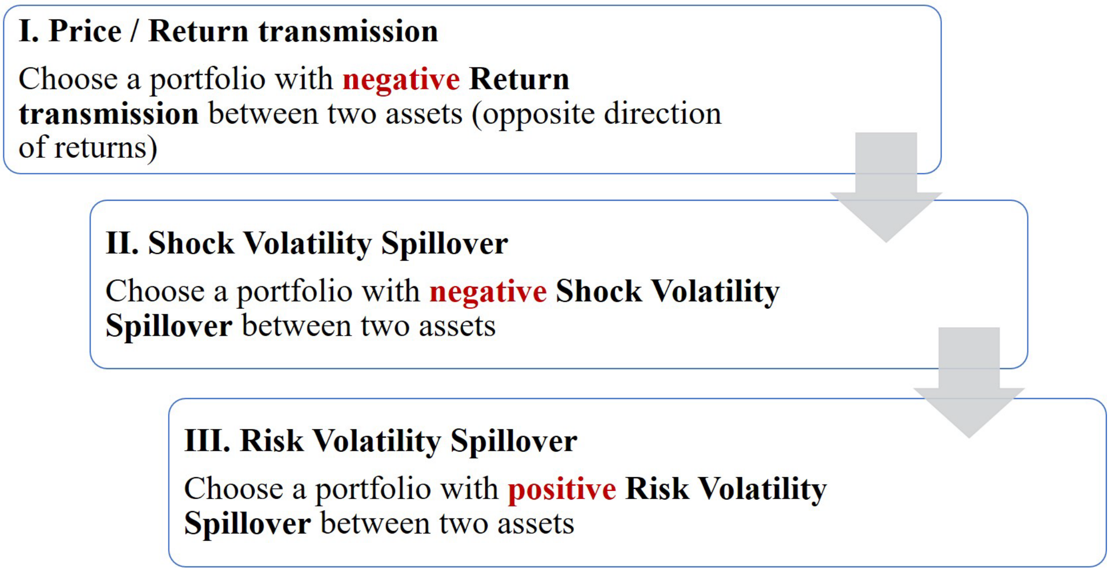


Figure 1. Meaning of different moment transmission

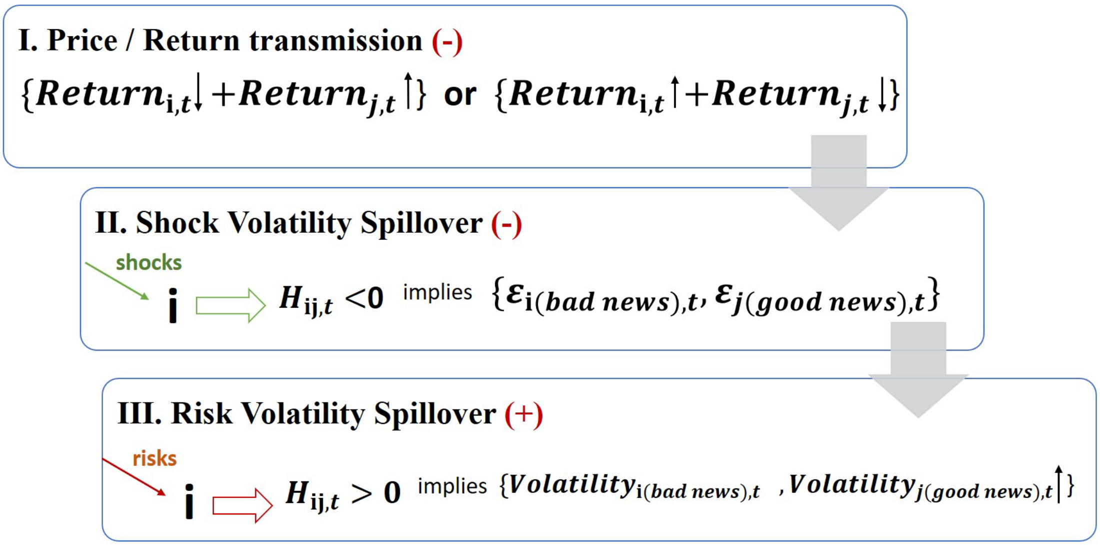


Figure 2. The implications of different moment transmission

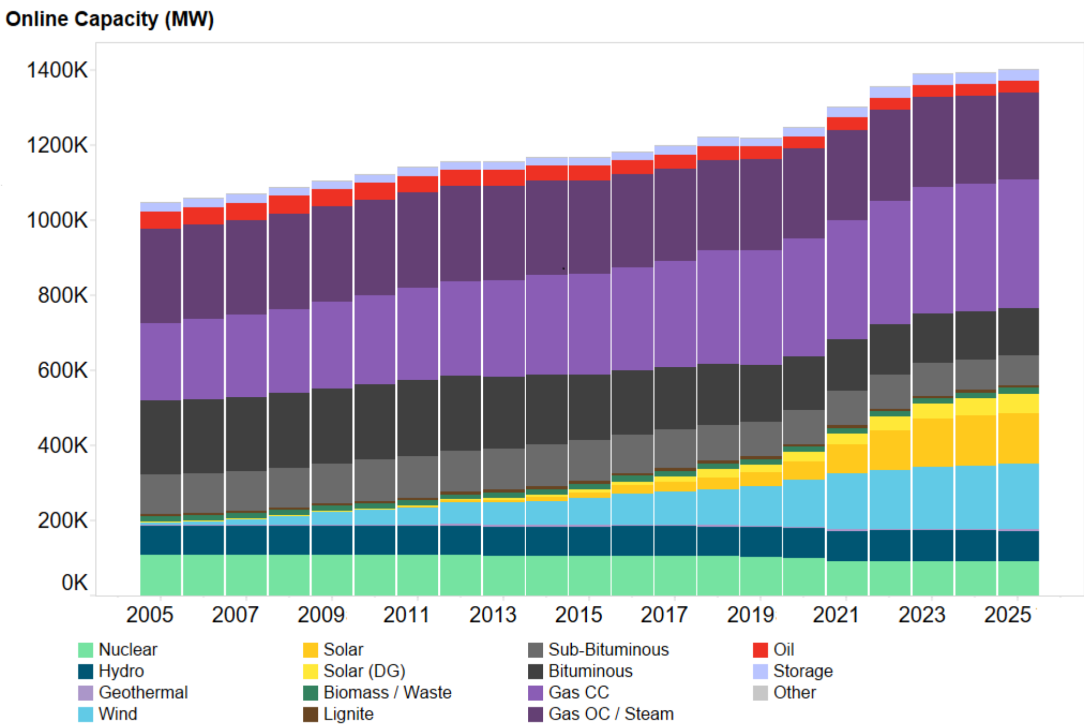


Figure 3. Energy Generation by Source, US

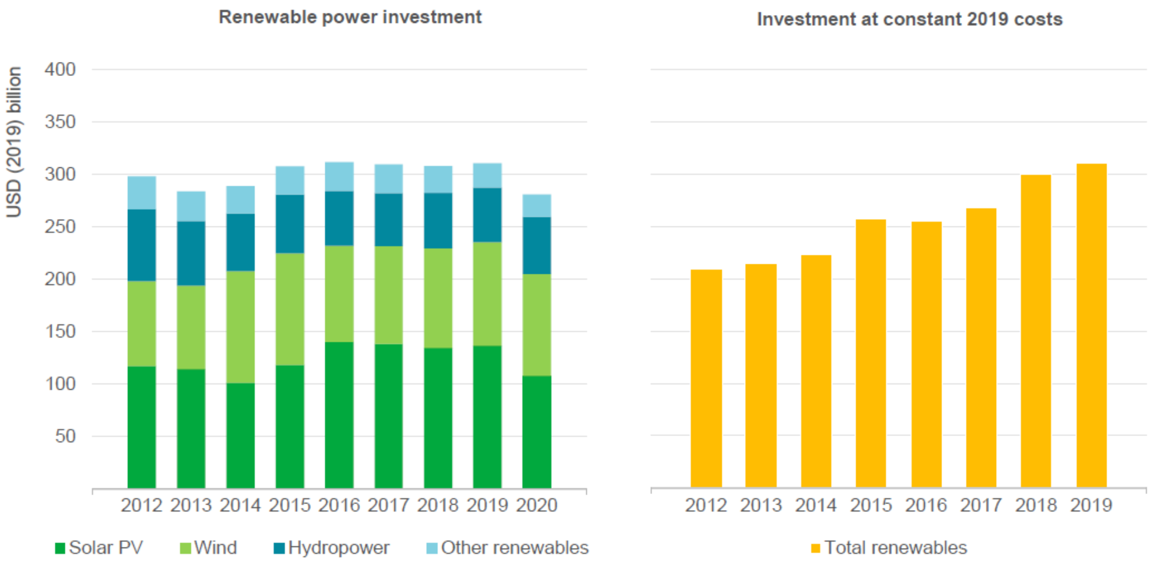


Figure 4. Global Energy Investment in Renewable Energy

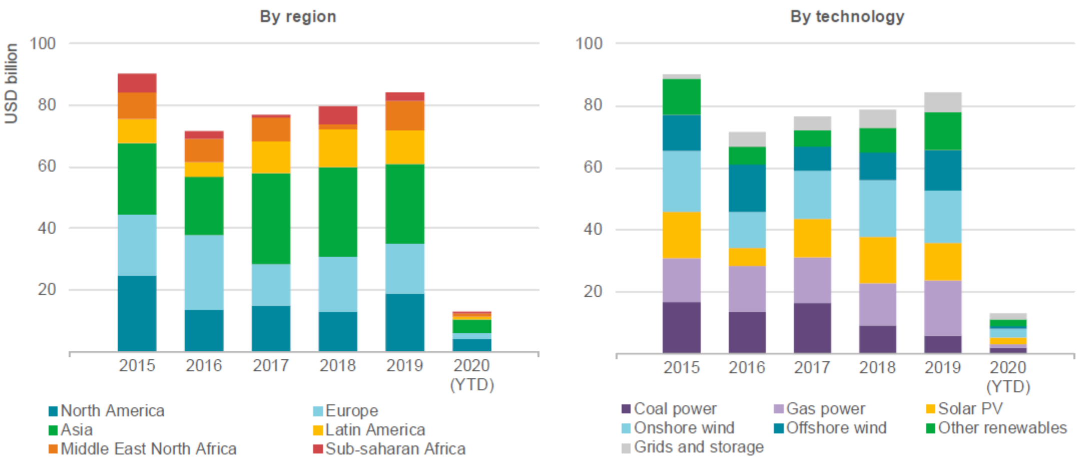
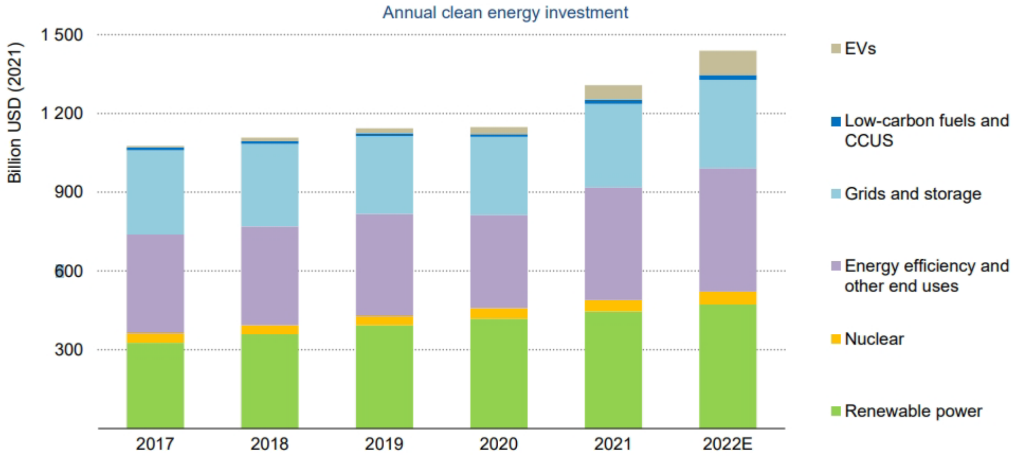


Figure 5. Global Energy Investment



Notes: Energy efficiency and other end-use includes spending on energy efficiency, renewables for end use and electrification in the buildings, transport and industry sectors. Low carbon fuels include modern liquid and gaseous bioenergy, low-carbon hydrogen, as well as hydrogen-based fuels that do not emit any CO2 from fossil fuels directly when used and also emit very little when being produced.

Figure 6. Annual Clean Energy Investment

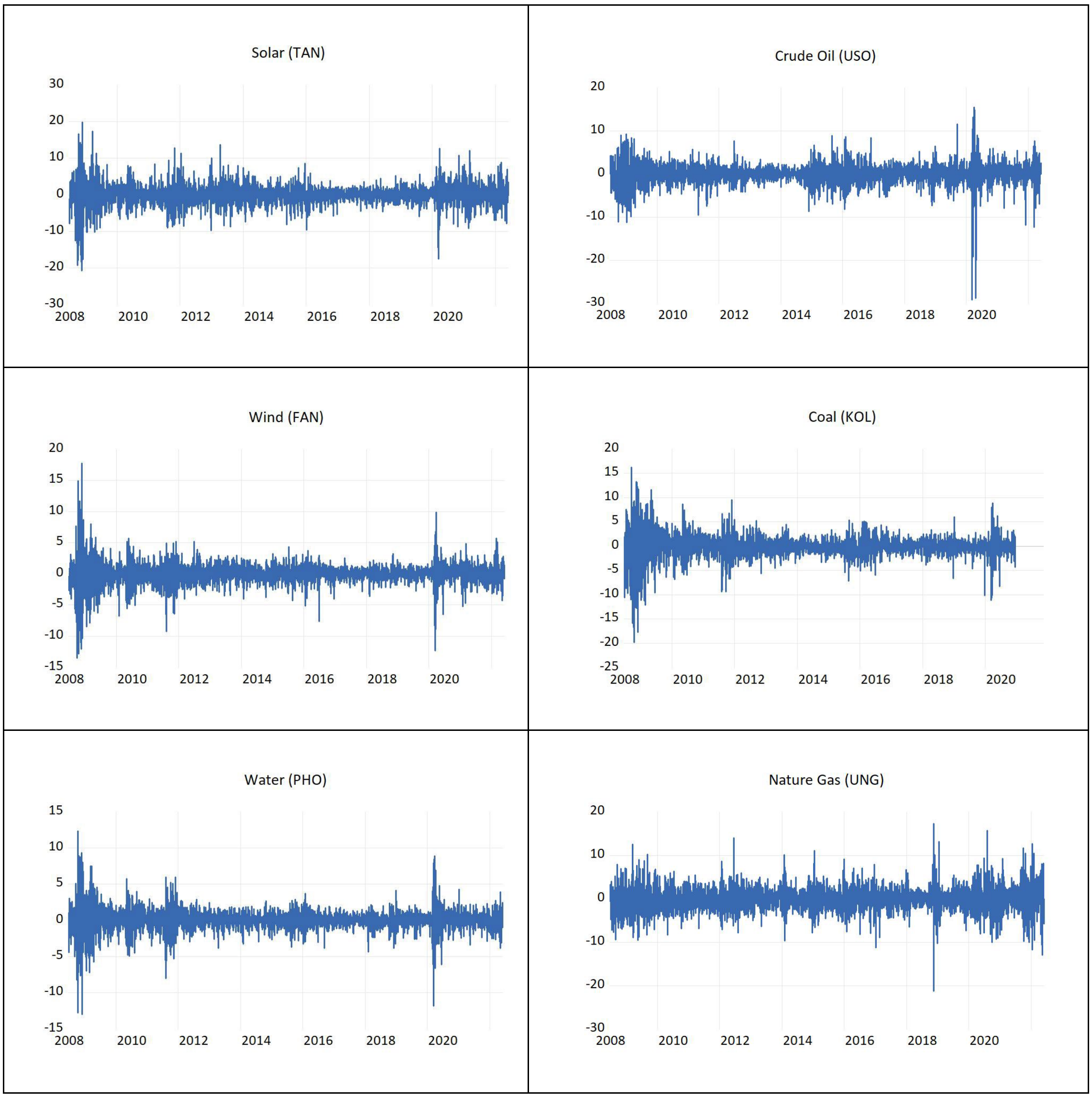


Figure 7. Renewable Energy and Fossil Fuel ETFs Returns (25 June 2008 - 31 May 2022)

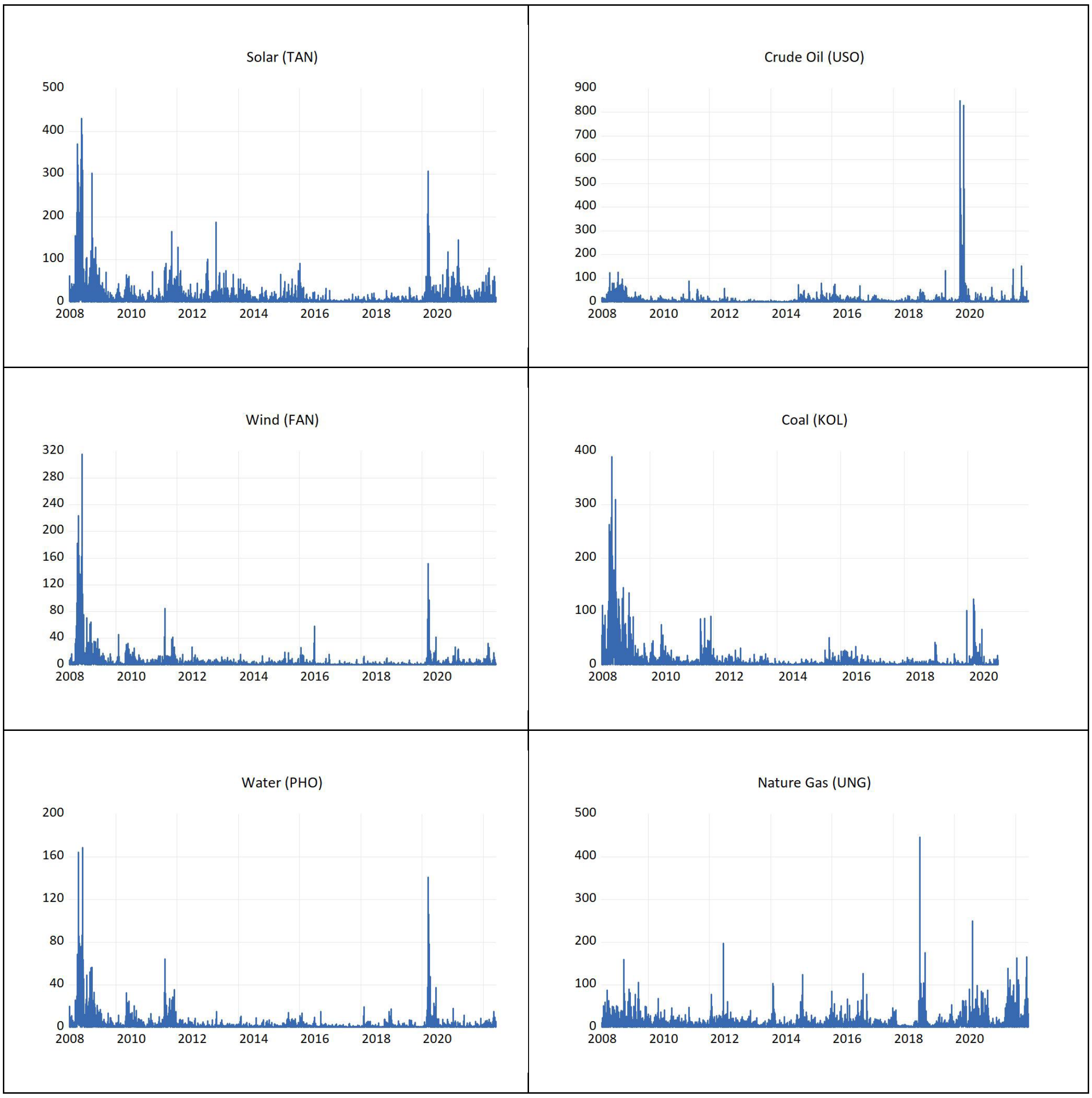


Figure 8. Unconditional Volatility for Renewable Energy and Fossil Fuel ETFs (25 June 2008 - 31 May 2022)

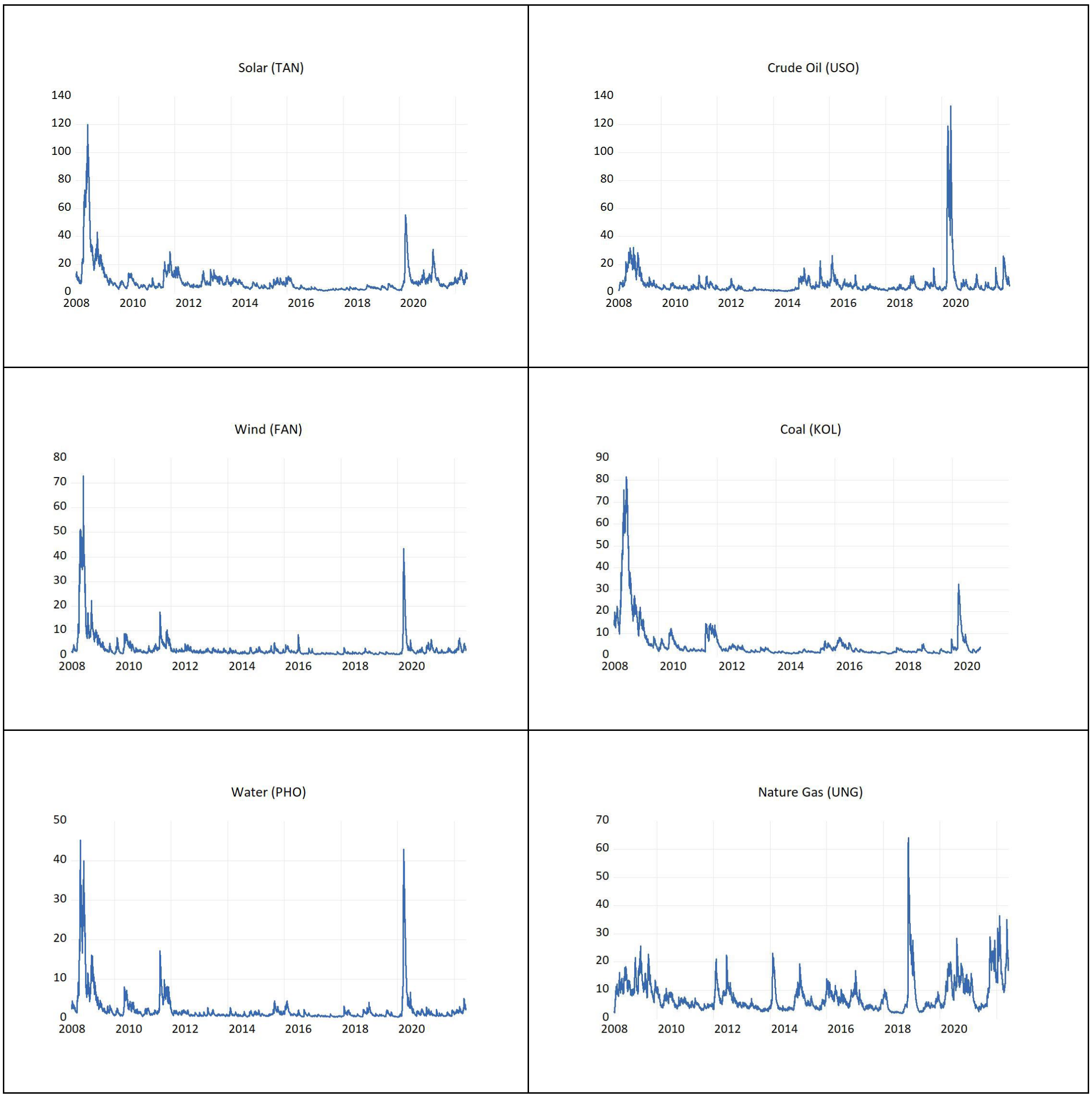


Figure 9. Conditional Volatility for Renewable Energy and Fossil Fuel ETFs (25 June 2008 - 31 May 2022)

Table 1. Data Sources

Variables	ETFs	Definition
Solar	TAN	Guggenheim Solar ETF
Wind	FAN	First Trust ISE Global Wind Energy Index Fund
Hydro	PHO	Invesco Water Resources ETF
Crude Oil	USO	United States Oil Fund
Coal	KOL	VanEck Vectors Coal ETF
Natural Gas	UNG	United States Natural Gas Fund

Table 2. Descriptive Statistics (25 June 2008 - 31 May 2022)

Returns	Mean	SD	Max	Min	Skewness	Kurtosis	Jarque-Bera
Solar	-0.037	2.861	19.761	-20.775	-0.461	10.295	7328.762
Wind	-0.011	1.764	17.746	-13.514	-0.485	16.271	23999.02
Hydro	0.023	1.588	12.318	-12.954	-0.446	12.978	13603.17
Crude Oil	-0.101	2.432	15.415	-29.189	-1.287	19.739	38876.71
Coal	-0.055	2.380	16.170	-19.787	-0.689	12.225	11792.25
Natural Gas	-0.163	2.667	17.311	-21.227	0.135	6.485	1656.255

Note: All Jarque-Bera statistics are significant at 1%.

Table 3. Unit Root Tests

Variables	ADF test		
	No Trend & Intercept	**With Intercept**	**With Trend & Intercept**
Solar	-52.597*	-52.614*	-52.679*
Wind	-57.814*	-57.815*	-57.888*
Hydro	-59.885*	-59.884*	-59.889*
Crude Oil	-55.214*	-55.318*	-55.310*
Coal	-54.420*	-54.448*	-54.441*
Natural Gas	-58.517*	-58.758*	-58.803*
Variables	**PP test**		
	No Trend & Intercept	**With Intercept**	**With Trend & Intercept**
Solar	-52.571*	-52.577*	-52.629*
Wind	-57.831*	-57.833*	-57.931*
Hydro	-60.157*	-60.174*	-60.189*
Crude Oil	-55.773*	-55.761*	-55.753*
Coal	-54.414*	-54.439*	-54.432*
Natural Gas	-58.470*	-58.737*	-58.780*

Note: * denotes the null hypothesis of a unit root is rejected at the 1% level of significance.

Table 4. Partial Co-Volatility Spillover (Negative Shock) for individual markets

Spillover= $\frac{\partial h_{ij,t}}{\partial \varepsilon_{j,t-1}}$			GFC	Before COVID-19	COVID-19
Solar	→	(Solar, Wind)		-0.011	-0.044
Solar	→	(Solar, Hydro)		-0.008	-0.013
Wind	→	(Wind, Solar)		-0.104	-0.221
Wind	→	(Wind, Hydro)			
Hydro	→	(Hydro, Solar)		-0.131	-0.293
Hydro	→	(Hydro, Wind)			-0.118
Crude Oil	→	(Crude Oil, Coal)	-0.183		0.166
Crude Oil	→	(Crude Oil, Natural Gas)			
Coal	→	(Coal, Crude Oil)	-0.021	-0.082	
Coal	→	(Coal, Natural Gas)			
Natural Gas	→	(Natural Gas, Crude oil)			
Natural Gas	→	(Natural Gas, Coal)			

Note: Partial Co-Volatility Spillover is defined in section 3.3: $\frac{\partial h_{ij,t}}{\partial \varepsilon_{j,t-1}} = a_{ii} \times a_{jj} \times \varepsilon_{i,t-1} + 2e_{ij}{}^{*} \times \varepsilon_{j,t-1}$, $i \neq j$ (The co-volatility spillover in Table 4 is calculated on the basis of the significant coefficients in Appendix 1 to 3.).

Table 5. Partial Co-Volatility Spillover (Negative Shock) for cross-sector market

Spillover= $\frac{\partial h_{ij,t}}{\partial \varepsilon_{j,t-1}}$			GFC	Before COVID-19	COVID-19
Solar	→	(Solar, Crude Oil)	-0.057	-0.041	
Solar	→	(Solar, Coal)	-0.145	-0.046	
Solar	→	(Solar, Natural Gas)		-0.072	0.007
Wind	→	(Wind, Crude Oil)	-0.074		
Wind	→	(Wind, Coal)	-0.152		
Wind	→	(Wind, Natural Gas)			
Hydro	→	(Hydro, Crude Oil)			-0.131
Hydro	→	(Hydro, coal)			0.014
Hydro	→	(Hydro, Natural Gas)			-0.017
Crude Oil	→	(Crude Oil, Solar)	-0.131	-0.057	-0.860
Crude Oil	→	(Crude Oil, Wind)	-0.094	-0.037	
Crude Oil	→	(Crude Oil, Hydro)	0.011		
Coal	→	(Coal, Solar)		-0.076	-0.105
Coal	→	(Coal, Wind)			-0.033
Coal	→	(Coal, Hydro)			-0.034
Natural Gas	→	(Natural Gas, Solar)			
Natural Gas	→	(Natural Gas, Wind)			
Natural Gas	→	(Natural Gas, Hydro)			

Note: Partial Co-Volatility Spillover is defined in section 3.3: $\frac{\partial h_{ij,t}}{\partial \varepsilon_{j,t-1}} = a_{ii} \times a_{jj} \times \varepsilon_{i,t-1} + 2e_{ij}{}^{*} \times \varepsilon_{j,t-1}$, $i \neq j$ (The co-volatility spillover in Table 5 is calculated on the basis of the significant coefficients in Appendix 4.).

Table 6. Partial Co-Volatility Spillover for Squared Shock for individual markets

Spillover for squared shock= $\frac{\partial h_{ij,t}}{\partial \varepsilon_{j,t-1}^2}$			GFC	Before COVID-19	COVID-19
Solar	→	(Solar, Wind)		-0.008	-0.009
Solar	→	(Solar, Hydro)		-0.007	-0.012
Wind	→	(Wind, Solar)		0.025	0.032
Wind	→	(Wind, Hydro)			
Hydro	→	(Hydro, Solar)		0.050	0.076
Hydro	→	(Hydro, Wind)			0.016
Crude Oil	→	(Crude Oil, Coal)	0.013		0.019
Crude Oil	→	(Crude Oil, Natural Gas)			
Coal	→	(Coal, Crude Oil)	-0.026	0.020	
Coal	→	(Coal, Natural Gas)			
Natural Gas	→	(Natural Gas, Crude oil)			
Natural Gas	→	(Natural Gas, Coal)		-0.031	

Note: Partial Co-Volatility Spillover for Squared Shock is defined as section 3.3: $\frac{h_{ij,t}}{\partial \varepsilon_{j,t-1}^2} = e_{ij}{}^*$, $i \neq j$. (The co-volatility spillover in Table 6 is calculated on the basis of the significant coefficients in Appendix 5 to 7.).

Table 7. Partial Co-Volatility Spillover for Squared Shock for cross-sector markets

Spillover for squared shock= $\frac{\partial h_{ij,t}}{\partial \varepsilon^2_{j,t-1}}$			GFC	Before COVID-19	COVID-19
Solar	→	(Solar, Crude Oil)	0.004	0.003	
Solar	→	(Solar, Coal)	0.010	0.007	0.007
Solar	→	(Solar, Natural Gas)		0.007	-0.008
Wind	→	(Wind, Crude Oil)	0.008		
Wind	→	(Wind, Coal)	0.008		0.015
Wind	→	(Wind, Natural Gas)			
Hydro	→	(Hydro, Crude Oil)			-0.045
Hydro	→	(Hydro, coal)			-0.023
Hydro	→	(Hydro, Natural Gas)			-0.044
Crude Oil	→	(Crude Oil, Solar)	0.019	0.008	0.083
Crude Oil	→	(Crude Oil, Wind)	0.014	0.007	
Crude Oil	→	(Crude Oil, Hydro)	-0.008		0.017
Coal	→	(Coal, Solar)	-0.003	0.020	0.022
Coal	→	(Coal, Wind)	-0.006		0.008
Coal	→	(Coal, Hydro)			0.008
Natural Gas	→	(Natural Gas, Solar)			
Natural Gas	→	(Natural Gas, Wind)			
Natural Gas	→	(Natural Gas, Hydro)			

Note: (The co-volatility spillover in Table 7 is calculated on the basis of the significant coefficients in Appendix 8.).

Table 8. Selections for individual markets

Volatility Spillover			GFC		Before COVID-19		COVID-19	
			shock	risk	shock	risk	shock	risk
Solar	→	(Solar, Wind)			-	-	-	-
Solar	→	(Solar, Hydro)			-	-	-	-
Wind	→	(Wind, Solar)			-	+	-	+
Wind	→	(Wind, Hydro)						
Hydro	→	(Hydro, Solar)			-	+	-	+
Hydro	→	(Hydro, Wind)					-	+
Crude Oil	→	(Crude Oil, Coal)		+			+	+
Crude Oil	→	(Crude Oil, Natural Gas)						
Coal	→	(Coal, Crude Oil)		-	-	+		
Coal	→	(Coal, Natural Gas)						
Natural Gas	→	(Natural Gas, Crude oil)						
Natural Gas	→	(Natural Gas, Coal)				-		

Table 9. Selections for cross-sector markets

Volatility Spillover			GFC		Before COVID-19		COVID-19	
			shock	**risk**	**shock**	**risk**	**shock**	**risk**
Solar	→	(Solar, Crude Oil)						
Solar	→	(Solar, Coal)		+	-	+		+
Solar	→	(Solar, Natural Gas)			-	+	+	-
Wind	→	(Wind, Crude Oil)		+				
Wind	→	(Wind, Coal)		+				+
Wind	→	(Wind, Natural Gas)						
Hydro	→	(Hydro, Crude Oil)					-	-
Hydro	→	(Hydro, coal)					+	-
Hydro	→	(Hydro, Natural Gas)					-	-
Crude Oil	→	(Crude Oil, Solar)		+	-	+	-	+
Crude Oil	→	(Crude Oil, Wind)		+	-	+		
Crude Oil	→	(Crude Oil, Hydro)		-				+
Coal	→	(Coal, Solar)		-	-	+	-	+
Coal	→	(Coal, Wind)		-			-	+
Coal	→	(Coal, Hydro)					-	+
Natural Gas	→	(Natural Gas, Solar)						
Natural Gas	→	(Natural Gas, Wind)						
Natural Gas	→	(Natural Gas, Hydro)						

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Appendix 1

Partial Co-Volatility Spillover- Renewable Energy and Fossil Fuel ETFs

Outcomes			GFC			Before COVID-19			COVID-19		
$\varepsilon_{j.t-1}$	$\rightarrow$	$h(i,j)_t$	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}
Renewable		(Renewable, Fossil fuel)	0.285*** (0.034)	0.112** (0.057)	0.009 (0.007)	0.232*** (0.014)	0.263*** (0.020)	-0.035*** (0.005)	0.294*** (0.029)	0.333*** (0.035)	-0.027*** (0.009)
Fossil fuel		(Fossil fuel, Renewable)	0.049 (0.063)	0.245*** (0.045)	0.018* (0.009)	0.240*** (0.018)	0.236*** (0.014)	-0.024*** (0.009)	0.294*** (0.035)	0.293*** (0.057)	0.009* (0.005)

Note: *** denotes significance level 1%, ** denotes significance level 5%, * denotes significance level 10%.

Appendix 2

Partial Co-Volatility Spillover- Renewable Energy ETFs

Outcomes			GFC			Before COVID-19			COVID-19		
$\varepsilon_{j.t-1}$	$\rightarrow$	$h(i,j)_t$	a_{ii}	a_{jj}	e_{ij}^*	a_{ii}	a_{jj}	e_{ij}^*	a_{ii}	a_{jj}	e_{ij}^*
Solar		(Solar, Wind)	-0.087 (0.084)	0.098 (0.067)	0.003 (0.005)	0.233*** (0.017)	0.170*** (0.011)	-0.008*** (0.003)	0.290*** (0.026)	0.242*** (0.028)	-0.009** (0.005)
Solar		(Solar, Hydro)	-0.050 (0.086)	0.098 (0.067)	-0.003 (0.005)	0.230*** (0.013)	0.170*** (0.011)	-0.007*** (0.002)	0.256*** (0.033)	0.242*** (0.028)	-0.012*** (0.004)
Wind		(Wind, Solar)	0.086 (0.078)	0.234*** (0.053)	-0.005 (0.010)	0.164*** (0.010)	0.202*** (0.016)	0.025*** (0.006)	0.218*** (0.028)	0.280*** (0.028)	0.032*** (0.010)
Wind		(Wind, Hydro)	0.089 (0.064)	0.234*** (0.053)	0.006 (0.006)	0.210*** (0.015)	0.202*** (0.016)	-0.001 (0.006)	0.250*** (0.035)	0.280*** (0.028)	0.033 (0.012)
Hydro		(Hydro, Solar)	0.063 (0.084)	0.080 (0.071)	-0.010 (0.010)	0.160*** (0.011)	0.183*** (0.013)	0.050*** (0.007)	0.213*** (0.031)	0.246*** (0.047)	0.076*** (0.020)
Hydro		(Hydro, Wind)	0.200*** (0.056)	0.080 (0.071)	-0.001 (0.007)	0.204*** (0.014)	0.183*** (0.013)	-0.004 (0.008)	0.272*** (0.029)	0.246*** (0.047)	0.016* (0.009)

Note: *** denotes significance level 1%, ** denotes significance level 5%.

Appendix 3

Partial Co-Volatility Spillover- Fossil Fuel ETFs

Outcomes			GFC			Before COVID-19			COVID-19		
$\varepsilon_{j.t-1}$	→	$h(i,j)_t$	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}
Crude Oil		(Crude Oil, Coal)	0.232*** (0.032)	0.127*** (0.036)	0.013* (0.007)	0.172*** (0.013)	0.169*** (0.013)	0.002 (0.004)	-0.371*** (0.116)	0.431*** (0.154)	0.019*** (0.006)
Crude Oil		(Crude Oil, Natural Gas)	-0.081 (0.049)	0.127*** (0.036)	-0.007 (0.006)	0.241*** (0.013)	0.169*** (0.013)	-0.001 (0.003)	0.084 (0.119)	0.431*** (0.154)	-0.002 (0.008)
Coal		(Coal, Crude Oil)	0.239*** (0.052)	0.334*** (0.087)	-0.026** (0.012)	0.191*** (0.012)	0.123*** (0.017)	0.020*** (0.004)	0.607*** (0.068)	0.261** (0.106)	0.023 (0.023)
Coal		(Coal, Natural Gas)	0.013 (0.080)	0.334*** (0.087)	0.004 (0.006)	0.242*** (0.013)	0.123*** (0.017)	0.003 (0.004)	-0.079 (0.062)	0.261** (0.106)	0.012 (0.014)
Natural Gas		(Natural Gas, Crude oil)	0.225*** (0.046)	0.073* (0.039)	0.007 (0.012)	0.201*** (0.012)	0.071 (0.047)	0.007 (0.019)	0.557*** (0.067)	-0.049 (0.065)	0.003 (0.007)
Natural Gas		(Natural Gas, Coal)	0.251*** (0.042)	0.073* (0.039)	0.001 (0.012)	0.204*** (0.014)	0.071 (0.047)	-0.031*** (0.010)	0.409*** (0.077)	-0.049 (0.065)	0.003 (0.008)

Note: *** denotes significance level 1%, ** denotes significance level 5%.

Appendix 4

Partial Co-Volatility Spillover- Renewable Energy and Fossil Fuel ETFs

Outcomes			GFC			Before COVID-19			COVID-19		
$\varepsilon_{j.t-1}$	$\rightarrow$	$h(i,j)_t$	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}
Solar		(Solar, Wind)	0.121*** (0.028)	0.140*** (0.028)	0.013*** (0.002)	0.148*** (0.011)	0.121*** (0.009)	0.006*** (0.002)	0.125*** (0.015)	0.244*** (0.031)	0.015*** (0.002)
Solar		(Solar, Hydro)	0.174*** (0.024)	0.140*** (0.028)	0.008*** (0.002)	0.165*** (0.009)	0.121*** (0.009)	0.007*** (0.001)	0.101*** (0.017)	0.244*** (0.031)	0.008 (0.003)
Solar		(Solar, Crude Oil)	0.080** (0.036)	0.140*** (0.028)	0.004** (0.002)	0.177*** (0.010)	0.121*** (0.009)	0.003** (0.001)	0.710*** (0.044)	0.244*** (0.031)	0.010 (0.007)
Solar		(Solar, Coal)	0.140*** (0.019)	0.140*** (0.028)	0.010*** (0.003)	0.148*** (0.009)	0.121*** (0.009)	0.007*** (0.002)	0.049 (0.036)	0.244*** (0.031)	0.007** (0.002)
Solar		(Solar, Natural Gas)	-0.034 (0.047)	0.140*** (0.028)	0.002 (0.002)	0.223*** (0.012)	0.121*** (0.009)	0.007** (0.003)	0.052*** (0.007)	0.244*** (0.031)	-0.008*** (0.001)
Wind		(Wind, Solar)	0.154*** (0.033)	0.152*** (0.035)	0.028*** (0.007)	0.130*** (0.009)	0.127*** (0.012)	0.024*** (0.004)	0.124*** (0.062)	0.034 (0.066)	0.065 (0.003)
Wind		(Wind, Hydro)	0.208*** (0.028)	0.152*** (0.035)	0.005* (0.003)	0.130*** (0.010)	0.127*** (0.012)	0.006* (0.004)	0.195*** (0.067)	0.034 (0.066	0.020* (0.011)
Wind		(Wind, Crude Oil)	0.090*** (0.029)	0.152*** (0.035)	0.008*** (0.002)	0.185*** (0.010)	0.127*** (0.012)	-0.002 (0.007)	0.575*** (0.066)	0.034 (0.066	-0.005 (0.031)

Outcomes			GFC			Before COVID-19			COVID-19		
$\varepsilon_{j.t-1}$	$\rightarrow$	$h(i,j)_t$	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}
Wind		(Wind, Coal)	0.197*** (0.022)	0.152*** (0.035)	0.008* (0.005)	0.126*** (0.009)	0.127*** (0.012)	-0.002 (0.007)	0.170*** (0.012)	0.034 (0.066	0.015*** (0.007)
Wind		(Wind, Natural Gas)	-0.051 (0.053)	0.152*** (0.035)	-0.001 (0.005)	0.230*** (0.013)	0.127*** (0.012)	-0.003 (0.007)	-0.174*** (0.084)	0.034 (0.066	-0.003 (0.011)
Hydro		(Hydro, Solar)	0.130*** (0.032)	0.224*** (0.025)	0.030*** (0.008)	0.124*** (0.008)	0.122*** (0.009)	0.049*** (0.005)	0.152*** (0.028)	0.143*** (0.020)	0.031*** (0.004)
Hydro		(Hydro, Wind)	0.139*** (0.036)	0.224*** (0.025)	0.008* (0.005)	0.137*** (0.011)	0.122*** (0.009)	0.006 (0.006)	-0.037*** (0.015)	0.143*** (0.020)	0.033*** (0.002)
Hydro		(Hydro, Crude Oil)	0.079*** (0.029)	0.224*** (0.025)	0.004 (0.005)	0.192*** (0.011)	0.122*** (0.009)	0.005 (0.006)	0.635*** (0.053)	0.143*** (0.020)	-0.045*** (0.013)
Hydro		(Hydro, coal)	0.190*** (0.021)	0.224*** (0.025)	-0.001 (0.010)	0.129*** (0.010)	0.122*** (0.009)	-0.001 (0.004)	0.089*** (0.017)	0.143*** (0.020)	-0.011*** (0.001)
Hydro		(Hydro, Natural Gas)	-0.036 (0.057)	0.224*** (0.025)	-0.011 (0.007)	0.228*** (0.012)	0.122*** (0.009)	0.001 (0.001)	0.060*** (0.009)	0.143*** (0.020)	-0.002*** (0.001)
Crude Oil		(Crude Oil, Solar)	0.116*** (0.019)	0.080*** (0.025)	0.019*** (0.004)	0.132*** (0.007)	0.152*** (0.011)	0.008** (0.003)	-0.181*** (0.050)	-0.722*** (0.084)	0.083*** (0.018)
Crude Oil		(Crude Oil, Wind)	0.116*** (0.028)	0.080*** (0.025)	0.014*** (0.004)	0.118*** (0.008)	0.152*** (0.011)	0.007* (0.004)	0.040 (0.043)	-0.722*** (0.084)	0.003 (0.010)
Crude Oil		(Crude Oil, Hydro)	0.176*** (0.019)	0.080*** (0.025)	-0.008* (0.004)	0.155*** (0.008)	0.152*** (0.011)	-0.004 (0.005)	0.043 (0.053)	-0.722*** (0.084)	0.017* (0.009)

Outcomes			GFC			Before COVID-19			COVID-19		
$\varepsilon_{j.t-1}$	$\rightarrow$	$h(i,j)_t$	a_{ii}	a_{jj}	e_{ij}^{*}	a_{ii}	a_{jj}	e_{ij}^{*}	a_{ii}	a_{jj}	e_{ij}^{*}
Crude Oil		(Crude Oil, Coal)	0.173*** (0.016)	0.080*** (0.025)	0.007 (0.005)	0.132*** (0.007)	0.152*** (0.011)	-0.001 (0.003)	0.098* (0.053)	-0.722*** (0.084)	-0.001 (0.001)
Crude Oil		(Crude Oil, Natural Gas)	-0.002 (0.024)	0.080*** (0.025)	0.001 (0.004)	0.230*** (0.012)	0.152*** (0.011)	0.002 (0.004)	-0.287** (0.096)	-0.722*** (0.084)	0.001 (0.006)
Coal		(Coal, Solar)	0.048 (0.035)	0.294*** (0.020)	-0.003 (0.002)	0.124*** (0.007)	0.126*** (0.009)	0.020*** (0.002)	0.201*** (0.029)	0.059*** (0.007)	0.022*** (0.002)
Coal		(Coal, Wind)	0.015 (0.020)	0.294*** (0.020)	-0.006** (0.003)	0.137*** (0.011)	0.126*** (0.009)	-0.002 (0.003)	0.079*** (0.009)	0.059*** (0.007)	0.008*** (0.001)
Coal		(Coal, Hydro)	0.154*** (0.024)	0.294*** (0.020)	-0.009 (0.001)	0.149*** (0.009)	0.126*** (0.009)	0.001 (0.003)	0.077*** (0.018)	0.059*** (0.007)	0.008*** (0.001)
Coal		(Coal, Crude Oil)	0.270*** (0.039)	0.294*** (0.020)	-0.016*** (0.001)	0.186*** (0.010)	0.126*** (0.009)	0.004 (0.003)	0.685*** (0.044)	0.059*** (0.007)	0.008*** (0.001)
Coal		(Coal, Natural Gas)	-0.052 (0.066)	0.294*** (0.020)	-0.004*** (0.001)	0.225*** (0.012)	0.126*** (0.009)	0.001 (0.005)	0.042*** (0.007)	0.059*** (0.007)	0.020*** (0.001)
Natural Gas		(Natural Gas, Solar)	0.216*** (0.018)	0.066** (0.042)	-0.001 (0.011)	0.140*** (0.008)	0.105** (0.041)	-0.020 (0.013)	0.225*** (0.030)	-0.148** (0.062)	0.010 (0.008)
Natural Gas		(Natural Gas, Wind)	0.266*** (0.021)	0.066** (0.042)	-0.005 (0.009)	0.153*** (0.013)	0.105** (0.041)	0.003 (0.013)	0.279*** (0.022)	-0.148** (0.062)	0.008 (0.008)

Outcomes			GFC			Before COVID-19			COVID-19		
$\varepsilon_{j.t-1}$	$\rightarrow$	$h(i,j)_t$	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}	a_{ii}	a_{jj}	e^*_{ij}
Natural Gas		(Natural Gas, Hydro)	0.262*** (0.021)	0.066** (0.042)	0.006 (0.012)	0.186*** (0.010)	0.105** (0.041)	0.021 (0.014)	0.452*** (0.036)	-0.148** (0.062)	0.002 (0.009)
Natural Gas		(Natural Gas, Crude oil)	0.193*** (0.022)	0.066** (0.042)	0.001 (0.013)	0.179*** (0.011)	0.105** (0.041)	0.006 (0.012)	0.573*** (0.050)	-0.148** (0.062)	0.001 (0.007)
Natural Gas		(Natural Gas, Coal)	0.194*** (0.015)	0.066** (0.042)	-0.001 (0.010)	0.161*** (0.008)	0.105** (0.041)	0.004 (0.013)	0.287*** (0.030)	-0.148** (0.062)	0.003 (0.008)

Note: *** denotes significance level 1%, ** denotes significance level 5%, * denotes significance level 10%.

Appendix 5

Partial Co-Volatility Spillover for Squared Shock - Renewable Energy and Fossil Fuel ETFs

Outcomes			GFC	Before COVID-19	COVID-19
$\varepsilon^2_{j,t-1}$	$\rightarrow$	$h(i,j)_t$	e^*_{ij}	e^*_{ij}	e^*_{ij}
Renewable		(Renewable, Fossil fuel)	0.009 (0.007)	-0.035*** (0.005)	-0.027*** (0.009)
Fossil fuel		(Fossil fuel, Renewable)	0.018* (0.009)	-0.024*** (0.009)	0.009* (0.005)

Note: *** denotes significance level 1%, ** denotes significance level 5%, * denotes significance level 10%.

Appendix 6

Partial Co-Volatility Spillover for Squared Shock - Renewable Energy ETFs

Outcomes			**GFC**	**Before COVID-19**	**COVID-19**
$\varepsilon^2_{j,t-1}$	$\rightarrow$	$h(i,j)_t$	e^*_{ij}	e^*_{ij}	e^*_{ij}
Solar		(Solar, Wind)	0.003 (0.005)	-0.008*** (0.003)	-0.009** (0.005)
Solar		(Solar, Hydro)	-0.003 (0.005)	-0.007*** (0.002)	-0.012*** (0.004)
Wind		(Wind, Solar)	-0.005 (0.010)	0.025*** (0.006)	0.032*** (0.010)
Wind		(Wind, Hydro)	0.006 (0.006)	-0.001 (0.006)	0.033 (0.012)
Hydro		(Hydro, Solar)	-0.010 (0.010)	0.050*** (0.007)	0.076*** (0.020)
Hydro		(Hydro, Wind)	-0.001 (0.007)	-0.004 (0.008)	0.016* (0.009)

Note: *** denotes significance level 1%, ** denotes significance level 5%, * denotes significance level 10%.

Appendix 7

Partial Co-Volatility Spillover for Squared Shock – Fossil Fuel ETFs

Outcomes			GFC	Before COVID-19	COVID-19
$\varepsilon^2_{j,t-1}$	$\rightarrow$	$h(i,j)_t$	e^*_{ij}	e^*_{ij}	e^*_{ij}
Crude Oil		(Crude Oil, Coal)	0.013* (0.007)	0.002 (0.004)	0.019*** (0.006)
Crude Oil		(Crude Oil, Natural Gas)	-0.007 (0.006)	-0.001 (0.003)	-0.002 (0.008)
Coal		(Coal, Crude Oil)	-0.026** (0.012)	0.020*** (0.004)	0.023 (0.023)
Coal		(Coal, Natural Gas)	0.004 (0.006)	0.003 (0.004)	0.012 (0.014)
Natural Gas		(Natural Gas, Crude oil)	0.007 (0.012)	0.007 (0.019)	0.003 (0.007)
Natural Gas		(Natural Gas, Coal)	0.001 (0.012)	-0.031*** (0.010)	0.003 (0.008)

Note: *** denotes significance level 1%, ** denotes significance level 5%, * denotes significance level 10%.

Appendix 8

Partial Co-Volatility Spillover for Squared Shock - Renewable Energy and Fossil Fuel ETFs

Outcomes			GFC	Before COVID-19	COVID-19
$\varepsilon^2_{j,t-1}$	$\rightarrow$	$h(i,j)_t$	e^*_{ij}	e^*_{ij}	e^*_{ij}
Solar		(Solar, Wind)	0.013*** (0.002)	0.006*** (0.002)	0.015*** (0.002)
Solar		(Solar, Hydro)	0.008*** (0.002)	0.007*** (0.001)	0.008 (0.003)
Solar		(Solar, Crude Oil)	0.004** (0.002)	0.003** (0.001)	0.010 (0.007)
Solar		(Solar, Coal)	0.010*** (0.003)	0.007*** (0.002)	0.007** (0.002)
Solar		(Solar, Natural Gas)	0.002 (0.002)	0.007** (0.003)	-0.008*** (0.001)
Wind		(Wind, Solar)	0.028*** (0.007)	0.024*** (0.004)	0.065 (0.003)
Wind		(Wind, Hydro)	0.005* (0.003)	0.006* (0.004)	0.020* (0.011)

Outcomes			GFC	Before COVID-19	COVID-19
$\varepsilon^2_{j,t-1}$	$\rightarrow$	$h(i,j)_t$	e^*_{ij}	e^*_{ij}	e^*_{ij}
Wind		(Wind, Crude Oil)	0.008*** (0.002)	-0.002 (0.007)	-0.005 (0.031)
Wind		(Wind, Coal)	0.008* (0.005)	-0.002 (0.007)	0.015*** (0.007)
Wind		(Wind, Natural Gas)	-0.001 (0.005)	-0.003 (0.007)	-0.003 (0.011)
Hydro		(Hydro, Solar)	0.030*** (0.008)	0.049*** (0.005)	0.031*** (0.004)
Hydro		(Hydro, Wind)	0.008* (0.005)	0.006 (0.006)	0.033*** (0.002)
Hydro		(Hydro, Crude Oil)	0.004 (0.005)	0.005 (0.006)	-0.045*** (0.013)
Hydro		(Hydro, coal)	-0.001 (0.010)	-0.001 (0.004)	-0.011*** (0.001)
Hydro		(Hydro, Natural Gas)	-0.011 (0.007)	0.001 (0.001)	-0.002*** (0.001)
Crude Oil		(Crude Oil, Solar)	0.019*** (0.004)	0.008** (0.003)	0.083*** (0.018)

Outcomes			GFC	Before COVID-19	COVID-19
$\varepsilon^2_{j,t-1}$	$\rightarrow$	$h(i,j)_t$	e^*_{ij}	e^*_{ij}	e^*_{ij}
Crude Oil		(Crude Oil, Wind)	0.014*** (0.004)	0.007* (0.004)	0.003 (0.010)
Crude Oil		(Crude Oil, Hydro)	-0.008* (0.004)	-0.004 (0.005)	0.017* (0.009)
Crude Oil		(Crude Oil, Coal)	0.007 (0.005)	-0.001 (0.003)	-0.001 (0.001)
Crude Oil		(Crude Oil, Natural Gas)	0.001 (0.004)	0.002 (0.004)	0.001 (0.006)
Coal		(Coal, Solar)	-0.003 (0.002)	0.020*** (0.002)	0.022*** (0.002)
Coal		(Coal, Wind)	-0.006** (0.003)	-0.002 (0.003)	0.008*** (0.001)
Coal		(Coal, Hydro)	-0.009 (0.001)	0.001 (0.003)	0.008*** (0.001)
Coal		(Coal, Crude Oil)	-0.016*** (0.001)	0.004 (0.003)	0.008*** (0.001)
Coal		(Coal, Natural Gas)	-0.004*** (0.001)	0.001 (0.005)	0.020*** (0.001)

Outcomes			GFC	Before COVID-19	COVID-19
$\varepsilon^2_{j,t-1}$	$\rightarrow$	$h(i,j)_t$	e^*_{ij}	e^*_{ij}	e^*_{ij}
Natural Gas		(Natural Gas, Solar)	-0.001 (0.011)	-0.020 (0.013)	0.010 (0.008)
Natural Gas		(Natural Gas, Wind)	-0.005 (0.009)	0.003 (0.013)	0.008 (0.008)
Natural Gas		(Natural Gas, Hydro)	0.006 (0.012)	0.021 (0.014)	0.002 (0.009)
Natural Gas		(Natural Gas, Crude oil)	0.001 (0.013)	0.006 (0.012)	0.001 (0.007)
Natural Gas		(Natural Gas, Coal)	-0.001 (0.010)	0.004 (0.013)	0.003 (0.008)

Note: *** denotes significance level 1%, ** denotes significance level 5%, * denotes significance level 10%.