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ORIGINAL RESEARCH

Is green investment different from grey? Return and volatility spillovers between green and grey energy ETFs

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Abstract
Investment in Green energy is becoming a popular alternative asset class for investors, primarily due to its environment-friendly attributes. However, there is a dire need for subjective evaluation of this emerging asset class based on the risk-return dynamics to which investors are exposed. To respond to this call, in this study, we conduct this evaluation utilizing a unique and rich data set consisting of daily prices of exchange-traded funds (ETFs) established on different asset classes. We use Vector autoregression and Baba-Engle-Kraft-Kroner parameterization of multivariate GARCH models and assess the relative strength of return and volatility spillovers from the Green and Grey energy markets. Our results reveal the return shocks originated in the Green energy market and transmitted to other markets are more pronounced. It is also observed that the potential to earn high returns and the weak correlation of Green energy ETFs with the traditional asset classes are the crucial factors helpful in inviting attention and investment of investors after 2015. Although our results further suggest that the role of Grey energy is diminishing, as shown by the Impulse response functions and the coefficients of multivariate ARCH and GARCH. Nonetheless, for some asset classes, e.g., Bonds, the volatility spillovers that originated in the Grey energy market are still prominent and robust.

Keywords Green energy · Grey energy · Energy derivatives · Exchange-traded funds (ETFs) · Return spillover · Volatility spillover · VAR · BEKK

JEL Classification Q40 · C58 · G11 · G15 · G23

1 Introduction

Energy has always been a strategic commodity due to its role in economic development. However, since the early 2000s, energy has gained the reputation of an asset class, and energy-based financial products have become an integral part of the overall financial system.

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Many studies reason that the financialization of the commodities market and institutional investors' participation has played a vital role in this development (Gagnon et al., 2020). In the financial markets, investors, typically, gain exposure to energy by pursuing investment in energy stocks, energy indices, and energy futures markets through exchange-traded funds (ETFs), exchange-traded notes (ETNs), and swaps, whose returns are tied to an index of energy futures prices (Yan & Garcia, 2017).

However, the increased participation of investors in commodities markets and the high use of the energy market as an asset class have altered its return and volatility dynamics (Kyritsis & Serletis, 2018). There has also been an unprecedented increase in the speculative activity in the energy market since 2003 [(Creti & Nguyen, 2015), (Ahmad, 2017)] coupled with the fact that recent years have witnessed significant volatility in the price of fossil fuel, oil and gas. The volatility in energy prices has also led to the emergence of green energy as a substitute for grey energy.[1] At the same time, the potential of green energy in combating climate change has also earned international recognition [(Miralles-Quirós et al., 2018), (Su et al., 2020)]. Given these developments, recent years have witnessed a strong interest among practitioners and academics in understanding the dynamics of energy markets. Therefore, this study complements the existing literature and investigates the interdependence and spillovers between grey and green energy markets and traditional financial markets. We argue that an unexpected shift in energy risk and return dynamics could lead to economic instability. Moreover, a financialized energy market may also spread contagion to traditional financial markets like equities and bonds, which are the heart of any financial system.

Spillovers occur when extreme and unexpected shocks in return and volatility in one market trigger volatility in other markets (Engle et al., 1990); and are harsh in markets with greater interdependence, liberalization, and integration [(Rizvi et al., 2013), (Mensi et al., 2013)]. A return spillover captures the return transmission among the financial markets, while volatility spillover is the transmission of volatility (Nguyen & Le, 2021). High return and volatility spillovers, however, not only indicate the markets' interconnectedness, but those could alter portfolio diversification and hedging strategies [(Mirza et al., 2020); (Li et al., 2021)]. On the one hand, return spillover that originated in one market reflects increased investor confidence in the particular market (Umar et al., 2020); on the other hand, volatility spillovers have implications for the financial system's stability. Nonetheless, they may cause financial contagion, exponentially increases the degree of market systemic risk [(French et al., 1987); (Allen & Gale, 2000); (Batra, 2002); (Scott, 2011)], and alter investor's decision making by effecting the required rate of returns (Umar et al., 2020) and the cost of capital (Bekaert & Wu, 2000).

Three strands of literature dominate the literature on return and volatility spillover in the energy market. The first group of studies examines the connection between oil prices and international equity markets [e.g., (Sadorsky, 1999), (Guesmi & Fattoum, 2014), (Diaz et al., 2016), (Maghyereh et al., 2016), (Zhang, 2017), (Kyritsis & Serletis, 2018), (Tiwari et al., 2020)]. The second group of studies focus on exploring the relationship between oil price and the stock prices of conventional and green energy [e.g., (Broadstock et al., 2012), (Managi & Okimoto, 2013), (Wen et al., 2014), (Reboredo et al., 2017), (Reboredo & Ugolini, 2018)]. In comparison, the third group of studies investigates the association between oil price and the stock prices of conventional, clean energy and the technology companies [e.g., (Henriques & Sadorsky, 2008), (Sadorsky, 2012a), (Kumar et al., 2012), (Bondia et al., 2016), (Ahmad, 2017), (Ferrer et al., 2018), (Maghyereh et al., 2019), (Elsayed et al., 2020)].

[1] In this study, we use the term Grey energy to refer to fossil fuels and conventional energy while green energy also means renewable energy.

However, to the best of our knowledge, no study treats grey and green energy as independent asset classes; and examines the connectedness between green and grey energy markets and the interdependence between the pair of the energy market with traditional financial assets markets. The literature has been surprisingly non-focused on the relationship between green energy and equities or bonds despite acknowledging green energy as a rising financial asset with a promising future potential and an asset class alternative to grey energy (Miralles-Quirós & Miralles-Quirós, 2019). It is also surprising, mainly when there is a parallel literature stream that studies the hedging and diversification benefits of green energy for a stock–bond portfolio [(Bessler & Wolff, 2015), (Rezec & Scholtens, 2017), (Miralles-Quirós et al., 2018), (Schmidt, 2019), (Henriksen et al., 2019), (Rehman & Vo, 2020), (Saeed et al., 2020)]. We strongly believe that the evidence on markets' connectedness and spillovers in the green energy market may have important implications for hedging and portfolio diversification, yet the studies explicitly exploring the return and volatility spillover among green energy and traditional asset classes remained missing. This study, therefore, fills this gap in the literature. It enhances the evidence on the linkages among grey, green energy markets, and traditional asset classes. It also examines the presence, nature, and magnitude of the volatility spillovers originated in and transmitted to the energy market or vice versa, which has important implications for the stability of the overall financial system.

We make several contributions to the literature. First, this study provides the first evidence on the green energy market in transmitting return and volatility spillovers to Equities and the Bond market. It contributes to the strand of literature on green energy as well as return and volatility spillovers. Debt has been a significant source of financing in the green market over the years (IRENA, 2020); however, to the best of our knowledge, no study studies the relationship between green energy and the bond market. Second, this study examines the level of connectedness across markets and compares the dominance of green energy to grey energy. Thus, it contributes to the strand of literature assessing the hedging and diversification benefits of green energy for portfolio management. Third, this study uses ETFs to represent all financial markets while the existing literature has been fixated on indices to study the relationship between grey and green energy; or between the grey energy market and the equities market. ETFs are passive investments but are traded like shares and have the potential to track the performance of an index (Miralles-Quirós & Miralles-Quirós, 2019).

Moreover, investors favor ETFs to gain realized returns instead of non-realizable returns of indices (Yan & Garcia, 2017). In addition, ETFs have higher liquidity and transparency, lower fees, and tax efficiency (Huang & Lin, 2011). Fourth, we deploy the most relevant methodology of Baba-Engle-Kraft-Kroner (BEKK) parameterization of multivariate GARCH model[2] as suggested by (Engle et al., 1995) to capture the spillovers across the financial markets during the time spanning from October 2015 to October 2020.

The fundamental objective of using multivariate GARCH is to extract the time-varying conditional covariance and correlation between the energy market and other financial markets. About GARCH models, it has been widely accepted that Vector error correction (VEC) specifications suggested by (Bollerslev et al., 1988) are arduous to handle while working with more than two variables due to the large number of parameters required. The proposed Diagonal VEC (DVEC) model by (Bollerslev et al., 1988) allows conditional variance but restricts the number of parameters and requires substantial restrictions on the parameters

[2] To have detailed understanding of GARCH family models, readers are requested to consult the following literature: [(Black, 1976; Christie, 1982); Campbell and Hentschel (1992); Bekaert and Wu (2000); Kroner and Ng (1998); Glosten, Jagannathan, and Runkle (1993); (Elyasiani et al., 2007); (Chou 1988; Song, Liu, and Romilly 1998; Theodossjiou, Kahya, and Koutmos 1997); (Franses and Van Dijk, 1996; Gokcan, 2000); (Brooks and Persand, 2003).

(Bauwens et al., 2006). Given these constraints, we decided to use BEKK specification proposed by (Engle et al., 1995) and calculate dynamic conditional correlations between the Green and Grey energy markets and other financial markets (Bond and Equity). Moreover, BEKK conveniently decomposes each conditional variance into its ARCH (news impact) and GARCH (persistence) components, simplifying the analysis.

Our results provide interesting insights. We find that the return shocks originated in Green energy and transmitted to grey energy and equities markets are more pronounced. Contrarily, the role of Grey Energy is diminishing, as shown by the Impulse response functions and the coefficients of multivariate ARCH and GARCH. We find a revealing relationship between bond and energy market and show that grey energy significantly affects the BOND market, while the reverse is not valid. However, we find that green energy does not affect bond markets, but the bond market influences the returns of green energy.

The remainder of the paper is structured as follows: Section 2 explains our data set. Section 3 presents the details of the econometric models used to achieve the research objectives. Section 4 presents our empirical results followed by the discussion of results in Sect. 5. Section 6 concludes.

2 Data

Our major objective in this paper is to understand and evaluate the dynamics of returns and volatility spillovers that originate in the energy market including Green and the Grey and transmit to other financial markets. To proxy the energy and other assets market we use the rich data set of exchange-traded funds (ETFs) that not only closely track the performance of these markets but are also the tradable financial instruments. This tradability of ETFs make them more realistic choice for any investor interested in taking exposure in the markets of financial assets (Yan & Garcia, 2017) and (Miralles-Quirós & Miralles-Quirós, 2019). We choose ETFs for four different markets, Green Energy, Grey Energy, Bond, and Equity, all based in the United State of America (USA). Table 1 below provides the detail of ETFs selected, their representation, coverage and scope.

The ETFs proxies have been selected based on the coverage provided by each index and covers a period of five years of daily frequency starting from October 2015 to October 2020. Adjusted closing prices of ETFs were obtained from Bloomberg and a proxy of monthly returns is calculated for each ETF by taking a natural log of the ratio of current price with the twenty days lagged price on each date available in our data set.

$$R_{i,t} = ln\left[\frac{P_{i,t}}{P_{i,t-20}}\right] \times 100 \tag{1}$$

where $R_{i,t}$ is the monthly continuously compounded return calculated for i ETF on day t for each day of sample. $P_{i,t}$ is the daily closing adjusted price for i ETF on day t, and $P_{i,t-20}$ represents price for the same ETF 20 days prior. As opposed to the traditional method of calculating monthly returns that relies on calendar-based definition of a month, this method is far superior as it considers each 20 days period as a month on rolling basis. It does not only conform to the real time trading norms where the investors are free to enter or exit the market any day but it also provides higher degree of efficiency making available a larger chunk of data where monthly returns are estimated for each day on rolling basis. This method is also reported to be helpful in curtailing excessive intraday volatility in financial markets (Naqvi et al., 2018).

Table 1 Asset classes in the portfolios. *Source*: Bloomberg

Asset Class	Proxy Index	Geo-Focus	Coverage
Green energy	First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN)	USA	The fund tracks the price and yield of an equity index called the *NASDAQ Clean Edge Green Energy Index*. The index tracks the performance of publicly traded clean energy companies in the United States. The fund invests at least 90% of its net assets in the common stocks and depositary receipts that comprise the index
Grey energy	Energy Select Sector SPDR Fund (XLE)	USA	The fund corresponds generally to the price and yield performance of publicly traded equity securities of companies in the *Energy Select Sector Index*. The index holds stocks of companies from oil, gas, consumable fuels, energy equipment and services' industries. The fund generally invests 95% of its total assets in the stocks comprising the index
Bond (BOND)	iShares Core U.S. Aggregate Bond ETF (AGG)	USA	The fund tracks the performance of the *Bloomberg Barclays U.S. Aggregate Bond Index* which itself measures the performance of the total U.S. investment-grade bond market. The fund invests generally at least 90% of its net assets in component securities of the underlying index; while remaining % is invested in the securities with substantially identical economic characteristics
Equity (EQUITY)	SPDR S&P 500 ETF Trust (SPY)	USA	The investment corresponds to the yield and price performance of the *S&P 500 Index*. The ETF is the portfolio of the common stocks that are included in the index; and the weight of each stock in the Portfolio corresponds to the weight of such stock in the index
Risk free rate	US 3 Months Treasury Bill Yield	USA	Short Term Treasury Bills

Figure 1 shows trends in the daily ETF prices of selected asset classes during the last five years (October 2015–October 2020). Equity ETF has been measured on secondary axis (right side) and rest of the ETFs are measured on primary axis (left side). The Grey energy market seems to exhibit a long-term declining trend since 2017, almost the same time when the Green Energy market has started climbing, albeit slowly. Interestingly, both the decline of Grey and the climb of Green energy markets seem to be exacerbated by the COVID-19 pandemic in early 2020.

The equity market exhibits a trend like Grey market and indicates a strong correlation between the two financial markets. However, a widening of gap in prices over the years could also be observed. The bond market, contrarily, exhibits a relatively less volatile price trend and quite resembles the trends in green energy market.

3 Models

3.1 Return spillovers

We begin our preliminary investigation about the existence of spillovers in excess returns, across time, and between different segments of asset classes, by estimating vector autoregressive model (VAR) for the excess returns of four asset classes i.e. Green Energy (GREEN), Grey Energy (GREY), Bond (BOND) and Equity (EQUITY) in the following manner;

$$\boldsymbol{ER_t} = \varnothing_0 + \varnothing_1 \boldsymbol{ER_{t-1}} + \cdots + \varnothing_{\mathbf{p}} \boldsymbol{ER_{t-\mathbf{p}}} + \varepsilon_{\boldsymbol{t}}(\varepsilon_t | \psi(t-1) \sim N(0, H_t)) \tag{2}$$

where $\boldsymbol{ER_t}$ is a four variable vector demonstrating excess returns in the four ETFs (GREEN, GREY, BOND, EQUITY) at time period t; p is the optimal lag length identified through AIC and BIC; $\varnothing_0$ is a 4×1 vector representing intercepts; $\varnothing_1$ through $\varnothing_{\mathbf{p}}$ are coefficient matrices, with their elements capturing their own, as well as the cross-market lag effects; and $\varepsilon_{\boldsymbol{t}}$ is a 4×1 vector of residual error terms. Our assumption is that the elements of $\varepsilon_{\boldsymbol{t}}$ are not serially correlated, with the conditional variance–covariance matrix represented by the 4×4 matrix H_t given the information set $\psi(t-1)$.

Equation (2) specifies that the excess return of each ETF is a linear function of lagged excess returns of the same as well as lagged returns of the ETF of the other market segments. For example, the excess return in the Green Energy Market (GREEN) depends on p lags of itself, as well as p lags of the other three ETF's excess returns:

$$\begin{aligned}
&\boldsymbol{ER}_{1,\boldsymbol{t}} = \varnothing_0 + \sum_{i=1}^{p} \varnothing_{1i} \boldsymbol{ER}_{1,\boldsymbol{t-\mathbf{i}}} + \sum_{i=1}^{p} \varnothing_{2i} \\
&\boldsymbol{ER}_{2,\boldsymbol{t-\mathbf{i}}} + \sum_{i=1}^{p} \varnothing_{3i} \boldsymbol{ER}_{3,\boldsymbol{t-\mathbf{i}}} + \sum_{i=1}^{p} \varnothing_{4i} \boldsymbol{ER}_{4,\boldsymbol{t-\mathbf{i}}} + \varepsilon_{1,\boldsymbol{t}} \\
&\boldsymbol{ER}_{2,\boldsymbol{t}} = \boldsymbol{\beta}_0 + \sum_{i=1}^{p} \boldsymbol{\beta}_{1i} \boldsymbol{ER}_{1,\boldsymbol{t-\mathbf{i}}} + \sum_{i=1}^{p} \boldsymbol{\beta}_{2i} \boldsymbol{ER}_{2,\boldsymbol{t-\mathbf{i}}} + \sum_{i=1}^{p} \boldsymbol{\beta}_{3i} \boldsymbol{ER}_{3,\boldsymbol{t-\mathbf{i}}} + \sum_{i=1}^{p} \boldsymbol{\beta}_{4i} \boldsymbol{ER}_{4,\boldsymbol{t-\mathbf{i}}} + \varepsilon_{2,\boldsymbol{t}} \\
&\boldsymbol{ER}_{\boldsymbol{n},\boldsymbol{t}} = \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
&\quad + \varepsilon_{\boldsymbol{n},\boldsymbol{t}}
\end{aligned} \tag{3}$$

The presence of excess return spillovers from the ETF of equity market, EQUITY(4) towards green energy market, GREEN(1) can be detected by validating the joint hypothesis that $\varnothing_{4i} = 0 (i = 1, \ldots, p)$ and alternatively to detect the spillovers from GREEN towards

other markets ETFs, equations similar to Eq. 3 can be developed for each ETF's excess returns having its own lagged excess returns as well as the lagged excess returns of other ETFs.

3.2 Volatility spillovers and volatility persistence

The second type of spillovers are volatility spillovers where return shocks (difference between actual and mean or expected returns) in one market on a given day, trigger the conditional variance or volatility next day, either in the same market or in some other market (Rizvi & Naqvi, 2008; Rizvi et al., 2014). Similarly, persistence in the volatility of one market can be spilled over next day towards the other markets. The overall concept may be called as temporal dependence of the conditional variance.

We propose in this paper to use Baba, Engle, Kraft and Kroner (BEKK) parameterization of multivariate GARCH model[3] as suggested by (Engle et al., 1995) to estimate the volatility spillovers, volatility persistence and volatility transmissions from GREY and GREEN energy markets to other financial markets and vice versa.

The basic objective to use multivariate GARCH was to extract the time varying conditional covariance and correlation between energy market and other financial markets. With reference to GARCH models, it has been widely accepted that vector error correction (VEC) specifications suggested by (Bollerslev et al., 1988) are extremely difficult to handle while working with more than two variables due to the large number of parameters required $\left[\frac{N(N+1)(N(N+1)+1)}{2} = 210 for N = 4\right]$. (Bollerslev et al., 1988) proposed Diagonal VEC (DVEC) model which allows conditional variance depending only on its own lag and on the lagged values of cross product of errors ($\boldsymbol{\epsilon_{it}\epsilon_{jt}}$) thus restricting the number of parameters up to $\left[\frac{N(N+5)}{2} = 18 for N = 4\right]$. Nonetheless even in diagonal VEC representation it is extremely difficult to ensure the positivity of conditional variance covariance matrix (H_t) unless we impose strong restrictions on the parameters (Bauwens et al., 2006). Keeping in view these constraints we decide to use BEKK specification proposed by (Engle et al., 1995) to calculate dynamic conditional correlations between Green/Grey energy markets and other financial markets: Bond and Equity. We assume that $\psi(t-1)$ is the information field generated by the past values of ϵ_t and that H_t is the conditional variance–covariance matrix of the k-dimensional random vector ϵ_t. We also assume that H_t is measurable with respect to past information set $\psi(t-1)$; in that case the structure of multivariate GARCH would be as

$$(\epsilon_t|\psi(t-1) \sim N(0, H_t))H_t = C + \sum_{i=1}^{q} A_i^{'}\epsilon_{t-i}\epsilon_{t-i}^{'}A_i + \sum_{i=1}^{p} G_i^{'}H_{t-i}G_i \tag{4}$$

where C,A_i and G_i are $k \times k$ parameter matrices.

For bivariate GARCH (1,1) the matrix structure would be as follows.

$$H_t = \begin{bmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \in_{1,t-1}^2 & \in_{1,t-1}\in_{2,t-1} \\ \in_{2,t-1}\in_{1,t-1} & \in_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$$

[3] To have detailed understanding of GARCH family models, readers are requested to consult the following literature: [(Black, 1976; Christie, 1982); Campbell and Hentschel (1992); Bekaert and Wu (2000); Kroner and Ng (1998); Glosten, Jagannathan, and Runkle (1993); (Elyasiani et al., 2007); (Chou 1988; Song, Liu, and Romilly, 1998; Theodossjiou, Kahya, and Koutmos, 1997); (Franses and Van Dijk, 1996; Gokcan, 2000); (Brooks and Persand, 2003).

We maximize the following log-likelihood function for our Multivariate GARCH model, written without a constant term;

$$\updownarrow = -\frac{1}{2}\sum_{t=1}^{T}\left[log|H_t| + \epsilon_t^{'} H_t^{-1}\epsilon_t\right] \tag{5}$$

We use the continuously compounder returns calculated through Eq. 1 and estimate excess returns (ER) by subtracting period adjusted risk free rate, for the construction of mean equation which would be modelled as Vector Auto regression (VAR) as specified in Eq. 3;

The superiority of BEKK model is that it conveniently decomposes each conditional variance into its ARCH (news impact) and GARCH (persistence) components. For example, the ARCH component which is the impact of lagged squared residuals in excess returns associated with the conditional variance of Green energy ETFs (GREEN) can be represented as:

$$\begin{aligned}\boldsymbol{H}_{(i.i),t} = \boldsymbol{c}_{11} + \boldsymbol{a}_{11}^2 \in_{1,t-1}^2 + \boldsymbol{a}_{21}^2 \in_{2,t-1}^2 + \boldsymbol{a}_{31}^2 \in_{3,t-1}^2 + \boldsymbol{a}_{41}^2 \in_{4,t-1}^2 + 2\boldsymbol{a}_{11}\boldsymbol{a}_{21} \in_{1,t-1}\in_{2,t-1} \\ + 2\boldsymbol{a}_{11}\boldsymbol{a}_{31} \in_{1,t-1}\in_{3,t-1} + 2\boldsymbol{a}_{11}\boldsymbol{a}_{41} \in_{1,t-1}\in_{4,t-1} + 2\boldsymbol{a}_{21}\boldsymbol{a}_{31} \in_{2,t-1}\in_{3,t-1} \\ + 2\boldsymbol{a}_{21}\boldsymbol{a}_{41} \in_{2,t-1}\in_{4,t-1} + 2\boldsymbol{a}_{31}\boldsymbol{a}_{41} \in_{3,t-1}\in_{4,t-1}\end{aligned} \tag{6}$$

In the above structure, 1, 2, 3, and 4are respectively the representation of GREEN, GREY, BOND and EQUITY ETFs. The structure clearly shows that ARCH volatility of GREEN excess returns not only depends on the lagged squared residuals (shocks) in all ETF markets, but on the cross-products of the lagged shocks in all four ETF markets. Here the ARCH coefficients, $\boldsymbol{a}_{11}$, $\boldsymbol{a}_{21}$, $\boldsymbol{a}_{31}$, and $\boldsymbol{a}_{41}$ capture the effects of past squared residuals (shocks) in excess returns of each market's ETF on today' volatility in green energy ETFs excess returns.

Alternatively, the persistence parameter or GARCH component of the green energy ETF's conditional variance can be decomposed as,

$$\begin{aligned}\boldsymbol{H}_{(i.i),t} = \boldsymbol{g}_{11}^2\boldsymbol{H}_{11,t-1} + \boldsymbol{g}_{21}^2\boldsymbol{H}_{22,t-1} + \boldsymbol{g}_{31}^2\boldsymbol{H}_{33,t-1} + \boldsymbol{g}_{41}^2\boldsymbol{H}_{44,t-1} + 2\boldsymbol{g}_{11}\boldsymbol{g}_{21}\boldsymbol{H}_{12,t-1} \\ + 2\boldsymbol{g}_{11}\boldsymbol{g}_{31}\boldsymbol{H}_{13,t-1} + 2\boldsymbol{g}_{11}\boldsymbol{g}_{41}\boldsymbol{H}_{14,t-1} + 2\boldsymbol{g}_{21}\boldsymbol{g}_{31}\boldsymbol{H}_{23,t-1} + 2\boldsymbol{g}_{21}\boldsymbol{g}_{41}\boldsymbol{H}_{24,t-1} \\ + 2\boldsymbol{g}_{31}\boldsymbol{g}_{41}\boldsymbol{H}_{34,t-1}\end{aligned} \tag{7}$$

where the volatility of GREEN excess returns is a function of past conditional variances in all four markets and the covariance structure associated with each of the four markets. Here, $\boldsymbol{g}_{11}$, $\boldsymbol{g}_{21}$, $\boldsymbol{g}_{31}$, and $\boldsymbol{g}_{41}$ capture the effects of past volatility (own conditional variance) in each market's ETF on today' volatility in GREEN excess returns.

3.3 Rationale to choose BEKK model

It is extremely important that we should justify our choice of using BEKK model in this study. Since it has been explained earlier that research objective of this study is to distinguish the spillover effect of Grey and Green energy to and from other financial markets based on historical data and not the forecasting of returns. Therefore, the BEKK-GARCH is much sounder, owing to its high number of parameters compared to the DCC-GARCH (Huang et al., 2010).

It is true that full BEKK model has its shortcomings such as "curse of dimensionality" but so is the case with the alternative model such as DCC. Such shortcomings of DCC-GARCH are clearly highlighted by (Chang, McAleer, and Wang, 2018a, 2018b) who preclude the usage of multivariate DCC-GARCH on the basis of its "lack of regularity conditions and

hence no statistical conditions" while supporting their argument citing the working paper by (Hafner and McAleer 2014). In fact if we look at not-so-distant past work of McAleer, not only it has supported BEKK (Caporin and Mcaleer 2012) but also used it extensively as well (Allen et al., 2017; Asai, Gupta, and McAleer 2020).

As a solution, the three most comprehensive works on the shortcomings of full BEKK and DCC, strongly recommend and use the Diagonal BEKK instead of full BEKK or DCC. All these studies confirm that the Quasi Maximum Liklihood Estimates (QMLE) of the parameters in Diagonal BEKK only, have both the asymptotic properties of consistency as well as asymptotic normality (Chang et al., 2018a, 2018b, 2019b).

However, as we have explained earlier that our objective is to estimate the spillovers running between Green/Grey Energy market and the other financial markets (Bond and Equity) which can only be captured through off-diagonal terms in ARCH and GARCH matrices and can only be estimated through full BEKK model. Therefore, estimating diagonal BEKK or DCC, both of which can only produce diagonal terms of ARCH and GARCH matrices or the partial covolatility spillovers, will add no value at all in our study (Chang et al., 2018a).

This is exactly the reason why (Chang et al., 2019a) despite their heavy criticism on full BEKK specifications, failed to estimate these parameters which we present in this paper and which they termed as full volatility and full covolatility spillovers. They also admitted full BEKK model as the "HOLY GRAIL" for the estimation of spillovers in totality. Moreover, This is precisely why two of the recent and comprehensive papers by (Li, 2015; Sarwar et al., 2020) have used the full BEKK specifications that also support our initial stance of relying on the same.

Even the (Sadorsky, 2012b) despite choosing DCC as first choice, admitted candidly that BEKK is not only the closest second choice but it also produces more evidences of volatility spillovers than does the DCC model. Similarly (Sadorsky, 2014) highlighted in foot notes the possibility of using several other specifications than DCC, including BEKK.

To summarize above, given the most important consideration of this paper is to evaluate cross market spillovers running two and from energy markets (Green and Grey) which can only be estimated through off-diagonal coefficients of ARCH and GARCH matrices, we do not have any other choice but to follow the lead of leading researchers by employing full BEKK. (Allen et al., 2017; Chang et al., 2019a; Gulzar et al., 2019; Huang et al., 2010; Li, 2015; Rizvi & Itani, 2021; Sadorsky, 2012a; Sarwar et al., 2019, 2020; Wang et al., 2019; Yousaf et al., 2021).

4 Results

4.1 Descriptive statistics

In this section we first present the descriptive statistics and correlations of the excess returns calculated for the ETFs representing four markets in Tables 2 and 3 respectively.

The descriptive statistics provided in Table 2 strongly reinforce our quest of examining the volatility dynamics in Green and Grey Energy markets and their spillovers towards other financial markets. In terms of returns, both Green and Grey energy markets are prominent as GREEN offers the most lucrative monthly average returns of 1.6% and GREY offers the worst returns equals to the negative 0.96% as monthly average. Both GREY and GREEN energy markets are highest in terms of risks with a standard deviation of 9.8% and 8.1% per

Table 2 Descriptive Statistics of Monthly Excess Returns (%)

	Green	Grey	Bond	Equity
Mean	1.6037	0.9673	0.2320	0.8731
Median	1.9687	0.1591	0.2239	1.5387
Maximum	26.979	31.8971	9.8768	20.7545
Minimum	58.9087	82.7384	6.8930	37.0844
Std. Dev	8.1341	9.8618	1.0506	4.9473
Skewness	1.7633	2.9950	0.8309	2.5054
Kurtosis	14.0692	22.0826	15.2020	18.6606
Jarque–Bera	6978.79	20,684.83	7841.67	13,980.07
Probability	0.0000	0.0000	0.0000	0.0000
Sum	1990.25	1200.50	287.95	1083.55
Sum Sq. Dev	82,042.93	120,596.60	1368.73	30,350.57
Observations	1241	1241	1241	1241

The table shows the descriptive statistics of the monthly returns of ETFs in four selected markets. The values are the percentages (%) wherever applicable

Table 3 Correlation (Kendall Tau) among Monthly Excess Returns (%) in Different ETFs

	Green	Grey	Bond	Equity
Green	1.0000			
	–			
Grey	0.2960	1.0000		
	0.0000	–		
Bond	0.0466	0.1105	1.0000	
	0.0137	0.0000	–	
Equity	0.5906	0.4966	0.0348	1.0000
	0.0000	0.0000	0.0662	–

The table shows the pairwise Kendall rank correlation coefficients (tau-a) between the monthly returns of four markets. The correlation coefficient ranges between -1 to 1. The correlation values are followed by the p-values

month respectively. In terms of returns skewness, other than BOND which has a positive skewness owing to its principal protection feature, the GREEN market has the lowest value of negative skewness offering better returns prospects. In terms of fat tail risk all markets have excess kurtosis indicating higher probability of extreme shocks. Besides, we find that the correlation coefficients of both Green and Grey energy markets with Bond and Equity are reasonably low and even negative sometimes (see Table 3) which is consistent with the literature arguing for the diversification potential of energy markets. Graphical representation of correlations structure is provided in Scatterplot matrix in Fig. 2.

4.2 Preliminary evaluation of unit root and stationarity

To ensure that the chosen series is appropriate for the implementation of full BEKK model, it is important that the series should be stationary and free from unit root. Foreseeing the potential issue of cointegration or non-stationarity, not only we base our entire analysis on

continuously compounder returns (log returns) but to further isolate the individual series from the global and common trends and to focus on the true and intrinsic relationship only between chosen series, we further synthesize our variables and convert them into Excess Returns by subtracting the US Tbills rate of return as a proxy of global risk free rate as all our original series were denominated in USD. This subtraction of US T bills rate minimizes the impact of systematic events that are reflected in the movement of US Tbills rate and are capable to affect different financial markets simultaneously. We therefore have already laid down the foundations to ensure that the series included in our data set are eligible for the application of chosen econometric analysis as it is highly unlikely to find unit root in such synthesized series. However, to ensure the stationarity of data we test all series for the potential Unit root, Unit root with Break and for possible Cointegration between GREEN, GREY, BOND and EQUITY returns. The results are reported in Fig. 3 and Tables 6, 7 and 8. For all return series ADF and PP test is rejected thus refuting the presence of unit root. Results also fail to reject the null of KPSS thus confirming that the series are stationary. Similarly, ADF Unit root with Break test also reject the presence of unit root confirming the stationarity of data. Finally no evidence of cointegration is found based on Trace and Max Eigen Statistics of Johansen's cointegration test.

4.3 Return spillover

Table 4 presents the results of Vector auto regression model where excess return in each ETF segment (each column) is explained by the two periods lagged excess returns in the same as well as in the other three markets. The lag length selection criteria is applied and based on the optimal AIC and BIC two period lag has been chosen for the VAR specification. The results of lag length selection criteria are reported in Table 9. Moreover, the graphical description of impulse responses of different markets and variance decomposition tables have also been provided in Fig. 4 and Table 10 respectively.

In Table 4 above if we focus on GREEN(-1) and GREEN(-2) which are the lagged coefficients of excess returns in Green energy market we would observe clearly that the past excess return shocks in Green market have a potential to impact current excess returns in GREY and EQUITY markets besides impacting its own excess returns today. This finding is also corroborated by the variance decomposition reported in Table 10 and can be visualized in the Impulse reponse functions provided in Fig. 4. Table 10 shows that the shocks in GREEN energy market are responsible for around 42% to 49% of the variations in GREY market, 66% to 70% of the variation in EQUITY market and 97% to 100% of the variation in the GREEN market itself. Interestingly the bond market (BOND) is completely immune to the return shocks originated in green energy market, however the reverse is not true as the Green energy market is getting affected by the return shocks in the Bond market. Again if we look at the variance decomposition, the percentage contribution of GREEN market in BOND market's variance is merely 1% at most. Exactly opposite to this phenomenon and linkages observed for the GREEN market, the return shocks in GREY market are only able to impact the Bond market besides impacting itself but the GREY market in turn is immune to the shocks originated in Bond market. Infact the share of GREY market in the variance of BOND market is around 1.5% to 3.5% percent. Finally, the equity market (EQUITY) has some impact on all markets except BOND. However the variance decomposition and the impulse response functions reported in Fig. 4 indicate clealry its weaker influence and less pronounced dominance within these markets. On the other hand and indeed surprisingly, the much greater influence and dominance is shown by the Green energy market which is

Table 4 Vector Autoregressive (VAR) Estimates

	Green	Grey	Bond	Equity
Green (−1)	1.1539	0.2006	0.0045	0.1614
	(0.0495)	(0.0544)	(0.0082)	(0.0333)
	[23.2758]	[3.6824]	[0.5477]	[4.8448]
Green (−2)	− 0.2440	− 0.2708	− 0.0013	− 0.1773
	(0.0495)	(0.0544)	(0.0082)	(0.0333)
	[− 4.9229]	[− 4.9721]	[− 0.1670]	[− 5.3217]
Grey (−1)	− 0.0280	0.9646	0.0208	0.0139
	(0.0419)	(0.0460)	(0.0070)	(0.0281)
	[− 0.6680]	[20.9447]	[2.9679]	[0.4936]
Grey (−2)	0.0355	0.0007	− 0.0180	0.0136
	(0.0419)	(0.0460)	(0.0070)	(0.0281)
	[0.8482]	[0.0170]	[− 2.5736]	[0.4843]
Bond (−1)	0.6946	0.2700	1.0041	0.1738
	(0.1701)	(0.1869)	(0.0284)	(0.1143)
	[4.0832]	[1.4448]	[35.2855]	[1.5203]
Bond (−2)	− 0.5843	− 0.2036	- 0.0957	− 0.0649
	(0.1704)	(0.1873)	(0.0285)	(0.1145)
	[− 3.4279]	[− 1.0873]	[− 3.3583]	[− 0.5672]
Equity (−1)	− 0.3911	− 0.4838	− 0.0131	0.5059
	(0.0823)	(0.0905)	(0.0137)	(0.0553)
	[− 4.7479]	[− 5.3441]	[− 0.9552]	[9.1374]
Equity (−2)	0.4495	0.5682	0.0036	0.4132
	(0.0822)	(0.0903)	(0.0137)	(0.0552)
	[5.4649]	[6.2870]	[0.2620]	[7.4760]
R-squared	0.9094	0.9255	0.8477	0.8890
Adj. R-squared	0.9089	0.9251	0.8468	0.8884

The table shows the VAR estimates for four markets. Each market's monthly returns in VAR are assumed to be the function of its own lagged returns (autoregressive) as well as the lagged returns of other three markets. The values of t-statistics are shown in brackets [] and p-values are shown in parenthesis ()

nonetheless perceived as a new and less prominent market segment compared to EQUITY. This behavior and dominance of GREEN is also interesting when we compare it with the GREY market which traditionally has been influencing major financial markets owing to the intrinsic economic importance of Oil, Gas and other fossil fuel energy products.

4.4 Volatility spillover and volatility persistence

Finally, Table 5 presents the estimated coefficients, standard errors (squared brackets) and t-statistics (bold) of ARCH[4] and GARCH represented in Eqs. 6 and 7. The oversized diagonal terms are own ARCH and own GARCH effect for all four markets. The full BEKK model is

[4] To confirm the presence of ARCH effects, we conducted ARCH LM test for all excess returns series of GREEN, GREY, BOND and EQUITY ETFs and found significant presence of ARCH effects in all series

Table 5 Estimated ARCH and GARCH coefficients in BEKK Model

Parameters	GREEN(., 1)	GREY(., 2)	BOND(., 3)	EQUITY(., 4)
ARCH Coefficients				
A(1, .)	**1.189430**	0.657219	0.021262	0.962439
	[0.033410]	[0.028170]	[0.014363]	[0.051930]
	35.601285	**23.330719**	**-1.480262**	**18.533473**
A(2, .)	0.561067	**0.410274**	0.460343	0.200531
	[0.354725]	[0.028016]	[0.086433]	[0.136999]
	1.581698	**14.644343**	**5.326005**	**1.463745**
A(3, .)	0.204550	0.080655	**0.952529**	0.265629
	[0.043509]	[0.018527]	[0.055875]	[0.115371]
	4.701302	**4.353353**	**17.047601**	**2.302378**
A(4, .)	0.963223	0.813633	- 0.528070	**2.073095**
	[0.169774]	[0.053967]	[0.151024]	[0.098148]
	5.673569	**15.076608**	**3.496585**	**21.122064**
Parameters	**GREEN(., 1)**	**GREY(., 2)**	**BOND(., 3)**	**EQUITY(., 4)**
GARCH Coefficients				
G(1, .)	**0.523681**	0.011634	0.004799	0.094553
	[0.084544]	[0.009768]	[0.005746]	[0.097550]
	6.194175	**1.191025**	**0.835092**	**0.969280**
G(2, .)	0.169109	**0.742943**	0.058581	0.795973
	[0.165252]	[0.022209]	[0.008321]	[0.137279]
	1.023337	**33.452222**	**7.040276**	**5.798222**
G(3, .)	4.533144	0.204812	**0.119789**	4.639357
	[0.949515]	[0.155328]	[0.029987]	[1.178895]
	4.774168	**1.318575**	**3.994697**	**3.935342**
G(4, .)	0.149024	0.762695	0.076811	**1.676974**
	[0.248317]	[0.273459]	[0.015415]	[0.082514]
	0.600133	**2.789061**	**4.982980**	**20.323544**

The table shows the estimated ARCH and GARCH coefficients, standard errors (squared brackets) and t-statistics (bold) estimated through Eqs. 6 and 7. The terms A(n, .) and G(n, .) in first column shows the ARCH and GARCH spillovers originated in ***nth*** market and runs through the markets given in column 2 to 5

estimated using RATS 10.0. The default algorithm to optimize the log-liklihood estimation function in RATS is BHHH (Berndt, Hall, Hall and Hausman) by (Berndt et al., 1974). However we also used the alternative optimization algorithm of BFGS (Broyden, Fletcher, Goldfarb and Shanno) by (Broyden, 1965, 1967; Fletcher & Powell, 1963) for robustness purposes. Both these algorithms are Hill climbing algorithms and our results are robust and are not subject to change by the change of algorithm. Similarly, for the choice of underlying distribution, although the results reported below are according to student's t distribution,

Footnote 4 continued
based on the LM test statistics $(T-q)R^2$ which was greater than $\chi^2_{(1-a,q)}$ thus rejecting the null hypothesis of No ARCH effects.

but they are robust to the usage of GED (generalized exponential distribution) the other alternative available in RATS 10.0.

The estimated coefficients to capture ARCH effects exhibit some interesting patterns. First, all oversized diagonal elements A(1, 1), A(2, 2), A(3, 3) and A(4, 4) are highly statistically significant based on the t-statistic below (in bold). This suggests that the conditional variances in each of the four market segments depend on their own lagged squared residuals. The equity market (EQUITY) has the largest own ARCH effect with the coefficient value of 2.073, while the grey energy (GREY) has the smallest own ARCH effect with the value of 0.410. The own ARCH effect in green energy market (GREEN) is largest after EQUITY with an approximate value of 1.189. If we focus on the row A(1, .) which tells us the impact of shock in green energy market (GREEN) on other market segments, the t-value is significantly greater than 2.0 for all three markets except BOND. This indicates the strong effect and news impact on volatility in all markets except BOND if there is any shock in green energy market. The same is not true for the row A(2, .) which captures the similar impact of shocks originated in GREY market. The shock in GREY market is only able to increase its own conditional variance and the conditional variance in BOND market. This is the identical behavior that we explored in case of return spillovers estimated through VAR in Table 4. The volatility transmission from the other two markets, Bond and Equity is significant and visible indicating the dominance of both markets in global financial system.

The persistence or GARCH parameters G(., i) in the lower half of Table 5 capture the responses of conditional variance (volatility) in market *i* to past conditional variance (volatility) in each of the four markets. To understand the volatility spillovers from green energy market (GREEN) to other markets we need to focus on estimated coefficients provided in row G(1, .). The Conditional variance in no market seem to be responsive towards the volatility spillover originated in GREEN market, other than the GREEN market itself. Put differently, the transfer of volatility persistence spillovers from GREEN market to other market is weak and insignificant. On the contrary the grey market (GREY) through parameter G(2, .) seems to transfer significant volatility shocks towards BOND and EQUITY if the turbulence in grey market persists. This observation is interesting as we find previously (ARCH and VAR) that GREEN market appears to be more prominent than GREY market in spilling over return shocks and news impact-based volatility shocks. However, the situation is reverse for the persistence-based volatility shocks and the GREY market still acts as a dominant market with the capability to shake the other markets if the volatility shocks persists in it. There is a mixed pattern in the transmission of volatility persistence spillovers from BOND and EQUITY to other markets with an interesting result that the equity market (EQUITY) despite being dominant otherwise, is unable to spillover its GARCH based volatility towards green energy market.

For the interested readers the estimated conditional standard deviation, conditional correlation and conditional variance covariance structures for the data are also reported in Figs. 5, 6 and 7 respectively.

5 Discussion

The findings show that Green energy has emerged as the prominent player in determining the returns of the equity market while the role of Grey is exhibiting diminishing trend. Our findings are different from the earlier studies that claimed that grey energy in the form of oil price changes are an important factor affecting stock market returns [(Sadorsky, 1999),

(Park & Ratti, 2008), (El-Sharif et al., 2005), (Guesmi & Fattoum, 2014), (Diaz et al., 2016), (Maghyereh et al., 2016)]. However, Our results are supported by recent studies which report skepticism on the role of conventional energy in explaining stock markets returns [(Zhang, 2017), (Kyritsis & Serletis, 2018), (Elsayed et al., 2020), (Tiwari et al., 2020)]. Contrarily, our findings on green energy are novel and non-comparable to the existing strand of literature and show that the relationship is bi-directional where green energy affects the returns of stock market while equities affects the returns of green energy.

Our results are interesting and also hints towards the increased financialization of energy markets (Ferrer et al., 2018) as they show that equities explain the changes in the returns of grey and green energy market. Earlier literature assumed energy price changes as an exogenous factor which was a reasonable assumption but only before the financialization of energy market. Now, energy market has deep presence in the financial market in the form of energy future, swaps, ETN and ETFs which exhibit characteristics that are like those of other financial assets (Zhang, 2017). Moreover, energy has itself become a financial asset with its price reacting to and influencing other assets in financial markets (Kyritsis & Serletis, 2018); and is used increasingly by portfolio managers and institutions to hedge and diversify their portfolios [(Bessler & Wolff, 2015), (Rehman et al., 2019), (Gagnon et al., 2020)]. In addition, (Creti & Nguyen, 2015) and (Ahmad, 2017) argue for an unprecedented increase in the speculative activities in the energy market after 2003; which also means that energy market and oil prices are no longer independent from the changes in financial markets.

Our results are also revealing for the relationship of green and grey energy with the bond market which has largely been overlooked by the literature. We show that grey energy is having a significant effect on bond market, while the reverse is not true. Intrigued about the reasoning of this interesting result, it was also very surprising for us to note that although there exists a rich literature studying the relationship between oil and equities, the same is not true for the relationship between oil and bond market. However, an extended literature does examine the relationship between oil prices and interest rates motivated by the fact that both variables have always increased prior to US postwar recession [(Hamilton, 1983), (Hamilton, 1996), (Bernanke et al., 1997), (Bernanke et al., 2004)]; and hence provides plausible rationale and support to our results that grey energy affects bond market via interest rate transmission channel. While we show that Grey energy market affects bond market, we find that green energy does not affect bond market. Instead, it is being significantly affected by the Bond Market. One plausible explanation of this unidirectional return spillovers is that most of the investment in Green energy is channeled through Bond market. Green energy projects are capital intensive and of long-term maturity; and debt represents a major source of financing for such projects (IRENA, 2020). Our results therefore have meanings since any turbulence in the overall bond market or changing yield spread could impact the financing and investment in Green energy projects and their returns subsequently.

While comparing our results of relationship between grey and green energy, however, our results are consistent with those of [(Henriques & Sadorsky, 2008), (Reboredo et al., 2017), (Ferrer et al., 2018), (Elsayed et al., 2020)] who show that there is a limited or no role of oil prices in effecting the prices of green energy. Besides, we find that green energy has taken the leader's position where the changes in the prices of green energy are affecting the returns of grey energy.

However, although the return spillovers (VAR) and news-based volatility spillovers (ARCH) from Green Energy to other markets are prominent but that's not true for Volatility Persistence Spillovers (GARCH). This could be explained by the fact that Grey energy market still dominates the energy market with the total share of around 84% (Ferrer et al., 2018) and persistence in volatility of grey energy (fossil fuel) still has the potential to threaten monetary and financial stability.

6 Conclusion

This research provides evidence on the connectedness of grey and green energy as independent asset classes with other financial assets and markets and reports results on the presence of return and volatility spillovers that may originate in energy market and are transmitted to the other major financial markets.

Our study is inspired by several recent developments in the energy market. Firstly, energy has earned the status of a financial asset class while still retaining its status of a strategic commodity. Secondly, the financialization of energy market has led to an unprecedented increase in the speculative and hedging activities in the energy based financial products. Thirdly, the prices of energy have become extremely volatile in recent years which may cause not only economic instability but also trigger the contagion in the financial markets. Lastly, a move towards sustainable economic development that has gained momentum around the world and consequently the role of green energy is strengthening as a substitute or an alternative of conventional grey energy not only as a commodity but as a financial asset too.

The study is, however, different from the existing literature because we emphasize on the relationship between green and grey energy and the spillover to and from pair of energy markets to equities-bonds markets. Earlier literature has either been focused on oil, fossil fuel or the conventional energy market and their relationship with the equities market; or the return-volatility relationships between conventional (grey) energy with green energy and technology companies' stocks and it does not view green energy as an alternative asset class. The fact however is that the green energy is a rising asset class as well as an alternative investment to grey energy with promising growth potential; and the evidence on green market connectedness and spillovers have important implications for hedging and portfolio diversification too; but yet the studies explicitly exploring green energy as an independent asset class remained missing; and therefore this study makes a significant contribution to the literature on green energy return and volatility spillover.

The results provide evidence on the diminishing role of Grey energy and the prominent role of Green Energy in Equity market return dynamics. First, we show that Green energy is more prominent in determining the returns of equity market while the role of Grey energy in US equity market is declining. Second, we find that equities explain the changes in the returns of both grey and green energy market and thus hints towards the increasing financialization of Green energy too. Third, while comparing our results of relationship between grey and green energy, we find that green energy again proves itself more important as it could guide the prices in grey energy market whereas the reverse is not true. However, although the return

spillovers (VAR) and news-based volatility spillovers (ARCH) from Green Energy to other markets are prominent but that's not true for Volatility Persistence Spillovers (GARCH). This is explainable as Grey energy market still dominates the energy market with the total share of around 84%.

The findings of this study have important implications for investors, portfolio managers and the overall financial system. Green energy has emerged as an independent asset class and a strong alternative to grey energy and hence have the potential to alter the investors' decision making and asset selection and allocation. The green energy also seems to take the leading role in energy segment and affect investors' sentiments as the confidence of investors in green energy is spilled over in the other financial markets. Our results also provide important insights for regulators and policy makers as the energy today enjoys the dual status. Energy has retained its status of a strategic commodity while it has also become an integral part of the financial system. Green energy, which is envisioned to provide a solution to climate change and to the volatile prices of grey energy, has become closely connected with equities and bonds as suggested by our results. Therefore, a larger financial oversight of green energy market by the regulators, just like other financial markets, is inevitable owing to its increased connectedness with the different segments of the financial system. This increased Financialization of green energy coupled with the strong interest of investors in it as an asset class also expose green energy to speculative activities which may make the prices of green energy volatile too. Moreover, any turbulence in the overall equities and bond market or changing yield spread could impact the Green energy investments hence impeding the world's efforts to achieve sustainable development goals.

Appendix

See Tables 6, 7, 8, 9, 10 and Figs. 1,2, 3, 4, 5, 6, 7 3.

Table 6 Unit Root and Stationarity Testing (Excess Returns of GREEN, GREY, BOND and ENERGY market Returns)

Variables	ADF		PP		KPSS	
	Null: Series has a unit root		Null: Series has a unit root		Null: Series is stationary	
	Intercept	Intercept and Trend	Intercept	Intercept and Trend	Intercept	Intercept and Trend
GREEN	– 4.3986***	– 4.6299***	– 5.5473***	– 5.6891***	0.2934	0.0970
GREY	– 4.4681***	– 4.5989***	– 5.4169***	– 5.4941***	0.2343	0.0365
BOND	– 4.7562***	– 4.8122***	– 7.5242***	– 7.6131***	0.4298*	0.1414*
EQUITY	– 5.2546***	– 5.2553***	– 5.9866***	– 5.9843***	0.0266	0.0269
	ADF	PP	KPSS			
Test Critical Values	Intercept	Intercept and Trend	Intercept	Intercept and Trend	Intercept	Intercept and Trend
1% level	– 3.435497	– 3.965586	– 3.435411	– 3.965464	0.739000	0.216000
5% level	– 2.863700	– 3.413499	– 2.863662	– 3.413440	0.463000	0.146000
10% level	– 2.567970	– 3.128795	– 2.567950	– 3.128760	0.347000	0.119000

***, ** and * denote statistical significance at 0.01, 0.05 and 0.10 levels, respectively

Table 7 Augmented Dickey-Fuller "Unit Root with Break" test Results

Variables		Break Date	t-Statistic
GREEN		4/01/2020	– 6.417479***
GREY		3/18/2020	– 5.150519***
BOND		11/08/2018	– 5.332880***
EQUITY		3/20/2020	– 6.045231***
Test critical values:	1% level		– 4.945706
	5% level		– 4.432140
	10% level		– 4.182082

Table 8 Johansen's System Cointegration Test

Sample (adjusted): 11/05/2015 10/02/2020

Included observations: 1236 after adjustments

Trend assumption: Linear deterministic trend

Series: GREEN GREY BOND EQUITY

Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.061495	209.6665	47.85613	0.0000
At most 1 *	0.051931	131.2218	29.79707	0.0000
At most 2 *	0.033001	65.30776	15.49471	0.0000
At most 3 *	0.019095	23.82967	3.841466	0.0000

Trace test indicates 4 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.061495	78.44476	27.58434	0.0000
At most 1 *	0.051931	65.91401	21.13162	0.0000
At most 2 *	0.033001	41.47810	14.26460	0.0000
At most 3 *	0.019095	23.82967	3.841466	0.0000

Max-eigenvalue test indicates 4 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b = I):

Green	Grey	Bond	Equity
− 0.005983	0.007802	− 0.858018	− 0.096607
0.247486	0.164768	− 0.186329	− 0.627852
0.059478	− 0.080105	− 0.619702	0.233127
0.125809	− 0.132376	0.136346	− 0.043107

Table 9 Lag Length Selection Criteria

Endogenous variables: ER_GREEN ER_GREY ER_BOND ER_EQUITY
Exogenous variables: C
Sample: 10/01/2015 10/02/2020
Included observations: 1233

Lag	AIC	SC (BIC)
0	20.54107	20.55767
1	12.44482	12.52782
2	12.44433*	12.43374*
3	12.45855	12.44436
4	12.46566	12.44788
5	12.51421	12.46282
6	12.68250	12.49752
7	12.67011	12.53154
8	12.74824	12.49607

Table 10 Variance Decomposition

Period	S.E	GREEN	GREY	BOND	EQUITY
Variance Decomposition of GREEN:					
1	2.456218	100.0000	0.000000	0.000000	0.000000
2	3.396743	97.82012	0.478303	0.779389	0.922190
3	4.101321	97.53893	0.405874	1.264791	0.790409
4	4.638263	97.44410	0.345879	1.510385	0.699631
5	5.071938	97.44545	0.292693	1.657588	0.604272
6	5.430215	97.45981	0.255778	1.755243	0.529171
7	5.732162	97.45974	0.237416	1.827023	0.475824
8	5.989963	97.43358	0.238776	1.884128	0.443515
9	6.212334	97.37691	0.260411	1.932497	0.430181
10	6.405670	97.28891	0.302386	1.975398	0.433309
Variance Decomposition of GREY:					
1	2.699016	49.01595	50.98405	0.000000	0.000000
2	3.597946	49.39526	49.21527	0.132070	1.257404
3	4.308043	49.20008	49.49228	0.240401	1.067241
4	4.861836	48.50200	50.30864	0.278637	0.910724
5	5.323832	47.60962	51.33298	0.291065	0.766334
6	5.717836	46.61245	52.42978	0.291949	0.665821
7	6.061402	45.56064	53.54096	0.288278	0.610122
8	6.365353	44.48406	54.63826	0.282991	0.594684
9	6.637417	43.40241	55.70681	0.277456	0.613328
10	6.883157	42.32955	56.73866	0.272286	0.659503

Table 10 (continued)

Period	S.E	GREEN	GREY	BOND	EQUITY
Variance Decomposition of BOND:					
1	0.410889	0.047193	1.513040	98.43977	0.000000
2	0.588046	0.552049	2.758699	96.65440	0.034852
3	0.703589	0.682140	3.129770	96.05267	0.135420
4	0.785450	0.757373	3.306698	95.73043	0.205496
5	0.845728	0.802895	3.386530	95.53816	0.272418
6	0.891278	0.834863	3.423876	95.40679	0.334472
7	0.926253	0.858333	3.438510	95.30956	0.393601
8	0.953395	0.876223	3.440880	95.23313	0.449769
9	0.974611	0.890086	3.436406	95.17055	0.502956
10	0.991276	0.900916	3.428235	95.11785	0.552997
Variance Decomposition of EQUITY:					
1	1.650696	66.01381	8.400665	0.066857	25.51866
2	2.051994	71.98577	7.172741	0.100904	20.74059
3	2.413953	73.19192	7.314578	0.252401	19.24110
4	2.690775	73.66278	7.703963	0.396401	18.23685
5	2.923541	73.55386	8.272292	0.542374	17.63147
6	3.120551	73.18652	8.927916	0.685526	17.20004
7	3.290762	72.65097	9.644044	0.825454	16.87953
8	3.439407	72.01145	10.40036	0.960803	16.62739
9	3.570478	71.30316	11.18469	1.090521	16.42163
10	3.686917	70.55006	11.98789	1.213713	16.24833

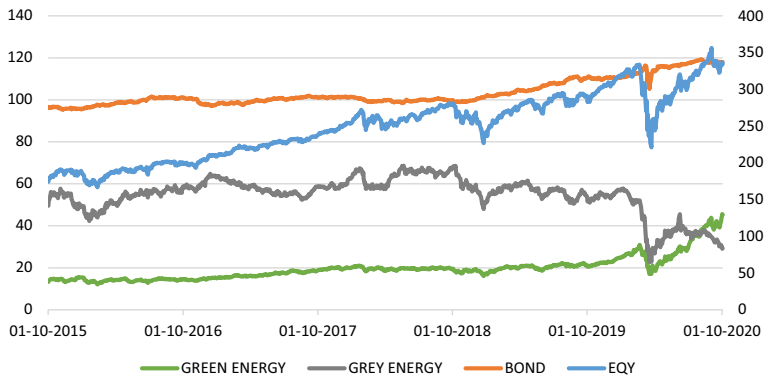


Fig. 1 Prices of ETFs of Selected Asset Classes. *Note*: Green Energy, Grey Energy and Bond ETFs' prices are measured on primary axis and Equity ETF's price is measured on secondary axis. The data spans from October 2015 to October 2020

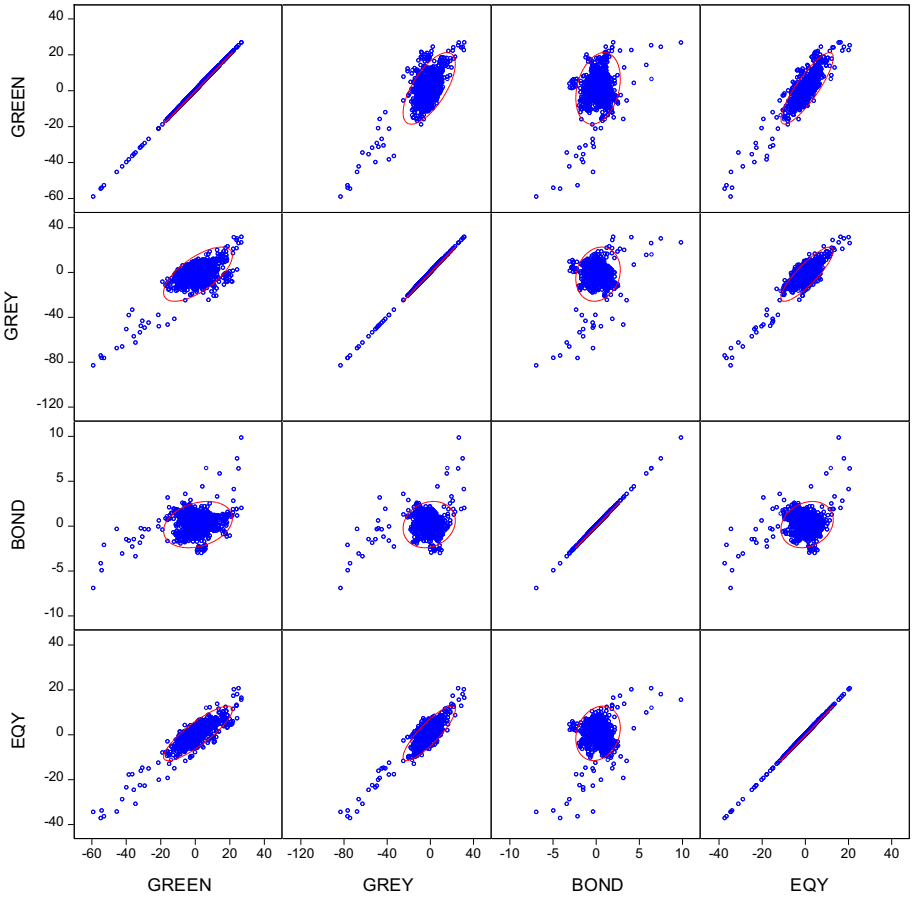
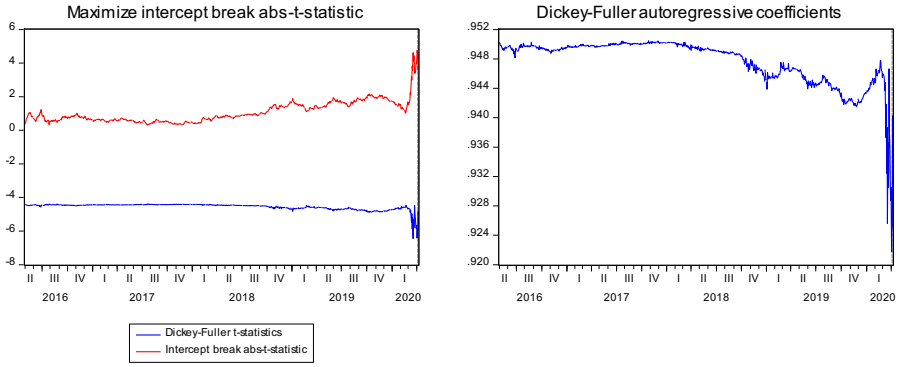
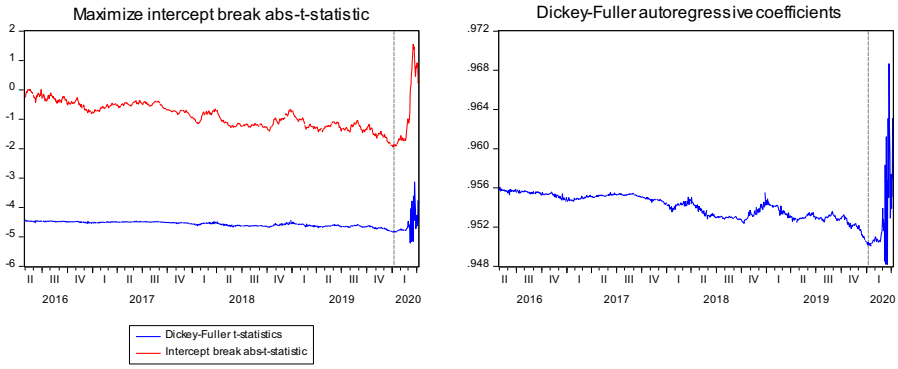


Fig. 2 Scatterplot Matrix

(A) ***ADF "Unit Root with Break" Statistics: GREEN Energy***



(B) ***ADF "Unit Root with Break" Statistics: GREY Energy***



(C) ***ADF "Unit Root with Break" Statistics: BOND***

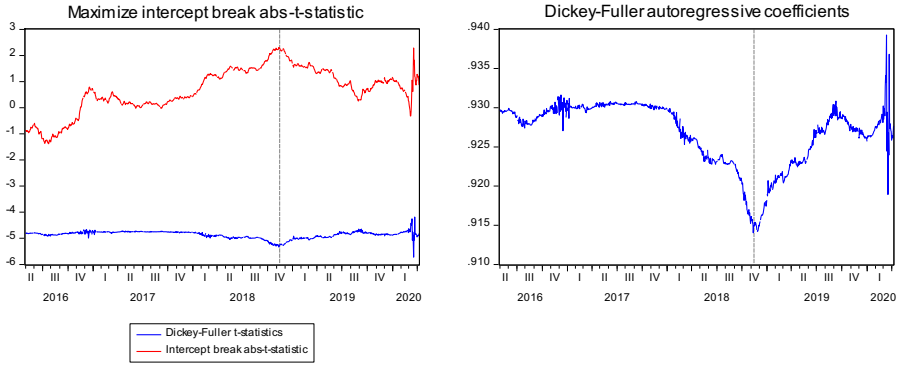


Fig. 3 Augmented Dickey-Fuller "Unit Root with Break" test Results. **a**: ADF "Unit Root with Break" Statistics: GREEN Energy. **b**: ADF "Unit Root with Break" Statistics: GREY Energy. c: ADF "Unit Root with Break" Statistics: BOND. d: ADF "Unit Root with Break" Statistics: EQUITY

(D) ***ADF "Unit Root with Break" Statistics: EQUITY***

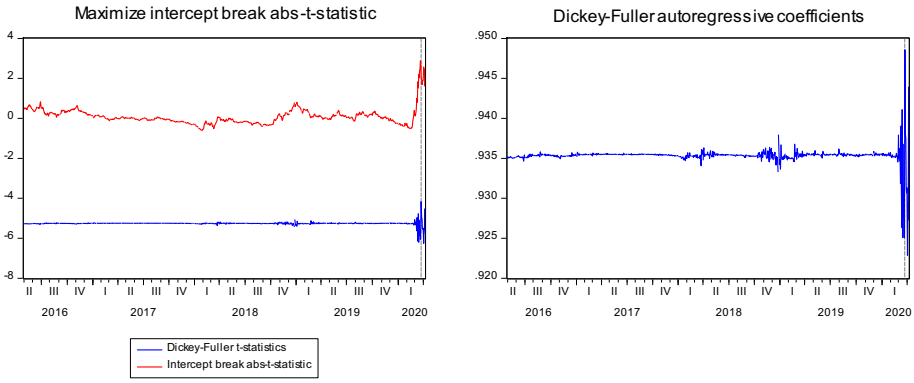


Fig. 3 continued

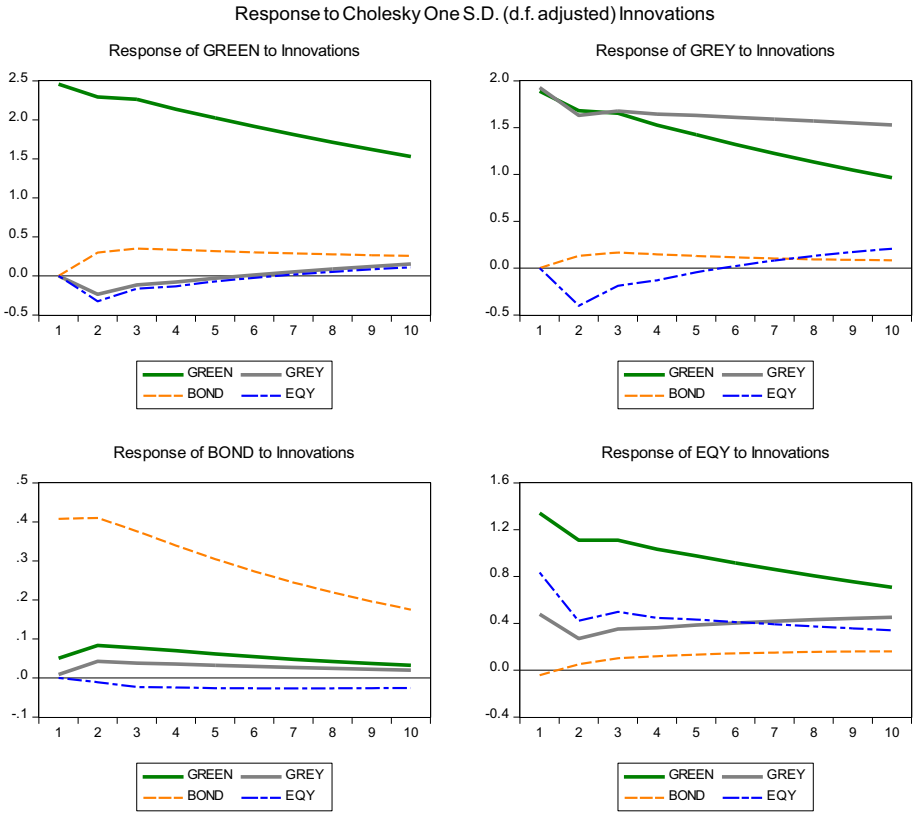


Fig. 4 Impulse response functions

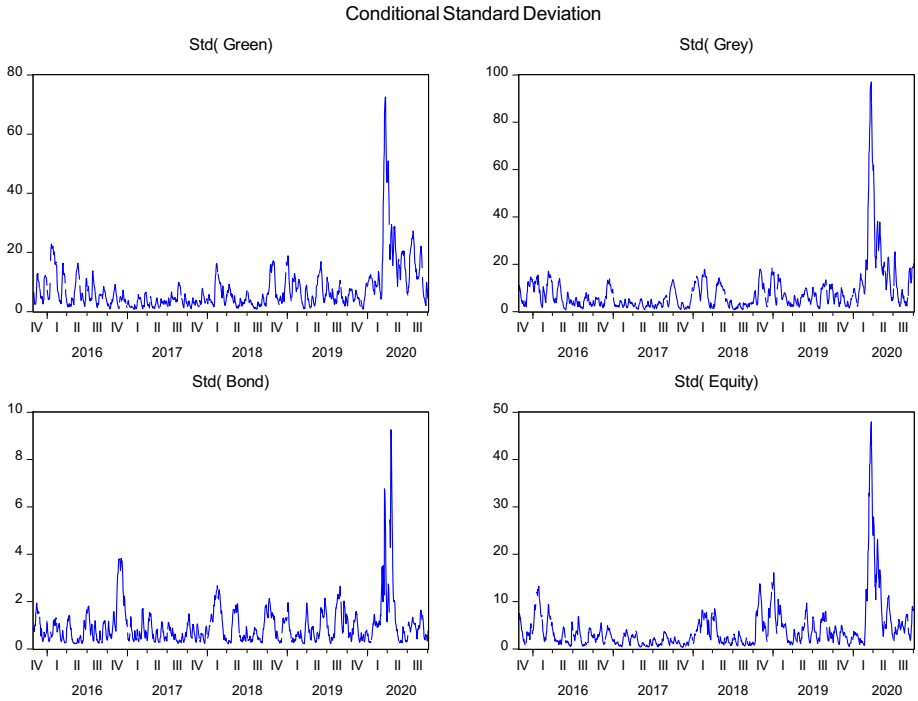


Fig. 5 Conditional standard deviations in excess returns (%)

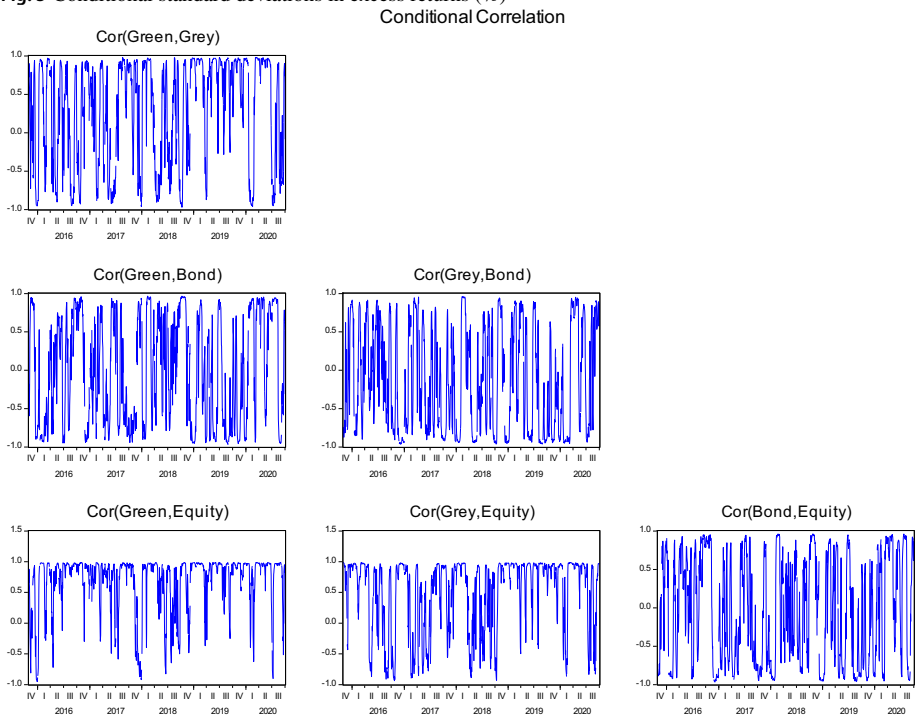


Fig. 6 Conditional correlations based on excess returns (%)

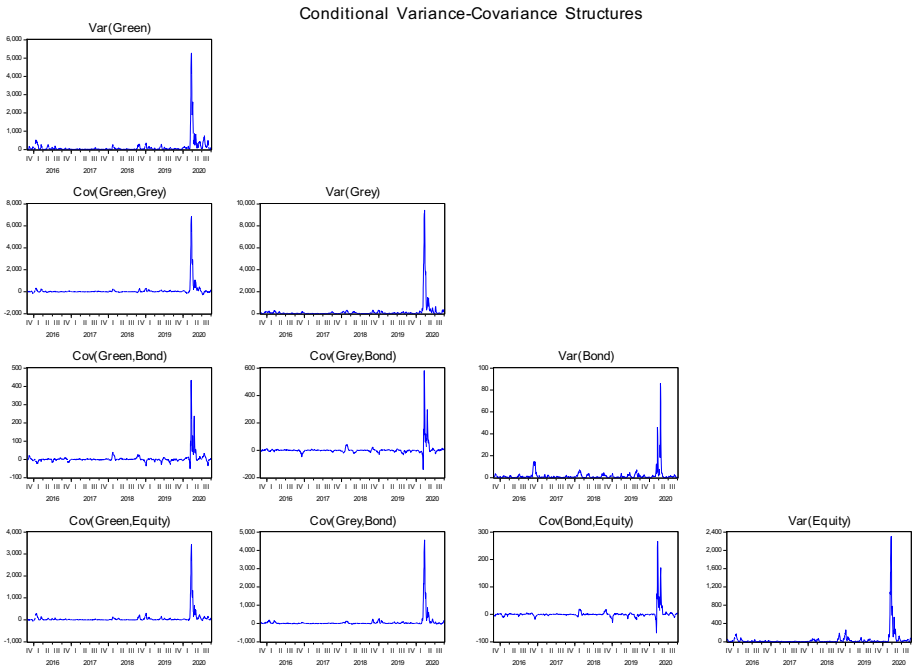


Fig. 7 Conditional variance–covariance structures based on excess returns (%)

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