Dynamic conditional correlation between green and grey energy ETF markets using cDCC-MGARCH model

ALGARHI, Amr Saber <http://orcid.org/0000-0003-2281-3021>

Citation:

ALGARHI, Amr Saber (2023). Dynamic conditional correlation between green and grey energy ETF markets using cDCC-MGARCH model. Applied Economics Letters. [Article]

Dynamic conditional correlation between green and grey ETF markets using cDCC-MGARCH model

(a preprint version)

Amr Saber Algarhi [1]

Sheffield Hallam University, United Kingdom

October 2023

Abstract

Using the cDCC form of the multivariate GARCH models (MGARCH), this paper examines the time-varying conditional correlations among green renewable, grey non-renewable, and the conventional investment strategy in the exchange-traded funds (ETFs) markets. Daily excess returns for the largest energy ETFs are used as proxies for the US energy sector over the period of 25 June 2008 to 9 May 2023. The empirical results find that the AR(1)-GARCH(1, 1)-cDCC model with *t*-distribution to be the best fit. The results indicate that the time-varying correlations between green and grey energy ETFs are between 0.42 and 0.55 and statistically significant at 10%, with lesser degree of persistence in green energy, while there is a high significant co-movement between the grey energy and the traditional investment strategy. This, in turn, implies that investing in green energy ETFs provides better diversification. These results provide important implications for policymakers, portfolio managers and investors on the benefits of portfolio diversification in energy markets amid the current global energy crisis.

Keywords: cDCC-MGARCH; energy sector; exchange-traded funds; oil market

JEL classification: C32; C58; G10; Q42

[1] Stoddart 7216b, Sheffield Business School, Howard St., Sheffield S1 1WB, UK.
ORCiD: https://orcid.org/0000-0003-2281-3021
E-mail address: *a.algarhi@shu.ac.uk* (A. S. Algarhi)

1. Introduction

In the recent two decades, renewable, that is 'green', energy has become increasingly crucial in addressing the global challenges of climate change and the dramatic growth in energy demand (Miralles-Quiros et al., 2018; Su et al., 2020). As governments and private energy companies take major steps to reduce their carbon emissions and shift away from non-renewable, namely 'grey', energy to ensure energy security, the demand for green energy resources and technologies has remarkably increased (Creti and Nguyen, 2015; Ahmad, 2017; Kyritsis and Serletis, 2018). Specifically, according to IRENA and CPI (2023), global investment in green energy amounted to a record level of $0.5 trillion in 2022 with 70% coming from private sources. Likewise, in the financial markets, the analysis of the exchange traded funds (ETFs) has recently attracted much attention due to their stock-like characteristics, tax efficiency, low fees, transparency, and trading flexibility (Huang & Lin, 2011; Yan & Garcia, 2017; Mariani & Florescu, 2020). Interestingly, as a more environmentally friendly and sustainable alternative to grey energy, green ETFs have been growing rapidly in recent years to a total of 552 green ETFs across the globe with assets under management (AUM) of $174 billion in 2020 (UNCTAD, 2021).

In this regard, Rizvi et al. (2022) examine the connectedness between the green and grey energy ETFs from 2015 to 2020 using a full/diagonal BEKK-MGARCH models. Their empirical results suggest that return shocks generated in green energy and transmitted to grey energy are more evident, while the impact of grey energy is diminishing. From a similar point of view, Saeed et al. (2020) consider hedging strategies of green assets against grey energy assets from 2012 to 2019 using the DCC-MGARCH. Their findings suggest that, especially for crude oil, clean energy stocks are more superior hedge than green bonds. More recently, Celik et al.

(2022) investigate the dynamic connectedness and hedging opportunities among green ETFs between 2011 and 2021 using asymmetric DCC-MGARCH models.

Although the DCC-MGARCH model developed by Engel (2002) is one of the most cited works in modelling time-varying correlations for multivariate framework, it is commonly accepted that its parameter estimates have severe negative biases for the case of larger dimensions. Importantly, Aielli (2006) shows that the DCC model has a considerable asymptotic bias in the estimator of the sample covariance matrix, which is a component of the correlation driving process. Consequently, Aielli (2006) proposes the corrected DCC (cDCC) to adjust this in such a way that it has martingale difference errors. The cDCC model is extended, in Aielli (2013) and Aielli and Caporin (2014), by allowing for a clustering structure of the univariate GARCH parameters, and the model has been used in several empirical applications (see for instance, Hafner & Reznikova 2012; Fresoli & Ruiz, 2016). Moreover, several studies showed that there is no significant difference in parameter estimates under both DCC and cDCC representations if the error terms are Gaussian (see Carnero & Ertalay, 2014; Bodnar & Hautsch, 2016). Yet, as the multivariate normality in DCC errors are rejected in this paper, we can rely on cDCC estimates in this setting.

All things considered; this paper makes three contributions to the literature. First, we follow the DCC-MGARCH and the cDCC-MGARCH models to estimate the time varying conditional correlations among grey and green energy ETFs, along with a more conventional market ETF representing the S&P500. Second, unlike previous studies, we consider a larger set of variables (Eight grey and green energy ETFs) with a dataset that fully accounts for the GFC and the pandemic periods. Third, to the best of our knowledge, this paper is one of the first papers attempts to model the energy excess returns using the cDCC representation.

This paper proceeds as follows: Section 2 describes the data and methodology. Section 3 discusses the results. Finally, section 4 concludes.

2. Data and methodology

We use daily data for the exchange-traded funds (ETFs) from Bloomberg, which span the period from 25 June 2008 through to 9 May 2023, a total of 3,744 observations. The data include four grey US energy ETFs (XLE, VDE, XOP and IEO), four green US energy ETFs (ICLN, TAN, QCLN and PBW), the SPDR S&P 500 ETF Trust (SPY) and iShare 1-3 Year Treasury Bond ETF (SHY). The list of the funds, their AUM and coverage are provided in Appendix Table A.1. With an average AUM of $40 billion over 2018-2023, the grey and green US energy ETFs used in this paper can be regarded as proxies for the financial performance of non-renewable and renewable US energy sectors, respectively. While SPY gives a traditional investment strategy against which the grey and green ETFs can be measured, SHY as a short-duration government bond fund is used to determine a risk-free rate. Let P_t be the ETF's price at time t for all ETFs separately, we calculate their daily excess returns r_t relative to the return on SHY as a risk-free return as follows,

$$r_t = (\log P_t - \log P_{t-1}) - (\log SHY_t - \log SHY_{t-1})$$

To investigate the dynamic correlation structure, we follow Engle's (2002) dynamic conditional correlation multivariate GARCH (DCC-MGARCH) and Aielli's (2006) corrected DCC-MGARCH (cDCC-MGARCH) models. we start with the mean equation,

$$\boldsymbol{r}_t = E(\boldsymbol{r}_t|\boldsymbol{F}_{t-1}) + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t = \boldsymbol{H}_t^{1/2}\boldsymbol{z}_t$$

where $\boldsymbol{r}_t = (r_{1,t}, r_{2,t}, \dots, r_{9,t})'$ is a vector of excess returns in the order of four grey, four green and SPY ETFs, $\boldsymbol{F}_{t-1}$ is the information available at $t-1$, $\boldsymbol{z}_t$ is an iid random vector with mean $\boldsymbol{0}$ and covariance matrix $\boldsymbol{I}_9$, and $\boldsymbol{H}_t = (h_{ij,t})$ is the multivariate dynamic conditional variance-covariance written as,

$$\boldsymbol{H}_t = \boldsymbol{D}_t^{1/2} \boldsymbol{R}_t \boldsymbol{D}_t^{1/2}$$

$$\boldsymbol{D}_t = diag(h_{11,t}, \dots, h_{99,t})$$

$$\boldsymbol{R}_t = \boldsymbol{Q}_t^{*-\frac{1}{2}} \boldsymbol{Q}_t \, \boldsymbol{Q}_t^{*-\frac{1}{2}}$$

$$\boldsymbol{Q}_t^{*-\frac{1}{2}} = diag\left(q_{11,t}^{-1/2}, \dots, q_{99,t}^{-1/2}\right)$$

where $\boldsymbol{D}_t$ is a diagonal matrix containing the conditional variances (h_t) from the univariate GARCH-type structures (Table A.2 in the Appendix shows several GARCH-type models used), $\boldsymbol{R}_t$ is a 9×9 conditional correlation matrix, and $\boldsymbol{Q}_t = (q_{ij,t})$ is a 9×9 symmetric positive definite matrix and is defined in the DCC as

$$\boldsymbol{Q}_t = (1 - \lambda_1 - \lambda_2)\overline{\boldsymbol{Q}} + \lambda_1 \boldsymbol{\eta}_{t-1} \boldsymbol{\eta}'_{t-1} + \lambda_2 \boldsymbol{Q}_{t-1}$$

while it is given in the cDCC by

$$\boldsymbol{Q}_t = (1 - \lambda_1 - \lambda_2)\overline{\boldsymbol{Q}} + \lambda_1 \boldsymbol{\eta}^*_{t-1} \boldsymbol{\eta}^{*\prime}_{t-1} + \lambda_2 \boldsymbol{Q}_{t-1}$$

where λ_1 and λ_2 are non-negative scalar parameters, $\boldsymbol{\eta}_t = (\eta_{1t}, \dots, \eta_{9t})'$ is the standardised error vector, where $\eta_{it} = \varepsilon_{it} / \sqrt{h_{ii,t}}$, $\boldsymbol{\eta}^*_t = \boldsymbol{Q}_t^{*\frac{1}{2}} \boldsymbol{\eta}_t$ and $\overline{\boldsymbol{Q}}$ is unconditional covariances matrix of $\boldsymbol{\eta}_t$. Both models have advantages using flexible GARCH specifications in the conditional variance. However, the cDCC allows for more tractable dynamic conditions (Aielli, 2013).

3. Results

In Table 1, Panel A shows the summary statistics on each daily excess return. All means are close to zero. Despite the standard deviation suggests little variation across all ETFs, SPY shows relatively small volatility. The skewness indicates all excess returns are skewed left with extreme losses in the grey energy sector, while higher kurtosis suggests more extreme outliers in this sector. The significance of Jarque-Bera implies none of the excess returns obeys normal distribution, whilst the ARCH tests identify the presence of ARCH effects. The volatility clustering of the daily excess returns is also evident in Figure 1. During mid-2008 to mid-2009, there were significantly bigger movements in green energy funds as a result of the GFC, while the variability in grey energy was much higher from 2020 to 2023 due to the pandemic. After checking each ETF for stationarity, we determined that stationarity holds for all ETFs after first difference. Panel B in Table 1 contains unit root tests which all rejects the presence of unit root in the excess returns.

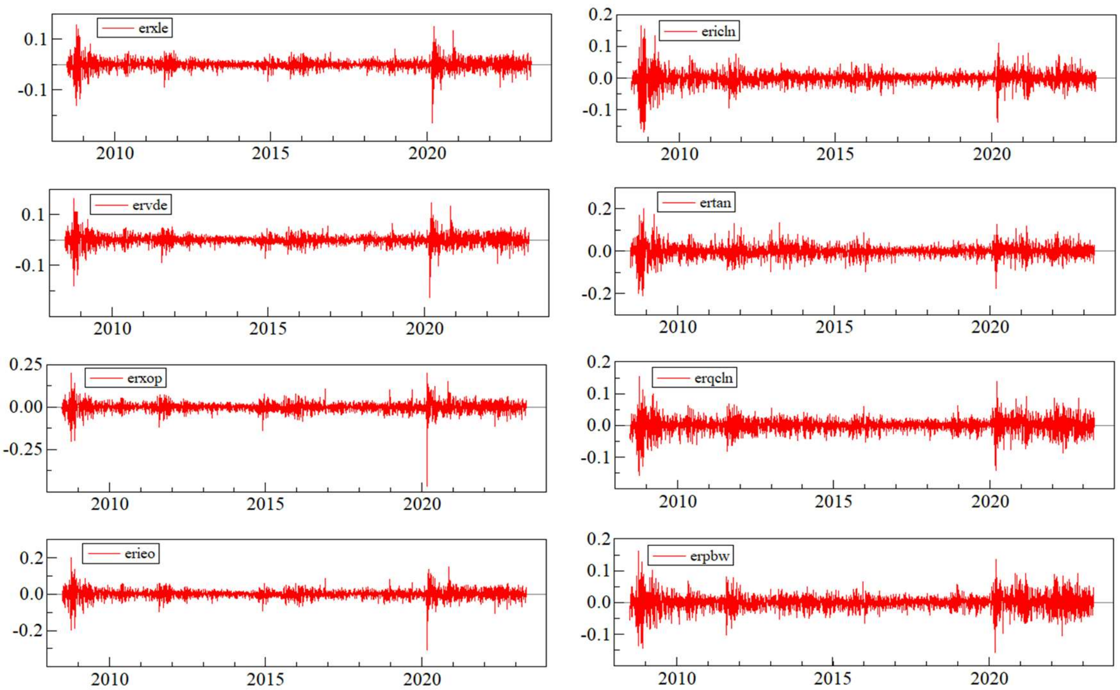

Figure 1. Daily excess returns of the grey and green energy ETFs.

Table 1. Descriptive statistics and unit root tests.

	Panel A: Descriptive statistics								**Panel B:** Unit root test statistics			
Indices	Mean	Max.	Min.	Std Dev.	Skewness	Kurtosis	JB	ARCH(5)	ADF	PP	DF-GLS	DF-B
XLE	-0.000020	0.15692	-0.23035	0.02051	-0.73764	16.6121	29237***	805.43***	-64.95***	-64.93***	-7.02***	-66.62***
VDE	-0.000037	0.16225	-0.22640	0.02070	-0.67980	15.1293	23233***	796.74***	-64.74***	-64.69***	-6.87***	-66.35***
XOP	-0.000218	0.20261	-0.46542	0.02793	-1.29595	28.1642	99806***	255.60***	-64.00***	-64.00***	-7.66***	-67.57***
IEO	-0.000004	0.20078	-0.30544	0.02457	-0.79202	16.1077	27186***	562.16***	-63.41***	-63.39***	-9.27***	-65.43***
ICLN	-0.000279	0.16442	-0.16877	0.02159	-0.58512	13.4989	17404***	1106.14***	-59.75***	-59.73***	-2.78*	-61.08***
TAN	-0.000377	0.20010	-0.20964	0.02919	-0.35198	9.1337	5945***	619.83***	-58.15***	-58.13***	-3.66***	-59.23***
QCLN	0.000149	0.15334	-0.15817	0.02253	-0.38065	8.0662	4093***	775.49***	-60.06***	-60.05***	-3.42**	-60.09***
PBW	-0.000294	0.16262	-0.15799	0.02399	-0.34566	7.7964	3662***	888.90***	-59.55***	-59.55***	-3.08**	-60.27***
SPY	0.000305	0.13999	-0.11751	0.01330	-0.38620	16.3959	28080***	1105.49***	-68.32***	-68.66***	-7.71***	-69.36***

Notes: JB denotes Jarque-Bera statistics. For unit root tests, ADF, PP, DF-GLS and DF-B represent the augmented Dicky-Fuller, Phillips and Perron test, Elliott, Rothenberg and Stock generalised least squares version of ADF, and the Perron modified DF with breakpoints, respectively. Significant at 10%, 5% and 1% *, **, ***, respectively.

Table 2 reports summary results of several MGARCH models with DCC and cDCC representations. The log-likelihood and all information criteria find the AR(1)-GARCH(1,1)-cDCC model with *t*-distribution as the best fit to capture the fat tails and the skewed features present in the daily excess returns. Interestingly, the parameters λ_1 and λ_2 are statistically significant, implying that the correlations between the ETFs change over time, however the estimated dynamic conditional correlation coefficients, reported in Table 3, are only statistically significant at 1% among SPY and all grey energy ETFs, indicating high co-movement among these asset classes. Furthermore, the multivariate diagnostics show the suitability of the fitted cDCC model.

Table 2. Summary results of several MGARCH models with DCC and cDCC representations under *t*-distribution.

		λ_1	λ_2	Tail: υ	Log-likelihood	AIC	BIC	LM(5)	LM^2(5)	M. Normality
DCC	GARCH	0.02029***	0.96728***	7.41***	120252	0.01301	0.11805	190.91	332.28	1299.7***
	GJR	0.02187***	0.96255***	7.44***	120199	0.02865	0.17130	187.38	290.87	1108.6***
	APARCH	0.02123***	0.96351***	7.43***	120163	0.03433	0.19467	190.19	288.63	1044.9***
	IGARCH	0.02061***	0.96754***	7.17***	120189	0.01724	0.12435	189.80	322.00	1278.5***
	FIGARCH	0.01789***	0.97233***	7.42***	120248	0.02870	0.17149	186.23	322.03	1273.7***
	HYGARCH	0.01796***	0.97204***	7.48***	120242	0.03443	0.19509	186.08	327.04	1280.4***
cDCC	GARCH	0.02439***	0.96391***	7.35***	**120337**	**0.01298**	**0.11803**	189.70	192.25	1290.6***
	GJR	0.02603***	0.95930***	7.39***	120284	0.02865	0.17134	186.48	287.98	1097.0***
	APARCH	0.02463***	0.02463***	7.37***	120242	0.03434	0.19473	188.35	284.55	1040.7***
	IGARCH	0.02556***	0.96432***	7.08***	120279	0.01724	0.12438	188.87	319.79	1261.8***
	FIGARCH	0.02048***	0.97081***	7.36***	120315	0.02638	0.16199	160.18	223.29	1041.1***
	HYGARCH	0.02039***	0.97040***	7.43***	120329	0.03183	0.18441	183.971	314.71	1257.6***

Notes: Standard errors in parentheses. LM and LM^2 are Li and McLeod multivariate portmanteau statistics on standardised and square standardised residuals, respectively. M. Normality denotes Multivariate Normality. Significant at 10%, 5% and 1% *, **, ***, respectively.

Table 3. The estimated dynamic conditional correlation coefficients for the AR(1)-GARCH(1,1)-cDCC.

	VDE	XOP	IEO	ICLN	TAN	QCLN	PBW	SPY
XLE	0.99429***	0.91401***	0.94700***	0.49179*	0.43217*	0.52962*	0.53720*	0.71162**
VDE		0.92802***	0.95342***	0.49855*	0.44014*	0.54114*	0.54987*	0.71198**
XOP			0.96824***	0.45861*	0.41861*	0.52320*	0.53843*	0.62252**
IEO				0.46972*	0.42593*	0.53096*	0.53805*	0.65049**
ICLN					0.82812**	0.72567**	0.73827**	0.59253*
TAN						0.78011**	0.79911**	0.51721*
QCLN							0.88379***	0.68773**
PBW								0.65913*

Notes: Significant at 10%, 5% and 1% *, **, ***, respectively.

Figures 2 and 3 present the dynamic conditional correlations for the best fitted DCC and cDCC models respectively, while Table 4 shows the summary statistics. It is evident that there are significant variations in the pathways of the conditional correlations. Some, in particular among grey funds, are always positive and higher than 0.78, while they reach values close to zero with alternating signs among grey and green funds, for example, XLE and VDE against all green funds, XOP versus TAN, and IEO versus ICLN, TAN and QCLN. Interestingly, a deep plunge can only be noticed in the conditional correlation between SPY and all grey energy funds, not the green, during the GFC and the pandemic periods. Importantly, the conditional correlation for all green funds significantly varies from – 0.22 to 0.91 with grey funds and SPY indicating their potential as alternative diversifiers. It can also be pointed out that although the time plots of the two models are qualitatively similar, the cDCC is more variable, particularly between the grey energy funds and SPY. Moreover, whilst the sample correlations means are very close for both models, the cDCC model have larger ranges. All in all, there is no distinction between the two models, indicating that we can rely on the cDCC representation in this case.

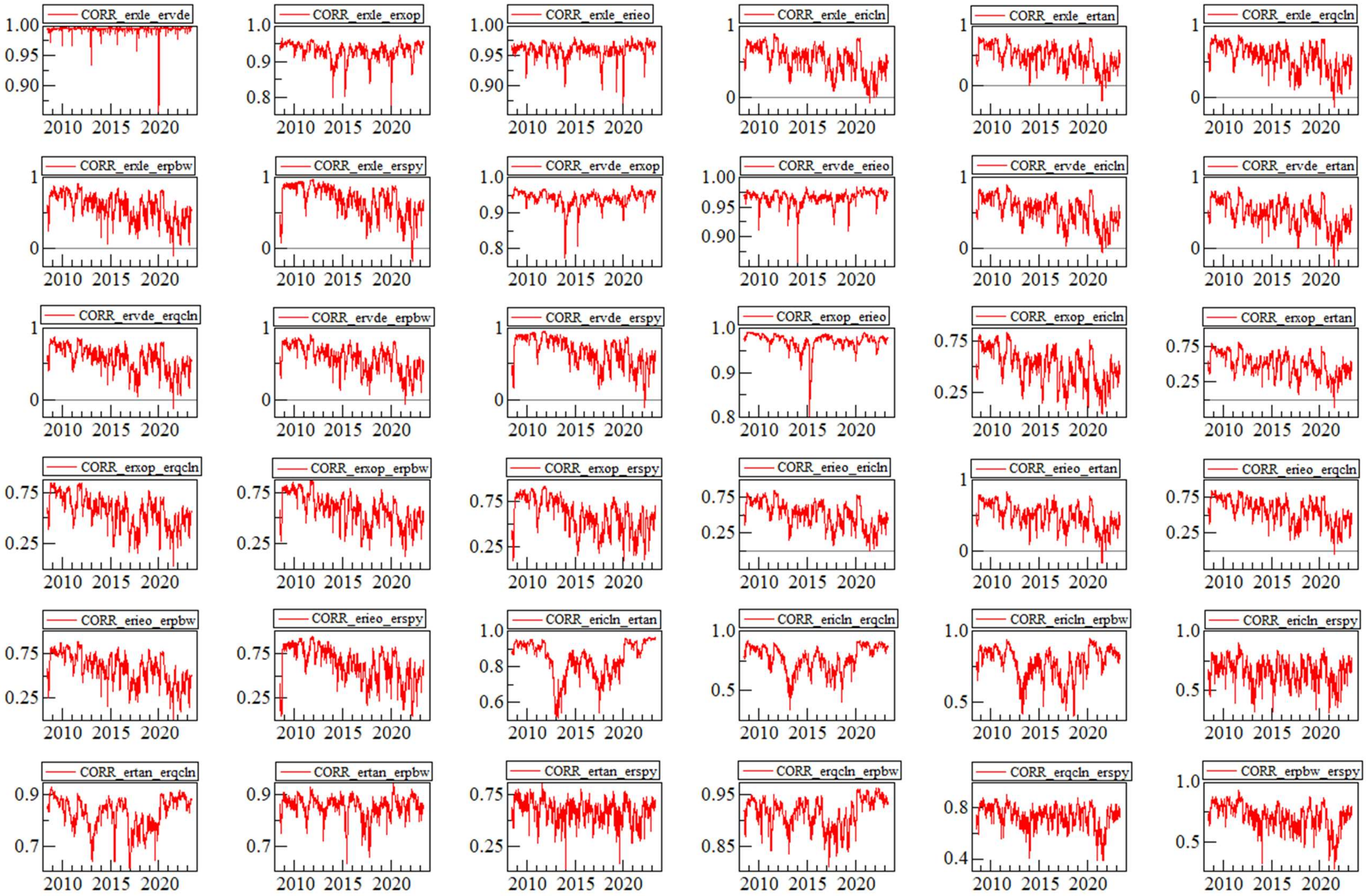

Figure 2. Time plot of time-varying correlation coefficients based on the DCC representation.

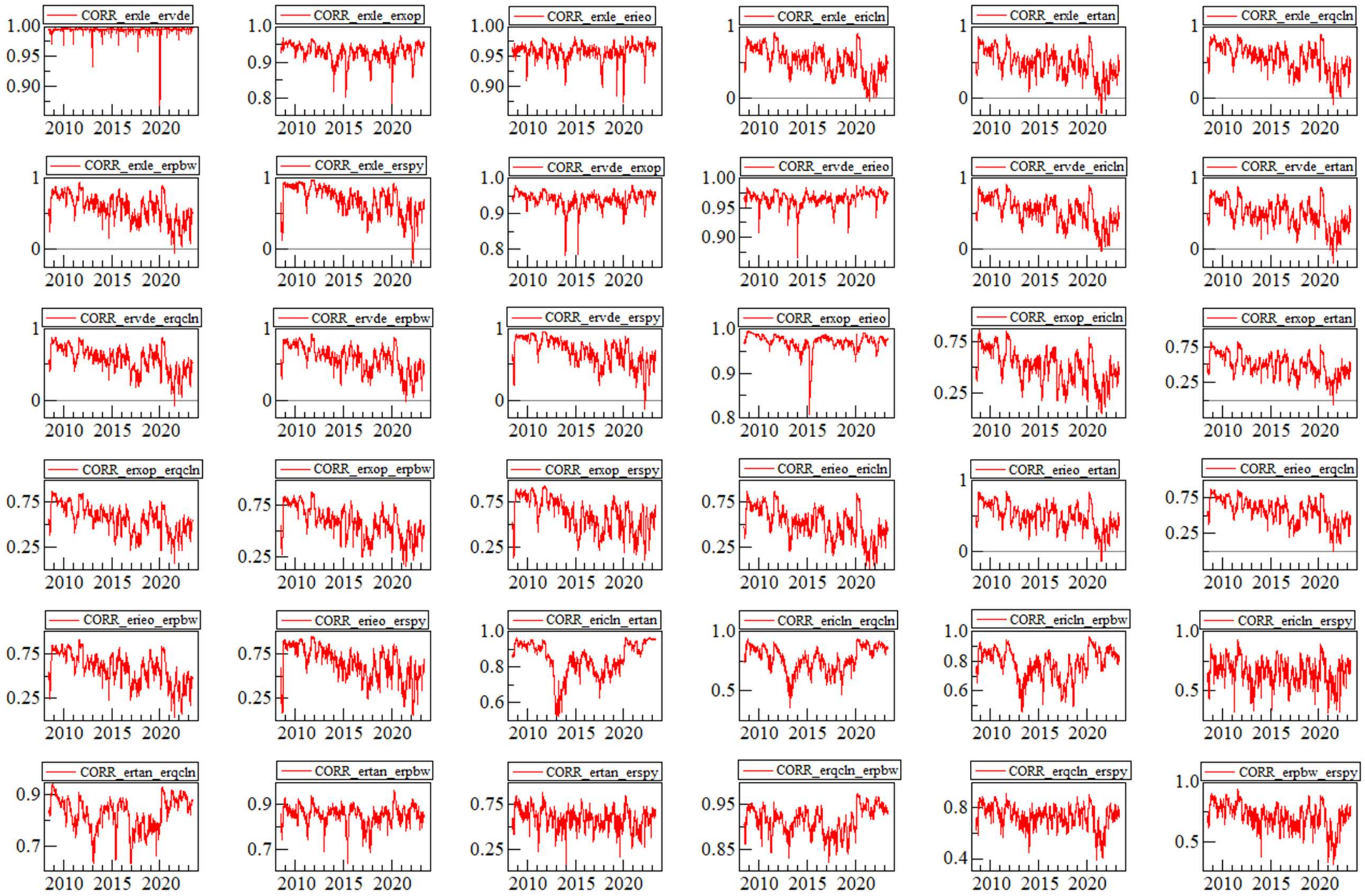

Figure 3. Time plot of time-varying correlation coefficients based on the cDCC representation.

Table 4. Descriptive statistics of time-varying correlations.

	AR(1)-GARCH(1,1)-DCC						AR(1)-GARCH(1,1)-cDCC					
	Mean	SD	Min.	Max.	Skewness	Kurtosis	Mean	SD	Min.	Max.	Skewness	Kurtosis
(XLE, VDE)	0.995	0.005	0.856	0.998	-14.201	294.41	0.995	0.005	0.866	0.999	-13.028	255.39
(XLE, XOP)	0.929	0.024	0.777	0.973	-1.963	9.46	0.928	0.024	0.784	0.975	-1.603	7.85
(XLE, IEO)	0.960	0.013	0.870	0.983	-2.462	12.99	0.959	0.013	0.873	0.984	-2.011	10.57
(XLE, ICLN)	0.527	0.193	-0.077	0.892	-0.506	2.64	0.527	0.191	-0.052	0.913	-0.400	2.79
(XLE, TAN)	0.487	0.189	-0.266	0.866	-0.453	2.97	0.487	0.187	-0.215	0.883	-0.325	3.00
(XLE, QCLN)	0.560	0.183	-0.143	0.879	-0.680	2.96	0.561	0.181	-0.100	0.890	-0.622	3.09
(XLE, PBW)	0.575	0.188	-0.106	0.915	-0.579	2.73	0.577	0.186	-0.060	0.933	-0.516	2.83
(XLE, SPY)	0.679	0.207	-0.178	0.964	-0.903	3.53	0.691	0.195	-0.189	0.969	-0.935	3.98
(VDE, XOP)	0.941	0.021	0.773	0.977	-2.496	14.08	0.940	0.021	0.781	0.980	-2.164	12.67
(VDE, IEO)	0.965	0.012	0.856	0.984	-2.684	16.34	0.965	0.012	0.865	0.988	-2.124	12.01
(VDE, ICLN)	0.535	0.191	-0.056	0.891	-0.504	2.61	0.535	0.188	-0.033	0.914	-0.383	2.68
(VDE, TAN)	0.494	0.187	-0.245	0.865	-0.467	3.00	0.495	0.185	-0.198	0.881	-0.325	2.95
(VDE, QCLN)	0.569	0.183	-0.125	0.881	-0.670	2.97	0.570	0.180	-0.076	0.887	-0.581	2.98
(VDE, PBW)	0.584	0.184	-0.067	0.913	-0.555	2.71	0.586	0.183	-0.023	0.929	-0.480	2.74
(VDE, SPY)	0.675	0.203	-0.113	0.963	-0.778	3.13	0.686	0.192	-0.125	0.968	-0.785	3.45
(XOP, IEO)	0.971	0.020	0.801	0.993	-3.800	24.54	0.971	0.019	0.808	0.995	-3.569	23.02
(XOP, ICLN)	0.507	0.168	0.033	0.835	-0.248	2.313	0.507	0.167	0.049	0.864	-0.098	2.31
(XOP, TAN)	0.491	0.157	-0.106	0.812	-0.290	2.73	0.491	0.155	-0.068	0.824	-0.137	2.67
(XOP, QCLN)	0.565	0.155	0.031	0.846	-0.396	2.59	0.567	0.152	0.073	0.879	-0.256	2.48
(XOP, PBW)	0.582	0.150	0.120	0.867	-0.241	2.40	0.585	0.150	0.154	0.885	-0.134	2.33
(XOP, SPY)	0.603	0.189	0.088	0.929	-0.391	2.35	0.612	0.183	0.098	0.936	-0.337	2.34
(IEO, ICLN)	0.513	0.177	-0.005	0.851	-0.341	2.40	0.513	0.177	0.008	0.877	-0.219	2.47
(IEO, TAN)	0.491	0.168	-0.172	0.832	-0.381	2.86	0.492	0.168	-0.134	0.851	-0.258	2.83
(IEO, QCLN)	0.568	0.165	-0.044	0.846	-0.554	2.74	0.569	0.165	-0.002	0.875	-0.487	2.75
(IEO, PBW)	0.578	0.169	0.004	0.883	-0.469	2.58	0.581	0.170	0.040	0.906	-0.406	2.60
(IEO, SPY)	0.632	0.190	0.043	0.936	-0.606	2.75	0.645	0.179	0.060	0.941	-0.572	2.86
(ICLN, TAN)	0.845	0.097	0.514	0.966	-0.961	3.36	0.848	0.093	0.524	0.967	-0.974	3.57
(ICLN, QCLN)	0.772	0.107	0.340	0.922	-0.931	3.44	0.772	0.104	0.362	0.940	-0.729	3.14
(ICLN, PBW)	0.781	0.106	0.405	0.946	-0.986	3.53	0.783	0.098	0.458	0.965	-0.699	3.02
(ICLN, SPY)	0.663	0.099	0.309	0.906	-0.462	2.83	0.661	0.103	0.311	0.929	-0.242	2.92
(TAN, QCLN)	0.829	0.060	0.615	0.931	-0.822	3.20	0.828	0.060	0.631	0.945	-0.593	2.99
(TAN, PBW)	0.855	0.042	0.629	0.946	-1.492	6.89	0.854	0.042	0.638	0.966	-1.027	5.68
(TAN, SPY)	0.599	0.105	0.030	0.862	-0.627	3.84	0.595	0.110	0.080	0.890	-0.307	3.43
(QCLN, PBW)	0.916	0.028	0.810	0.963	-0.619	2.64	0.915	0.029	0.819	0.975	-0.354	2.43
(QCLN, SPY)	0.734	0.083	0.385	0.903	-1.034	4.32	0.734	0.084	0.391	0.915	-0.830	4.00
(PBW, SPY)	0.712	0.104	0.276	0.929	-0.840	3.91	0.714	0.103	0.309	0.939	-0.669	3.74

4. Conclusion

This paper investigates the dynamic linkages among excess returns representing grey and green ETF energy against the conventional investment strategy. Using cDCC-MGARCH, we find that the time-varying correlations between green energy and the other ETFs tend to be weak, between 0.42 and 0.55, and statistically significant at 10%. Although the correlations among all the ETFs change over time, the estimated cDCC coefficients are only statistically significant at 1% among all grey energy funds. All in all, green energy shows the least degree of persistence between 2008 and 2023. Moreover, it should be noted that these results aid policymakers, analysts, portfolio managers and investors in understanding the benefits of portfolio diversification. Weak dynamic correlation between green energy funds versus grey and conventional ones indicates better diversification by investing in these ETFs.

Acknowledgment

The author is grateful for valuable feedback from the editor (Professor Mark P. Taylor) and two anonymous referees.

Disclosure statement

No potential conflict of interest was reported by the author.

References:

Ahmad, W. (2017). On the dynamic dependence and investment performance of crude oil and clean energy stocks. *Research in International Business and Finance*, *42*, 376–389. https://doi.org/10.1016/j.ribaf. 2017.07.140

Aielli, G.P. (2006). *Consistent estimation of large scale dynamic conditional correlations*. [Unpublished manuscript, Department of Statistics, University of Florence]

Aielli, G.P. (2013). Dynamic conditional correlations: on properties and estimation. *Journal of Business and Economic Statistics, 31*(3), 282-299.

Aielli, G.P. & Caporin, M. (2014). Variance clustering improved dynamic conditional correlation MGRACH estimators. *Computational Statistics & Data Analysis, 76*, 556-576.

Bodnar, T., & Hautsch, N. (2016). Dynamic conditional correlation multiplicative error processes. *Journal of Empirical Finance, 36*, 41-67. https://doi.org/10.1016/j.jempfin.2015.12.002

Carnero, M.A. & Eratalay, M.H. (2014). Estimating VAR-MGARCH models in multiple steps. *Studies in Nonlinear Dynamics & Econometrics, 18*(3), 339-365. https://doi.org/10.1515/snde-2012-0065

Celik, I., Sak, A.F., Ozdemir A. & Vergili, G. (2022). The dynamics connectedness and hedging opportunities of implied and realised volatility: Evidence from clean energy ETFs, *The North American Journal of Economics and Finance*, *60*, 101670. https://doi.org/10.1016/j.najef.2022.101670

Creti, A. & Nguyen, D.K. (2015). Energy markets' financialization, risk spillovers, and pricing models. *Energy Policy*, *82*, 260-263. https://doi.org/10.1016/j.enpol.2015.02.007

Engle, R.E. (2002). Dynamic conditional correlations: A simple class of multivariate GARCH models. *Journal of Business and Economic Statistics, 20*, 339-350.

Fresoli, D.E. and Ruiz, E. (2016). The uncertainty of conditional returns, volatilities, and correlations in DCC models. *Computational Statistics & Data Analysis, 100*, 170-185. https://doi.org/10.1016/j.csda.2015.03.017

Hafner, C.M. & Reznikova, O. (2012). On the estimation of dynamic conditional correlation models, *Computational Statistics & Data Analysis, 56*(11), 3533-3545. https://doi.org/10.1016/j.csda.2010.09.022

Huang, M.Y. and Lin, J. B. (2011). Do ETFs provide effective international diversification? *Research in International Business and Finance*, 25, 335-344. https://doi.org/10.1016/j.ribaf.2011.03.003

IRENA & CPI (2023). *Global landscape of renewable energy finance*. Abu Dhabi: International Renewable Energy Agency.

Kyritsis, E., & Serletis, A. (2018). The zero lower bound and market spillovers: Evidence from the G7 and Norway. *Research in International Business and Finance*, *44*, 100–123. https://doi.org/10.1016/J.RIBAF. 2017.05.015

Mariani, M.C., & Florescu, I. (2020). *Quantitative Finance*. John Wiley & Sons.

Miralles-Quirós, J.L., Miralles-Quirós, M.M. & Nogueira, J.M. (2018). Diversification benefits of using exchange-traded funds in compliance to the sustainable development goals. *Business Strategy and the Environment*, *28*(1), 244–255. https://doi.org/10.1002/bse.2253

Rizvi, S.K.A., Naqvi, B., & Mirza, N. (2022). Is green investment different from grey? Return and volatility spillovers between green and grey energy ETFs. *Annals of Operations Research*, *313*(1), 495-524. https://doi.org/10.1007/s10479-021-04367-8

Saeed, T., Bouri, E., & Tran. D.K. (2020). Hedging strategies of green assets against dirty energy assets. *Energies*, *13*(12), 3141. https://doi.org/10.3390/en13123141

Su, C.W., Naqvi, B., Shao, X.F., Li, J.P., & Jiao, Z. (2020). Trade and technological innovation: The catalysts for climate change and way forward for COP21. *Journal of Environmental Management*, *269*, 110774. https://doi.org/10.1016/j.jenvman.2020.110774

UNCTAD (2021). *The rise of the sustainable fund market and its role in financing sustainable development*. New York and Geneva: United Nations.

Yan, L., & Garcia, P. (2017). Portfolio investment: Are commodities useful? *Journal of Commodity Markets*, *8*, 43-55. https://doi.org/10.1016/j.jcomm.2017.10.002

Appendix A

Table A.1. A list of used ETFs tracking a specific asset class.

Asset class	Ticker	Index ETF	AUM	Coverage
Grey energy	XLE	Energy Select Sector SPDR	22.83	XLE targets investment results of the *Energy Select Sector Index*, an index of U.S. companies in the oil, gas and consumable fuel, and energy equipment and services industries.
	VDE	Vanguard Energy	5.239	VDE tracks the performance of the *MSCI US Investable Market Index,* an index made up of stocks of large, mid-size, and small U.S. companies within the energy sector as classified under the GICS.
	XOP	SPDR S&P Oil & Gas Exploration & Production	3.175	XOP tracks the performance of the *S&P Oil & Gas Exploration & Production Select Industry Index*, which represents the oil and gas exploration and production segment of the S&P Total Market Index.
	IEO	iShares US Oil & Gas Exploration & Production	0.460	IEO tracks the investment results of the *Dow Jones U.S. Select Oil Exploration & Production Index* composed of US equities in the oil and gas exploration and production sector.
Green energy	ICLN	iShares Global Clean Energy	3.192	ICLN tracks the investment results of the *S&P Global Clean Energy Index*, an index tracks the performance of approximately 100 clean energy companies.
	TAN	Invesco Solar	1.836	TAN tracks the investment results of the *MAC Global Solar Energy Index*, an index seeks to track the performance of companies in global solar energy businesses.
	QCLN	First Trust NASDAQ Clean Edge Green Energy	1.330	QCLN fund tracks the investment results of the *NASDAQ Clean Edge Green Energy Index*, which tracks the performance of small, mid, and large capitalisation clean energy companies.
	PBW	Invesco WilderHill Clean Energy	0.920	PBW tracks the investment results of the *WilderHill Clean Energy Index*, an index tracks the performance of companies that engage in the business of advancement of cleaner energy and conservation.
Equity	SPY	SPDR S&P 500	333	SPY tracks the investment performance of the *S&P 500 Index*.
Bond	SHY	iShares 1-3 Year Treasury Bond	21.68	SHY tracks the investment results of an index composed of *US Treasury 1-3 Year Bond Index*, which measures the performance of public obligations of the US Treasury that have a remaining maturity of 1-3 years.

Note: AUM is the assets under management in billion dollars and averaged over 2018-2023. *Source:* Bloomberg and YCharts.

Table A.2. GARCH-type models used.

GARCH	$h_t = \frac{\omega}{\beta(L)} + \left[1 - \frac{\psi(L)}{\beta(L)}\right] \varepsilon_t^2$
GJR	$h_t = \frac{\omega}{\beta(L)} + \left[1 - \frac{\psi(L)}{\beta(L)}(1-L)\right] (\lvert\varepsilon_t\rvert - \gamma\varepsilon_t)^2$
APARCH	$h_t^{\delta/2} = \frac{\omega}{\beta(L)} + \left[1 - \frac{\psi(L)}{\beta(L)}\right] (\lvert\varepsilon_t\rvert - \gamma\varepsilon_t)^\delta$
IGARCH	$h_t = \frac{\omega}{\beta(L)} + \left[1 - \frac{\psi(L)}{\beta(L)}(1-L)\right] \varepsilon_t^2$
FIGARCH	$h_t = \frac{\omega}{\beta(L)} + \left[1 - \frac{\psi(L)}{\beta(L)}(1-L)^d\right] \varepsilon_t^2$
FIAPARCH	$h_t^{\delta/2} = \frac{\omega}{\beta(L)} + \left[1 - \frac{\psi(L)}{\beta(L)}(1-L)^d\right] (\lvert\varepsilon_t\rvert - \gamma\varepsilon_t)^\delta$
HYGARCH	$h_t = \frac{\omega}{\beta(L)} + \left[1 - \frac{\psi(L)}{\beta(L)}(1 + a[(1-L)^d - 1])\right] \varepsilon_t^2$

Note: The polynomials $\beta(L) = 1 - \beta_1 L - \cdots - \beta_P L^p$ and $\psi(L) = 1 - \psi_1 L - \cdots - \psi_q L^q$. The GJR, FIAPARCH and HYGARCH are Glosten, Jagannathan, and Runkle, fractionally integrated asymmetric power ARCH and hyperbolic GARCH models.