Vol.17 Iss.3 pp.46-66 International Journal of Scientific Research & Engineering Technology (IJSET)

Can alternative hedging assets add value to clean energy portfolio: Evidence from MGARCH models

Asma Abdallah[#1], Ahmed Ghorbel[#2]

[#] *Department of Quantitative Methods*
CODECI Laboratory
Faculty of Economics and Management (FSEG) of Sfax,
B.P.3018 Sfax, Tunisia
[1]abdallah.asma25@gmail.com
[2]ahmed_isg@yahoo.fr

***Abstract*— In this work, our aim is to estimate time-varying optimal hedge ratio to determine which investment alternative (between CDS, Crude Oil, Bond, GOLD, Euro Stoxx 50, VSTOXX, VIX, VVIX, and OVX) can be considered as the most efficient alternative to hedge clean energy market.**

Based on daily data covering the period from December 19, 2007 to October 17, 2018, the time-varying optimal hedge ratios are estimated by applying three versions of multivariate GARCH models (DCC, ADCC and GO-GARCH) for the purpose of whether the Wilder Hill New Energy Global Innovation (NEX) can be hedged by Crude Oil, CDS, BOND, GOLD, VSTOXX, Euro_Stoxx_50, OVX, VIX and its volatility (VVIX).

Our empirical findings show that the VIX is the best hedge for clean energy stocks as it has the biggest hedging effectiveness index value in most cases, followed by VSTOXX, then Euro Stoxx 50. However, the TC/HE results indicate that the VSTOXX is the best hedging instrument since it offers the lowest TC/HE ratio of all assets.

***Keywords*— Optimal hedge ratios, renewable energy indices, Euro_Stoxx_50, VIX and VSTOXX, Multivariate GARCH models, transaction costs, hedging effectiveness.**

I. Introduction

From the beginning of the 21st century, investment in renewable energy stocks has attracted a sustainable amount of international and significant interest in order to move to the area of green economy and reducing environment related risks Ahmad [1], Eder et al. [2], Broadstock et al. [16] and Elie et al. [11]. Recently, it has become on the top of our agenda in world-wide economy, not only due to concerns over climate change, global warming, sustainable economic development, pollution, emerging CO2 emissions or growth energy consumption and energy security issues, but also due to new technologies and ecologically conscious consumers as well as the need for moving away from conventional energy resources to clean energies, which are available almost worldwide Ahmad [1], Bamati el al. [3], Kumar et al. [4] and Bouraiou [5]. Consequently, the international Energy outlook predicts that global investment in clean energy sources will drastically increase the most till 2040, by providing around 14% of total primary energy [6].

In the mean time, analyzing clean energy performance has attracted significant attentiveness among researchers and investors in different countries or areas due to the high-speed growth in renewable energy investment. In this context, and as the progressively development, the growth in the number of clean energy firms, which become more and more bigger, and the volatility of renewable energy assets, it is necessary, nowadays, for investors to hedge their investment and manage risks beyond volatility dynamics Ahmad et al. [7] and Pham, L. [8].

By using various approaches, several methods as Sadorsky [9], Sanchez [10], Ahmad [1], Ahmad et al. [7], and Bouri [11] are focused on the evaluation of the time-varying hedge ratios and the estimation of hedging effectiveness, but they forgot the effect of the tradeoff between transaction costs and effectiveness hedging on the portfolio decisions. The main novelty of our paper is to examine firstly the time varying optimal hedging ratios from rolling window analysis among three MGARCH models (DCC, ADCC and GO-GARCH). Then we investigate the impact of the tradeoff between transaction costs and hedging effectiveness measured by the ratio (TC/HE) on portfolio hedging decisions. The current paper can be considered as the first paper that aims to fulfill

ISSN: 2356-5608

this gap in the literature and analyzing, therefore, its value and implication on renewable hedging strategies [7, 12].

The reminder of this paper is laid as follow: Section 2 reviews briefly the previous empirical studies. Section 3 provides data descriptions. Section 4 describes estimation methodology. Section 5 details the empirical results. Finally, concluding remarks, implications and future research opportunities are presented in the last section.

II. Relevant Literature

Table 1: Literature review

Authors	Purposes	Methodology		Main findings
		Model	Data period	
Henriques and Sadorsky [13]	-Analyzing the relationship between stock prices of clean energy and technology companies, oil prices and interest rates.	Vector Autoregression (VAR) model	From 2001 to 2007	-They find that interest rates and technology stocks have a larger influence on alternative energy stock prices than oil prices which holds a little significant impact on stock prices of clean energy firms.
Sadorsky [14]	-Studying conditional correlations and volatility spillovers between oil prices, clean energy stock prices and technology stock prices.	Multivariate generalized autoregressive conditional heteroskedasticity (GARCH)model	From 2001 to 2007	-Clean Energy Index Combined with Crude Oil Offers Better Investment Opportunities and Portfolio Coverage. -Alternative energy firms' stock prices correlate more exhaustively with technology companies' stock prices than with oil prices.
Kumar et al. [4]	-Analyzing the relationship between oil prices and alternative energy prices.	Vector autoregressive approach (VAR-Causality)	From 2005 to 2008	-Movements in oil prices, interest rates and technology stock prices affect clean energy stock prices. -There is no impact of carbon allowance prices on renewable energy variations.
Ferstl et al. [15]	-Investigating the impact of the Fukushima disaster on the daily nuclear and clean energy stock prices in France, Germany, Japan, and U.S.A.	The Fama and French (1993) three-factor model.	From 2008 to 2011	- Finding positive abnormal returns for alternative energy stock returns in France, Germany and Japan, against significantly negative cumulative abnormal returns for nuclear companies in the same countries.
Sadorsky [9]	-Identifying some of the key drivers of systematic risk for U.S.-listed renewable energy companies.	Variable beta model	From 2001 to 2007	-Rising oil prices provide a positive effect on clean energy stock prices.
Broadstock et al. [16]	-Investigating the relationship between international fossil fuel prices and energy related stocks in China.	Time-varying correlation	From 2000 to 2011	-They demonstrated a much stronger association, especially after the onset of the global financial crisis between 2007 and 2008. -This significant linkage suggest that China's new energy stocks were influenced by oil prices dynamics, particularly when correlation increased noticeably.
Managi and Okimoto [17]	-Analyzing the relationships among oil prices, clean energy stock prices, and technology stock prices (By extending then developing the study of Henriques and Sadorsky (2008)).	Markov-switching vector autoregressive models (MSVAR)	From 2001 to 2010	-Strong co-movement / strong convergence between clean energy stocks and oil prices. -A positive relationship between oil prices and clean energy stock prices was founded.
Bohl et al. [18]	-Studying the performance of German renewable energy stocks by analyzing the impact of global stock market returns on clean energy stock prices.	Multifactor asset pricing model	From 2004 to 2011	- Between 2004 and 2007, German renewable energy stocks presented a sustainable systematic risk given by a significant and strongly positive beta. -After the outbreak of the 2008–2009 global financial crises, they found risk-adjusted returns. - Detection of speculative bubbles, presented in Germany's renewable energy stocks, by the ADF test.

ISSN: 2356-5608

Ortas and Moneva [19]	-Measuring the financial behavior of 21 primary clean-technology equity indices.	State-space market model	From 2002 to 2011	-Clean techs indices yielded higher risk levels during market stability's period, resulting a clear and positive interaction between financial and environmental performance.
Wen et al. [20]	-Documented return and volatility spillover effects between Chinese renewable energy stock prices and fossil fuel companies.	An asymmetric Baba–Engle–Kraft–Kroner (BEKK) model	From 2006 to 2012	-Results indicate that fossil fuel and alternative energy stocks are considered as competing assets. -Investments in renewable energy are riskier than fossil fuels investments.
Inchauspe et al [21]	-Examining the impact of oil prices, technology stocks and the MSCI World Stock Index on renewable energy stocks.	State-space multi-factor model with time-varying coefficients	From 2001 to 2014	-There is a positive connection between clean energy and oil prices as well as a high correlation with MSCI World Index and technology stock returns
Reboredo [22]	-Investigating systematic risk and dependence structure between oil prices and various alternative energy sector equity indexes.	Time-varying Copulas and the CQ approach	From 2005 to 2013	-Reported evidence of a significant association between oil and renewable energy stock prices. - Oil price dynamics contribute to nearly 30% of clean energy stock price risk.
Sanchez [10]	-Calculating in-sample optimal hedge ratios -Investigating volatility spillovers between oil prices and stock prices of alternative energy and technology.	Multivariate GARCH models	From 2002 to 2015	-Alternative energy hedge ratios vary considerably over the sample period. -Volatility spillovers founding between clean energy and technology stock prices are stronger than those between renewable energy and oil prices. -The best hedge ratio for alternative energy is providing by technology global markets.
Bondia et al. [23]	-Exploring the long-term dependence structure between clean energy and technology stock prices, the returns of global oil prices and US interest rate.	VECM (Vector Error Correction Model)	From 2003 to 2015	-They find a significant short-run linkage between stock prices of alternative energy, technology companies, crude oil and US interest rate, while, in the long-run there is no significant relationship.
Reboredo et al [24]	-Analyzing dynamic correlation and causality in an alternative time-frequency setting between international oil prices and new energy stocks prices.	Wavelet approach	From 2006 to 2015	-Finding a weak short-term linkage between oil prices and renewable energy stock prices, but in the long run the interaction is getting stronger.
Ahmad [25]	-Testing the dynamic interdependence and investment performance between clean energy, oil and technology stock prices.	The directional spillover approach and the Dynamic Conditional Correlation Models	From 2005 to 2015	-There is a high interdependence structure moving from technology to alternative energy. -However, crude oil displays a restricted association renewable energy stocks and technology firms. - Crude oil, when combined with clean energy and technology indices, provides better profitable hedge and portfolio investment diversification.
Dutta A. [26]	-Investigating the impact of oil price uncertainty, as measured by the crude oil volatility index (OVX) on the variance of clean energy stocks.	Employing three different range-based estimators proposed by Parkinson (1980) (henceforth RVP), Rogers and Satchell (1991) (Hence forth RVRS) and Alizadeh et al. (2002) (henceforth RVABD).	From 2007 to 2016	-Oil market uncertainty emerged as a positive, statically and highly significant variable for modeling, forecasting and predicting the realized volatility of renewable energy stock returns, especially during the subprime crisis.

ISSN: 2356-5608

Asma A, Ahmed G. [27]	-Studying correlations and volatility spillovers between Brent oil and clean energy stock prices then analyzing the optimal weights and hedge ratio for management risk and building optimal portfolio.	Four multivariate GARCH model (BEKK, CCC, DVEC and DCC)	From 2005 to 2016	-Hedging ratio varies from pair Oil/Renewable Energy to another, from one period to another and from one MGARCH version to another. - The BEKK model is found as the best and the most efficient model on reducing Oil/Renewable energy portfolio risk.
Ahmad et al. [7]	-Estimating the time-varying optimal hedging ratios between clean energy equities and various other financial instruments such as oil, bonds, gold, VIX, OVX and Carbon prices.	Three variants of multivariate GARCH models: DCC, ADCC and GO-GARCH	From 2008 to 2017	-Showing that VIX provides the most effective hedge for alternative energy stocks followed by crude oil and OVX respectively.
Bouri [11]	-Investigating whether gold and crude oil can act as safe haven mechanism against the clean energy stocks fluctuations.	Copulas	From 2003 to 2018	-Their findings indicate that both gold and crude oil are qualified as no more than weak safe-haven investment against extreme price drops of clean energy market. -Although crude oil serves as an upper weak safe haven asset than gold.
Linh Pham [8]	-Exploring the heterogeneous volatility co-movements between oil prices and different clean energy sub-sectors, as well as examining its implications on portfolio diversifications strategies.	The GVAR model: Three multivariate GARCH models; DCC, ADCC and GO-GARCH	From 2010 to 2018	-Results document that interactions between oil prices and alternative energy stocks is obviously homogenous and various significantly over time and across renewable energy stock sub-sectors, which means that hedging cost and effectiveness of clean energy investment portfolio depends especially on clean energy types.

The existing literature has employed econometric models (Multivariate GARCH, wavelet approach, VECM, Copulas, MSVAR, VAR model ...) in order to analyze the interdependence phenomen between clean energy sector and other financial sectors. While previous studies focuses on estimating time varying hedge ratio, our paper extend the literature on hedging clean energy equities and takes a new approach and analyzing the impact of the tradeoff between transaction costs and effectiveness hedging on the portfolio decisions, which is considered as new insight into hedging strategies for clean energy investments.

III. Data

Our dataset is composed of daily time series observations for the WilderHill New Energy Global Innovation Index (NEX), Oil prices represented by (Crude Oil), and its volatility index (OVX), the Credit Default Swap Index (CDS), the VIX, the VIX volatility (VVIX), Euro Stoxx 50 and its volatility index (VSTOXX), as well as Bond and Gold prices. The entire dataset is collected from Thomson DataStream and covers the period ranging from December 19, 2007 to October 17, 2018; making up a total of 2826 available daily observations. The data analysis and treatment are essentially prepared by the R Studio program.

In order to ovoid model dependencies, and reducing heteroskedasticity, each data series is converted into logarithmic differences calculated as $100*\ln(P_t/P_{t-1})$ where P_t is the daily closing price at time t. All data are in dollars. Our Sample has maintaining a detailed description as follow:

A. NEX: the WilderHill New Energy Global Innovation:

Created by WilderHill New Energy Finance, is an equal modified dollar weighted index. Since 2006, it has been the first, leading and best known global index for clean, renewable and alternative energy stocks [28]. This international stock index, contains 106 constituents from 25 countries, mostly from outside the U.S. whose activities focuses not only on renewable energy, but also on solving climate change and on the reduction of carbon dioxide emissions relative to traditional fossil fuel use, as clever solution in order to avoid greenhouse gases. According to Inchaupse et al. [21], this index dispose of a diversified portfolio through clean energy which is composed of: Solar energy (20,6%), Wind energy (15,1%), Biofuel and Biomass (13,9%), renewable energy efficiency (34,8%), energy storage and conversion (3.4%) and (12,2%) for other renewable energy projects. The investments are distributed by regions with weights of 43.8% for the Americas, 29.1% for Asia and Oceania and 27.1% for Europe, the Middle East and Africa

ISSN: 2356-5608

B. CDS: Credit Default Swap

The Credit Default Swap (CDS) is a credit derivative contract between two counterparties which bring protection against credit losses. More precisely, the developed credit default swap (CDS) market allows CDS buyers to transfer Credit risk to CDS sellers.
More importantly, a CDS can also act as a hedge.

C. Crude Oil

Oil, conventional fossil fuel energy, is the most heavily traded physical commodity in the world. In this paper, oil price returns (dollars per barrel) are measured by using the average of the closing prices on the West Texas Intermediate (WTI) nearest Crude Oil futures contract which exchanges on the New York Mercantile Exchange (NYMEX).

D. OVX: Crude Oil Volatility

In 2008, Chicago Board Option Exchange (CBOE) introduced OVX as a new barometer to examine the systematic behaviour of crude oil market uncertainty. As the VIX, the idea of OVX is to measure the market's expectation of 30-day volatility of crude oil futures prices.

E. GOLD

For Gold, options data are treated on Chicago Mercantile Exchange 100 ounces Continuous futures contracts settlement price. Many previous studies as Tully and Lucey [29]; Shahzad et al. [30] have shown that gold has been usually used as an efficient asset to store value and still treated as a significant valuable metal in modern economies.

F. VIX: Implied volatility of S&P500 on US Stock index

Introduced by the Chicago Board Options Exchange (CBOE) in 1993, the VIX is used as a RISK-Neutral forward measure of the US stock market volatility.
As such, the VIX is compiled from a portfolio of S&P500 index options in order to measure the implied aggregate volatility in options markets of the S&P500 index during the next 30-Calender day period and is commonly used as a proxy. Based on previous findings, Higher values of the VIX index denote a much riskier stock market, whilst, lower values showed a less risky market. On a worldwide scale, it is one of the most recognized measures of volatility.

G. VVIX: Volatility VIX Index

Constructed at the aggregate market and represented by Chicago Board Options Exchange (CBOE), we can look at the VVIX as the volatility of volatility index calculated from a portfolio of VIX options (VVIX portfolio) through the same algorithm used to measure the VIX.
Moreover, the VIX index can be viewed as an important indicator of market expectations regarding the future distribution of the implied volatility.

H. Euro Stoxx 50: The European stock market index

Euro_Stoxx_50 index used for the Euro Area was introduced on February 1998.
This index considered as Europe's leading Blue-Chip index specialist aims to provide a blue-Chip representation of super sector leaders in the Eurozone.
In principal, the Euro_Stoxx_50 is a composite index represents the performance of the 50 most important companies of up to 11 Eurozone countries (20 companies from France, 14 from Germany, 5 each from Spain and Netherlands, 3 from Italy, and the remaining 3 are respectively from Belgium, Finland and Ireland).
It is the one of the most liquid European equity indices and the most followed in the Eurozone.

I. VSTOXX: Euro Stoxx 50 Volatility Index

VSTOXX is a Measure of the implied volatility of Euro Stoxx 50 in the Euro Area Market. Additionally, according to Zghal, R. et al. [31], the VSTOXX index helps to capture the equity risk as a whole, since it relies heavily on equity-based options.

IV. METHODOLOGY: EMPIRICAL MODELS

Recently, modeling the volatility dynamics and correlations are highly relevant in finance.
In this context, two models belonging to the DCC family (DCC model of Engle [32] and ADCC model of Cappiello et al. [33]) as well as the GO-GARCH model of Van der Weide [34] have been applied for the purpose of modelling volatilities, conditional correlations and hedge ratios between NEX and CDS, Crude Oil, GOLD, Bond, Euro Stoxx 50, VSTOXX, VIX, VVIX and OVX.
Let r_t be a n x 1 vector of series of returns. The specification of the multivariate GARCH models, with AR (1) process for r_t conditional on the information set Ω_{t-1}, is defined as follows:

$$r_t|\Omega_{t-1} = \mu_t + \varepsilon_t$$

ISSN: 2356-5608

Where the vector of residuals ε_t can be modelled as:

$\varepsilon_t = H_t^{½} z_t$; $z_t \sim$ iid $(0, I_n)$

H_t Represents the n x n conditional covariance matrix of r_t , z_t is a n x 1 i.i.d random vector of errors and I_n denotes an n x n identity matrix.

1) *The DCC-GARCH model*

The Engle [32] Dynamic Conditional Correlation (DCC) model, generalization of CCC model, follows two step procedures. The GARCH parameters are estimated, in the first step, followed by correlations in the second step such as:

$H_t = D_t R_t D_t$

Where $D_t = (h_{11t}^{½} ,\ldots, h_{nnt}^{½})$ is a diagonal matrix that includes varying standard deviations on the diagonal and R_t which composed as follow is the conditional correlation matrix:

$$R_t = \text{diag}(Q_t)^{-½} Q_t \,\text{diag}(Q_t)^{-½}$$

Where Q_t is a n x n symmetric positive definite matrix given by:

$$Q_t = (1-\theta_1-\theta_2)\overline{Q} + \theta_1 z_{t-1} z_{t-1}^T + \theta_2 Q_{t-1}$$

$\overline{Q}$ Denotes the n x n unconditional correlation matrix of the standardized residuals $z_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$ and Q_t is its conditional variance-covariance matrix of the residuals ε_t .

The parameters θ_1 and θ_2 are non-negative scalar parameters satisfying $\theta_1 + \theta_2 < 1$ which implies that $Q_t > 0$.

Under the DCC specification, the time-varying conditional correlation series are described by:

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

Where $q_{ij,t}$ denotes the covariance between asset returns i and j at time t, and $q_{ii,t}$ as well as $q_{jj,t}$ are the conditional variance estimates of i and j respectively both at time t.

2) *The ADCC-GARCH model*

By extending the DCC model and the asymmetric GARCH model of Glosten et al. [35], the asymmetric DCC (ADCC) model have been built by Capiello et al. [33] on this models by adding an asymmetric term. In order to beat the problem of asymmetry effects, the ADCC model serves to elaborate either the positive and negative news are of same magnitude or have different impacts on conditional standard deviations and correlations. Thus, it is described as follow:

$$Q_t = (1-\alpha-\beta)\overline{Q} + \lambda\overline{Z} + \alpha z_{t-1} z'_{t-1} + \beta Q_{t-1} + \lambda \zeta_{t-1} \zeta'_{t-1}$$

Where the coefficient λ indicate the asymmetric effect or "leverage effect" in the model. It tends to explain the role of bad news in increasing volatility than do good news during downturn period.

$\overline{Q}$ and $\overline{Z}$ are the unconditional matrices of $z_{t-1} z'_{t-1}$ and $\zeta_{t-1}\zeta'_{t-1}$ respectively.

The variable ζ_t defined as Hadamard product of an indicator function and residuals ε_t is formally given by $\zeta_{t-1} = \text{I}[\varepsilon_t < 0] \odot \varepsilon_t$. The indicator function which is expressed by $\text{I}[\varepsilon_t < 0]$ is equal to one if the standardized residuals ε_t is negative, and 0 otherwise.

Leverage effects tend to explain the role of bad news in increasing volatility than do good news during downturn period. Besides, both models DCC and ADCC are estimated by a maximum likelihood estimator.

3) *The GO-GARCH model*

The GO-GARCH model assumes two things:

-Firstly, the mixing matrix A is time-invariant.

-Secondly, as the DCC model, it contains only diagonal elements.

Under the GO-GARCH model, the residual ε_t is modelled as follows:

$\varepsilon_t = A f_t$

Where f_t indicates a set of invisible independent factors ($f_t = (f_{1t}, f_{2t}, \ldots, f_{nt})$). A is a time-invariant and invertible n x n and can be decomposed into an unconditional covariance matrix Σ and an orthogonal matrix U.

$$A = \Sigma^{½} U$$

The matrix A is composed into rows which represent the factor weights assigned to each time series and columns of representing the factors f. The specification of the factors f_t is as follows:

$$f_t = H_t^{½} u_t$$

Where u_t is a random variable satisfying $\text{E}[u_{it}] = 0$ and $\text{E}[u_{it}^2] = 1$. H_t denotes the diagonal matrix with elements $h_{1t}, h_{2t}, \ldots, h_{nt}$ being the conditional variances of the factors. The factor conditional variance h_{it} can be modeled using the GARCH process in equation (11) (i=1, 2,…,n). Furthermore, the unconditional distribution of the factors f

ISSN: 2356-5608

satisfies $E[f_t] = 0$ and $F[f_t f_t^T] = I$. The returns r_t can be formuled as:

$$r_t = u_t + AH_t^{1/2} u_t$$

Finally, the conditional covariance matrix of the returns $r_t - u_t$ is:

$$\Sigma_t = AH_t A^T$$

4) The hedging effectiveness

The hedging effectiveness (HE) index (e.g. Ku et al. [36] and Chang et al. [37]), described by the following equation, is used to evaluate the hedging performance of hedge ratio and optimal portfolio.

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}}$$

The larger HE index value means the most favorable hedging effectiveness.

5) The tradeoff between transaction costs and hedging effectiveness.

According to Chen and Sutcliffe [38], we can measure the transaction cost (TC) as the sum of the absolute changes in the dynamic hedge ratios. Then we calculate the TC/HE ratio as a measure of the tradeoff between hedging effectiveness and transaction cost. A low TC/HE ratio indicates a better hedging instrument.

V. RESULTS AND DISCUSSION

First of all, we analyze, as shown below in table 2, the descriptive statistics of the returns of each series in the natural logarithm from over the period 2007-2018.

Table 2: Preliminary statistics

	NEX	CDS	Crude_Oil	GOLD	BOND	Euro_Stoxx_50	VSTOXX	VIX	VVIX	OVX
Mean	-0.0328	0.0325	-0.0044	0.0148	0.0014	-0.0099	-0.0065	-0.0077	0.0095	-0.0039
Median	0.0234	0.0000	0.0000	0.0000	0.0000	0.0000	-0.2374	-0.2919	-0.2473	-0.1811
Std. dev.	1.4851	2.8456	2.1678	1.1629	0.3850	1.4594	6.5320	7.4383	5.0225	4.7163
Min.	-10.485	-32.1330	-16.7095	-9.8233	-2.7373	-9.0111	-43.4376	-35.0588	-23.6414	-43.9905
Max.	12.070	25.3664	17.9691	8.5889	3.5661	10.4376	47.0666	76.8245	37.3161	42.4968
Q1	-0.6530	-0.8733	-1.0734	-0.5029	-0.2012	-0.6685	-3.8065	-3.9941	-2.7529	-2.5016
Q3	0.6736	0.8438	1.0852	0.5772	0.2105	0.6760	3.1236	3.2537	2.2389	2.1002
Skewness	-0.4680	0.0962	0.1864	-0.3865	-0.1202	-0.0498	0.5613	1.0685	0.9459	0.6585
Kurtosis	8.5689	14.5229	5.5904	7.5714	5.6903	6.0269	4.3152	7.3226	5.3219	10.1832
JB test	8746	2483	3695.1	6818.3	3818.2	4276.9	2340.2	6849.3	3755.1	1241
P-Value	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
Q (12)	135.79	29.954	9.9302	24.145	25.453	29.994	29.818	47.211	41.731	80.644
P-Value	0.000*	0.002*	0.622	0.019*	0.012*	0.002*	0.002*	0.000*	0.000*	0.000*
Q^2 (12)	3496.9	405.06	590.65	276.08	308.48	1293.4	363.25	200.83	182.47	337.21
P-Value	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
N obs	2825	2825	2825	2825	2825	2825	2825	2825	2825	2825

N.B:* denotes 5% significance level. JB test indicates Jarque-Bera statistics and Q(12) and $Q(12)^2$ are the Ljung–Box statistics. The ARCH-LM test reports the LM-statistic.

ISSN: 2356-5608

CDS exhibits the highest average daily returns among the series (0.032), while NEX have the lowest average return (-0.032). The mean daily return is positive for CDS (0.032), GOLD (0.0148), Bond (0.0014), and for VVIX (0.0095), whereas it is negative for NEX (-0.032), Crude Oil (-0.0044), Euro Stoxx 50 (-0.0099), VSTOXX (-0.0065), VIX (-0.0077) and OVX (-0.0039).

VIX shows the greatest volatility designed by its high standard deviation (7,438), while Bonds have the lowest standard deviation (0.3850). The nullity of normal distribution is decisively rejected by the Jarque-Bera (JB) test for each one of the variables at the 5% significance level. Besides maximum and minimum values indicate that the volatility of all sample series was similar in magnitude, with the exception of GOLD, Bond, and Euro Stoxx 50 which had lower volatility.

For the Ljung-Box Q-statistics on returns, we find that only the Crude Oil doesn't exhibit significantly high serial correlation, unless on squared returns, Q-statistics indicate that all sample variables present significant serial correlation and strong volatility clustering effects. The Skewness values are negative for returns of NEX, Gold, Bond, and Euro Stoxx 50; however, they are positive for the other series. This means that negative (positive) Skewness denotes luck of higher negative (positive) returns without corresponding opportunities of positive (negative) returns. Kurtosis statistics suggest that all variables have kurtosis greater than 4, and as we know that kurtosis for a normal distribution is 3, so we can deduct that all series display of fat or heavy tails in their distributions (leptokurtic). Our observations are confirmed by graphs of the time series and squared returns (Figure 1 and 2 respectively).

Figure 1 reveals that there is some heterogeneity in price co-movements of each index. For example, during the subprime crisis (2007 – 2009) and 2011 – 2014 periods, Crude Oil and NEX, Gold, Bond, Euro Stoxx 50 tends to move together with a strong trend. Although, CDS, VSTOXX, VIX, VVIX and OVX show a similar time series patterns but display of a little increase trend around the 2007 –2009 financial crisis. Moreover, visual inspection of figure 1 also reveals that NEX and Crude Oil commove jointly during higher and lower phases of the latter one.

Time series plots of the squared time series shown in Figure 2 exhibit how volatility has changed over time. We can observe that all variables present a strong volatility clustering around the Subprime Mortage crisis with the exception of CDS, VIX and VVIX which show a little clustering effect at the same period.

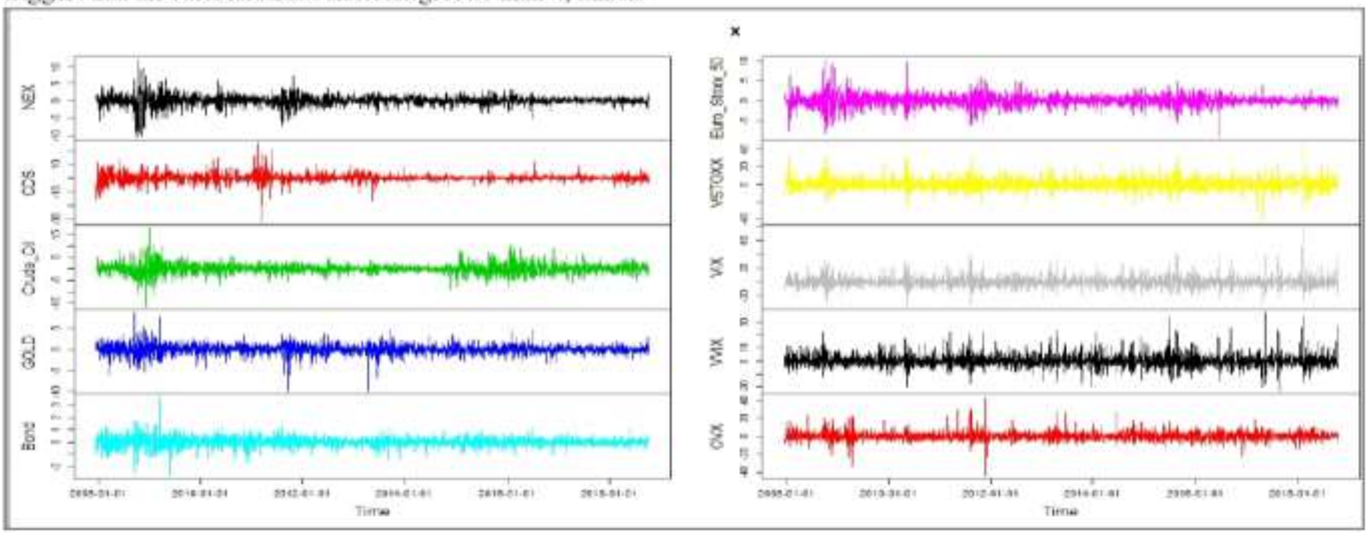

Figure 1: Time series of sample variables

ISSN: 2356-5608

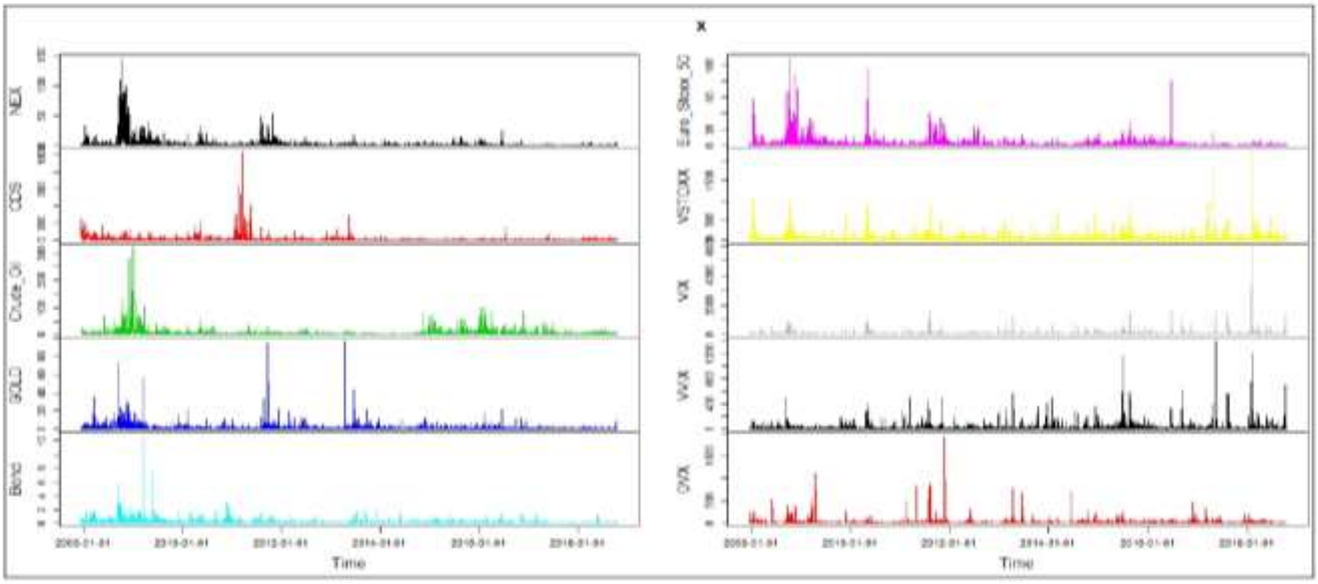

Figure 2: Squared daily returns

Now, we turn to examine the unconditional correlation between raw returns and squared returns which are summarized in table 3 and 4 respectively.

From table 3, we find that NEX correlates positively with CDS, Crude Oil, GOLD and Euro Stoxx 50 and negatively with the other indexes. The Euro Stoxx 50 tend to have a stronger correlation (0,7194) than the other variables, followed by the VSTOXX (-0,5269). Whereas, the lowest correlation is found between NEX and CDS (0,0955).

Table 4, show a positive correlation between NEX and each squared asset return, where the strongest correlation occurs for NEX/Euro Stoxx 50 (0,5176) while the pairwise NEX/CDS have the weakest correlation (0,0091).

Overall, Table 4 denotes positive correlation among the squared returns. However, the degree of correlation varies widely among both raw returns (between 0,7 and 0,09), and squared returns (between 0,5 and 0,009).

Table 3: Unconditional correlation between raw returns

	NEX	CDS	Crude Oil	GOLD	BOND	Euro Stoxx 50	VSTOXX	VIX	VVIX	OVX
NEX	1	0.0955	0.3831	0.1208	-0.2800	0.7194	-0.5269	-0.5255	-0.3879	-0.3181
CDS	0.0955	1	0.0509	-0.0272	-0.0266	0.0967	-0.0859	-0.0238	-0.0200	-0.0354
Crude Oil	0.3831	0.0509	1	0.1888	-0.2005	0.3710	-0.2592	-0.1831	-0.1261	-0.2430
GOLD	0.1208	-0.0272	0.1888	1	0.1368	-0.0178	0.0121	0.0075	0.0145	-0.0190
BOND	-0.2800	-0.0266	-0.2005	0.1368	1	-0.3475	0.2627	0.2871	0.2274	0.1620
Euro Stoxx 50	0.7194	0.0967	0.3710	-0.0178	-0.3475	1	-0.7415	-0.4850	-0.3739	-0.2903
VSTOXX	-0.5269	-0.0859	-0.2592	0.0121	0.2627	-0.7415	1	0.5368	0.4382	0.3146
VIX	-0.5255	-0.0238	-0.1831	0.0075	0.2871	-0.4850	0.5368	1	0.8132	0.4305
VVIX	-0.3879	-0.0200	-0.1261	0.0145	0.2274	-0.3739	0.4382	0.8132	1	0.3431
OVX	-0.3181	-0.0354	-0.2430	-0.0190	0.1620	-0.2903	0.3146	0.4305	0.3431	1

ISSN: 2356-5608

Table 4: Unconditional correlation between squared returns

	NEX	CDS	Crude Oil	GOLD	BOND	Euro Stoxx 50	VSTOXX	VIX	VVIX	OVX
NEX	1	0.0091	0.1468	0.0145	0.0784	0.5176	0.2777	0.2761	0.1505	0.1011
CDS	0.0091	1	0.0025	0.0007	0.0007	0.0093	0.0073	0.0005	0.0004	0.0012
Crude Oil	0.1468	0.0025	1	0.0356	0.0402	0.1377	0.0671	0.0335	0.0159	0.0590
GOLD	0.0145	0.0007	0.0356	1	0.0187	0.0003	0.0001	0.0386	0.0002	0.0003
BOND	0.0784	0.0007	0.0402	0.0187	1	0.1207	0.0690	0.0824	0.0517	0.0262
Euro Stoxx 50	0.5176	0.0093	0.1377	0.0003	0.1207	1	0.5499	0.2353	0.1398	0.0843
VSTOXX	0.2777	0.0073	0.0671	0.0001	0.0690	0.5499	1	0.2881	0.1920	0.0989
VIX	0.2761	0.0005	0.0335	0.0386	0.0824	0.2353	0.2881	1	0.6613	0.1853
VVIX	0.1505	0.0004	0.0159	0.0002	0.0517	0.1398	0.1920	0.6613	1	0.1177
OVX	0.1011	0.0012	0.0590	0.0003	0.0262	0.0843	0.0989	0.1853	0.1177	1

Following, the table 5 (See annex) presents the estimated results of the DCC and ADCC models. First of all, for all time series, the short-term persistence (α) and the long-term persistence (β) are statistically significant and for each case α is less than β, their sums are close to unity providing evidence of volatility clustering in all variables which is proves in fig2.

Secondly, as known, if the shape parameters (λ), the equivalence of the degrees of freedom in the distribution, tend to infinity, the t-distribution tends to the normal distribution. In this case, crude oil shows the highest estimated shape (7,26) followed by NEX (6,84) and Bond (6,22), while the lowest shape parameter is found by CDS (3,12).

Thirdly, we find that the estimated coefficients on θ_1 and θ_2 are each positive and statistically significant at the 1% significance level and the sum of both parameters is less than one meaning that the dynamic conditional correlations are mean-reverting.

Table 6 presents the GO-GARCH model results. Panel I of the table shows the rotation matrix U which is orthogonal as $U^T U = 1$, the second panel II denotes the mixing matrix A and third panel III shows the parameters estimates.

As considered an estimator of factors, the GO-GARCH model does not create any standard errors. For each time series, the estimated short-run persistence (α) is significantly lower than the long-run persistence (β) which is agreed with DCC and ADCC results. Moreover, "The DCC model is mean reverting as long as $\alpha+\beta<1$", based on the expression above, we calculate the sum of the persistence parameters (α and β), we found that is less than one, which proof the mean-reverting of volatility process.

ISSN: 2356-5608

Table 6: The GO-GARCH results for NEX

The rotation matrix U										
	U(1)	U(2)	U(3)	U(4)	U(5)	U(6)	U(7)	U(8)	U(9)	U(10)
U(1)	-0.6610	-0.3590	-0.0862	0.0041	0.0201	-0.5035	0.0736	0.1041	0.2419	0.3128
U(2)	-0.5060	0.1387	0.3123	-0.0685	-0.0201	0.7191	-0.0909	0.0709	0.0447	0.2991
U(3)	0.1950	0.0627	0.0765	0.0261	-0.0109	0.0962	0.1198	0.0902	0.9497	-0.1321
U(4)	0.0094	-0.0711	0.0793	0.9860	0.0783	0.0569	-0.0192	-0.0407	-0.0199	0.0672
U(5)	-0.3872	-0.2516	0.0960	0.0297	0.0048	0.1116	0.0582	-0.0164	-0.0505	-0.8705
U(6)	-0.1200	0.2414	-0.0490	0.0122	0.0710	-0.1688	-0.9107	-0.1690	0.14607	-0.1088
U(7)	-0.2981	0.8219	-0.0041	0.0898	-0.0725	-0.2542	0.3423	-0.1682	-0.0126	-0.1085
U(8)	0.0257	0.1954	0.0830	0.0573	-0.0294	-0.1152	-0.1183	0.9506	-0.1032	-0.0916
U(9)	-0.1205	0.0473	-0.9252	0.0766	-0.1046	0.3096	0.0043	0.1073	0.0473	-0.0248
U(10)	-0.0188	0.0717	-0.0903	-0.0642	0.9852	0.0439	0.0870	0.0432	-0.0011	-0.0083
The Mixing Matrix A										
	A(1)	A(2)	A(3)	A(4)	A (5)	A (6)	A (7)	A (8)	A (9)	A (10)
A (1)	0.2040	1.3074	-0.2792	0.0530	-0.1086	0.3489	-0.1765	-0.2480	-0.1603	-0.1542
A (2)	-0.0497	0.2695	-0.1181	-2.8071	-0.2338	0.1705	0.0749	0.1066	-0.0602	-0.1137
A (3)	0.0861	0.4941	-0.0044	-0.1189	0.1318	0.2232	-2.0640	-0.2121	-0.2381	0.0092
A (4)	-0.0863	-0.0285	-0.0122	-0.0284	0.0809	-0.0055	-0.1298	-1.1382	0.1111	0.1071
A (5)	-0.0576	-0.1380	-0.0100	0.0211	-0.3395	-0.0517	0.0213	-0.0673	0.0342	0.0312
A (6)	0.1988	1.0811	0.7511	-0.0449	-0.0355	0.4982	-0.2264	-0.0329	-0.1820	-0.1341
A(7)	-1.3194	-2.1636	-1.7498	0.1134	0.1819	-5.6649	0.5178	0.1836	0.6065	0.5564
A (8)	-6.3392	-2.4786	0.0876	-0.0544	0.1194	-2.0252	0.2165	0.7542	1.1420	1.6219
A (9)	-2.9602	-0.9141	-0.0545	-0.1058	0.0414	-1.1028	0.1503	0.5612	0.3837	3.7184
A (10)	-0.9145	-0.5092	0.1047	0.0273	0.0126	-0.8044	0.4212	0.6083	4.4062	0.5134
GO-GARCH parameters										
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
Omega	0.1681	0.0046	0.0091	0.0109	0.0018	0.0940	0.0027	0.0051	0.1398	0.1643
Alpha	0.1652	0.0743	0.0613	0.1394	0.0229	0.1183	0.0410	0.0321	0.1081	0.1111
Beta	0.6582	0.9203	0.9298	0.8595	0.9745	0.7867	0.9563	0.9622	0.7383	0.7304
Skew	-0.1771	0.0181	0.0157	-0.0667	0.2102	-0.1953	-0.0194	0.0958	0.2476	0.2755
Shape	1.7192	2.7872	2.4955	0.4475	1.5198	1.0692	2.3265	0.9274	0.9762	1.1700

ISSN: 2356-5608

Following table 7, we find that dynamic conditional correlations realized by DCC and ADCC models are similar. Furthermore, for each pair of correlations, the correlations between DCC/GO-GARCH or ADCC/GO-GARCH are significantly less correlated. Otherwise, the lowest correlation between DCC/GO-GARCH and ADCC/GO-GARCH is found among NEX/Crude Oil followed by NEX/GOLD and NEX/CDS. However, we note a higher correlation for NEX/Bond, NEX/OVX and NEX/VVIX. In either case, OVX present a negative association with NEX which means that our model exhibits a higher level of interdependence in this case. Summary findings of correlations between hedge ratios estimated from three MGARCH models (DCC, ADCC and GO-GARCH) are presented in table 8, which suggest that hedge ratios obtained from DCC and ADCC models show a perfect high correlation.

Table 7: Correlations between correlations

NEX	CDS	Crude Oil	GOLD	BOND	Euro Stoxx 50	VSTOXX	VIX	VVIX	OVX
DCC/ADCC	0.9094	0.9640	0.9904	0.9784	0.7206	0.9539	0.9435	0.9245	0.9570
DCC/GOGARCH	0.6535	0.4161	0.4623	0.9056	0.8557	0.8457	0.7952	0.8447	0.8472
ADCC/GOGARCH	0.6201	0.4147	0.4187	0.8824	0.5320	0.7660	0.6997	0.6993	0.7864

Table 8: Correlations between hedge ratios

NEX	CDS	Crude Oil	GOLD	BOND	Euro Stoxx 50	VSTOXX	VIX	VVIX	OVX
DCC/ADCC	0.9240	0.9968	0.9986	0.9979	0.9825	0.9561	0.9802	0.9816	0.9905
DCC/GOGARCH	0.1812	0.4677	0.5385	0.6160	0.4736	0.0924	0.2038	0.3640	-0.4857
ADCC/GOGARCH	0.0662	0.4601	0.5296	0.6186	0.4653	0.1267	0.2141	0.3544	-0.4669

Summary statistics of hedge ratio and hedging effectiveness are reported in table 9, in order to examine the robustness of our findings with the change in the number of model refits. Our results find that, for each pair, hedging effectiveness values estimated with a student distribution are extremely similar beyond all three model refits and for each GARCH model specification. As example, hedging effectiveness values presented by the DCC model for the pair NEX/VVIX are equal for all models (0.2276), the same thing for the ADCC model, where HE values are equals to 0,2145.

Taking another example, the case of NEX/CDS hedge, the hedging effectiveness values obtained by the DCC model are 0.0155, 0.0153 and 0.0145 for the refits 10, 20 and 60 days respectively. In the case of NEX/VIX, the ADCC model shows the following values of HE: 0.3006, 0.3010 and 0.3015 respectively for the refits 10, 20 and 60 days. Thus, it means that all hedging results are robust to model refits.

According to first part of the table 9 (Refit=10), the average value of the hedge ratio between NEX and VIX is 0,40 for the GO-GARCH model, this means that a $1 long position in NEX can be hedged for 40 cents with a short position in the VIX market.

Moreover, results show that ADCC hedge provide the highest hedging effectiveness for CDS, Gold and Euro Stoxx 50 and GO-GARCH hedge provide the highest HE for the other indices with the exception of NEX/Bond pair series which imply that its highest HE is achieved with DCC model. Opposed to what have been reported by Ahmad et al [7], we find that both ADCC and GO-GARCH are chosen over DCC model. Additionally, our analysis suggest that NEX/VIX has

ISSN: 2356-5608

the highest HE ratio (HE= 0,40) which means that VIX is the best hedge for clean energy stocks followed by VSTOXX (HE= 0,37) and Euro Stoxx 50 (HE= 0,36). Overall, as for investment and hedging their risk inside portfolio creation, investors who are looking for higher returns from NEX should join it with VIX. This finding is compatible with those of Ahmad et al. [7] and Hood and Malik [39] who prove that VIX is the best hedge for ECO and US equities respectively.

For each GARCH model specification, Hedging effectiveness, transaction cost, and the TC/HE ratio produced from model refits every 10days, 20 days and 60 days are summarized in table 10. Based on the above, our findings suggest that the VSTOXX is the most appropriate hedging instrument due its lowest TC/HE ratio= 0,09 of all variables with the DCC model followed by the VIX index (TC/HE=0,11). However, GOLD is the least suitable hedging instrument due its highest TC/HE ratio = 4,32.

Table 9: Summary statistics of hedge ratios (β) and hedge effectiveness (HE) for NEX investors – MVT

	Refit=10				Refit=20				Refit=60			
	mean	min	max	HE	mean	min	max	HE	mean	min	max	HE
NEX/CDS												
DCC	0.0717	0.0150	0.2325	0.0155	0.0713	0.0150	0.2325	0.0153	0.0686	0.0018	0.2325	0.0145
ADCC	0.0440	0.0121	0.1984	**0.0158**	0.0437	0.0121	0.1984	**0.0158**	0.0417	0.0088	0.1984	**0.0148**
GOGARH	0.0670	-0.0526	0.0836	0.0090	0.0671	-0.0526	0.0829	0.0090	0.0707	-0.0448	0.5459	0.0090
NEX/Crude Oil												
DCC	0.1048	-0.0387	0.3881	0.0891	0.1050	-0.0343	0.3881	0.0891	0.1057	-0.0343	0.3877	0.0892
ADCC	0.1141	-0.0419	0.3888	0.0957	0.1143	-0.0376	0.3888	0.0957	0.1151	-0.0376	0.3888	0.0959
GOGARH	0.7663	0.3585	1.4717	**0.1489**	0.7740	0.3585	1.4746	**0.1554**	0.7714	0.3608	1.5144	**0.1516**
NEX/GOLD												
DCC	0.0485	-0.8271	0.6082	0.0463	0.0486	-0.8271	0.6082	0.0458	0.0490	-0.8211	0.6082	0.0455
ADCC	0.0655	-0.8638	0.8278	**0.0466**	0.0656	-0.8638	0.8193	**0.0462**	0.0655	-0.8586	0.8060	**0.0459**
GOGARH	0.2529	-0.2155	0.5371	0.0411	0.2586	0.0028	0.5348	0.0396	0.1467	0.0167	0.1796	0.0401
NEX/BOND												
DCC	-0.7984	-2.4314	0.3467	**0.0714**	-0.8000	-2.4314	0.3334	**0.0714**	-0.8054	-2.4463	0.3334	**0.0718**
ADCC	-0.7848	-2.4459	0.4512	0.0679	-0.7860	-2.4459	0.4376	0.0679	-0.7903	-2.4611	0.4376	0.0683
GOGARH	-0.1905	-0.7619	-0.0048	0.0542	-0.2491	-0.3208	-0.0250	0.0542	-0.2515	-0.3204	-0.0555	0.0544
NEX/Euro Stoxx 50												
DCC	0.4591	0.2458	0.7096	0.3445	0.4594	0.2497	0.7096	0.3446	0.4607	0.2570	0.7050	0.3459
ADCC	0.4934	0.2487	0.8101	**0.3638**	0.4936	0.2519	0.8129	**0.3637**	0.4952	0.2572	0.8084	**0.3653**
GOGARH	0.8448	0.7043	0.9421	0.3247	0.3888	0.1090	0.7547	0.3249	0.8374	0.6866	0.9255	0.3232
NEX/VSTOXX												
DCC	-0.0709	-0.1730	-0.0227	0.2908	-0.0709	-0.1731	-0.0232	0.2896	-0.0713	-0.1731	-0.0232	0.2898
ADCC	-0.0717	-0.1657	-0.0280	0.2787	-0.0717	-0.1655	-0.0280	0.2787	-0.0721	-0.1655	-0.0280	0.2793
GOGARH	-0.3128	-0.5966	-0.1536	**0.3703**	-0.3130	-0.5956	-0.1537	**0.3707**	-0.3143	-0.5955	-0.1540	**0.3712**
NEX /VIX												
DCC	-0.0671	-0.1642	-0.0155	0.3187	-0.0672	-0.1642	-0.0155	0.3192	-0.0676	-0.1642	-0.0156	0.3198
ADCC	-0.0680	-0.1786	-0.0208	0.3006	-0.0681	-0.1786	-0.0208	0.3010	-0.0684	-0.1786	-0.0211	0.3015
GOGARH	-1.3149	-7.2498	-0.5511	**0.4065**	-1.3134	-7.2479	-0.5528	**0.4073**	-0.3409	-0.6472	-0.1192	**0.4092**
NEX /VVIX												
DCC	-0.0813	-0.1946	-0.0240	0.2276	-0.0814	-0.1946	-0.0237	0.2276	-0.0817	-0.1946	-0.0237	0.2276
ADCC	-0.0824	-0.1962	-0.0232	0.2145	-0.0824	-0.1978	-0.0232	0.2145	-0.0826	-0.1944	-0.0232	0.2145

ISSN: 2356-5608

GOGARH	-1.1675	-7.1408	-0.3309	**0.2966**	-1.1671	-7.1407	-0.3309	**0.2965**	-0.2823	-0.5352	-0.1129	**0.2970**
NEX /OVX												
DCC	-0.0641	-0.1828	-0.0035	0.1098	-0.0642	-0.1828	-0.0033	0.1099	-0.0645	-0.1828	-0.0037	0.1100
ADCC	-0.0616	-0.1619	-0.0001	0.1011	-0.0617	-0.1619	0.0001	0.1010	-0.0618	-0.1619	-0.0003	0.1012
GOGARH	-0.2375	-0.3846	-0.1746	**0.1623**	-0.2422	-1.1264	-0.1746	**0.1640**	-0.7089	-1.8406	-0.2874	**0.1619**

Table 10: The hedging effectiveness (HE), the transaction cost TC, and the TC/HE ratio under different model refits

	Refit=10			Refit=20			Refit=60		
	HE	TC	$\frac{TC}{HE}$	HE	TC	$\frac{TC}{HE}$	HE	TC	$\frac{TC}{HE}$
NEX/CDS									
DCC	1.55%	4.15	2.67	1.53%	4.18	2.72	1.45%	4.34	2.98
ADCC	1.58%	3.95	**2.49**	1.58%	3.90	**2.46**	1.48%	3.85	**2.60**
GOGARH	0.91%	2.48	2.73	0.90%	2.47	2.72	0.90%	4.59	5.06
NEX/Crude Oil									
DCC	8.91%	5.10	**0.57**	8.91%	5.08	**0.57**	8.92%	5.08	**0.56**
ADCC	9.57%	6.10	0.63	9.57%	6.09	0.63	9.59%	6.08	0.63
GOGARH	14.89%	26.76	1.79	15.54%	27.62	1.77	15.16%	26.75	1.76
NEX/GOLD									
DCC	4.63%	24.36	5.26	4.58%	24.31	5.29	4.55%	24.26	5.32
ADCC	4.66%	25.85	5.53	4.62%	25.79	5.57	4.59%	25.71	5.59
GOGARH	4.11%	17.80	**4.32**	3.96%	17.11	**4.31**	4.01%	2.69	**4.67**
NEX/BOND									
DCC	7.14%	40.08	5.61	7.14%	40.05	5.60	7.18%	39.96	5.56
ADCC	6.79%	45.59	6.70	6.79%	45.55	6.70	6.83%	45.54	6.66
GOGARH	5.42%	13.61	**2.50**	5.42%	5.64	**1.03**	5.44%	5.52	**1.01**
NEX/Euro Stoxx 50									
DCC	34.45%	14.10	0.40	34.46%	14.07	0.40	34.59%	13.97	0.40
ADCC	36.38%	22.61	0.62	36.37%	22.56	0.62	36.53%	22.55	0.61
GOGARH	32.48%	6.98	**0.21**	32.49%	20.01	**0.21**	32.32%	6.65	**0.20**
NEX/VSTOXX									
DCC	29.08%	2.83	**0.09**	28.96%	2.84	**0.09**	28.98%	2.84	**0.09**
ADCC	27.87%	3.52	0.12	27.87%	3.52	0.12	27.93%	3.54	0.12
GOGARH	37.03%	9.52	0.25	37.07%	9.55	0.25	37.12%	9.68	0.26
NEX /VIX									
DCC	31.87%	3.81	**0.11**	31.92%	3.82	**0.11**	31.98%	3.85	**0.12**
ADCC	30.06%	4.55	0.15	30.10%	4.56%	0.15	30.15%	4.57	0.15
GOGARH	40.65%	153.60	3.77	40.73%	153.51	3.76	40.92%	17.55	0.42
NEX /VVIX									
DCC	22.76%	5.31	**0.23**	22.77%	5.31	**0.23**	22.76%	5.30	**0.23**
ADCC	21.45%	6.08	0.28	21.46%	6.09	0.28	21.45%	6.08	0.28
GOGARH	29.66%	150.41	5.07	29.65%	150.16	5.06	29.70%	10.48	0.35

ISSN: 2356-5608

NEX /OVX									
DCC	10.98%	3.41	**0.31**	10.99%	3.42	**0.31**	11.00%	3.40	**0.30**
ADCC	10.11%	3.76	0.37	10.10%	3.77	0.37	10.12%	3.75	0.37
GOGARH	16.23%	5.08	0.31	16.40%	6.58	0.40	16.19%	44.46	2.74

In order to investigate the robustness of our findings on different forecast length, we calculate hedge ratio from fixed length rolling window analysis. To this end, we fix, firstly, our rolling window and refit the DCC, ADCC and GO-GARCH models every 20 observations, results are shown in table 11**(see Annex).** The forecasts lengths chosen are of 500, 1000 and 1500. We estimate GARCH models (DCC and ADCC) with a student distribution (MVT). The GO-GARCH estimated using a multivariate affine negative inverse Gaussian (MANIG) distribution. Results show that Euro Stoxx 50 provides the most effective hedge for NEX only for forecast length of 500, however, for both 1000 and 1500 forecast lengths, the VIX is the best hedge ratio. Additionally, for the NEX/VIX hedge, the DCC model is preferred (largest HE value) across all forecast horizons. The same case for the NEX/VSTOXX, NEX/VIX and NEX/Crude Oil hedges. For the NEX/CDS hedge, the DCC model is preferred for 500 and 1000 forecasts lengths, and ADCC is preferred for 1500 forecast. For the pair NEX/GOLD hedge the DCC model is preferred for 500 and 1000 forecast length, while the GO-GARCH model is preferred for 1500 forecast length. However, for the NEX/OVX, the DCC model is chosen only for 500 forecast and GO-GARCH model for 1000 and 1500.

Table 12 **(see Annex)** report the transaction costs, the hedging effectiveness and the TC/HE of the rolling window estimations with different forecasts length. Results show that the VIX is the best hedge ratio for NEX in all cases. Moreover, in most situations the GO-GARCH model makes the best hedge decision with the exception of VSTOXX, VIX, and VVIX where the DCC yields the best hedge ratio.

VI. CONCLUSIONS

Elicited from previous challenges, investors need to hedge their investments against risk fluctuations of renewable energy assets. Based on several multivariate GARCH models refitted every 10, 20 and 60 observations, our findings suggest that the VIX is the best hedge ratio for renewable energy as it has the highest HE, followed by VSTOXX and Euro Stoxx 50 which is robust through the different forecast windows.

Additionally, our significantly different results show that the VSTOXX is the best hedging instrument for renewable energy since it offers the lowest TC/HE followed by the VIX.

To further the research, it would be interesting in future works to study the effect of combining two or more alternative assets in the improvement of hedging effectiveness in clean energy markets. In addition, optimal hedge ratio is determined based on the minimization of portfolio risk measured by variance and standard deviation that are two critical risk measurement tools. We can repeat the same methodology, but our objective becomes the minimization of coherent risk measurement tools as expected Shortfall instead of minimizing variances.

ACKNOWLEDGMENT

I gratefully thank an anonymous referee for the helpful comments and suggestions that have improved the quality of the paper.

REFERENCES

[1] 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.

[2] Eder, L. V., Provornaya, I. V., Filimonova, I. V., Kozhevin, V. D., & Komarova, A. V. (2018). World energy market in the conditions of low oil prices, the role of renewable energy sources. Energy Procedia, 153, 112-117.

[3] Bamati, N., & Raoofi, A. (2019). Development level and the impact of technological factor on renewable energy production. Renewable Energy.

[4] Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. Energy Economics, 34(1), 215-226.

[5] Bouraiou, A., Necaibia, A., Boutasseta, N., Mekhilef, S., Dabou, R., Ziane, A., ... & Touaba, O. (2019). Status of renewable energy potential and utilization in Algeria. Journal of Cleaner Production, 119011.

[6] International Energy outlook 2017, U.S. Energy Information Administration, September 14, 2017. www.eia.gov/ieo.

[7] Ahmad, W., Sadorsky, P., & Sharma, A. (2018). Optimal hedge ratios for clean energy equities. Economic Modelling, 72, 278-295.

[8] Pham, L. (2019). Do all clean energy stocks respond homogeneously to oil price?. Energy Economics, 81, 355-379.

[9] Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Economics, 34(1), 248-255.

[10] Sánchez, E. R. (2015). VOLATILITY SPILLOVERS AMONG ALTERNATIVE ENERGY, OIL AND TECHNOLOGY GLOBAL MARKETS (Doctoral dissertation, Universidad de Castilla-La Mancha).

[11] Elie, B., Naji, J., Dutta, A., & Uddin, G. S. (2019). Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. Energy, 178, 544-553.

[12] Jitmaneeroj, B. (2018). The effect of the rebalancing horizon on the tradeoff between hedging effectiveness and transaction costs. International Review of Economics & Finance, 58, 282-298.

[13] Henriques, I., & Sadorsky, P. (2008). Oil prices and the stock prices of alternative energy companies. Energy Economics, 30(3), 998-1010.

[14] Sadorsky, P. (2012). Modeling renewable energy company risk. Energy Policy, 40, 39-48.

[15] Ferstl, R., Utz, S., & Wimmer, M. (2012). The effect of the Japan 2011 disaster on nuclear and alternative energy stocks worldwide: An event study. Business Research, 5(1), 25-41.

ISSN: 2356-5608

[16] Broadstock, D. C., Cao, H., & Zhang, D. (2012). Oil shocks and their impact on energy related stocks in China. Energy Economics, 34(6), 1888-1895.

[17] Managi, S., & Okimoto, T. (2013). Does the price of oil interact with clean energy prices in the stock market?. Japan and the World Economy, 27, 1-9.

[18] Bohl, M. T., Kaufmann, P., & Stephan, P. M. (2013). From hero to zero: Evidence of performance reversal and speculative bubbles in German renewable energy stocks. Energy Economics, 37, 40-51.

[19] Ortas, E., & Moneva, J. M. (2013). The Clean Techs equity indexes at stake: Risk and return dynamics analysis. Energy, 57, 259-269.

[20] Wen, X., Guo, Y., Wei, Y., & Huang, D. (2014). How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. Energy Economics, 41, 63-75.

[21] Inchauspe, J., Ripple, R. D., & Trück, S. (2015). The dynamics of returns on renewable energy companies: A state-space approach. Energy Economics, 48, 325-335.

[22] Reboredo, J. C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices?. Energy Economics, 48, 32-45.

[23] Bondia, R., Ghosh, S., & Kanjilal, K. (2016). International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. Energy, 101, 558-565.

[24] Reboredo, J. C., Rivera-Castro, M. A., & Ugolini, A. (2017). Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. Energy Economics, 61, 241-252.

[25] 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.

[26] Dutta, A. (2017). Oil price uncertainty and clean energy stock returns: new evidence from crude oil volatility index. Journal of Cleaner Production, 164, 1157-1166.

[27] Asma A, Ahmed G. Hedging Oil Prices with Renewable Energy Indices: A Comparison between Various Multivariate Garch Versions. Biostat Biometrics Open Acc J. 2018; 6(3):

[28] http://www.wildershares.com/stock.php

[29] Tully, E., & Lucey, B. M. (2007). A power GARCH examination of the gold market. Research in International Business and Finance, 21(2), 316-325.

[30] Shahzad, S. J. H., Raza, N., Shahbaz, M., & Ali, A. (2017). Dependence of stock markets with gold and bonds under bullish and bearish market states. Resources Policy, 52, 308-319.

[31] Zghal, R., Ghorbel, A., & Triki, M. (2018). Dynamic model for hedging of the European stock sector with credit default swaps and EURO STOXX 50 volatility index futures. Borsa Istanbul Review, 18(4), 312-328.

[32] Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3), 339-350.

[33] Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial econometrics, 4(4), 537-572.

[34] Van der Weide, R. (2002). GO-GARCH: a multivariate generalized orthogonal GARCH model. Journal of Applied Econometrics, 17(5), 549-564.

[35] Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. The journal of finance, 48(5), 1779-1801.

[36] Ku, Y. H. H., Chen, H. C., & Chen, K. H. (2007). On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios. Applied Economics Letters, 14(7), 503-509.

[37] Chang, C. L., McAleer, M., & Tansuchat, R. (2011). Crude oil hedging strategies using dynamic multivariate GARCH. Energy Economics, 33(5), 912-923.

[38] Chen, F., & Sutcliffe, C. (2012). Better cross hedges with composite hedging? Hedging equity portfolios using financial and commodity futures. The European Journal of Finance, 18(6), 575-595.

[39] Hood, M., & Malik, F. (2013). Is gold the best hedge and a safe haven under changing stock market volatility?. Review of Financial Economics, 22(2), 47-52.

ISSN: 2356-5608

ANNEX :

Table 5: Estimation results from DCC and ADCC models

	DCC				ADCC			
	Coeff.	SE	t-value	Prob.	Coeff.	SE	t-value	Prob.
η_{NEX}	0.0408	0.0204	1.9984	0.0456	0.0191	0.0221	0.8642	0.3874
δ_{NEX}	0.1885	0.0186	10.0983	0.0000	0.1905	0.0183	10.3655	0.0000
ϖ_{NEX}	0.0076	0.0042	1.7897	0.0734	0.0135	0.0053	2.5189	0.0117
α_{NEX}	0.0746	0.0174	4.2688	0.0000	0.0716	0.0173	4.1335	0.0000
β_{NEX}	0.9241	0.0174	52.9593	0.0000	0.9333	0.0168	55.4445	0.0000
					0.5689	0.1019	5.5808	0.0000
λ_{NEX}	6.8474	0.7404	9.2479	0.0000	7.1522	0.6230	11.4794	0.0000
η_{CDS}	0.0415	0.0208	1.9895	0.0466	0.0487	0.0208	2.3421	0.0191
δ_{CDS}	-0.0107	0.0189	-0.5682	0.5698	-0.0157	0.0203	-0.774	0.4388
ϖ_{CDS}	0.0835	0.0480	1.7392	0.0819	0.066121	0.0281	2.3494	0.0188
α_{CDS}	0.1425	0.0347	4.1066	0.0000	0.2837	0.0596	4.75860	0.0000
β_{CDS}	0.8564	0.0447	19.1560	0.0000	0.8524	0.0313	27.1688	0.0000
					0.0342	0.0657	0.5203	0.6028
λ_{CDS}	3.1267	0.1274	24.5337	0.0000	2.3601	0.0407	57.9273	0.0000
$\eta_{Crude\ Oil}$	0.0164	0.0297	0.5514	0.5813	-0.0082	0.0304	-0.2720	0.7855
$\delta_{Crude\ Oil}$	0.0281	0.0181	1.5483	0.1215	0.0266	0.0120	2.2030	0.0275
$\varpi_{Crude\ Oil}$	0.0100	0.0043	2.3066	0.0210	0.0058	0.0024	2.3910	0.0168
$\alpha_{Crude\ Oil}$	0.0409	0.0025	15.8787	0.0000	0.0409	0.0019	20.5665	0.0000
$\beta_{Crude\ Oil}$	0.9575	0.0010	933.6031	0.0000	0.9661	0.0004	2411.8898	0.0000
					0.5459	0.0995	5.4856	0.0000
$\lambda_{Crude\ Oil}$	7.2684	0.9173	7.9237	0.0000	8.1356	1.1478	7.0876	0.0000
η_{GOLD}	0.0273	0.0149	1.8293	0.0673	0.0305	0.0145	2.0929	0.0363
δ_{GOLD}	-0.0301	0.0153	-1.9643	0.0494	-0.0313	0.0155	-2.0217	0.0432
ϖ_{GOLD}	0.0050	0.0019	2.6489	0.0080	0.0053	0.0020	2.6639	0.0077
α_{GOLD}	0.0309	0.0026	11.4900	0.0000	0.0464	0.0031	14.8321	0.0000
β_{GOLD}	0.9669	0.0006	1575.9395	0.0000	0.9628	0.0003	2599.6359	0.0000
					-0.1609	0.1070	-1.5034	0.1327
λ_{GOLD}	4.0247	0.2794	14.4039	0.0000	4.0191	0.2769	14.5112	0.0000
η_{BOND}	0.00314	0.0053	0.5857	0.5580	0.0030	0.0056	0.5440	0.5864
δ_{BOND}	-0.0292	0.0186	-1.5667	0.1171	-0.0292	0.0175	-1.6678	0.0953
ϖ_{BOND}	0.0002	0.0001	1.8772	0.0604	0.0012	0.0005	2.3139	0.0206
α_{BOND}	0.0274	0.0019	14.2146	0.0000	0.0406	0.0024	16.7819	0.0000
β_{BOND}	0.9703	0.0009	1065.1186	0.0000	0.9657	0.0003	2598.4020	0.0000
					-0.0451	0.1119	-0.4030	0.6868
λ_{BOND}	6.2265	0.6231	9.9917	0.0000	6.1271	0.6026	10.1664	0.0000
$\eta_{Euro\ Stoxx\ 50}$	0.0407	0.0182	2.2299	0.0257	0.0023	0.0158	0.1504	0.8804

ISSN: 2356-5608

$\delta_{Euro\ Stoxx\ 50}$	-0.0317	0.0184	-1.7191	0.0855	-0.0218	0.0172	-1.2630	0.2065
$\varpi_{Euro\ Stoxx\ 50}$	0.0174	0.0069	2.5028	0.0123	0.0242	0.0070	3.4610	0.0005
$\alpha_{Euro\ Stoxx\ 50}$	0.0927	0.0170	5.4501	0.0000	0.0845	0.0116	7.2541	0.0000
$\beta_{Euro\ Stoxx\ 50}$	0.9045	0.0163	55.2967	0.0000	0.9176	0.0129	71.0612	0.0000
					1.0000	0.0852	11.7246	0.0000
$\lambda_{Euro\ Stoxx\ 50}$	5.7800	0.6096	9.4815	0.0000	6.8810	0.8834	7.7884	0.0000
η_{VSTOXX}	-0.3298	0.0982	-3.3582	0.0007	-0.2023	0.0946	-2.1373	0.0325
δ_{VSTOXX}	-0.0123	0.0188	-0.6556	0.5120	-0.00244	0.0188	-0.1297	0.8967
ϖ_{VSTOXX}	3.3758	1.2242	2.7575	0.0058	0.3035	0.0794	3.8194	0.0001
α_{VSTOXX}	0.0993	0.0234	4.2337	0.0000	0.0721	0.0119	6.0455	0.0000
β_{VSTOXX}	0.8281	0.0453	18.2606	0.0000	0.8980	0.0186	48.0341	0.0000
					-0.9999	0.2024	-4.9385	0.0000
λ_{VSTOXX}	4.4813	0.3289	13.6222	0.0000	4.694234	0.3642	12.8869	0.0000
η_{VIX}	-0.3901	0.0994	-3.9227	0.0000	-0.2189	0.1045	-2.0935	0.0363
δ_{VIX}	-0.0628	0.0185	-3.3921	0.0006	-0.0632	0.0191	-3.3008	0.0009
ϖ_{VIX}	7.4052	1.6436	4.5054	0.0000	0.4678	0.0975	4.7942	0.0000
α_{VIX}	0.1748	0.0314	5.5623	0.0000	0.1058	0.0125	8.4552	0.0000
β_{VIX}	0.7099	0.0471	15.0428	0.0000	0.8561	0.0201	42.5314	0.0000
					-0.9999	0.1373	-7.2833	0.0000
λ_{VIX}	4.0119	0.2720	14.7467	0.0000	4.3257	0.3342	12.9413	0.0000
η_{VVIX}	-0.2930	0.0699	-4.1919	0.0000	-0.1933	0.0826	-2.3386	0.0193
δ_{VVIX}	-0.0300	0.0203	-1.4809	0.1386	-0.0214	0.0245	-0.8738	0.3822
ϖ_{VVIX}	5.0313	1.4783	3.4033	0.0006	0.4967	0.0991	5.0093	0.0000
α_{VVIX}	0.2143	0.0428	5.0042	0.0000	0.1136	0.0184	6.1563	0.0000
β_{VVIX}	0.6240	0.0812	7.6787	0.0000	0.8164	0.0287	28.4237	0.0000
					-1.0000	0.2018	-4.9536	0.0000
γ_{VVIX}	3.7410	0.2356	15.8774	0.0000	3.8765	0.2624	14.7711	0.0000
η_{OVX}	-0.2378	0.0641	-3.7062	0.0002	-0.2040	0.0688	-2.9638	0.0030
δ_{OVX}	-0.0367	0.0191	-1.9216	0.0546	-0.0362	0.0201	-1.8005	0.0717
ϖ_{OVX}	1.8563	0.6504	2.8540	0.0043	0.2326	0.0690	3.3709	0.0007
α_{OVX}	0.0935	0.0211	4.4205	0.0000	0.0690	0.0141	4.8866	0.0000
β_{OVX}	0.8254	0.0438	18.8065	0.0000	0.8990	0.0213	42.1825	0.0000
					-0.6710	0.2040	-3.2882	0.0010
γ_{OVX}	3.8468	0.2489	15.4516	0.0000	3.793325	0.2415	15.7032	0.0000
θ_1	0.0137	0.0022	6.1294	0.0000	0.0136	0.0023	5.9024	0.0000
θ_2	0.9597	0.0098	97.7030	0.0000	0.9614	0.0095	100.97545	0.0000
θ_3					0.0006	0.0005	1.2401	0.2149
Λ	7.0383	0.2749	25.5941	0.0000	6.4757	0.2369	27.3320	0.0000
AIC	38.753				38.967			
BIC	38.980				39.218			
Shibata	38.750				38.964			

ISSN: 2356-5608

H-Q	38.835	39.058
LL	-54630.72	-54922.55
Nobs	2825	2825

Table 11: Summary statistics of hedge ratios (β) and Hedging Effectiveness (HE) for NEX investors under alternative forecast length

	Forecast length= 500				**Forecast length= 1000**				**Forecast length= 1500**			
	mean	**min**	**max**	**HE**	**mean**	**min**	**max**	**HE**	**mean**	**min**	**max**	**HE**
NEX/CDS												
DCC	0.0485	-0.0963	0.2343	**0.0096**	0.0543	-0.0377	0.2343	**0.0105**	0.0619	-0.0271	0.2343	0.0119
ADCC	0.0330	-0.0250	0.2006	0.0095	0.0350	-0.0119	0.2006	0.0103	0.0389	-0.0105	0.2006	**0.0120**
GOGARH	0.0689	-1.2063	1.5832	0.0076	0.1088	-0.0137	0.6195	0.0081	0.0670	-0.0641	0.0828	0.0091
NEX/Crude Oil												
DCC	0.2301	-0.0668	1.0334	0.1408	0.1832	-0.0668	0.8780	0.1009	0.1140	-0.0668	0.3880	0.0736
ADCC	0.2283	-0.0618	0.9754	0.1455	0.1831	0.0103	0.7553	0.1074	0.1224	-0.0618	0.3899	0.0806
GOGARH	0.3701	0.1468	1.7304	**0.1836**	0.3405	0.1468	1.4826	**0.1772**	0.2701	0.1468	0.7834	**0.1618**
NEX/GOLD												
DCC	0.1330	-1.0938	0.8862	0.0677	0.1133	-0.8265	0.8106	0.0571	0.0440	-0.8265	0.6126	0.0364
ADCC	0.1465	-1.1444	0.9811	**0.0678**	0.1263	-0.8630	0.9576	**0.0571**	0.0546	-0.8630	0.8328	0.0366
GOGARH	0.1520	-1.0978	0.2884	0.0646	0.1554	0.0502	0.1869	0.0476	0.2794	0.0167	0.8705	**0.0451**
NEX/BOND												
DCC	-0.9658	-2.5751	0.3289	**0.0860**	-0.9348	-2.4287	0.3289	**0.0807**	-0.7716	-2.4287	0.3289	**0.0662**
ADCC	-0.920	-2.5475	0.4353	0.0793	-0.9065	-2.5475	0.4353	0.0759	-0.7463	-2.4430	0.4353	0.0615
GOGARH	-0.2361	-1.1139	-0.0020	0.0707	-0.2686	-0.3406	-0.0271	0.0714	-0.2503	-0.3196	-0.0271	0.0521
NEX/Euro Stoxx 50												
DCC	0.5699	0.2506	1.1414	0.4275	0.5303	0.2506	0.9443	0.3876	0.4854	0.2506	0.8614	0.3501
ADCC	0.6140	0.2540	1.1822	**0.4425**	0.5792	0.2540	1.1647	**0.4064**	0.5286	0.2540	0.9909	**0.3704**
GOGARH	0.8550	0.5774	1.1323	0.3917	0.4365	0.1046	1.3443	0.3645	0.8442	0.6759	0.9389	0.3328
NEX/VSTOXX												
DCC	-0.1056	-0.3288	-0.0216	0.3311	-0.0938	-0.3288	-0.0216	0.3140	-0.0766	-0.1730	-0.0216	0.2900
ADCC	-0.1054	-0.3158	-0.0277	0.3174	-0.0947	-0.3118	-0.0277	0.3020	-0.0777	-0.1654	-0.0277	0.2818
GOGARH	-0.3652	-1.1997	-0.1536	**0.3829**	-0.3592	-1.1999	-0.1536	**0.3853**	-1.2500	-4.5260	-0.4900	**0.3780**
NEX /VIX												
DCC	-0.0966	-0.2815	-0.0155	0.3548	-0.0870	-0.2463	-0.0155	0.3435	-0.0752	-0.1642	-0.0155	0.3397
ADCC	-0.0972	-0.3267	-0.0207	0.3368	-0.0873	-0.3073	-0.0207	0.3245	-0.0759	-0.1784	-0.0207	0.3215
GOGARH	-0.3775	-1.0042	-0.1178	**0.4137**	-0.3793	-0.9238	-0.1178	**0.4278**	-0.3459	-0.6472	-0.1178	**0.4206**
NEX /VVIX												
DCC	-0.1103	-0.3970	-0.0245	0.2212	-0.1006	-0.3970	-0.0245	0.2264	-0.0869	-0.1946	-0.0245	0.2327
ADCC	-0.1105	-0.4311	-0.0232	0.2100	-0.1005	-0.3047	-0.0232	0.2143	-0.0877	-0.1970	-0.0232	0.2200
GOGARH	-0.2807	-0.9639	-0.1129	**0.2594**	-0.2873	-0.9648	-0.1129	**0.2827**	-1.1917	-7.1704	-0.3309	**0.2985**
NEX /OVX												
DCC	-0.0870	-0.3836	-0.0033	**0.1343**	-0.0780	-0.3836	-0.0033	0.1246	-0.0667	-0.1827	-0.0033	0.1102
ADCC	-0.0826	-0.3665	0.0035	0.1246	-0.0743	-0.3665	0.0001	0.1161	-0.0634	-0.1616	0.0001	0.1016
GOGARH	-0.5673	-2.4910	-0.0826	0.1272	-0.6503	-2.4910	-0.2147	**0.1517**	-0.2403	-0.3843	-0.1748	**0.1574**

ISSN: 2356-5608

Table 12: The Hedging Effectiveness, the Transaction Cost, and the TC/HE ratio for different forecast lengths

	Forecast length = 500			Forecast length= 1000			Forecast length= 1500		
	HE	*TC*	$\frac{TC}{HE}$	*HE*	*TC*	$\frac{TC}{HE}$	*HE*	*TC*	$\frac{TC}{HE}$
NEX/CDS									
DCC	0.96%	12.99	13.48	1.05%	9.26	8.81	1.19%	7.51	6.28
ADCC	0.95%	9.61	**10.12**	1.03%	5.86	**5.64**	1.20%	5.77	4.80
GOGARH	0.76%	21.54	28.08	0.81%	12.31	15.18	0.91%	1.56	**1.71**
NEX/Crude Oil									
DCC	14.08%	18.60	1.32	10.09%	15.97	1.58	7.36%	9.01	1.22
ADCC	14.55%	18.93	**1.30**	10.74%	15.73	1.46	8.06%	9.76	1.21
GOGARH	18.36%	25.20	1.37	17.72%	21.40	**1.20**	16.18%	10.31	**0.63**
NEX/GOLD									
DCC	6.77%	38.34	5.65	5.71%	30.66	5.36	3.64%	26.25	7.20
ADCC	6.78%	42.31	6.23	5.71%	33.75	5.90	3.66%	27.37	7.46
GOGARH	6.46%	12.83	**1.98**	4.76%	1.25	**0.26**	4.51%	18.71	**4.14**
NEX/BOND									
DCC	8.60%	51.53	5.99	8.07%	39.63	4.90	6.62%	37.78	5.70
ADCC	7.93%	70.68	8.91	7.59%	47.83	6.30	6.15%	43.93	7.14
GOGARH	7.07%	21.93	**3.09**	7.14%	4.00	**0.56**	5.21%	5.14	**0.98**
NEX/Euro Stoxx 50									
DCC	42.75%	20.06	0.46	38.76%	17.66	**0.45**	35.01%	15.78	0.45
ADCC	44.25%	31.67	0.71	40.64%	30.46	0.74	37.04%	26.54	0.71
GOGARH	39.17%	16.78	**0.42**	36.45%	32.06	0.87	33.28%	7.71	**0.23**
NEX/VSTOXX									
DCC	33.11%	6.08	**0.18**	31.40%	4.58	**0.14**	29.00%	3.94	**0.13**
ADCC	31.74%	7.68	0.24	30.20%	5.87	0.19	28.18%	4.81	0.17
GOGARH	38.29%	19.72	0.51	38.53%	16.42	0.42	37.80%	70.08	1.85
NEX /VIX									
DCC	35.48%	4.99	**0.14**	34.35%	4.66	**0.13**	33.97%	4.69	**0.13**
ADCC	33.68%	6.42	0.19	32.45%	5.64	0.17	32.15%	5.49	0.17
GOGARH	41.37%	19.74	0.47	42.78%	18.50	0.43	42.06%	18.63	0.44
NEX /VVIX									
DCC	22.12%	6.95	**0.31**	22.64%	5.74	**0.25**	23.27%	6.33	**0.27**
ADCC	21.00%	7.37	0.35	21.43%	5.98	0.27	22.00%	6.80	0.30
GOGARH	25.94%	11.15	0.43	28.27%	10.76	0.38	29.85%	132.62	4.44
NEX /OVX									
DCC	13.43%	7.91	**0.58**	12.46%	4.41	**0.35**	11.02%	4.08	**0.37**
ADCC	12.46%	8.20	0.65	11.61%	4.53	0.39	10.16%	4.37	0.43
GOGARH	12.72%	18.56	1.45	15.17%	40.91	2.69	15.74%	6.00	0.38

ISSN: 2356-5608