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Are alternative energies a real alternative for investors?

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ABSTRACT

Fossil fuels supply most of the energy we need for many functions but alternative energy global consumption is expected to increase in the future supported by great incentives, advances in technologies, and the depletion of fuel oil reserves. In that context, investors begin to consider the possibility of investing in the alternative energy sector using different assets such as the Exchange Traded Funds (ETFs). We evaluate the out-of-sample performance of four strategies using the returns and volatility forecasts from a VAR-ADCC approach. We provide evidence that Alternative Energy ETFs clearly outperform Energy ETFs and, therefore, they are a real alternative for investors. These findings are relevant not only for academics but also for active professional managers who can use this technique to add value to their investment strategies.

1. Introduction

Recent years have been characterized by significant increases and decreases of oil and gas prices. That volatile behavior, jointly with some movements in favor of reducing economic dependences on fossil fuels, leads investors to consider the overweight of the Alternative Energy sector, which encompasses wind, solar, geothermal, biomass, biofuels, hydro, wave and tidal energies, on their portfolios. This sector is expected to experiment a fast growth over the next decades due to the depletion of fossil fuel reserves, greater incentives for renewables and the advances in technologies which have made green power more feasible.

From the analysis of the previous empirical literature, we find two ways of analyzing energy markets. Firstly, we observe that several studies have mainly focused on using different multivariate volatility models to calculate optimal hedge ratios and optimal portfolio weights that minimize risk between two assets, such as crude oil spots and futures (Chang et al., 2011), or between oil prices and the stock prices of clean energy and technology companies (Sadorsky, 2012), but also to observe spillovers and interactions commonly between pairs of energy markets or energy and other markets, see Henriques and Sadorsky (2008), Mollick and Assefa (2013), Efimova and Serletis (2014), Lin et al. (2014), and more recently Maghyereh et al. (2017) and Kyritsis and Serletis (2018). Their results reveal different dynamic correlations and hedge ratios and suggest that a better understanding of volatility links is crucial for portfolio management.

Secondly, studies related to alternative energies, see Silva and Cortez (2016), Reboredo et al. (2017) and Rezec and Scholtens (2017), use different linear regression models based on excess returns and additional factors like those proposed by Fama and French (1993) or risk factors used by Carhart (1996), Bollen and Busse (2001) and Inchauspe et al. (2015) in order to analyze the performance of renewable energies. All of them suggest that renewable energies underperform the respective benchmarks and, therefore, they are not a financially attractive portfolio investment.

The aim of this study is to refute those suggestions and enhance the evidence on the benefits for investors of using Alternative Energy ETFs. We improve the previous literature in various ways. Firstly, in contrast with the previous empirical evidence which employs multivariate GARCH models, such as the DCC-GARCH, just for analyzing the time-varying correlations or dynamic spillover effects we use its forecasts for estimating optimal portfolios and comparing the performance ratios of the alternative energy sector with other benchmarks. Therefore, we use a rolling window analysis, based on a VAR-ADCC approach, in order to obtain out-of-sample one-step-ahead forecasts of returns, volatilities and correlations which are used for constructing four different strategies derived from using different constraints of the minimum-variance and mean-variance optimization approaches.

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Secondly, instead of using different indexes or oil futures prices we use five energy ETFs and five alternative energy ETFs. Exchange Traded Funds, ETFs, are passive investments that are traded like shares and mirror the performance of a sector or a market index. Therefore, we avoid the problem for individuals who cannot invest in those indexes which have been mostly used in the previous empirical evidence but, in contrast, they can invest in ETFs.

Finally, the database used from June 27, 2008 through November 30, 2017, comprises different environments of high and low oil prices which gives more value to the possibility of finding an approach where the performance of classical energy sector is improved.

Our results show that it is possible to obtain benefits from using alternative energies and significant improvements in portfolio performance, compared to the naïve rule and energy sector. It is also shown that this better performance is maintained for many out-of-samples, including those whose in-sample periods coincide with high oil and gas prices.

The rest of the paper is organized as follows. In Section 2, we describe the theoretical background of this paper. In Section 3, the database is defined. Section 4 reports the empirical results of the proposed investment strategies and the robustness test. Finally, Section 5 provides the main conclusions.

2. Theoretical background

This section is divided into two main sub-sections. Firstly, we present the multivariate GARCH model. Secondly, we describe the methodology for the construction of the diversification portfolio and the criterion employed to evaluate the performance of the alternative framework proposed.

2.1. The VAR-ADCC approach

The objective of this paper is to analyze alternative investment strategies using out-of-sample forecasted returns, volatilities and covariances obtained from a Multivariate GARCH approach. In our case, we opt for using the Asymmetric Dynamic Conditional Correlation, ADCC-GARCH, model proposed by Cappiello et al. (2006). The choice of this model is based on the results of Gupta and Donleavy (2009), Kalotychou et al. (2014), Zhou and Nicholson (2015), Yuan et al. (2016) and Badshah (2018) who show that modeling covariance asymmetry on the basis of the ADCC model contributes significantly to the economic value of the model due to the fact that conditional volatility, and the correlation of financial returns, tend to rise more after negative return shocks than after positive ones of the same size.

The VAR Asymmetric Dynamic Conditional Correlation, VAR-ADCC-GARCH, model estimation is performed using a two-step approach. Firstly, a VAR-GARCH model for each time series was estimated. We agree with Ewing and Malik (2005) that it is very important to specify correctly the mean equation because its misspecification may lead to an incorrect estimation of the variance equation. Thus, the return generating process is conceptualized as:

$$r_{i,t} = c_i + \sum_{\substack{i=1 \\ j=1}}^{5} \alpha_{ij} r_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

$$\varepsilon_{it}|\Omega_{t-1} \approx N(0, H_t)$$

where $r_{i,\,t}$ are the daily returns for the ETFs, c_i and α_{ij} are the parameters to be estimated, and $\varepsilon_{i,\,t}$ is a 5×1 vector of error terms which is assumed to be conditionally normal with zero mean and conditional variance matrix $\mathrm{H_t}$. We have to highlight that, from each model the conditional variances, $h_{i,t}$, and the standardized residuals, $\delta_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}}$, are generated separately. More precisely, the conditional covariance matrix is specified as:

$$\mathrm{H_t} = \mathrm{D_t R_t D_t} \tag{2}$$

where $\mathrm{D_t} = \mathrm{diag}(\sqrt{\mathrm{h_{it}}})$, is a diagonal matrix which contains the time-varying conditional volatilities of the previous GARCH models and $\mathrm{R_t}$ is a time-varying 3×3 correlation matrix with diagonal elements equal to 1 which is specified as:

$$\mathrm{R_t} = \left(\mathrm{Q_t^*}\right)^{-1} \mathrm{Q_t} \left(\mathrm{Q_t^*}\right)^{-1} \tag{3}$$

where $\mathrm{Q_t} = \{\mathrm{q_{ij,t}}\}$ is a covariance matrix of the standardized residuals denoted as:

$$Q_t = (1-\alpha-\beta)\overline{Q} - \gamma\overline{N} + \alpha\left(\delta_{t-1}\delta_{t-1}'\right) + \gamma\eta_{t-1}\eta_{t-1}' + \beta Q_{t-1} \tag{4}$$

$\overline{\mathrm{Q}} = \mathrm{E}[\delta_t \delta_t']$ is the unconditional correlation matrix of the standardized residuals; $\mathrm{Q_t^*} = \mathrm{diag}(\sqrt{\mathrm{q_{ij,t}}})$ is a diagonal matrix containing the square root of the diagonal elements of the $\mathrm{n} \times \mathrm{n}$ positive matrix Q; $\eta_t = I[\delta_t < 0] \odot \delta_t$ ($I[\cdot]$ is a 3×1 indicator function which takes on value 1 if the argument is true and 0 otherwise while $\odot$ is the Hadamard product) and $\overline{\mathbf{N}} = [\eta_t \eta_t']$. Positive definiteness of $\mathrm{Q_t}$ is ensured by imposing $\alpha + \beta + \lambda\gamma < 1$, where λ = maximum eigenvalue $[\overline{\mathrm{Q}}^{-1/2}\overline{\mathrm{N}}\overline{\mathrm{Q}}^{-1/2}]$.

2.2. Investment strategies

We employ the forecasted returns, volatilities and correlations from the previous model to construct four investment strategies which are based on two classical portfolio optimization problems.

The so called minimum-variance portfolio is the first optimization problem to be solved, which is given by the following equation:

$$\min_{w_t} \quad w_t' \, \mathrm{H}_{t+1|t} \, w_t \tag{5}$$

where $w_t' \, \mathrm{H}_{t+1|t} \, w_t$ is the portfolio risk equation to be minimized. Following this strategy, we consider that the investor is exclusively interested in minimizing volatility. However, we know that this is not true in real life because they are also interested in obtaining profits from their investments.

Meanwhile, the second optimization problem is the classic mean-variance strategy proposed by Markowitz (1952). The goal of this optimization problem is also to minimize the portfolio risk but it adds a target portfolio return constraint. Therefore, the optimization problem is given by:

$$\min_{w_t} \quad w_t' \, \mathrm{H}_{t+1|t} \, w_t$$

$$\text{s.t.} \quad w_t' E\{R_{t+1}\} \geq R^* \tag{6}$$

where $\mathrm{R^*}$ denotes the desired target return performance. We use the equally weighted portfolio, also known as the naïve portfolio, as the benchmark for $\mathrm{R^*}$.

Portfolios can be created with or without short-selling constraints. Initially, we solve the optimization problem by excluding short-sellings. Therefore, the general constraints $w_t' 1 = 1 \quad \mathrm{w_i} \geq 0 \quad \mathrm{i} = 1, 2, \ldots, \mathrm{N}$ are included. However, the evidence on the effect of short-selling constraints is mixed as pointed out by Grullon et al. (2015). Previous studies investigate the strategies of international portfolio management with or without short-selling constraints, see Diether et al. (2009), Beber and Pagano (2013) and Omar et al. (2017) but the effects remain unclear. At this point, we consider interesting the findings of Bohl et al. (2016) who found econometric evidence that the financial crisis was accompanied by an increase in volatility persistence and that this effect is particularly pronounced for those

Table 1
Descriptive statistics of Energy ETFs.

	XLE	VDE	IXC	IYE	OIH	Equality Test
Mean	$-9.48 \cdot 10^{-5}$	$-1.23 \cdot 10^{-4}$	$-1.50 \cdot 10^{-4}$	$-1.11 \cdot 10^{-4}$	$-4.45 \cdot 10^{-4}$	0.141 (0.966)
Std. Dev.	0.018	0.018	0.017	0.018	0.023	39.078 (0.000)
Skewness	−0.517	−0.528	−0.317	−0.502	−0.524	
Kurtosis	15.973	14.774	13.346	25.568	11.974	
Jarque-Bera	17,353.79 (0.000)	14,318.86 (0.000)	11,010.38 (0.000)	52,291.20 (0.000)	8372.906 (0.000)	
Q (20)	64.134 (0.000)	74.102 (0.000)	55.871 (0.000)	113.84 (0.000)	45.420 (0.000)	
Q^2 (20)	3661.5 (0.000)	3673.1 (0.000)	4799.9 (0.000)	2030.0 (0.000)	2837.4 (0.000)	
ARCH (1)	103.197 (0.000)	170.989 (0.000)	180.202 (0.000)	390.471 (0.000)	81.659 (0.000)	

This table contains the descriptive statistics for the daily return series for the XLE, VDE, IXC, IYE and OIH ETFs for the sample period from June 27, 2008 through November 30, 2017. The last column reports the mean and variance equality tests using the ANOVA and Levene statistics, respectively. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera statistic tests the normality of the series. This statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. Q (20) and Q^2 (20) are Ljung–Box tests for 20th-order serial correlation in the returns and squared returns. ARCH (1) is the Engle test for the 1st-order ARCH. These three tests are distributed as $\chi^2(1)$. The *p* values of these tests are reported in brackets.

stocks that were subject to short-selling constraints. For that reason, we have also solved the optimization problems not excluding the short-selling constraints following Bohl et al. (2016) who also state that regulators should avoid imposing short-selling restrictions. In that case only the constraints $w_t'1 = 1 \quad i = 1, 2, \ldots, N$ were included. In both cases w_i is the weight of each asset from the portfolio vector, $w_t = [w_1, w_2, \ldots, w_N]$, and 1 is a vector of ones.

Finally, we evaluate the performance of the optimization frameworks over the out of sample period $t = \tau + 1, \ldots, T$, in terms of the Sharpe ratio, SR_p which is defined as the average out-of-sample returns divided by their sample standard deviation:

$$SR_p = \frac{\overline{\mu}_p}{\sigma_p} \tag{7}$$

3. Database

The data used in this paper are daily returns from June 27, 2008 through November 30, 2017 (amounting to 2459 usable observations) of ten Exchange Trade Funds, ETFs, five Energy ETFs and five Alternative Energy ETFs. The five Energy ETFs are the Energy Select Sector SPRD (XLE), the Vanguard Energy ETF (VDE), the IShares Global Energy ETF (IXC), the iShares US Energy ETF (IYE) and the VanEck Vectors Oil services ETF (OIH). Those which represent the Alternative Energy ETFs are: the PowerShares Cleantech Portfolio (PZD), the PowerShares WilderHill Clean Energy Portfolio (PBW), the First Trust Global Wind Energy ETF (FAN), the First Trust Nasdaq Clean Edge Green Energy Index Fund (QCLN) and the VanEck Vectors Global Alternative Energy ETF (GEX).

The Energy ETFs (XLE, VDE, IXC, IYE, and OIH) mostly track US companies that primarily develop and produce oil and natural gas, and provide drilling and other energy-related services while Alternative Energy ETFs (PZD, PBW, FAN, QCLN, and GEX) hold a diverse portfolio of companies worldwide which are involved in the clean-tech industry, wind, solar, biofuels and geothermal, as well as companies focused on energy efficiency. All these ETFs are the largest in assets in their sectors, the ones with older inception dates and are considered interesting picks by most of the traders.

The reason for using ETFs is twofold. Firstly, ETFs are an attractive method of investing indirectly in international equities. They are similar to mutual funds because they are also valued on the basis of their holdings, but while mutual funds are priced once a day the prices of ETFs are set throughout the day. Therefore, ETFs are traded like a stock and, as a consequence, an investor may take advantage of market developments in real time. That stock-like quality of ETFs allows investors to use strategies such as short-selling or margin trading, unlike mutual funds. Additionally, ETFs have lower fees on average than mutual

Table 2
Descriptive statistics of Alternative Energy ETFs.

	PZD	PBW	FAN	QCLN	GEX	Equality test
Mean	$9.42 \cdot 10^{-5}$	$-5.69 \cdot 10^{-4}$	$-3.35 \cdot 10^{-4}$	$-8.17 \cdot 10^{-5}$	$-3.88 \cdot 10^{-4}$	0.417 (0.796)
Std. Dev.	0.016	0.021	0.018	0.020	0.021	31.868 (0.000)
Skewness	−0.812	−0.422	−0.330	−0.489	−0.595	
Kurtosis	15.335	9.153	14.901	9.510	14.831	
Jarque-Bera	15,859.87 (0.000)	3952.555 (0.000)	14,556.62 (0.000)	4440.888 (0.000)	14,488.56 (0.000)	
Q (20)	48.215 (0.000)	42.252 (0.000)	64.495 (0.000)	44.210 (0.000)	53.832 (0.000)	
Q^2 (20)	3542.0 (0.000)	4273.3 (0.000)	3610.5 (0.000)	3701.0 (0.000)	6304.0 (0.000)	
ARCH (1)	83.805 (0.000)	176.855 (0.000)	64.640 (0.000)	104.439 (0.000)	379.215 (0.000)	

This table contains the descriptive statistics for the daily return series for the XLE, VDE, IXC, IYE and OIH ETFs for the sample period from June 27, 2008 through November 30, 2017. The last column reports the mean and variance equality tests using the ANOVA and Levene statistics, respectively. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera statistic tests the normality of the series. This statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. Q (20) and Q^2 (20) are Ljung–Box tests for 20th-order serial correlation in the returns and squared returns. ARCH (1) is the Engle test for the 1st-order ARCH. These three tests are distributed as $\chi^2(1)$. The *p* values of these tests are reported in brackets.

funds and some advantages in terms of intraday liquidity, transparency and tax efficiency.

Secondly, there are thousands of ETFs covering indices, equity market sectors, countries, etc. These ETFs help investors to create a diversified portfolio that meets their specific asset allocation needs. Tsai and Swanson (2009) show that ETFs provide US investors with greater diversification benefits than country funds. Huang and Lin (2011) conclude that international diversification with ETFs is a reasonable strategy. More recently, Miralles-Marcelo et al. (2015) and Miralles-Quiros and Miralles-Quiros (2017) document the benefits for US investors of diversifying internationally by combining their domestic ETF with ETFs from developed and emerging markets such as the UK and Japan on the one hand, and Brazil and Malaysia on the other. Following these studies, we analyze the existence of diversification opportunities by combining the world's best-recognized ETF from the Energy and Alternative Energy (renewable) sectors.

The summary statistics for the whole sample of Energy ETFs are reported in Table 1 while those referred to Alternative Energy ETFs are shown in Table 2. We observe that only one (PZD) out of all the ETFs

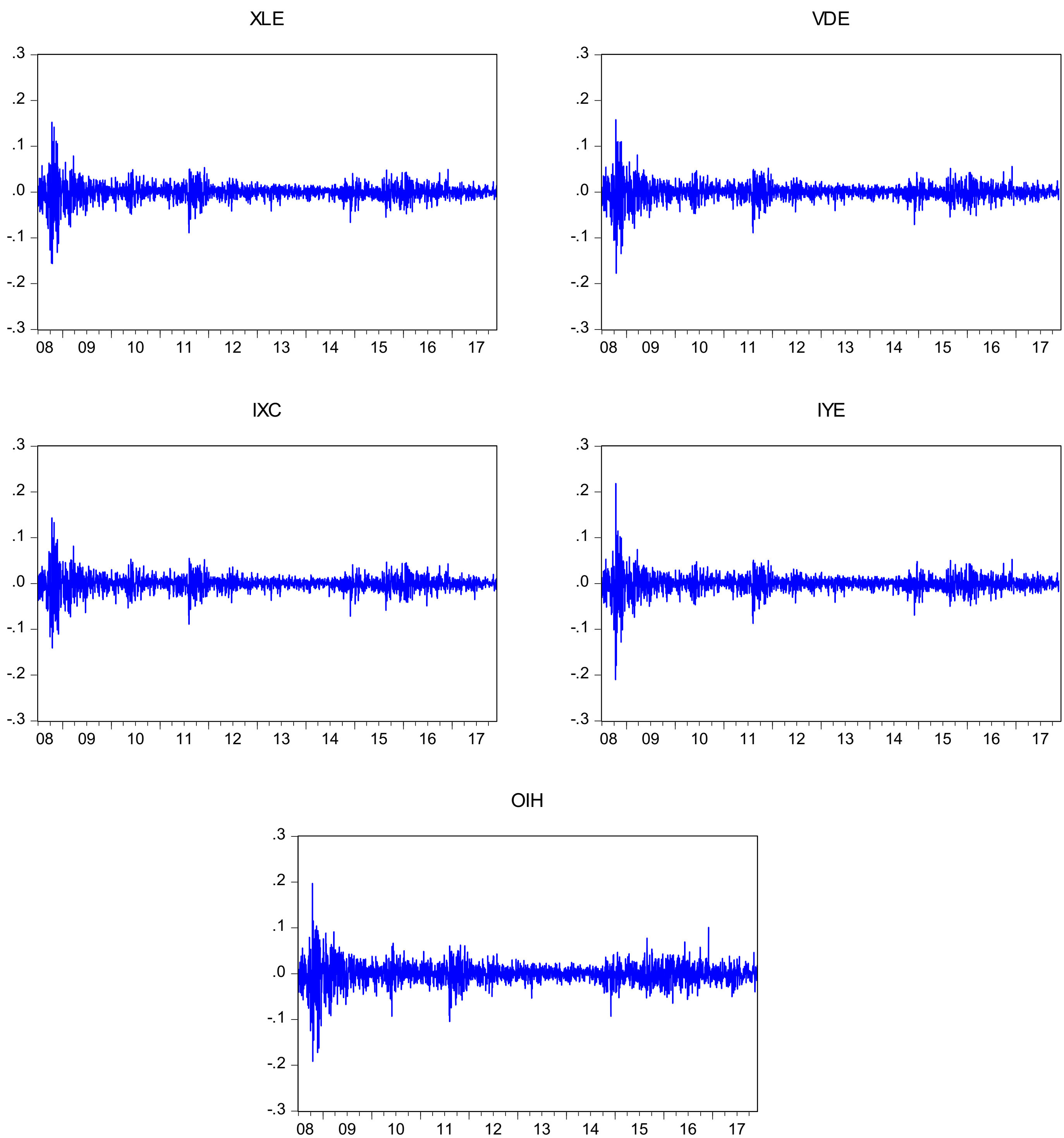

Fig. 1. Returns of the energy ETFs.

shows positive returns and that mean returns are worse in Alternative Enegy ETFs, except for PZD. However, on the basis of the Anova test, we cannot reject the null that all the series in the group have the same mean since those differences are not statistically significant.

With respect to standard deviation, we find that Energy ETFs mostly show lower volatility values than Alternative Energy ETFs. However, the lowest volatility value is provided by PZD, an Alternative Energy ETF. In this case, the rejection of the null of equality of variances leads us to conclude that differences are statistically significant. Skewness and kurtosis values indicate that the distributions of returns for most of the ETFs are negatively skewed and leptokurtic. Specifically, negative skewness indicates a higher probability of negative returns, indicating that the market has a higher probability of decreases in asset prices than increases, while excess kurtosis makes extreme observations more likely than in the normal case, which means that the market has a higher probability of extreme observations than with a normal distribution (Boubaker and Sghaier, 2013). The Jarque–Bera statistic rejects the null hypothesis that the returns are normally

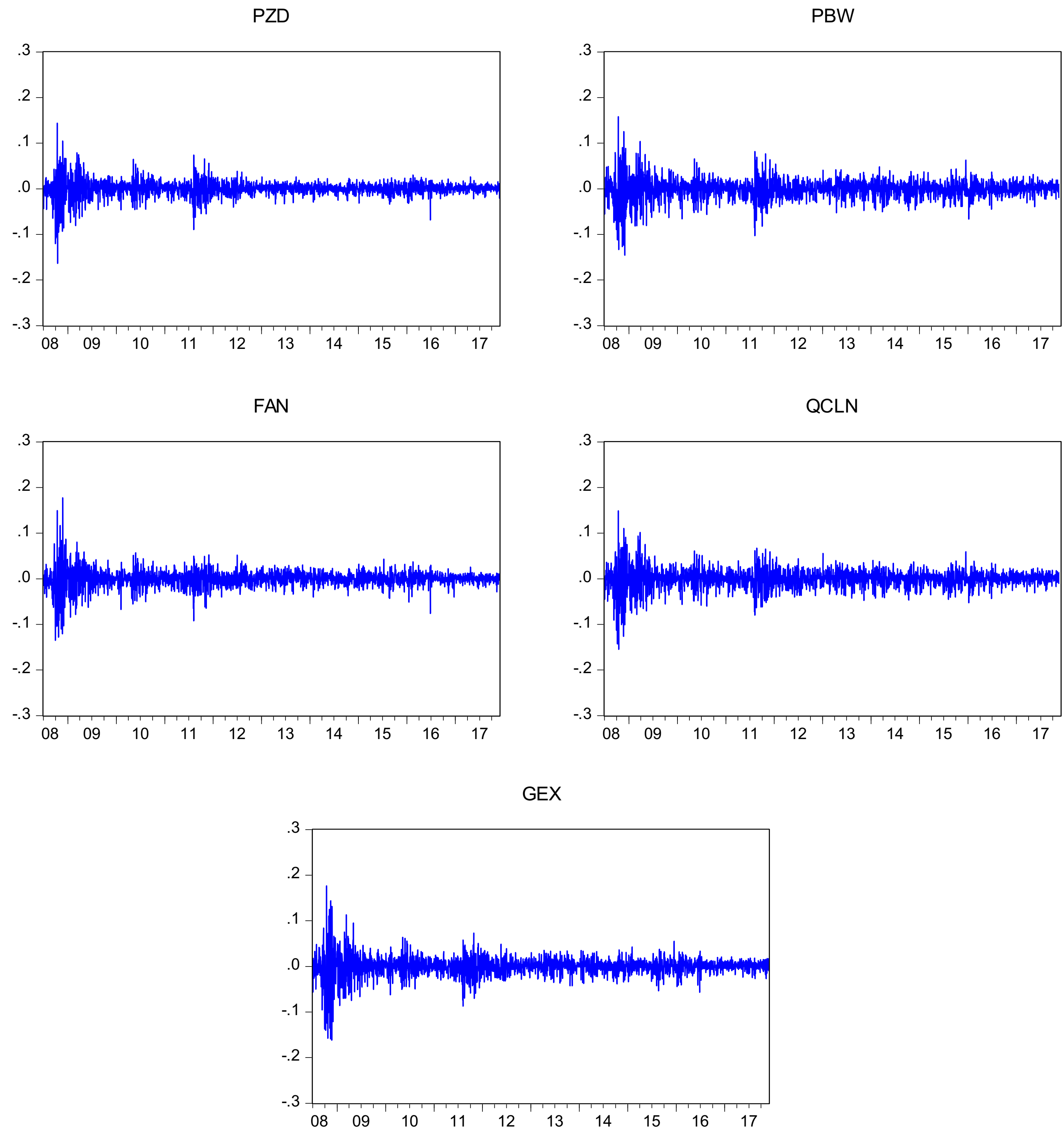

Fig. 2. Returns of the alternative Energy ETFs.

Table 3
Estimates from the ADCC-GARCH model on energy ETFs.

	XLE Coeff.	p-Value	VDE Coeff.	p-Value	IXC Coeff.	p-Value	IYE Coeff.	p-Value	OIH Coeff.	p-Value
Panel A: Mean equations										
c_i	$3.61 \cdot 10^{-4}$	(0.11)	$3.45 \cdot 10^{-4}$	(0.14)	$2.46 \cdot 10^{-4}$	(0.27)	$3.34 \cdot 10^{-4}$	(0.15)	$2.49 \cdot 10^{-4}$	(0.43)
$R_{XLE,\ t-1}$	0.212	(0.17)	0.357^{**}	(0.03)	0.386^{**}	(0.01)	0.563^{***}	(0.00)	0.599^{***}	(0.00)
$R_{VDE,\ t-1}$	−0.166	(0.29)	-0.355^{**}	(0.03)	−0.211	(0.16)	−0.164	(0.29)	−0.157	(0.50)
$R_{IXC,\ t-1}$	0.003	(0.96)	0.018	(0.81)	−0.105	(0.17)	0.029	(0.71)	0.042	(0.69)
$R_{IYE,\ t-1}$	−0.154	(0.32)	−0.124	(0.50)	−0.149	(0.35)	-0.531^{**}	(0.01)	-0.569^{**}	(0.01)
$R_{OIH,t-1}$	0.060^{*}	(0.25)	0.062^{*}	(0.08)	0.051	(0.12)	0.035	(0.12)	0.050	(0.32)
Panel B: GARCH parameters										
c_i	$1.76 \cdot 10^{-6***}$	(0.00)	$1.87 \cdot 10^{-6***}$	(0.00)	$1.58 \cdot 10^{-6***}$	(0.00)	$2.05 \cdot 10^{-6***}$	(0.00)	$2.30 \cdot 10^{-6***}$	(0.00)
$\varepsilon^2_{i,t-1}$	0.078^{***}	(0.00)	0.077^{***}	(0.00)	0.077^{***}	(0.00)	0.077^{***}	(0.00)	0.065^{***}	(0.00)
$h^2_{i,t-1}$	0.915^{***}	(0.00)	0.916^{***}	(0.00)	0.917^{***}	(0.00)	0.914^{***}	(0.00)	0.930^{***}	(0.00)
Panel C: ADCC-GARCH persistence parameters										
α	-0.058^{***}	(0.00)								
β	0.894^{***}	(0.00)								
γ	0.126^{***}	(0.00)								

This table contains the estimations from the VAR-ADCC-GARCH model. Panel A shows the mean equations for the index returns series (p-values in brackets). Panel B shows the variance equations (p-values in brackets). Panel C reports the persistence parameters of the model.
*** Represents the 1% significance level.
** Represents the 5% significance level.
* Represents the 10% significance level.

distributed in all cases. The Ljung–Box statistic for up to 20 lags indicates the presence of significant linear and non-linear dependencies in the returns of most of the ETFs. Finally, the ARCH test reveals that returns exhibit conditional heteroscedasticity in all series. These preliminary results highlight that it is important to more accurately study the dynamics between these ETFs.

From this point, and accordingly with Weiss (1986), Schüler and Schröder (2003) and Miralles-Marcelo et al. (2013), the estimations were conducted under the assumption that the residuals of the models follow a normal distribution which is, in fact, not true. However, they show that this assumption leads to a consistent estimation of the parameters if all the equations are specified correctly. Additionally, it is proven that when a distribution different from the normal one is employed and it is not the true one, the estimates are not consistent. That is the reason why we apply the normal distribution.

To illustrate the differences between the ten ETFs, in Figs. 1 and 2 we show their return charts for the period analyzed. We find similarities in terms of upward and downward movement. We can point out the more volatile behavior patterns in the Energy ETF, OIH, and in the Alternative Energy ETF, GEX, especially around mid-2008 to late 2008 bubble compared with the others.

4. Empirical results and robustness test

This section presents the empirical results for the model proposed and their economic implications for the calculation of portfolio strategies. A rolling window of 1000 observations, about 4 years of daily data, was used to generate the expected returns and conditional variance matrix.

Tables 3 and 4 display the estimates of the model for the in-sample period – from June 27, 2008 through April 27, 2012 (1000 observations) for Energy ETFs and Alternative Energy ETFs, respectively. In Pane A we show the estimated coefficients of the mean equations. We observe the existence of some significant dynamic relationships between the ETFs. In Panels B we observe that the coefficients in the variance

Table 4
Estimates from the ADCC-GARCH model on Alternative Energy ETFs.

	PZD Coeff.	p-Value	PBW Coeff.	p-Value	FAN Coeff.	p-Value	QCLN Coeff.	p-Value	GEX Coeff.	p-Value
Panel A: Mean equations										
c_i	$5.58 \cdot 10^{-4***}$	(0.00)	$-1.54 \cdot 10^{-4}$	(0.61)	$1.16 \cdot 10^{-4}$	(0.63)	$3.54 \cdot 10^{-4}$	(0.24)	$2.57 \cdot 10^{-4}$	(0.35)
$R_{PZD,\ t-1}$	-0.072^{*}	(0.09)	0.078	(0.22)	0.024	(0.61)	0.106^{*}	(0.07)	0.059	(0.26)
$R_{PBW,\ t-1}$	0.032	(0.30)	-0.150^{***}	(0.00)	0.007	(0.83)	0.001	(0.97)	−0.018	(0.65)
$R_{FAN,\ t-1}$	−0.012	(0.71)	−0.026	(0.54)	-0.096^{**}	(0.01)	−0.067	(0.12)	0.013	(0.73)
$R_{QCLN,\ t-1}$	0.025	(0.50)	0.160^{***}	(0.00)	−0.022	(0.60)	−0.016	(0.77)	0.124^{**}	(0.01)
$R_{GEX,t-1}$	0.034	(0.40)	0.054	(0.36)	0.008^{*}	(0.07)	0.042	(0.48)	-0.130^{**}	(0.01)
Panel B: GARCH parameters										
c_i	$2.13 \cdot 10^{-6***}$	(0.00)	$4.91 \cdot 10^{-6***}$	(0.00)	$3.68 \cdot 10^{-6***}$	(0.00)	$3.24 \cdot 10^{-6***}$	(0.00)	$3.24 \cdot 10^{-6***}$	(0.00)
$\varepsilon^2_{i,t-1}$	0.091^{***}	(0.00)	0.073^{***}	(0.00)	0.099^{***}	(0.00)	0.061^{***}	(0.00)	0.084^{***}	(0.00)
$h^2_{i,t-1}$	0.898^{***}	(0.00)	0.912^{***}	(0.00)	0.888^{***}	(0.00)	0.929^{***}	(0.00)	0.905^{***}	(0.00)
Panel C: ADCC-GARCH persistence parameters										
α	0.039^{***}	(0.00)								
β	0.919^{***}	(0.00)								
γ	0.020^{***}	(0.00)								

This table contains the estimations from the VAR-ADCC-GARCH model. Panel A shows the mean equations for the index returns series (p-values in brackets). Panel B shows the variance equations (p-values in brackets). Panel C reports the persistence parameters of the model.
*** Represents the 1% significance level.
** Represents the 5% significance level.
* Represents the 10% significance level.

equations are significant for the ten ETFs. Moreover, asymmetric dynamic correlations in the markets are supported by the significant coefficients of α, β and γ in Panels C.

Table 5 reports the out-of-sample performance results for the optimal portfolios based on the VAR-ADCC-GARCH approach, excluding and including short-selling constraints, as well as those relating to the naïve strategy which is used as the benchmark. Panels A and B show the results for the minimum variance strategy and those for the mean-variance strategy with the portfolio return constraint of outperforming the naïve portfolio return for the Energy ETFs while Panels C and D report those relating to the Alternative Energy ETFs. Returns, standard deviations and Sharpe ratios are reported in annualized terms.

We can clearly draw three main conclusions from these results. Firstly, most of the proposed strategies provide significant benefits in terms of the Sharpe ratio as compared to the naïve portfolio. Secondly, the performance results are improved when no short-selling constraints are included. Finally, based on the results of the Sharpe ratio, the best strategies are obtained by using the Alternative Energy ETFs. All of them outperform the naïve strategy with positive results, especially the mean variance strategy when no short-selling constraints are included.

The mean portfolio weights for each index following the different procedures are reported in Table 6. The high values of the PZD ETF in all the strategies must be pointed out which makes sense due to its higher mean return and lower standard deviation when compared with the rest of ETFs.

Apparently there is a kind of inconsistency related to the descriptive statistics which suggest that Energy ETFs were better in term of mean (less negative) and standard deviation. However, it must be pointed out that those statistics are referred to the whole sample. Figs. 3 and 4 show the out-of-sample mean returns for each Energy and Alternative ETFs estimated by taking a rolling window of the in-sample size which is 1000 observations (therefore, the initial sample is the in-sample period which covers from June 27, 2008 through April 27, 2012 while the last one covers the period from January 30, 2014 through November 30, 2017). We find that out-of-sample mean returns of Alternative ETFs are mostly positive, without sharp movements which mean low volatilities, while those referred to the Energy ETFs are initially positive but turn sharply to negative values which mean high volatility. Those values are the basis for the out-of-sample one-step-ahead forecasts of returns, volatilities and correlations which are used for estimating the portfolios which returned that Alternative Energy ETFs outperform Energy ETFs.

From the previous results, it seems clear that the suggested procedure yields higher profits when Alternative Energy ETFs are used to estimate the optimal weights. However, the criticism could still remain that these results may be influenced by the sample used for their estimation. At this point, as a kind of test of robustness, most of the empirical evidence divides the sample into two or more subsamples with the aim of testing the suggested procedure in each case, see Galvani and Plourde (2010), Angelidis et al. (2015), Han et al. (2016) and Narayan et al. (2017), among others. However, instead of checking the robustness of our approach by dividing the sample into two or three subsamples we have opted for re-estimating the Sharpe ratio for multiple samples (more than 1300 samples till reach a minimum of 100 observations in a sample). More precisely, we take an initial out-of-sample period from April 30, 2012 through November 30, 2017 (1459 observations). We kept the end of the sample fixed and used a rolling start date (which means that the number of observations is reduced by one for each estimation of the Sharpe ratio). As a result, the values of the Sharpe ratio shown on the left hand side of Figs. 5 to 7 derive from large out-of-sample periods while those on the right are from small out-of-sample periods.

Figs. 5 and 6 show the values of the Sharpe ratio for the naïve and the mean-variance strategies with and without short-selling constraints, respectively, for Alternative Energy and Energy ETFs. The x-axis represents the starting point for estimating the Sharpe ratio while the y-axis shows the annualized value of the Sharpe ratio. Fig. 7 compares the Sharpe ratio for the mean-variance strategy for Alternative Energy ETFs with and without short-selling constraints.

We observe in all cases that the Sharpe ratio values obtained from the mean-variance strategy for the Alternative Energy ETFs always outperform the values of its naïve strategy and mostly those obtained by using Energy ETFs with or without short-selling constraints. Additionally, in Fig. 7 we observe that there is a clear improvement of the performance ratios of the mean-variance strategy without short-selling constraints for Alternative Energy ETFs when compared to the mean-variance strategy with short-selling constraints. For that reason,

Table 5
Out-of-sample performance evaluation.

	Naïve	Short-selling constraints	No short-selling constraints
Energy			
Panel A: minimum variance			
Return	−0.0282	−0.0171	0.0556
SD	0.2051	0.1917	0.2438
Sharpe ratio	−0.1376	−0.0891	0.2280
Panel B: mean-variance (naïve)			
Return	−0.0282	−0.0376	0.1792
SD	0.2051	0.1795	0.2369
Sharpe ratio	−0.1376	−0.2096	0.7565
Alternative Energy			
Panel C: minimum variance			
Return	0.0837	0.0938	0.1168
SD	0.1811	0.1551	0.1576
Sharpe ratio	0.4619	0.6044	0.7407
Panel D: mean-variance (naïve)			
Return	0.0837	0.0853	0.1375
SD	0.1811	0.1579	0.1593
Sharpe ratio	0.4619	0.5405	0.8630

This table contains the out-of-sample performance evaluation of the proposed portfolios based on the annualized mean, annualized standard deviation and annualized Sharpe ratios.

Table 6
Mean daily portfolio weights.

Energy					
	XLE	VDE	IXC	IYE	OIH
Panel A: With short-selling constraints					
Naïve	20%	20%	20%	20%	20%
Minimum variance	25,62%	4,66%	55,09%	12,70%	1,93%
Mean-variance (naïve)	24,99%	7,21%	43,75%	13,62%	3,23%
Panel B: Without short-selling constraints					
Naïve	20%	20%	20%	20%	20%
Minimum variance	102,69%	−31,83%	67,62%	49,24%	−87,85%
Mean-variance (naïve)	105,25%	−29,57%	57,31%	49,65%	−83,03%
Alternative Energy					
	PZD	PBW	FAN	QCLN	GEX
Panel C: With short-selling constraints					
Naïve	20%	20%	20%	20%	20%
Minimum variance	78,27%	1,69%	15,97%	1,23%	2,83%
Mean-variance (naïve)	70,45%	2,17%	17,00%	3,71%	4,89%
Panel D: Without short-selling constraints					
Naïve	20%	20%	20%	20%	20%
Minimum variance	100,62%	−4,60%	17,59%	3,22%	−16,82%
Mean-variance (naïve)	101,73%	−8,85%	16,42%	4,62%	−13,98%

This table contains the mean daily portfolio weights for the naïve strategy (equally weighted) and those obtained from solving the optimization problems when the time-varying returns and volatility forecasts from the VAR-ADCC-GARCH are used.

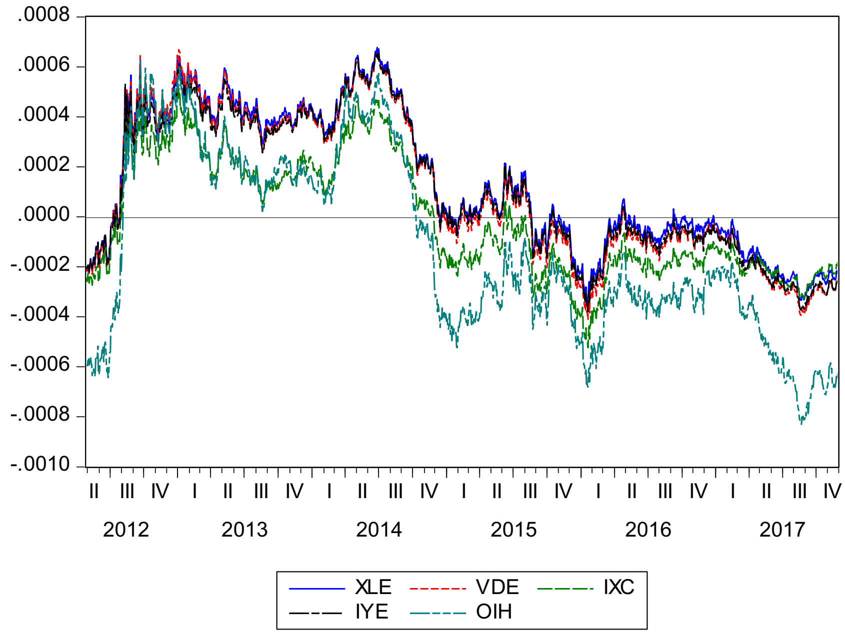

Fig. 3. Energy ETFs out-of-sample mean returns. This figure displays the out-of-sample mean returns for each Energy ETF.

we focus on analyzing the values of Fig. 6 where short-selling are allowed. The initial values of 0.8630 and 0.7565 for the mean variance strategy from the Alternative Energy and Energy ETFs respectively, and 0.4619 for the naïve one corresponds with the Sharpe ratios derived from the mean returns and standard deviation of the whole out-of-sample period. However, if we had chosen an initial in-sample window from August 25, 2011 to June 24, 2015 for our procedure, which coincides with some years of high oil prices that could lead us to avoid the investment in Alternative Energy ETFs, we would obtain the largest difference between the Sharpe ratios from the Mean Variance Alternative Energy strategy and that from its naïve strategy. In that case, the out-of-sample period from June 25, 2015 to November 30, 2017 (first vertical line) leads us to obtain a Sharpe ratio of 1.4385 for the mean variance strategy and 0.0988 for the naïve one. We can also observe that the Sharpe ratio from the Mean Variance Energy ETFs strategy is lower (1.2503) than that obtained from using Alternative Energy ETFs. A similar situation is obtained for an in-sample of low oil prices (September 26, 2012 to July 26, 2016). At that point, from the out-of-sample period (July 27, 2016 to November 30, 2017, second vertical line) we obtain a Sharpe ratio of 2.6067 for the mean variance strategy using Alternative ETFs, 0.7046 using Energy ETFs, and 1.3966 for the naïve strategy using Alternative ETFs. That means that Alternative Energy ETFs are highly profitable in any economic context.

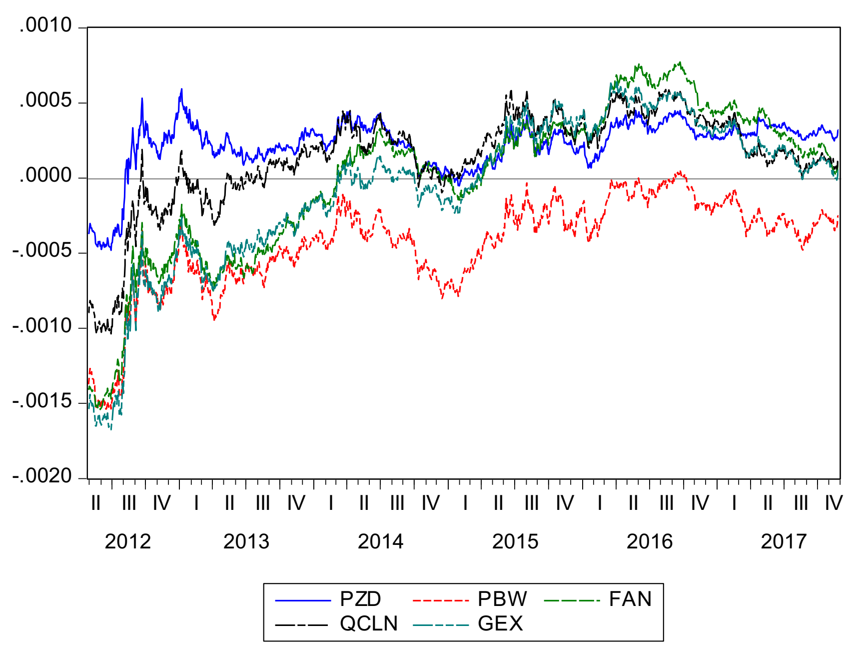

Fig. 4. Alternative Energy ETFs out-of-sample mean returns. This figure displays the out-of-sample mean returns for each Alternative Energy ETF.

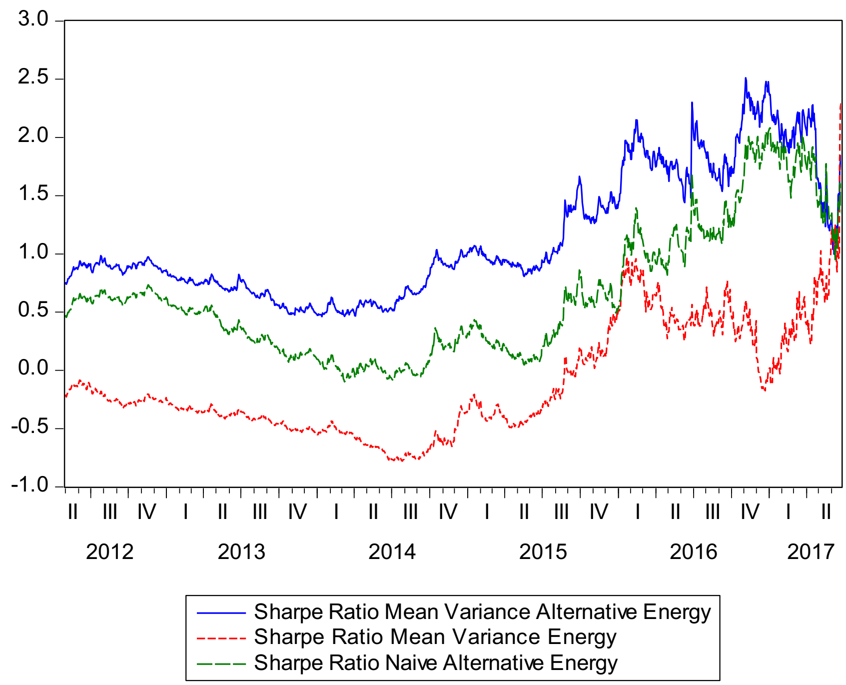

Fig. 5. Evolution of the Sharpe ratios (no short-sellings). This figure displays the annualized Sharpe ratios estimated for different samples over the out-of-sample period for the naïve rule and the Mean-Variance (Naive) strategy based on the use of return and volatility forecasts obtained from a VAR-ADCC-GARCH model.

These results are consistent with those reported by Tsai and Swanson (2009), Huang and Lin (2011), Miralles-Marcelo et al. (2015) and Miralles-Quiros and Miralles-Quiros (2017) who have shown the benefits of diversification in stock markets. Therefore, we confirm that it is possible to outperform the naïve diversification strategy when we construct optimal portfolios which include an accurate prediction of the vector of expected returns and the covariance matrix in the optimization problem. Some explanations could be argued to explain the results that are suitable of being analyzed in future papers. Firstly, the better performance of Alternative Energy ETFs may be due to the fact that Alternative Energy ETFs mostly hold a diverse portfolio of companies worldwide while Energy ETFs are focused on the US market. Secondly, it should also be mentioned that the ongoing transition from fossil fuels to alternative energy sources has been heavily subsidized, and therefore caution should be taken in the future when alternative energies are supported with fewer, or even without any, subsidies.

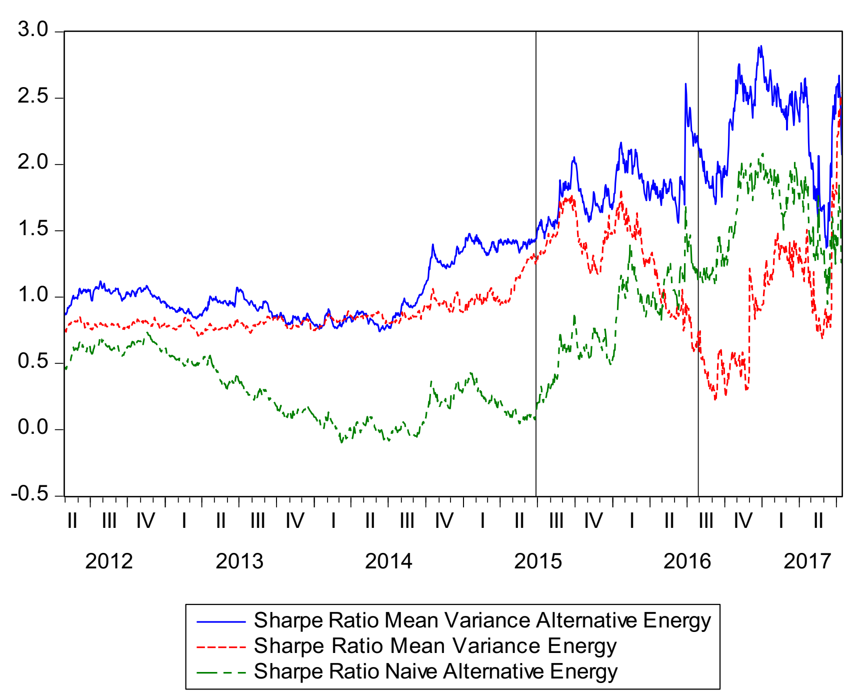

Fig. 6. Evolution of the Sharpe ratios (short-sellings allowed). This figure displays the annualized Sharpe ratios estimated for different samples over the out-of-sample period for the naïve rule and the Mean-Variance (Naive) strategy based on the use of return and volatility forecasts obtained from a VAR-ADCC-GARCH model.

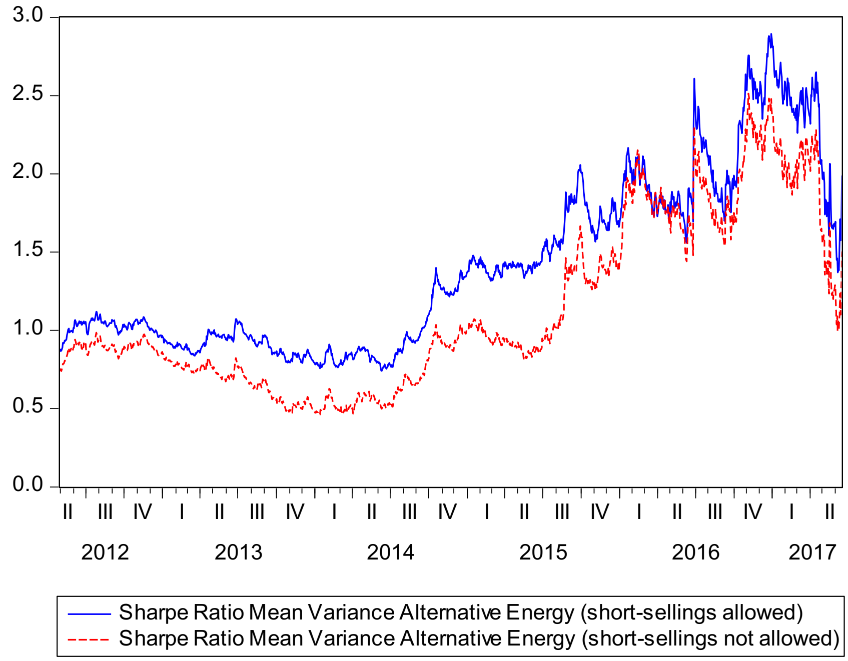

Fig. 7. Evolution of the Sharpe ratios for Alternative Energy. This figure displays the annualized Sharpe ratios estimated for different samples over the out-of-sample period for the naïve rule and the Mean-Variance (Naive) strategy based on the use of return and volatility forecasts obtained from a VAR-ADCC-GARCH model.

5. Conclusions

The objective of this article has been to enhance the evidence on the benefits for investors of using Alternative Energy ETFs. From the analysis of the out-of-sample performance of different portfolio strategies using the returns and volatility forecasts from a VAR-ADCC-GARCH approach, we show that it is possible to obtain profits from diversification since most of the strategies outperformed the naïve rule. However, the most important finding is the fact that investments in Alternative Energy ETFs significantly outperform the naïve strategy but also the Energy ETFs performance. It is also shown that this better performance is maintained for many out-of-samples, including those whose their in-sample periods coincide with high oil and gas prices. Therefore, we conclude that Alternative Energy ETFs are a real alternative for investors who want to obtain significant profits for their investments.

These findings are relevant not only for academics but also for active professional managers who can use this technique to add value to their international diversification strategies. Moreover, it may prove interesting in future research to investigate the robustness of our findings for alternative investment purposes such as hedging strategies.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.12.008.

References

Angelidis, T., Sakkas, A., Tessaromatis, N., 2015. Stock market dispersion, the business cycle and expected factor returns. J. Bank. Financ. 59, 265–279. https://doi.org/10.1016/j.jbankfin.2015.04.025.
Badshah, I.U., 2018. Volatility spillover from the fear index to developed and emerging markets. Emerg. Mark. Financ. Trade 54 (1), 27–40. https://doi.org/10.1080/1540496X.2016.1220294.
Beber, A., Pagano, M., 2013. Short-selling bans around the world: evidence from the 2007–09 crisis. J. Financ. 68, 343–381. https://doi.org/10.1111/j.1540-6261.2012.01802.x.
Bohl, M.T., Reher, G., Wilfling, B., 2016. Short selling constraints and stock returns volatility: empirical evidence from the German stock market. Econ. Model. 58, 159–166. https://doi.org/10.1016/j.econmod.2016.05.025.
Bollen, N.P.B., Busse, J.A., 2001. On the timing ability of mutual fund managers. J. Financ. 56 (3), 1075–1094. https://doi.org/10.1111/0022-1082.00356.
Boubaker, H., Sghaier, N., 2013. Portfolio optimization in the presence of dependent financial returns with long memory: a copula based approach. J. Bank. Financ. 37, 361–377. https://doi.org/10.1016/j.jbankfin.2012.09.006.
Cappiello, L., Engle, R.F., Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. J. Financ. Economet. 4 (4), 537–572. https://doi.org/10.1093/jjfinec/nbl005.
Carhart, M.M., 1996. On the persistence in mutual fund performance. J. Financ. 52 (1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x.
Chang, C., McAleer, M., Tansuchat, R., 2011. Crude oil hedging strategies using dynamic multivariate GARCH. Energy Econ. 33, 912–923. https://doi.org/10.1016/j.eneco.2011.01.009.
Diether, K.B., Lee, J., Werner, J., 2009. It's SHO time! Short-sale price tests and market quality. J. Financ. 64, 37–73. https://www.jstor.org/stable/20487963.
Efimova, O., Serletis, A., 2014. Energy markets volatility modelling using GARCH. Energy Econ. 43, 264–273. https://doi.org/10.1016/j.eneco.2014.02.018.
Ewing, B.T., Malik, F., 2005. Re-examining the asymmetric predictability of conditional variances: the role of sudden changes in variance. J. Bank. Financ. 29, 2655–2673. https://doi.org/10.1016/j.jbankfin.2004.10.002.
Fama, E., French, K.R., 1993. Common risk factors in the returns of stocks and bonds. J. Financ. Econ. 33 (1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5.
Galvani, V., Plourde, A., 2010. Portfolio diversification in energy markets. Energy Econ. 32, 257–268. https://doi.org/10.1016/j.eneco.2009.05.015.
Grullon, G., Michenaud, S., Weston, J.P., 2015. The real effects of short-selling constraints. Rev. Financ. Stud. 28 (6), 1737–1767. https://doi.org/10.1093/rfs/hhv013.
Gupta, R., Donleavy, G.D., 2009. Benefits of diversifying investments into emerging markets with time-varying correlations: an Australian perspective. J. Mult. Financ. Manag. 19, 160–177. https://doi.org/10.1016/j.mulfin.2008.10.001.
Han, Y., Hu, T., Yang, J., 2016. Are there exploitable trends in commodity futures prices. J. Bank. Financ. 70, 214–234. https://doi.org/10.1016/j.jbankfin.2016.04.013.
Henriques, I., Sadorsky, P., 2008. Oil prices and the stock prices of alternative energy companies. Energy Econ. 30, 998–1010. https://doi.org/10.1016/j.eneco.2007.11.001.
Huang, M.Y., Lin, J.B., 2011. Do ETFs provide effective international diversification? Res. Int. Bus. Financ. 25, 335–344. https://doi.org/10.1016/j.ribaf.2011.03.003.
Inchauspe, J., Ripple, R.D., Trück, S., 2015. The dynamics of returns on renewable energy companies: a state-space approach. Energy Econ. 48, 325–335. https://doi.org/10.1016/j.eneco.2014.11.013.
Kalotychou, E., Staikouras, S.K., Zhao, G., 2014. The role of correlation dynamics in sector allocation. J. Bank. Financ. 48, 1–12. https://doi.org/10.1016/j.jbankfin.2014.06.025.
Kyritsis, E., Serletis, A., 2018. The zero lower bound and market spillovers: evidence from the G7 and Norway. Res. Int. Bus. Financ. 44, 100–123. https://doi.org/10.1016/j.ribaf.2017.05.015.
Lin, B., Wesseh Jr., P.K., Appiah, M.O., 2014. Oil price fluctuation, volatility spillover and the Ghanaian equity market: implication for portfolio management and hedging effectiveness. Energy Econ. 42, 172–182. https://doi.org/10.1016/j.eneco.2013.12.017.
Maghyereh, A.I., Awartani, B., Tziogkidis, P., 2017. Volatility spillovers and cross-hedging between gold, oil and equities: evidence from the Gulf Cooperation Council countries. Energy Econ. 68, 440–453. https://doi.org/10.1016/j.eneco.2017.10.025.
Markowitz, H.M., 1952. Portfolio selection. J. Financ. 7, 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x.

Miralles-Marcelo, J.L., Miralles-Quiros, J.L., Miralles-Quiros, M.M., 2013. Multivariate GARCH models and risk minimizing portfolios: the importance of medium and small firms. Span. Rev. Financ. Econ. 11 (1), 29–38. https://doi.org/10.1016/j.srfe.2013.03.001.
Miralles-Marcelo, J.L., Miralles-Quiros, M.M., Miralles-Quiros, J.L., 2015. Improving international diversification benefits for US investors. N. Am. J. Econ. Financ. 32, 64–76. https://doi.org/10.1016/j.najef.2015.01.005.
Miralles-Quiros, M.M., Miralles-Quiros, J.L., 2017. The role of time-varying return forecasts for improving international diversification benefits. Int. J. Financ. Econ. 22, 201–215. https://doi.org/10.1002/ijfe.1578.
Mollick, A.V., Assefa, T.A., 2013. U.S. stock returns and oil prices: the tale from daily data and the 2008–2009 financial crisis. Energy Econ. 36, 1–18. https://doi.org/10.1016/j.eneco.2012.11.021.
Narayan, P.K., Phan, D.H.B., Bannigidadmath, D., 2017. Is the profitability of Indian stocks compensation for risk? Emerg. Mark. Rev. 31, 47–64. https://doi.org/10.1016/j.ememar.2017.02.001.
Omar, A.M.A., Wisniewski, T.P., Nolte, S., 2017. Diversifying away the risk of war and cross-border political crisis. Energy Econ. 64, 494–510. https://doi.org/10.1016/j.eneco.2016.02.015.
Reboredo, J.C., Quintela, M., Otero, L.A., 2017. Do investors pay a premium for going green? Evidence from alternative energy mutual funds. Renew. Sust. Energ. Rev. 73, 512–520. https://doi.org/10.1016/j.rser.2017.01.158.
Rezec, M., Scholtens, B., 2017. Financing energy transformation: the role of renewable energy equity indices. Int. J. Green Energy 14 (4), 368–378. https://doi.org/10.1080/15435075.2016.1261704.
Sadorsky, P., 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ. 34, 248–255. https://doi.org/10.1016/j.eneco.2011.03.006.
Schüler, M., Schröder, M., 2003. Systemic risk in European banking: evidence from bivariate GARCH models. ZEW Discussion Papers, No. 03-11 ftp://ftp.zew.de/pub/zew-docs/dp/dp0311.pdf.
Silva, F., Cortez, M.C., 2016. The performance of US and European green funds in different market conditions. J. Clean. Prod. 135, 558–566. https://doi.org/10.1016/j.jclepro.2016.06.112.
Tsai, P., Swanson, P.E., 2009. The comparative role of iShares and country funds in internationally diversified portfolios. J. Econ. Bus. 61, 472–494. https://doi.org/10.1016/j.jeconbus.2009.06.003.
Weiss, A., 1986. Asymptotic theory for ARCH models: estimation and testing. Economet. Theor. 2, 107–131. https://www.jstor.org/stable/3532216.
Yuan, T., Gupta, R., Roca, E., 2016. Why not diversify into emerging equity markets via ADRs? J. Invest. 25 (2), 18–27. https://doi.org/10.3905/joi.2016.25.2.018.
Zhou, J., Nicholson, J.R., 2015. Economic value of modeling covariance asymmetry for mixed-asset portfolio diversifications. Econ. Model. 45, 14–21. https://doi.org/10.1016/j.econmod.2014.10.054.