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Energy Market Investment Methodologies

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Abstract

As more and more renewable energy market investment opportunities come to the fore, investors intend to optimize their assets through risk-return diversification. In the light of Markowitz's modern portfolio theory aimed at recognizing the potential for higher returns and lower risks, the identification of different energy market segments has become essential. In this regard, through the research of the conventional and alternative/ renewable energy market segments, as well as various international statistical models, the optimal methodology was identified. The optimal methodology allows the aggregation of different energy and alternative/ renewable energy ETFs into international investment portfolios using a variable weighing of assets and is expected to result in an adequate outcome.

Keywords: Energy Market, Investment, ETF, Alternative/ Renewable

Introduction

In the light of the international energy trends and climate policy measures, a new emerging paradigm started to exert its effect on the economy. The so-called sustainability idea ringed over all areas of the economy. Due to the actions aimed at the reduction of CO_2 emissions, acceleration of renewable energy deployment and energy efficiency, new capital market investing opportunities appeared in recent years (Reboredo et al., 2017; Rezec & Scholtens, 2017; Sadorsky, 2012; Silva & Cortez, 2016). As a result of the paradigm shift in widespread financial trends, green financing or the so-called socially responsible investment (SRI) took over the place of traditional investments and subsequently affected investments in the electricity, gas, oil,

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and alternative energy sectors. The declining popularity of fossil energy use and the global aim to reduce CO_2 emissions have led to the use of innovative technologies in both developed and emerging countries for the exploration and development of conventional energy oil and gas reserves, oil refining, and gas drilling. On the other hand, the new trends have brought a shift towards the introduction of sustainable energy initiatives, which have resulted in significant advances in alternative energy production, storage, and efficiency development. Due to technological advancements, more feasible alternative power generations methods have been developed. The global sustainability objectives led to greater incentives for renewables, and the alternative/ renewable energy sector became an attractive investment branch in the capital markets.

Through the dynamic evolution of the international energy trends and climate policy measures, the alternative/ renewable energy sector underwent a fast growth over the last decades and is expected to continue this accelerated pace. Respectively, the expanded global investment market with the new green energy opportunities has now become a priority research field. Besides the conventional energy commodities and financial instruments, alternative and renewable energy-related stocks, futures, options, and exchange-traded funds (hereinafter mentioned as ETFs) have aroused more and more individual and institutional investors' interest due to their risk-return diversification potential. In recent years, several studies based on modern portfolio theory demonstrated the raison d'être of diversification. The modern portfolio theory approved the benefits of diversification through a wide range of investment opportunities, illustrating the potential for higher returns and lower risks (Markowitz, 1952). Through their investments, international investors can participate directly in the economic development of other countries, offset exchange rate risk in their investments, reap the benefits of diversification, and take advantage of opportunities offered by global market segmentation. Despite the many proven benefits of portfolio diversification, the risks and conditions of international portfolio investments arose. International capital investments proved to be risky, not only because of their exposure to exchange rate and political risk but also because of many institutional exposures and obstacles, as well as tax issues. To overcome these barriers of various natures, several international statistical models have been introduced, allowing market segmentation to be exploited.

Objectives

The main objective of this paper is to explore the methodology used to present the investment opportunities offered by the conventional and alternative/ renewable energy market segments. The conventional energy sector encompasses gas and oil, while the alternative energy sector

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encompasses wind, solar, geothermal, biomass, biofuels, hydro, wave, and tidal energies on their portfolios.

Furthermore, there was an introduction to the alternative/ renewable energy market segment into the concept of investment portfolio diversification, which in contrary to the conventional energy market segment, is unknown to the wider public.

To identify the differences between the two energy market segments, conventional and alternative/ renewable ETFs will be used as investing instruments. The reason ETFs was chosen is because ETFs are passive investment tools just like equities with the difference that ETFs can reflect more of the performance of an entire sector or a market benchmark. There are thousands of index-tracking and capital market sector ETFs that broaden the concept of investment diversification by adapting to asset allocation needs. Consequently, instead of using stock market index investments which are sometimes unavailable to some, as used in previous studies, research can be expected to have broader implications by using ETFs that are predictable for all individual and institutional investors.

In parallel with the above objectives, this study plan to later incorporate the conclusions of this paper into a larger energy market research of a wide range of investment opportunities in light of the theoretical and practical application of modern portfolio theory. After presenting the concepts on a theoretical level, this study further intend to explore the investment potential of conventional and alternative/ renewable energy markets, influenced by higher returns and lower risks, using Markowitz's modern portfolio theory.

Exchange Traded Funds (ETFs)

From the analysis of the previous empirical literature aimed at exploring the optimal methodology to present the investment opportunities of the conventional and alternative/ renewable energy market segments, this paper focuses on examining different multivariate volatility and linear regression models. To make the models result in comprehensive outcomes in terms of finding the optimal energy market investment opportunity, ten energy ETFs (five conventional and five alternative/ renewable energy ETFs) was applied as financial market instruments.

ETFs were chosen as financial market instruments due to several reasons. First of all, ETFs are the latest innovative indirect global investment vehicles in the capital market that proved to be beneficial investment concepts in terms of risk diversification, liquidity, and rational cost-sharing. Various ETFs provide good chances for risk-return optimization through the potentially lower risk they offer. On the other hand, ETFs are open-ended investment funds with a diversified equity portfolio, which are subject to stock

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exchange trading regulation. The investment value of ETFs, similarly to that of mutual funds, is based on equity holdings, given the difference that the latter are priced once a day, while the former are priced several times during the day. ETFs, in contrast to mutual funds, generally charge lower fees and offer more liquidity, transparency, and tax efficiency. ETFs follow a benchmark index and allow trading at a price set by the market. The value of an ETF, similarly to that of other financial instruments, is determined by supply and demand. Concerning conventional energy ETFs, it should be noted that global energy supply and demand greatly affect the performance of the sector and are not static. Oil and gas producers generally perform better when oil and gas prices are high and, consequently, their performance declines when the value of the product also declines. When crude oil prices fall, oil refineries benefit from declining raw material costs for the production of petroleum products such as gasoline. This attribution thus makes the traditional energy sector more sensitive to policies that often cause changes in oil prices.

ETFs and equities present a similar picture in terms of stock exchange trading and therefore contribute greatly to the real-time exploitation of diverse investment market developments. For specific energy and alternative/ renewable energy ETFs, corporate activity is divided into a wide range of types, regions, and risk profiles. For ETFs, both conservative and aggressive investment strategies are possible. ETFs, unlike mutual funds, allow the use of short-selling and margin trading strategies. However, the review of the ETF‘s composition is highly recommended especially in the case of volatile markets such as energy. Any special sector-based ETF, such as energy, can add volatility to a portfolio. It is worth being careful as many alternative/ renewable energy companies in the industry are still considered risky investments in their category.

Literature Review

A typical periodic portfolio selection problem was originally formulated during a non-linear double-criteria system optimization process, taking into account maximizing expected return and minimizing risk (Markowitz, 1952).

The Capital Asset Pricing Model (hereinafter mentioned as CAPM) was developed as a follow-up to Markowitz’s portfolio model based on the largest capital markets. The purpose of the CAPM is to analyze the pricing of financial instruments available on the international capital markets. In the case of integrated capital markets, optimal diversification is obtained through the creation of an international portfolio of financial instruments in which all the risks associated with the assets are taken into account. Consequently, the rethought model is the International Capital Asset Pricing Model (hereinafter

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mentioned as ICAPM), and is formulated by Bartram and Dufey (2001) as follows:

$$E[R_i] = R_F + \beta^w{}_i RP^w + \sum_{K=1}^{K} \gamma_{ik} RP_k \qquad (1)$$

In ICAPM, RP^w and RP_k are the risk premiums of the international portfolio and exchange rate, while R_F is the risk-free rate. The model is based on the assumption that national risk and return influence the investment decision. In an international context, not only the risk associated with the portfolio's assets but also the exchange rate risk must be taken into account when creating the investment portfolio.

However, in the case of ICAPM, the mean-variance efficiency of all assets cannot be determined automatically. Deviations from PPPs pose a real exchange rate risk, so a common risk-free rate does not exist in reality. In the case of national capital markets, value-weighted portfolios are often used as benchmarks, but the use of value-weighting in an international context is a more complex issue. Appropriate weighting of volatility clusters and returns, over time, is closely related to the concepts of asset allocation and active portfolio management (Brinson et al., 1991). Asset allocation and active portfolio management require restoring the balance of the existing portfolio in order to continuously improve the performance of the managed portfolio while adapting to specific market conditions. International capital markets are segmented, investors have different risk preferences, and expected risk and return change over time. So it is a question of which international benchmark should be applied as the international portfolio is created based on the individual market capitalization, thus its mean-variance is inefficient (Solnik & Noetzlin, 1982).

Multiple complex investment models were developed to adapt more to the international environment. Theoreticians have created approaches based on the assumption that the homogeneity of investor preferences does not necessarily prevail internationally. In addition, they expanded categories of financial assets used in the models. As a result, the role of the risk premium and investor wealth in asset pricing strengthened in the segmented capital markets.

While the equity's constant value parameters, such as the expected returns and variance, determined the traditional CAPM, more and more evidence pointed out that these factors are time-dependent. Therefore, in order to measure the temporary changes, the expected return, and the variance, they introduced the so-called conditional models. In the case of the Autoregressive Conditional Heteroskedasticity Model (hereinafter mentioned as ARCH model), the variation of financial returns was demonstrated to be not constant

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over time, but autocorrelated or conditional to/ dependent on each other. In other words, the ARCH process explicitly recognized the difference between the unconditional and the conditional variance allowing the latter to change over time as a function of past errors. Stock returns are typical examples of autocorrelated financial returns, where periods of return volatility tend to be clustered together. In the ARCH, the weighted mean square of the estimated margin of error became the conditional variance. To model a time series using an ARCH process, let ε_t denote the error terms (return residuals, with respect to a mean process), i.e., the series terms. These ε_t are split into a stochastic piece z_t and a time-dependent standard deviation σ_t characterizing the typical size of the terms so that

(2) $$\varepsilon_t = \sigma_t z_t$$

The random variable z_t is a strong white noise process. The series σ^2_t modeled by

(3) $$\sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \ldots + \alpha_q \varepsilon^2_{t-q} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i},$$

where $\alpha_0 > 0$ and $\alpha_i \geq 0, i > 0.$

An ARCH(q) model can be estimated using ordinary least squares. A methodology to test for the lag length of ARCH errors using the Lagrange multiplier test was proposed. During the process, the best fitting autoregressive model $AR(q)y_t$ is estimated as follows:

(4) $$AR(q)y_t = \alpha_0 + \alpha_1 y_{t-1} + \ldots + \alpha_q y_{t-q} + \varepsilon_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i y_{t-i} + \varepsilon_t$$

The squares of the error $\hat{\varepsilon}^2$ are obtained and regressed on a constant and q lagged values as follows:

(5) $$\hat{\varepsilon}^2_t = \hat{\alpha}_0 + \sum_{i=1}^{q} \hat{\alpha}_i \hat{\varepsilon}^2_{t-i}$$

where q is the length of ARCH lags.

The null hypothesis, in the absence of ARCH components, is given as $\alpha_i = 0$ for all $i = 1, \ldots , q$. The alternative hypothesis is that, in the presence of ARCH components, at least one of the estimated α_i coefficients must be significant. In a sample of T residuals under the null hypothesis of no ARCH errors, the

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test statistic $T'R^2$ follows X^2 distribution with q degrees of freedom, where T' is the number of equations in the model which fits the residuals vs the lags (i.e. $T'=T-q$). If $T'R^2$ is greater than the Chi-square table value, the null hypothesis is *rejected* and it is concluded that there is an ARCH effect in the autoregressive-moving-average or the so-called ARMA model. If $T'R^2$ is smaller than the Chi-square table value, the null hypothesis is not rejected.

If an Autoregressive Moving Average model (ARMA) is assumed for the error variance, the model is a Generalized Autoregressive Conditional Heteroskedasticity (hereinafter: GARCH) model. In that case, the GARCH *(p, q)* model (where p is the order of the GARCH terms σ^2 and q is the order of the ARCH terms ε^2), following the notation of the original paper, is given by:

(6)
$$y_t = x`_t b + \varepsilon_t$$
$$\varepsilon_t | \Psi_{t-1} \sim N(0, \sigma^2_t)$$

(7)
$$\sigma^2_t = w + \alpha_1 \varepsilon^2_{t-1} + \ldots + \alpha_q \varepsilon^2_{t-q} + \beta_1 \sigma^2_{t-1} + \ldots + \beta_p \sigma^2_{t-p} = w + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2_{t-i}$$

Generally, when testing for heteroskedasticity in econometric models, the best test is the White test. However, when dealing with time series data, this means to test for ARCH and GARCH errors. Exponentially Weighted Moving Average (EWMA) is an alternative model in a separate class of exponential smoothing models. As an alternative to GARCH modelling, it has some attractive properties such as a greater weight upon more recent observations, and also drawbacks such as an arbitrary decay factor that introduces subjectivity into the estimation.

The original GARCH model is formulated as shown below:

(8) *Conditional mean:*
$$y_t = E(y_t | \Omega_{t-1}) + \varepsilon_t$$

(9) *Conditional variance:*
$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j}$$

where $\varepsilon_t = \sqrt{h_t} v_t$ is the residuals; v_t is the innovation; $v_t \sim I.\ I.\ D.$,which follows $E(v_t) = 0$, $E(v^2_t) = 1$. $E(y_t | \Omega_{t-1})$ is the expectation taking into account the information set, Ω_{t-1}, dated $t-1$ and earlier. Non-negative integers, p and q, are the order of the variance equation, and $\alpha_0 > 0$, $\alpha_i \geq 0$, $(i = 1, 2, \cdots q)$; $\beta_j \geq 0$, $(j = 1, 2 \cdots p)$, respectively.

Since the introduction of the extension of the ARCH, or the generalized ARCH, also known as GARCH model, developed by Bollersev in 1986, that incorporates a moving average component together with the autoregressive component, many variations of GARCH have emerged. An example is the Nonlinear GARCH (NGARCH), which addresses correlation and observes the volatility clustering of returns, or the Integrated GARCH (IGARCH), which restricts the volatility parameter. The introduction of a moving average component allows the methodology to both model the conditional change in variance over time as well as changes in the time-dependent variance. Examples include conditional increases and decreases in variance. All GARCH model variations seek to incorporate the direction of returns (positive or negative) in addition to the magnitude (addressed in the original model). Each derivation of GARCH can be used to accommodate the specific qualities of the stock, industry, or economic data. In assessing risk, financial institutions incorporate GARCH models into their Value-at-Risk (VAR), maximum expected loss (whether for a single investment or trading position, portfolio, or at a division or firm-wide level) over a specified time period projections. GARCH models are viewed to provide better gauges of risk than can be obtained through tracking standard deviation alone.

In the case of the GARCH model, the conditional variance depends on the past error limit and the conditional variances. In the case of the GARCH model, the so-called structure-volatility estimates converge to the average volatility over the long run, and GARCH parameters can be optimally determined, so GARCH covariance matrices represent time-varying volatilities, and multivariate return distributions without bias (Xinodas et al., 2018).

Based on the available empirical literature, two methods of energy market analysis stand out. Using different multivariate volatility models, several authors have examined the optimal margin allocation and portfolio weighting options for two selected asset prices, such as crude oil spot and futures asset prices or oil and clean energy company share price (Sadorsky, 2012). Other authors examined the intermittent co-movement of the oil and renewable energy markets with continuous wavelet analysis and nonlinear Granger casuality. The analysis revealed that non-linear causality moves from clean energy indices to oil prices. On the other hand, other literature examined spill-over processes and interactions between energy and other markets and explored new dynamic correlations and margin-sharing opportunities to identify volatility correlations that fundamentally determine portfolio management (Henriques & Sadorsky, 2008).

Malinda and Jo-Hui (2016) proved that asset price returns are characterized by long-term memory and asymmetry in both conventional and alternative/ renewable ETFs, while there is a strong relationship between financial performance and other exogenous factors in renewable energy stocks.

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Several authors explored renewable energy performance using other linear regression models (Silva & Cortez, 2016). Others developed their linear regression models underpinning the methodology of alternative energy research based on risk factors (Fama & French, 1993). Each of the listed studies leads to the conclusion that the performance of renewable energies is significantly lower than the benchmark. Therefore the range of alternative and renewable energy investment opportunities is not very attractive. However, in contrast to the studies listed above, few authors proved that the potential for alternative energy ETF investments in renewable energy is real (Miralles-Marcelo et al., 2018). It was demonstrated that the VAR-ADCC-GARCH approach allows the analysis of the non-sample performance of different portfolio strategies by using estimated returns and volatilities. The VAR-ADCC-GARCH approach thus proved to offer real diversification opportunities that lead to higher returns.

The aim of the research is to create and analyze alternative investment strategies using out-of-sample estimated returns, volatilities, and covariances. Thus, the multivariate GARCH model proved to be feasible. Using the Asymmetric Dynamic Conditional Correlation (ADCC) model, Cappiello et al. (2006), Gupta ls Donleavy (2009), Kalotychou et al. (2014), Zhou and Nicholson (2015), Yuan et al. (2016), and Badshah (2018) demonstrated that the covariance asymmetry of the ADCC model contributes greatly to the economic value of the model through rapid, positive reversal of the correlation between conditional volatility, and financial returns after negative return-generation.

In order to improve the available literature, this paper uses the predictions of multivariate GARCH models such as DCC-GARCH models to study time-varying correlations and dynamic spill-over effects. This study aims to create an optimal portfolio by which it can easily compare the alternative and conventional energy sector performance rates. Consequently, in order to obtain well-grounded, practical predictions of returns, volatility and correlations based on the VAR-ADCC methodology, this paper decided to research alternative energy sector investment opportunities. In this analysis, four different investment strategies was constructed and applied through minimum and mean-variance optimization. The main objective was to compare the performance of five conventional energy and five alternative/ renewable energy ETFs.

The VAR-ADCC Approach

This paper aims to explore the methodology to present the investment opportunities of conventional on one hand and alternative/ renewable energy market segments on the other. Furthermore, the objective is to analyze the

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alternative investment strategies using out-of-sample forecasted returns, volatilities, and covariances obtained from a multivariate GARCH approach. Due to the above presented empirical literature, the Asymmetric Dynamic Conditional Correlation GARCH model (hereinafter mentioned as ADCC GARCH model) was selected. The ADCC GARCH model demonstrates the covariance asymmetry of such investment opportunities the best 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 Garch models have been proven reliable during different market conditions, especially during the periods leading up to and after the 2007 financial crisis.

The VAR Asymmetric Dynamic Conditional Correlation model (hereinafter mentioned as VAR-ADCC GARCH model) estimation is performed using a two-step approach. Firstly, a VAR-GARCH model for each time series is estimated. Specifying the correct mean equation in the model is crucial because its misspecification may lead to an incorrect estimation of the variance equation. Thus, the return generating process is conceptualized as:

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

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

where $r_{i,t}$ are the daily returns for the ETFs, ci and αij 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 H_t. It is important that from each model, the conditional variances h_{it}, and the standardized residuals $\delta_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$, are generated separately. More precisely, the conditional covariance matrix is specified as:

(11) $$H_t = D_t R_t D_t$$

where $D_t \frac{1}{4}\, diag(\sqrt{h_{it}})$, is a diagonal matrix which contains the time-varying conditional volatilities of the previous GARCH models and R_t is a time-varying 3 × 3 correlation matrix with diagonal elements equal to 1 which is specified as:

(12) $$R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1}$$

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

(13) $$Q_t = (1\text{-}\alpha\text{-}\beta) - \gamma + \alpha(\delta_{t-1}\delta'_{t-1}) + \gamma\eta_{t-1}\eta'_{t-1} + \beta Q_{t-1}$$

$= E[\delta_t\delta'_t]$ is the unconditional correlation matrix of the standardized residuals; $Q_t^* = diag(\sqrt{q_{ij,t}})$ is a diagonal matrix containing the square root of the diagonal elements of the n × 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 $= [\eta_t\eta'_t]$. Positive definiteness of Q_t is ensured by imposing $\alpha + \beta + \lambda\gamma < 1$, where λ ¼ maximum eigenvalue $\lambda = [\ ^{-1/\ 2-1/2}]$.

Investment Strategies

With the help of the forecasted returns, volatilities and correlations from the previous model, four investment strategies was constructed 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:

(14) $$\min_{w_t} \quad w'_t H_{t+1|t} w_t$$

where $w'_t H_{t+1|t} w_t$ is the portfolio risk equation to be minimized. Following this strategy, the investor is exclusively interested in minimizing volatility. However, it should be noted that this is not true in real life because investors are usually interested in obtaining profits from their investments. Meanwhile, the second optimization problem is the classic mean-variance strategy. 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:

(15) $$\min_{w_t} \quad w'_t H_{t+1|t} w_t$$

$$s.t. \quad w'_t E\{R_{t+1}\} \geq R^*$$

where R^* denotes the desired target return performance. This study uses the equally weighted portfolio, also known as the naïve portfolio, as the benchmark for R^*. Portfolios can be created with or without short-selling constraints. Initially, the optimization problem will be solved by excluding short-selling. Therefore, the general constraints $w'_t 1 = 1$ $w_i \geq 0$ $i = 1, 2, \cdots, N$

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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 (Diether et al., 2009; Beber & Pagano, 2013; Omar et al., 2017), but the effects remain unclear. At this point, the findings of Bohl et al. (2016) should be considered as well. These authors found econometric evidence that the financial crisis was accompanied by an increase in volatility persistence and that this effect is particularly pronounced for those stocks that were subject to short-selling constraints. For that reason, it is also stated that the regulators should avoid imposing short-selling restrictions. The optimization problems not excluding the short-selling constraints should also be solved. In that case, only the constraints $w'_t1 = 1$ $i=1, 2, \ldots, N$ 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, the performance of the optimization frameworks over the out of sample period $t = \tau + 1, \ldots, T$ can be evaluated in terms of the Sharpe ratio SR_p which is defined as the average out-of-sample returns divided by their sample standard deviation:

(16) $$SR_p = / \sigma_p$$

Database

The data used in this paper will be daily returns from January 1st 2010 through January 1st 2020 (by applying the usable observations) of ten ETFs, five Energy ETFs, and five Alternative Energy ETFs. A period of prosperity and development was chosen right after the economic crisis of 2007–2008 and just before the outbreak of the coronavirus pandemic that turned out to be only the origo point of an economically less stable period.

Furthermore, daily returns were used for a variable of reasons. For the VAR-ADCC GARCH methodology to work, the time series that is the best autocorrelated and predictable was found. Several studies that provided a wide range of results on the autocorrelation of stock returns were analyzed. First, Campbell et al. (1997) proved that significant positive autocorrelation exist for daily, weekly, and monthly stock index returns calculated from the CRSP database, but with the autocorrelation slightly stronger for daily data. Lo and MacKinlay (1990) further connected the positive autocorrelation in daily stock returns to nonsynchronous trading. However, Lewellen (2002) demonstrated momentum and autocorrelation of stock returns with monthly data from CRSP and reported negative autocorrelation, although the correlation was generally

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weak. On the other hand, daily stock market returns in stock markets turned out to be autocorrelated and not equal. Louhelainen (2005) tested the predictability of daily returns from the previous weekday's returns with the Periodic Autoregressive (PAR) model and proved that at least some weekday returns are periodically predicted. Consequently, daily returns in the model were used as the best autocorrelated and predictable time series.

The five Energy ETFs are Energy Select Sector SPDR (XLE), Vanguard Energy ETF (VDE), SPDR S&P Oil & Gas Exploration & Production ETF (XOP), iShares Global Energy ETF (IXC), VanEck Vectors Oil Services ETF (OIH). The five Alternative/ Renewable Energy ETFs are iShares Global Clean Energy ETF (ICLN), Invesco Solar ETF (TAN), First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN), First Trust Nasdaq Clean Edge Smart GRID Infrastructure Index (GRID), and Invesco MSCI Sustainable Future ETF (ERTH).

The five energy ETFs (XLE, VDE, XOP, IXC, OIH) mostly track U.S. companies that extract and process oil and gas and provide other conventional energy-related services. The five alternative energy ETFs (ICLN, TAN, QCLN, GRID, ERTH) bring together alternative energy companies with diverse portfolios interested in clean technologies, solar, wind and geothermal energy, biofuels, and energy-efficiency related services offer. In terms of asset value, all of these ETFs are the largest in assets in their market segment categories.

Conclusion

As the global green energy market investment opportunities became priority research fields, alternative and renewable energy-related stocks, options, and ETFs created risk-return diversification challenges. In recent years, various international statistical models emerged, and some studies based on modern portfolio theory have demonstrated the benefits of diversification through a wide range of investment opportunities by illustrating the potential for higher returns and lower risks.

The objective of this paper was to explore the methodology to present the investment opportunities of the conventional and alternative/ renewable energy market segments. Through the evolution of the investment models, the concepts of portfolio selection and optimal investment strategy was presented. The ICAPM, which aims to analyze the pricing of international financial instruments, taught us that optimal diversification is possible by creating an international portfolio of financial instruments on a global scale, taking into account the risk of all the assets that make up the portfolio. However, especially in an international environment, the model takes into account the assumption that risk associated with the portfolio's assets and return influence the investment decision. However, the exchange rate risk was excluded. As a

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result, more complex investment models developed to adapt to specific market conditions such as the so-called conditional models to temporarily measure the change in time, the expected return, and the variance. In the case of the ARCH model, the variation of financial returns turned out not to be constant over time but autocorrelated or conditional to/dependent on each other. It was further understood that if an ARMA model is assumed for the error variance, the model is a GARCH model that incorporates a moving average component together with the autoregressive component. The introduction of a moving average component allowed us to model the conditional change in variance over time as well as the changes in the time-dependent variance. Thus, it can be seen that the conditional variance in GARCH depends on the past error limit and the conditional variances; the so-called structure-volatility estimates converge to the average volatility over the long run, and GARCH parameters can be optimally determined, so GARCH covariance matrices represent time-varying volatilities and multivariate return distributions without bias.

To identify the differences between the two energy market segments, the conventional and alternative/ renewable energy ETFs was used as investing instruments due to their obvious benefits as passive investment vehicles that reflect the performance of a sector or a market benchmark. By applying the VAR-ADCC GARCH methodology, the theoretical basis of a larger energy market investment research, which is expected to result in return-risk diversification, was established. It was demonstrated that the selected approach allows the aggregation of different energy and alternative/ renewable energy ETFs into international investment portfolios by using a variable weighting of assets. The selected VAR-ADCC methodology turned out to expect out-of-sample one-step-ahead forecasts of returns, volatilities, and correlations. In conclusion, this model will allow us to construct four different strategies to further analyze the conventional and alternative/ renewable energy markets by using different constraints of the minimum-variance and mean-variance optimization approaches. However, despite the clear description of the characteristics of the models, it is still not clear and it requires further specification if and to what extent there is an empirical outcome of this research.

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References:

1. Badshah, I. U. (2018). Volatility spillover from the fear index to developed and emerging markets. *Emerging Markets Finance and Trade* 54 (1), 27–40.
2. Bartram, S. M., & Dufey, G. (2001). International Portfolio Investment: Theory, Evidence, and Institutional Framework', *Finance Markets Institutions and & Instruments.*
3. Beber, A., & Pagano, M. (2013). Short-selling bans around the world: evidence fromthe 2007–09 crisis. *Journal of Finance* 68, 343–381.
4. Ben-David, I., Franzoni, F., & Moussawi, R. (2017). Exchange-Traded Funds. *Annual Review of Financial Economics*, 9, 169-189.
5. Bohl, M. T., Reher, G., & Wilfling, B. (2016). Short selling constraints and stock returns volatility: empirical evidence from the German stock market. *Economic Modelling* 58, 159–166.
6. Bollen, N. P. B., & Busse, J. A. (2001). On the timing ability of mutual fund managers. *Journal of Finance* 56 (3), 1075–1094 57–82
7. Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics 31 (3).
8. Brinson, G. P., Singer, B. D., & Beebower, G. L. (1991) Determinants of Portfolio Performance II: An Update. *Financial Analysts Journal*, 47, 40-48.
9. Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). The Econometrics of Financial Markets, *Princeton University Press*, Princeton, NJ, USA.
10. 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.
11. Carhart, M. M. (1996). On the persistence in mutual fund performance. *Journal of Finance* 52 (1)
12. Diether, K. B., Lee, J., & Werner, J. (2009). It's SHO time! Short-sale price tests and market quality. *Journal of Finance* 64, 37–73.
13. Efimova, O., & Serletis, A. (2014). Energy markets volatility modelling using GARCH, *Energy Economics* 43, 264–273.
14. Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica* 50, (4).
15. Henriques, I., & Sadorsky, P. (2008). Oil prices and the stock prices of alternative energy companies, *Energy Economics* 30, 998–1010.
16. Ewing, B. T., & Malik, F. (2005). Re-examining the asymmetric predictability of conditional variances: the role of sudden changes in variance. *Journal of Banking and Finance* 29, 2655–2673.

ISSN: 1857-7881 (Print) e - ISSN 1857-7431

17. Fama, E., & French, K. R. (1993). Common risk factors in the returns of stocks and bonds. *Journal of Financial Economics* 33 (1), 3–56.
18. Gupta, R., & Donleavy, G. D. (2009). Benefits of diversifying investments into emerging markets with time-varying correlations: an Australian perspective. *Journal of Multinational Financial Management* 19, 160–177.
19. Grullon, G., Michenaud, S., & Weston, J. P. (2015). The real effects of short-selling constraints. *The Review of Financial Studies* 28 (6), 1737–1767.
20. Huang, M. Y., & Lin, J. B. (2011). Do ETFs provide effective international diversification?. *Research in International Business Finance*, 25, 335–344;
21. Ibbotson, R. G., & Kaplan, P. (2000). Does Asset Allocation Policy Explain 40, 90, 100 Percent of Performance?. *Financial Analysts Journal* 56.
22. 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.
23. Kalotychou, E., Staikouras, S. K., & Zhao, G. (2014). The role of correlation dynamics in sector allocation *Journal of Banking and Finance* 48, 1–12.
24. Kyritsis, E., & Serletis, A. (2018). The zero lower bound and market spillovers: evidence from the G7 and Norway, *Research in International Business Finance*, 44, 100–123.
25. Lewellen, J. (2002). Momentum and autocorrelation in stock returns, *Review of Financial Studies*, vol. 15, no. 2, pp. 533–564, 2002.
26. Lo, A. W., & MacKinlay, A. C. (1990). An econometric analysis of nonsynchronous trading, *Journal of Econometrics*, vol. 45, no. 1-2, pp. 181–211, 1990.
27. Longin, F. M., & Solnik, B. (2001). Extreme Correlation of International Equity Markets. *Journal of Finance* LVI (2).
28. Louhelainen, M. (2005). Weekly Predictability of Daily Returns: A Periodic Autoregressive Model Approach, ISBN 952-458-666-5, ISSN 1458-686X, no. 23.
29. 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 Economics* 68, 440–453
30. Malinda, M., & Jo-Hui, C. (2016). The Study of the Long Memory in Volatility of Renewable Energy Exchange-Traded Funds (ETFs), *Journal of Economics, Business and Management* 4, (4).

31. Markowitz, H. M. (1952). Portfolio selection. *The Journal of Finance*, Vol. 7, No. 1. 77-91.
32. Miralles-Marcelo, J. L., Miralles-Quiros, M. M., & Miralles-Quiros, J. L. (2015). Improving international diversification benefits for US investors. *The North-American Journal of Economics and Finance,* 32, 64–76.
33. Miralles-Marcelo, J. L., & Miralles-Quiros, M. M. (2017). The role of time-varying return forecasts for improving international diversification benefits. *International Journal of Finance & Economics*, 22, 201–215.
34. Miralles-Marcelo, J. L., Miralles-Quiros, M. M., & Miralles-Quiros, J. L. (2018). Are alternative energies a real alternative for investors?. *Energy Economics* 78.
35. 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 Economics* 36, 1–18.
36. Odier, P., & Solnik, B. (1993). Lessons for International Asset Allocation. *Financial Analysts Journal* 49.
37. Omar, A. M. A., Wisniewski, T. P., & Nolte, S. (2017). Diversifying away the risk of war and cross-border political crisis. *Energy Economics* 64, 494–510.
38. Reboredo, J. C., Quintela, M., & Otero, L. A. (2017). Do investors pay a premium for going green? Evidence from alternative energy mutual funds. *Renewable and Sustainable Energy Reviews*, Rev. 73, 512–520.
39. Reboredo, J., 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 (C), 241-252.
40. Rezec, M., & Scholtens, B. (2017). Financing energy transformation: the role of renewable energy equity indices. *International Journal of Green Energy* 14 (4), 368–378.
41. Sadorsky, P. (2012) Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics* 34, 248–255.
42. Silva, F., & Cortez, M. C. (2016). The performance of US and European green funds in different market conditions. *Journal of Cleaner Production* 135, 558–566.
43. Solnik, B., & Noetzlin, B. (1982). Optimal international asset allocation. *The Journal of Portfolio Management Fall* 9 (1), 11-21.
44. Tsai, P. J., & Swanson, P. E. (2009). The comparative role of iShares and country funds in internationally diversified portfolios. *Journal of Economics and Business*. 61(6), 472–494.

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

45. Thai-Ha, L., & Chang, Y. (2011). Oil and gold: correlation or causation?. *Munich Personal RePEc Archive*, https://mpra.ub.uni-muenchen.de/31795/
46. Xinodas, P., Hassapis, C., & Mavrotas, G. (2018). Multiobjective portfolio optimization: bridging mathematical theory with asset management practice. *Annals of Operations Research* 267(3).
47. Yuan, T., Gupta, R., & Roca, E. (2016). Why not diversify into emerging equity markets via ADRs?. *The Journal of Investing* 25 (2), 18–27.
48. Zhou, J., & Nicholson, J. R. (2015). Economic value of modeling covariance asymmetry for mixed-asset portfolio diversifications. *Economic Modelling* 45, 14–21.