Energy ETF performance: the role of fossil fuels.

Rita Laura D'Ecclesia* Giacomo Morelli† Kevyn Stefanelli‡

January 30, 2023

Abstract

The Principles for Responsible Investment (PRI) affected the financial markets since the year 2000. Asset managers and investors consider Exchange Traded Funds (ETFs) as a popular investment vehicle which represents a source of growth for sustainable strategies. Clean Energy ETFs (CE ETF) are funds that invest in stocks of alternative energy sectors as solar energy, wind, hydroelectric and geothermal companies. In 2022, CE ETF have recorded a rate of return equal to 3.3% in a quarter. The increasing interest by policy makers and investors in sustainable finance fostered the development of new classes of green assets. In this context, it is important to analyze the role sustainable ETFs may play to build portfolio strategies. The aim of this paper is to investigate the features of the most capitalized ETFs over the last decade (2012-2022) distinguishing between CE ETFs and Fossil Fuels ETFs (FF ETFs). Using daily quotes, we build minimum variance portfolios composed of only CE ETFs, Mixed Energy ETFs, and FF ETFs. Computing the Sharpe and the Sortino ratios, we show that the CE ETFs portfolio does not always provide a better risk-return trade off, but it often beats the FF one. Given the time-varying features of the volatility of ETFs returns, we use a GARCH framework and analyze the various portfolios' performance in different sub-periods, to take into account the pandemic crisis, the Paris Agreement, the Ukranian conflict. We find that portfolios' performance is highly affected by i) the market condition, and ii) the investors attention to sustainability. Moreover, the exclusion of fossil fuels ETFs does not deteriorate the profitability.

Keywords: Energy ETF, Renewable Energy, Portfolio Optimization, Green Finance, Fossil Fuels.
JEL Code: C58, G11, G41, Q01, Q42.

*Corresponding author. Department of Statistics, Sapienza University of Rome, Rome, 00185 Rome, Italy. E-mail: rita.decclesia@uniroma1.it

†Department of Statistics, Sapienza University of Rome, Rome, 00185 Rome, Italy. E-mail: giacomo.morelli@uniroma1.it

‡Department of Statistics, Sapienza University of Rome, Rome, 00185 Rome, Italy. E-mail: kevyn.stefanelli@uniroma1.it

1 Introduction

The Principles for Responsible Investments plays a crucial role in the development of asset management strategies (UNEP Finance and UN Global Compact (2022)). The investment community deals with nature-related regulations and the associated risks. Europe has been a pioneer in establishing sustainable regulations, mainly focused on Environmental, Social, and Governance (ESG) criteria. The EU Taxonomy Regulation directly addresses the role of the financial industry in funding environmentally and socially sustainable activities using comprehensive science-backed criteria and numerous thresholds (European Union (2022)). It aims to reorient capital flows to more sustainable activities, while the EU Sustainable Finance Disclosure Regulation (SFDR) requires the improvement of transparency in the market for investment products and to reporting of specific Principle Adverse Impact (PAI) (Eurosif (2021)). Among mandatory PAIs, there is a wide range of indicators assessing non-linear biodiversity impacts as, for instance, carbon footprint and exposure to companies active in the fossil fuel sector to energy consumption intensity per high climate impact sector.

Local regulations for investors require asset managers and owners to set strategies that comply with key objectives for 2030 and every five years afterward. Investors must assess companies' pressure on ecosystems and how such negative impacts can be mitigated. The regulator also highlights the need to identify the nature dependencies of portfolio companies and enterprises contributing to preserving and protecting ecosystems. On the banking side, the European Banking Authority introduced the "Pillar 3 disclosures on ESG risks" regulation, that impose institutions to report the Green Asset Ratio (the percentage of assets in the loan book aligned with EU Taxonomy) for the entire lending portfolio (European Banking Authority (2022)). Measuring the global sustainability effect of a portfolio or an individual asset has, therefore, become crucial. For instance, Nasdaq recently created a platform for investors and managers to access the real-life effects of each investment, along with alternatives that may better suit individuals' sustainability goals (Metrio (2022)). In this context, investments in sustainable Exchange-Traded Funds (ETFs) or ESG ETFs have attracted the attention of investors and, in the last decade, have shown unprecedented growth accounting for 2/3 of US dollars invested worldwide in 2020 (Morningstar (2021)). From 2014, green investment vehicles have racked up over \$300 billion in net flows and have grown at a compound annual growth rate (CAGR) of 75% from \$4.7 billion in Assets under Management (AuM) on January 1st, 2014, to \$425 billion AuM by 2021 year-end. ESG ETFs boomed in 2020, witnessing an incredible 223% growth over the year and achieving a new record of \$189 Billion in AuM. In 2021, 14% of the total ETF flows went to ESG. Europe remains the primary ESG ETFs hub with \$263 billion in AuM. America lags with \$152 billion, while Asia Pacific (APAC) has a meager \$12 billion exposure. Last year, Europe accounted for 63% of net inflows into ESG-focused investment products. America took in 33% and APAC the rest. 55% of all net inflows into Europe went into ESG ETFs, compared to just 11% of APACs and 6% of Americas (Trackinsight (2022)). Among the ESG ETFs, the Clean Energy (CE) ETFs have been the best-performing ones in 2022, followed by the Cybersecurity and Artificial Intelligence (AI) ETFs. In this paper, we study the main features of Energy ETFs launched in the first decade of this century with the goal to asses the impact of their performance.

The CE transition represents one of the largest multi-decade secular growth opportunities. According to the International Energy Agency (International Monetary Fund (2021)), investment in renewable energy needs to triple by the end of the current decade if the world hopes to effectively fight climate change and keep volatile energy markets under control. The International Energy Agency (2022) (IEA) forecast suggests that governments and other financial entities need to significantly boost their investments in CE, such as wind, solar, hydrogen, battery storage, and electric vehicles (EVs). As a result, companies focused on green energy should prosper as more investment flows into the sector over the coming years. The IEA optimistic projections come despite the negative impact of the COVID-19 pandemic and the Russian invasion of Ukraine, which have fueled inflation to multi-decade highs and contributed to soaring energy prices in some advanced economies. However, the rising energy costs have helped push policymakers to find cheaper and more reliable alternative energy sources. In the last few years, renewable and fossil-fuel-free stocks registered skyrocketing performance, reporting unexpected performance in periods of distress.[1] Investor's long-term strategies are built to best position their portfolio and profit from the upside potential so that you can invest in a specific alternative energy stock; however, it could happen that even if you are right about the thesis (clean energy investment will rise), you end up investing in the wrong company that underperforms the sector over the long term. A solution to this problem is to invest in a CE ETFs portfolio. That should reduce the risk of being right on the thesis but picking the wrong green energy stock to express that view. Also, several sources define the CE market as a tipping point (Morningstar (2018), NYSE (2021), United Nations Conference on Trade and Development (2020), iShares (2022)). Differently, fossil-fuel-based assets suffered several periods of stress, like the 2014 oil plunge and the world production slowdown related to the Covid-19 crisis. The excellent performance of CE ETFs in the last few years brings scholars and asset managers to expect diversification benefits when using CE ETFs compared to other Energy ETFs.

For this reason, in this paper, we analyze the role of Energy ETFs in portfolio diversification

[1] The denomination 'fossil-fuel-free' indicates companies that do not hold physical reserves of oil, gas, coal, and other fossil fuels. However, it does not exclude firms that exploit polluting energy sources.

strategies. We use daily quotes of the largest capitalized ETFs over the period 2012-2022 to build three different portfolios: the first containing only CE ETF (ME_P), the second only FF ETFs (FE_P), and the third Mixed ETFs (ME_P). We investigate whether green screening process deteriorates financial performance. We compare the two energy quasi-sectors' profitability (CE vs. FF) and assess the possible drawbacks of a green screening strategy (CE vs. ME). The aim of the paper is twofold; first, we study the market features of the most capitalized ETFs, analyzing their performance by sector (CE vs. FF or Mixed) over the last decade; second, we assess the risk-return trade-off of ETF portfolios built choosing i) only CE ETFs; ii) only FF ETFs, and iii) all Energy ETFs. We measure the portfolios performance estimating the Sharpe and Sortino ratios along with the market risk. We analyze the features of ETF over the entire decade 2012-2022 and divide the data by sub-intervals to capture possible energy market distress, such as the 2014 oil price plunge, and variation in the attention to sustainability themes analyzing the time series before and after the Paris Agreement (December 2015).

We find that the CE_P performs as the ME_P when using data for the entire decade, while it often outperforms the FE_P. Different results are shown when working with data of sub-periods. For instance, the world economic slowdown caused by the Covid-19 outbreak did not impact the performance of the CE_P, while it severely affected the FF_P. On the other hand, FF_P was highly affected by the rise in raw materials' price caused by the Russia-Ukraine conflict. CE ETFs seems resilient during market distress, unlike FF ETFs, which help manage periods of lack of energy supply. The ME_P performance highlights a significant effect of the Paris Agreement (2015) as a milestone in the climate change fight. The composition of the ME_P changes dramatically for the various periods: in 2012-2014, the weights of CE ETFs and FF ETFs in the portfolio are quite stable (CE (40%); FF (60%)), while in the period 2015-2017, the weights of CE (app. 90%) are by far larger than the FF (app. 10%) and quite volatile, moving to 50-50 weights in the periods after 2018. The sharp increase of CE weights in the portfolio after the third quarter of 2015 embeds the outcomes of the Paris Agreement, which affected asset managers short-term choices.

The remainder of the paper is organized as follows. Section 2 illustrates the recent literature o this topic; Section 3 describes the methodology. Section 4 discusses the dataset and the empirical analysis. Section 5 summarizes the main results and concludes the paper. In the Appendix, the reader can find additional tables and figures.

2 Literature Review

The literature on green ETFs is still inconclusive and fragmented. Alexopoulos (2018) examines discrepancies in financial performance within the energy sector during the period 1999-2016 considering three subsets of funds, namely (i) clean energy funds (CEF), (ii) conventional energy funds (COF), and (iii) all energy funds (AEF), and build seven types of portfolios according to as many selection criteria (e.g., mean, mean-variance, minimum volatility). The author concludes that the AEF portfolio outperforms the two others because of evident portfolio diversification benefits. Moreover, the CEF outcome is more affected by exogenous factors, like the 2008 global financial crisis compared to its conventional peer. According to Fahmy (2022a) and Fahmy (2022b), clean energy assets are also more responsive to variations in the climate attention than those oil-based. Their prices positively react to the increase of investors' environmental concerns after the Paris Agreement (United Nations Framework Convention on Climate Change (2015)), while no conclusion is derived for a related effect on FF stock. Similar results are obtained by Ramiah et al. (2013), Miralles-Quirós et al. (2019), Wallace and McIver (2019), and El Ouadghiri et al. (2021) analyzing green funds' cumulative abnormal returns (CAR) in the days around climate fight related announcements or events. On the same line, Kanamura (2020) shows how ESG factors successfully mitigate the downside risk during the COVID-19 outbreak period (March 2020), highlighting the singular resilience of green assets during phases of market distress. Still, several empirical evidence show the profitability of FF ETFs. Henriques et al. (2022) build several optimal portfolios choosing among a collection of 60 energy ETFs selected from 2014 to 2018. The analysis of the portfolios' compositions exhibits how the natural gas and oil-based funds are the most represented assets, while the CE ones are barely picked. Also, Dutta et al. (2020) exhibit that CE ETFs suffer during high volatility phases of the energy market.

3 Methodology

In this section, we describe the methodologies used to conduct the analysis. We estimate the returns' conditional volatility through a dynamic conditional correlation (DCC) - GARCH model (Engle (2002)), which allows us to consider the time-varying correlations between different time series. Then, we build optimal portfolios according to the mean-variance criterion. We select holdings to minimize the volatility, chosen as a risk measure, taking into account the assets' returns, as well. We compare the portfolios' performance through several metrics. First, we compute the Sharpe and the Sortino ratios to compare risk-weighted returns. Then, we adopt the Value-at-Risk (VaR) and the Expected Shortfall (ES) to assess risk discrepancies. Finally, we conduct tests, like the t-test, F-test, and the modified Sharpe Ratio test, to infer the empirical outcome.

3.1 DCC-GARCH model

We denote r_t the collection of serially uncorrelated log-returns computed for each asset:

$$r_t = log(P_t) - log(P_{t-1}),$$

where P_t is its price at time t. We define a zero-mean white noises vector $\varepsilon_t = r_t - \mu$. Then:

$$r_t = \mu + \varepsilon_t \qquad \varepsilon_t = H_t^{1/2} z_t \qquad z_t|\mathcal{F}_{t-1} \sim N(0,1) \qquad H_t = D_t R_t D_t \tag{3.1}$$

where μ is the expected value of the conditional returns, typically roughly equal to zero, ε describes the error at time t which is function of the conditional variance H_t and the normal innovation z_t, *i.i.d.*; D_t is the diagonal matrix containing the $\sqrt{h_{i,t}}$ time varying standard deviations of the asset i at time t from univariate GARCH model and R_t is the time varying correlation matrix defined as follows:

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & \cdots & \sqrt{h_{Nt}} \end{bmatrix}, \qquad R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1N,t} \\ \rho_{12,t} & 1 & \ddots & \rho_{2N,t} \\ \vdots & \ddots & \ddots & \vdots \\ \rho_{1N,t} & \cdots & \cdots & 1 \end{bmatrix}, \tag{3.2}$$

and in the simplest case of a GARCH(1,1) model for each asset i we have:

$$h_{i,t} = \psi_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{3.3}$$

where ψ_i represents a constant value for the conditional variance of the asset i, α_i is the weight assigned to the lagged errors and β_i accounts for the past variance. To ensure weak stationarity and positiveness of $h_{i,t}$, the following conditions must be satisfied: (i) $\psi_i > 0$, (ii) $\alpha_i \geq 0$, (iii) $\beta_i \geq 0$, and (iv) $\alpha_i + \beta_i < 1$.

The GARCH-DCC estimation process involves two steps: (i) firstly, it estimates the conditional heteroskedasticity for each series of return $r_{i,t}$ through a GARCH-type model, and then (ii) it attributes a dynamic correlation structure. For instance, we can write a DCC(1,1) model as follows:

$$\begin{aligned} Q_t &= (1 - \gamma - \phi)\bar{Q} + \gamma\eta^2 + \phi Q_{t-1} \\ R_t &= Q_t^{*-1} Q_t Q_t^{*-1} \end{aligned} \tag{3.4}$$

where $\bar{Q}$ is the unconditional covariance of the standardized residuals resulting from the first estimation and Q_t^* is a diagonal matrix containing the square root of the elements of Q_t as follows:

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22}} & \ddots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & \cdots & \sqrt{q_{NN}} \end{bmatrix} \tag{3.5}$$

In order to ensure H_t to be positive definite, R_t has to be positive definite and all the elements of R_t must be equal or less than one, by definition. Hence, its elements will be like

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

.

We estimate the univariate conditional volatility choosing among different GARCH specifications and select the best according to the Bayesian Information Criterion (BIC). We choose three different GARCH model specifications, namely the standard GARCH (sGARCH) (Bollerslev (1986)), the exponential-GARCH (eGARCH), and the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) (Glosten et al. (1993)) to account for the skewness and the leptokurtosis which usually characterize the financial returns' distributions. Also, we try several specifications for the error terms distributions (Gaussian, Skewed-Gaussian, Student-t, Skewed Student-t, Generalized Error Distribution (GED), and Skewed GED) to model the empirical distributions' fat tails.

3.2 Portfolio Optimization

We calibrate the portfolio weights solving the following optimization problem:

$$\begin{aligned} \min_{\omega} \frac{1}{2}\omega'\Sigma\omega - \omega'\mu \\ s.t.\ \omega' 1_n =& 1 \\ \omega \geq& 0, \end{aligned} \tag{3.6}$$

where ω is the p vector of weights relative to each assets considered, μ is the p vector of average daily returns computed over the quarter k, and short sales are not allowed. We assume null costs of transactions.

3.3 Risk metrics

We search for possible discrepancies between two assets by comparing their market risk. Considering a confidence level equal to $1-\alpha$, we define at time t the Value-at-Risk (VaR) for the asset i as:

$$VaR_{i,t}(\alpha) = F_{i,t}^{-1}(\alpha), \tag{3.7}$$

where $F_{i,t}^{-1}(\alpha)$ is the inverse of the cumulative distribution function of the asset i at time t, and the Expected Shortfall (ES) as:

$$ES_{i,t}(\alpha) = \mathbb{E}\left[r_{i,t} | r_{i,t} \leq VaR_{i,t}(\alpha)\right], \tag{3.8}$$

with $r_{i,t}$ the return of the asset i at time t.

3.4 Portfolio performance metrics

We evaluate the portfolio performance according to different criteria. We compute the portfolio annualized daily returns, the cumulative returns ($R_{p,t}$), the annualized volatility $\sigma_{p,t}$, the Sharpe ratio (ShR), and the Sortino ratio (SoR) as follows:

$$R_{P,t} = (1+r_t)(1+r_{t+1})(1+r_{t+2})\dots(1+r_{t+\tau}) - 1 = \prod_{s=t}^{\tau}(1+r_s) - 1,$$

$$ShR_t = \frac{\mu_{P,t} - r_{rf,t}}{\sigma_{p,t}}, \qquad SoR_t = \frac{\mu_{P,t} - r_{rf,t}}{\sigma_{p,t}^d},$$

$$\sigma_{p,t} = \left(\frac{1}{\tau}\sum_{t=1}^{\tau}(r_t - \mu_{P,t})^2\right)^{1/2}, \qquad \sigma_{p,t}^d = \left(\frac{1}{\tau}\sum_{r_t<0}(r_t - \mu_{P,t})^2\right)^{1/2},$$

where $\mu_{P,t}$ is the portfolio average return at time t computed over the period $[t, t+\tau]$ and $r_{rf,t}$ is the risk free daily rate of return at time t.[2] We set τ equal to 252 trading days.

We exploit the modified Sharpe ratio (mSh) to better represents the assets' risk weighted performance (Favre and Galeano (2002) and Gregoriou and Gueyie (2003)). We rely on the Cornish-Fisher expansion to compute the modified VaR (mVaR) as a risk measure:

$$mShR^{VaR_t} = \frac{\mu_{P,t} - r_{rf,t}}{mVaR_t}, \qquad mVaR^{\alpha} = r_p - Z \cdot \sigma_{t,p},$$

with

[2] We use the Fama-French risk free daily rate of return: mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

$$Z = z_c + \frac{1}{6}(z_c^2 - 1) \cdot S + \frac{1}{24}(z_c^3 - 3z_c) \cdot K - \frac{1}{36}(2z_c^3 - 5z_c) \cdot S^2,$$

where z_c is the critical value for probability α, S is the skewness of returns' distribution and K its excess kurtosis. An alternative version of the modified Sharpe ratio uses the ES instead of the VaR (mShR-ES). It is computed as the expected values of the losses that exceed the $mVaR^{\alpha}$.

3.5 Inferential Tests

We use the independent two-samples *t-test* to search for possible differences in the average returns of two portfolios, i and j. The relative statistic is defined as:

$$t = \frac{\mu_i - \mu_j}{s_p\sqrt{\frac{2}{n}}}, \tag{3.9}$$

where μ_i and μ_j are the average returns of the two portfolios, $n = n_1 + n_2$ is the sum of the sizes of i and j, and s_p is the pooled standard deviation unbiased estimator defined as:

$$s_p = \sqrt{\frac{(n_1 - 1)s_i^2 + (n_2 - 1)s_j^2}{n_1 + n_2 - 2}},$$

where s_i and s_j are the unbiased estimators of the standard deviation of the two assets, which we assumed as relatively similar ($\frac{1}{2} < \frac{s_i}{s_j} < 2$).

We test the hypothesis of null difference in the volatility of i and j using a two-tailed F-test. The relative statistic is defined as the variances ratio:

$$F = \frac{s_i^2}{s_j^2}, \tag{3.10}$$

where the null hypothesis is $H_0 : F = 1$.

We search for statistical differences between the mShRs of two portfolios following Ardia and Boudt (2015) who, extending the results of Ledoit and Wolf (2008), recur to a bootstrap approach to test the equality in ShR to improve the inference accuracy. The mShR difference between two assets i and j is defined as:

$$\hat{\Delta} = mSRh_i(\alpha) - mSRh_j(\alpha) = \frac{\mu_i}{mVaR_i^{\alpha}} - \frac{\mu_j}{mVaR_j^{\alpha}},$$

which is asymptotically normal (Memmel (2003)). We test the null hypothesis $H_0 : \hat{\Delta} = 0$ through the following statistic:

$$Z = \frac{|\hat{\Delta}| - \Delta}{s(\hat{\Delta})}, \tag{3.11}$$

where Δ is the true difference and $s(\hat{\Delta})$ is the estimated standard error of $\hat{\Delta}$.

4 Empirical Analysis

We collect the time series of the ten most capitalized clean energy (CE), fossil fuels (FF), and mixed energy (ME) ETFs worldwide observed from 2012-01-01 to 2022-06-30.[3] These funds are chosen to represent the total energy ETFs market. The sample contains only assets characterized by a sufficient historical depth, chosen at least equal to two thousand observations to ensure the consistency of results. All data are collected from the Refinitiv database.

Table 1 and Table 2 contain a brief description of the fund's objectives, tickers, and issue dates. Each fund tracks a specific energy financial index and is rebalanced quarterly or semi-annually. Some invest in the entire energy sector, whereas others are fully dedicated to companies specialized in producing energy from a single source. For instance, the LYNRJ fund tracks the World Alternative Energy CW Net Total Return Index, while the FAN fund aims to replicate the ISE Global Wind Energy Index, which targets only the wind industry. Similarly, in the FF subset, we find the IYE, whose aim consists in replicating the performance of the Dow Jones US Energy Sector Index, and the FCG, which is exclusively focused on the natural gas sector by tracking the ISE-Revere Natural Gas Index.

Table 3 shows the last available ESG ratings, divided by pillar, and the Controversial scores of the two groups (June 2022, source Refinitiv). Each fund score is computed as the weighted average of its components. The ESG score, and the relative pillars, range from 0 to 100 and represent a yearly aggregate disclosure of environmental, social, and governance performance. The higher the rating, the more a company aligns with the ESG principles. Refinitiv computes the ESG score as a weighted sum of each pillar. The Controversies score estimates the possibility for a company to be involved in an ESG scandal according to several firm characteristics. It ranges from 0 to 100, with 100 that indicates the slightest probability of such events. We do not observe significant differences between the CE and FF ETFs' ESG ratings. Surprisingly, the lowest E score belongs to the CE group (37 PBW), while the highest to the FF one (75, IXC). Differently, CE ETFs show high Controversies scores, from 72 to 90, while the FE funds exhibit lower ratings, from 40 to 87. The IXC ETF case stresses the importance of a joint analysis of both the ESG and the Controversies scores. This fund is highly ESG-rated compared to its FE peers (74, divided by 75 E, 74 S, and 71 G), but it shows the lowest Controversies score (40).

[3]The ETFs market capitalizations are available at eftdb.com.

ETF	Ticker	Inception Date	Description
Invesco MSCI Sustainable Future ETF	ERTH	24 Oct 2006	The fund tracks the investment results of the MSCI Global Environment Select Index, designed to maximize the exposure to environmental related sectors. It invests at least 90% of its total assets in stocks comprised in the underlying index.
First Trust Global Wind Energy ETF	FAN	16 Jun 2008	The fund tracks the ISE Global Wind Energy Index. It invests at least 90% of its net assets in stocks comprised in the underlying index.
First Trust NASDAQ Clean Edge Smart Grid Infrastructure Index ETF	GRID	16 Nov 2009	The fund invests at least 90% of its assets in NASDAQ OMX Clean Edge Smart Grid Infrastructure Index's stocks, which is the target for price and yield performance.
iShares Global Clean Energy ETF	INRG	09 Jul 2007	The fund tracks the S&P Global Clean Energy Index, which contains the 30 most liquid global public CE companies.
Lyxor New Energy (DR) UCITS ETF	LYNRJ	17 Oct 2007	The fund tracks the World Alternative Energy CW Net Total Return Index, is Euro-denominated, and it is comprised of companies which generate a significant share of their income from the global alternative energy sector, combining the renewable energy, energy efficiency and energy distribution sectors.
Invesco Global Clean Energy ETF	PBD	13 Jun 2007	The fund seeks to track the results of the WilderHill Clean Energy Index, investing at least 90% of its total assets in common stocks of companies comprised in the index. These companies are engaged in the business of the advancement of cleaner energy and conservation.
Invesco WilderHill Clean Energy ETF	PBW	03 Mar 2005	The fund is based on the WilderHill Clean Energy Index. This last is composed of stocks publicly traded in the US and engaged in the business of advancement of cleaner energy and conservation.
First Trust NASDAQ Clean Edge Green Energy Index ETF	QCLN	08 Feb 2007	The fund tracks the NASDAQ Clean Edge U.S. Liquid Series Index, which is an equity index comprised of US CE public companies.
VanEck Vectors Low Carbon Energy ETF	SMOG	03 May 2007	The fund seeks to replicate the price and yield performance of the Ardour Global Index. Under normal market conditions, the fund invests at least 80% of its total assets in stocks of low carbon energy companies.
Invesco Solar ETF	TAN	15 Apr 2008	The fund seeks to track the performance of the MAC Global Solar Energy Index, investing at least 90% of its total assets in the comprised stocks.

Table 1: CE ETFs: name, ticker, inception date, and description.

ETF	Ticker	Inception Date	Description
First Trust Natural Gas ETF	FCG	08 May 2007	The fund tracks the ISE-Revere Natural Gas Index investing, under normal circumstances, at least 90% of its net assets in the common stocks, depositary receipts, and MLP units that comprise the index.
First Trust Energy AlphaDEX ETF	FXN	08 May 2007	The fund seeks investment results that correspond generally to the price and yield of the StatraQuant Energy Index. Under normal circumstances, the Fund invests at least 90% of its net assets in common stocks that comprise the index.
iShares US Oil & Gas Exploration & Production ETF	IEO	01 May 2006	The fund invests at least 90% of its assets in the US oil and gas exploration and production equities comprised in the Dow Jones US Select Oil Exploration & Production Index.
iShares Global Energy ETF	IXC	12 Nov 2001	The fund tracks the investment results of the S%P Global 1200 Energy Index which is composed by global equities belonging to the energy sector. The Fund invests at least 90% of its assets in stocks of the underlying index.
iShares US Energy ETF	IYE	12 Jun 2000	The fund seeks the results of the Dow Jones US Energy Sector Index, which is comprised of oil companies and services, oil-major, oil-secondary and pipelines.
VanEck Vectors Oil Services ETF	OIH	20 Dec 2011	The fund replicates the performance of the Market Vectors US Listed Oil Services 25 Index, which is comprised of US stocks belonging to the oil services sector.
Invesco S&P 500 Eql Wght Energy ETF	RYE	11/01/2006	The fund seeks to track the investment results of the S&P 500 Equal Weight Energy Index investing, under normal circumstances, least 90% of its total assets in the underlying index' stocks.
Vanguard Energy ETF	VDE	23 Sep 2004	The fund tracks the performance of the MSCI U.S. Investable Market Energy Index that measures the investment return of energy stocks. It is a stocks index of large-, mid-, and small-size US companies within the energy (oil and gas) sector.
Energy Select Sector SPDR ETF	XLE	16 Dec 1998	The fund seeks to track the performance of the Energy Select Sector Index. Under normal market conditions, it invests at least 95% of its total assets in the stocks comprising the index.
SPDR S&P Oil & Gas Exploration & Production ETF	XOP	19 Jun 2006	The fund seeks to replicate the total returns of the the S&P Oil & Gas Exploration & Production Select Industry Index.

Table 2: FF ETFs name, ticker, inception date, and description.

ETF	ESG	E	S	G	Contr	ETF	ESG	E	S	G	Contr
ERTH	58	62	59	52	84	FCG	51	40	50	68	86
FAN	66	70	63	64	81	FXN	61	58	62	64	74
GRID	69	69	76	63	73	IEO	60	54	61	65	73
INRG	63	66	69	55	77	IXC	74	75	74	71	40
LYNRI	62	62	66	58	82	IYE	69	70	71	64	51
PBD	54	55	56	51	90	OIH	53	47	55	56	87
PBW	42	37	46	46	89	RYE	69	66	72	70	70
QCLN	55	51	61	54	77	VDE	68	68	69	66	52
SMOG	62	66	65	56	72	XLE	71	72	73	66	48
TAN	57	57	63	52	80	XOP	50	42	51	60	81

Table 3: Latest data available (May 2022) on the ESG, E, S, G, and Controversies scores of the twenty sampled ETFs.

4.1 Descriptive Statistics

We report the time series of prices along with the estimated structural changes (Bai and Perron (1998), Bai and Perron (2003)) separated by CE and FF ETFs in Figure 4 and in Figure 5, respectively. CE ETFs show similar patterns. Their price series fluctuations increased between 2014 and 2016, and a steep rise started in the first period of 2020. Similarly, we observe co-movements within the FF ETFs prices' dynamics. Only the FCG pattern slightly diverges from their peers, especially in the last years of analysis. This divergence is probably due to the scope of this fund, which invests only in the natural gas industry.

In Table 4, we report the structural changes' dates estimated on the ETFs daily prices series, highlighting those occurred on the same days.[4] A large part of them are related to specific market phases that affect several ETFs at the same time, like the oil plunge of the period 2014-2016, the Brexit, and the spread of the COVID 19 outbreak. During these periods, we observe common structural breaks on: (i) October 2014, during the oil market crisis, (ii) December 2015, so close to the Paris Agreement, (iii) November 2018, during a period of the energy market expansion, (iv) February 2020, characterized by the introduction of COVID-19 restrictions worldwide, and (v) February 2021, when the crude oil demand raised following the economic recovery. In particular, we observe a massive drop in all the FF ETFs prices on 21-25 February 2020, when the stock markets

[4] We consider two (or more) structural breaks related to the same event when they appear in the same time interval of ± 10 days.

worldwide collapsed because of the fear of the coronavirus outbreak. During these months, a large part of the heavy industry has slowed down production, and the total demand for energy strongly decreased. Consequently, on Monday, 20 April 2020, the Crude Oil West Texas Intermediate (WTI) price crashed to its lowest historical point, assuming the record negative value of -37.63 USD per barrel.

Interestingly, the massive growth of the CE ETFs prices during 2020 and the relatively slight retracement observed at the beginning of 2021 coincide with the run for the election of the 46^{th} president of the USA. The increase of CE asset prices reflects the expectation of the global markets on the potential victory of Joseph R. Biden Jr., who would have carried on a severe pro-environmental program, which also included the return of the USA under the Paris Agreement. The prices drop in the days following the announcement of the new US president's election, reflecting a typical market behavior in correspondence with meaningful events (sell the news).

Table 9 summarizes the descriptive statistics of the sample returns. All ETFs show: null mean, negative skewness and positive kurtosis (Jarque-Bera (JB) test statistically significant), uncorrelated returns, and ARCH effect (squared returns are autocorrelated, and ARCH-LM, Augmented Dickey-Fuller (ADF), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are statistically significant).

4.2 Estimation of conditional volatilities

We estimate the conditional volatilities to investigate the relationship among the energy ETFs as a whole and within each group, CE and FF funds. We select the best model specification according to the Bayesian information criterion (BIC) to estimate the conditional volatility dynamic of each ETFs, among those reported in Section 3.1. The GJR-GARCH is chosen as the best model for all ETFs. The optimal combination of the p and q parameters varies between $\{(1,0),(1,1),(2,0)\}$, suggesting the use of a parsimonious model. Moreover, the autocorrelation function (ACF) and partial ACF (pACF) exhibit the lack of autoregressive moving average (ARMA) dynamics in the conditional means of the ETFs' log returns. The Student-t distribution is widely chosen for the innovation processes, as it fits the fat tails observed in the descriptive analysis.

We estimate the time-varying correlations among ETFs by fitting a DCC-GARCH model on the entire sample, choosing the Normal distribution for the error terms of the dynamic model. Table 5 shows the estimated DCC averages computed over the sample period and their standard deviations. All the energy ETFs are strongly and positively correlated, with values between 30% and 99%. Variations in this interval seem to primarily occur because of the funds' scope. Among the CE, the highest average correlation is between the PBW and the QCLN (91%) because they both invest in the entire US renewable energy market. Also, the SMOG fund, which has a similar

ETF	2013	2014	2015	2016	2017	2018	2019	2020	2021
ERTH	07/19	09/22		04/19	05/03		04/02	07/10	07/01
FAN	07/24	10/01		04/12	04/26	06/20	10/04	09/30	
GRID	02/11	03/14	05/26	08/15	08/29	09/27	10/17	11/18	
ICLN	09/09		08/19				06/19	09/25	
LYNRI	09/25		07/28		05/03		06/17	08/04	
PBD	09/04		08/05		06/21	06/18	10/04	09/30	
PBW	07/10	10/08		01/05	09/11		06/17	07/10	07/01
QCLN	06/28		08/05		05/31		10/09	10/02	
SMOG	05/09	06/09	08/18		04/21		10/11	10/06	
TAN	09/17		08/18	10/19	10/19		07/30	09/25	
FCG	09/16	10/06	12/17		05/16	11/19	11/15		05/13
FXN	09/16	09/30	12/14		12/12	12/07		01/30	02/19
IEO	08/29	10/01	12/15		12/08	12/04		02/24	05/04
IXC	10/11	11/26		02/24	10/31	11/12		02/26	02/23
IYE	02/11	03/14	06/24	09/06	11/24	11/19		02/25	02/23
OIH	07/17	11/24		02/23	05/24	11/09		02/21	02/12
RYE	07/16	10/01	12/15		11/24	11/19		02/26	02/22
VDE	05/03		06/26	09/09	11/24	11/19		02/25	02/22
XLE	02/11	03/14	06/23	09/02	11/24	11/19		02/25	02/22
XOP	09/06	10/06	12/17		12/08	12/04		01/28	02/19

Table 4: Estimated breakpoints dates relative to CE (in blue) and FF (in brown) ETFs (1 Jan 2012 - 30 June 2022).

aim, is highly correlated with these two ETFs (82% and 87%, respectively). The LYNRI fund, the only one exchanged in Europe, shows the lowest average correlations in the CE group (between 52% and 68%). The GRID ETF exhibits lower correlations than the others (from 54% to 68%) because it is entirely dedicated to the smart grid and electrical energy infrastructure sectors.[5] Conversely, the PBD and the PBW are the most correlated within the CE ETFs. Their holdings cover a large part of the CE quasi sector, like alternative energy, energy efficiency, green buildings, water management, pollution prevention and control, and sustainable agriculture. For this reason,

[5]The smart electric grid, or just smart grid, consists of a network of transmission lines, substations, transformers, and more, that allows for more efficient delivery of electricity from power plants to users, minimizing electricity overloading and waste.

their financial performance is related to the entire CE sector. The INRG has the largest market capitalization, and thus it can be seen as the market driver. Then, the correlation with all its peers is high.

All the FF ETFs show a high average DCC. Only the couples FCG-IXC and FCG-OIH exhibit values equal to 83%, while the others fluctuate over 88%. The pairs IYE-VDE, IYE-XLE, and VDE-XLE, show the highest value (99%), but several correlations within this group are over 95%. The FCG is the only FF entirely focused on natural gas industries. For this reason, it has the lowest correlations, albeit still extremely high, in this subset. Moreover, the most capitalized FF ETF, the XLE, shows the highest average associations within its group, with values that span between 90% and 99%, except for the FCG (88%).

CE and FF ETFs show positive and not negligible correlations, which span between 26% (ENER-FCG) and 60% (SMOG-IXC). The LYNRI has the lowest associations with FF funds, with correlations between 26% and 34%. To summarize, results highlight a significant, strong, and positive association all over the energy ETFs market, and similar financial features of funds justify this. However, the different carbon footprint of funds affects correlations. This evidence partially contradicts the Fahmy (2022a) conclusion, with CE ETFs that cannot be considered a new asset class.

4.3 Portfolio Selection

We empirically assess whether excluding polluting assets reduces financial performance as follows. We conduct a comparative dynamic analysis among a mixed energy ETFs portfolio (ME_P), which contains both CE and FF funds, and two others, CE_P and FE_P, which are comprised of only CE and FF funds, respectively. This way, we quantify possible drawbacks entailed by a green screening process (ME_P vs. CE_P) and compare the performance of alternative energy ETFs portfolios (FE_P vs. CE_P). Also, we investigate potential benefits entailed by including CE funds in a FF funds portfolio (ME_P vs. FE_P).

We calibrate the weights quarterly, assuming no transaction costs. We compute the vector of the ETFs' quarterly returns from daily data and estimate each covariance matrix as the quarterly average of the daily covariance matrices estimated through the DCC-GARCH model. In particular, we use the outcome of the DCC model described in Section 4.2 for the ME_P and estimate two new DCC-GARCH models, one for the CE_P and the other for the FE_P, separately for the two groups of ETFs.

The attention to climate change strongly influences the composition of the ME_P. We report in Figure 1 the proportions of CE and FF ETFs which quarterly constitute the ME_P. At the beginning of the analysis, we observe a balanced composition between clean and fossil fuel energy funds within

	ERTH	FAN	GRID	ICLN	PBW	LYNRI	PBD	QCLN	SMOG	TAN	FCG	FXN	IEO	IXC	IYE	OIH	RYE	VDE	XLE	XOP
ERTH	1 -	0.69 0.07	0.73 0.09	0.70 0.07	0.73 0.05	0.66 0.06	0.77 0.07	0.75 0.05	0.79 0.06	0.63 0.06	0.44 0.09	0.53 0.09	0.50 0.10	0.56 0.10	0.53 0.10	0.50 0.10	0.50 0.10	0.53 0.10	0.53 0.10	0.48 0.09
FAN		1 -	0.60 0.07	0.72 0.04	0.55 0.06	0.65 0.06	0.72 0.05	0.56 0.06	0.71 0.04	0.54 0.07	0.36 0.08	0.43 0.08	0.41 0.09	0.51 0.09	0.45 0.09	0.42 0.09	0.41 0.09	0.45 0.09	0.45 0.09	0.39 0.09
GRID			1 -	0.6 0.08	0.61 0.08	0.60 0.05	0.67 0.07	0.64 0.08	0.68 0.07	0.54 0.09	0.43 0.08	0.5 0.08	0.48 0.09	0.53 0.08	0.51 0.09	0.47 0.09	0.49 0.09	0.51 0.09	0.50 0.09	0.46 0.08
ICLN				1 -	0.75 0.06	0.62 0.05	0.81 0.06	0.73 0.06	0.78 0.05	0.81 0.05	0.40 0.08	0.47 0.08	0.44 0.09	0.50 0.09	0.46 0.09	0.43 0.09	0.44 0.09	0.46 0.10	0.45 0.10	0.43 0.09
LYNRI						0.66 0.06	0.55 0.04	0.58 0.04	0.68 0.04	0.52 0.05	0.30 0.08	0.37 0.07	0.34 0.08	0.42 0.08	0.37 0.08	0.35 0.08	0.36 0.08	0.36 0.08	0.36 0.08	0.32 0.08
PBD							0.81 0.07	0.81 0.06	0.84 0.06	0.77 0.06	0.44 0.08	0.52 0.08	0.48 0.09	0.53 0.1	0.5 0.09	0.48 0.09	0.48 0.09	0.5 0.1	0.5 0.1	0.47 0.08
PBW								0.91 0.02	0.82 0.04	0.85 0.03	0.47 0.07	0.55 0.07	0.50 0.08	0.50 0.09	0.51 0.08	0.48 0.08	0.5 0.08	0.51 0.09	0.5 0.09	0.51 0.07
QCLN								1 -	0.87 0.04	0.80 0.04	0.45 0.08	0.53 0.08	0.49 0.09	0.49 0.09	0.48 0.09	0.45 0.09	0.49 0.09	0.48 0.10	0.48 0.10	0.49 0.08
SMOG									1 -	0.75 0.05	0.46 0.08	0.54 0.08	0.50 0.09	0.53 0.09	0.52 0.09	0.48 0.09	0.50 0.09	0.51 0.10	0.51 0.10	0.49 0.09
TAN										1 -	0.38 0.08	0.45 0.08	0.40 0.10	0.42 0.10	0.41 0.10	0.39 0.10	0.40 0.10	0.41 0.10	0.40 0.10	0.40 0.09
FCG											1 -	0.93 0.02	0.93 0.02	0.84 0.03	0.89 0.02	0.83 0.04	0.91 0.03	0.89 0.03	0.88 0.02	0.96 0.01
FXN												1 -	0.96 0.01	0.90 0.02	0.95 0.01	0.91 0.02	0.96 0.02	0.95 0.01	0.94 0.01	0.96 0.01
IEO													1 -	0.91 0.02	0.96 0.01	0.86 0.03	0.96 0.02	0.96 0.01	0.95 0.01	0.97 0.01
IXC														1 -	0.96 0.02	0.88 0.02	0.91 0.03	0.96 0.01	0.95 0.01	0.87 0.03
IYE															1 -	0.90 0.01	0.95 0.02	0.99 0.01	0.99 0.01	0.92 0.02
OIH																1 -	0.90 0.02	0.91 0.02	0.90 0.02	0.86 0.03
RYE																	1 -	0.96 0.02	0.96 0.02	0.94 0.02
VDE																		1 -	0.99 0.00	0.93 0.02
XLE																			1 -	0.92 0.02
XOP																				1 -

Table 5: Average values of the dynamic conditional correlations estimated by the DCC-GARCH model. We highlight the correlations greater than 80% in dark green and those greater than 70% in bright green to improve the visualization.

the portfolio. Lately, between the third quarter of 2015 and the last one of 2017, we observe a predominance of CE ETFs among the ME_P holdings. The previous balance between CE and FF funds is restored afterward. We interpret this variation as a consequence of increased environmental concerns around the Paris Agreement (December 12, 2015). According to the literature, this event severely affected investors' preferences, implying green assets outperform their brown peers, but only in the short run (see Monasterolo and De Angelis (2020) and Fahmy (2022b) among others). We read a similar effect through the heavy depletion of the ME_P from FF funds, with the shock reabsorbed in the short or medium term. Conversely, we do not observe any portfolio holdings variation occurring during periods of market crisis or expansion.

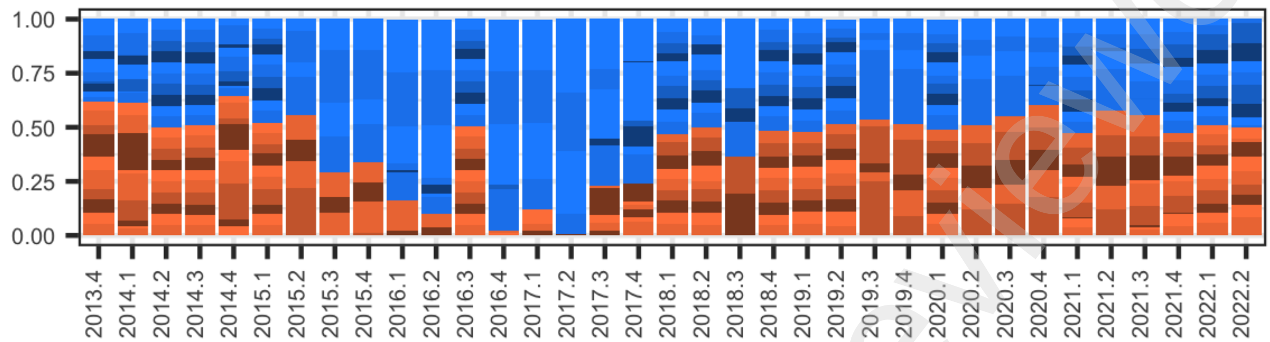


Figure 1: Portfolio weights of the ME_P by calibration period (2014/01/01 - 2022/01/01). The blue bar's sections represent weights of CE ETFs, while those brown the FF ones.

4.4 Portfolio performance: results

This section reports results obtained over the entire analysis period and within interesting market phases. Several financial and environmental-related events entailed structural breaks in the ETFs time series. Also, the energy market dynamics and variations in the attention to climate change demand a segmented study of the last market decades. We compare the portfolios' outcomes over a list of interesting periods: (i) before and (ii) after the Paris Agreement (January 3, 2014 - December 14, 2015, and December 15, 2015 - June 30, 2022, respectively), (iii) during the 2014-2016 oil price plunge (January 1, 2014 - June 6, 2016), (iv) in the year following the Covid-19 related market shock, and (v) during the Russian invasion of Ukraine (February 24, 2022 - June 30, 2022). This way, we analyze the impact of environmental-related events (i and ii), energy commodity market shocks (iii), and phases of systemic distress (iv and v) on the portfolio performance. We compare the outcome in terms of average annualized return (AARet) and volatility (AVol), the Sharpe and Sortino ratio, and the modified Sharpe ratio computed using the VaR and the ES as risk measures.

Table 6 summarizes the portfolios' performance. Results over the whole sample show the ME_P and the CE_P as similarly performing assets. They exhibit positive average annualized returns (11% vs. 11%) and similar volatility (25% vs. 28%). The ME_P slightly outperforms the CE_P in weighted returns, probably because of the CE ETFs' high volatility observed over the last years of analysis.

The FE_P underperforms its peers showing null, albeit negative, annualized returns and also greater volatility (32%). Consequently, its risk-weighted measures are the worst, as well.

The three portfolios' behavior massively mutates over the analyzed time intervals. Before the Paris Agreement, they all suffer huge losses. The FE_P shows the worst performance, also because it is the most affected by the oil price plunge period, followed by the ME_P and the CE_P, which exhibit similar negative outcomes. After the climate change milestone, we observe a turning point. The ME_P and CE_P average annualized returns become largely positive (18% and 17%, respectively), assuming values three times larger than the FE_P. The latter exhibits a smaller, albeit positive, outcome (6%). Their volatilities also increase compared to the pre-Paris Agreement values. The comparison between these two sub-periods suggests an impact of the Paris Agreement on the profitability of green assets, which is widely confirmed in the literature.

The 2014-2016 oil market distress phase entails a deterioration in all the portfolios' outcomes. During this period, the FE_P is the most penalized, with its average annualized return that assumes the lowest value (-14%). The CE_P and the ME_P average annual returns are also negative (-6% and -8%, respectively). This confirms the positive correlation within the total energy ETFs sector shown through the DCC analysis in Section 4.2.

The Covid-19 outbreak and the consequent slowdown of the world industry production marks a severe mismatch between the FE_P's performance and that of its cleaner peers. The average annualized returns of the ME_P and the CE_P are outstanding (88% and 86%, respectively), pitted against the still positive of the FE_P (20%). This difference is far more significant in terms of risk-weighted returns. This period is characterized by the largest annualized volatility overall. The FE_P peaks at the highest value overall (45% for both ME_P and CE_P and 59% for the FE_P), implying a greater risk-weighted performance of the cleaner portfolios than the fossil-fuel-based one.

Analyzing the months after the Russian invasion of Ukraine, the FE_P outperforms both its greener peers. The CE_P exhibits the worst, albeit slightly positive, performance in this period. The FE_P's average annual return hits 40%, and although it has larger volatility, its risk-weighted performance measures are greater than those of the other portfolios.

A joint analysis of the last three time intervals described (the oil price plunge, the Covid-19 outbreak, and the Russian invasion of Ukraine) shows how FF ETFs heavily suffer in periods of energy commodity market distress and lack of power demand. At the same time, they benefit from the scarcity of raw materials. Differently, the CE ETFs are less influenced by the energy market health than their brown peers, while they exhibit a marked sensibility to variations in the attention to climate issues. Consequently, a portfolio containing both FF and CE funds allows investors to exploit the profitability of the green assets and make the most of the FF's positive fluctuations.

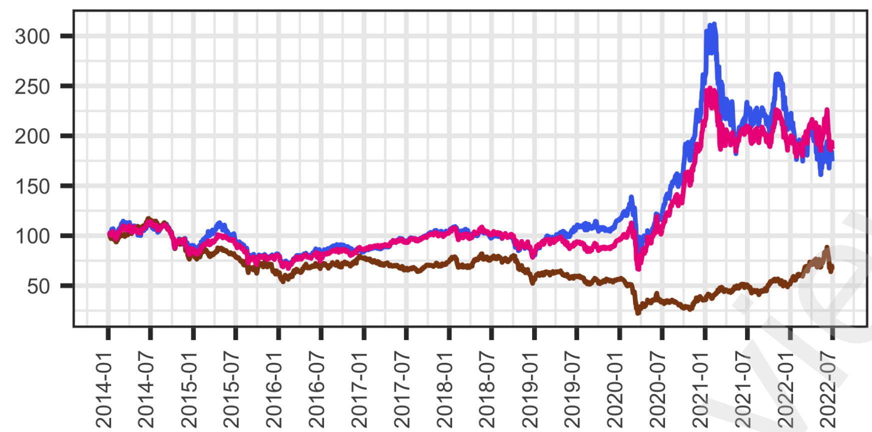
However, the comparison between the ME_P and the CE_P does not highlight any considerable benefit implied by including brown assets in the investor's portfolio.

Further dissimilarities among the three portfolios spawn in the dynamic comparison reported in Figure 2 and Figure 3, where we graphically show the performance of each portfolio in terms of compounded returns, Sharpe ratio, and risk measures. The ME_P and the CE_P show similar patterns all over the analysis period. Investing a unit of wealth in one of the two portfolios at the beginning of 2014 would have led to large profits at the end of the sample period. Their cumulative returns peak over 200%, having experienced a steep rise during 2020, and do not show significant drawdowns from the initial portfolio value. Differently, carrying out the same investment strategy on the FE_P would have brought losses, with the portfolio value halved at the beginning of 2020. The Sharpe ratio of the FE_P reported in Figure 2b is almost always lower than the other two, except in the last analysis period characterized by the shortage of raw materials, which vastly increased the FF commodity prices. Also, the VaR and the ES show how the FE_P is almost constantly riskier than its greener peers. Interestingly, the volatility entailed by the Covid-19 outbreak affected all three portfolios, but it negatively affected the FE_P.

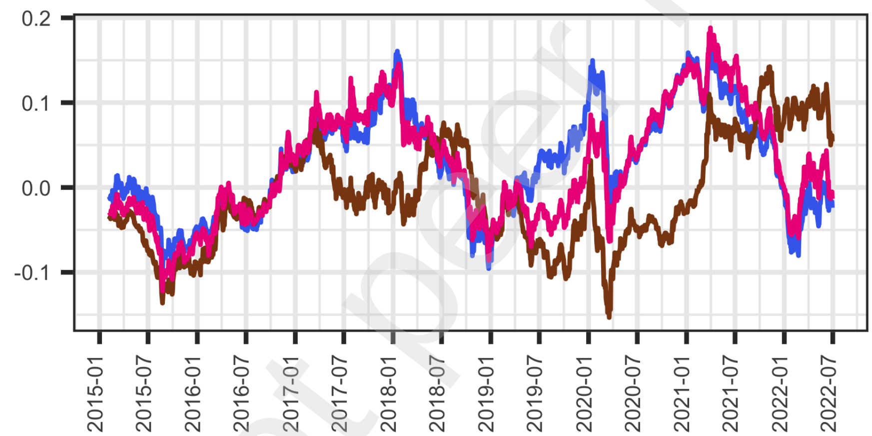
The discrepancies between the portfolios' performance over the entire period and the same time intervals analyzed before are minimized according to the inferential tests reported in Table 7. There are no statistically significant differences in the three portfolios' average returns nor in their modified Sharpe ratios. We find statistical discrepancies only during the Covid-19 period between the ME_P and the FE_P, where CE assets outperformed those FF-based. The F-tests denote differences in portfolios' volatility over the time frames analyzed. For instance, the ME_P is the less volatile portfolio both before and after the Paris Agreement and during the oil-plunge period. Also, the CE_P does not beat the FE_P before the climate change fight milestone in terms of volatility, but it does in all the following time frames analyzed, suggesting a possible turning point for CE funds. During the Covid-19 period, the ME_P's m-ShR is statistically greater than the FE_P, which confirms the suffering of FF funds during this exceptional production slowdown.

Port	AARet	AVol	ShR	mShR-VaR	mShR-ES	SoR
Whole sample: 2014/01/03-2022/06/30, 1990 trading days.						
ME_P	0.11	0.25	0.32	3.26	1.66	0.61
CE_P	0.11	0.28	0.26	2.66	1.54	0.55
FE_P	-0.00	0.32	-0.16	-1.67	-0.97	-0.00
Before Paris: 2014/01/03 - 2015/12/14, 422 trading days.						
ME_P	-0.14	0.22	-0.70	-6.47	-4.13	-0.86
CE_P	-0.12	0.25	-0.58	-5.42	-3.58	-0.67
FE_P	-0.24	0.25	-0.96	-8.97	-5.75	-1.30
After Paris: 2015/12/15 - 2022/06/30, 1571 trading days.						
ME_P	0.18	0.26	0.59	5.98	2.98	0.96
CE_P	0.17	0.29	0.49	5.01	2.86	0.84
FE_P	0.06	0.33	0.02	0.24	0.14	0.27
Oil Price Plunge: 2014/01/01 - 2016-06-01, 517 trading days.						
ME_P	-0.08	0.22	-0.46	-4.29	-2.78	-0.50
CE_P	-0.06	0.24	-0.36	-3.34	-2.19	-0.34
FE_P	-0.14	0.27	-0.62	-6.03	-4.15	-0.75
Covid Outbreak: 2020/02/28 - 2021/02/28, 247 trading days.						
ME_P	0.88	0.45	2.62	25.63	13.76	44.32
CE_P	0.86	0.45	2.52	25.12	13.63	43.16
FE_P	0.20	0.59	0.05	0.46	0.23	0.48
Russian invasion of Ukraine: 2022/02/24 - 2022/06/30, 83 trading days.						
ME_P	0.18	0.37	0.34	3.05	2.19	0.68
CE_P	0.09	0.43	-0.01	-0.05	-0.05	0.30
FE_P	0.40	0.47	0.71	6.38	4.85	1.15

Table 6: Annualized financial performance (average return, volatility, Sharpe Ratio, modified SharpeRatio computed using the VaR and the ES risk measures and Sortino Ratio) of the portfolio returns computed on the whole sample (01 Jan 2014 - 30 June 2022) and over interesting market periods.

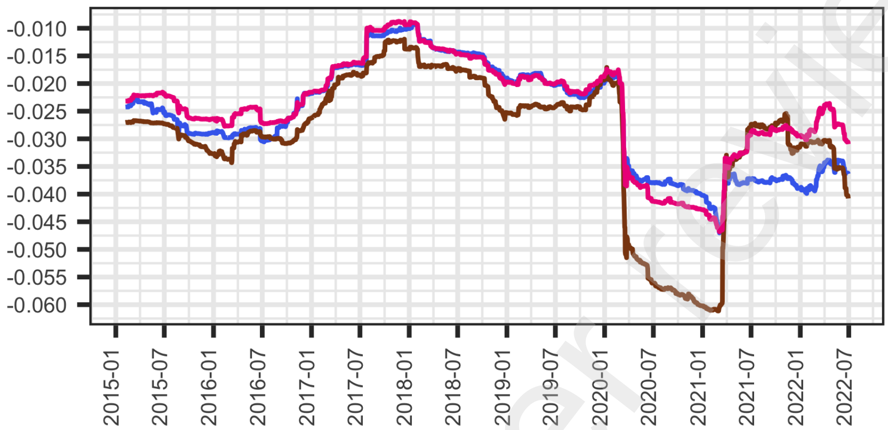


(a) Cumulative returns. Initial investment 100$

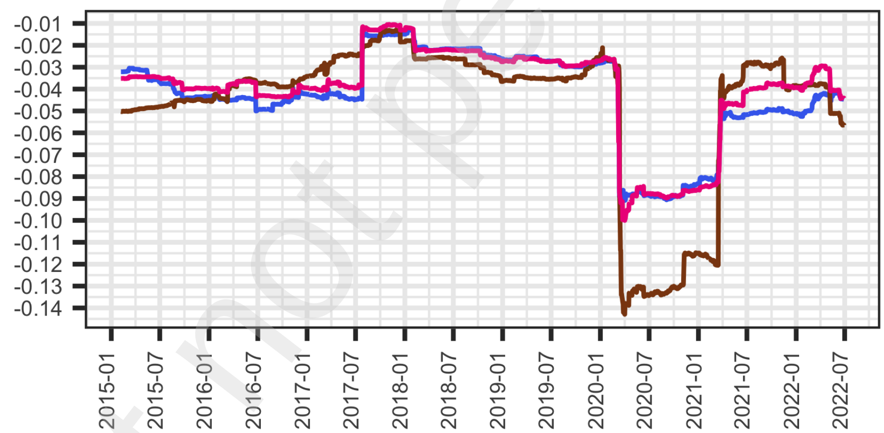


(b) Sharpe ratios

Figure 2: Cumulative daily returns of the three energy portfolios obtained through an initial investment of 100 USD and the relative Sharpe ratios (2014/01/03-2022/03/07). In blue the CE_P, in brown the FE_P, and in pink the ME_P.



(a) VaR



(b) ES

Figure 3: Portfolios daily risk measures, VaR in Figure 3a and ES in 3b, computed over the sample period (2014/01/03-2022/06/30) using a rolling window of size $\tau = 252$ observations. In blue the CE_P, in brown the FE_P, and in pink the ME_P.

Test	t	F	mSR-VaR
ME_P vs. CE_P	0.002	1.052	0.625
ME_P vs. FE_P	0.112	0.983	0.785
CE_P vs. FE_P	0.110	0.934	0.559

(a) Whole sample

Test	t	F	mSR-VaR
ME_P vs. CE_P	-0.017	0.773***	-0.506
ME_P vs. FE_P	0.104	0.746***	0.728
CE_P vs. FE_P	0.120	0.965	0.758

(b) Before Paris

Test	t	F	mSR-VaR
ME_P vs. CE_P	0.007	0.837***	0.901
ME_P vs. FE_P	0.115	0.617***	0.450
CE_P vs. FE_P	0.108	0.737***	0.212

(c) After Paris

Test	t	F	mSR-VaR
ME_P vs. CE_P	-0.021	0.813**	-0.482
ME_P vs. FE_P	0.062	0.666***	0.395
CE_P vs. FE_P	0.083	0.820**	0.513

(d) Oil Plunge

Test	t	F	mSR-VaR
ME_P vs. CE_P	0.019	0.996	0.020
ME_P vs. FE_P	0.671	0.571***	1.736*
CE_P vs. FE_P	0.652	0.573***	1.460

(e) Covid Outbreak

Test	t	F	mSR-VaR
ME_P vs. CE_P	0.094	0.996	0.301
ME_P vs. FE_P	-0.222	0.593**	-0.330
CE_P vs. FE_P	-0.316	0.824	-0.344

(f) Russian invasion of Ukraine

Table 7: Estimate and p-value of the inferential tests (t-test, F-test, modified Sharpe ratio-VaR test) conducted at a confidence level of 95% to assess potential dissimilarities between the performance of (i) the ME and CE portfolios (MEvsCE), (ii) the ME and FE portfolios (MEvsFE), and (iii) the CE and FE portfolio (CEvsFE) over the whole sample period (2014/01/03-2022/06/30) and interesting market phases. Note: $^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$

The yearly performance comparison confirms the benefits entailed by including CE ETFs in an energy funds portfolio. Inferential test results are reported in Table 8. The FE_P never statistically outperforms the ME_P and the CE_P, which are also often more profitable. For instance, investing in CE funds during 2014-2016 allowed containing the ME_P's losses, offering an alternative to the suffering FF assets. Similarly, the steep rise of CE ETFs' prices in 2017 leads the ME_P returns to overcome those of the FE_P. The CE_P outperforms the latter only in 2017 and 2020, when the production slowdown implied a massive decrease in FF asset prices overall. Interestingly, empirical evidence indicates the CE_P is more profitable than the ME_P in some years, as well. For instance, in 2019, the possibility of the USA return under the Paris Agreement increased the market expectation on renewable energies investments; hence, the prices of pro-environmental committed stocks rose. For this reason, the ME_P showed outstanding risk-weighted performance in 2019, large enough to overcome the benefits of the ME_P's greater diversification.

Test	t	F	mSR-VaR
ME_P vs. CE_P	0.941	-2.08	-3.021**
ME_P vs. FE_P	64.546**	9.117	0.141
CE_P vs. FE_P	-0.665	0.294	0.473

(a) 2014

Test	t	F	mSR-VaR
ME_P vs. CE_P	13.122***	0.591	-12.531***
ME_P vs. FE_P	0.393	33.404*	85.074**
CE_P vs. FE_P	0.112	1.065	0.852

(b) 2015

Test	t	F	mSR-VaR
ME_P vs. CE_P	-3.639	3.059	6.698*
ME_P vs. FE_P	149.544**	1.183	0.008**
CE_P vs. FE_P	0.312	-0.688	-0.705

(c) 2016

Test	t	F	mSR-VaR
ME_P vs. CE_P	-1.543	1.471	3.014
ME_P vs. FE_P	0.434	1291***	2978***
CE_P vs. FE_P	-1.104	2.105**	2.178**

(d) 2017

Test	t	F	mSR-VaR
ME_P vs. CE_P	0.555	1.426	0.871
ME_P vs. FE_P	2.630	12.543	4.770
CE_P vs. FE_P	0.314	0.080	-0.096

(e) 2018

Test	t	F	mSR-VaR
ME_P vs. CE_P	7.586**	-6.362**	-13.948**
ME_P vs. FE_P	0.492	15.064	30.615*
CE_P vs. FE_P	-1.649	1.419	1.869*

(f) 2019

Test	t	F	mSR-VaR
ME_P vs. CE_P	2.809***	1.715	-1.094
ME_P vs. FE_P	1.854	0.130	0.070
CE_P vs. FE_P	-0.562	3.121***	2.903***

(g) 2020

Test	t	F	mSR-VaR
ME_P vs. CE_P	-3.992	-10.476*	-6.484
ME_P vs. FE_P	0.111	0.092	0.829
CE_P vs. FE_P	0.148	-1.251	-1.167

(h) 2021

Test	t	F	mSR-VaR
ME_P vs. CE_P	16.732*	7.638	-9.095*
ME_P vs. FE_P	5.670	3.344	0.590
CE_P vs. FE_P	1.092	-1.638*	-1.527

(i) 2022

Table 8: Estimate and p-value of the inferential tests (t-test, F-test, modified Sharpe ratio-VaR test) conducted at a confidence level of 95% to assess potential dissimilarities between the performance of (i) the ME and CE portfolios (ME_P vs. CE_P), (ii) the ME and FE portfolios (ME_P vs. FE_P), and (iii) the CE_P and FE_P portfolio (CE_P vs. FE_P) over the whole sample period (2014/01/03-2022/06/30) and interesting market phases. Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

5 Conclusion

Clean energy ETFs experienced a significant increase in volumes and profitability in the last two decades. Their popularity is probably due to a joint combination of the appealing financial features of ETFs as a whole and the increase in the investors' climate concerns. Do investors still need FF assets in their portfolios?

In this paper, we evaluated the performance of energy ETFs analyzing whether excluding FF funds decreases the financial outcome. We built a portfolio composed of mixed energy ETFs and two others using only CE and FF funds, respectively. This way, we assessed possible financial drawbacks entailed by a green screening process and compared two similar assets, which drastically diverge in terms of carbon footprint.

We conducted an empirical analysis considering a sample of the ten most capitalized CE and FF ETFs currently exchanged on the global markets observed from January 1, 2012, to June 30, 2022. Results pointed out a significant difference in volumes, with the FF funds far more capitalized than their CE peers. Environmental-related news and variation in the market health strongly influence both CE and FF ETFs, often determining breaking points in their financial time series. A dynamic correlation analysis conducted through a DCC-GARCH model has shown that a large part of ETFs is strongly and positively linear dependent. However, the associations among FF funds are massively higher than those within the CE group. We selected the portfolios holdings choosing the mean-variance strategy to to minimize the volatility without penalizing returns. We re-balanced the weights quarterly, assuming no transaction costs, and analyzed the performance over interesting market phases and across crucial milestones in the climate change fight.

Results deny any financial drawback led by excluding the polluting energy ETFs from the investment portfolio. The three portfolios do not show statistically significant differences, but the ME_P and the CE_P outperform the FE_P in terms of cumulative returns and market risk. Cleaner portfolios produce a better financial outcome in several periods than the FE_P. Still, these differences often turn out to be not significant according to the inferential tests. Interestingly, we see the FF ETFs are largely excluded from the ME_P holdings in the period following the Paris Agreement, confirming the literature findings on its significant effect on the investors' preferences. During the Covid-19 period, characterized by the lack of raw materials demand, the FF funds suffered from the world production slowdown. On the contrary, the market expectation of green assets contributed to the CE funds skyrocketing performance. This entails an outstanding performance of the CE_P, which overcame those of the FE_P in 2020. Still, the market expectation on the future role of renewable energies plays a more central role than the actual economic situation. The 2019 Democratic pro-environmental campaign for the 46^{th} USA presidency makes the CE_P also more financially performant than the ME_P. Differently, the energy crisis triggered by the Russian invasion of Ukraine increased the profitability of FF funds. However, the short period of raw material scarcity analyzed does not allow us to conclude statistically through an actual outperformance of the FE_P over the CE_P.

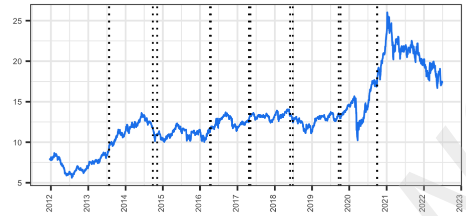
This empirical study underlines the absence of tangible financial benefits implied by including FF ETFs in investment strategies. The CE_P outcome matches that of the ME_P almost over the entire time horizon analyzed and exceeds that of the FE_P, albeit this difference is often not statistically significant. Concerning the energy ETFs market, investors ethical choice does not imply extra profit, nor does it deteriorate the portfolio performance. Periods of low power demand increase the CE stocks' prices while they annihilate those of the FF-based assets. On the contrary, oil & gas stocks' prices are enormously raised in energy supply scarcity phases, when the CE assets' behavior remains unclear. The comparison between the behavior of CE and FF ETFs in periods of stress of the energy demand and supply is left for further studies.

6 Appendix

6.1 Daily time series (2012-2021) of volumes in USD separated by ETF.

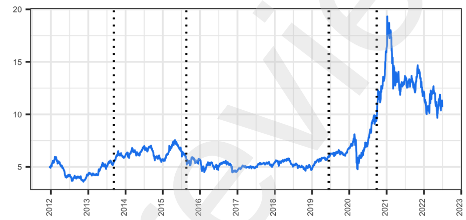
6.2 Descriptive statistics of ETFs log-retruns.

(a) ERTH

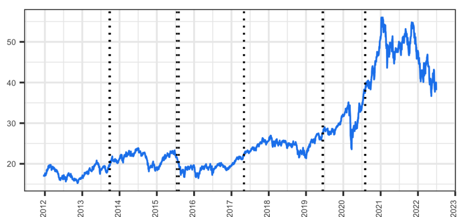


(b) FAN

(c) GRID

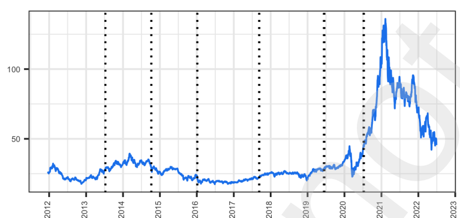


(d) INRG

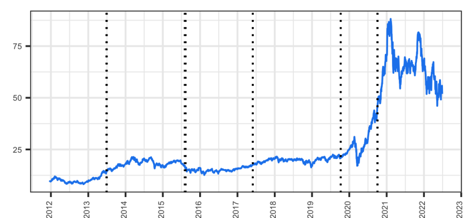


(e) LYNRI

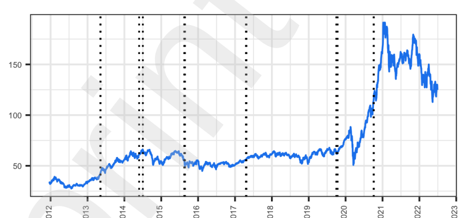
(f) PBD



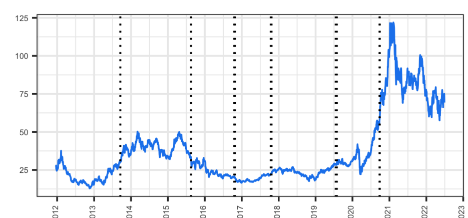
(g) PBW



(h) QCLN

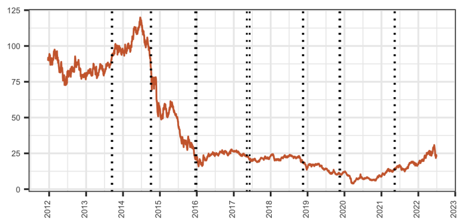


(i) SMOG

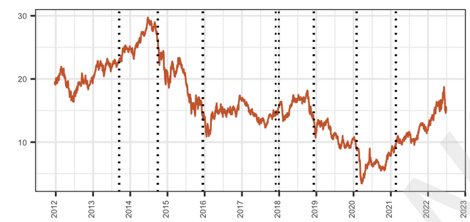


(j) TAN

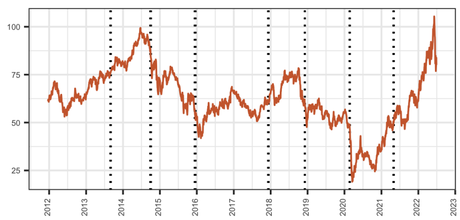
Figure 4: Time series of CE ETFs prices from 2012-01-03 to 2022-03-07. Vertical dotted lines indicate the estimated structural breaks.



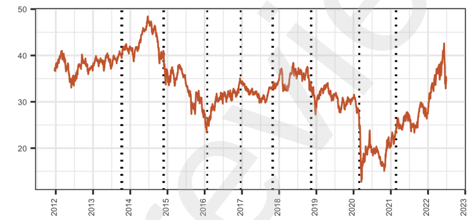
(a) FCG



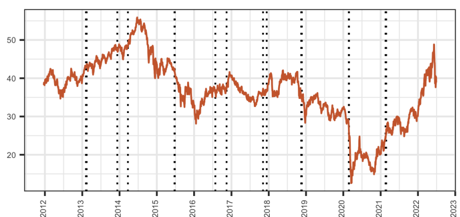
(b) FXN



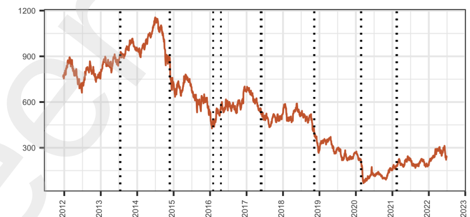
(c) IEO



(d) IXC

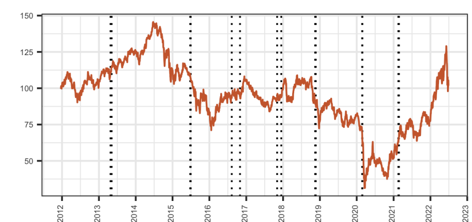


(e) IYE

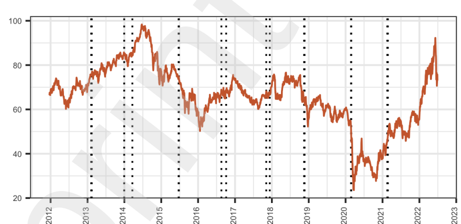


(f) OIH

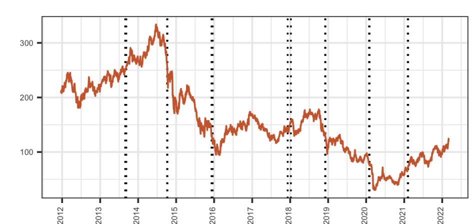
(g) RYE



(h) VDE



(i) XLE



(j) XOP

Figure 5: Time series of FF ETFs prices from 2012-01-03 to 2022-03-07. Vertical dotted lines indicate the estimated structural breaks.

ETF	Min	Max	Skew	Kurt	AARet	ASD	JB	LB	LB2	ARCH-LM	ADF	KPSS
FAN	-0.12	0.1	-0.59	8.33	0.06	0.22	7156.31***	1.89	282.79***	656.15***	-12.8**	0.06**
GRID	-0.14	0.1	-0.72	9.93	0.1	0.24	10176.1***	15.59***	299.01***	704***	-12.89**	0.05**
ICLN	-0.16	0.11	-0.54	7.02	0.05	0.27	5095.64***	12***	76.76***	440.05***	-11.72**	0.1**
LYNRI	-0.1	0.11	-0.25	4.05	0.06	0.23	1683.86***	0.11	121.07***	453.39***	-13.29**	0.06**
PBD	-0.2	0.1	-1.09	14.89	0.06	0.26	22886.43***	2.13	217.79***	651.96***	-11.45**	0.09**
PBW	-0.16	0.14	-0.42	4.99	0.00	0.35	2586.8***	1.70	67.99***	622.21***	-11.51**	0.12**
ERTH	-0.13	0.08	-1.1	10.03	0.07	0.22	10657.89***	2.33	102.03***	447.96***	-12.38**	0.07**
QCLN	-0.14	0.14	-0.4	4.73	0.13	0.32	2324.58***	0.00	55.53***	565.33***	-11.79**	0.08**
SMOG	-0.11	0.12	-0.41	4.92	0.11	0.27	2517.29***	0.00	69.21***	607.41***	-11.93**	0.08**
TAN	-0.18	0.16	-0.16	4.10	0.01	0.41	1713.61***	4.25**	19.21***	254.43***	-12.05**	0.15**
FCG	-0.34	0.14	-0.69	12.32	-0.21	0.43	15531.36***	0.94	50.70***	179.71***	-12.11**	0.26**
FXN	-0.32	0.14	-0.98	18.48	-0.09	0.36	34891.31***	0.13	62.32***	277.51***	-11.67**	0.10**
IEO	-0.3	0.15	-0.98	17.28	-0.04	0.36	30580.01***	2.91*	71.25***	324.19***	-11.86**	0.10**
IXC	-0.22	0.16	-1.09	21.38	-0.04	0.28	46680.9***	3.09*	64.54***	675.69***	-13.19**	0.07**
IYE	-0.23	0.15	-0.9	17.6	-0.04	0.3	31649.1***	7.52***	61.93***	630.1***	-12.27**	0.09**
OIH	-0.39	0.17	-1.16	23.38	-0.19	0.42	55789.57***	0.91	42.35***	239.4***	-11.72**	0.08**
RYE	-0.31	0.16	-1.12	21.31	-0.06	0.35	46422.23***	0.80	57.2***	344.13***	-12.08**	0.09**
VDE	-0.22	0.15	-0.76	15.18	-0.04	0.3	23525.49***	2.51	67.07***	625.86***	-12.23**	0.09**
XLE	-0.22	0.15	-0.9	17.52	-0.03	0.3	31345.35***	6.39**	88.28***	694.24***	-12.3**	0.09**
XOP	-0.46	0.2	-1.76	36.7	-0.14	0.43	137379.59***	5.54**	118.99***	162.4***	-12.11**	0.10**

Table 9: Summary Statistics of energy ETFs: sample mean (Mean), median (Median), minimum (Min), maximum (Max), Standard Deviation (SD), skewness (Skew), Kurtosis (Kurt), Jarque-Bera test (JB), Ljung-Box on returns (JB) and squared returns (JB2), Augmented Dickey-Fuller (ADF) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

References

Alexopoulos, T. A. (2018). To trust or not to trust? a comparative study of conventional and clean energy exchange-traded funds. *Energy Economics*, 72:97–107.

Ardia, D. and Boudt, K. (2015). Testing equality of modified Sharpe ratios. *Finance Research Letters*, 13:97–104.

Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, pages 47–78.

Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1):1–22.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3):307–327.

Dutta, A., Bouri, E., Saeed, T., and Vo, X. V. (2020). Impact of energy sector volatility on clean energy assets. *Energy*, 212:118657.

El Ouadghiri, I., Guesmi, K., Peillex, J., and Ziegler, A. (2021). Public attention to environmental issues and stock market returns. *Ecological Economics*, 180:106836.

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.

European Banking Authority (2022). Pillar 3 disclosures on ESG risks. <<eba.europa.eu/eba-publishes-binding-standards-pillar-3-disclosures-esg-risks>>.

European Union (2022). The EU Taxonomy. <<eu-taxonomy.info>>.

Eurosif (2021). The Sustainable Finance Disclosure Regulation. <<eurosif.org/policies/sfdr>>.

Fahmy, H. (2022a). Clean energy deserves to be an asset class: A volatility-reward analysis. *Economic Modelling*, 106:105696.

Fahmy, H. (2022b). The rise in investors' awareness of climate risks after the Paris Agreement and the clean energy-oil-technology prices nexus. *Energy Economics*, 106:105738.

Favre, L. and Galeano, J.-A. (2002). Mean-modified Value-at-Risk optimization with hedge funds. *The Journal of Alternative Investments*, 5(2):21–25.

Glosten, L. R., Jagannathan, R., and 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.

Gregoriou, G. N. and Gueyie, J.-P. (2003). Risk-adjusted performance of funds of hedge funds using a modified Sharpe ratio. *The Journal of Wealth Management*, 6(3):77–83.

Henriques, C. O., Neves, M. E., Castelão, L., and Nguyen, D. K. (2022). Assessing the performance of exchange traded funds in the energy sector: a hybrid dea multiobjective linear programming approach. *Annals of Operations Research*, pages 1–26.

International Energy Agency (2022). World Energy Outlook 2022. <<iea.org/reports/world-energy-outlook-2022>>.

International Monetary Fund (2021). World Economic Outlook. <<imf.org/en/Publications/WEO>>.

iShares (2022). Three reasons why clean energy is at a tipping point. <<ishares.com/us/insights/3-reasons-clean-energy>>.

Kanamura, T. (2020). Are green bonds environmentally friendly and good performing assets? *Energy Economics*, 88:104767.

Ledoit, O. and Wolf, M. (2008). Robust performance hypothesis testing with the Sharpe ratio. *Journal of Empirical Finance*, 15(5):850–859.

Memmel, C. (2003). Performance hypothesis testing with the Sharpe ratio. *Available at SSRN 412588*.

Metrio (2022). Metrio: end-to-end sustainability reporting software. <<metrio.net/en/solutions/sustainability-reporting>>.

Miralles-Quirós, J. L., Miralles-Quirós, M. M., and Nogueira, J. M. (2019). Diversification benefits of using exchange-traded funds in compliance to the sustainable development goals. *Business Strategy and the Environment*, 28(1):244–255.

Monasterolo, I. and De Angelis, L. (2020). Blind to carbon risk? an analysis of stock market reaction to the paris agreement. *Ecological Economics*, 170:106571.

Morningstar (2018). Sustainable Funds U.S. Landscape Report 2018. <<morningstar.com/insights/2019/02/19/esg-landscape>>.

Morningstar (2021). Sustainable Funds U.S. Landscape Report 2021. <<morningstar.com/lp/sustainable-funds-landscape-report>>.

NYSE (2021). NYSE Q2 2021 Quarterly ETF Report. <<nyse.com/etf/exchange-traded-funds-quarterly-report>>.

Ramiah, V., Martin, B., and Moosa, I. (2013). How does the stock market react to the announcement of green policies? *Journal of Banking & Finance*, 37(5):1747–1758.

Trackinsight (2022). ESG ETF investing outlook for 2022. <<trackinsight.com/en/etf-news/esg-etf-investing-outlook-2022>>.

UNEP Finance and UN Global Compact (2022). Principles for Responsible Investment. <<unpri.org>>.

United Nations Conference on Trade and Development (2020). Leveraging the Potential of ESG ETFs for Sustainable Development. <<unctad.org/system/files/official-document/diae2020d1_en.pdf>>.

United Nations Framework Convention on Climate Change (2015). The Paris Agreement. <<unfccc.int/files/meetings/paris_nov_2015/application/pdf/paris_agreement_english_.pdf>>.

Wallace, D. and McIver, R. (2019). The effects of environmental announcements on exchange traded funds. *Emerging Markets Finance and Trade*, 55(2):289–307.