Energy ETF performance: the role of fossil fuels.

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

First Version: May 21, 2021;
This Version: May 11, 2022

Abstract

Clean energy (CE) Exchange Traded Funds (ETFs) experienced a massive growth in the last years. In this paper, we provide investors with an empirical analysis of a sample of energy ETFs which shows how the exclusion of the CE polluting peers, namely the fossil fuels ETFs, does not lead to a deterioration in the financial performance of a portfolio of funds. Furthermore, investigating the connectedness of the CE ETFs with a sample of indexes representing the mainstream markets, we find evidence of significative association only with the stocks and renewables energies markets.

Keywords: Energy ETF, Renewable Energy, Investment Strategies, Systemic risk.
JEL Code:

*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, 00197 Rome, Italy. E-mail: giacomo.morelli@uniroma1.it

‡Corresponding author. Department of Economics and Social Sciences, Sapienza University of Rome, Rome, 00185 Rome, Italy. E-mail: kevyn.stefanelli@uniroma1.it

1 Introduction

According to Morningstar (2021), during the tumultuous year 2020, investments in sustainable exchange-traded funds (ETFs) account for two out of every three US dollars invested worldwide. The flow of money that overwhelmed this brand new market resulted in four times greater than that relative to the previous year and fifteen times more than in 2018. For this reason, the massive growth of these assets is under the lens of both academics and financial agents (Morningstar (2018)).

The number of Environmental, Social, and Governance (ESG) ETFs worldwide has risen from 39 in 2009 to 221 in June 2019, with a marked acceleration of the growth started in 2015, in correspondence with the Paris Agreement (United Nations Framework Convention on Climate Change (2015)), and continues in the following years peaking 47.8% in 2018 (United Nations Conference on Trade and Development (2020)). The European market is the largest one for these assets (130, 59%), followed by the North American (69, 31%) and the Asia Pacific one (10%). However, as Morningstar (2021) reported, both AUM and net inflows in the US exploded in 2020. This year only, 71 new sustainable funds have been launched, and seven of them overcome the threshold of 100 million US dollars at the end of the same year. Furthermore, 25 funds repurposed in sustainable funds changed their investment strategies.

As a result of the rapid increase of the green market inflows, environmental ETFs have outperformed their conventional peers in recent years. In particular, the renewable energy sector has been the most appealing one for sustainable ETFs investors, with renewable and fossil-fuel-free stocks that registered skyrocketing performance.[1] However, it is still unclear whether excluding the fossil fuels (FF) themed funds implies a reduction in the financial performance of an ETFs portfolio.

In this paper, we focus on energy ETFs by assessing whether (i) a sustainable screening process based on the exclusion of polluting assets affects financial performances and (ii) if the green ETFs show low connectedness with the other mainstream markets. In other words, we are searching for evidence that clean energy (CE) ETFs provide a satisfying risk-return trade-off compared to mixed energy ETFs and that they do not suffer from the low diversification entailed by the exclusion of fossil fuels funds. Moreover, by measuring the association with the other markets, we assess the potential use of these securities as hedging tools to increase portfolio diversification.

We analyze the performance of the ten most capitalized fossil fuels and renewable energy-based ETFs from an investor point of view, choosing as a time window the period 2012-2021. In particular, we first describe the daily time series of every single security to highlight their features and possible dissimilarities between CE and FF ETFs. Secondly, we build a CE and a mixed energy (ME) global

[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.

minimum variance portfolios composed of energy ETFs to determine the potential drawbacks led by the exclusion of fossil fuels-based assets in terms of (i) average returns, (ii) volatility, (iii) Sharpe Ratio (SR), and (iv) market risk, adopting measures like the Value-at-Risk (VaR) and the Expected Shortfall (ES). In the last section of the empirical analysis, we assess the relationship of the CE ETFs portfolio with the other mainstream markets (e.g., bonds, treasury, stocks). In pursuing this aim, we seek potential diversification benefits led by investing in these green securities through a copula and a Conditional VaR (CoVaR) analysis.

Our main findings show that the financial performance of the CE ETFs portfolio matches that of the mixed energy one all over the sample period and outperforms it in the last years of analysis, which have been characterized by the COVID-19 global outbreak and the increase in environmental concerns. The results on the relation with the other mainstream markets are partially in line with the previous literature findings, revealing a strong association of the CE portfolio with the stocks and the renewable energy markets. Differently, the association with the green bonds and the other sectors strongly depends on the period analyzed.

The remainder of this paper is organized as follows. Section refsec:lit reports the state of the art in this field of research. Section 3 outlines the methodology used in this paper. Section 4 describes the data and shows the empirical results. Section 5 summarizes the main results and concludes the paper. In Appendix **??** the reader can find additional tables and figures.

2 Literature Review

The green finance literature is characterized by the lack of homogeneous results concerning the financial costs of a screening process finalized to reduce the investment portfolio's carbon footprint. For instance, analyzing the green bonds (GBs) market, several authors find positive, negative, and null *greenium*, known as the premium paid for being *green* (Baker et al. (2018), Flammer (2021), Gianfrate and Peri (2019), Hachenberg and Schiereck (2018), Larcker and Watts (2020), Zerbib (2019)). Similarly, researchers disagree on the economic effect generated by the exclusion of polluting stocks or stock indexes (Cornett et al. (2016), Martí-Ballester (2017), Nguyen et al. (2020), Oberndorfer et al. (2013), Petitjean (2019), Trinks et al. (2018)), and on the screening process impact on sustainable funds performances (Capelle-Blancard and Monjon (2014), Cornett et al. (2016), Joliet and Titova (2018)). Divergences also emerge concerning the effect of the public attention to environmental themes on the green assets returns (Capelle-Blancard and Petit (2019), El Ouadghiri et al. (2021), Monasterolo and De Angelis (2020), Mukanjari and Sterner (2018)), on the relative risk and on their associations with the other mainstream markets (Pham (2016), Ferrer et al. (2021), Reboredo and Ugolini (2020), Reboredo et al. (2020)).

Alexopoulos (2018) examines discrepancies in financial returns and risk within the energy sector during the period 1999-2016. The author considers 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 benefits of a more significant portfolio diversification are evident, with the AEF portfolio outperforming the two others. Furthermore, CEF results are more affected by exogenous factors, like the 2008 GFC, than its conventional peer. Conversely, Kanamura (2020) shows how the ESG factors successfully mitigate the downside risk during the COVID-19 outbreak period (March 2020), highlighting the singular resilience of these securities during phases of market distress. Reboredo (2018) analyzes the co-movement between the GBs and the financial markets using a copula model to search for potential diversification benefits of including sustainable assets in the portfolio. The author finds a high (low) correlation of GBs with fixed-income (stock and commodity) markets, also observing tail dependence between some securities.

3 Methodology

We estimate the conditional volatility of the ETFs' returns 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 run a portfolio optimization based on the minimization of the volatility without the constraint on a target return. Risk metrics, like the Value-at-Risk and the Expected Shortfall, and inferential tests, like t-test, F-test, and Heteroskedasticity and Autocorrelation (HAC) inference, are computed to operate comparisons between couples of assets. Finally, we model the dependence structure between the ETFs portfolio and the mainstream markets using a copula-based approach. At the same time, we exploit the Conditional Value-at-Risk (CoVaR) measure to evaluate possible tail dependences.

3.1 DCC-GARCH model

Let y_t be a collection of serially uncorrelated time series. We define a zero-mean white noises vector $\varepsilon_t = y_t - \mu$, where y_t is the vector of expected returns. Then:

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

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 $y_{i,t}$ 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). More in detail: (i) we let the lag parameters of the GARCH(p,q) model span in predetermined intervals, $p \in \{1, 2, 3\}$ and $q \in \{0, 1, 2\}$; (ii) we choose three different GARCH model specifications, namely standard GARCH (sGARCH) (Bollerslev (1986)), exponential-GARCH (eGARCH), and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) (Glosten et al. (1993)); and (iii) we specify several specifications for the error terms distributions like Gaussian, Skewed-Gaussian, Student-t, Skewed Student-t, Generalized Error Distribution (GED), and Skewed GED.

3.2 Portfolio Optimization

We use the time series of the daily covariance matrices Σ_t returning from the DCC-model estimation to build a global minimum variance (GMV) portfolio for each trading day t. We determine the daily components of the portfolio by solving the following optimization problem:

$$
\begin{aligned}
&\min_{\omega_t} \frac{1}{2}\omega_t' \Sigma_t \omega_t \\
&s.t.\ \omega_t' 1_n = 1 \\
&\qquad \omega_t \geq 0,
\end{aligned}
\tag{3.6}
$$

where for each trading day t, ω_t is the n vector of weights, the number of assets considered, Σ_t is the estimated conditional covariance matrix, and short sales are not allowed. The model in Equation (3.6) is solved daily to assure a daily recalibration of the portfolio, assuming null costs of transactions.

3.3 Modeling dependence

We model the dependence between assets using copula functions following Reboredo (2018). According to the Sklar (1959) theorem, we can model the dependence between two time series in terms of a copula function "C". Let

$$y_{i,t} = \mu_{i,t} + \sigma_{i,t} u_{i,t}$$

and

$$y_{j,t} = \mu_{j,t} + \sigma_{j,t} u_{j,t}$$

be the dynamics of two series of financial returns, relative to the assets i and j, with $u_{s,t} \sim iid\mathcal{F}(0, 1)$, $s = \{i, j\}$. Then, the dependence structure, in the bivariate case, can be modeled as:

$$(u_{i,t}, u_{j,t}) \sim \mathcal{F}_{i,j}(u_{i,t}, u_{j,t}) = C[\mathcal{F}_i(u_{i,t}), \mathcal{F}_j(u_{j,t})], \tag{3.7}$$

where C is a copula function.

In this paper, we exploit the class of Elliptical copulas, namely those based on elliptical distributions, which contains (i) the Gaussian copula model, that implies tail independence, and (ii) the t-Student, which conversely allows for a tail dependence structure (Nelsen (2007)). The popularity of these models is mainly due to the straightforward interpretation of the parameters.

The Gaussian copula is described as:

$$C_\rho(u_1, \dots, u_n) = \Phi^n_\rho(F^{-1}(u_1), \dots, F^{-1}(u_n)),$$

where Φ is the Gaussian cumulative density function (CDF) and ρ a nxn correlation matrix. The relative copula density function is:

$$C(u_1, \dots, u_n) = \frac{1}{\sqrt{|\rho|}} \exp\left\{-\frac{1}{2} y(u)'(\rho^{-1} - I) y(u)\right\},$$

where $y(u_i) = \Phi^{-1}(u_i)$. The CDF of a Student t-copula can be written as follows:

$$C_{\nu,\rho}(u_1, \dots, u_n) = t^n_{\nu,\rho}\left(t^{-1}_\nu(u_1), \dots, t^{-1}_\nu(u_n)\right),$$

where t^n is the multivariate Student CDF, ρ represents the shape matrix, and ν the degrees of freedom. Furthermore, for $\nu > 2$, ρ is proportional to the correlation matrix (Malevergne and Sornette (2003)). The multivariate Student-t CDF is:

$$t^n_{\nu,\rho}(x) = \frac{1}{\sqrt{|\rho|}} \frac{\Gamma(\frac{\nu+n}{2})}{\Gamma(\frac{\nu}{2})(\pi\nu)^{n/2}} \cdot \int_{-\infty}^{x_1} \cdots \int_{-\infty}^{x_n} \frac{dx}{(1 + \frac{x'\rho^{-1}x}{\nu})^{(\nu+n)/2}},$$

and the density function of the t-copula is expressed as follows:

$$C(u_1, \dots, u_n) = \frac{1}{\sqrt{|\rho|}} \frac{\Gamma(\frac{\nu+n}{2})(\Gamma(\frac{\nu}{2}))^{n-1}}{(\Gamma(\frac{\nu+1}{2}))^n} \cdot \frac{\prod_{k=1}^n (1 + \frac{y_k^2}{\nu})^{(\nu+1)/2}}{(1 + \frac{y'\rho^{-1}y}{\nu})^{(\nu+n)/2}}$$

where $y_k = t^{-1}_\nu(u_k)$ and t_ν is the univariate t-Student distribution with ν degrees of freedom.

3.4 Risk metrics

We search for possible discrepancies in the financial performances of two securities by comparing the relative market risks. Considering a confidence level equal to $1 - \alpha$, we define at time t the Value-at-Risk (VaR) for the asset i as:

$$VaR_{i,t}(\alpha) = F^{-1}_{i,t}(\alpha), \tag{3.8}$$

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:

$$ES_{i,t}(\alpha) = \mathbb{E}\left[r_{i,t} | r_{i,t} \leq VaR_{i,t}(\alpha)\right], \tag{3.9}$$

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

To evaluate the VaR of the asset i, conditional on the fact that the security (or a market) j is in financial distress, we use the Conditional-VaR (CoVaR) metric proposed by Adrian and Brunnermeier (2011) and generalized by Girardi and Ergün (2013), which for the downside risk and for the given levels α and β is defined as:

$$P\left(r_{i,t} \leq CoVaR_{\beta,t}^{i|j} | r_{j,t} \leq VaR_{i,t}(\alpha)\right) = \beta. \tag{3.10}$$

We numerically find the CoVaR by solving

$$\int_{-\infty}^{CoVaR_{\beta,t}^{i|j}} \int_{-\infty}^{VaR_{i,t}(\alpha)} f_t(r_{i,t}, r_{j,t}) dr_{i,t} dr_{j,t} = \alpha\beta \tag{3.11}$$

where $f_t(r_{i,t}, r_{j,t})$ is the bivariate density of the two series of returns $r_{i,t}$ and $r_{j,t}$.

3.5 Inferential Tests

We adopt different tests to assess potential discrepancies in the financial performances of the securities analyzed. In particular, we use the independent two-samples *t-test* to search for possible differences in the average returns of a couple of assets, A_1 and A_2. The relative statistic is defined as:

$$t = \frac{\mu_{A_1} - \mu_{A_2}}{s_p\sqrt{\frac{2}{n}}}, \tag{3.12}$$

where μ_{A_1} and μ_{A_2} are the average returns of the two assets, $n = n_1 + n_2$ is the sum of the sizes of A_1 and A_2, and s_p is the pooled standard deviation unbiased estimator defined as:

$$s_p = \sqrt{\frac{(n_1 - 1)s_{A_1}^2 + (n_2 - 1)s_{A_2}^2}{n_1 + n_2 - 2}},$$

where s_{A_1} and s_{A_2} are the unbiased estimators of the standard deviation of the two samples, which we assumed as relatively similar ($\frac{1}{2} < \frac{s_{A_1}}{s_{A_2}} < 2$).

We test the hypothesis of null difference in the volatility of A_1 and A_2 using a two-tailed F-test. The relative statistic is defined as the variance ratio:

$$F = \frac{s^2_{A_1}}{s^2_{A_2}}, \tag{3.13}$$

where the null hypothesis is F=1.

Following Ledoit and Wolf (2008), we use the methodology called Heteroskedasticity and Autocorrelation (HAC) inference to search for statistical dissimilarities in the financial performances of two securities in terms of SR (?, ?). The estimator of the difference between the two SRs is defined as:

$$\hat{\Delta} = \frac{\mu_{A_1}}{s_{A_1}} - \frac{\mu_{A_2}}{s_{A_2}},$$

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

$$Z = -\frac{|\hat{\Delta}|}{s(\hat{\Delta})}, \tag{3.14}$$

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

4 Empirical Analysis

We collect the time series of the ten most capitalized clean energy (CE) and fossil-fuels (FF), or mixed, energy ETFs worldwide observed from 2012-04-19 to 2021-03-24.[2]. These assets are chosen to represent the total energy ETFs market. The sample contains only those 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 funds' objectives, issue dates, and the MSCI ESG Rating, ranging from CCC (low) to AAA (high).

Overall, every fund tracks a specific energy financial index designed and is reconstituted and rebalanced quarterly or semi-annually. Some of them invest in the energy sector, whereas others are fully dedicated to companies specialized in the production of energy from a single source. For example, the GRID tracks the price and yield of the NASDAQ OMX Clean Edge Smart Grid Infrastructure Index, while the FAN those of 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

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

ETF	Ticker	Inception Date	Description	ESG
Lyxor New Energy (DR) UCITS ETF	ENER	17 Oct 2007	The fund tracks the World Alternative Energy CW Net Total Return Index, is Euro-denominated, and 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.	AA
Invesco MSCI Sustainable Future ETF	ERTH	24 Oct 2006	The fund tracks the investment results of the MSCI Global Environment Select Index. It invests at least 90% of its total assets in securities comprised in the underlying index, which is designed to maximize the exposure to environmental related sectors.	BBB
First Trust Global Wind Energy ETF	FAN	16 Jun 2008	The fund tracks the ISE Global Wind Energy Index. It normally invests at least 90% of its net assets in stocks comprised in the underlying index.	AA
First Trust NASDAQ Clean Edge Smart Grid Infrastructure Index ETF	GRID	16 Nov 2009	The fund normally invests at least 90% of its assets in common stocks comprised in the NASDAQ OMX Clean Edge Smart Grid Infrastructure Index, which represent the target objective for price and yield performance.	AA
iShares Global Clean Energy ETF	INRG	09 Jul 2007	The fund tracks the S&P Global Clean Energy Index, which is designed to track the performance of approximately 30 of the most liquid and tradable global companies that represent the listed clean energy universe.	A
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.	A
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 of companies that are publicly traded in the US and engaged in the business of advancement of cleaner energy and conservation.	A
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 clean energy companies that are publicly traded in the US.	A
VanEck Vectors Low Carbon Energy ETF	SMOG	03 May 2007	The fund seeks to replicate the price and yield performances 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.	A
Invesco Solar ETF	TAN	15 Apr 2008	The fund seeks to track the performances of the MAC Global Solar Energy Index, investing at least 90% of its total assets in the comprised securities.	A

Table 1: Description of the CE ETFs comprised in the final sample of analysis.

focused on the natural gas sector by tracking the ISE-Revere Natural Gas Index. The ESG ratings of the two groups of ETFs are enormously different because a large part of the firsts are A+ ESG rated, except the ERTH, which is BBB-rated, while the seconds are mostly BBB- or BB-rated, except IXC, which is A-rated.

4.1 Descriptive Statistics

We report the time series of prices along with the estimated structural changes (**?**, Bai and Perron (2003)) separated by CE, in Figure 1, and FF ETFs, in Figure 2.

The CE ETFs show similar patterns. Their volatilities increased between 2014 and 2016, and a steep rise in prices started in the first period of the year 2020. Similarly, the FF ETFs seem to co-move, except for the FCG, which presents a pretty different pattern, especially in the last years of analysis. This divergence is probably due to the scope of this energy ETF that invests only in companies involved in the natural gas industry.

In Table 3, we report the dates of the structural changes estimated on the ETFs daily prices series, highlighting those that occurred on the same days.[3] A large part of them are related to

[3]We consider two (or more) structural breaks related to the same event when they appear in the same time

ETF	Ticker	Inception Date	Description	ESG
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.	BB
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.	BB
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.	BBB
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 securities of the underlying index.	A
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.	BBB
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.	BBB
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 securities that comprise the underlying index.	BBB
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 U.S. companies within the energy (oil and gas) sector.	BBB
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 securities comprising the index.	BBB
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.	BBB

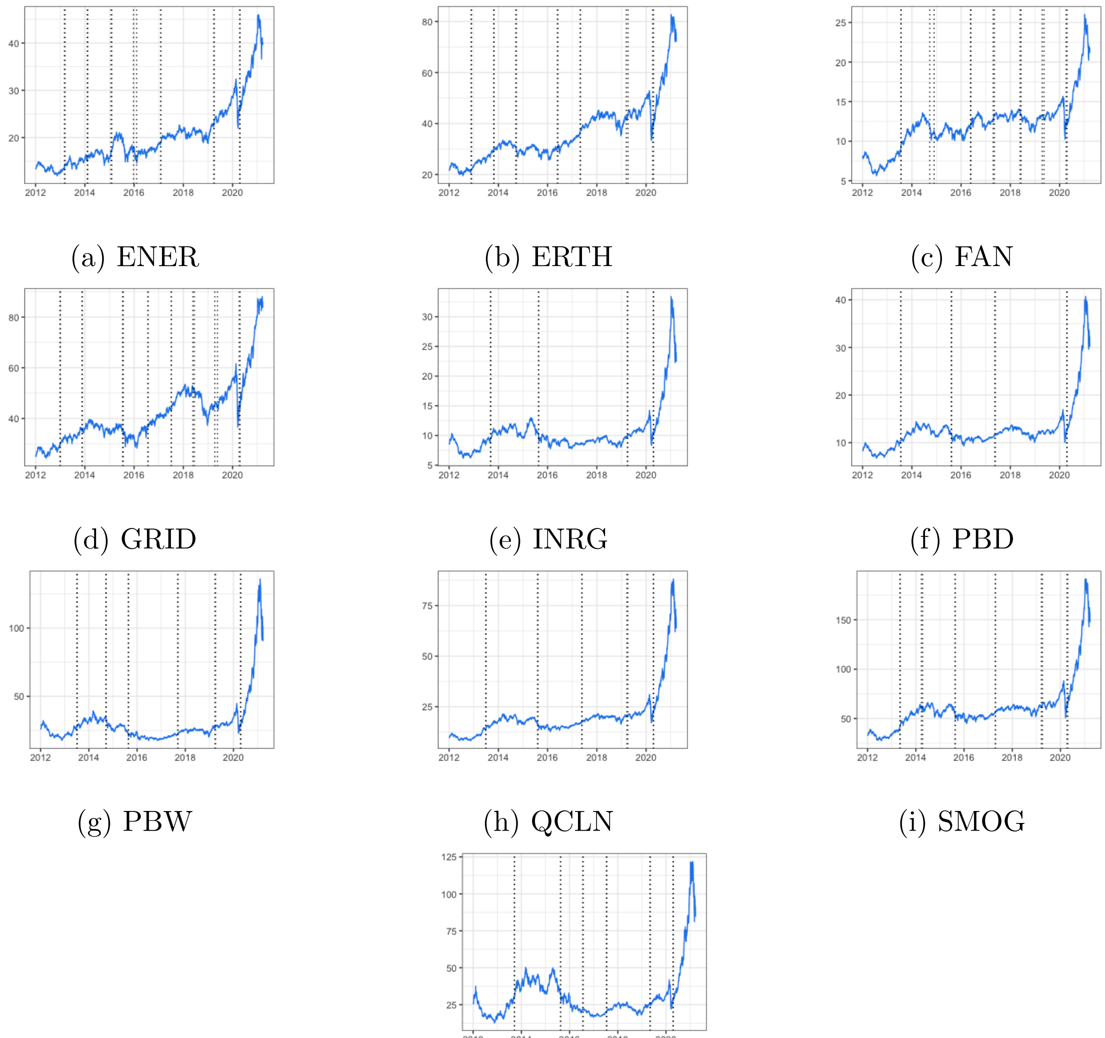
Table 2: Description of the FF ETFs comprised in the final sample of analysis.

particular market phases, but we also register the impact of exogenous events. For instance, during December 2012, September 2014, and November 2018, the FF ETFs suffered from market uncertainty, while their CE peers benefited from the market expansion that occurred at the beginning of 2019. In line with the current literature, we denote the resilience of green securities in periods of market distress, with only the FF-based funds which are negatively affected by uncertainty.

Interestingly, the massive growth of the CE ETFs prices during 2020 and the relatively slight retracement observed at the beginning of 2021 exactly coincide with the run for the election of the 46^{th} president of the USA. The increase of CE assets 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 climate pact. The prices drop in the days following the announcement of the new US president's election reflects a typical market behavior in correspondence with meaningful events (sell the news).

During the COVID-19 period, two critical events entailed structural changes in the energy ETFs groups. In particular, we observe a massive drop in all the FF ETFs prices on 21-25 February 2020, when the stock markets 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

interval of $\pm$ 10 days.



(a) ENER (b) ERTH (c) FAN

(d) GRID (e) INRG (f) PBD

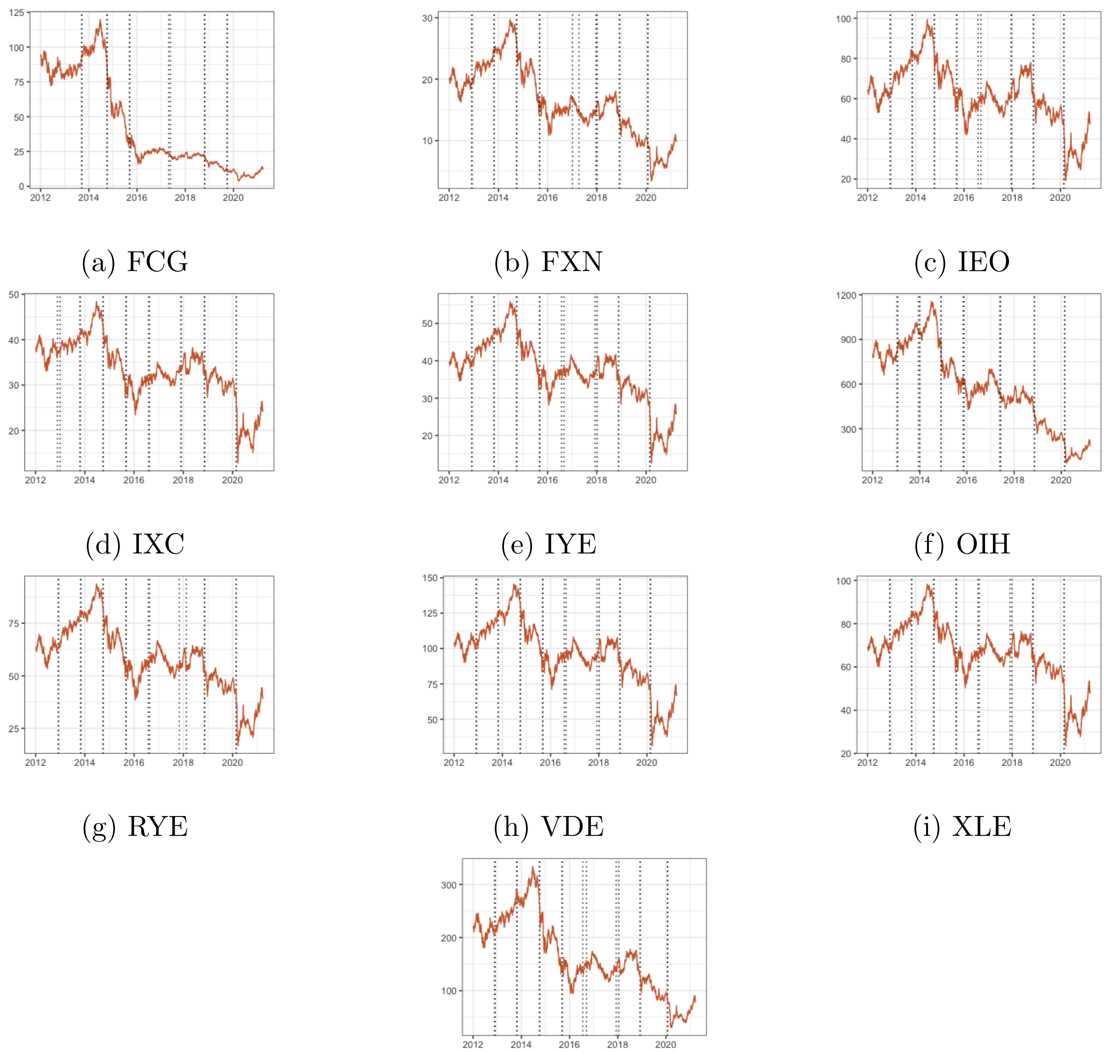
(g) PBW (h) QCLN (i) SMOG

(j) TAN

Figure 1: Time series of CE ETFs prices from 2012-01-03 to 2021-03-24. The confidence intervals computed at level $\alpha = 5\%$ of the estimated breakpoints are reported in black.

for energy strongly decreased. For this reason, 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. On the same day, we observed structural breaks in all the CE ETFs, indicating a variation in the energy ETFs investors' preferences.

We collect evidence of investors' increasing appetite for CE ETFs in the last years also from the analysis of the volumes reported in Figure 11 and Figure 12, respectively, for CE and FF. Overall, almost every sampled energy ETF registered a significant increase in the last two years, in line with the growth of the ETFs market as a whole. The CE ETFs present lower capitalizations than their



(a) FCG (b) FXN (c) IEO

(d) IXC (e) IYE (f) OIH

(g) RYE (h) VDE (i) XLE

(j) XOP

Figure 2: Time series of FF ETFs prices from 2012-01-03 to 2021-03-24. The confidence intervals computed at level $\alpha = 5\%$ of the estimated breakpoints are reported in black.

FF peers, except for the INRG, which has experienced the most significant increase in volume from late 2019, from 40 to more than 200 units exchanged daily.

4.2 Estimation of conditional volatilities

In this section, we estimate the conditional volatilities to investigate the relations between both the energy ETFs as a whole and within each group of securities, CE and FF. In particular, we are interested in evaluating whether the different carbon footprints of CE and FF assets entail lower associations among them and then if the CE ETFs effectively constitute a new asset class, as Fahmy

ETF	2012	2013	2014	2015	2016	2017	2018	2019	2020
ENER		03/07	02/10	02/03	01/05	02/01		04/02	04/20
ERTH		11/27	10/24	09/23	05/31	04/28		04/02	04/20
FAN		07/24	10/01		05/23	04/26	06/06	05/09	04/20
GRID	12/28	11/21		07/21	07/26	07/06	06/06	05/09	04/20
ICLN		09/06		08/19				04/03	04/20
PBD		07/19		08/10		05/22			04/20
PBW		07/05	09/17	08/21		09/11		04/04	04/20
QCLN		06/28		08/05		05/23		04/04	04/20
SMOG		05/07	04/01	08/18		04/19		04/02	04/20
TAN		09/17		08/18	07/20	07/17		05/09	04/20
FCG		09/16	10/06	09/09		04/26	10/23	09/30	
FXN	12/04	10/31	09/30	09/03		12/29	12/04		01/28
IEO	12/11	11/07	10/08	09/11	08/12	12/19	11/19		02/24
IXC	11/27	10/24	09/30	09/03	08/05	11/29	11/09		02/25
IYE	12/04	10/31	09/30	09/03	08/05	12/19	11/19		02/25
OIH		12/23	11/25	11/09		05/24	11/09		02/21
RYE	12/04	10/31	09/30	09/03	08/05	12/12	11/09		02/25
VDE	12/04	10/31	09/30	09/03	08/05	12/19	11/19		02/24
XLE	12/04	10/31	09/30	09/03	08/05	12/12	11/09		02/25
XOP	11/27	10/24	10/06	09/09	08/10	12/29	12/04		01/24

Table 3: Estimated breakpoints dates relative to CE (in blue) and FF (in brown) ETFs (1 Jan 2012 - 24 March 2021).

(2022) concludes.

We compute the logreturns r_t of each ETF as:

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

where P_t is the price of the ETF at time t.

Table 11 summarizes the descriptive statistics of the sample returns. All the ETFs, in line with the stylized facts of the daily financial time series (Cont (2001)), show: null mean, negative skewness and positive kurtosis (Jarque-Bera (JB) test statistically significative), uncorrelated returns, and presence of ARCH effect (squared returns autocorrelated, and ARCH-LM, Augmented Dickey-Fuller (ADF), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests significative). Moreover, we denote peaks of abnormal returns during phases of market distress (e.g., 2012, 2016, and 2020). Comparing the returns of CE and FF ETFs, we observe more significant fluctuations in the second group, especially in the period characterized by the COVID-19 global crisis.

According to the Bayesian information criterion (BIC), the GJR-GARCH is the best model specification to represent the ETFs dynamics among those presented in Section 3.1, highlighting a leverage effect in the time series. The optimal combination of the p and q parameters varies between $\{(1, 0), (1, 1), (2, 0)\}$, which suggests the use of a parsimonious model. Furthermore, the autocorrelation function (ACF) and partial ACF (pACF) exhibit the lack of autoregressive moving average (ARMA) dynamics in the conditional means of log returns, which can be considered null. According to the BIC, the Student-t distribution is chosen for the innovation processes as it better fits the fat tails observed in the descriptive analysis of the sample.

We estimate the one-day-ahead volatility for each time series using the relative best GARCH model and a rolling window containing the last 250 observations. The annualized conditional daily volatilities obtained by multiplying values by $\sqrt{250}$ are reported in Figure 11 and Figure 12. Overall, the estimated volatilities are relatively high and characterized by peaks over 120% and 200%, respectively, for CE and FF ETFs, observed during the same tumultuous periods of the market. More in detail, FF funds volatilities show very similar patterns within each other. Still, although their values are identical to those of the CE in periods of normal markets, their spikes are massively more considerable than the others.

We estimate the time-varying correlations among the ETFs by fitting a DCC-GARCH model on the entire sample, choosing the Normal distribution for the error terms of the dynamic model. Table 4 shows the averages of the estimated DCC computed all over the sample period, along with the relative standard deviations. All the energy ETFs are positively correlated, with values that span between 26% and 99%. Among the CE, the most correlated in mean are the PBW and the QCLN (90%) because they both contain almost exclusively US-listed wind, solar, biofuels, and geothermal companies. Similarly, the SMOG, which has a similar scope, is highly correlated with these two ETFs (81% and 86%, respectively). The lowest average correlations in this group are those relative to the ENER (between 46% and 60%), which is the only one that is exchanged in Europe, and the GRID (from 52% and 65%), which is entirely dedicated on global equities belonging to the smart grid and electrical energy infrastructure sectors.[4] Conversely, the ERTH and the INRG are those most correlated with all the other CE ETFs. The holdings of the first fund cover a large part of the CE quasi sectors, like alternative energy, energy efficiency, green buildings, water, pollution

[4] 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.

prevention and control, and sustainable agriculture. Then, its financial performance is related to the entire CE industry. The INRG shows the most significant market capitalization, and thus it represents the market driver. For this reason, the correlation with its peers is high.

All the FF ETFs show high average DCC, with only the couples FCG-IXC and FCG-OIH that present values equal to 83%, while the others fluctuate over 88%. The three pairs, IYE-VDE, IYE-XLE, and VDE-XLE, exhibit the highest value (99%), but we denote several correlations over 95% in this group. The FCG is the only FF that does not invest in oil but is focused only on natural gas industries. For this reason, it registers the lowest correlations, albeit still extremely high, in this subset. Furthermore, the most capitalized FF ETF, the XLE, shows the highest linear associations with the large part of the FF assets, with values that span between 90% and 99% except for the FCG (88%). CE and FF ETFs show positive and not negligible correlations between them, with values that span between 26% (ENER-FCG) and 60% (SMOG-IXC). The ENER also exhibits the lowest relations with the FF funds, with correlations between 26% and 34%. Hence, results highlight a significant positive association all over the energy ETFs market, which is justified by the marked similarities of these two classes of securities that differ only in their carbon footprints.

4.3 Portfolio Selection

Our aim consists in determining the price of the decarbonization of an energy ETFs portfolio in terms of the possible reduction of financial performances implied by the exclusion of polluting funds. For this reason, we conduct a comparative dynamic analysis among a mixed energy ETFs portfolio (MEP), which contains both CE and FF funds, and a CE ETFs portfolio (CEP), which comprises only CE assets. This analysis sheds light on the economic relevance of the inclusion (exclusion) of the FF ETFs.

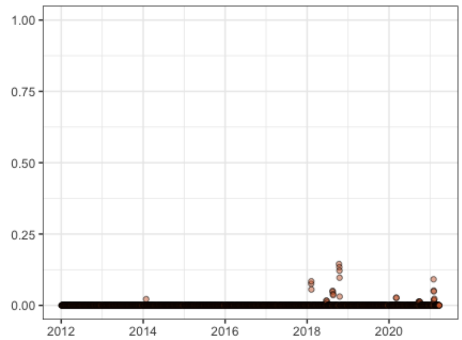
A portfolio selection process conducted on highly correlated assets could generate issues. Hence, according to the DCC results shown in Section 4.2 and the specific features that characterize every asset, we select a subset of energy ETFs for each group, CE and FF. The final sample includes only the following funds: (i) the ENER, (ii) the FAN, (iii) the GRID, (iv) the INRG, and (v) the TAN, belonging to the CE set, and only (vi) the FCG and (vii) the XLE among FF ETFs. In particular, the INRG and the XLE belong to the final sample because of their large volumes, making them representative of the two groups. We select the ENER for the relatively low correlations, compared to the others, that it exhibits with all the other energy ETFs. Then, we include the FAN, the GRID, and the TAN, which are almost entirely focused on a unique renewable energies quasi sector (i.e., wind energy, smart grid, and solar energy). For the same reason, we also consider the FCG because, albeit it shows high correlations with all the other FF ETFs, it invests only in natural gas

	ENER	ERTH	FAN	GRID	INRG	PBD	PBW	QCLN	SMOG	TAN	FCG	FXN	IXC	IEO	IYE	OIH	RYE	VDE	XLE	XOP
ENER	1 -	0.59 (0.04)	0.50 (0.07)	0.50 (0.06)	0.52 (0.06)	0.56 (0.06)	0.51 (0.05)	0.54 (0.04)	0.60 (0.04)	0.46 (0.06)	0.26 (0.06)	0.34 (0.06)	0.37 (0.06)	0.33 (0.06)	0.34 (0.06)	0.32 (0.06)	0.34 (0.06)	0.34 (0.06)	0.34 (0.06)	0.29 (0.06)
ERTH		1 -	0.72 (0.05)	0.73 (0.07)	0.70 (0.05)	0.78 (0.06)	0.73 (0.04)	0.76 (0.04)	0.80 (0.03)	0.63 (0.06)	0.49 (0.06)	0.59 (0.06)	0.64 (0.07)	0.57 (0.07	0.60 (0.07)	0.56 (0.07)	0.56 (0.06)	0.60 (0.07	0.60 (0.07)	0.54 (0.07)
FAN			1 -	0.57 (0.08)	0.71 (0.04)	0.72 (0.05)	0.55 (0.06)	0.56 (0.06)	0.71 (0.04)	0.52 (0.06)	0.40 (0.07)	0.47 (0.07)	0.56 (0.07)	0.46 (0.07)	0.50 (0.07	0.46 (0.07)	0.46 0.07)	0.50 (0.07)	0.50 (0.07)	0.42 (0.07)
GRID				1 -	0.57 (0.08)	0.64 (0.08)	0.59 (0.09)	0.61 (0.09)	0.65 (0.08)	0.52 (0.09)	0.43 (0.08)	0.50 (0.08)	0.54 (0.08)	0.49 (0.08)	0.51 (0.08	0.48 (0.08)	0.49 (0.08)	0.51 (0.08)	0.51 (0.08)	0.46 (0.08)
INRG					1 -	0.79 (0.06)	0.73 (0.06)	0.71 (0.06)	0.76 (0.05)	0.79 (0.05)	0.43 (0.07)	0.51 (0.07)	0.55 (0.07)	0.48 (0.08)	0.51 (0.08)	0.47 (0.08	0.49 (0.08)	0.51 (0.08)	0.50 (0.08)	0.46 (0.08)
PBD						1 -	0.79 (0.07)	0.79 (0.06)	0.83 (0.06)	0.75 (0.06)	0.47 (0.07	0.55 (0.08)	0.59 (0.08)	0.53 (0.08)	0.56 (0.08)	0.52 (0.07)	0.53 (0.07)	0.55 (0.08)	0.55 (0.08)	0.5 (0.08)
PBW							1 -	0.90 (0.02)	0.81 (0.04)	0.84 (0.03)	0.51 (0.06)	0.59 (0.06)	0.56 (0.07)	0.56 (0.06)	0.56 (0.07)	0.53 (0.06)	0.55 (0.06)	0.56 (0.07)	0.56 (0.07)	0.54 (0.06)
QCLN								1 -	0.86 (0.04)	0.79 (0.04)	0.49 (0.06)	0.57 (0.06)	0.54 (0.07)	0.54 (0.07)	0.54 (0.07)	0.5 (0.07)	0.53 (0.07)	0.54 (0.07)	0.54 (0.07)	0.52 (0.07)
SMOG									1 -	0.74 (0.05)	0.51 (0.07)	0.58 (0.07)	0.60 (0.07)	0.56 (0.07)	0.58 (0.07)	0.54 (0.07)	0.56 (0.07)	0.58 (0.07)	0.58 (0.07)	0.54 (0.07)
TAN										1 -	0.42 (0.07)	0.49 (0.07)	0.47 (0.08)	0.46 (0.08)	0.46 (0.08)	0.43 (0.08)	0.46 (0.08)	0.46 (0.08)	0.46 (0.08)	0.44 (0.08)
FCG											1 -	0.92 (0.02)	0.83 (0.03)	0.93 (0.02)	0.88 (0.02)	0.83 (0.04)	0.91 (0.03)	0.89 (0.02)	0.88 (0.02)	0.96 (0.01)
FXN												1 -	0.90 (0.01)	0.96 (0.01)	0.95 (0.01)	0.91 (0.02)	0.95 (0.02)	0.95 (0.01)	0.94 (0.01)	0.96 (0.01)
IXC													1 -	0.91 (0.02)	0.96 (0.01)	0.88 (0.02)	0.90 (0.03)	0.95 (0.01)	0.95 (0.01)	0.87 (0.02)
IEO														1 -	0.96 (0.01)	0.87 (0.03)	0.95 (0.02)	0.96 (0.01)	0.95 (0.01)	0.97 (0.01)
IYE															1 -	0.91 (0.01)	0.94 (0.02)	0.99 (0.00)	0.99 (0.00)	0.92 (0.01)
OIH																1 -	0.90 (0.02)	0.91 (0.01)	0.90 (0.01)	0.87 (0.03)
RYE																	1 -	0.95 (0.02)	0.95 (0.02)	0.94 (0.02)
VDE																		1 -	0.99 (0.00)	0.93 (0.02)
XLE																			1 -	0.92 (0.01)
XOP																				1 -

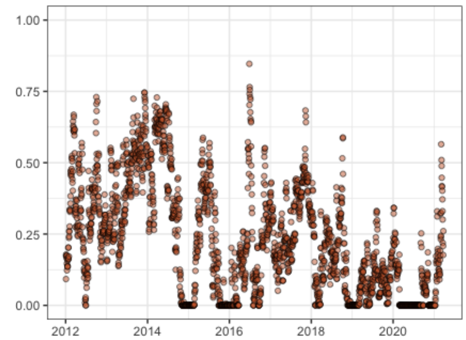
Table 4: Average values of the dynamic conditional correlations estimated by the DCC-GARCH model. We highlight the correlations greater than 86% in light green and those greater than 70% in olive green for a quicker visualization.

companies, and hence it is oil and coal-free. The other ETFs are excluded from the final sample as deemed as represented by these seven assets.

We build the GMV MEP and CEP, estimating the optimal weights of each energy ETF by solving the optimization problem reported in Equation (3.6). More in detail, for each portfolio, we estimate a new DCC model daily which considers only the relative feasible companies, the entire final subset of ETFs for the MEP and only those green for the CEP, and a rolling window of 250 daily observations. We calibrate the weights daily, assuming no transaction costs, and prohibit short sales. We report in Figure 3 the optimal weights relative to the two FF ETFs chosen daily for the MEP. The XLE is widely included in the portfolio all over the time horizon considered, with weights that broadly fluctuate, peaking over 75% in normal market periods and becoming null in phases characterized by market uncertainty (e.g., 2016, 2020). Conversely, the FCG is barely selected all over the period. This result implies that: (i) the significant volatility of the FF funds presented in Section 4.1 leads to their exclusion from a GMV portfolio during phases of market distress, and (ii) the CEP and MEP show consistent dissimilarities in their compositions, with FF assets which become a substantial part of the portfolio holdings in periods of market expansion.



(a) FCG portfolio weigths



(b) XLE portfolio weigths

Figure 3: Portfolio weights of the two FF ETFs included in the GMV MEP (2012/01/03 - 2021/03/24).

4.4 Portfolio performance: results

We compute several financial performance metrics to evaluate the possible drawbacks of excluding the FF ETFs. In particular, we estimate the portfolio annualized daily returns, the cumulative returns, the annualized volatility, and the Sharpe ratio (SR) computed as follows:

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

$$SR_t = \frac{\mu_{P,t}}{\sigma_{p,t}} \qquad \sigma_p = \frac{1}{\tau}\sum_{t=1}^{\tau}(r_t - \mu_{P,t})^2$$

where $\mu_{P,t}$ is the portfolio average return at time t computed over the period $[t, t + \tau]$, with τ set to 22 trading days.[5]

Table 5 summarizes the performances of the two portfolio returns evaluated over the sample period. The MEP and the CEP present similar statistics and features, like null averages, slightly positive medians, and almost the same ranges. The close, albeit strongly negative, skewness values exhibit large negative asymmetry in both the returns distributions. Conversely, while both portfolios show kurtosis greater than the Gaussian distribution, the CEP shows a value that is 15 times greater than that of the MEP, highlighting fatter tails. The annualized volatilities computed almost

[5]The annualized quantities are obtained as the daily estimates multiplied by $\sqrt{250}$.

coincide, while the SR of the CE portfolio is greater than that of FF. While a t-test conducted on the two series of returns rejected the hypothesis of null difference in means, showing a slight difference in the portfolio's returns (CEP > MEP), an F-test conducted on the volatilities ratio results not significative for the inequality in variance and the HAC-test concludes to the lack of a statistical difference in SR (Ledoit and Wolf (2008)), although the relative p-value is close to the critical value (0.11).

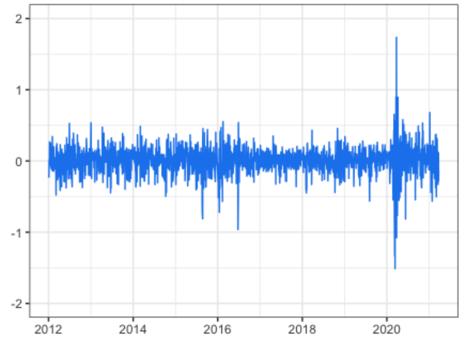
Port	Min	Max	Skew	Kurt	AAvgR	AVol	AShR	ASoR	t-test	F-test	ShR-test
Whole sample: 2012/01/04-2021/03/24, 3367 obs.											
MEP	-0.10	0.10	-0.66	11.97	0.06	0.17	0.33	0.40	-0.31	0.94	-1.53
CEP	-0.10	0.10	-0.66	10.65	0.08	0.18	0.46	0.57			
Before Paris: 2012/01/04 - 2015/12/14, 1440 obs.											
MEP	-0.05	0.04	-0.47	2.32	0.00	0.15	0.02	0.02	-0.25	0.87**	-1.03
CEP	-0.05	0.03	-0.39	1.53	0.03	0.16	0.19	0.27			
After Paris: 2015/12/14 - 2021/03/24, 1926 obs.											
MEP	-0.10	0.10	-0.73	13.87	0.10	0.19	0.52	0.61	-0.20	0.98	-1.25
CEP	-0.10	0.10	-0.78	13.47	0.12	0.19	0.64	0.74			
Oil Price Plunge: 2014/01/01 - 2016-06-01, 882 obs.											
MEP	-0.05	0.03	-0.63	2.66	-0.07	0.17	-0.39	-0.50	-0.17	0.92	-0.94
CEP	-0.05	0.03	-0.52	1.99	-0.04	0.18	-0.22	-0.29			
Covid Outbreak: 2020/02/28 - 2021/03/24, 390 obs.											
MEP	-0.10	0.10	-0.67	6.85	0.32	0.32	0.99	1.13	0.02	1.00	0.18
CEP	-0.10	0.10	-0.67	6.75	0.31	0.32	0.97	1.10			

Note: $^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$

Table 5: Distribution statistics, annualized financial performances (annualized average daily returns, volatility, Sharpe Ratio, and Sortino Ratio), and the inferential tests statistics relative to GMVPs log returns computed on the whole sample (Jan 2012 - Oct 2021) and over interesting market periods.

The dissimilarities between the MEP and CEP spawn in the dynamic comparison reported in Figure 4, where we graphically summarize the time-dependent performance of each portfolio in terms of annualized simple and compounded returns, volatilities, and Sharpe ratios. We do not observe significant differences in simple annualized returns. They are both characterized by volatility clustering in correspondence of phases of market distress, showing peaks that coincide both in timing and magnitude ($\pm$150%). They span in the interval [-50%,50%], which highlights large fluctuations of these securities. Cumulative returns show substantial differences. Having invested a unit of wealth in the two portfolios at the beginning of the analysis, a financial agent would have registered a more significant profit investing in the CEP than in the MEP. The active investment strategies conducted over the 3367 days led to gross profits (transaction costs not considered) of 176% and 219%, respectively, for the MEP and CEP.

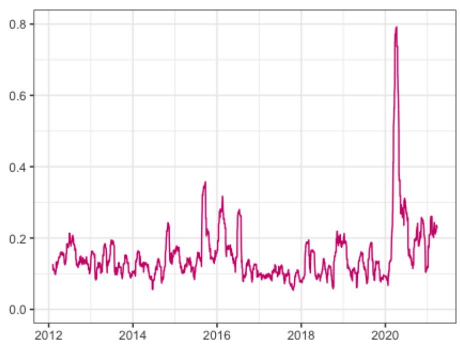
(a) MEP annualized returns



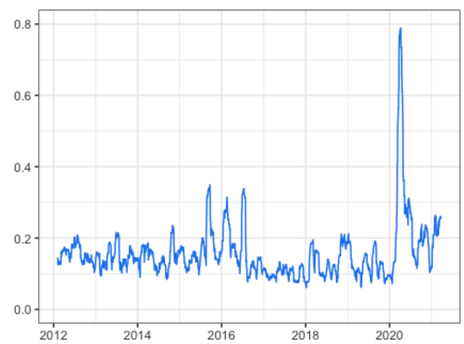
(b) CEP annualized returns

(c) MEP cumulative returns

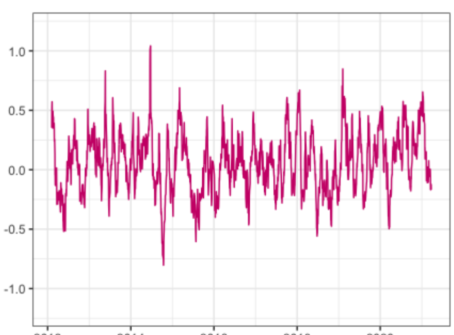
(d) CEP cumulative returns



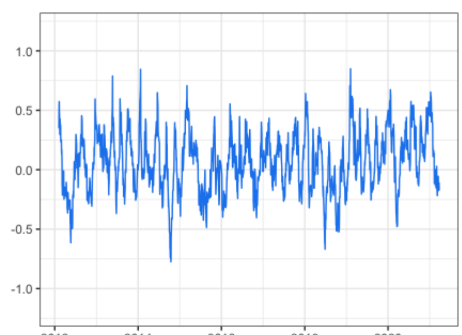
(e) MEP annualized volatilities



(f) CEP annualized volatilities



(g) MEP annualized SR



(h) CEP annualized SR

Figure 4: Annualized daily returns, cumulative daily return, annualized volatility, and monthly Sharpe Ratio of the two GMV portfolios (2012/01/03- 2021/03/24).

Comparing the dynamics of the cumulative returns of the two portfolios, we observe similar patterns in the first years (2012 - 2016). Still, the CEP experienced fast growth in the last analysis period, outperforming its mixed energy peer. Annualized volatilities patterns are highly similar, suggesting co-movements between the energy ETFs, with a series of peaks slightly below 40% and the mass of estimates that span between 10% and 20% for the large part of the sample period. Moreover, both portfolios show a consistent positive spike at the beginning of 2020 due to the rise of CE ETFs prices and the relative in-flows of money in the market. The two SR plots exhibit almost the same fluctuations: the MEP values range from -80% to 104%, while those of the CEP from -77% to 85%.

The analysis conducted on the entire sample shows the absence of a significant variation in the financial performances of an energy ETFs portfolio entailed by the exclusion of FF-based funds. However, time-dependent portfolios dissimilarities are observed in different phases of the market and in the last period of study, which is characterized by increased environmental concerns. The descriptive analysis highlights several structural breaks in the energy ETFs time series, which can influence the two portfolios' performances. For this reason, we search for portfolios' financial discrepancies depending on the market's health and the variations in the investors' attention to sustainability themes by testing the differences between the MEP and the CEP each year. Table 6 shows the results of the annual comparison.

In the first years of the study, there are no significant differences in financial performances, except for the year 2013, where the MEP slightly statistically outperforms its clean peer in average returns. Conversely, in 2019 and 2020, the CEP beats the MEP. While the MEP shows statistically larger, albeit low, average returns than those of the CEP, the HAC-test rejects the hypothesis of null difference in the SRs of the two portfolios, which lets us conclude that the CEP outperforms the other in terms of weighted returns. According to the recent ETFs market history, we interpret this result as the combined effect of an increase in the investors' appetite for green securities in the most recent years and the resilience of these assets in phases of market uncertainty. In fact, in 2019, the larger appreciation of the CE ETFs compared to those FF is the result of the expectation of the market on the renewable energies assets growth, as shown in Section 4.1, while in 2020, the CE securities are shown as less influenced by the COVID-19 market shocks, showing slighter fluctuations.

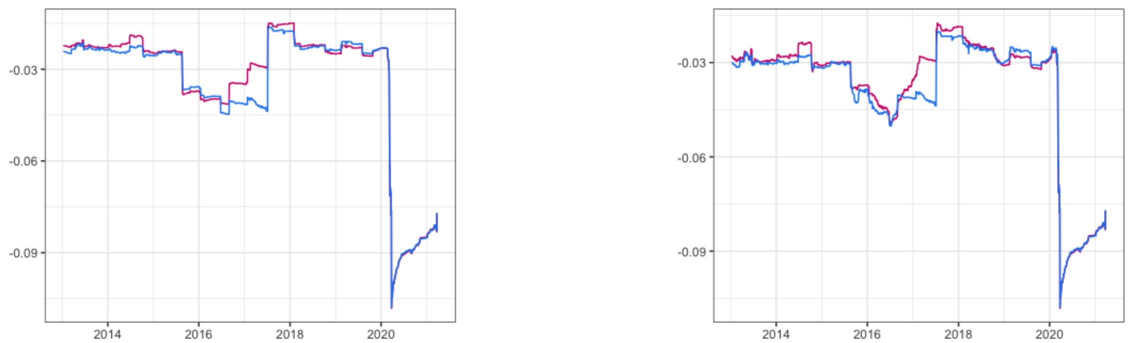
We test the hypothesis of an increase in the discrepancies between the two energy ETFs portfolios after the Paris Agreement to evaluate the effect of the attention to sustainability. The analysis conducted on the subset of data relative to the period that spans from 12 December 2015 to the end of the observation sample does not show significative differences in the two portfolios, highlighting, in contrast with the recent literature (Fahmy (2022), Monasterolo and De Angelis (2020)), the lack of a severe impact of this event on the ETFs market.

Year	t-test	F-test	ShR-test
2012	-0.0449	0.8931	-0.0034
	(0.109)	(–)	(–)
2013	0.2616 **	0.8115	-0.0074
	(0.102)	(–)	(–)
2014	-0.058	0.8221	-0.0005
	(0.105)	(–)	(–)
2015	-0.0482	0.9413	-0.0243
	(0.128)	(–)	(–)
2016	0.009	0.8945	0.002
	(0.13)	(–)	(–)
2017	0.1004	0.8962	-0.0334
	(0.07)	(–)	(–)
2018	-0.1774 *	1.0141	0.0027
	(0.103)	(–)	(–)
2019	0.2891 ***	1.0138	-0.0244 **
	(0.09)	(–)	(–)
2020	0.3309	1.0174	-0.0105 **
	(0.229)	(–)	(–)
2021	-0.0378	0.9042	0.0206
	(0.357)	(–)	(–)

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6: Statistics and standard deviations, in brackets, of a t-test, a F-test, and a HAC-test conducted on the returns of the MEP and the CEP separated by year.

We conclude the portfolios comparison by focusing on the market risk of energy ETFs, computing the VaR and the ES metrics, considering a rolling window of 250 daily observations and a probability fixed at $\alpha = 0.01$. In this way, we evaluate the portfolios' reactions to unexpected negative market shifts. Results, presented in Figure 5, show slight differences between the risk metrics of the two portfolios, but their similar patterns exclude any tangible benefits led by the investment in FF ETFs. In particular, the VaR and the ES of the two portfolios consistently diverge only for a short period between 2016 and 2017, when the CEP shows values lower than the other. In contrast, they reveal almost the same values at the end of the sampled period.



(a) VaR

(b) ES

Figure 5: VaR and ES of the MEP (in pink) and CEP (in blue) (2013/01/03 - 2021/03/24).

4.5 The relation of the CEP with the mainstream markets

Several academics show the possible use of green assets as hedging tools for investors' portfolios. We conduct a systemic risk analysis by studying the relation between the CEP and the other mainstream markets (MM), aiming to provide investors with a global overview of the financial features of this class of assets.

We choose a sample of financial indexes considered representative of the global markets, including (i) the Bank of America (BofA) Merrill Lynch High Yield Index, which accounts for the High Yield Bond market, (ii) the Trade Weighted US Dollar Index, to represent the currency market, (iii) the Solactive Green Bond Index, for the global green bonds (GBs) market, (iv) the MSCI International World Price Index, for the stocks markets, (v) the Renewable Energy Industries Index (RENIXX), to represent the renewable energies market, (vi) the S&P GSCI Commodity Index, which accounts for the commodities market, and (vii) the Chicago Board Options Exchange (CBOE) 10 Year Treasury Yield Index, for the US treasury market. The large number of the securities jointly covered by these financial indexes makes them representative of almost the entire market. The reader can find the description of these assets in Table 7.[6]

Figure 6 shows the price series of these indexes and the estimated structural breaks (Bai and Perron (2003)), which are detailed in Table 8. We observe increasing trends both regarding the

[6]We collected data from Refinitiv Workspace, except for (i) and (ii), which are obtained from the Federal Reserve Economic Data (FRED) library.

Index	Ticker	Market	Description
BofA Merrill Lynch High Yield Index	BAMLHY	High Yield	The ICE BofA US High Yield Index is comprised of US dollar denominated investment grade rated corporate debt publicly issued in the US domestic market.
Trade Weighted US Dollar Index: Broad, Goods and Services	DTWEX	Currency	The trade-weighted US dollar index, also known as the broad index, is a measure of the value of the US dollar relative to the other major world currencies.
Solactive Green Bond Index	SGREENIG	Green Bond	The Solactive Green Bond Index mirrors the green bond market. The index was developed in 2007 by the World Bank and the European Investment Bank.
MSCI World Index	MSCIW	Stocks	The MSCI World Index invests in large and mid cap firms across 23 developed countries. With 1562 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in each country.
Renewable Energy Industrial Index - World	RENIXX	Ren Energy	The RENIXX tracks the 30 largest companies belonging to the renewable energy industry worldwide by market capitalization. The RENIXX World comprises stocks e.g. from sectors as wind energy, solar energy industry, hydropower, geothermal energy, bioenergy or fuel cell technology.
S&P GSCI Commodity Index	SPGSCI	Commodities	The S&P GSCI is a broadly diversified composite index of the US commodity sector.
CBOE 10 Year Treasury Yield Index	TNX	Treasury	The TNX is based on 10 times the yield-to-maturity on the most recently auctioned 10-year Treasury note. The yields are paid by the U.S. government as interest for borrowing money via selling the bond. The index is broadly considered as the safest investment.

Table 7: Description of the mainstream markets comprised in the final sample of analysis.

BAMLHY and the MSCIW, which continue their growth, passing (almost) safely the 2016 and 2020 global crisis. Others, like the DTWEX, the SPGSCI, and the TNX, saw their prices broadly fluctuate over the studied period, showing clear evidence of huge losses experienced during phases of market distress. The RENIXX and the SGREENIG prices time series move similar to those of the CE ETFs, highlighting a fast growth of the green securities markets in the last years of analysis overall. Both energy ETFs and MM experienced structural changes in similar periods, for instance: (i) at the end of the tumultuous year 2012 and (ii) on April 20, 2020, when the oil price turned negative. These results suggest possible co-movement among the CEP and some MM.

Index	2012	2013	2014	2015	2016	2017	2018	2019	2020
BAMLHY	11-28		01-03	07-29	06-29	05-31	04-30	04-02	04-20
DTWEXBGS		02-11	01-08	11-05		07-11	06-11	07-31	
SGREENIG	11-27	10-30		01-15	03-16	07-06	06-06	05-09	04-20
MSCIW	12-28	11-21		08-20	12-06	11-06		04-02	04-20
RENIXX		09-27		02-02				05-09	04-20
SPGSCI		04-02	11-12	10-16	09-28	11-03	11-09		02-24
TNX		06-18	10-06	12-10	11-10		01-18	03-18	02-27

Table 8: Estimated structural breaks dates relative to the MM indexes (Apr 2012 - Oct 2021).

(a) BAMLHY

(b) DTWEX

(c) SGREENIG

(d) MSCIW

(e) RENIXX

(f) SPGSCI

(g) TNX

Figure 6: Time series of MM prices from 2012-01-03 to 2021-03-24. Vertical dotted lines represent the estimated structural changes.

We compute the log returns of the MM indexes and report the relative summary statistics in Table 12. Returns show null mean, the absence of autocorrelation, and the ARCH effect mainly manifested during the COVID-19 period. The DTWEX shows null skewness and a kurtosis similar to that normal, related to the asset features. The TNX exhibits positive skewness and large fluctuations. It peaks the lowest (-0.35), and the highest (0.41) returns on 09 March 2020 and the following day, respectively, corresponding to the beginning of the COVID-19 crisis. Overall, we observe the least volatile returns for the BAMLHY, the DTWEX, and the SGREENIG, which share the same issuer type (governments) and probably also investors (long-term, institutional), which jointly influence the price stability. The MSCIW, the RENIXX, and the SPGSCI returns span the same wide range of values, being stocks and commodities indexes.

For the descriptive purpose, we firstly investigate the relation of the CEP with the MM by computing correlations over the sample period, which are reported in Table 9. We observe a positive high linear relation with the stock market (80%), justified by their similar investment features (time horizon and profit/risk trade-off), which attract the same investors type. The strong correlation with the renewable energy sector (64%) is mainly due to the similar holdings of the RENIXX and the CE ETFs, while the large number of USA firms in these funds explains the significant positive relation with the BAMLHY (59%). Conversely, the low positive values estimated for the associations with the treasury market (32%) and TNX (36%) are justified by the different features of these securities. For the same reason, the CEP shows an almost null correlation (1%) with the GBs market, even if they are both labeled as green securities. Only the DTWEX exhibits negative linear dependence (-35%).

	BAMLHY	DTWEX	SGREENIG	MSCIW	RENIXX	SPGSCI	TNX	CEP
BAMLHY	1	-0.40	0.15	0.65	0.45	0.37	0.26	0.59
DTWEX		1	-0.53	-0.43	-0.13	-0.33	-0.04	-0.35
SGREENIG			1	0.03	-0.10	0.04	-0.37	0.01
MSCIW				1	0.50	0.43	0.41	0.80
RENIXX					1	0.23	0.20	0.64
SPGSCI						1	0.26	0.36
TNX							1	0.32
CEP								1

Table 9: Sample correlation among MM indexes and CEP computed all over the sample. Jan 2013 - Oct 2021.

Following Reboredo (2018), we model the relation between the CEP and the MM using copulas to measure dependence. In particular, for each couple $R_i = (r_{CE}, r_i)$, composed by the returns of the CEP, r_{CE}, and those of the $i-th$ MM index, r_i, we select the best copula model among those reported in Section 3.3 according to the BIC. Results conducted on the entire sample indicate the simple Gaussian model as the best choice among all the couples analyzed. To measure the time-varying dependence for each couple R_i and capture its strength in different market phases, we estimate the time-varying Gaussian copula models on a rolling window of the width chosen as equal to one financial year (250 days).

Table 10 shows the average values of the estimation results. The Gaussian copula parameters, ρ and Kendall's τ, assume positive values for all the MM indexes, except for the DTWEX, for which they are negative (-0.30 and -0.19), and for the SGREENIG that shows values close to zero (-0.03 and -0.03). The MSCIW only shows strong linear dependence, with the relative copula parameter ρ that peaks at 78%. However, the BAMLHY and the RENIXX also exhibit large values (0.56 and 0.63, respectively). The other two indexes, the SPGSCI and the TNX, exhibit a positive, albeit low, relation with the CEP, showing values of ρ respectively equal to 30% and 28%. The substantial dependence between the CEP and the (i) stocks, (ii) the REN, and (iii) the high yield markets, along with the almost absent relation with that of GBs, confirms the literature results (Ferrer et al. (2021), Reboredo (2018)). Overall, the results shed light on the possibility of recurring to a combination of CE ETFs and GBs to build a well-diversified green portfolio. On the same line, the CEP works as a hedging tool for the currency market, but its fluctuations are positively related to those of the SPGSCI and the TNX.

	BAMLHY	DTWEX	SGREENIG	MSCIW	RENIXX	SPGSCI	TNX
ρ	0.56 (0.09)	-0.30 (0.16)	-0.03 (0.18)	0.78 (0.04)	0.63 (0.06)	0.30 (0.1)	0.28 (0.12)
τ	0.38 (0.07)	-0.19 (0.11)	-0.03 (0.12)	0.57 (0.04)	0.43 (0.05)	0.19 (0.07)	0.18 (0.08)

Table 10: Time varying average of the Gaussian copula parameters and the relative standard deviations for each couple R_i (2012-01-03 - 2021-03-24). First line refers to the copula parameter ρ, while the second to the Kendall's τ.

We analyze the time-varying dependence between the CEP and the MM indexes by observing the time series of the estimated ρ parameters, reported in Figure 7. The correlations with the MSCIW, the RENIXX, and the BAMLHY are high and almost constant over the sample period, without significant fluctuation caused by variation in the market's health. Conversely, we observe several changes in the associations with the other MM. The CEP is positively related (50%) with the TNX in several periods (e.g., 2013, 2016, and 2021) but almost unrelated in other phases (e.g., 2014, 2017). Similarly, the association of the CEP with the commodity market fluctuates between $\approx 10\%$ and $\approx 50\%$, with peaks of correlation that follow those of the treasury index. On the other hand, the relation with the DTWEX broadly swings from $\approx -50\%$ to values close to zero. Hence, the relations between the CE ETFs portfolio and these three markets (treasury, commodity, and currency) depend on the period analyzed, making it impossible to provide a unique representation of the sign and the strength of these connections. The correlation with the SGREENIG significatively changes over the years, with the negative values ($\approx$ -50%) observed at the beginning of the analysis period that become positive ($\approx$ 25%) at the end. This evidence highlights the evolution of the dependence between the CE ETFs and the GBs through the years. These markets went from being a good hedging tool for each other to being uncorrelated to then ending up being positively related in the last years of analysis. We can interpret the change in the sign of the relation between these two markets by analyzing the investors' preferences: in the early 2010s, there was a clear difference between bonds and stocks/ETFs investors, but the growth of the green finance, along with the spread of brand new low-carbon investments, creates a new class of pro-environmental investors which choose only among green assets.

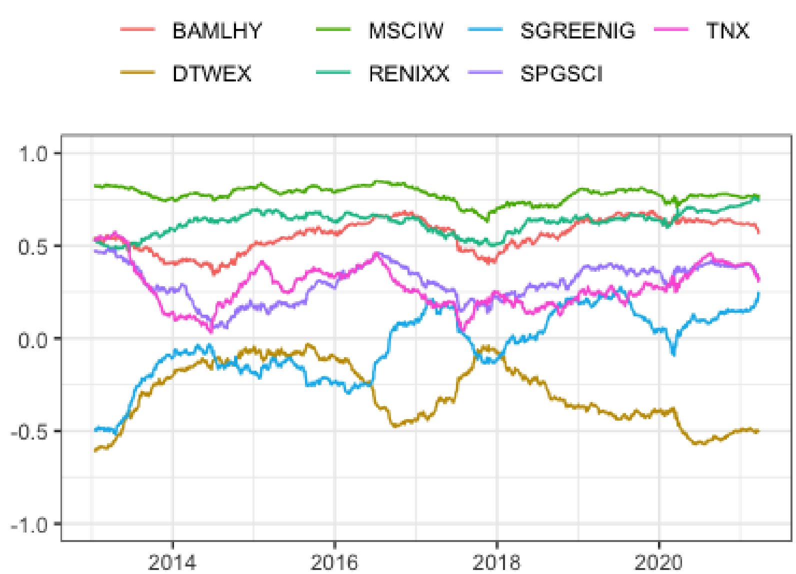
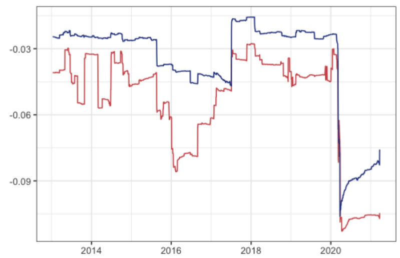
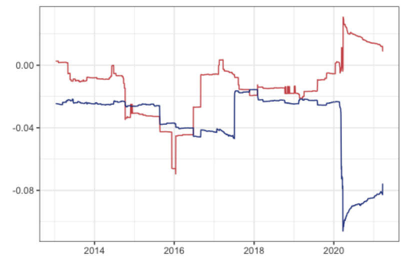


Figure 7: Time varying Gaussian copula parameters (ρ) estimated on each bivariate distribution composed by a MM index and the CE portfolio (2012-01-03 - 2021-03-24).

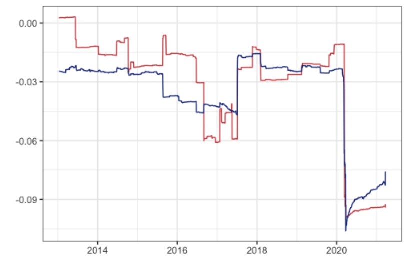
We investigate the dependence of the CEP with the MM on the left tail of the distributions to analyze the response of the CE ETFs sector to massive downward movements of the markets (downside risk). We compare the VaR_α of the CEP with the CoVaR_β computed considering each mainstream market in financial distress: possible discrepancies in the two metrics indicate a left tail dependence between the CEP and the MM indexes, showing the ETFs portfolio as influenced by adverse shocks in the markets considered. In this analysis, we fix both the probabilities α and β equal to 1% and choose a rolling window of 250 daily observations to estimate the time series of the two risk metrics. Figure 8 shows the estimation results. Although we denote discrepancies between the VaR and the CoVaR in all the graphs, the two risk measures follow similar patterns for the large part of the MM studied. More in detail, the CoVaR series obtained by stressing the BAMLHY, the MSCIW, the RENIXX, and the SPGSCI show values lower than the VaR of the CEP all over the sample period, following almost precisely its variations. Hence, periods of uncertainty (or shocks) in these markets imply a negative and roughly constant impact on the CEP performance, increasing its downside risk. Conversely, downward movements of the DTWEX imply a decrease in the CE ETFs sector's risk since the CoVaR is greater than the CEP VaR for almost the entire period of analysis. Conversely, the dynamics of the risk metrics relative to the SGREENIG and the TNX are not constant, alternating periods characterized by positive, negative, and null differences between the VaR and the CoVaR.



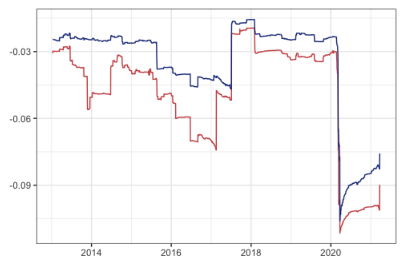
(a) BAMLHY



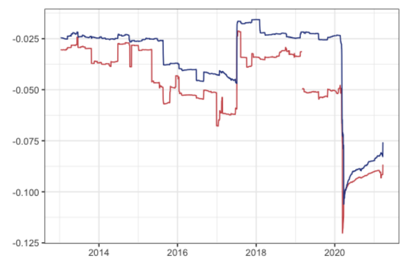
(b) DTWEX



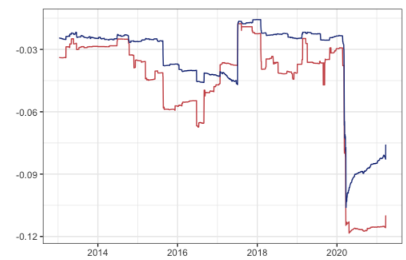
(c) SGREENIG



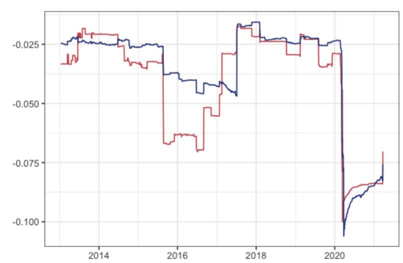
(d) MSCIW



(e) RENIXX



(f) SPGSCI



(g) TNX

Figure 8: Time varying estimates over the period 2013/01/03-2021/03/24 of the VaR (blue) and the CoVaR (red) computed considering α and β equal to 1%, a rolling window of 250 daily observation, and considering each mainstream market in financial distress.

5 Conclusion

Clean energy ETFs experienced a significant increase in volumes and popularity in the last few years. This effect is probably due to the joint combination of the ETFs market profitability as a whole and the increase in the investors' climate concerns. However, the literature lacks a comprehensive and up-to-date disclosure on the financial performances of these assets and of comparison with their fossil fuels-based peers.

In this paper, we investigate the financial performances of a sample of energy ETFs to assess whether excluding the FF funds decreases the outcome of an energy ETFs portfolio dynamically re-calibrated according to the GMV technique. We complete the CE ETFs analysis by evaluating their systemic risk, measuring the dependence with a sample of indexes that represent the mainstream markets.

We conduct an empirical analysis on a sample comprised of the ten most capitalized clean energy and fossil fuels ETFs currently exchanged on the global markets observed from 2012 to 2021. Results point out a significant difference in volumes, with the FF funds which result far more capitalized than their CE peers, also after the steep rise of the green ETFs observed during the year 2020 related to the Joseph R. Biden, Jr. race for the US presidency. Environmental-related news strongly influence both CE and FF ETFs and often determines breaking points in their financial time series. A dynamic correlation analysis, conducted through a DCC-GARCH model, shows the large part of FF ETFs as a strongly linear dependent. At the same time, the association results are lower for those CEs.

After having excluded the most correlated ETFs, we build two portfolios: (i) a mixed energy and (ii) a clean energy portfolio, which consists of a subset of the (i) comprised exclusively of CE funds. Results exclude any financial drawback led by excluding the polluting energy ETFs from the investors' portfolio, highlighted by the absence of statistically significant differences between the returns and the market risk of the MEP and the CEP. Moreover, the clean energy portfolio outperforms the other in terms of cumulative returns in the last analysis period. Both the investment in energy ETFs resulted profitably, also following a strategy whose objective consists in minimizing the total variance without constraints on the target return. Still, the environmental screening process entails a better financial outcome assuming the same risk level.

Testing the hypothesis of a discrepancy in the portfolios' performances in different market phases, we show how the CEP outperforms the MEP in terms of SR during 2019 and 2020 when we observe an increase in the investors' expectation of green ETFs. Moreover, the CE securities suffered less than their FF peers during the COVID-19 crisis. Conversely, we reject the hypothesis of a positive medium/long-term effect on the performances of the green funds entailed by the Paris Agreement, with the energy ETFs portfolios that do not exhibit significant differences after this event.

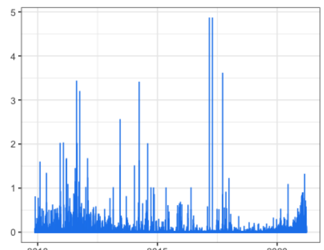
In the last part of the analysis, we study the relationship between the CEP and the other mainstream markets, investigating the systemic risk of the CE ETFs. We observe a contemporary sample of seven indexes representing the mainstream markets (e.g., treasury, stocks, bonds). We find several market-related events which imply structural breaks both in the (large parts of) the MM and in the CE ETFs, which suggest a non-negligible influence of the market on the fluctuation of the green funds. Results of a time-varying copula-based analysis indicate a positive and strong association of the CEP with the stocks, the high yield, and the renewable energies markets, which results in line with the literature. The other markets show lower relations with the CE ETFs portfolio, but none of them are uncorrelated or negatively related all over the studied period. For instance, while the green bonds market results linearly independent in mean with the CE ETFs sector, these two markets show negative and significative correlations in the first years of study (2012-2016), which become null and then positive in the last period. These fluctuations make it impossible to determine the sign and the strength of the dependence of the CE ETFs on the green bonds, the currency, the commodity, and the treasury markets.

We measure the dependence on the loss tail of the distribution by comparing the VaR of the CEP with the CoVaR computed by stressing the MM returns. While a shock in the BAMLHY, the MSCIW, the RENIXX, and the SPGSCI indexes contribute to increasing the downside risk of the CEP (CoVaR lower than the VaR of the CEP all over the sample period), negative shifts of the currency market lead the opposite effect. Similarly, we cannot conclude on the downward movements of the CEP after a shock registered in the green bonds or the treasury markets.

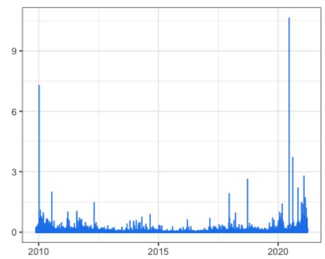
This empirical study encourages investors to exclude the fossil fuel-based ETFs from their portfolios, with the CE funds that ensured the same financial performances and outperformed them in recent years. The evolution of this fast-growing market and the research of the determining factors is left for further study.

6 Appendix

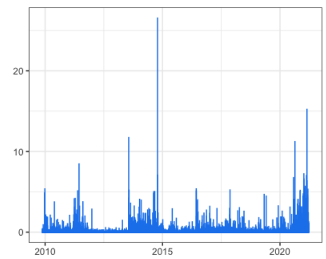
6.1 Daily time series (2012-2021) of volumes in USD separated by ETF.



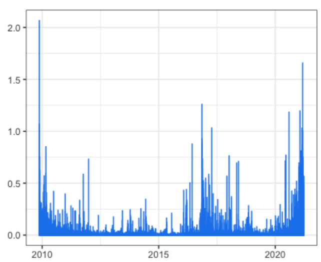
(a) ENER



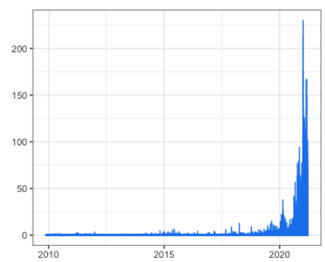
(b) ERTH



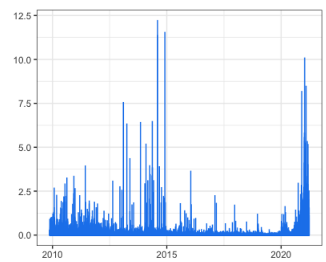
(c) FAN



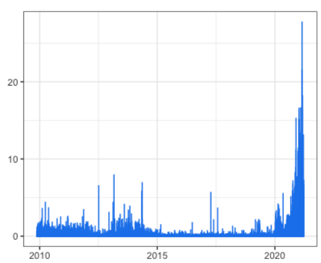
(d) GRID



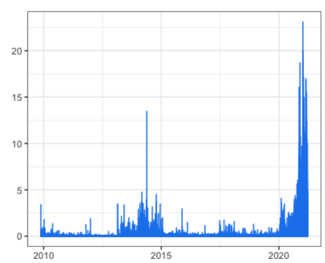
(e) INRG



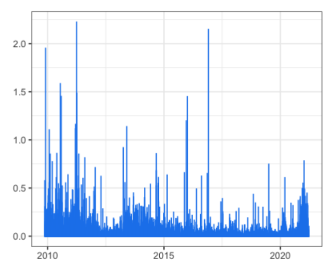
(f) PBD



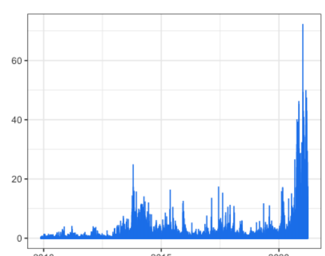
(g) PBW



(h) QCLN

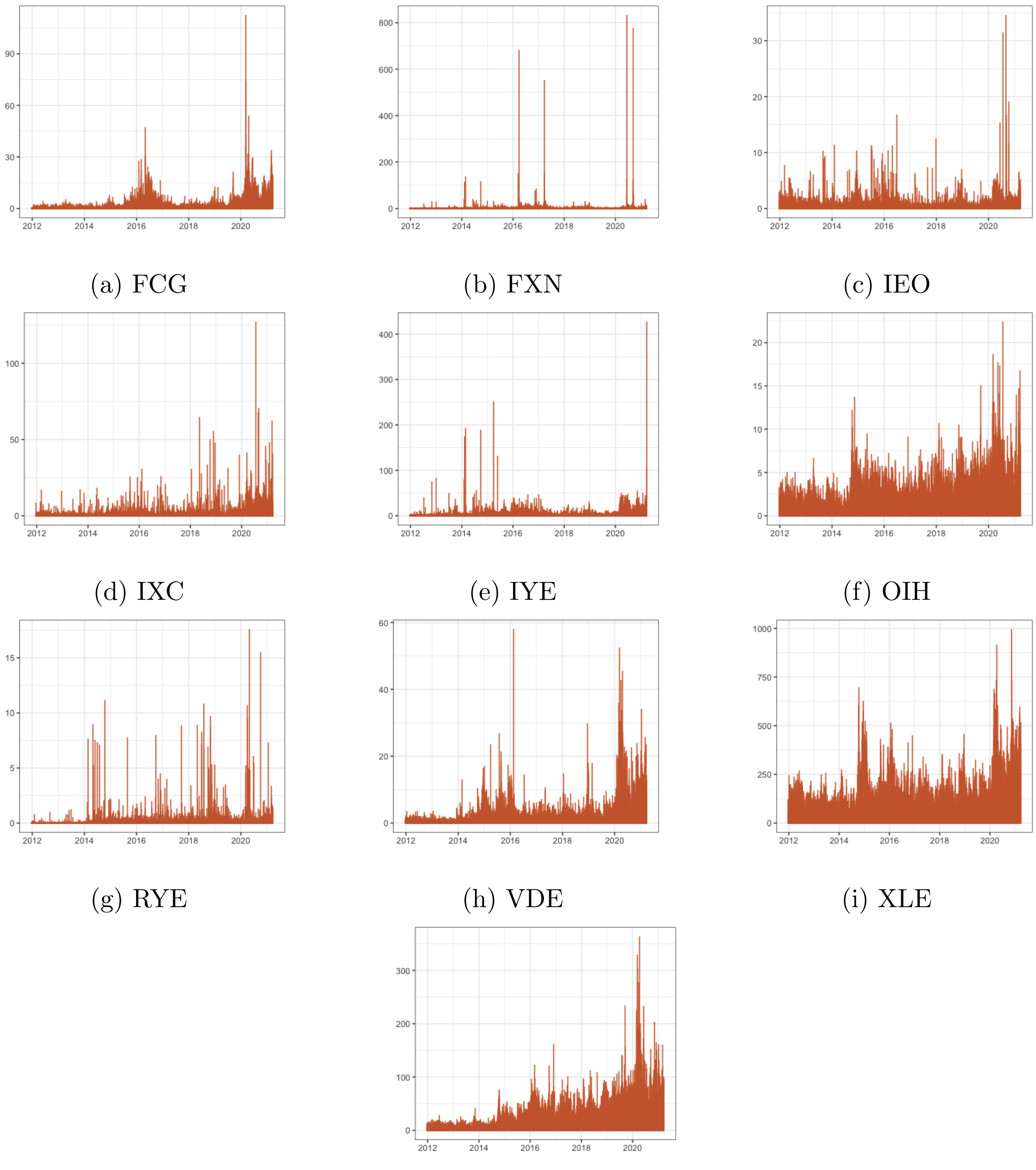


(i) SMOG



(j) TAN

Figure 9: Time series of CE ETFs volumes from 2012-01-03 to 2021-03-24.



(a) FCG (b) FXN (c) IEO

(d) IXC (e) IYE (f) OIH

(g) RYE (h) VDE (i) XLE

(j) XOP

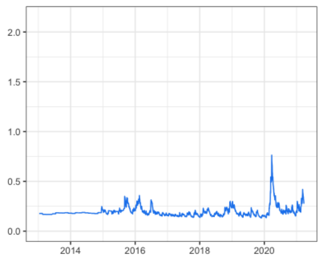
Figure 10: Time series of FF ETFs volumes from 2012-01-03 to 2021-03-24.

6.2 Descriptive statistics of ETFs log-retruns.

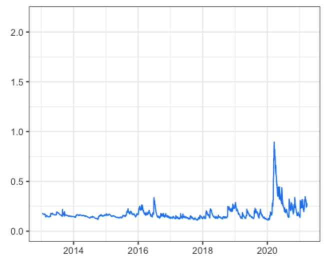
ETF	Mean	Median	Min	Max	SD	Skew	Kurt	JB	LB	LB2	ARCH-LM	ADF	KPSS
ENER	0.00	0.00	-0.09	0.10	0.01	-0.29	4.27	1732.55	1.07	167.90	465.90	-13.37	0.12
ERTH	0.00	0.00	-0.12	0.08	0.01	-1.05	10.38	10483.20	2.17	211.58	740.60	-12.56	0.10
FAN	0.00	0.00	-0.12	0.10	0.01	-0.79	10.02	9620.70	1.57	296.35	636.48	-12.66	0.10
GRID	0.00	0.00	-0.14	0.10	0.01	-0.98	12.17	14196.49	8.31	229.01	654.59	-12.81	0.10
INRG	0.00	0.00	-0.14	0.11	0.02	-0.71	8.63	7158.71	0.00	157.89	638.06	-11.33	0.27
PBD	0.00	0.00	-0.20	0.10	0.01	-1.50	21.61	44500.11	5.17	236.18	677.08	-11.50	0.27
PBW	0.00	0.00	-0.16	0.14	0.02	-0.54	7.34	5137.92	1.35	90.51	644.23	-11.91	0.46
QCLN	0.00	0.00	-0.14	0.14	0.02	-0.47	6.69	4261.97	0.00	71.92	601.88	-11.92	0.26
SMOG	0.00	0.00	-0.11	0.12	0.02	-0.45	6.35	3841.76	0.06	82.96	606.78	-11.96	0.19
TAN	0.00	0.00	-0.17	0.14	0.03	-0.23	4.48	1894.95	5.38	34.27	336.62	-11.71	0.30
FCG	-0.00	-0.00	-0.34	0.14	0.03	-0.74	14.38	19541.41	0.10	53.53	175.57	-11.88	0.09
FXN	-0.00	0.00	-0.32	0.14	0.02	-1.02	21.08	41932.72	0.73	60.82	273.36	-11.79	0.06
IXC	-0.00	0.00	-0.22	0.16	0.02	-1.28	26.64	66949.38	3.14	61.46	643.77	-13.20	0.04
IEO	-0.00	0.00	-0.30	0.15	0.02	-1.11	21.51	43684.92	4.22	70.08	312.32	-11.89	0.05
IYE	-0.00	0.00	-0.23	0.15	0.02	-1.08	21.96	45510.95	9.84	59.15	605.62	-12.26	0.07
OIH	-0.00	-0.00	-0.39	0.17	0.03	-1.45	29.63	82820.23	0.33	41.49	234.75	-11.52	0.10
RYE	-0.00	-0.00	-0.31	0.16	0.02	-1.28	26.18	64668.79	1.52	57.38	335.08	-12.13	0.06
VDE	-0.00	0.00	-0.22	0.15	0.02	-0.90	19.22	34820.35	3.90	64.47	601.26	-12.18	0.06
XLE	-0.00	0.00	-0.23	0.15	0.02	-1.06	22.05	45880.61	8.24	85.35	660.70	-12.28	0.06
XOP	-0.00	0.00	-0.46	0.20	0.03	-2.01	44.12	183407.67	9.86	113.40	153.44	-12.00	0.07

Table 11: 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.

6.3 Estimated volatilities of the CE and FF ETFs by the DCC-GARCH models

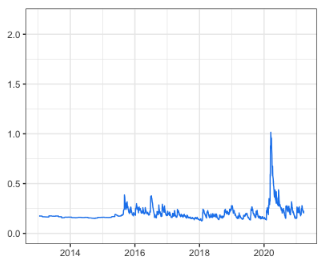


(a) ENER

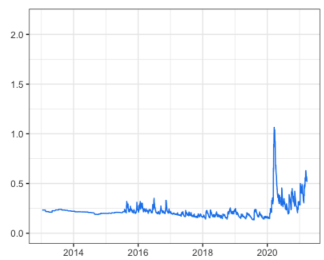


(b) ERTH

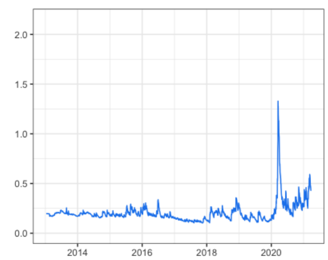
(c) FAN



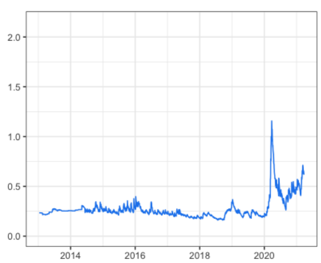
(d) GRID



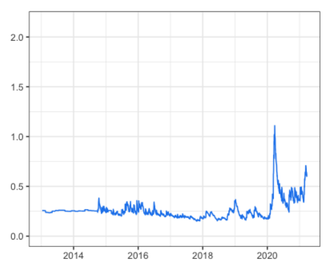
(e) INRG



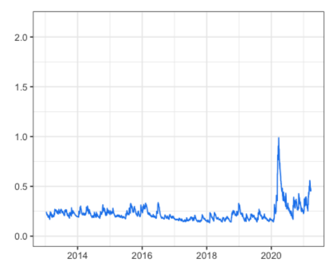
(f) PBD



(g) PBW



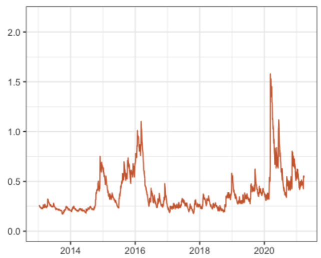
(h) QCLN



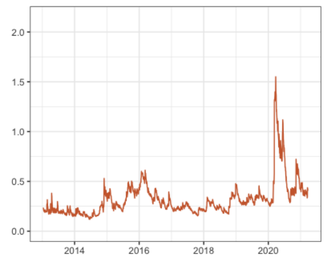
(i) SMOG

(j) TAN

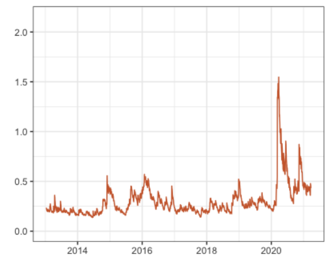
Figure 11: Time series of CE ETFs estimated volatilities from 2012-01-03 to 2021-03-24.



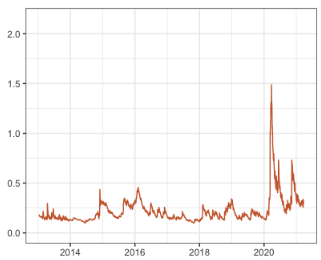
(a) FCG



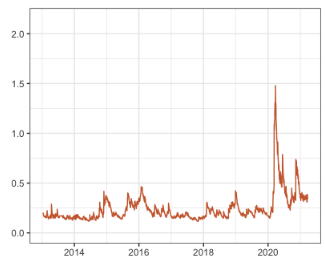
(b) FXN



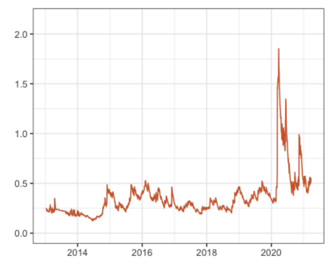
(c) IEO



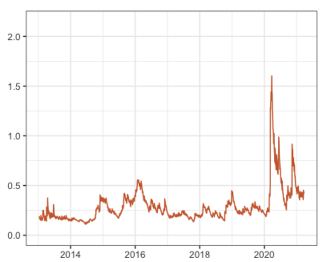
(d) IXC



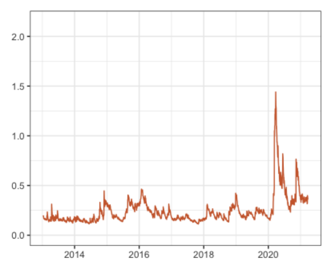
(e) IYE



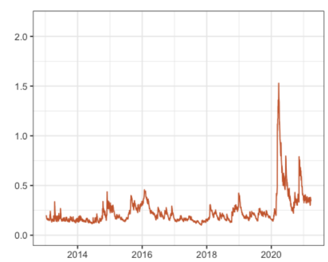
(f) OIH



(g) RYE



(h) VDE



(i) XLE

(j) XOP

Figure 12: Time series of FF ETFs estimated volatilities from 2012-01-03 to 2021-03-24.

6.4 Descriptive statistics of the MMs log-returns.

Index	Mean	Median	Min	Max	SD	Skew	Kurt	JB	LB	LB2	ARCH-LM	ADF	KPSS
BAMLHYH	0.00	0.00	-0.04	0.03	0.00	-1.96	41.14	159515.74	292.00	167.95	833.58	-12.56	0.05
DTWEXBGS	0.00	0.00	-0.02	0.02	0.00	0.07	4.30	1728.14	2.56	13.69	137.67	-12.69	0.17
SGREENIG	0.00	0.00	-0.03	0.02	0.00	-0.46	5.12	2532.45	7.26	120.37	294.99	-13.52	0.11
MSCIW	0.00	0.00	-0.10	0.08	0.01	-1.32	21.87	45345.58	0.44	257.13	793.11	-13.03	0.04
RENIXX	0.00	0.00	-0.16	0.17	0.02	-0.15	12.04	13550.74	17.52	338.37	397.85	-11.80	0.30
SPGSCI	-0.00	0.00	-0.13	0.07	0.01	-0.86	11.23	12058.61	2.76	89.76	322.69	-11.54	0.19
TNX	-0.00	-0.00	-0.35	0.41	0.03	0.39	31.32	91670.41	0.82	886.65	1160.20	-13.63	0.08

Table 12: Summary Statistics of MM indexes: 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

Adrian, T. and Brunnermeier, M. K. (2011). Covar. Technical report, National Bureau of Economic Research.

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.

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

Baker, M., Bergstresser, D., Serafeim, G., and Wurgler, J. (2018). Financing the response to climate change: The pricing and ownership of us green bonds. Technical report, National Bureau of Economic Research.

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

Capelle-Blancard, G. and Monjon, S. (2014). The performance of socially responsible funds: Does the screening process matter? *European Financial Management*, 20(3):494–520.

Capelle-Blancard, G. and Petit, A. (2019). Every little helps? esg news and stock market reaction. *Journal of Business Ethics*, 157(2):543–565.

Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative Finance*, 1(2):223.

Cornett, M. M., Erhemjamts, O., and Tehranian, H. (2016). Greed or good deeds: An examination of the relation between corporate social responsibility and the financial performance of us commercial banks around the financial crisis. *Journal of Banking & Finance*, 70:137–159.

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.

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

Ferrer, R., Shahzad, S. J. H., and Soriano, P. (2021). Are green bonds a different asset class? evidence from time-frequency connectedness analysis. *Journal of Cleaner Production*, 292:125988.

Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*.

Gianfrate, G. and Peri, M. (2019). The green advantage: Exploring the convenience of issuing green bonds. *Journal of Cleaner Production*, 219:127–135.

Girardi, G. and Ergün, A. T. (2013). Systemic risk measurement: Multivariate garch estimation of covar. *Journal of Banking & Finance*, 37(8):3169–3180.

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.

Hachenberg, B. and Schiereck, D. (2018). Are green bonds priced differently from conventional bonds? *Journal of Asset Management*, 19(6):371–383.

Joliet, R. and Titova, Y. (2018). Equity sri funds vacillate between ethics and money: An analysis of the funds' stock holding decisions. *Journal of Banking & Finance*, 97:70–86.

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

Larcker, D. F. and Watts, E. M. (2020). Where's the greenium? *Journal of Accounting and Economics*, 69(2-3):101312.

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

Malevergne, Y. and Sornette, D. (2003). Testing the gaussian copula hypothesis for financial assets dependences. *Quantitative Finance*, 3(4):231.

Martí-Ballester, C.-P. (2017). Sustainable energy systems and company performance: Does the implementation of sustainable energy systems improve companies' financial performance? *Journal of Cleaner Production*, 162:S35–S50.

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>>.

Mukanjari, S. and Sterner, T. (2018). Do markets trump politics? evidence from fossil market reactions to the paris agreement and the us election.

Nelsen, R. B. (2007). *An introduction to copulas*. Springer Science & Business Media.

Nguyen, P.-A., Kecskés, A., and Mansi, S. (2020). Does corporate social responsibility create shareholder value? the importance of long-term investors. *Journal of Banking & Finance*, 112:105217.

Oberndorfer, U., Schmidt, P., Wagner, M., and Ziegler, A. (2013). Does the stock market value the inclusion in a sustainability stock index? an event study analysis for german firms. *Journal of Environmental Economics and Management*, 66(3):497–509.

Petitjean, M. (2019). Eco-friendly policies and financial performance: Was the financial crisis a game changer for large us companies? *Energy Economics*, 80:502–511.

Pham, L. (2016). Is it risky to go green? a volatility analysis of the green bond market. *Journal of Sustainable Finance & Investment*, 6(4):263–291.

Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, 74:38–50.

Reboredo, J. C. and Ugolini, A. (2020). Price connectedness between green bond and financial markets. *Economic Modelling*, 88:25–38.

Reboredo, J. C., Ugolini, A., and Aiube, F. A. L. (2020). Network connectedness of green bonds and asset classes. *Energy Economics*, 86:104629.

Sklar, M. (1959). Fonctions de repartition an dimensions et leurs marges. *Publ. Inst. Statist. Univ. Paris*, 8:229–231.

Trinks, A., Scholtens, B., Mulder, M., and Dam, L. (2018). Fossil fuel divestment and portfolio performance. *Ecological Economics*, 146:740–748.

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>>.

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance*, 98:39–60.