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Dynamic comparison of portfolio risk: Clean vs dirty energy

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ABSTRACT

This paper analyses whether investing in clean energy significantly worsens the risk level of investors. To that aim, we propose a dynamic strategy to carry out a comparative risk analysis of three minimum-variance portfolios: a portfolio made up exclusively of dirty energies, a portfolio made up only of clean energy assets, and a portfolio combined with the two types of energies. To that aim, we use multivariate GARCH models, concretely Asymmetric Dynamic Conditional Correlations models (ADCC-GARCH) to predict the variance and covariance matrices of the daily asset returns and we compare the portfolio volatilities using the methodology proposed by Engle and Colacito (2006). The analysed period was from January 2010 to September 2021, so that the data include half of phase II, full phase III and the onset of phase IV of the EU ETS, as well as the Brexit and COVID-19 outbreaks in the European context. Our results show that, unlike what happened in other economic crises (subprime, Brexit), from the pandemic crisis, the investment in clean energies is preferable to fossil energies, not only in terms of profitability, as other studies have shown, but also in terms of risk. Therefore, investing in clean energy companies, which are aligned with their role towards socially responsible initiatives, is valuable not only for its contribution to a sustainable energy transition to renewable sources but also for the attractiveness from a financial point of view.

1. Introduction

Since the United Nations Framework Convention on Climate Change and the Kyoto Protocol agreement, European Union countries have played a very active role in proposing measures to help combat environmental degradation. The Green Deal that was presented in the Paris Agreement established the roadmap to make Europe the first climate-neutral continent by 2050. With this ambitious goal, the EU countries have set binding emission targets for key sectors of the economy in order to substantially reduce greenhouse gas emissions by at least 55% by 2030.

The energy sector, responsible for 80% of greenhouse gas emissions, is in the spotlight for action against climate change. The solutions to the unsustainability of the current energy model are to reduce the dependence of economy on fossil fuels. For this, it is necessary to involve the growing implementation of technologies that allow the decarbonisation of the energy mix, with the predominant actions aimed at promoting renewable energy.

However, despite the significant progress made in implementing renewables in recent years, this transition needs to be scaled up at least six times faster for the world to start meeting the goals set out in the 2015 Paris Agreement (Polzin, 2017). Therefore, the

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decarbonisation of the energy system needs appropriated financial resources that help speed it up in the coming years. To achieve this goal, the financial system should be aligned with energy transition requirements, shifting large capital investment from the fossil energy sector to clean energy-based enterprises. For this to happen, renewables should be considered an appealing investment destination not only for environmentally responsible investors but also for those investors who are only concerned about profits. Currently, literature does not clarify whether investments in clean energies are consistent with what investors want. Within this context, being aware that support of capital markets is vitally important to achieve the energy transition, our paper aims to encourage any type of investor to consider clean energy. We intend to convince the reader that switching to more sustainable energy will not have a significant negative impact on the risk and return levels of their portfolios.

To accomplish this goal, information on the correlation and transmission of volatility in these markets is useful to adequately diversify the portfolio and implement hedging strategies to reduce risk and/or increment profitability, as some works related to the energy market have shown. The main objective of these studies was to improve diversification and coverage in clean energy portfolios from fossil fuels such as oil, gas, coal or through emission rights, (Sadorsky, 2012; Zhang and Du, 2017; Dutta et al., 2018; Lin and Chen, 2019). Other works such as those by Zhang and Sun (2016) and Wang and Guo (2018) confirmed the usefulness of oil to also cover changes in the price of carbon (EUA) and the change to gas hedging in cases of extreme volatility. Along the same lines, Jebabli et al. (2021) showed greater effectiveness with the change from oil to gas for the coverage of portfolios of the stock market in general during the COVID-19 crisis.

Some studies have compared the performance of clean and dirty energy companies. Arslam-Ayaydin and Thewissen (2016) showed higher performance in the portfolio made up of energy companies with a good environmental performance compared to energy companies with the worst environmental score in the period 2000–2007. However, these results were not significant in periods of greater uncertainty generated during the subprime crisis. Rameli et al. (2018) analysed the role of the Environmental Protection Agency of the United States in the time of Donald Trump and showed a better market performance of the companies most responsible with climate change. More recently, Wan et al. (2021) found that the COVID-19 pandemic exerted a negative impact on the performance of dirty energy companies and positive on clean energy companies. They attribute the influence of the implementation of governments' green recovery plans on investors' behaviour.

Moreover, while there is extensive literature on renewables investment risk, there is little to no empirical study on the dynamics of renewable energies investment risk over time. This is surprising given that investment risk evolves over time as technologies develop (Kitzing et al., 2020) and the effectiveness of policies aiming to attract renewable investments depend largely on their ability to reduce investment risk (Komendantova et al., 2019; Polzin et al., 2019; Schinko and Komendantova, 2016). Our study contributes to the literature by covering this gap. It also analyses whether currently investing in renewable energy not only contributes to improving the environment but is also less risky than investing in dirty energy.

To that aim, a dynamic portfolio selection strategy based on minimal risk is carried out through a correlation and transmission of volatility analysis in energy markets. Besides, in order to evaluate the risk of investing in renewables and dirty energies, we compare the volatility of three types of portfolios. The first portfolio is made up exclusively of dirty energy assets (named as Dirty Portfolio); the second portfolio is made up only of shares of companies in the clean energy sector (named as Clean Portfolio); and, the third portfolio combines both types of energy (named as Energy Portfolio). We use a minimum-variance dynamic strategy based on multivariate GARCH models, concretely on the Asymmetric Dynamic Conditional Correlation family of models (Engle, 2002; Tse and Tsui, 2002) that allow time varying correlations (called ADCC-GARCH models hereinafter). Given that risk conditions can change over time, in each period we have selected the model that provides the best estimate of the conditional covariance matrix of the daily asset returns because, as Engle and Colacito (2006) proved, it provides the optimum portfolio of minimum variance.

The analysed period was from January 2010 to September 2021, so it includes half of phase II, full phase III and the onset of phase IV of the EU ETS, as well as the COVID-19 outbreak in the European context. Our work shows that a dynamic analysis is crucial to carry out optimal diversification that reduces risk and allows control of changes that may occur in the relationship between the markets. The economic situation affected by COVID-19, the recovery aid policies aligned with the Green Pact or the greater restrictions with the mechanisms that adjust the supply of allowances are situations that have had an impact on minimum variance portfolios, becoming more attractive renewables investment. In particular, our findings highlight that from 2020 on optimal risk-minimum portfolios take long positions in renewable energies and short positions in dirty energies, and that investing only in clean energy companies does not significantly raise risk levels.

Summarising, the main contribution of the paper is twofold:

1) The design of a sequential rolling selection strategy of ADCC-GARCH models, which allows for calculating the dynamic optimum minimum variance portfolios by using the model in each period that best estimates the conditional covariance matrix of the return series.
2) The proof is that from 2020 on investing in clean energy companies is worthwhile and does not significantly raise risk levels. For this reason, supporting a sustainable energy transition is also attractive from a financial viewpoint.

The structure of this paper is as follows: Section 2 describes the data, the models and the methodology used in the paper. Section 3 provides and discusses the empirical results. Finally, Section 4 is the conclusion.

2. Setting up the problem

2.1. The data

We use data from five ($n = 5$) series of daily closing prices from January 19, 2010 to September 17, 2021 that make $T = 2829$ observations. The assets that make up the Dirty Portfolio are the fossil fuel series (GAS and OIL), that refer to oil and gas futures prices in Europe,[1] and the "dirty" energy indicator EURO STOXX® Oil & Gas Index (called OIL.GAS in our database). The assets that compose the Clean Portfolio are the S&P Global Clean Energy Index (called CLEAN in our database) and the European emission allowance prices (EUA). Finally, the Energy Portfolio is composed of these five assets.

The price series are not stationary, and, for this reason, we work as usual in finance with the returns of assets, which are stationary and, in addition, are more interesting from an investment point of view. The average return of the series is gross zero and all the returns are leptokurtic. In addition, they also show the heteroscedastic character with the typical volatility clustering of financial series, which leads us to use GARCH models.

2.2. The model

Let $\{\mathbf{r}_t = (r_{1,t}, \ldots, r_{n,t}); t = 1,\ldots,T\}$ be the series of daily financial return vectors with $r_{i,t} = 100 \cdot \log\left(\frac{p_{i,t}}{p_{i,t-1}}\right)$ and $p_{i,t}$ is the closing price of the i th asset in period t for $i = 1,\ldots,n$.

We assume that:

$$\mathbf{r}_t|\mathscr{F}_{t-1} = \boldsymbol{\mu}_t + \boldsymbol{\varepsilon}_t$$

where $\mathscr{F}_t = \{\mathbf{r}_1, \ldots, \mathbf{r}_t\}$ is the information set in period t, the conditional mean vector $\boldsymbol{\mu}_t = E[\boldsymbol{r}_t|\mathscr{F}_{t-1}]$ is given by the VAR(1) expression:

$$\boldsymbol{\mu}_t = \boldsymbol{\Phi}_1 \mathbf{r}_{t-1}$$

and $\varepsilon_t = (\varepsilon_{1t},\ldots,\varepsilon_{n,t})'$ is a conditional heterocedastic error term with $\mathrm{var}(\boldsymbol{\varepsilon}_t|\mathscr{F}_{t-1}) = \mathbf{H}_t$. In order to model the evolution of $\mathbf{H}_t$ we use an ADCC(1,1)-GARCH(1,1) model introduced by Engle (2002), and Tse and Tsui (2002) that allows for correlations and covariances to vary over time, by keeping up the flexibility of the univariate GARCH approach to captures the volatility of each univariate series and being a reliable tool for estimating interconnections between them.

In the specification, $\mathbf{H}_t$ is given by:

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t$$

where $\mathbf{D}_t = \mathrm{diag}(\sqrt{h_{11,t}}, \cdots, \sqrt{h_{nn,t}})$ with $h_{ii,t} = \mathrm{var}(\varepsilon_{i,t}|\mathscr{F}_{t-1})$ for $i = 1,\ldots,n$ and $\mathbf{R}_t$ is the conditional correlation matrix. The conditional variances $h_{ii,t}$ are given by n independent GARCH(1,1) models that can be written in vector form as:

$$\mathrm{diag}(\mathbf{H}_t) = \boldsymbol{\Omega} + \mathbf{A}_1 \boldsymbol{\varepsilon}_{t-1} \odot \boldsymbol{\varepsilon}_{t-1} + \mathbf{B}_1 \mathrm{diag}(\mathbf{H}_{t-1})$$

where $\boldsymbol{\Omega}$, $\mathbf{A}_1$and $\mathbf{B}_1$ are $n \times n$ diagonal matrices, and $\odot$ denotes the Hadamard operator. With respect to the time varying correlation matrix, $\mathbf{R}_t$, we assume that

$$\mathbf{R}_t = \mathbf{Q}_t^{*-1} \mathbf{Q}_t \mathbf{Q}_t^{*-1} \text{ with } \mathbf{Q}_t^* = \mathrm{diag}(\mathbf{Q}_t)$$

and $\mathbf{Q}_t$ is given by:

$$\mathbf{Q}_t = \overline{\mathbf{Q}} + a(\mathbf{z}_{t-1}\mathbf{z}'_{t-1} - \overline{\mathbf{Q}}) + b(\mathbf{Q}_{t-1} - \overline{\mathbf{Q}}) + g\mathbf{z}_t^- \mathbf{z}_t^{-'}$$

with $a, b \geq 0$ and $a + b<1$ which is imposed to ensure stationary and positive definiteness of $\mathbf{Q}_t$, $\mathbf{z}_t = \mathbf{D}_t^{-1}\boldsymbol{\varepsilon}_t$ are the standardized residuals, $z_t^- = \mathbf{z}_t I(\mathbf{z}_t < 0)$, $\overline{Q}$ is the unconditional covariance matrix of the standardized residuals resulting from the first stage estimation and $\mathbf{Q}_0$, the starting value of $\mathbf{Q}_t$, has to be positive definite to guarantee $\mathbf{H}_t$to be positive definite. The parameters of the model are estimated by means of a three-step procedure based on Engle and Sheppard (2001) and we have used the routines in the ***rmgarch*** package of R.

2.3. Optimal weights and comparison of risk portfolios

In order to minimize the risk we determine, for each period t, the minimum variance portfolio subject to a given unitary return. This problem can be formulated as:

[1] The oil and gas futures are daily closing prices and have been used in the literature as a meaningful benchmark for oil and gas prices (Ping et al., 2018; Tsuji, 2018; Li et al., 2021).

$$\min_{\omega_t}\mathrm{Var}\left(\boldsymbol{\omega}_t^{'}\mathbf{r}_t \mid \mathscr{F}_{t-1}\right) = \min_{\omega_t}\boldsymbol{\omega}_t^{'}\mathbf{H}_t\boldsymbol{\omega}_t$$

$$\text{s.t. } \boldsymbol{\omega}_t^{'}\boldsymbol{\mu}_t = 1$$

where $\boldsymbol{\omega}_t$ is the vector of portfolio weights for time t chosen at time t −1. The solution to this problem is $\boldsymbol{\omega}_t = \frac{\mathbf{H}_t^{-1}\boldsymbol{\mu}_t}{\boldsymbol{\mu}_t^{'}\mathbf{H}_t^{-1}\boldsymbol{\mu}_t}$. Note that $\sum_{i=1}^{n}\omega_{i,t}$, with $\omega_{i,t}$ being the share on asset i for time t, generally will not need to be equal to 1. Indeed, 1-$\sum_{i=1}^{n}\omega_{i,t}$ is the share in the risk-free asset.

Engle and Colacito (2006) proved that if σ_t is the standard deviation of the portfolio obtained in period t, then t $\geq \sigma_t^*$ where σ_t^* is the standard deviation of the minimum variance portfolio obtained with the true matrix of variances and covariances $\Omega_t = \mathrm{Var}(\mathbf{r}_t|\mathscr{F}_{t-1})$ and, hence, $\frac{1}{T}\sum_{t=1}^{T}(\sigma_t^*)^2 \leq \frac{1}{T}\sum_{t=1}^{T}(\sigma_t)^2$. Misestimating Ω_t entails an increase of the risk of the portfolio and, therefore, we must try to estimate Ω_t as best as possible. Based on this result our objective will be to choose the model that minimizes the average volatility of the minimum portfolio, for any vector of expected returns. Using these ideas, we proposed the following rolling window sequential algorithm to determine the weights of a dynamic optimal portfolio using the volatilities estimated by a set of models $\mathbf{M} = \{M_1,\ldots,M_k\}$.

2.3.1. Procedure to determine the weights and volatilities of the optimal portfolio

Step 0 (Start)

Set the size h_1 of the estimation window of the models and the size h_2 (with $1 \leq h_2 \leq h_1$) of the model selection window of the best model. For $t = h_1+h_2+1,\ldots,T$ carry out the Steps 1 to 3.

Step 1 (Estimation of the models and their variance and covariance matrices)

For each M∈ **M** and for each time period $u = t\text{-}h_2 + 1,\ldots,T$, estimate the variance and covariance matrix $\mathbf{H}_{u,h_1,M} = \mathrm{Cov}(r_u|M,\widehat{\theta}_{M,u,h_1}, \mathscr{F}_{u-1,h_1})$ where $\widehat{\boldsymbol{\theta}}_{M,u,h_1}$ is and estimation of $\boldsymbol{\theta}_M$ vector of parameters of M using the data $\{\mathbf{r}_{u-h_1},\ldots,\mathbf{r}_{u-1}\}$ and $\mathscr{F}_{u-1,h_1} = \{\mathbf{r}_{u-h_1},\ldots,\mathbf{r}_{u-1}\}$

Step 2 (Determination of the minimum variance portfolios for each of the models)

For each of the M∈ **M** models and for the time period $u = t\text{-}h_2+1,\ldots, t$ calculate the minimum variance portfolios weights $w_{u,h_1,M} = \frac{\mathbf{H}_{u,h_1,M}^{-1}\mathbf{m}_{u,h_1}}{\mathbf{m}_{u,h_1}^{'}\mathbf{H}_{u,h_1,M}^{-1}\mathbf{m}_{u,h_1}}$ where $\mathbf{m}_{u,h_1} = \frac{1}{h_1}\sum_{v=u-h_1}^{u-1}\mathbf{r}_v$. Calculate the portfolio variance $\sigma_{u,h_1,M}^2 = \frac{1}{\mathbf{m}_{u,h_1}^{'}\mathbf{H}_{u,h_1,M}^{-1}\mathbf{m}_{u,h_1}} = \mathbf{w}_{u,h_1,M}^{'}\mathbf{H}_{u,h_1,M}\mathbf{w}_{u,h_1,M}$.

Step 3 (Dynamic selection of the optimal portfolio)

For each period t, select the best model $M_{opt,t}$ such that:

$$\frac{1}{h_2}\sum_{u=t-h_2+1}^{t}\sigma_{u,h_1,M_{opt,t}}^2 = \min_{M\in\mathbf{M}}\frac{1}{h_2}\sum_{u=t-h_2+1}^{t}\sigma_{u,h_1,M}^2$$

Take as optimum portfolio in period t, that with vector of weights $w_{t,h_1,M_{opt,t}}$ and volatility $\sigma_{t,h_1,M_{opt,t}}^2$.

The size h_1 of the estimation window of the models must be set large enough to estimate model parameters accurately, but small enough to capture possible changes in market risk levels. The size h_2 of the model selection window must be set large enough to avoid selecting models based only on a few data, but small enough to avoid the influence of values too far away in time. In our case, we have taken a 2-year (around $h_1 \approx 504$ observations) estimation window due to the complexity of the models to be analysed; and a 1-year (around $h_2 \approx 252$ observations) model selection window because this is the period generally used to present asset returns, company results or the close of an accounting year. We discard the first $h_1 + h_2$ observations to weaken the influence of the initial observations.[2]

2.3.2. Optimal portfolios comparison

To carry out the comparison between pairs of portfolios we apply the procedure proposed by Engle and Colacito (2006) based on the test of Diebold and Mariano (1995). Let (1) and (2) be the two optimal dynamic portfolios that are going to be compared. Let $\mathbf{w}_{(1),t}^{'}$ and $\mathbf{w}_{(2),t}^{'}$ be the corresponding portfolios weights, and $\pi_t^{(1)} = \mathbf{w}_{(1),t}^{'}(\mathbf{r}_{t,(1)} - \mathbf{m}_{t,h_1,(1)})$ and $\pi_t^{(2)} = \mathbf{w}_{(2),t}^{'}(\mathbf{r}_{t,(2)} - \mathbf{m}_{t,h_1,(2)})$ the portfolio returns where $\mathbf{m}_{t,h_1,(i)} = \frac{1}{h_1}\sum_{v=t-h_1}^{t-1}r_{v,(i)}$. Let $u_t^{(1),(2)} = (\pi_t^{(1)})^2 - (\pi_t^{(2)})^2$ be and $v_t^{(1),(2)} = u_t^{(1),(2)}[0.5(\mathbf{m}_{t,(1)}^{'}\mathbf{H}_{t,(1)}^{-1}\mathbf{m}_{t,(1)}))(\mathbf{m}_{t,(2)}^{'}\mathbf{H}_{t,(2)}^{-1}\mathbf{m}_{t,(2)}))]^{1/2}$

We perform the following regression:

$$\mathbf{V}_{T_1:T_2}^{(1),(2)} = \beta_v^{(1),(2)}1_{(T_2-T_1+1)x1} + \boldsymbol{\varepsilon}_{v,T_1:T_2}^{(1),(2)} \quad (1)$$

where $\mathbf{V}_{T_1:T_2}^{(1),(2)} = (v_{T_1}^{(1),(2)},\ldots,v_{T_2}^{(1),(2)})^{'}$ and $T_1 < T_1+1 < \ldots < T_2$ is the period of comparison. We test H_0:$\beta_v^{(1),(2)} = 0$ where we use a *t*-test using a robust Newey-West estimator of the standard error of $\widehat{\beta}_v^{(1),(2)}$.

3. Results

We have considered k = 6 possible models resulting of the combination of Constant Conditional Correlation (CCC), Dynamic Conditional Correlation (DCC) and Asymmetric Dynamic Conditional Correlation (ADCC) models with the multivariate normal

[2] The results are quite robust when the values of h_1 and h_2 are slightly modified, however, they are not shown for the sake of brevity.

distribution and multivariate Student's t for errors. Table 1 provides the t-statistics of the regression model (1) for different sub-periods. The null hypothesis of this test is that there is no difference between the portfolios variances. In our case, we have compared the optimum portfolios selected for each of the three kinds of portfolios considered in the paper. The t-statistics provided in the table are the result of comparing the case in the column with the one in the row. A negative (positive) value of the t statistic is evidence in favour of better (worse) performance, in terms of volatilities, of the row case. If we consider the full period, no significant differences in risk can be observed between the Clean and the Energy Portfolios while Dirty Portfolios tend to have significant higher level of risks. However, this result has not been homogeneous during the analysed period.

Fig. 1 shows the portfolio weights $w_{t,h_1,M}$ for each one of the selected Dirty, Clean and Energy Portfolios while Fig. 2 shows the corresponding portfolio's observed returns whose oscillations reflect their volatility size. Five sub-periods can be distinguished.

In the first period (2012–2013), which could be characterized as the end of the debt crisis, the volatilities of the Dirty Portfolios tend to be significantly lower than those of the Clean and Energy Portfolios (Table 1 and Fig. 2). Examining their weights, the minimum risk portfolio advised investing in long positions in dirty energy and risk-free asset and short in clean energy (see Fig. 1).

The second period (2014–2015) was one of economic recovery in which energy efficiency policies promoted by the climate and energy framework adopted by the European Council in 2014 began to take hold, all of which increased the ecological awareness of investors. Consequently, the volatilities of Clean Portfolio were significantly lower than the other two (Table 1 and Fig. 2), and the selected portfolios tend to invest long in clean and short in dirty energies (Fig. 1).

The third period (2016–2017) was of great uncertainty caused especially by the holding of the referendum on Brexit (June 23, 2016). All the portfolios tend to take long positions in risk-free asset and long in the rest of assets (Fig. 1), with the Clean portfolios having the least amount of risk (Table 1 and Fig. 2) but, in this case the selected portfolios tend to invest long in risk-free asset and short in clean energies (Fig. 1).

The fourth period (2018–2019) includes the moment in which the market stability reserve was established within the EU ETS.[3] In this period, no clear pattern emerges and no significant differences are appreciated between Dirty and Clean Portfolios with the Energy Portfolio tending to have a significantly lower volatility than Clean Portfolio (Table 1). However, it can be noticed that, at the end of this period, the minimum variance portfolios tend to increase the weight of allowances and clean firms (Fig. 1).

Finally, in the fifth period (2020–2021), where the COVID-19 pandemic started, Clean Portfolios tend to have significantly lower risk levels than Dirty Portfolios and similar levels than Energy Portfolios (Table 1 and Fig. 2). The minimum risk portfolio bets on long positions in clean assets and on short positions in dirty assets, but there is also an important influence in risk-free assets due to the risk of the pandemic itself (Fig. 1). It is in this period where we see an important change in the transition to clean energy: it is the first period where in times of economic crisis the portfolio is made up of long positions in renewable energy assets and short or underweight positions in dirty assets or fossil fuel. These results are aligned with those of Wan et al. (2021) in China, and they are likely to have occurred because of how the implementation of governments' green recovery plans influenced investors.

However, and given that the 5 periods have been chosen endogenously and somewhat arbitrarily, it could have happened that some of the corresponding break points are spurious. Moreover, the regression model (1) analyses the global variances performance of each of the three compared portfolios but not their local variances performance in each period. For these reasons, we have also applied the fluctuation test proposed by Giacomini and Rossi (2010) to detect time-variation in the difference of variances of the compared portfolios and to test the null hypothesis that this difference is zero at each period.[4] For this, we have used the following as loss functions:

$$\mathrm{loss}_i = \mathbf{w}'_{(i),t}\left(\mathbf{r}_{t,(i)} - \mathbf{m}_{t,h_1,(i)}\right)\left[0.5\left(\mathbf{m}'_{t,(1)}\mathbf{H}^{-1}_{t,(1)}\mathbf{m}_{t,(1)}\right)\right)\left(\mathbf{m}'_{t,(2)}\mathbf{H}^{-1}_{t,(2)}\mathbf{m}_{t,(2)}\right)\Big)\Big]^{1/2} \quad \text{for } i = 1,\ 2$$

Fig. 3 contains the evolution of the fluctuation test statistics along time with the 95% confidence bands for the three portfolios variance pairwise comparisons: Energy portfolio vs Clean portfolio (left); Energy portfolio vs Dirty portfolio (middle); Clean portfolio vs Dirty portfolio (right). When the series exceeds the upper (lower) ends of the confidence band it means that the null hypothesis of equality is rejected, and conclude that there are periods during which the second portfolio (subtrahend) of the difference has less (higher) variance.

We can see that even though the trend of the difference in volatility of the compared portfolios tend to coincide with those described previously, these differences are significant in only a few periods. The only exception corresponds to the fifth sub-period (2020–2021), where it can be appreciated that for most of the period (from February 3, 2020 to April 14, 2021) the volatilities of Clean and Energy portfolio tended to be significantly lower than those of Dirty portfolio. In the rest of this sub-period, the volatilities are also lower, but not significant very probably due to the recent rise in energy prices. These last results highlight that from 2020 on investing in clean energy companies is worthwhile and significantly reduces the risk regarding dirty energy. For this reason, supporting a sustainable energy transition is also attractive from a financial viewpoint.

[3] The market stability reserve mechanism was devised by the European Commission to intervene the price of allowances in the CO_2 market. Its purpose was to correct the large surplus of allowances that had accumulated in the EU ETS and to increase the resistance of the regime to imbalances between supply and demand. Entered into force on January 1, 2019.

[4] We would like to thank one of the referees for suggesting the use of this test. To carry out this test we have used the function *fluctuation_test* from the package *murphydiagram* of R. We took mu =0.1 as size of the rolling window (relative to evaluation sample) and a truncation lag equal to 5.

Table 1
Engle and Colacito Test of comparison of volatility (in blue (red) the 5% significant positive (negative) differences).

	November 8, 2012 - December 30, 2013			January 2, 2014 - December 30, 2015			January 4, 2016 - December 30, 2017			January 2, 2018 - December 30, 2019			January 2, 2020 - September 17, 2021			November 8, 2012 - September 17, 2021		
	Energy portfolio	Clean portfolio	Dirty portfolio	Energy portfolio	Clean portfolio	Dirty portfolio	Energy portfolio	Clean portfolio	Dirty portfolio	Energy portfolio	Clean portfolio	Dirty portfolio	Energy portfolio	Clean portfolio	Dirty portfolio	Energy portfolio	Clean portfolio	Dirty portfolio
Energy portfolio		-1,424	**4,809**		**2,161**	**-4,407**		**3,256**	**-2,106**		**-2,060**	0,224		0,266	**-5,015**		-0,459	**-3,576**
Clean portfolio	1,424		**4,265**	**-2,161**		**-4,542**	**-3,256**		**-3,779**	**2,060**		0,620	-0,266		**-5,522**	0,459		**-2,771**
Dirty portfolio	**-4,809**	**-4,265**		**4,407**	**4,542**		**2,106**	**3,779**		-0,224	-0,620		**5,015**	**5,522**		**3,576**	**2,771**	

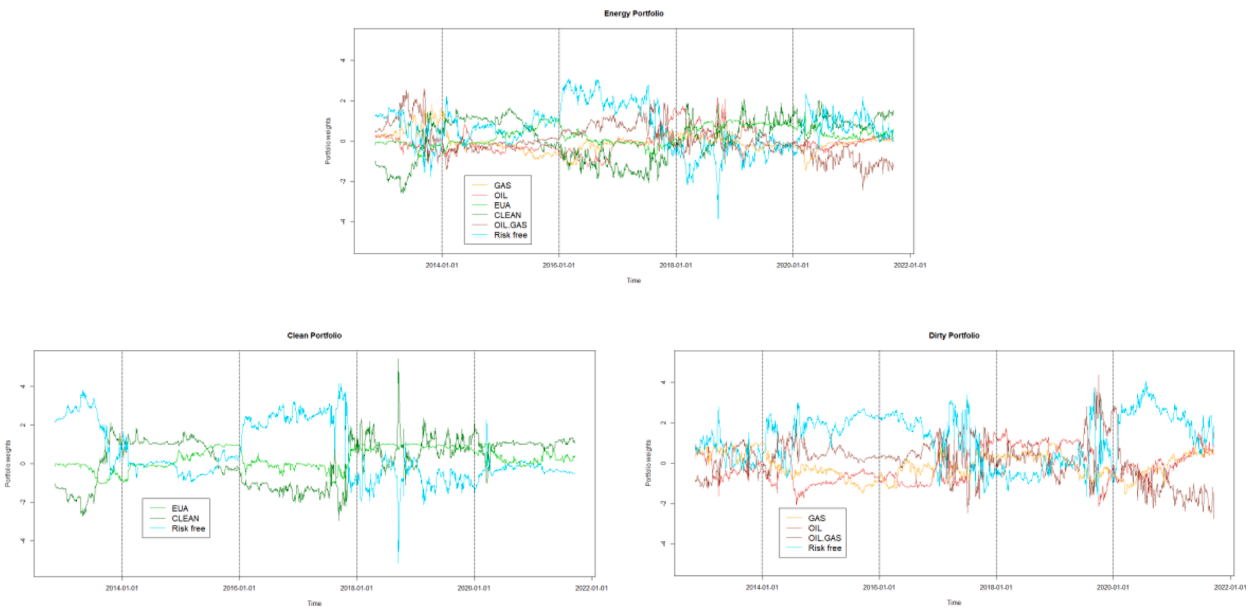

Fig. 1. Evolution of the three optimal portfolio weights (Energy portfolio (top), Clean Portfolios (bottom left) and Dirty Portfolios (bottom right).

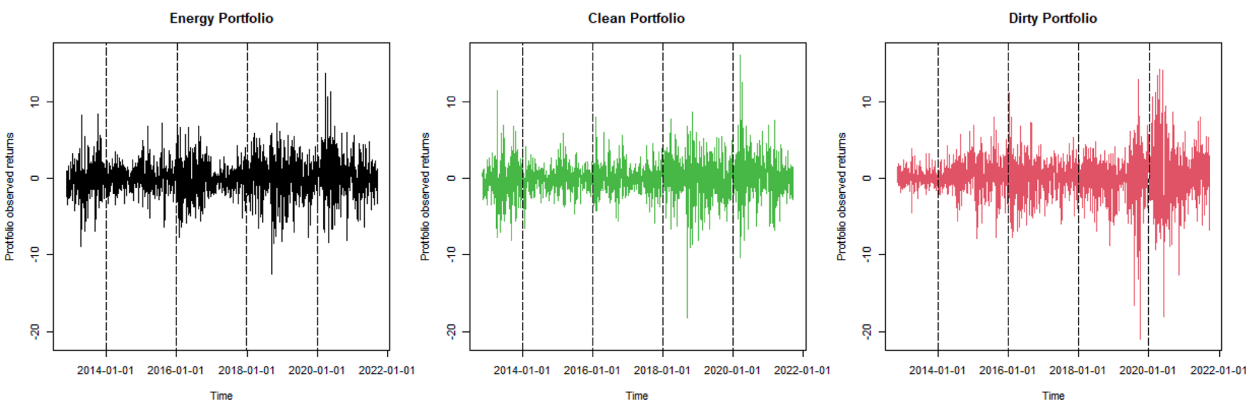

Fig. 2. Evolution of the three portfolios observed returns (red line – Dirty portfolios, green line – Clean Portfolios and black line – Full Portfolios).

4. Conclusions

This work analyses whether investing in clean energy significantly worsens the risk level of investors. To that aim, it estimates the risk levels of three types of minimum variance portfolios: one built with clean energy assets, the second with dirty energy assets and the third with both types of assets. Using a sequential rolling procedure for selecting and estimating ADCC-GARCH models, the observed volatility levels of each portfolio are compared and their composition is analysed over time. Both the dynamic weights and the

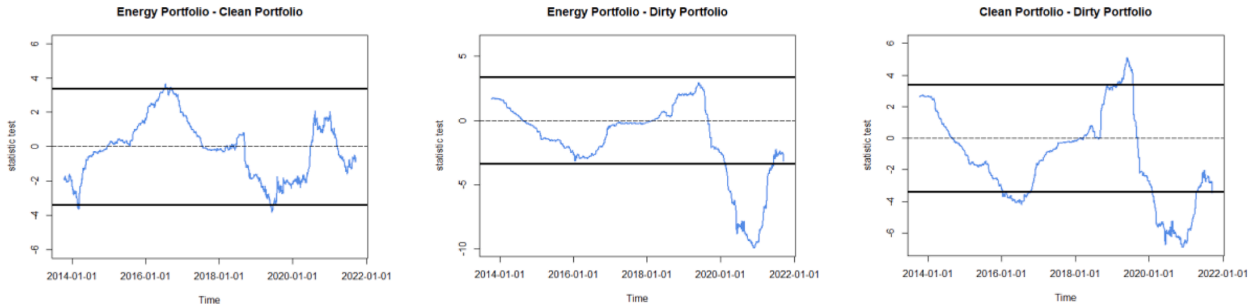

Fig. 3. Fluctuation test statistic for the three portfolios variance pairwise comparisons: Energy vs Clean (left); Energy vs Dirty (middle); Clean vs Dirty (right).

volatilities have been estimated from a careful and adaptive selection of models that alternated constant correlations in periods of calm and asymmetric models with changing correlations in periods of greater turmoil. The importance of identifying the spillover effect of volatility and correlation in a dynamic way is crucial to efficiently managing investment portfolios and to carrying out optimal diversification of assets. This intelligent management has allowed to reduce the risk and controlling the ups and downs, as well as the most relevant events that have taken place in the European markets during the analysed period (i.e. the end of the debt crisis, the stability mechanism of EU ETS, the Brexit or the COVID-19). Our findings highlight that in periods of economic prosperity it is worth investing in clean energy, but not in crisis periods in which risk levels tend to be significantly higher. However, from 2020 on, investing in clean energy does not significantly raise risk levels even after the first period of pandemic crisis, very likely due to the influence on investors of governments' green recovery plans. Therefore, the last period shows investing in clean energy companies is interesting not only for its contribution to an energy transition to renewables sources, but it is also attractive from a financial point of view, which will have great implications for global sustainable development.

As previously mentioned, investing in renewable energies can be one of the best ways to protect our planet because they do not emit greenhouse gases, which makes them an indispensable ally in the fight against climate change. For this reason, an economically efficient and sustainable global financial system that creates value long-term should reward investing in renewables amongst other responsible investments, benefiting both the environment and the society as a whole.

In addition, renewable energy reduces energy dependence, as it is an indigenous resource, eliminating the need to import fossil fuels from countries rich in gas and oil. Importing energy raw materials has economic costs, and strategic ones. A high dependence on energy from abroad can cast uncertainty on the supply due to political or economic problems in the supplying countries. Therefore, investing in renewable energies could help reduce territorial and geopolitical conflicts due to the dispute over the control and ownership of raw materials, which currently exist in several countries.

Renewable energies are also a source of wealth because they do not need to be imported. Having a basic raw material such as energy establishes a competitive base for the industrial fabric. Due to their nature, renewable energies activate development in rural areas, favouring a better structuring of the territory. Renewables can act as an industrial and technological locomotive of the economy, achieving smart, inclusive and sustainable growth and territorial cohesion. Rural areas can offer more than simply food, given that as main holders of renewable resource deposits, they are at the forefront of the energy transition, which could help overcome obstacles associated with their low demographic density or their peculiar geographical characteristics. Investment in renewables allows creating employment and can contribute to solving another serious problem such as depopulation, which exists in many rural areas in Europe.

We hope that our paper has been able to convince any type of investor to switch to more sustainable energy portfolios. This kind of investment will not only have a significant negative impact on the risk, and return levels of the portfolios; but they will also protect the environment, help prevent geopolitical conflicts, and promote balanced territorial development by fighting against depopulation.

However, despite the importance the investment in renewable energies has in the fight against climate change, there are many other areas, which are also necessary to invest in to support sustainable development. For example, regarding the environment it would be interesting to invest in other mitigation and adaptation measures of climate change in handling water and marine resources, in sustainable waste management or in sustainable land use, etc. Regarding social issues, it would be valuable to support actions directed at protecting human rights as well as requiring good governance to invest in policies that prevent corruption. That is why we consider broadening the context of our paper to deal with different sustainable objectives (environmental, social and good governance) by considering portfolios that incorporate green and sustainability bonds. This analysis is left for future lines of research.

All the authors have contributed equally to the realization of this work

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