Energy Reports 8 (2022) 15654–15668

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Research paper

Dynamic risk management in European energy portfolios: Evolution of the role of clean and carbon markets

Pilar Gargallo [a,1], Luis Lample [b,1], Jesús A. Miguel [c,1], Manuel Salvador [a,*,1]

[a] IEDIS and Department of Applied Economics, Faculty of Economics and Business, University of Zaragoza, 50009 Zaragoza, Spain
[b] Department of Accounting and Finance, Faculty of Economics and Business, University of Zaragoza, 50009 Zaragoza, Spain
[c] Department of Applied Economics, Faculty of Economics and Business, University of Zaragoza, 50009 Zaragoza, Spain

ARTICLE INFO

Article history:
Received 23 May 2022
Received in revised form 15 September 2022
Accepted 17 November 2022
Available online xxxx

Keywords:
Energy market
EU ETS
Climate change
Portfolio management
ADCC-GARCH

ABSTRACT

This paper examines the potential of clean energy stocks and emission permits to reduce downside risk when combining them in a portfolio with dirty energy assets. We propose a strategy for building portfolios that are well diversified between equity energy and carbon markets that takes into account their dynamic price relationship. The asset allocation proposed is framed in a volatility-timing context, which reacts to changing market conditions, holding different weights at different times. To achieve this objective, we use multivariate GARCH models, specifically the Asymmetric Dynamic Conditional Correlations family, which allow us to obtain good estimations of the conditional covariance matrices of the daily asset returns. To determine the weights of the optimum minimum-risk portfolio, we use a method based on Engle and Colacito (2006) to compare the portfolio volatilities obtained with different models. The analysed period runs from January 19, 2010, to April 4, 2022, which, on the one hand, includes more than twelve years of the EU Emissions Trading System (EU ETS) beyond the Phase I pilot; and, on the other, considers the latest crisis episodes (Sovereign debt crisis, Brexit COVID-19, and the recent Russo–Ukrainian war). Our findings show that investing in clean energy companies is now valuable not only because of its contribution to a sustainable energy transition to renewable sources, but also due to its attractiveness from a financial point of view. This fact provides a ray of hope in terms of the climate emergency and avoiding the current geopolitical conflicts principally caused by certain countries' energy dependence because their energy mix is still heavily overpowered by fossil fuels. The results of this research should encourage investors to decarbonise their equity portfolios, thus promoting the needed alignment of the financial system with the requirements of the energy transition.

1. Introduction

The acceleration of climate change in recent decades, because of the increase in greenhouse gases (GHG) is a reality that seriously threatens both economies and human health. Temperature increases are accompanied by exceptional weather conditions such as floods, storms, droughts, and forest fires that are becoming more intense and frequent. Moreover, every year, 4 million people die due to poor air quality, a number that far exceeds the deaths caused by COVID-19: 5.8 million people from 2020 to February 2021, according to World Health Organisation (WHO) data. There is currently a scientific consensus that the cost of inaction is much greater than taking adequate mitigation and adaptation actions to combat climate change, which constitute one of the key challenges of the 21st century according to the European Environment Agency (EEA, 2007).

Among the European Union policies to combat climate change, the Emissions Trading Scheme (EU ETS) settled in January 1, 2005, is one of the leading tools for supervising and achieving the reduction of carbon dioxide, the main greenhouse gas (Bing et al., 2015). This scheme is organised in four stages: a pilot period (phase I spanned from 2005 to 2007); a second period of full operation (phase II comprised from 2008 to 2012); a third period within the "Climate Change Package 2020" (phase III encompassed from 2013 to 2020); and a fourth period, which is currently in force (phase IV spanned from 2021 to 2030). Since phase I, the bylaw of the emission rights market has experienced a number of amendments that have attempted to sort out the existing excess supply due to the dramatic financial crisis of 2008. The EU ETS establishes a limit on the entire quantity of carbon emission allowances assigned per year to the entities covered by the system. Enterprises that do not adjust to their emission permits, meet serious sanctions. However, a firm can emit less

* Corresponding author.
E-mail address: salvador@unizar.es (M. Salvador).

[1] All the authors have contributed equally to the realisation of this work.

https://doi.org/10.1016/j.egyr.2022.11.146

carbon than is permitted, thus provoking an excess. This excess can be traded with firms, whose emission is greater than the tolerance. For this reason, the EU ETS is established through a cap-and-trade program, making carbon permits a marketable commodity, which imitate of the financial assets (Benz and Trück, 2006; Uddin and Holtedahl, 2013).

At the spotlight of mitigating climate change is the energy sector, which is responsible for 80% of greenhouse gas emissions. Energy is an important engine of economic growth, on which most economic activity depends. However, the current energy model is based on finite resources, mainly fossil fuels, which shows its clear economic unsustainability (Qadir et al., 2021). With the consciousness that oil and gas are some of the main motives of pollution and drive to environmental deterioration, decarbonising the energy system is another urgent and important step to combat climate change that is becoming a pressing issue for European policymakers (Malik et al., 2019; Hafner and Raimondi, 2020). However, the growth of energy demand, on the one hand, and the constraints of reduced carbon emissions, on the other hand, make achievements harder to come by for the global economy's green growth (Wang et al., 2020). For a successful carbon-neutral economy and to achieve a cleaner future, the International Renewable Energy Agency (IRENA, 2018) established that the necessary energy transition should be based on clean alternative energies, which emit only what the planet can absorb and mitigate climate change, reducing its associated environmental and health impacts (Imteyaz et al., 2021; Pilz et al., 2018). Qadir et al. (2021) and Wang et al. (2022) suggested that EU countries should reduce the use of dirty fossil fuels and increase certain types of renewable sources in their energy mix to fulfil the European Green Deal and achieve the Sustainable Development Goals related to improving environmental quality. Renewables have a multitude of advantages that justify their position as one of the main elements of change in the energy model (Panwar et al., 2011). They are based on autochthonous resources (wind, sun, water, etc.), so, they provide easy access to energy, contributing to social and economic development. They can also help solve the issue of improving the living standards of rural populations (Sen and Ganguly, 2017). While some remote areas are hard to reach, establishing grid connectivity with neighbouring countries is a viable option that could also bring regional harmony and create an atmosphere of friendliness between nations (Xiangchengzhen and Yilmaz, 2020). This kind of initiative offers several other benefits, such as reducing the external dependence of an economy on fossil fuels and, hence, price and quantity risks in the face of possible energy shocks. In all recent armed conflicts, geopolitics has been present to control energy, as a scarce commodity that it is, cushioning the measures to be adopted by blackmailing the need to maintain the supply of oil and gas from countries in conflict. Following the Russian invasion of Ukraine, the desire for a speedy conversion to renewable energy has never been stronger and more evident. According to data from the European Commission, the EU buys 90% of the gas it consumes and Russia supplies more than 40% of the gas consumed in the EU. Additionally, 27% of oil importations and 46% of coal importations also hail from Russia.

Therefore, besides to the carbon market, governments are also pushing up the clean energy sector to encourage a safer, more accessible, and sustainable energy supply, and to moderate the unpleasant effects induced by GHG emissions (Kazemilari et al., 2017; Xia et al., 2019; Kuang, 2021) and by the latest geopolitical conflicts. Thus, the green energy sector has seen a surge in interest, and has become vertical to the global economy while providing the best way to achieve the majority of the emission reductions needed (Balcılar et al., 2016; Reboredo et al., 2019; Khurshid and Deng, 2021). In this way, the policies of the European Union are playing an important role in facilitating this energy transition. In fact, some research found that EU ETS is materially improving renewable energy production, just like that indicating that the growth of clean energies has been successfully boosted because of it (Yu et al., 2017). However, to achieve an effective renewable energy transition, an enormous amount of capital is required (Hall et al., 2017), making the financing of this transition probably one of the biggest problems of the 21st century (Qadir et al., 2021).

Although the overall costs associated with renewable production have decreased significantly in recent years due to technological advancements, there has been no corresponding increase in investment. It appears that investors are less willing to take investment risk due to changes in policies and the amount of capital involved; however, some findings such as those of Chang et al. (2020) should encourage investment change from fossil to renewable energy. These authors suggest that moving average trading rules do not help predict the returns of fossil energy companies, whereas they more reliably forecast those of renewable energy companies.

It is clear that clean energy equities and tradable emission permits should represent new attractive green investment vehicles for equity market participants. Both markets have experienced noteworthy growth and are expected to rise in the future and, therefore requiring more support (Arouri et al., 2015). For all the above reasons, and because EU CO_2 emission allowances (EUA) and renewables are decisive for cutting carbon emissions on a worldwide scale, building an energy system compatible with the Paris Agreement requires an understanding of the dynamics of investment risk in carbon and renewable sectors. Thus, in recent years, the risk of the carbon market has been attracting more and more attention in the field of energy economics and finance. The carbon market risk stems from various aspects, not only its own internal volatility (Hintermann, 2010; Lin and Jia, 2019), but also from the interactions with other energy markets. In this context, exploring the risk spillover effects between the carbon and energy markets can help us better understand the risk pattern and volatility mechanism and promote the stable development of the carbon market (Zhu et al., 2020). Other authors have already analysed to a greater or lesser extent their relationship with the fossil fuel and dirty energy markets. Thus, Chevallier (2011), Hammoudeh et al. (2014, 2015), and Chevallier et al. (2019) analysed the relationship between the price of EUA and the prices of the three fossil fuels (Oil, Gas and Coal). Other authors such as Liu and Chen (2013), Marimoutou and Soury (2015), Zhang and Sun (2016), and Wang and Guo (2018) showed the dynamism in the transmission of volatility and correlation between these markets. Sadorsky (2008, 2012), Kumar et al. (2012), Managi and Okimoto (2013), Reboredo (2015) and Bondia et al. (2016) studied the influence of oil price on clean energy companies. Later, authors such as Ji et al. (2018), Dutta et al. (2018), and Lin and Chen (2019) included the carbon market together with clean energy and fossil fuel markets, showing significant dynamic correlations and volatility transmission among them. A more recent work (Cao et al., 2020) showed the negative impact of oil price volatility on investment in renewable energy companies in China. More recently, Gargallo et al. (2021) made an exhaustive analysis of how EUA, clean and dirty energy markets interact regarding correlation and volatility spillovers.

However, while in-depth studies of the understanding of how those stocks interact; their chance for diversification of conventional asset portfolios has not been completely analysed. In general, clarification on the correlation and dissemination of the volatility of these markets can be helpful to appropriately diversify the portfolio to reduce risk. Some authors have showed a better coverage of clean energy assets by fossil fuels (Sadorsky, 2012; Zhang and Du, 2017; Dutta et al., 2018; Lin and Chen, 2019). Superseding fuel oil and natural gas affects carbon allowance prices due to the large quantity of carbon emissions of these fossil fuels, which gives them huge value for diversification in portfolios (Luo and Wu, 2016). Carbon assets can reduce the risk of energy assets in portfolio management (Reboredo, 2015). Reboredo (2013, 2014), Luo and Wu (2016), and Dutta et al. (2018) indicated that carbon assets have probable diversification profits due to their absence of relation from financial markets. In the same way, Kanwal and Khan (2021) revealed the relative independence of the European renewable energy market from the carbon market providing diversification benefits and added value by including carbon assets in a clean energy stock portfolio. Wen et al. (2017) supported the results by building portfolios that incorporated EUAs. Zhang and Sun (2016), and Wang and Guo (2018) confirmed the usefulness of oil to also cover changes in the price of carbon and the change to gas hedging in cases of extreme volatility. Recently, 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.

As a branch of those previous studies, this paper researches the potential of clean energy stocks and emission permits to reduce downward risk by combining them in a portfolio with dirty energy assets. Despite all those studies, what is lacking is understanding how responsible investors in clean energy stocks and EUA can cover their investments. On aggregating carbon assets to mixed clean and dirty energy stock portfolios, the risk could decrease and diversification profits could be obtained. To that aim, we want to find a strategy that produces optimum well-diversified portfolios, which motivates investors to remove carbon from their equity portfolios and to swap dirty energy for clean energy assets, thereby stimulating the energy transition.

Within this context, an effective portfolio optimisation procedure to carry out the diversification process is necessary. Due to the time changing interdependence among carbon price, renewable and conventional energy assets, the process must be dynamic and allow a recurrent re-balancing of portfolios to reach a satisfactory risk over time. Saeed et al. (2020) also support this statement. From their results on clean asset hedging effectiveness, they indicate that investors should follow a dynamic hedging strategy. Their main findings evidence that the hedge ratios are time varying, which implies that investors have to regularly monitor and adjust their hedged positions. Usually, financial risks are not equally dispensed over time, but they can be accentuated at certain points in time. Moving exposure into relatively quiet markets during times of financial commotion could decrease the overall risk taken. Because investment markets are constantly changing, also, optimal portfolio weights should be changed over time, for which dynamic risk management is needed. Risk management in portfolios is very important in extreme moments, when the carbon and energy markets can move together (Ji et al., 2018). Therefore, in this research, we propose an asset allocation in a volatility-timing framework, which reacts to shifting market environments, keeping different portfolios at distinct points in time, because of climate policy evolution and the changing expectations of investors, which are obviously interrelated (Sen and von Schickfus, 2020). Climate policies and policy proposals provide signals that shape how investors perceive the asset risk. For this reason, rather than using a buy-and-hold strategy, i.e. passively investing, we propose that investors actively decide which asset classes to over or underweight are and they are able to adapt their investment strategies and holdings based on their market outlook. Therefore, this study considers dynamic hybrid portfolios to analyse in-depth the diversification benefits among allocations in clean and dirty energy and in emission permits.

More specifically, our paper is encompassed within a volatility timing strategy that rebalances the portfolio weights within a mean–variance optimisation framework based only on expected volatility changes, while treating expected returns as constants. Different investors at different times will have different vectors of expected excess returns. Our portfolio optimisation strategy is therefore based on the idea of choosing covariance matrices that achieve the lowest portfolio variance for all relevant expected returns. Definitively, our portfolios are chosen to minimise predicted variance subject to a required return but the analysis involves a full range of hypothetical required returns. In this way, we have isolated the effect of covariance information from expected returns, by applying our optimisation procedure for a number of alternative time-invariant vectors of expected returns that any investor may want to use in his/her asset allocation decision. Thus, we are taking into account the uncertainty associated with the problem of choosing the average return vectors. The set of supposed constant vectors of expected returns is intended to capture several scenarios, where profits could be elevated, and others in which they could be small or even null. This way of incorporating the uncertainty associated with the problem of choosing the average return therefore validates and provides robustness to the analysis carried out.

To achieve this goal, we use multivariate GARCH models, concretely the Asymmetric Dynamic Conditional Correlations (ADCC) model family, to obtain good estimations of the conditional covariance matrices of the daily asset returns. The covariance matrix is used to calculate the standard deviation of a portfolio of stocks, which, in turn, is used by portfolio managers to quantify the risk associated with a particular portfolio. Those models are simple and flexible but they are also able to reflect correlation changes among assets through time. In order to determine the weights of the optimum minimum-risk portfolio, we use a methodology based on Engle and Colacito (2006) and Giacomini and Rossi (2010) to compare the portfolio volatilities obtained with different models. The analysed period goes from January 2010 to April 2022, which, on the one hand includes more than twelve years of life of the EU ETS beyond the phase I pilot; and, on the other hand, it considers the latest crisis episodes (Sovereign debt crisis, Brexit, COVID-19 and Ukrainian war).

Our findings show that the minimum risk portfolios are based on the use of DCC models, which captures changing correlations over time. Most selected dynamic portfolios take long positions in CLEAN and short position in OIL.GAS and some times in the free risk asset, with these weights tending to have the larger absolute values from the Paris Agreement (December 2015). The role of the EUA is secondary but with stable behaviour in terms of risk and a positive contribution around 20% of long positions since 2016. These results motivate investors to remove carbon from their equity portfolios. We show that investing in clean energy companies is valuable not only for its contribution to a sustainable energy transition to renewable sources but also for the attractiveness from a financial viewpoint.

The main contributions of the paper are fourfold. Firstly, we provide a procedure based on Engle and Colacito (2006) for correctly estimating the conditional covariance matrix of asset returns, which allows us to build the weighting for an optimal minimum risk portfolio. Secondly, we supply sequential information processing that helps investors perform smart portfolio management, enabling them to learn day-by-day and adapt the asset weights over time. Thirdly, we isolate the effect of estimated covariance from expected returns, by applying the optimisation procedure for a set of several scenarios where profits could be elevated, and others in which they could be small or even null. Fourthly, by analysing the evolution of the weights of the optimal energy portfolio provided in the paper, we highlight the fact that, currently, investment in clean energy is consistent with what all investors want, whether they are environmentally or socially responsible or only concerned about profit. In addition, we highlight that although investors often panic during times of geopolitical noise, such as the current Russo–Ukrainian War (the most severe conflict since World War II), our dynamic optimum portfolio continues to support investment in renewables. An important reason for this could be found in the fact that renewable energies, in addition to protecting the environment, can prevent energy dependence between countries and, therefore, catastrophic geopolitical conflicts.

The remainder of the study proceeds as follows. In Section 2, we set-up the problem and we explain the procedures used, on the one hand, to obtain the weights of a minimum risk portfolio and, on the other hand, to compare the risk of the portfolios provided by different models. In Section 3, we apply these procedures to the energy equity and carbon markets. The study concludes with main remarks, policy consequences, and future areas of research.

2. Setting up the problem and methodology

In Section 2.1 we set-up the problem and explain the procedure used to obtain the weights of the minimum risk portfolio. In Section 2.2, we describe the risk comparison technique, which is based in Engle and Colacito (2006) and it is used to estimate the conditional covariance matrices of the asset returns as well as the portfolio weights.

2.1. Minimum risk portfolio

Let $\left\{\mathbf{r}_t = \left(\mathrm{r}_{1,t}, \ldots, \mathrm{r}_{n,t}\right)'; \mathrm{t} = 1, \ldots, T\right\}$ be the sequence of day-to-day financial return vectors with $\mathrm{r}_{i,t} = 100 \cdot \log\left(\frac{\mathrm{p}_{i,t}}{\mathrm{p}_{i,t-1}}\right)$ and $\mathrm{p}_{i,t}$ is the closing price of the ith asset in period t for i = 1,…,n.

Let $\mathcal{F}_t = \{\mathbf{r}_1, \ldots, \mathbf{r}_t\}$ be the data ensemble in period t.

Let $\boldsymbol{\Omega}_t = var\left(\mathbf{r}_t | \mathcal{F}_{t-1}\right)$ be the conditional covariance matrix in period t.

Our aim is to explore portfolio diversification chances among diverse energy equity and carbon markets. Given that most investors are risk averse, preferring a lower level of risk for the equal level of expected return (Fleming et al., 2001, 2003), and given the impossibility of knowing the true value of the expected returns, in this paper, we adopt an asset allocation strategy within a volatility-timing framework, determining the minimum variance Markowitz portfolios.

Therefore, we solve the following optimisation problem consisting of minimising the variance of the portfolio subject to a given expected return $\boldsymbol{\mu}$. This issue can be written as:

$$\min_{\mathbf{w}_t} \mathrm{Var}\left(\mathbf{w}_t'\mathbf{r}_t \ |\mathcal{F}_{t-1}\right) = \min_{\mathbf{w}_t} \mathbf{w}_t'\boldsymbol{\Omega}_t\mathbf{w}_t$$
$$\text{s.t. } \mathbf{w}_t'\boldsymbol{\mu} = \mu_0$$

where $\mu_0 > 0$ is the required return, $\mathbf{w}_t = \left(\mathrm{w}_{1,t}, \ldots, \mathrm{w}_{n,t}\right)'$ is the vector of portfolio weights for time t chosen at time t – 1 with $\mathrm{w}_{i,t}$ being the share on asset i for time t for i = 1, .., n. The solution to this problem is:

$$\mathbf{w}_t = \frac{\boldsymbol{\Omega}_t^{-1}\boldsymbol{\mu}}{\boldsymbol{\mu}'\boldsymbol{\Omega}_t^{-1}\boldsymbol{\mu}}\mu_0$$

Note that $\sum_{i=1}^{n} \mathrm{w}_{i,t}$ usually will not require being equal to 1. In fact, $1-\sum_{i=1}^{n} \mathrm{w}_{i,t}$ is the portion in the risk-free asset. In what follows we will take $\mu_0 = 1$.

However, it is not easy to choose the average return vectors $\boldsymbol{\mu}$ (Engle and Colacito, 2006). For this reason, and in order to take into account the uncertainty associated with this problem, we implement the optimisation process for a set of supposed constant vectors of expected returns $\boldsymbol{\mu} \in \mathbf{E}$. The $\mathbf{E}$ set tries to capture several scenarios, where profits could be elevated, and others in which they would be able to be small or even null. Once we have determined $\mathbf{E}$, we calculate the minimum variance portfolio weights for each $\boldsymbol{\mu} \in \mathbf{E}$. Finally, our proposed final optimal portfolio is built averaging the weights of the selected portfolios.

2.2. Dynamic estimation of the covariance matrix

Engle and Colacito (2006) proved that if σ_t is the standard deviation of the minimum variance portfolio obtained in period t using an estimation $\mathbf{H}_t$ of $\boldsymbol{\Omega}_t$, then $\sigma_t \geq \sigma_t^*$ where σ_t^* is the standard deviation of the minimum variance portfolio obtained with $\boldsymbol{\Omega}_t$ and, hence, $\frac{1}{T}\sum_{t=1}^{T}\left(\sigma_t^*\right)^2 \leq \frac{1}{T}\sum_{t=1}^{T}\left(\sigma_t\right)^2 \ \forall\boldsymbol{\mu}$. Hence, misestimating $\boldsymbol{\Omega}_t$ entails an increase of the risk of the portfolio or, equivalently, a decrease of the required return μ_0 for a fixed risk level. Therefore, we must try to estimate $\boldsymbol{\Omega}_t$ as best as possible.

To that aim we use a set of statistical models $\mathbf{M} = \{\mathrm{M}_1, \ldots, \mathrm{M}_K\}$, usually conditionally heteroscedastic, which try to describe in a parsimonious and reliable way, the evolution of $\boldsymbol{\Omega}_t$ over time. In order to select the most adequate model, we apply a procedure proposed by Engle and Colacito (2006) based on the test of Diebold and Mariano (2002), which carries out pairwise comparison of the risk of minimum variance portfolios. The weights of these portfolios are calculated, for each $\boldsymbol{\mu} \in \mathbf{E}$, from the covariance matrices $\left\{\mathbf{H}_{t,\mathrm{M}_i}; \mathrm{t} = 1, \ldots, \mathrm{T}\right\}$ estimated by $\mathrm{M}_i \in \mathbf{M}$. Next, we briefly describe this procedure:

Let $\mathbf{E} = \{\mathbf{m}_i; \mathrm{i} = 1, \ldots, \mathrm{R}\}$ be the set of plausible return vectors.

Let $\mathbf{w}_{t,\mathrm{M}_i}^{j} = \frac{\mathbf{H}_{t,\mathrm{M}_i}^{-1}\mathbf{m}_j}{\mathbf{m}_j'\mathbf{H}_{t,\mathrm{M}_i}^{-1}\mathbf{m}_j}$ the corresponding minimum variance portfolios weights assuming an expected return $\boldsymbol{\mu} = \mathbf{m}_j$ for j = 1,…, R.

Let $\pi_{t,\mathrm{M}_i}^{(j)} = \mathbf{w}_{t,\mathrm{M}_i}^{j'}\left(\mathbf{r}_t - \bar{\mathbf{r}}_T\right)$ where $\bar{\mathbf{r}}_T = \frac{1}{T}\sum_{v=1}^{T}\mathbf{r}_v$ for i = 1, 2.

Let $\mathrm{v}_{t,\mathrm{M}_1,\mathrm{M}_2}^{i} = \mathrm{u}_{t,\mathrm{M}_1,\mathrm{M}_2}^{i}\left[0.5\left(\mathbf{m}_i'\mathbf{H}_{t,\mathrm{M}_1}^{-1}\mathbf{m}_i\right)\left(\mathbf{m}_i'\mathbf{H}_{t,\mathrm{M}_2}^{-1}\mathbf{m}_i\right)\right]^{1/2}$ where

$$\mathrm{u}_{t,\mathrm{M}_1,\mathrm{M}_2}^{i} = \left(\pi_{t,\mathrm{M}_1}^{(i)}\right)^2 - \left(\pi_{t,\mathrm{M}_2}^{(i)}\right)^2$$

We perform the following regression:

$$\mathbf{V}_{t,\mathrm{M}_1,\mathrm{M}_2} = \beta_{\mathrm{M}_1,\mathrm{M}_2}\mathbf{1}_{\mathrm{Rx1}} + \boldsymbol{\varepsilon}_{v,t,\mathrm{M}_1,\mathrm{M}_2} \quad \text{for } t = 1, \ldots, \mathrm{T} \tag{1}$$

where $\mathbf{V}_{t,\mathrm{M}_1,\mathrm{M}_2} = \left(\mathrm{v}_{t,\mathrm{M}_1,\mathrm{M}_2}^{1}, \ldots, \mathrm{v}_{t,\mathrm{M}_1,\mathrm{M}_2}^{R}\right)'$, and we test the hypothesis H_0: $\beta_{\mathrm{M}_1,\mathrm{M}_2} = 0$ versus H_1: $\beta_{\mathrm{M}_1,\mathrm{M}_2} \neq 0$ using a t-test with a robust Newey–West estimator of the standard error of $\hat{\beta}_{\mathrm{M}_1,\mathrm{M}_2}$. If we accept H_0, we conclude that there are not significant differences between the risks of the compared portfolios and, hence, there are not significant differences between the estimations of $\boldsymbol{\Omega}_t$ provided by both models (M_1 and M_2). Otherwise, if we accept that $\beta_{\mathrm{M}_1,\mathrm{M}_2} > 0$ we conclude that $\left\{\mathbf{H}_{t,\mathrm{M}_2}; \mathrm{t} = 1, \ldots, \mathrm{T}\right\}$ describes the evolution of $\boldsymbol{\Omega}_t$ along time better than $\left\{\mathbf{H}_{t,\mathrm{M}_1}; \mathrm{t} = 1, \ldots, \mathrm{T}\right\}$. The contrary happens if we accept that $\beta_{\mathrm{M}_1,\mathrm{M}_2} < 0$.

If the solution to this model comparison process is unique, we keep the selected model as the best one. However, if there are several models that provide adequate estimates of $\boldsymbol{\Omega}_t$, we resort to model selection criteria to determine, within the set of models that have turned out to be indifferent, the optimal one.

2.3. Weights minimum risk portfolio

Once we have determined the best model, M_{opt}, the final optimal portfolio is built averaging the weights of the mini-

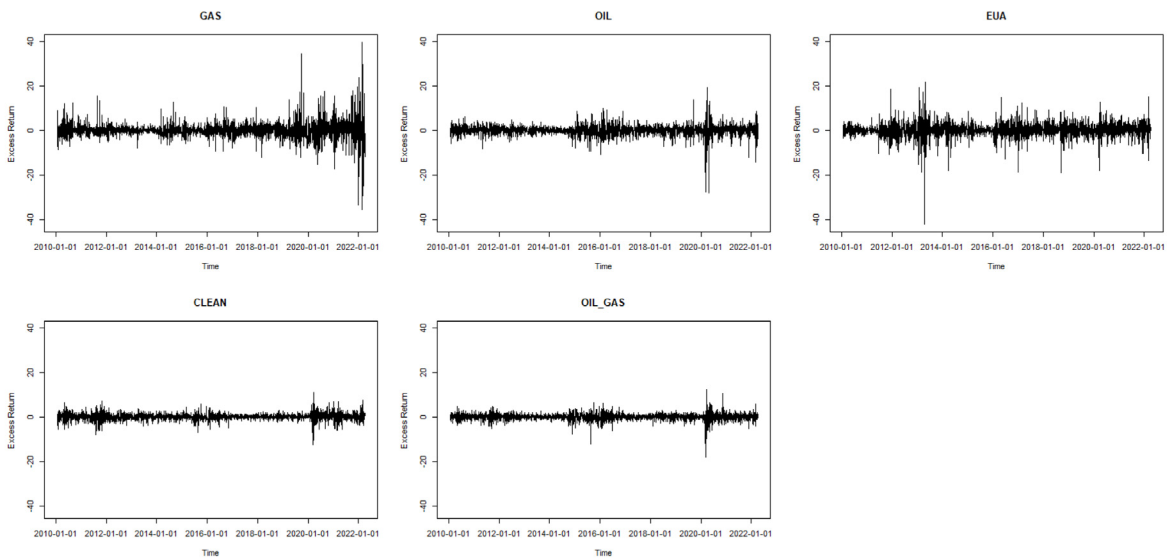

Fig. 1. Evolution of the daily excess returns of GAS, OIL, EUA (first row), and CLEAN and OIL_GAS (second row) in the period from 19 Jan, 2004, to 4 Apr, 2022. All series are heteroscedastic with volatility clustering. The most volatile series tend to be GAS and EUA, while the least are CLEAN and OIL_GAS.

mum risk optimal portfolios $\left\{\mathbf{w}^{i}_{t,M_{opt}} = \frac{\mathbf{H}^{-1}_{t,M_{opt}}\mathbf{m}_i}{\mathbf{m}_i'\mathbf{H}^{-1}_{t,M_{opt}}\mathbf{m}_i}; i = 1, \ldots, R\right\}$ in such a way that $\mathbf{w}_{t,M_{opt}} = \frac{1}{R}\sum_{i=1}^{R}\mathbf{w}^{i}_{t,M_{opt}}$. Notice that $\mathbf{w}_{t,M_{opt}}$ is an equally weighted portfolio of minimum-variance portfolio, which considers the uncertainty associated with the value of the expected returns vector $\boldsymbol{\mu}$, and it provides a smoothing of the asset weights.

3. Empirical analysis of the european energy market

In this section, we factually analyse the daily evolution of prices in the European energy and carbon markets and apply the method from Section 2 to determine the optimum minimum risk portfolios. Then, we study the composition of the portfolios while paying special attention to the role of clean energy in them.

3.1. Data

The data used in this work are day-to-day shutdown prices (in euros) from January 19, 2010 to April 4, 2022 (amounting to 2959 observations) of five assets. The time span starts in 2010, thus avoiding Phase I of the EU ETS that started in 2005 and which was a pilot phase. This is a common practice in the energy economics literature (Chang et al., 2018). However, we selected 2010 within Phase II, which was a period of full operation of the EU ETS, and not 2008, since 2010 was a year of energy recovery after the Great Recession. The time span ends on April 4, 2022, since this was the latest data available at the time of the analysis. The entire period covers the latest crisis episodes (Sovereign debt crisis, Brexit, COVID-19 and the start of the recent Russo–Ukrainian war). The two fossil fuel series (designated GAS and OIL in our paper) recount to oil and gas futures prices in Europe, which are important generators of "dirty" energy. We have considered the "Brent" oil futures, recorded in the United Kingdom, which are the European leading reference for a barrel price of this fuel. Regarding gas, we have taken the Natural Gas Futures, the reference in Europe, which are listed on the stock exchange market of United Kingdom. In addition, we have taken the S&P Global Clean Energy Index and the EURO STOXX® Oil & Gas Index as the series of securities prices of clean and dirty energy industries, respectively. The first index (designated CLEAN in our paper) measures the yield of 31 worldwide enterprises in businesses related to clean energy (more information and details on the weights and the formula for calculating this index can be found at https://www.spglobal.com/spdji/en/indices/esg/sp-globalclean-energy-index/#overview, accessed on April 4, 2022). As clean energy companies are younger and their market is less mature, we preferred to select a world index instead of a European one, because it already includes consolidated companies and, therefore, is a better representative of the clean energy market. Moreover, we considered the S&P Global Clean Energy Index and not a green bond index because according to the hedging effectiveness findings of Saeed et al. (2020), clean energy stocks have a greater ability than green bonds to lessen the risk of dirty energy investment, and are therefore a more effective hedge. The "dirty" energy index (nominated OIL_GAS in our paper) provides data on the 12 largest European enterprises in the mining, drilling, manufacturing, refining, delivery and retail sale of oil and gas (more information and details on the weights and the calculation formula can be found at https://www.stoxx.com/index-details?symbol=SXEE, accessed on April 4, 2022). Finally, the variable EUA in our database picks the prices of European Unit Allowances from SENDECO2 (European CO_2 Trading System), a firm that trades emission permits independently, and that provides technical and managerial counselling to manufacturing installations submitted to the EU ETS system.

3.2. Descriptive analysis

Fig. 1 displays the excess return series matching to the five assets and Table 1 reveals the results of a descriptive statistical analysis. The average return of the series is not significantly different from zero and all series are strongly leptokurtic and have significant but not very strong asymmetries. In addition, they also show the heteroscedastic character with the characteristic volatility clustering of financial series. The less volatile series tend to be CLEAN and OIL_GAS given that they are stock indices. It can also be observed that the kurtosis of OIL_GAS tend to be significantly higher than kurtosis of CLEAN due to the greater trend of OIL_GAS to have a heavier left tail, which reflects a tendency to take more extreme negative excesses returns. The most volatile series tend to be GAS and EUA. In the case of GAS, the higher volatility is mainly due to the last period 2019–2022 (see Fig. 1) and more intensely that corresponding to the Russo–Ukrainian war; while in the case of EUA, its higher volatility

Table 1
Descriptive study of the day-to-day excess returns of the five assets in the period from 19 Jan, 2004 to 4 Apr, 2022.

	Minimum	Maximum	Mean	Std. Dev.	Skewness	Kurtosis
GAS	−35.467	39.533	0.066	3.709	0.377***	19.268***
OIL	−27.975	19.079	0.001	2.323	−1.031***	19.182***
EUA	−42.256	21.582	0.057	3.222	−0.950***	14.791***
CLEAN	−12.495	11.034	−0.002	1.574	−0.449***	6.348***
OIL_GAS	−17.951	12.388	−0.007	1.510	−1.010***	16.243***

Note: The rows correspond to the five assets (GAS, OIL, EUA, CLEAN and OIL_GAS), and the columns correspond to the usual descriptive statistics (minimum, maximum, mean, standard deviation, skewness and kurtosis). The three asterisks indicate that skewness and kurtosis differ significantly from zero at 1% for the excess returns of the five assets.

reflects the different changes in the CO_2 emission allowances granting systems.

Fig. 2 represents a two-panel chart, which shows a matrix graphic in the top panel with the pairwise cross-correlations of the five daily returns in the outside of diagonal elements, and the values of their autocorrelations in the diagonal cells. The diagonal elements show small non-significant autocorrelations, specific of financial series. So, we propose a VAR(1) model in order to explain that relations among the five series return. In addition, in the bottom panel, the autocorrelation function of the quadratic returns can be seen, which indicate the presence of values significant positive for all the lags. This reflects the presence of a lasting volatility clustering in all the assets. Consequently, a GARCH model for the volatility of each series is proposed. Finally, the off-diagonal elements in the upper board of Fig. 3 include the correlations between returns, which advise a multivariate GARCH modelling, enabling correlation between all of the assets. Concretely, we opted to use Asymmetric Dynamic Conditional Correlation (ADCC) models in order to capture the possible asymmetric impact of recent market information.

3.3. Estimation and selection of the model

This section first describes the six models used, and determines the best model to estimate the evolution of the conditional covariance matrix of the analysed series.

3.3.1. Description of the models

We propose to use a VAR(1)-ADCC(1,1)-GARCH(1,1) family to estimate $\mathbf{\Omega}_t$. This family was introduced by Cappiello et al. (2006) and is one of the key references for both its flexibility and its feasibility of implementation because of the separate specifications of the conditional volatilities and of the conditional correlations. Concretely, we assume that

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

where $\boldsymbol{\mu}_t$ is given by the VAR(1) expression:

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

and $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \ldots, \varepsilon_{nt})'$ is a conditional heteroscedastic error term with $\mathbf{H}_t = \mathrm{var}(\boldsymbol{\varepsilon}_t|\mathcal{F}_{t-1})$. The conditional covariance matrix is broken down as follows:

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

where $\mathbf{D}_t$ is a matrix with off-diagonal zeros and the conditional variances, $h_{ii,t} = \mathrm{var}(\varepsilon_{i,t}|\mathcal{F}_{t-1})$ for $i = 1,\ldots,n$, on diagonal elements, and $\mathbf{R}_t$ is the conditional correlation matrix of $\mathbf{r}_t$. We use independent GARCH(1,1) to model the n conditional variances, which are written in vector form as:

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

where $\mathbf{\Omega} = \mathrm{diag}(\omega_i)$, $\mathbf{A}_1 = \mathrm{diag}(\alpha_i)$ and $\mathbf{B}_1 = \mathrm{diag}(\beta_i)$ are $n \times n$ non-negative diagonal matrices, and $\odot$ denotes the Hadamard operator. Regarding the correlation matrix, $\mathbf{R}_t$, we suppose 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:

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

with a, b being non-negative unknown constants verifying $a + b < 1$, which is enforced to assure stationarity and positive definiteness of $\mathbf{Q}_t$. In addition, $\mathbf{z}_t = \mathbf{D}_t^{-1}\boldsymbol{\varepsilon}_t$ are the standardised residuals, $\mathbf{z}_t^- = \mathbf{z}_t I(\mathbf{z}_t < 0)$ in order to capture asymmetric effects, $\overline{\mathbf{Q}}$ is a definitive positive symmetrical matrix and $\mathbf{Q}_0$ is the onset value of $\mathbf{Q}_t$, which has to be positive definite to assurance $\mathbf{H}_t$ to be positive definite. The model parameters are estimated with a procedure of three stages based on Engle and Sheppard (2001). In the initial stage, a VAR(1) model for $\mathbf{r}_t$ is applied and the estimation $\hat{\boldsymbol{\varepsilon}}_t$ of the residuals $\boldsymbol{\varepsilon}_t$ is obtained. In the next stage, n univariate GARCH(1,1) models are estimated separately for each residual univariate time series. In the third step using the estimated standardised residuals $\hat{\mathbf{z}}_t = \hat{\mathbf{D}}_t^{-1}\hat{\boldsymbol{\varepsilon}}_t$, obtained from the estimated volatilities from the second stage, we take $\overline{\mathbf{Q}} = \frac{1}{T}\sum_{t=1}^{T} \hat{\mathbf{z}}_t \hat{\mathbf{z}}_t'$ and we estimate a, b and $\mathbf{Q}_0$ using maximum likelihood. The two last steps are used to estimate the elements in $\mathbf{H}_t$ separately, first the elements that are on the diagonal are determined and then, from them, the off-diagonal elements are estimated.

In order to select the most adequate models, we consider the following three subfamilies of VAR(1)-ADCC(1,1)-GARCH(1,1) models:

- The VAR(1)-CCC(1,1)-GARCH(1,1) model, which uses the Constant Conditional Correlation (CCC) model of Bollerslev (1990), supposing that a constant correlation matrix links the univariate models for conditional variances GARCH(1,1) to one another. It assumes that $a = b = g = 0$ and, hence, $\mathbf{R}_t = \mathbf{R}\ \forall t$
- The VAR(1)-DCC(1,1)-GARCH(1,1) model, which uses the Dynamic Conditional Correlation (DCC) model presented by Engle (2002) and Tse and Tsui (2002), generalising the CCC model because the assumption of constant conditional correlations may not seem realistic for many practical financial applications. The DCC allows for dynamic evolution of the correlations and assumes that the asymmetric effects are not significant ($g = 0$).
- The VAR(1)-ADCC(1,1)-GARCH(1,1) model, which uses the Asymmetric Dynamic Conditional Correlation (ADCC) model, by allowing to examine the degree in which changes in asset correlation show evidence of asymmetric responses to negative returns.

Therefore, we have considered $k = 6$ possible models resulting from the combination of the CCC, DCC and ADCC family models with the multivariate normal distribution (MVN) and multivariate Student's t (MVT) for the conditional error distributions $\boldsymbol{\varepsilon}_t|\mathcal{F}_{t-1}$. So, and in order to abbreviate the notation, these models are denoted CCC_MVN, DCC_MVN and ADCC_MVN, when the errors are jointly normally distributed and CCC_MVT, DCC_MVT and ADCC_MVT, when the used distribution is the multivariate Student's t.

We have considered both error distributions because in many financial applications the Gaussian assumption is usually rejected due to the existence of conditional leptokurtosis. This fact is especially interesting for risk analysis where the tail properties of return distributions are of primary concern.

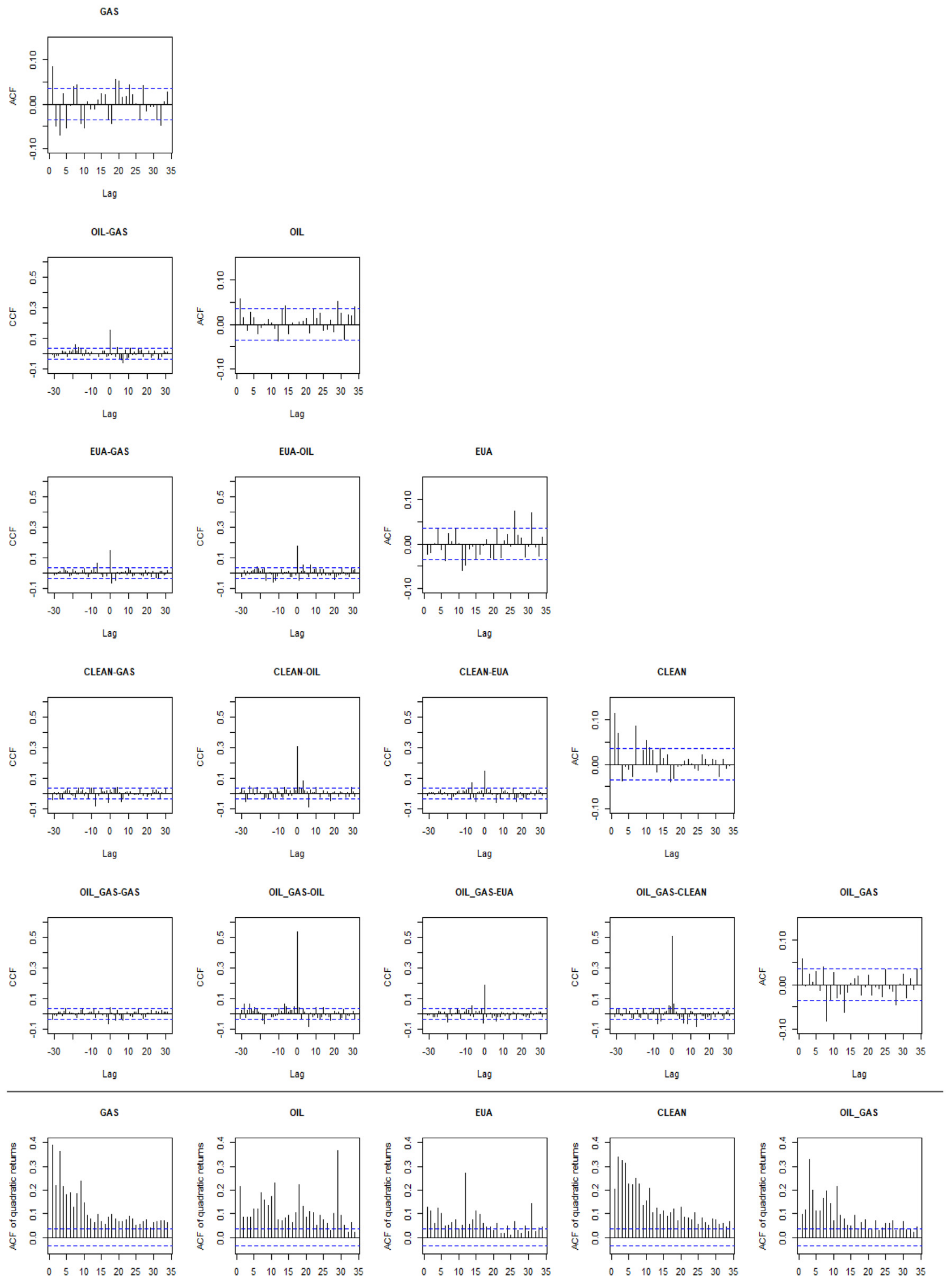

Fig. 2. Two-panel chart: The top panel (the first five rows) is a matrix graph showing the pairwise cross-correlations of the daily excess returns of the five assets in the off-diagonal elements, and their autocorrelations in the diagonal cells. Most of the series are contemporaneously correlated in a positive way. The bottom panel (last row) contains the autocorrelation function of the quadratic excess returns of the five assets. GARCH time-varying volatility can be appreciated for each series.

3.3.2. Determination of the best model

All the estimation presented below were obtained using the statistical package **rmgarch** of R program.

Table 2 shows the results of the estimation of the mean of the asset returns as well as their joint links by means of the VAR(1). The short-term progression of the EUA series is inversely affected by GAS and OIL.GAS. A price rise of GAS and OIL.GAS envisage a decline in CO_2 emissions and, hence, a decrease in EUA prices. Conversely, the anterior evolution of EUA does not affect any of the other assets, reflecting that the incentive to

Fig. 3. The figure consists of a two-panel chart with the results of the pairwise comparison between the models. The first panel is a matrix with the results of the Diebold and Mariano test, as well as the fluctuation tests of Giacomini and Rossi. The crossing of each row and each column contains the result of the risk comparison of the optimal portfolios built with the models that are indicated in the corresponding places on the diagonal. The lower triangular matrix contains the values of the t statistic from the Diebold and Mariano tests. Highlighted in red (blue) are the positive (negative) significance results regarding the value of the parameter β_{M_1,M_2} from the regression model (1). For example, 4.8097 is the value of the t statistic from the Diebold and Mariano tests corresponding to the comparison of the risk of the optimal portfolios built with the M_1 = CCC_MVT and M_2 = DCC_MVN models. As this value is greater than 1.96, it is concluded at 5% of significance that the parameter $\beta_{M_1,M_2} > 0$, and, therefore, the riskier portfolio is that built with model M_1 = CCC_MVT. The upper triangular matrix shows the graphic evolution of the statistics from the fluctuation test that analyses the existence of time varying differences in portfolio volatilities built with model M_2 minus those of model M_1. Therefore, for example, the graph located in the crossing of row 2 and column 4 shows that the differences take many negative values and exceed the lower end of the confidence band, from 2020 on. Therefore, portfolios built with M_2 tend to be less risky than those built with M_1. The second panel in the table (last row) displays the index number (normalised to 100) of the volatility ratios for each model. In bold is the model with the minimum volatility ratio. Thus, the value 101.6428 is the ratio between the estimated mean standard deviation of the minimum risk portfolio built with the CCC_MVT model and that with ADCC_MVN. Therefore, ADCC models tend to select less risky portfolios than CCC_MVT, improving their level of required level return for the same level of risk by1.64%. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

shifting from unclean to clean energy is not channelled across the average return of the series. Finally, increments in CLEAN stock prices are generally related to economic heyday periods and, therefore, foresee growths in CLEAN and in OIL.GAS stock prices. This fact indirectly enhancements the advisability in investing and fostering the activity of clean enterprises not only for the noticeable environmental motives but also for economic aims.

Table 3 shows the results of the estimation of the conditional variances of the five assets. Every one of the coefficients are meaningful, and the volatility persistence is very elevated in all the assets. The sum of alpha and beta is over 0.99. Table 3 also suggests the heteroscedastic nature of the series and the presence of medium/long-term effects of sudden shock. Lastly, a volatility-clustering phenomenon is appreciated in all the assets.

Table 4 shows the results of the estimation of the coefficients that govern the evolution of the correlation matrix of the five assets in the case of the dynamic conditional correlation models. All of the coefficients are significantly different from zero except for the asymmetric coefficient g in ADCC models. The sum of the coefficients a and b is very close to one, highlighting the changing character in time of the correlation between all the assets and reflecting a high perseverance in their evolution.

Table 2
Estimations of the VAR(1) model coefficients.

VAR coefficients	GAS(−1)	OIL(−1)	EUA(−1)	CLEAN(−1)	OIL_GAS(−1)
GAS	**0.086*****	0.021	0.002	−0.091	**−0.131****
OIL	−0.007	**0.077*****	−0.013	0.023	−0.057
EUA	**−0.052*****	−0.012	−0.004	0.032	**−0.112****
CLEAN	−0.001	0.008	0.008	**0.119*****	−0.021
OIL_GAS	0.003	0.011	**−0.015***	**0.047****	0.030

Note: This table contains the estimated elements of the autoregressive matrix Φ_1 of the VAR(1) model. In bold, the coefficients significantly different from 0 to 10% (*), to 5% (**), and to 1% (***). For example, GAS(-1) denotes the one-period lagged value of the excess return of GAS, i.e., the estimated expression for the evolution of the conditional mean of the excess return of GAS is $\mu_t^{GAS} = E\left(r_t^{GAS}|\mathcal{F}_{t-1}\right) = 0.086r_{t-1}^{GAS} + 0.021r_{t-1}^{OIL} + 0.002r_{t-1}^{EUA} - 0.091r_{t-1}^{CLEAN} - 0.131r_{t-1}^{OIL\_GAS}$.

Table 5 shows the value of the AIC, BIC, Shibata and HQ criteria. It can be seen that the best goodness of fit to data corresponds to the DCC_MVT model whose parameters a, and b are statistically significant, which provides evidence of time changing correlations between the five series.

In order to obtain the best estimate of the conditional covariance matrices, we apply the procedure detailed in Section 2.2

Table 3
Estimations of the GARCH model coefficients.

GARCH coefficients	ω_i	α_i	β_i
GAS	**0.082***	**0.117*****	**0.882*****
OIL	**0.043****	**0.091*****	**0.907*****
EUA	**0.125***	**0.124*****	**0.874*****
CLEAN	**0.026*****	**0.098*****	**0.894*****
OIL_GAS	**0.026*****	**0.089*****	**0.903*****

Note: The first column shows the estimated values of ω_i (diagonal elements of matrix $\mathbf{\Omega}$), the second column shows the estimated values of α_i (diagonal elements of matrix $\mathbf{A}_1$), and the third column shows the estimated values of β_i (diagonal elements of matrix $\mathbf{B}_1$). In bold, the coefficients of $\mathbf{\Omega}$, $\mathbf{A}_1$ and $\mathbf{B}_1$ significantly different from 0 to 10% (*), to 5% (**), to 1% (***). The diagonal of matrices $\mathbf{\Omega}$, $\mathbf{A}_1$ and $\mathbf{B}_1$ defines the univariate GARCH(1,1) models for each of the five assets. For example, in the case of GAS, the resulting equation is $h_t^{GAS} = \mathrm{Var}\left(r_t^{GAS}|\mathcal{F}_{t-1}\right) = 0.082 + 0.117\left(\varepsilon_{t-1}^{GAS}\right)^2 + 0.882h_{t-1}^{GAS}$.

Table 4
Estimated coefficients of the DCC and ADCC models.

DCC coefficients	DCC_MVN	ADCC_MVN	CCC_MVT	DCC_MVT	ADCC_MVT
a	**0.013*****	**0.013*****		**0.013****	**0.013*****
b	**0.970*****	**0.970*****		**0.972*****	**0.972*****
g		0.001			0.001
ν			7.504	7.614	7.628

Note: The three first rows of the table show the estimated values of the coefficients a, b and g of the evolution of the matrix $\mathbf{Q}_t - \overline{\mathbf{Q}}$ for the different dynamic conditional correlation models. In bold, the coefficients significantly different from 0 to 10% (*), to 5% (**), to 1% (***). Notice that no value of g is significantly different from zero, i.e., the existence of significant asymmetrical effects is not appreciated. The last row contains the estimated values of the degrees of freedom for the multivariate student t conditional error distribution for models CCC_MVT, DCC_MVT, ADCC_MVT. Thus, for example, in the case of ADCC_MVT model, the resulting equation is $\mathbf{Q}_t - \overline{\mathbf{Q}} = 0.013\left(\mathbf{z}_{t-1}\mathbf{z}_{t-1}^{'} - \overline{\mathbf{Q}}\right) + 0.972\left(\mathbf{Q}_{t-1} - \overline{\mathbf{Q}}\right) + 0.001\mathbf{z}_t^{-}\mathbf{z}_t^{-'}$ with a multivariate student distribution of 7.628 freedom degrees for the error term.

and its results are displayed in Fig. 3, which contains two panels. The top panel shows a matrix that encompasses, in the lower triangular part, the pairwise model comparisons by using the procedure proposed by Engle and Colacito (2006) based on the test of Diebold and Mariano (2002) and, in the upper triangular part, the statistic evolution of the fluctuation tests of Giacomini and Rossi (2010). To apply the test described in Section 2.2, following Gargallo et al. (2021), we have taken the nonconcurrent quarterly measurements included in the analysed period, rejecting those vectors with negative components, as elements of the $\mathbf{E}$ set of possible returns. The number of possible scenarios was $R = 43$. Thus, the lower triangular matrix shows the t-statistic values of the regression model β parameters (1) for each pairwise comparison of the six models. These t-statistics are the outcome of collating the case in the column with the one in the row. A negative (positive) value of the t statistic indicates a better (worse) performance of the row, with reference to volatilities.

Fig. 3 indicates that dynamic conditional correlation models provide lower risk portfolios than constant conditional correlation models, but that no significant differences are found between their symmetrical and asymmetrical versions.

The regression model (1) analyses the global variance performance of each of the six compared portfolios but not their local variance 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. For this, we have used the following loss functions for each scenario $j = 1, \ldots, R$:

$$\mathrm{loss}_{t,M_i}^{(j)} = \mathbf{w}_{t,M_i}^{j'}\left(\mathbf{r}_t - \overline{\mathbf{r}}_T\right)\left[0.5\left(\mathbf{m}_j'\mathbf{H}_{t,M_1}^{-1}\mathbf{m}_j\right)\left(\mathbf{m}_j'\mathbf{H}_{t,M_2}^{-1}\mathbf{m}_j\right)\right]^{1/2}$$

and, from them, we have calculated the mean for the R scenarios:

$$\mathrm{loss}_{t,M_i} = \frac{1}{R}\sum_{j=1}^{R}\mathrm{loss}_{t,M_i}^{(j)} \quad \text{for } i = 1, 2 \text{ and } t = 1, \ldots, T$$

The upper triangular part of the matrix in the top panel contains the evolution of the fluctuation test statistics along time with the 95% confidence bands for the fifteen portfolio variance pairwise comparisons. When the series exceeds the upper (lower) ends of the confidence band it means that the null hypothesis of equality is rejected, and we conclude that there are periods during which the second portfolio (subtrahend) of the difference has less (higher) variance. We observe that the predominant signs of the differences analysed with the fluctuation test are in line with the corresponding t-statistics in the lower triangular matrix (see Fig. 3). However, these differences only are significantly different from zero between the DCC models and the CCC models, as well as, between the ADCC models and the CCC models, from 2020 on. In this period the EU, before recovering from the social and economic consequences of the COVID-19, has had to face the most severe episode since World War II, the current Russo–Ukrainian War.

Finally, the bottom panel of Fig. 3 (last row) shows, for each compared model M, the index numbers corresponding to the average of the estimated standard deviation of the observed one-step-ahead returns $\left\{\mathbf{w}_{t,M}^{i'}\mathbf{r}_t;\, t = t_0, \ldots, T;\, i = 1, \ldots, R\right\}$ of the selected portfolios for each return $\mathbf{m_i} \in \mathbf{E}$, by taking the minimum average as reference. These volatility ratios allow evaluating, from an economic viewpoint, the existing differences in risk among the minimum variance portfolios selected by each compared model for each possible return scenario of $\mathbf{E}$. Again, it can be seen that DCC and ADCC models tend to select significantly less risky portfolios than CCC models by improving 1.16% their level of required daily return for the same level of risk. In addition, there are no significant differences between the level of risk of the DCC and ADCC models, and the averages of the standard deviations of the returns of their minimum variance portfolios are essentially the same (the largest difference is 0.0003%).

Given that significant differences between DCC and ADCC models do not exist with respect to the risk level of their selected portfolios, we choose model M = DCC_MVT to obtain all the results from here on. Thus, Fig. 4 displays the estimated volatility of the five daily asset returns in the diagonal elements, and the correlation between two assets in the off-diagonal elements. A constant correlation corresponding to a CCC_MVT model is marked with a red horizontal line.

Fig. 4 shows that the CLEAN and OIL.GAS series have the lowest volatilities because they are balanced averages of equity prices, which flattens their day-to-day evolution. Moreover, they possess great positive correlation, although decreasing in the last period, which highlights the presence of risk synergy effects. The risks of GAS and EUA series measured through their volatilities are the greatest. Finally, except in the EUA series, an elevated value of volatility is distinguished in March 2020, coinciding with the beginning of the coronavirus pandemic. In the case of GAS, the volatility is very high also during the year 2022 due to the Russo–Ukrainian war. The values of EUA volatility reflect the different changes that happened in the CO_2 emission allowance granting systems. Thus, the EUA series exhibits a wide volatility at the outset of phase III because the manner of obtaining permits was modified. In addition, this series is also positively related with all the assets, but with levels of correlation close 0.2.

Table 5
Selection criteria for the six models.

Criteria	CCC_MVN	DCC_MVN	ADCC_MVN	CCC_MVT	DCC_MVT	ADCC_MVT
Akaike	19.527	19.802	19.802	19.527	**19.476**	19.477
Bayes	19.630	19.907	19.910	19.630	**19.584**	19.586
Shibata	19.526	19.801	19.802	19.526	**19.476**	19.476
Hannan–Quinn	19.564	19.840	19.841	19.564	**19.515**	19.516

Note: This table shows the goodness of fit values (AIC, BIC, Shibata and HQ) for the six models compared. The optimal model for each criterion is indicated in bold. It can be seen that DCC_MVT is the model that best fits the data for all the criteria.

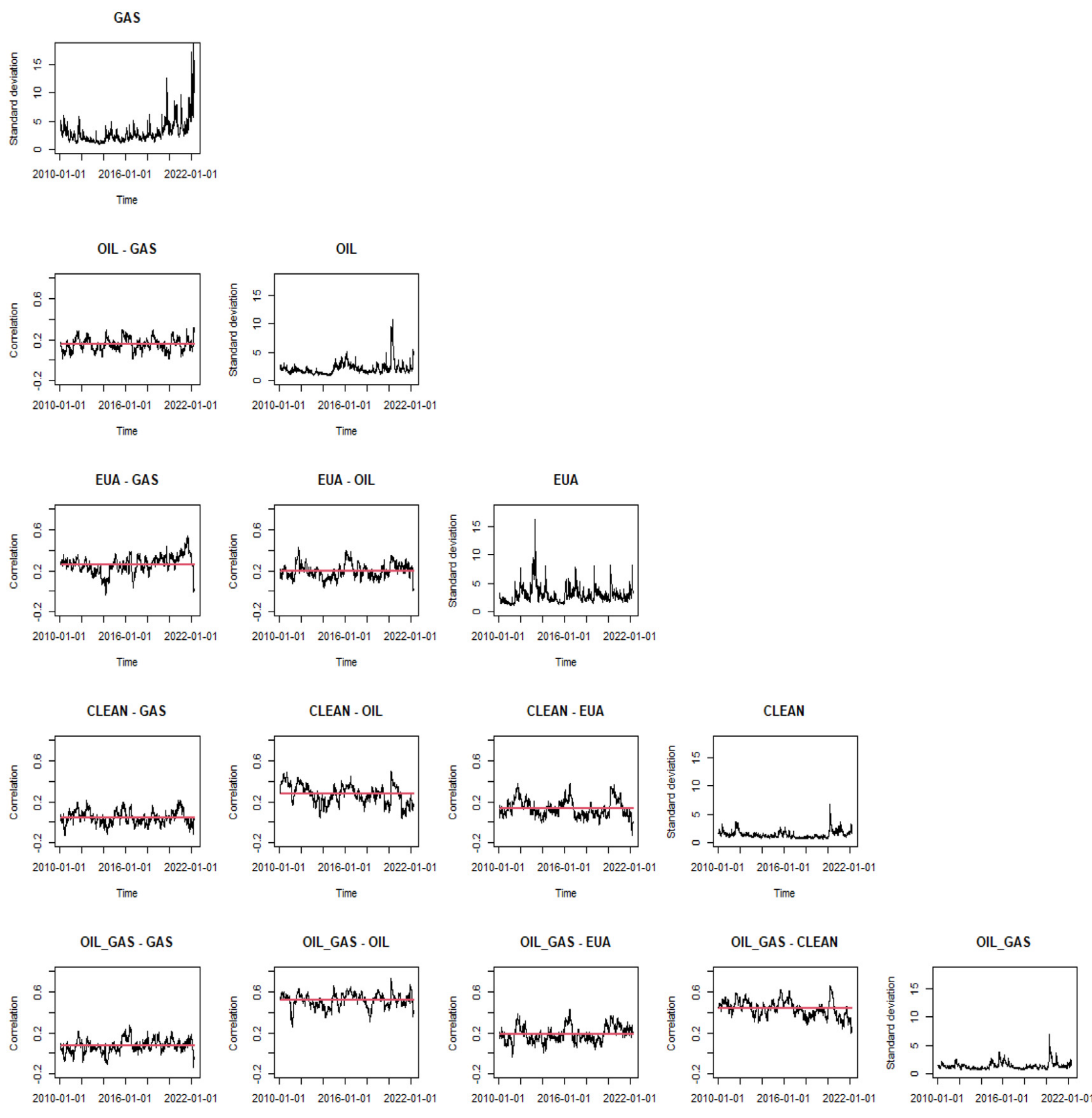

Fig. 4. Matrix graph whose elements outside the diagonal show the evolution of the estimated pairwise correlations among the six series in the period from 19 Jan, 2004, to 4 Apr, 2022, while those in the diagonal include the estimated volatility of the day-to-day excess returns. The estimated constant correlation of a CCC_MVT model is marked in red. The correlations change over time and range between 0.1 and 0.6, oscillating around the red line, the highest being those corresponding to OIL_GAS with CLEAN and OIL_GAS with OIL. In terms of volatilities, it is estimated that the most volatile asset is GAS, especially in pandemic and war periods. The rest of the assets show a very specific increase at the start of the pandemic, except for the EUA, which shows a peak in the first quarter of the year 2013 caused by the beginning of Phase III of the EU ETS. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.4. Selected portfolios

Once we have determined the best model, the final optimal portfolio is built averaging the weights of the minimum risk optimal portfolios obtained for each of the $R = 43$ scenarios, as indicated in Section 2.3. Fig. 5 shows, for model $M =$ DCC_MVT, the evolution of portfolios weights $\left\{\mathbf{w}_{t,M}; t = t_0, \ldots, T\right\}$ and Figs. 6 and 7 displays the expected portfolios volatilities $\sigma_{t,M} = \sqrt{\mathbf{w}'_{t,M}\mathbf{H}^{-1}_{t,M}\mathbf{w}_{t,M}}$ and the observed volatilities $\sigma_{t,M,obs} = \left|\mathbf{w}'_{t,M}\left(\mathbf{r}_t - \bar{\mathbf{r}}_T\right)\right|$, respectively. The weights and the volatilities of the rest of models are similar and are left out for brevity reasons.

In general, most of the optimum portfolios take long positions in GAS, OIL and CLEAN and short positions in OIL.GAS and the free risk asset. Several sub-periods can be distinguished. In the

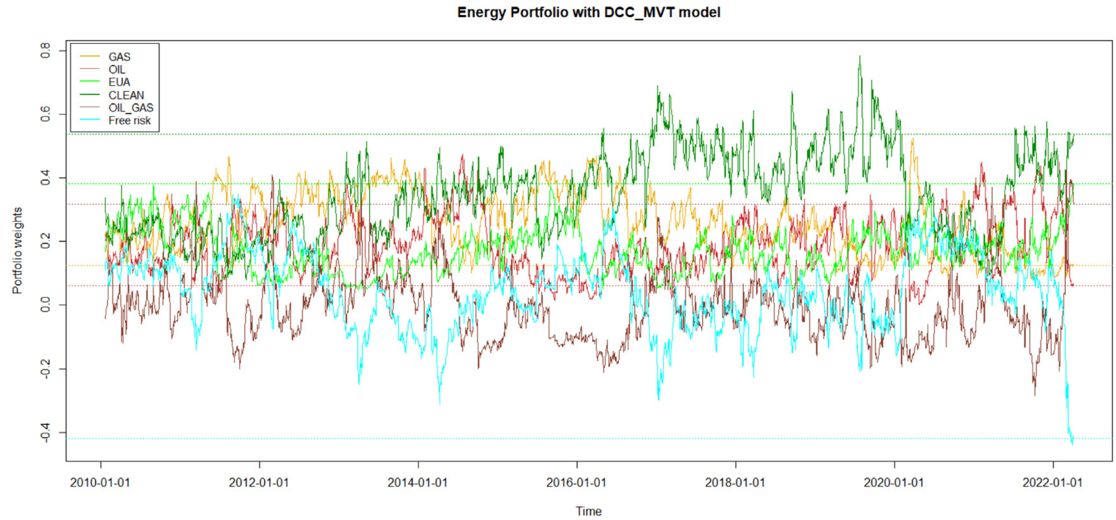

Fig. 5. Daily evolution of the optimal portfolio weights in the period from 19 Jan, 2004, to 4 Apr, 2022. These weights are calculated by the expression $\mathbf{w}_{t,M_{opt}} = \frac{1}{R}\sum_{i=1}^{R}\mathbf{w}^{i}_{t,M_{opt}}$ where M_{opt} = DCC_MVT. The weights corresponding to GAS are coloured in orange, those of OIL in red, those of EUA in light green, those of CLEAN in dark green, those of OIL_GAS in brown and those of the risk free asset in cyan. Horizontal lines have been incorporated in order to reflect the composition of the minimum risk portfolio in the last period (April 4, 2022) in comparison to the rest of the series. Specifically, the weight of GAS is 0.12, of OIL is 0.06, of EUA is 0.38, of CLEAN is 0.53, of OIL_GAS is 0.32 and of the risk free asset is −0.42. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

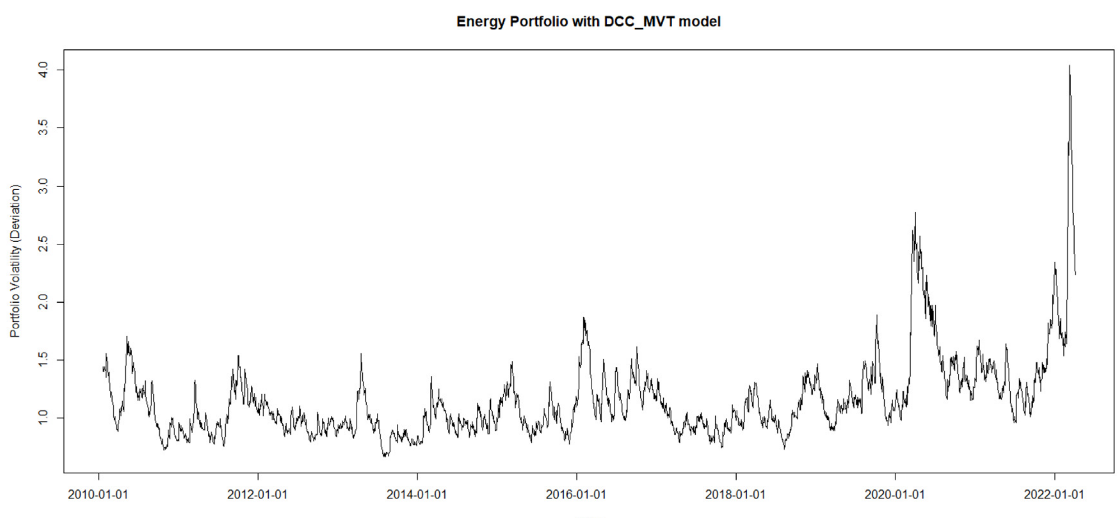

Fig. 6. Daily evolution of the expected portfolio volatility one step ahead $\sigma_{t,M} = \sqrt{\mathbf{w}'_{t,M}\mathbf{H}^{-1}_{t,M}\mathbf{w}_{t,M}}$ obtained with the model M = DCC_MVT in the period from 19 Jan, 2004 to 4 Apr, 2022. Homogeneous volatility behaviour is observed over time with the only exception being the start of the pandemic period (March 18, 2020) and the start of the Russo–Ukrainian war (March 10, 2022).

first period (2010–2011), the EUAs had the highest weights in the portfolio, corresponding with phase II of the EU ETS, in which the objectives to which the member countries had committed themselves with the Kyoto Protocol, should be met. It came from phase I, from 2005 to 2007, in which the bases and objectives for effective action in the following three phases were established. Phase I was called the ⟨learning phase⟩ , being minimal measures were put into action (Ellerman et al., 2010), but whose main objective was to prepare for the strong entry of phase II, reflecting the preponderance of the EUA in the portfolio. Subsequently, in the period 2012 to 2014 (Sovereign debt crises) and in 2015 (with the Brexit announcement), the highest weights correspond to GAS reflecting its importance in the European energy mix. Bear in mind that GAS can be considered as a substitute refuge value for oil because it is an energy source that is less dirty[2] and, therefore, can be a better alternative than oil for the energy transition. However, in 2014, when the European Council promoted energy efficiency policies in the climate and energy framework, and especially since the Paris Agreement (December 2015), the optimal portfolio in each period tends to allocate the highest weight to CLEAN. The Paris Agreement was a milestone in climate change action because, for the first time, a mandatory agreement brought together all countries in a common cause to launch determined efforts to combat climate change and adapt to its consequences. Therefore, the Paris Agreement underpinned the change towards an economy that will gradually do without oil and gas as support.

2 https://www.eia.gov/energyexplained/natural-gas/natural-gas-and-the-environment.php.

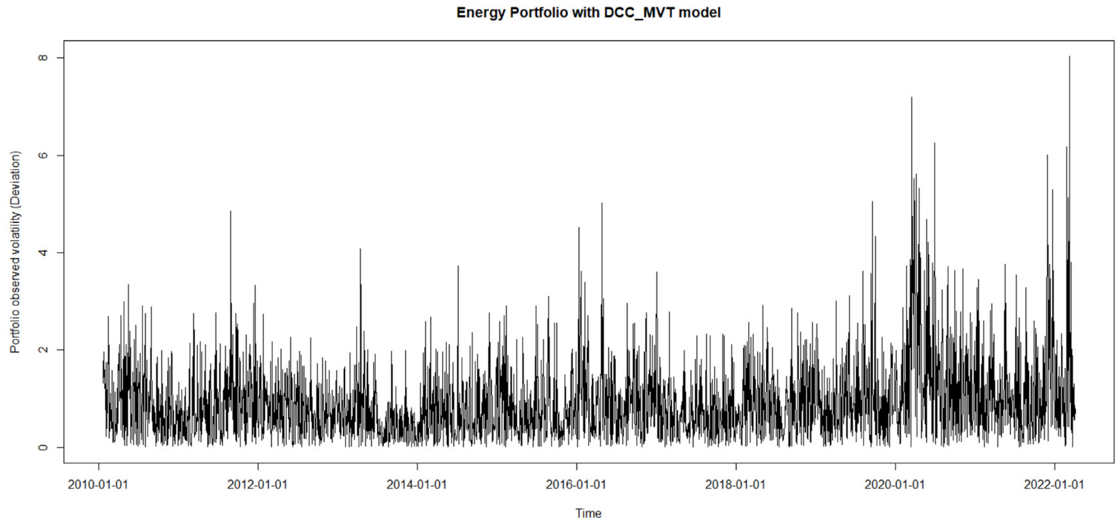

Fig. 7. Daily evolution of the observed portfolio volatility $\sigma_{t,M,obs} = \left|\mathbf{w}'_{t,M}\left(\mathbf{r}_t - \bar{\mathbf{r}}_T\right)\right|$ obtained with the model M = DCC_MVT in the period from 19 Jan, 2004 to 4 Apr, 2022. Again, homogeneous volatility behaviour is observed over time, with the most significant increases being at the start of the pandemic period (March 18, 2020) and the start of the Russo–Ukrainian war (March 10, 2022).

Since 2016, the preponderance of CLEAN has only been lost at certain moments in the 2020–2021 period, coinciding with the most atypical years globally in recent generations due to the COVID 19 pandemic. However, despite all the difficulties and uncertainty that 2020 and the first part of 2021 brought, with a high percentage of the European population vaccinated, renewable energies have once again positioned themselves strongly with the greatest weights in the optimal portfolio with minimum risk. The reason was the search for a better, more equitable, resilient, clean and fair future.

To sum up, our findings show that since the Paris agreement, portfolios should hold weights between 40 and 60% in investments indexed (ETF) to the clean energy indicator (CLEAN), and weights in emission rights (EUA) of around 20 and 30%. With respect to the dirty energy market, minimum risk portfolios should diminish the investment weight in GAS and OIL from levels of 20 and 30% to just over 3 and 6%, respectively. The Dirty Energy Indicator (OIL_GAS) tends to keep short positions with weights oscillating between −20% and 0% throughout most of this period. Only at the end of the analysed period (from March 2022 on) the portfolio recommends weighting 30% of the investments indexed (ETF) to OIL_GAS. The risk-free asset evolves according to market uncertainty, tending to take long (short) positions in crisis (calm) periods. Finally, in the last period (April 4, 2022) the portfolio advises a leverage of 42% of the total portfolio, losing its safe-haven character in a context of low interest rate levels and the Russian–Ukrainian war, and it recommends a long position both in clean energy (CLEAN, 53%; EUA, 38%) and dirty energy (OIL_GAS, 32%) (see Fig. 5). We can see that, in general, these weights reflect the evolution of the political-economic situation in European countries and the energy policies adopted by their governments.

Our results are in line with other papers on the efficient management of energy portfolios. Batten et al. (2016) and Mukanjari and Sterner (2018) conclude that the announcement of the Paris Agreement in December 2015 had a positive effect on the valuation of renewable energy companies, but no significant effect on fossil fuel companies. Chang et al. (2020) encouraged investing in renewable energies, especially to the risk-averse investor, since these are more predictable according to MA rules than dirty energies. Wan et al. (2021) showed a better performance of clean than dirty energy companies both before and during the COVID-19 pandemic, due to the implementation of governmental green recovery plans. Finally, Rokhmawati (2021), analysing Indonesia's power industry, established that reducing the fossil fuel portion and increasing the portion of renewable energy produces portfolios that are more efficient and that minimise risk.

To end the comments on the results obtained with our analysis, we would like to indicate that the evolution of the expected (Fig. 6) and observed (Fig. 7) volatilities tends to be similar, confirming the validity of the volatility expectations of the selected model. A greater increase in volatility is only observed in specific periods that coincide with the start of unexpected events (Sovereign debt crisis, Brexit, COVID-19 and Russo–Ukrainian war) that significantly raise risk levels, but which is immediately corrected by the selected portfolio reducing these increases quickly, which shows that our procedure performs adequate risk management. Therefore, in the current context of uncertainty in which we are immersed, active management of energy markets through multivariate dynamic models that minimise risk is still more valuable.

4. Conclusions

In this paper, we have proposed a strategy to build well-diversified portfolios among both clean and dirty equity energy, and carbon markets framed in a volatility-timing context, which reacts to changing market environments, and providing different portfolios at different points in the time. In order to achieve this goal, we have used ADCC-GARCH models that permit to obtain good estimations of the conditional covariance matrices of the daily asset returns. The weights of the portfolios have been obtained by means of a methodology based on Engle and Colacito (2006) that has allowed us to determine the best model to calculate the weights of the optimum minimum-risk portfolio. The analysed period has been long enough to capture important events (Sovereign debt crisis, Brexit, COVID-19 and Ukrainian war) and observe their impact on the minimum risk portfolios.

Our findings highlight that since 2016 most of the selected portfolios take long positions in CLEAN (between 40% and 60%) and short positions in OIL_GAS (between −20% and 0%) and sometimes in the free risk asset (between −20% and 20%), with these weights tending to have the larger absolute values from the Paris Agreement on. The role of the EUA is secondary but with stable behaviour in terms of risk and a positive contribution around 20% in long positions. The results for the last period

2020–2022 show that, at first, the COVID-19 pandemic and the consequent economic crisis had a significant negative impact on decarbonisation. However, the greater resilience of renewable investments and, above all, the huge stimulus packages that many governments have introduced to relaunch the economy seem to have given a new impetus to the decarbonisation process. In the last year, 2022, the invasion of Ukraine by Russia has had as a malicious precedent on the increase of the price of gas, which has posed a threat to the coverage of energy needs. Our optimal minimum risk portfolio has also captured this fact by showing a fall in the importance of GAS weights accompanied by an increase in CLEAN and OIL_GAS weights and a fall in the risk-free asset.

An advantage of our method is that in the face of an unexpected event, the selected model immediately reacts and allows a portfolio to be built that keeps its volatility levels under control, an important aspect for investor decisions. It is, therefore, important to actively manage the energy markets because the weights change according to the volatility of the portfolio, the evolution of the market environment, and external events. We recommend that portfolio managers adopt our method, i.e., controlling risk using minimum risk portfolios built from models that best estimate the joint evolution of the conditional asset volatilities.

Together with the COVID-19 pandemic, the Russo–Ukrainian war has highlighted the need for countries to strengthen their domestic capacity to build clean technologies. The recent geopolitical and energy market actuality demands to speed up the transition towards renewables and to increase the energy independence from untrustworthy providers and unstable fossil fuels. In order to reduce external energy dependency and fight climate change more quickly and more effectively, there is no other option than to speed up the implementation of renewable energies. For this reason, the financial system should be aligned with energy transition requirements. Accordingly, large capital investment must shift from the fossil energy sector to clean energy-based enterprises, so, we hope that our paper has been able to convince any type of investor, be it an environmental or socially responsible investor or an investor who is only concerned about profits, to switch to more sustainable energy portfolios. This kind of investment will not only have a significant decrease on the portfolios risk; but it will also control climatic emergency and prevent geopolitical conflicts.

However, as Sen and von Schickfus (2020) pointed out, in order to avoid a disruptive and messy energy transition with a sudden devaluation of energy companies, clear signals must be sent to financial markets about a credible commitment to climate policies. Given the size of energy companies and their interconnectedness with the rest of the economy, which makes them "too big to fail", policymakers should opt for compensation policies, which is what investors expect them to do.

The research results leave some avenues open for exploring future developments and addressing certain limitations of the paper. Thus, in this paper we have made daily asset allocations, however, we want to broaden the investment horizon taking into account that decision making can be made not only based on daily returns but also on other horizons such as weeks, months, quarters or years, depending on whether it is a short, medium or long term investment. The results of this paper were obtained assuming that neither the model nor the values of its parameters change through time. In our future work, we want to provide sequential information processing that weakens this hypothesis, letting us employ simpler and more parsimonious models in moments of market calm and more complicated models in times of turbulence or crisis. This would make our method more flexible and adaptive.

Likewise, we should extend our method to exploring the design of market timing strategies along the lines of Chang et al. (2020), which take into account the transaction costs associated with position changes in the constructed portfolios.

We want also to address other ways of quantifying and managing market risk, such as CVaR, since this has been one of the central concerns of finance researchers to have permanent control of the risk being incurred when making an either short or long- term investment.

Finally, despite the importance of the investment in renewable energies in the fight against climate change, some authors, such as Wang et al. (2020), have shown that not all renewable energies contribute in the same way to reducing CO_2. In future work, instead of using an index in its aggregated form, it might be interesting to deconstruct it into its component elements, since not all renewable sources share the same characteristics. Similarly, there are disparate areas from renewables that should also be invested in to support sustainable development. For this reason, broadening the context when building portfolios that incorporate assets related to other sustainable objectives (environmental, social and good governance) is part of our future research agenda.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This research was supported by grant S41-20 R of the Government of Aragon (Spain)

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