Hedging financial risks with a climate index based on EU ETS firms

Mattia Chiappari[1], Francesco Scotti[1], and Andrea Flori[1]

[1]*Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Via Lambruschini, 4/B, 20156, Milan, Italy.*

Abstract

This paper proposes a stock market index that captures the environmental performance of firms regulated by the European Union Emissions Trading System (EU ETS). Unlike alternative methods based on market capitalization, ESG scores, and Scope 1 and 2 estimated emissions, the proposed approach relies on total verified emissions to better reflect firms' carbon abatement efforts. A DCC-GARCH model is employed to estimate the hedge ratios, optimal weights, and hedge effectiveness of the index across various asset classes. The proposed index offers superior hedging performance compared to the European Union Allowances (EUAs), a common benchmark for tracking carbon abatement, although hedging with the EU ETS index tends to be more expensive. The proposed index constitutes a valuable tool for investors seeking climate-conscious equity investments in carbon-intensive firms with strong environmental performance.

Keywords: EU ETS index; Verified Emissions; Hedge Ratios; Optimal Weights; Hedge Effectiveness.

1 Introduction

The urgent need to address climate change and mitigate the environmental impacts stemming from human activities has placed the transition toward a low-carbon economy and the promotion of environmental innovation at the forefront of global attention [28]. Sustainable Development Goal (SDG)-based[1] policy frameworks could facilitate a gradual shift toward cleaner energy consumption across both industrial and household sectors [85]. Additionally, carbon taxes and cap-and-trade systems are intended to incentivize investments in low-carbon technologies. For instance, Wong and Zhang [88] highlight that carbon taxes, by placing a cost on carbon emissions, can encourage firms to lower their carbon footprint by increasing the operational costs of carbon-intensive activities. Similarly, cap-and-trade systems may promote innovation through investments in cleaner technologies and more efficient production processes [36]. In particular, carbon markets play a critical role in minimizing the risk of negative economic impacts on domestic industries, fostering technological innovation, and generating revenues that can be reinvested into sustainable initiatives [55].

Although carbon-intensive assets still represent a large share of invested capital [75] and the ”greenness” of Euro Area investors' portfolios remains lower than their exposure to transition risk [8], the financial sector is crucial in directing investments away from fossil fuels sectors toward low-carbon innovations. Consequently, the growing awareness of climate risks has induced firms to signal their commitment to achieving improved environmental outcomes, a trend reflected in the proliferation of green investment funds [78]. Since climate change risks increasingly affect asset prices, investors, therefore, face the challenge of identifying investment opportunities aligned with environmental objectives [67].

While investors frequently use ESG scores to identify sustainable firms [70], the reliability of these scores is often questioned [14]. ESG rating agencies employ proprietary methodologies that lack transparency, resulting in conflicting evaluations [19], particularly in the environmental dimension [54]. Further, ESG scores can be compromised by contamination between different sustainability metrics [64], the use of industry-specific aggregation rules that reduce inter-firm variability within sectors [18], and greenwashing concerns [90].

Investors may also turn to emissions data when evaluating sustainable firms. However, Scope 1 and 2 emissions[2] are often self-reported or estimated by external vendors [23]. Self-reported emis-

[1]Table A1 in the Appendix lists all the abbreviations and parameters of the models used throughout the manuscript.
[2]Scope 1 emissions are direct emissions from sources that are owned or controlled by the company. Scope 2 emissions

sions, lacking a consistent legal framework, raise concerns about accuracy, while vendor estimates show only moderate correlation among themselves and are based on assumptions about business models and industry factors, casting doubt on their validity [13]. Although vendor-estimated emissions have shown a strong positive correlation with stock returns [21], this relationship is negative for firms with verified emissions data [17]. This highlights the importance of using independently verified emissions data to avoid distorted conclusions [17], particularly as carbon risk becomes more significant in investment decisions.

Another potential avenue to identify investment aligned with environmental goals is through tradable indices reflecting the performance of firms in carbon-intensive sectors [22] that are subject to an environmental regulatory framework fostering carbon abatement.[3] Relatedly, the European Union Emissions Trading System (EU ETS) stands as the largest greenhouse gas (GHG) trading system, covering approximately 40-45% of Europe's GHG emissions [30] and accounting for approximately 90% of global carbon market trading.[4] Firms regulated by the EU ETS must disclose their emissions, which are independently verified by third parties, thereby addressing concerns over data reliability. Under the EU ETS, firms can trade European Union Allowances (EUAs), which represent the right to emit one tonne of carbon dioxide (CO_2) equivalent. These firms must surrender sufficient allowances to cover their annual emissions or trade allowances on the carbon market to comply with the regulation. The EU ETS has undergone multiple phases of increasing environmental targets: Phase I (2005-2007), II (2008-2012), III (2013-2020), and IV (2021-2030).

While the EUA price may serve as a potential index to track firms' carbon abatement efforts [50], several other factors may influence its market dynamics [7, 58], including carbon policy surprises [56], stock market dynamics [73], energy prices [61], fundamentals [72], macroeconomic [25] and weather [46] conditions. For instance, Hintermann [57] identifies fuel prices, summer temperatures, and precipitation as key determinants of allowance prices. Analogously, Aatola et al. [1] show that EUA prices are driven by electricity prices and the gas–coal difference. Additionally, specific events are shown to influence carbon markets. For example, unexpected lower-than-predicted verified emis-

are indirect emissions from the consumption of purchased electricity, heat, or steam, which occur at the facility where electricity, steam, or heat is generated.

[3] Indices like the Morningstar Low Carbon Transition Leaders Index allow investors to align portfolios with companies committed to progress toward net-zero emissions (https://assets.contentstack.io/v3/assets/bltabf2a7413d5a8f05/bltc346c6a704b9736f/65fdbd2401e311562bcb03f1/Climate-Investing-with-the-Morningstar-Low-Carbon-Transition-Leaders-Indexes-v2.pdf).

[4] Source: https://www.refinitiv.com/content/dam/marketing/en_us/documents/gated/reports/carbon-market-year-in-review-2020.pdf.

sions in 2006 led to a significant drop in EUA prices [44], causing a long-lasting effect on the quality of the European carbon market [74]. More recently, the COVID-19 pandemic caused EUA prices to plunge from €24 to €15 per tonne of CO_2 in just 12 days in March 2020 [38]. Similarly, EUA prices dropped from €95 to €58 per tonne of CO_2 in just over a week in February 2022, following Russia's invasion of Ukraine. Such volatility in the EUA price has been found to be exacerbated by speculative bubbles in response to energy-related announcements [32]. Finally, policy adjustments can significantly influence the EUA price [49]. For instance, decisions by the European Commission on the second National Allocation Plans have been shown to exert a strong and immediate impact on EUA prices [31]. Furthermore, reductions in price and increased volatility tend to occur when European Parliament decisions are made under specific conditions, such as when they are not driven by party-political factors, during periods of low market sentiment, or when market attention is limited [34].

Despite the importance of EUA, there is a clear need for a more comprehensive index that better captures the environmental performance of carbon-intensive firms subject to stringent GHG reduction policies. This work aims to fill this gap by proposing an equity index based on EU ETS-listed firms to test its hedge effectiveness (HE) against a range of traditional asset classes, mirroring investors' strategies to hedge environmental risks. The focus on EU ETS firms is due to their pivotal role in Europe's carbon abatement strategy. These firms, spanning sectors such as manufacturing, energy, and mining, are highly sensitive to environmental aspects concerning green innovation, policy changes, and climate disasters, making them ideal for assessing market reactions.

Various approaches for weighting firms within the EU ETS index are examined in this study. The first method relies on market capitalization, while the second focuses on ESG scores. The other approaches use environmental performance metrics, calculated as the negative logarithm of the ratio between emissions and total assets. Specifically, the analysis considers Scope 1 and Scope 2 emissions, along with verified emissions data. The verified emissions-based approach is used as the benchmark for constructing the EU ETS index in the core analyses.

Subsequently, the hedge effectiveness of the EU ETS index is evaluated against a range of asset classes, including European developed and emerging market stocks, a clean energy equity index, European government and corporate bonds, a green bond index, Brent oil, gold, Bitcoin (BTC), and EUA. Hedge ratios (HRs), optimal weights (OWs), and hedge effectiveness are calculated for the EU

ETS index relative to these assets and compared with the corresponding results for EUA.

The key findings of this paper can be summarized as follows:

i) OWs favor the EU ETS index when combined with volatile assets. On the other hand, the EUA is consistently underweighted in all pairings, except when paired with Bitcoin.

ii) Hedging with the EU ETS index is generally more expensive compared with EUA. The average HRs of the EU ETS index are between -0.076 (vs. gold) and 1.474 (vs. clean energy stocks). Conversely, the average HRs of EUA are generally lower and lie between -0.016 (vs. gold) and 0.129 (vs. Brent oil).

iii) However, the EU ETS index offers a superior hedging effectiveness compared to the EUA. The average HEs of the EU ETS index computed with respect to the HRs range between -0.020 (vs. corporate bonds) and 0.824 (vs. developed stocks). In comparison, the HEs of EUA span from -0.012 (vs. green bonds) to 0.010 (vs. the EU ETS index), highlighting its limitations as a hedging instrument.

The remainder of the paper is structured as follows. Section 2 reports the literature review. Section 3 and Section 4 describe data and methods, respectively. Next, Section 5 discusses the empirical results, while Section 6 reports the conclusions and policy implications.

2 Literature review

The analysis of hedge ratios, optimal weights, and hedging effectiveness concerning green assets, such as green bonds [59] and clean energy stocks [40], has recently gained significant attention.

Green bonds offer notable diversification benefits for Treasury and corporate bonds [62], energy commodities [76], and the risk management of stock and energy markets [80]. Precisely, green bonds act as a safe haven during periods of heightened geopolitical, economic, or climate policy uncertainty [39]. For instance, during the COVID-19 pandemic, green bonds effectively hedged risk [5], especially in high-emission stock sectors [29]. The S&P Green Bond index has also proven to be an effective hedge for EUA futures, outperforming other indices like the CBOE Volatility Index (VIX), the S&P Commodity Futures Index, and the S&P Energy Index [63].

Similarly, clean energy markets acted as strong hedges during different turmoil periods, such as the COVID-19 pandemic [81], the 2020 energy crisis, and the Russia-Ukraine war [77]. Green stocks, in particular, offer valuable hedging against brown stocks due to their decreased long-term return correlation with climate risks [68], and against the oil market risk [42].

Relatedly, the EU ETS serves as a key data source for evaluating corporate carbon reduction efforts, being the largest GHG emissions trading system globally. However, studies on hedge ratios, optimal weights, and hedging effectiveness between EU ETS and other assets are limited (Table 1 provides a summary of the main previous works). Fan et al. [48] show that dynamic hedge ratios in the carbon offset credit market under the EU ETS reduce variance better than unhedged portfolios. Other research indicates that EUA can hedge risks in stock indices [35], crude oil [79] and energy markets [71], particularly when paired with indices like the European Renewable Energy Index (ERIX) and the WilderHill Clean Energy Index (ECO) [41] or the Nord Pool electricity market [87]. Nevertheless, indices such as VIX and the CBOE Crude Oil Volatility Index (OVX) tend to perform better than EUA as hedges for clean energy equities [4]. Additionally, while EUA outperforms China's carbon emission allowance (CEA) in terms of hedging costs and stability, it shows lower hedge effectiveness for crude oil [92]. Lastly, the hedge effectiveness of EUA may significantly vary over the Phases of the EU ETS [15], providing a better hedge against higher-order moments risk of oil, natural gas, and coal at short-run timescales during Phase III [33].

This analysis complements previous studies in multiple ways. First, it introduces a stock index based on EU ETS-listed firms, with weights determined by verified emissions rather than the self-reported data or third-party estimates commonly used in prior research. This approach provides a more reliable and accurate measure of environmental performance for carbon-intensive firms, providing deeper insights into their carbon abatement efforts than relying solely on EUA prices.

Second, to provide a comprehensive representation of allocation strategies, the extant literature on hedge ratios and optimal weights is enriched by estimating the hedge effectiveness properties of the EU ETS index against a variety of assets, such as MSCI Europe, MSCI Emerging Markets (EM) Eastern Europe ex Russia, ERIX, European Government and corporate bonds, green bonds, Brent oil, gold, EUA, and Bitcoin. A less traditional asset class like Bitcoin is considered motivated by previous research pointing out the links with carbon markets. For instance, Dogan et al. [37] find that the price and trading volume of Bitcoin Granger cause environmentally-related financial assets, such as S&P carbon emissions allowances and the global clean energy index.

Table 1: Comparison of relevant literature contributions.

Study	Asset classes compared	Approach	Main results
Fan et al. (2013)	Carbon offset credits, stocks, bonds, currencies, commodities	HEs based on HRs	Carbon offset credits reduce variance compared to unhedged portfolios
Reboredo (2013)	EUA, crude oil	Copula models	EUA has hedging potential for crude oil
Balcilar et al. (2016)	EUA, CER, natural gas, coal, electricity	HEs based on HRs and OWs	The HEs of EUA significantly varies across EU ETS phases
Ahmad et al. (2018)	EUA, ECO, gold, bonds, VIX, oil, OVX	HEs based on HRs, OWs	VIX and OVX outperform EUA as hedges for clean energy stocks
Dutta et al. (2018)	EUA, ERIX, ECO	HEs based on HRs and OWs	EUA has hedging potential for ERIX and ECO
Jin et al. (2020)	EUA, green bonds, S&P commodity futures, VIX	HEs based on HRs	Green bonds outperform EUA in hedging
Dai et al. (2021)	EUA, oil, natural gas, coal	OW against skewness and kurtosis risk	EUA provides better HEs against higher-order risk moments in Phase III
Demiralay et al. (2022)	EUA, stock indices, commodities	HEs based on HRs and OWs	EUA has higher (lower) hedging potential for equities than agriculture (precious metal) commodities
Liu et al. (2023)	EUA, crude oil, natural gas, coal	HEs based on HRs and OWs	EUA has hedging potential for energy commodities
Zhu et al. (2023)	EUA, China's CEA, oil	HEs based on HRs and OWs	EUA performs better in cost and stability than CEA, but lower HE for oil
Vaissalo et al. (2024)	EUA, Nord Pool electricity market	HEs based on HRs and OWs	EUA hedges effectively Nordic electricity markets irrespective of the COVID-19 sub-periods
This study	EU ETS index, EUA, European stocks, ERIX, bonds, Brent oil, gold, BTC	HEs based on HRs and OWs	The EU ETS index offers superior HEs than EUA across multiple asset classes

Third, this work has several implications for market participants and policymakers with raising attention toward climate risks and sustainable finance [67]. For example, the composition of the proposed index can be exploited to detect sectoral or geographical imbalances in the firms' environmental performances. Further, strong regulatory measures are crucial to address the adverse impacts of climate change, primarily caused by fossil fuel consumption, with uncertainty around the implementation of climate policies that tend to affect more severely firms with carbon-intensive business models [60]. Daily calculations of HRs and OWs may help guide asset allocation, allowing investors to adjust their positions based on their exposure to the proposed EU ETS index. By doing so, investors can mitigate risks and optimize trading strategies in response to changing market conditions.

3 Data

3.1 EU ETS dataset construction

Data related to the EU ETS are retrieved from the ”European Union Transaction Log” (EUTL).[5] This repository collects information on annual allowance allocations and verified emissions for each installation as well as allowance transactions between accounts. Every installation is required to open an operator holding account (OHA) that is responsible for managing allowances transactions with other OHAs, government accounts, and voluntary participating entities in order to comply with allowance surrendering requirements. Each OHA is also associated with an Account Holder, which represents the firm owning the installation and managing the underlying account(see Figure 1 for an overview of the structure of EU ETS data). The analysis is performed by aggregating data at the account holder level.

The EUTL repository is matched with the ORBIS Bureau van Dijk[6] based on the company registration number, or the company name and address, to obtain additional firm identifiers (e.g., ”International Securities Identification Number” (ISIN) or the ”Legal Entity Identifier” (LEI)). Only active firms that owned at least one EU ETS installation in the period 2005-2022 are considered. Finally, the sample is restricted to firms listed on stock exchanges. To identify listed firms, the matched EUTL dataset is linked with Eikon Refinitiv[7] using ISIN or LEI as company identifiers. Eikon is employed to retrieve data on daily stock closing price and other financial and environmental variables, including market capitalization, total assets, ESG score, Scope 1 and Scope 2 emissions at annual frequency. Table B1 reports the descriptive statistics for such variables.

[5]The EUTL repository is available at the following link: https://ec.europa.eu/clima/ets/. Within this repository, emissions at the installation level are available in the ”Compliance” section. Information regarding the accounts and how they are related to installations is retrieved from the ”Accounts” and ”Operator Holding Accounts” sections.

[6]Source: https://orbis.bvdinfo.com.

[7]Source: https://eikon.refinitiv.com/.

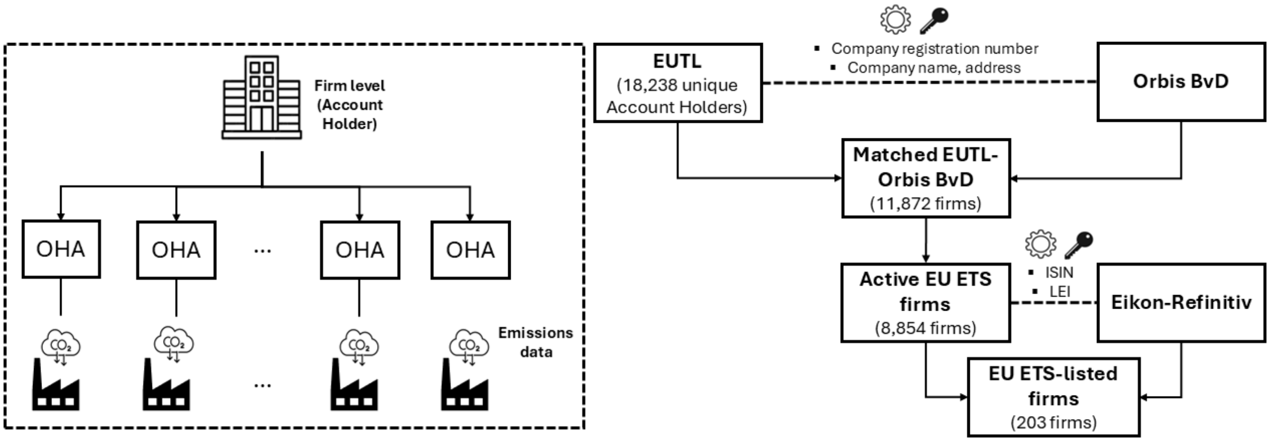

Figure 1: A simplified version of the structure of data available in the EUTL repository for EU ETS firms is reported (see e.g., [2] for a complete overview of the structure of EUTL). Information related to verified emissions is disclosed at the installation level. Each installation is associated with an OHA that is responsible for managing transactions to comply with surrendering requirements. The analysis is performed at the firm level where the emissions of all installations owned by a single firm are aggregated. Overall, the sample extracted from the EUTL repository encompasses information related to 18,238 OHAs. The EUTL and Orbis Bureau van Dijk are matched based on the company registration number, or name and address (11,872 firms). The analysis is then restricted to only active EU ETS firms (8,854). Finally, EU ETS-listed firms (203) are identified by linking their ISIN or LEI with listed firms in Eikon Refinitiv.

Overall, the final dataset consists of 203 listed firms. Figure 2 highlights the relevance of this sample within the EU ETS framework over the analyzed period.[8] Interestingly, the number of installations owned by listed firms has progressively increased, shifting from 2.9% during Phase I to almost 5.6% in the first two years of Phase IV. Notice how the number of listed firms instead was more stable, fluctuating between 2.5% and 3.0%.

Although this sample represents a limited portion of total firms, they refer to a substantial portion of transactions performed within the EU ETS. Indeed, listed firms were responsible for a portion of allowance transfers that is above 9% in all analyzed years, with peaks around 20% in 2005 and 2016. Even in terms of allowances purchases, listed firms account for an average portion of around 12% during Phases I and II and equal to 9.6% in Phase III.

Finally, listed firms experienced an upward trend regarding allowance allocation and verified emissions over the analyzed period. The former absorbed a portion between 5.7% and 7.7% over the time frame 2005-2012. Such percentage rose to 8.4% during the period 2013-2020 and to 9.6% in the first two years of Phase IV. Similarly, verified emissions ranged between 5.6% and 7.9% during Phases I and II while being on average equal to 9.7% during the time frame 2013-2020 and above 10% in the most recent phase.

Overall, this sample offers a representative view of the main dynamics observed in the EU ETS

[8]Data related to the number of firms, installations, and the amount of allowances allocation and verified emissions are available until 2022 at the moment of writing. Conversely, information related to allowance purchases and transfers stopped in 2020 due to a three-year embargo in the EUTL dataset for transaction information.

market and reflects relevant signals related to carbon abatement.

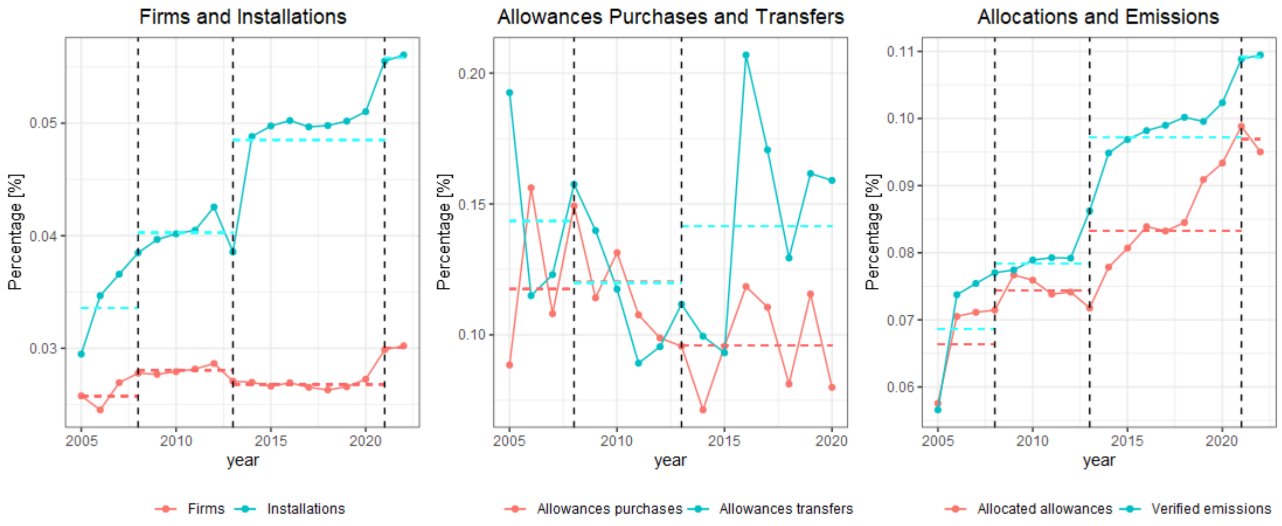

Figure 2: Sample representativeness of EU ETS-listed firms in terms of the number of firms and managed installations. Moreover, the annual percentage of allowances purchases and transfers, as well as allowance allocations and emissions of EU ETS-listed firms compared to the fully matched sample of EU ETS firms is highlighted. The solid line refers to annual values. Dotted horizontal lines indicate average values over each phase of the EU ETS. Dotted vertical lines stand for the different EU ETS phases.

3.2 EU ETS index construction

Regarding the construction of the EU ETS index, the daily close price of the 203 EU ETS-listed firms is considered. Data span from April 22, 2005[9] to December 31, 2022.

Different approaches are employed to calculate the weight of each stock in the EU ETS index. The first approach utilizes a capitalization-weighted method, where each stock's weight is proportional to its market capitalization. The second method assigns weights based on each company's ESG score. The third set of approaches focuses on environmental performance, weighting stocks according to the ratio of the company's reported emissions during a compliance period to its size, as measured by total assets or sales [12, 52]. In this study, the environmental performance measure based on total assets is considered.[10] Particularly, the weights are computed as the negative natural logarithm of the ratio between firms' emissions and total assets. Three distinct measures of emissions are considered: Scope 1, Scope 2, and total verified emissions. Scope 3 emissions are excluded from the analysis as they rely on strong assumptions and can introduce significant uncertainty [13]. The proposed EU ETS indices are rebalanced yearly (every June) according to the most recent ESG scores, balance sheet, and emissions data.

[9]This is when the EUA futures were first quoted.

[10]The results obtained by considering the environmental performance based on sales are similar to those of this study. Appreciation is extended to an anonymous Reviewer for this valuable suggestion.

To conduct the analysis presented in Section 5, the EU ETS index based on total verified emissions is chosen. The exclusion of the other indices is motivated as follows. The capitalization-weighted index may mask relevant sectoral differences in environmental performances, being only based on accounting variables. The ESG and Scope emissions indices may suffer from reliability issues in their estimates as explained in Section 1. Note that the best-performing approach is not selected, as the cumulative performance of the index based on verified emissions falls in the middle when compared to the other approaches (see Figure 3).

Table 2 summarizes the average daily return, standard deviation (in percentage), and annualized Sharpe ratio (SR) of portfolios and EUA based on EU ETS phases. Notably, the total verified emissions EU ETS index yields a higher average return than the market capitalization-weighted index (0.005% vs. −0.002%). Moreover, its average daily return (0.005%) and SR (0.089) are comparable to those of the ESG index (0.007% and 0.091, respectively). However, the total verified emissions index underperforms when compared to the Scope 1 and Scope 2 indices, which exhibit higher average returns (0.014% and 0.012%, respectively) and significantly better SRs (0.195 for Scope 1 and 0.157 for Scope 2). Nevertheless, the total verified emissions index stands out for having the lowest volatility (0.943%) among all indices. In contrast, EUA demonstrates higher returns (0.038%) and much greater volatility (13.024%), resulting in a relatively low SR (0.046).

Table 2: Performance of EU ETS indices vs. EUA price, divided by EU ETS phases.

	Phase I			Phase II			Phase III			Phase IV			Total		
	Return (%)	Std. dev. (%)	SR (ann)	Return (%)	Std. dev. (%)	SR (ann)	Return (%)	Std. dev. (%)	SR (ann)	Return (%)	Std. dev. (%)	SR (ann)	Return (%)	Std. dev. (%)	SR (ann)
Total verified	0.036	0.667	0.868	-0.028	1.189	-0.375	0.018	0.823	0.347	0.014	0.877	0.248	0.005	0.943	0.089
Market cap	0.043	0.794	0.865	-0.033	1.475	-0.360	0.000	1.094	0.005	0.032	0.980	0.519	-0.002	1.187	-0.026
ESG	0.051	0.888	0.904	-0.022	1.574	-0.221	0.013	1.105	0.191	0.021	1.050	0.318	0.007	1.243	0.091
Scope 1	0.058	0.784	1.172	-0.002	1.374	-0.027	0.015	1.122	0.212	0.020	1.037	0.300	0.014	1.168	0.195
Scope 2	0.041	0.778	0.827	-0.006	1.396	-0.070	0.014	1.126	0.203	0.022	1.036	0.343	0.012	1.178	0.157
EUA	0.072	41.164	0.028	-0.094	2.720	-0.547	0.077	3.342	0.366	0.182	3.015	0.956	0.038	13.024	0.046

Figures 4 and 5 illustrate the composition of the total verified emissions index by sectors and countries, respectively, across each phase of the EU ETS. It is noteworthy that the index is predominantly composed of manufacturing firms. However, the share of energy firms has increased over the phases, driven by the progressively stricter EU ETS regulations applied to this sector. Interestingly, German, Polish, Spanish, British, and Italian companies constitute around 60%-65% of the index. Table C1 lists the ten biggest companies in the index in terms of total assets in each phase.

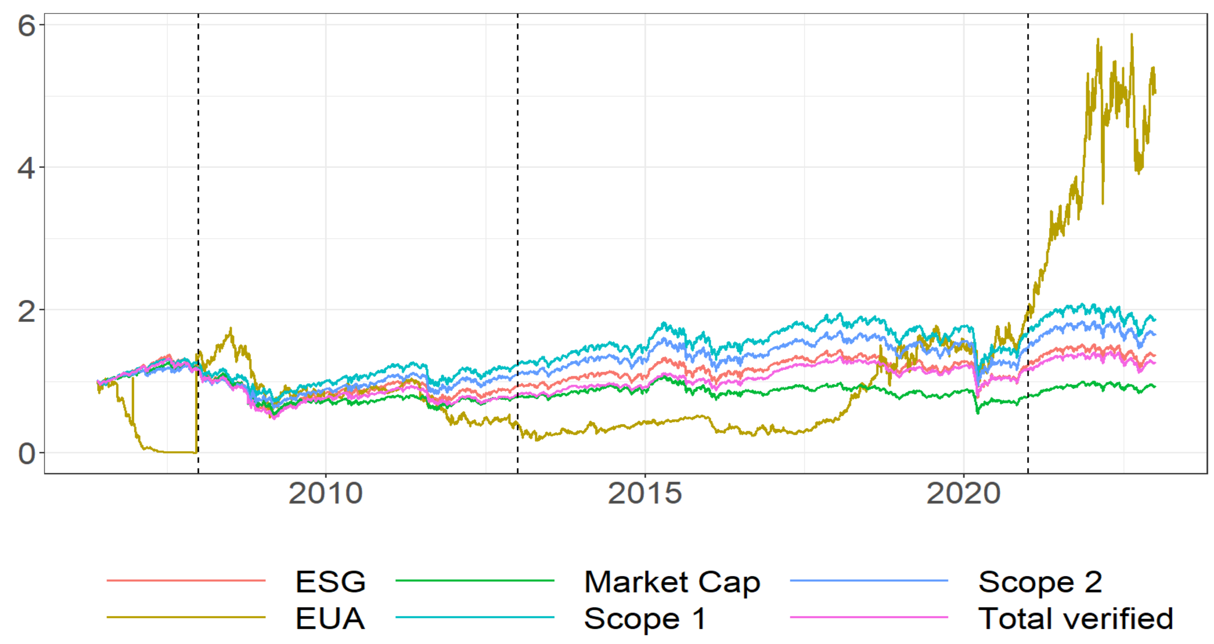

Figure 3: Gross cumulative performance of EU ETS indices and EUA. The dashed vertical lines correspond with the beginning of an EU ETS phase.

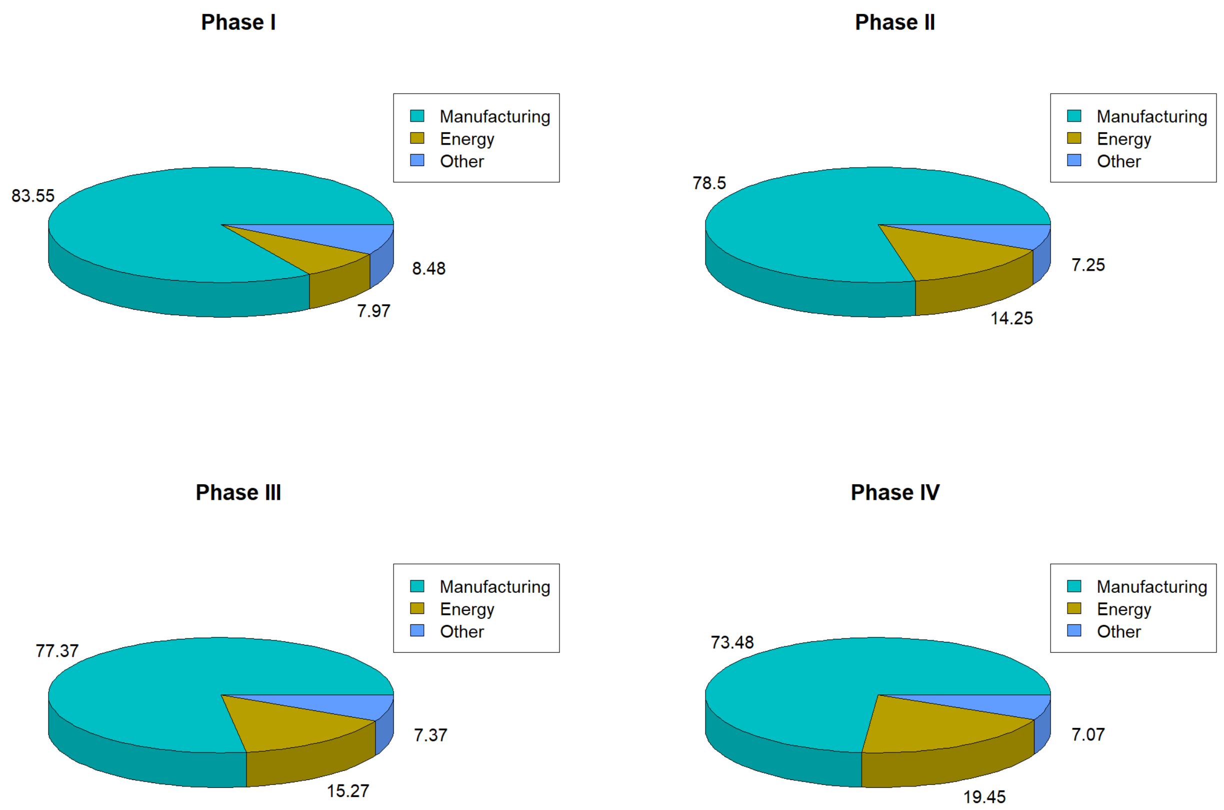

Figure 4: Sector composition of the EU ETS index divided by EU ETS phases.

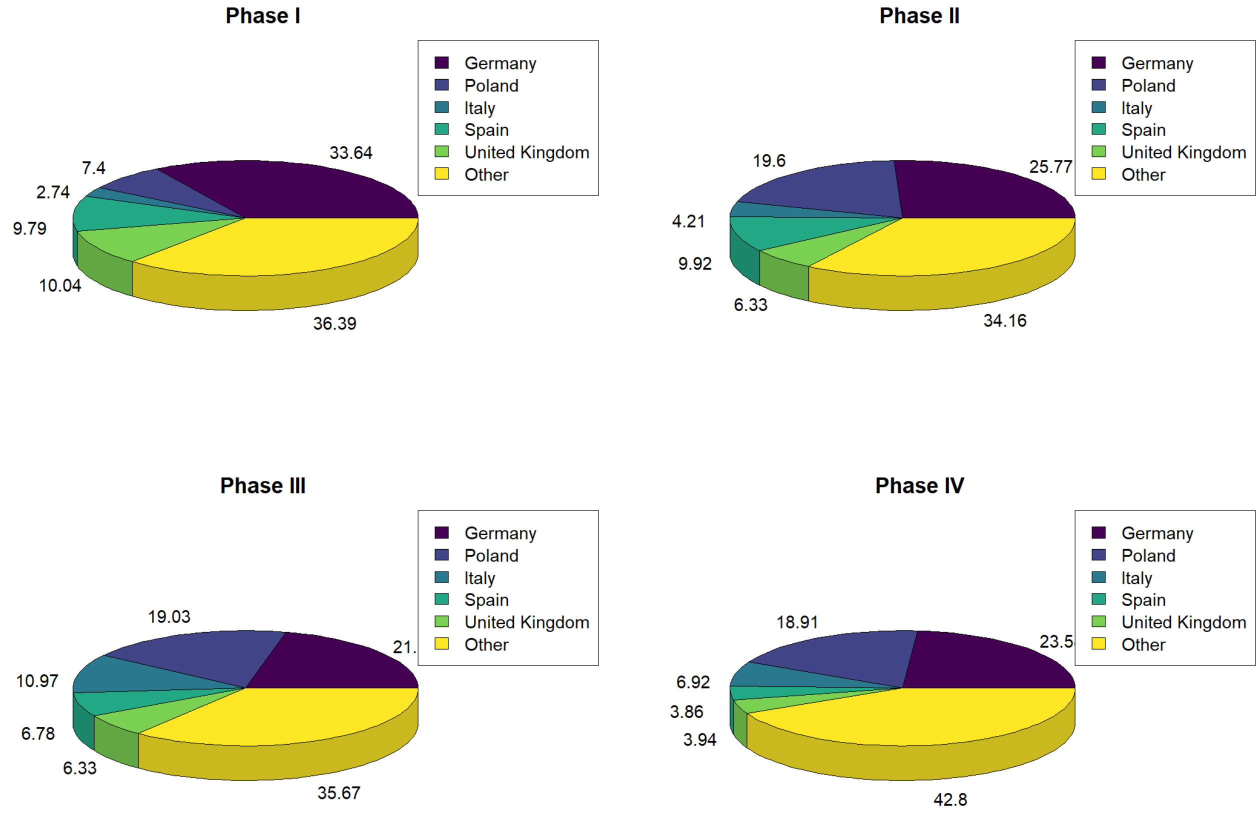

Figure 5: Countries composition of the EU ETS index divided by EU ETS phases.

3.3 Portfolio asset classes

To test the hedging properties of the proposed EU ETS index, the daily closing price of a variety of asset classes, namely equity indices (MSCI Europe, MSCI EM Eastern Europe ex Russia, and ERIX), bond indices (corporate, Government, and green bonds), commodities (Brent oil and gold), Bitcoin, and EUAs, is considered. For these analyses, the sample begins on July 19, 2010,[11] and ends on December 31, 2022. Table D1 lists the specific contracts considered for the analysis.

From the daily closing prices P_t at t, the natural logarithmic returns are computed as $r_t = \ln(P_t) - \ln(P_{t-1})$.[12] Table 3 summarizes the descriptive statistics and some statistical tests for the analyzed assets. Bonds have, on average, a slightly negative daily performance, with a low standard deviation (on average, around 0.245%). Equity indices provide different results in terms of average daily returns. For instance, MSCI EM offered a negative performance (-0.004%), whereas the per-

[11] Daily closing price of Bitcoin are available from this date on Thomson Reuters Eikon.

[12] Prices in euros are considered to avoid possible biases related to currency appreciation or depreciation when computing returns.

formance of the EU ETS index and MSCI Europe are 0.015% and 0.016%. ERIX provides a lower performance (0.012%) with a significantly higher standard deviation (2.121%, about double as much as the other equity indices). Concerning commodities, the mean return of gold (0.018%) more than doubled that of Brent oil (0.007%), which is also more volatile. Interestingly, Bitcoin provides the highest average returns (0.393%) and standard deviation (6.920%) among assets.

Notice that the return distribution of the analyzed assets is left-skewed, meaning that the median typically exceeds the mean. Except for green bonds, the kurtosis is greater than three, meaning that a leptokurtic distribution, typical for financial assets, characterizes the analyzed data.

The null hypothesis of normal distribution (Jarque-Bera and Shapiro-Wilk tests) is rejected at the 1% significance level for all time series. The Augmented Dickey-Fuller and the Phillips-Perron tests provide strong evidence in favor of the stationarity of the series since the null hypothesis is rejected at the 1% significance level. Lastly, the Ljung-Box Q rejects the null hypothesis at the 1% level for up to the 5^{th} order serial correlation, evidencing significant serial autocorrelations in the returns of all time series except Brent oil, MSCI EM, MSCI Europe, ERIX, and gold (for the latter two the null is rejected at the 5% level).

Table 3: Descriptive statistics of single assets and the EU ETS index. SW and JB rows report the p-values of the Shapiro-Wilk and Jarque Bera tests for the null hypothesis of Gaussian distribution, respectively. ADF and PP denote the p-values of the Augmented Dickey-Fuller and Phillips-Perron unit root tests, respectively. LB (l) is the Ljung-Box p-value for up to the l^{th} order serial correlation.

	Brent	BTC	Corp Bond	ERIX	EU ETS	EUA	Gold	Gov Bond	Green Bond	MSCI EM	MSCI Europe
Mean (%)	0.007	0.393	-0.005	0.012	0.015	0.054	0.018	-0.005	-0.002	-0.004	0.016
Median (%)	0.047	0.189	0.002	0.001	0.048	0.068	0.017	0.007	0.002	0.025	0.056
Std. dev. (%)	2.325	6.920	0.161	2.121	0.852	3.202	0.972	0.265	0.309	1.340	1.057
Skewness	-0.947	-0.166	-0.969	-0.248	-1.414	-0.797	-0.463	-0.026	-0.151	-0.974	-0.859
Kurtosis	19.182	16.241	12.735	4.135	14.030	15.278	7.038	5.178	2.633	9.921	10.252
JB	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SW	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ADF	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
PP	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
LB(5)	0.766	0.000	0.000	0.019	0.000	0.001	0.038	0.001	0.000	0.567	0.652
LB(20)	0.009	0.000	0.000	0.031	0.000	0.000	0.068	0.000	0.003	0.014	0.006

4 Methodology

This Section outlines the methodological approach followed in this paper. After developing the equity climate index based on EU ETS-listed firms, portfolios that include the other assets are created as detailed in Section 3. Then, HRs, OWs, and HEs are estimated to evaluate the capacity of the proposed index to hedge portfolios' risks (see Figure 6).

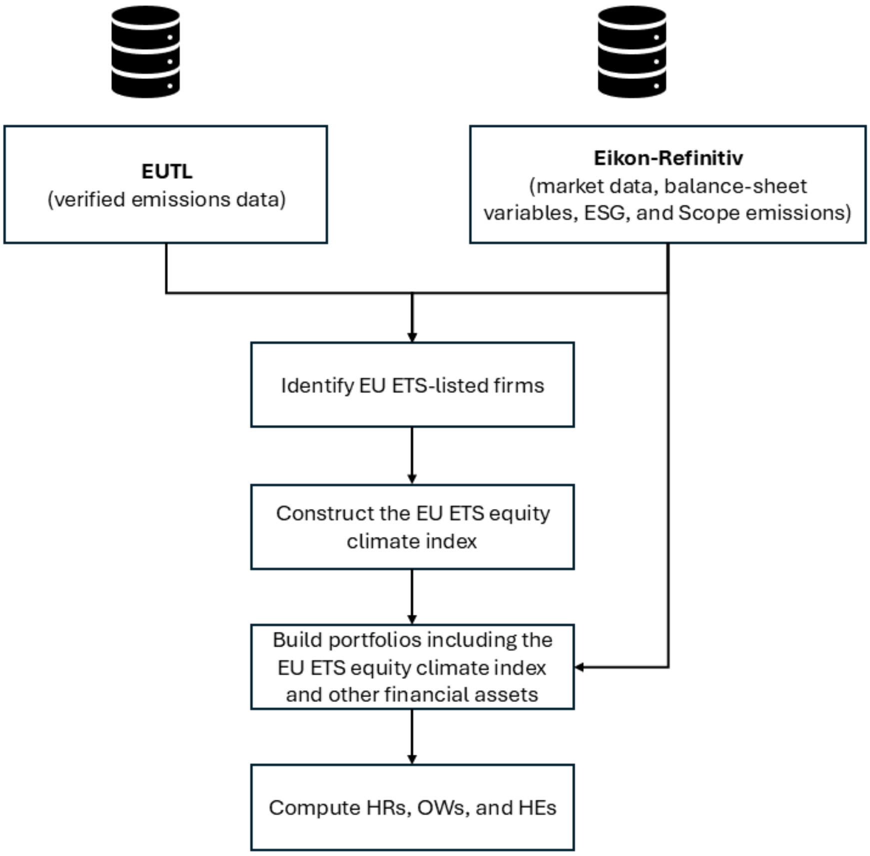

Figure 6: Workflow of the methodological approach.

4.1 DCC-GARCH

In line with previous research [41, 11, 63], the dynamic conditional correlation GARCH (DCC-GARCH) model of Engle [45] is employed to study the time-varying correlations between the returns of the assets. Particularly, a DCC-GARCH(1,1) is used following previous studies [82, 4]. This technique is preferred over other multivariate GARCH models (e.g., VAR-GARCH and BEKK) since the latter may be subject to the curse of dimensionality [16], making the estimation of the covariance matrix very hard when increasing the number of covariance terms [82]. By contrast, the DCC-GARCH process computes the correlation matrix by employing the standardized residuals, thereby reducing the number of estimated parameters.

The DCC-GARCH process is defined as:

$$r_t = \mu_t(\theta) + \epsilon_t, \tag{1}$$

with $\epsilon_t|\Omega_{t-1} \sim N(0, H_t)$ and

$$\epsilon_t = H_t^{1/2} u_t, \tag{2}$$

where $u_t \sim N(0, I)$ and

$$H_t = D_t R_t D_t. \tag{3}$$

Hence, $r_t = [r_{it}, ..., r_{Nt}]'$ is a $N \times 1$ vector of returns, $\mu_t(\theta) = [\mu_{it}, ..., \mu_{Nt}]'$ is the conditional $N \times 1$ mean vector of r_t, H_t is the conditional covariance matrix, and $D_t = diag(h_{iit}^{1/2}, ..., h_{NNt}^{1/2})$ is a diagonal matrix of square root conditional variances. In particular, h_{iit} is estimated using a univariate GARCH model, and R_t is the $t\frac{N(N-1)}{2}$ matrix that includes the time-varying conditional correlations, calculated as:

$$R_t = diag(q_{iit}^{-1/2}) Q_t diag(q_{iit}^{-1/2}), \tag{4}$$

with $Q_t = (q_{iit})$ denoting a $N \times N$ symmetric positive definite matrix such that:

$$Q_t = (1 - a - b)\overline{Q} + a u_{t-1} u_{t-1}' + b Q_{t-1}, \tag{5}$$

with $u_t = [u_{1t}, u_{2t}, ..., u_{Nt}]'$ indicating the $N \times 1$ vector of standardized residuals, $\overline{Q}$ the $N \times N$ unconditional variance matrix of u_t, and a and b non-negative scalar parameters such that $a+b < 1$. A two-step procedure to estimate the DCC model is implemented. First, the individual conditional variances are estimated using univariate GARCH processes, estimated via a quasi-maximum likelihood estimator (QML) under a multivariate Student's t distribution in line with previous literature dealing with non-normal time series [69, 10]. Second, the conditional correlation matrix is constructed by utilizing the standardized residuals from the first step.

4.2 Hedge ratios, optimal weights, and hedge effectiveness

To compute hedging costs, the hedge ratios are estimated as described in Kroner and Sultan [66]. Hedge ratios represent the cost of hedging a €1 long position in the asset i with €δ_{ijt} short position in the asset j at time t. In particular,

$$\delta_{ijt} = \frac{h_{ijt}}{h_{jjt}} \tag{6}$$

h_{ijt} being the conditional covariance of assets i and j, estimated as presented in Section 4.1. Hence, the higher the conditional covariance, the higher the long-position hedging costs. By contrast, increasing the conditional variance leads to lower long-position hedging costs.

The optimal portfolio weights are estimated as described in Kroner and Ng [65]. More precisely, w_{ijt} is the weight of the asset i in a €1 portfolio of assets i and j and is computed as follows:

$$w_{ijt} = \frac{h_{jjt} - h_{ijt}}{h_{iit} - 2h_{ijt} + h_{jjt}} \tag{7}$$

It is also imposed that only long positions are allowed and the following restrictions on the weights are applied:

$$w_{ijt} = \begin{cases} 0, \; if \; w_{ijt} < 0 \\ w_{ijt}, \; if \; 0 \leq w_{ijt} \leq 1 \\ 1, \; if \; w_{ijt} > 1 \end{cases} \tag{8}$$

Consequently, the weight of asset j at time t is calculated as:

$$w_{jit} = 1 - w_{ijt}. \tag{9}$$

Lastly, the method proposed by Ederington [43] is employed to estimate the hedge effectiveness of the portfolios constructed based on either the hedge ratios or the optimal weights. From a financial perspective, the hedge effectiveness HE_i of asset i represents the percentage reduction in the variance of the unhedged portfolio and can be calculated as follows:

$$HE_i = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}}, \tag{10}$$

with $Var_{unhedged}$ denoting the variance of the unhedged strategy while Var_{hedged} indicating the variance of the hedged portfolio obtained either by using the hedge ratios or the optimal weights.

Specifically, the hedged portfolio variance from the hedge ratios is:

$$Var_{hedged} = Var(x_{it} - \delta_{ijt} x_{jt}), \tag{11}$$

where x_{it} is the return of asset i at time t.

Consistently, the hedged portfolio variance from the optimal weights is:

$$Var_{hedged} = Var(w_{ijt}x_{it} - w_{jit}x_{jt}) \tag{12}$$

5 Empirical results

Table 4 presents the average HRs and HEs for all pairs of assets that include the EU ETS index. The highest HRs are obtained with MSCI Europe, MSCI EM, and ERIX, indicating that hedging these stock indices through the EU ETS index is more expensive. For instance, the hedging cost of a €1 long position in MSCI Europe and MSCI EM requires corresponding short positions of about €1.14 and €1.15, respectively. Nevertheless, these assets also exhibit the best average HEs, with values of 0.82 and 0.53, reflecting strong risk reduction. Conversely, bond indices represent the least expensive assets to hedge as their HRs are near zero. For a €1 long position in Government and green bonds, an investor would only need to short the EU ETS index by approximately 1 to 3 cents. However, these strategies yield slightly negative HEs (-0.02 and -0.01).

It is also worth noting that some HRs are negative, indicating that hedging can be achieved by taking either a long or short position in both the EU ETS index and the paired asset [84]. Specifically, a €1 long (short) position in gold and corporate bonds is hedged with about an 8-cent and 1-cent long (short) position in the EU ETS index. Consistently, Demiralay et al. [35] also observe negative HRs for European stocks against gold over the period 2014–2021. Finally, hedging a €1 long position in Brent oil (0.76), EUA (0.72), and Bitcoin (0.41) is relatively costly, although their HEs are low (0.08, 0.03, and -0.004).

Figure 7 illustrates the time-varying HRs for the EU ETS index. HRs between bond indices and the EU ETS index are relatively stable over time, as reflected by their low standard deviation in Table 4. By contrast, HRs between Bitcoin, ERIX, or Brent oil and the EU ETS index are far more volatile due to the high price fluctuations of these assets. Specifically, several significant spikes are observed, with the most prominent being a 3.83 spike in ERIX that occurred on November 10, 2017, during COP23, which focused on the practical implementation guidelines for the Paris Agreement (COP21), known as the Paris Rulebook. Similarly, a 3.27 spike in EUA occurred on December 22, 2011, following COP17, when countries agreed to establish a legally binding climate deal by 2015.

Interestingly, these spikes in HRs for ERIX and EUA coincide with increased investor attention to climate risks, as evidenced by similar rises in Google's Search Volume Index for green assets and climate risk topics [47, 9].

Table 4: Hedge ratios (EU ETS vs. other assets). HR represents the average hedge ratio, namely the average hedging cost of a €1 long position in the left asset with a short position in the EU ETS index. Std. dev. indicates the standard deviation of the daily hedge ratio time series, while 5% and 95% denote its 5^{th} and 95^{th} percentiles, respectively. HE is the average hedge effectiveness of the EU ETS index.

	HR	Std. dev.	5%	95%	HE
Brent/EU ETS	0.758	0.375	0.300	1.490	0.080
BTC/EU ETS	0.412	0.656	-0.700	1.440	-0.004
Corp Bond/EU ETS	-0.006	0.025	-0.040	0.040	-0.020
ERIX/EU ETS	1.474	0.405	0.880	2.240	0.239
EUA/EU ETS	0.715	0.416	0.200	1.440	0.029
Gold/EU ETS	-0.076	0.121	-0.290	0.090	-0.009
Gov Bond/EU ETS	0.008	0.041	-0.050	0.080	-0.016
Green Bond/EU ETS	0.030	0.049	-0.040	0.120	-0.008
MSCI EM/EU ETS	1.149	0.206	0.850	1.530	0.526
MSCI Europe/EU ETS	1.139	0.172	0.880	1.440	0.824

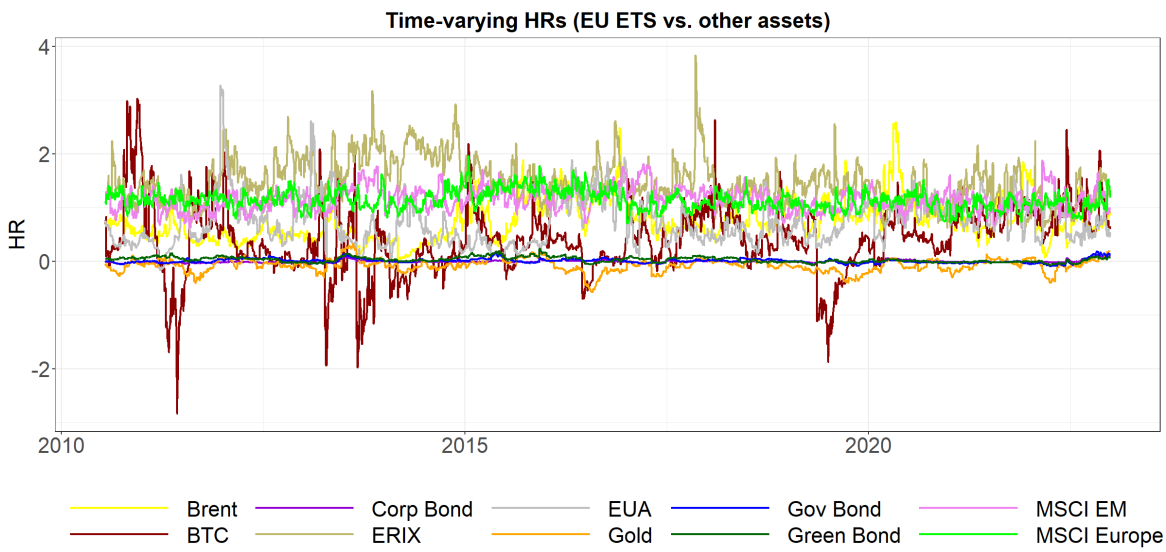

Figure 7: Time-varying HRs (EU ETS vs. other assets).

Significantly negative HRs were also recorded with Bitcoin (-2.83) on June 9, 2011, following a peak in the cryptocurrency's price, and on February 24, 2022 (2.61), after Russia's invasion of Ukraine. This aligns with findings from Ustaoglu [86], who highlights higher hedging costs for Bitcoin during the Russia-Ukraine conflict.

For comparison purposes, Table 5 lists the average HRs and HEs for all asset pairs including EUA. The HRs range from -0.02 for gold to 0.13 for Brent oil. However, all HEs lie between -0.01 and 0.01. This indicates that while hedging various assets using EUA is generally less costly than using the EU ETS index, such strategies are often ineffective in reducing risk, given the consistently low HEs. Figures 8 and E1 further reinforce this finding, showing that the time-varying HE of the EU ETS compared to EUA is typically higher, with significant upward positive spikes during key events. For instance, green bonds show a notable difference in HE of approximately 0.49 in December 2015, coinciding with COP21. Similarly, Brent oil (3.38) and MSCI Europe (6.02) experienced improved hedging by the EU ETS index during the COVID-19 pandemic, likely due to the stagnation in crude oil production and the lockdown restrictions imposed by governments to curb the spread of the virus.

Table 5: Hedge ratios (EUA vs. other assets). HR represents the average hedge ratio, namely the average hedging cost of a €1 long position in the left asset with a short position in EUA. Std. dev. indicates the standard deviation of the daily hedge ratio time series, while 5% and 95% denote its 5^{th} and 95^{th} percentiles, respectively. HE is the average hedge effectiveness of EUA.

	HR	Std. dev.	5%	95%	HE
Brent/EUA	0.129	0.112	0.020	0.370	-0.003
BTC/EUA	0.003	0.164	-0.210	0.230	-0.006
Corp Bond/EUA	-0.002	0.005	-0.010	0.000	-0.011
ERIX/EUA	0.117	0.087	0.020	0.290	-0.008
EU ETS/EUA	0.056	0.047	0.010	0.150	0.010
Gold/EUA	-0.016	0.029	-0.060	0.020	-0.008
Gov Bond/EUA	-0.004	0.009	-0.020	0.010	-0.010
Green Bond/EUA	-0.007	0.011	-0.020	0.000	-0.012
MSCI EM/EUA	0.055	0.048	0.000	0.140	0.007
MSCI Europe/EUA	0.068	0.061	0.010	0.180	0.004

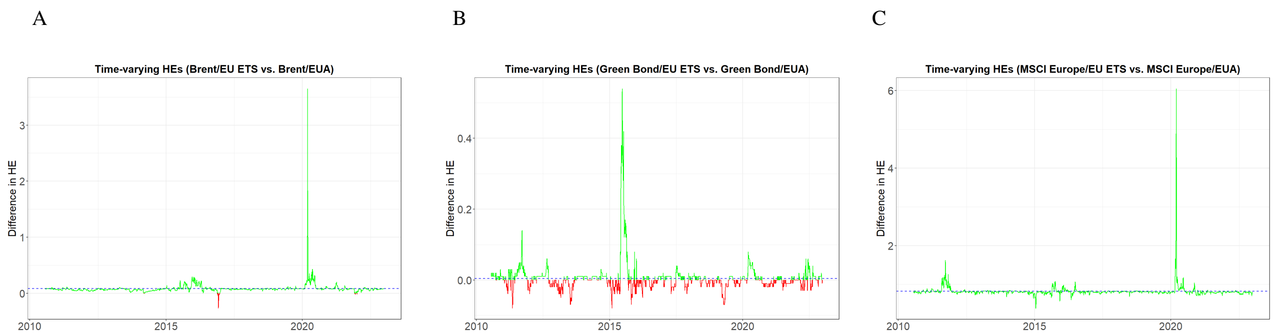

Figure 8: Difference in the time-varying HEs of the EU ETS index vs. other assets and EUA vs. other assets. The plot illustrates the difference in time-varying HE between EU ETS indices and other assets (Brent oil, green bonds, and MSCI Europe), and between EUA and other assets. A positive difference, indicating that the EU ETS index provides superior hedge effectiveness compared to EUA, is highlighted in green, while a negative difference is shown in red. The dashed horizontal blue line represents the mean of the HE difference over time.

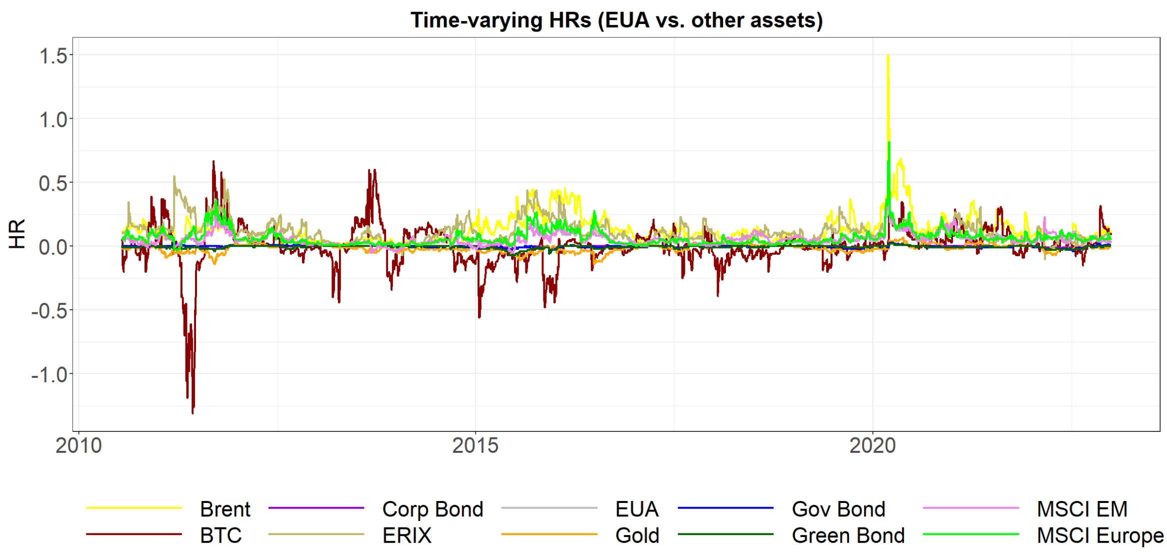

Figure 9: Time-varying HRs (EUA vs. other assets).

Figure 9 plots the time-varying HRs for EUA. In line with the low standard deviations in Table 5, these HRs are generally stable, with only a few notable peaks. For example, a significant dip is observed with Bitcoin on June 9, 2011 (-1.27), while Brent oil shows spikes on March 10 and May 7, 2020 (1.61 and 0.73, respectively), driven by the heightened volatility in oil futures due to the COVID-19 pandemic. These findings align with existing literature, which reports substantial increases in hedging costs during the pandemic [6, 91].

Table 6 displays the average OWs and HEs for all asset pairs including the proposed EU ETS index. Consistent with previous results for HRs, optimal portfolios tend to overweight bond indices when paired with the EU ETS. Similarly, Abuzayed and Al-Fayoumi [3] show how green bonds have the highest OW relative to stock indices. Nonetheless, the HEs for such portfolios are particularly low (0.000 for the pair green bonds/EU ETS and 0.018 for Government bonds/EU ETS) or even slightly negative (-0.007 for corporate bonds). The OWs of the EU ETS index increase in portfolios containing more volatile assets. For instance, the Bitcoin/EU ETS portfolio exhibits an average OW of 0.975, with low volatility (std. dev.: 0.032) compared to that of its corresponding HR (std. dev.: 0.656). This portfolio also offers strong hedging benefits (HE: 0.98). In contrast, the MSCI Europe/EU ETS portfolio shows the highest volatility (std. dev.: 0.187) since the OW of the EU ETS index ranges between 0.47 and 1 (at the 5^{th} and 95^{th} percentiles, respectively). This instability is reflected in the average HE (0.33), which is significantly lower than that of its corresponding HR (0.82).

Table 6: Optimal weights (EU ETS vs. other assets). OW represents the average optimal weight, namely the average weight the left asset should be assigned in the portfolio with the EU ETS index. Std. dev. indicates the standard deviation of the daily optimal weight time series, while 5% and 95% denote its 5^{th} and 95^{th} percentiles, respectively. HE is the average hedge effectiveness of the EU ETS index.

	OW	Std. dev.	5%	95%	HE
Brent/EU ETS	0.076	0.093	0.000	0.260	0.857
BTC/EU ETS	0.025	0.032	0.000	0.090	0.980
Corp Bond/EU ETS	0.957	0.028	0.910	1.000	-0.007
ERIX/EU ETS	0.006	0.033	0.000	0.040	0.838
EUA/EU ETS	0.049	0.077	0.000	0.180	0.923
Gold/EU ETS	0.399	0.124	0.220	0.620	0.555
Gov Bond/EU ETS	0.901	0.067	0.770	0.980	0.018
Green Bond/EU ETS	0.868	0.078	0.720	0.980	0.000
MSCI EM/EU ETS	0.030	0.080	0.000	0.190	0.591
MSCI Europe/EU ETS	0.071	0.187	0.000	0.530	0.330

Table 7 presents the average OWs and HEs for all pairs of assets that contain EUA. The findings consistently show that EUA should be underweighted in most asset combinations, with the exception of Bitcoin, which offers the highest HE (0.75). This result supports prior research identifying the carbon market as a safe haven and an effective hedge against cryptocurrency risk [89]. Furthermore, EUA demonstrates hedging potential against both Brent oil and ERIX, corroborating findings by Liu et al. [71] and Dutta et al. [41], respectively. However, over time, EUA should be underweighted, even when considering the 5^{th} quantile of the OWs distribution, except for Brent oil and ERIX. In all cases, the corresponding HEs are smaller than those achieved with the EU ETS index.

Overall, these results support the purpose of creating an equity index that reflects the cross-sectional heterogeneity of firms' environmental performance [27] and mitigates investors' portfolios against carbon risk premiums [24]. Similar to EUA, the EU ETS index can be utilized to monitor trends in firms' carbon abatement efforts and environmental innovation. However, the EU ETS equity index consistently demonstrates higher HEs against a broad range of asset classes, highlighting the added value of this proposed index over investing solely in the European carbon price.

Table 7: Optimal weights (EUA vs. other assets). OW represents the average optimal weight, namely the average weight the left asset should be assigned in the portfolio with EUA. Std. dev. indicates the standard deviation of the daily optimal weight time series, while 5% and 95% denote its 5^{th} and 95^{th} percentiles, respectively. HE is the average hedge effectiveness of EUA.

	OW	Std. dev.	5%	95%	HE
Brent/EUA	0.662	0.228	0.240	0.960	0.125
BTC/EUA	0.298	0.211	0.020	0.710	0.745
Corp Bond/EUA	0.994	0.008	0.980	1.000	-0.023
ERIX/EUA	0.637	0.192	0.300	0.930	0.103
EU ETS/EUA	0.951	0.077	0.820	1.000	-0.092
Gold/EUA	0.870	0.091	0.670	0.970	-0.017
Gov Bond/EUA	0.986	0.016	0.950	1.000	-0.033
Green Bond/EUA	0.976	0.027	0.910	1.000	-0.076
MSCI EM/EUA	0.838	0.131	0.570	0.980	-0.048
MSCI Europe/EUA	0.904	0.125	0.650	1.000	-0.145

6 Conclusions and policy implications

This paper proposes a stock index that captures the cross-sectional heterogeneity in the environmental performance of EU ETS-listed firms. Such an index could be attractive to investors interested in equity-focused climate investing, while still retaining exposures to carbon-intensive sectors. Including carbon-intensive firms progressing toward net-zero emissions helps minimize deviation from broad market performance and prevents underperformance in specific market conditions. Therefore, the findings of this paper hold significant implications for investors seeking to optimize returns while reducing climate-related risks, and may be summarized as follows:

i) Concerning optimal weights, the EU ETS index tends to be underweighted when paired with bonds, while being overweighted in portfolios featuring more volatile assets. Instead, the EUA is underweighted in all analyzed pairs, except Bitcoin.

ii) Hedging with the EU ETS index is generally more expensive than hedging with EUA, as indicated by its higher average hedge ratios.

iii) However, the EU ETS index provides better hedge effectiveness compared to the EUA.

Importantly, an environmental performance-focused index enhances the transparency and accountability of corporate sustainability efforts by providing a clearer framework for tracking and monitoring environmental performance. This aspect increases visibility into corporate climate actions and boosts investors' confidence in sustainable investments, ensuring capital flows toward firms demonstrating responsible environmental practices.[13] From a policy perspective, facilitating investment in companies within the energy and manufacturing sectors that prioritize responsible environmental practices provides a significant opportunity to further enhance energy efficiency and reduce emissions. For instance, key strategies to improve energy efficiency might include increasing the use of renewable energy, switching to lower-carbon fuels like natural gas, and adopting advanced emissions abatement technologies, all crucial measures for achieving the EU's ambitious target of reaching carbon neutrality by 2050 [53]. These sectors are pivotal, as they account for a substantial share of the EU's GHG emissions [51] and drive the sustainability transition [83].

Additionally, the geographical and sectoral compositions of the proposed index can be exploited to highlight which countries and sectors are leading the low-carbon transition. For example, the composition of the index reflects the growing importance of energy firms over time, while the weight of manufacturing firms is declining. These shifts may stem from the different free allocation policies under the EU ETS across sectors, with power generators required to purchase all of their allowances since Phase III [26]. Policymakers can leverage this information to broaden sectoral coverage within the ETS framework. Notably, ETS2, set to begin in 2027, will cover emissions from fuel combustion in buildings, road and maritime transports, and other sectors currently excluded by the EU ETS. Similarly, establishing a price to emissions from agricultural activities along the agri-food value chain

[13] Source: `https://www.ecb.europa.eu/press/financial-stability-publications/fsr/special/html/ecb.fsrart202105_02~d05518fc6b.en.html`.

may facilitate a more comprehensive decarbonization effort at the EU level [20].

Despite its methodological rigor, this study has some limitations. For instance, future research may quantify to which extent including the EU ETS index in diversified portfolios may improve their risk-adjusted performance, for instance in terms of Sharpe and Omega ratios, Value at Risk, and Expected Shortfall. Second, only EU ETS-listed firms are considered. Future works may propose indices including firms subject to ETS regulations other than the European one.

Declaration of Interest

'Declarations of interest: none'.

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References

[1] Piia Aatola, Markku Ollikainen, and Anne Toppinen. Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals. *Energy Economics*, 36:380–395, 2013.

[2] Jan Abrell. Database for the European Union Transaction Log. *Database*, 2021.

[3] Bana Abuzayed and Nedal Al-Fayoumi. Diversification and hedging strategies of green bonds in financial asset portfolios during the covid-19 pandemic. *Applied Economics*, 55(36):4228–4238, 2023.

[4] Wasim Ahmad, Perry Sadorsky, and Amit Sharma. Optimal hedge ratios for clean energy equities. *Economic Modelling*, 72:278–295, 2018.

[5] Md Akhtaruzzaman, Ameet Kumar Banerjee, Wafa Ghardallou, and Zaghum Umar. Is greenness an optimal hedge for sectoral stock indices? *Economic Modelling*, 117:106030, 2022.

[6] Md Akhtaruzzaman, Sabri Boubaker, and Ahmet Sensoy. Financial contagion during COVID–19 crisis. *Finance Research Letters*, 38:101604, 2021.

[7] Emilie Alberola, Julien Chevallier, and Benoıˆt Chèze. Price drivers and structural breaks in European carbon prices 2005–2007. *Energy Policy*, 36(2):787–797, 2008.

[8] Lucia Alessi and Stefano Battiston. Two sides of the same coin: Green taxonomy alignment versus transition risk in financial portfolios. *International Review of Financial Analysis*, 84:102319, 2022.

[9] Mauro Aliano, Giuseppe Galloppo, and Viktoriia Paimanova. People and investor attention to climate change. *The European Journal of Finance*, 29(18):2107–2127, 2023.

[10] Nikolaos Antonakakis, Juncal Cunado, George Filis, David Gabauer, and Fernando Perez De Gracia. Oil volatility, oil and gas firms and portfolio diversification. *Energy Economics*, 70:499–515, 2018.

[11] Nikolaos Antonakakis, Juncal Cunado, George Filis, David Gabauer, and Fernando Perez de Gracia. Oil and asset classes implied volatilities: Investment strategies and hedging effectiveness. *Energy Economics*, 91:104762, 2020.

[12] Juan Alberto Aragón-Correa. Strategic proactivity and firm approach to the natural environment. *Academy of Management Journal*, 41(5):556–567, 1998.

[13] Jitendra Aswani, Aneesh Raghunandan, and Shiva Rajgopal. Are carbon emissions associated with stock returns? *Review of Finance*, 28(1):75–106, 2024.

[14] Doron Avramov, Si Cheng, Abraham Lioui, and Andrea Tarelli. Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*, 145(2):642–664, 2022.

[15] Mehmet Balcılar, Rıza Demirer, Shawkat Hammoudeh, and Duc Khuong Nguyen. Risk spillovers across the energy and carbon markets and hedging strategies for carbon risk. *Energy Economics*, 54:159–172, 2016.

[16] Luc Bauwens, Sébastien Laurent, and Jeroen VK Rombouts. Multivariate GARCH models: A survey. *Journal of Applied Econometrics*, 21(1):79–109, 2006.

[17] Inessa Benchora and Sébastien Galanti. Verified carbon emissions and stock returns in the EU Emissions Trading System. *Energy Policy*, 193:114264, 2024.

[18] Florian Berg, Julian F Koelbel, and Roberto Rigobon. Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, 26(6):1315–1344, 2022.

[19] Monica Billio, Michele Costola, Iva Hristova, Carmelo Latino, and Loriana Pelizzon. Inside the ESG ratings:(dis) agreement and performance. *Corporate Social Responsibility and Environmental Management*, 28(5):1426–1445, 2021.

[20] Julia Bognar, Long Lam, Oana Forestier, Andrea Finesso, Hans Bolscher, Krystyna Springer, Martin Nesbit, Elisabet Nadeu, Nora Hiller, Robin van Dijk, et al. Pricing agricultural emissions and rewarding climate action in the agri-food value chain, 2024.

[21] Patrick Bolton and Marcin Kacperczyk. Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549, 2021.

[22] Patrick Bolton, Marcin Kacperczyk, and Frédéric Samama. Net-zero carbon portfolio alignment. *Financial Analysts Journal*, 78(2):19–33, 2022.

[23] Timo Busch, Matthew Johnson, and Thomas Pioch. Corporate carbon performance data: Quo vadis? *Journal of Industrial Ecology*, 26(1):350–363, 2022.

[24] Hongwei Cheng, Yi Feng, and Dingrui Dong. Will emission reduction commitments hedge the carbon risk premium? *Journal of Cleaner Production*, 430:139747, 2023.

[25] Julien Chevallier. A model of carbon price interactions with macroeconomic and energy dynamics. *Energy Economics*, 33(6):1295–1312, 2011.

[26] Benoît Chèze, Julien Chevallier, Nicolas Berghmans, and Emilie Alberola. On the CO2 emissions determinants during the EU ETS Phases I and II: a plant-level analysis merging the EUTL and Platts power data. *The Energy Journal*, 41(4), 2020.

[27] Mattia Chiappari, Francesco Scotti, and Andrea Flori. Portfolio hedging through a novel equity index based on the verified emissions of eu ets-regulated firms. *Economics Letters*, 247:112132, 2025.

[28] Darwin Choi, Zhenyu Gao, and Wenxi Jiang. Attention to global warming. *The Review of Financial Studies*, 33(3):1112–1145, 2020.

[29] Monika Chopra and Chhavi Mehta. Going green: Do green bonds act as a hedge and safe haven for stock sector risk? *Finance Research Letters*, 51:103357, 2023.

[30] European Commission. EU Emissions Trading System (EU ETS). `https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets_en`, 2023.

[31] Christian Conrad, Daniel Rittler, and Waldemar Rotfuß. Modeling and explaining the dynamics of european union allowance prices at high-frequency. *Energy Economics*, 34(1):316–326, 2012.

[32] Anna Creti and Marc Joëts. Multiple bubbles in the European Union emission trading scheme. *Energy Policy*, 107:119–130, 2017.

[33] Xingyu Dai, Ling Xiao, Qunwei Wang, and Gurjeet Dhesi. Multiscale interplay of higher-order moments between the carbon and energy markets during Phase III of the EU ETS. *Energy Policy*, 156:112428, 2021.

[34] Peter Deeney, Mark Cummins, Michael Dowling, and Alan F Smeaton. Influences from the European Parliament on EU emissions prices. *Energy Policy*, 88:561–572, 2016.

[35] Sercan Demiralay, Hatice Gaye Gencer, and Selcuk Bayraci. Carbon credit futures as an emerging asset: Hedging, diversification and downside risks. *Energy Economics*, 113:106196, 2022.

[36] Christos N Dimitriadis, Evangelos G Tsimopoulos, and Michael C Georgiadis. Optimal bidding strategy of a gas-fired power plant in interdependent low-carbon electricity and natural gas markets. *Energy*, 277:127710, 2023.

[37] Eyup Dogan, Muhammad Tariq Majeed, and Tania Luni. Are clean energy and carbon emission allowances caused by Bitcoin? A novel time-varying method. *Journal of Cleaner Production*, 347:131089, 2022.

[38] Feng Dong, Yujin Gao, Yangfan Li, Jiao Zhu, Mengyue Hu, and Xiaoyun Zhang. Exploring volatility of carbon price in European Union due to COVID-19 pandemic. *Environmental Science and Pollution Research*, pages 1–12, 2022.

[39] Xiyong Dong, Youlin Xiong, Siyue Nie, and Seong-Min Yoon. Can bonds hedge stock market risks? Green bonds vs conventional bonds. *Finance Research Letters*, 52:103367, 2023.

[40] Anupam Dutta, Elie Bouri, Debojyoti Das, and David Roubaud. Assessment and optimization of clean energy equity risks and commodity price volatility indexes: Implications for sustainability. *Journal of Cleaner Production*, 243:118669, 2020.

[41] Anupam Dutta, Elie Bouri, and Md Hasib Noor. Return and volatility linkages between CO2 emission and clean energy stock prices. *Energy*, 164:803–810, 2018.

[42] Anupam Dutta, Elie Bouri, Timo Rothovius, and Gazi Salah Uddin. Climate risk and green investments: New evidence. *Energy*, 265:126376, 2023.

[43] Louis H Ederington. The hedging performance of the new futures markets. *The Journal of Finance*, 34(1):157–170, 1979.

[44] A Denny Ellerman and Barbara K Buchner. Over-allocation or abatement? A preliminary analysis of the EU ETS based on the 2005–06 emissions data. *Environmental and Resource Economics*, 41:267–287, 2008.

[45] Robert Engle. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350, 2002.

[46] Mohammadehsan Eslahi and Paolo Mazza. Can weather variables and electricity demand predict carbon emissions allowances prices? Evidence from the first three phases of the EU ETS. *Ecological Economics*, 214:107985, 2023.

[47] Hany Fahmy. The rise in investors' awareness of climate risks after the Paris Agreement and the clean energy-oil-technology prices nexus. *Energy Economics*, 106:105738, 2022.

[48] John Hua Fan, Alexandr Akimov, and Eduardo Roca. Dynamic hedge ratio estimations in the European Union emissions offset credit market. *Journal of Cleaner Production*, 42:254–262, 2013.

[49] Ying Fan, Jun-Jun Jia, Xin Wang, and Jin-Hua Xu. What policy adjustments in the eu ets truly affected the carbon prices? *Energy Policy*, 103:145–164, 2017.

[50] Carmen Fernández-Cuesta, Paula Castro, María T Tascón, and Francisco J Castaño. The effect of environmental performance on financial debt. European evidence. *Journal of Cleaner Production*, 207:379–390, 2019.

[51] Andrea Flori. Energy commodities spillover analysis for assessing the functioning of the European Union Emissions Trading System trade network of carbon allowances. *Scientific Reports*, 14(1):21708, 2024.

[52] Andrea Flori, Simone Borghesi, and Giovanni Marin. The environmental-financial performance nexus of EU ETS firms: A quantile regression approach. *Energy Economics*, 131:107328, 2024.

[53] Panagiotis Fragkos, Nikos Tasios, Leonidas Paroussos, Pantelis Capros, and Stella Tsani. Energy system impacts and policy implications of the European Intended Nationally Determined Contribution and low-carbon pathway to 2050. *Energy Policy*, 100:216–226, 2017.

[54] Rajna Gibson Brandon, Philipp Krueger, and Peter Steffen Schmidt. ESG rating disagreement and stock returns. *Financial Analysts Journal*, 77(4):104–127, 2021.

[55] Erik Haites, Paolo Bertoldi, Michael König, Christopher Bataille, Felix Creutzig, Dipak Dasgupta, Stéphane de la rue du Can, Smail Khennas, Yong-Gun Kim, Lars J Nilsson, et al. Contribution of carbon pricing to meeting a mid-century net zero target. *Climate Policy*, 24(1):1–12, 2024.

[56] Martina Hengge, Ugo Panizza, and Richard Varghese. Carbon policy surprises and stock returns: Signals from financial markets. *Available at SSRN 4343984*, 2023.

[57] Beat Hintermann. Allowance price drivers in the first phase of the EU ETS. *Journal of Environmental Economics and Management*, 59(1):43–56, 2010.

[58] Beat Hintermann, Sonja Peterson, and Wilfried Rickels. Price and market behavior in Phase II of the EU ETS: A review of the literature. *Review of Environmental Economics and Policy*, 2016.

[59] Jie Huang, Yu Cao, and Pengshu Zhong. Searching for a safe haven to crude oil: Green bond or precious metals? *Finance Research Letters*, 50:103303, 2022.

[60] Emirhan Ilhan, Zacharias Sautner, and Grigory Vilkov. Carbon tail risk. *The Review of Financial Studies*, 34(3):1540–1571, 2021.

[61] Qiang Ji, Dayong Zhang, and Jiang-bo Geng. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production*, 198:972–978, 2018.

[62] Yonghong Jiang, Jieru Wang, Zhiming Ao, and Yujou Wang. The relationship between green bonds and conventional financial markets: Evidence from quantile-on-quantile and quantile coherence approaches. *Economic Modelling*, 116:106038, 2022.

[63] Jiayu Jin, Liyan Han, Lei Wu, and Hongchao Zeng. The hedging effect of green bonds on carbon market risk. *International Review of Financial Analysis*, 71:101509, 2020.

[64] Sakis Kotsantonis and George Serafeim. Four things no one will tell you about ESG data. *Journal of Applied Corporate Finance*, 31(2):50–58, 2019.

[65] Kenneth F Kroner and Victor K Ng. Modeling asymmetric comovements of asset returns. *The Review of Financial Studies*, 11(4):817–844, 1998.

[66] Kenneth F Kroner and Jahangir Sultan. Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, 28(4):535–551, 1993.

[67] Philipp Krueger, Zacharias Sautner, and Laura T Starks. The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111, 2020.

[68] Haohua Li, Elie Bouri, Rangan Gupta, and Libing Fang. Return volatility, correlation, and hedging of green and brown stocks: is there a role for climate risk factors? *Journal of Cleaner Production*, page 137594, 2023.

[69] Shiqing Ling and Michael McAleer. Asymptotic theory for a vector ARMA-GARCH model. *Econometric Theory*, 19(2):280–310, 2003.

[70] Karl V Lins, Henri Servaes, and Ane Tamayo. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *Journal of Finance*, 72(4):1785–1824, 2017.

[71] Jian Liu, Yue Hu, Li-Zhao Yan, and Chun-Ping Chang. Volatility spillover and hedging strategies between the European carbon emissions and energy markets. *Energy Strategy Reviews*, 46:101058, 2023.

[72] Yuliya Lovcha, Alejandro Perez-Laborda, and Iryna Sikora. The determinants of CO2 prices in the EU emission trading system. *Applied Energy*, 305:117903, 2022.

[73] Benjamin Johannes Lutz, Uta Pigorsch, and Waldemar Rotfuß. Nonlinearity in cap-and-trade systems: The EUA price and its fundamentals. *Energy Economics*, 40:222–232, 2013.

[74] Vicente Medina, Ángel Pardo, and Roberto Pascual. The timeline of trading frictions in the european carbon market. *Energy Economics*, 42:378–394, 2014.

[75] Irene Monasterolo and Luca De Angelis. Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. *Ecological Economics*, 170:106571, 2020.

[76] Muhammad Abubakr Naeem, Elie Bouri, Mabel D Costa, Nader Naifar, and Syed Jawad Hussain Shahzad. Energy markets and green bonds: A tail dependence analysis with time-varying optimal copulas and portfolio implications. *Resources Policy*, 74:102418, 2021.

[77] Rana Muhammad Nasir and Feng He. Do clean energy stocks and sub-sectors hedge China economic policy uncertainty: New evidence from wavelet analysis. *Journal of Cleaner Production*, 429:139385, 2023.

[78] Aneesh Raghunandan and Shiva Rajgopal. Do ESG funds make stakeholder-friendly investments? *Review of Accounting Studies*, 27(3):822–863, 2022.

[79] Juan C Reboredo. Modeling EU allowances and oil market interdependence. Implications for portfolio management. *Energy Economics*, 36:471–480, 2013.

[80] Juan C Reboredo. Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, 74:38–50, 2018.

[81] Ghulame Rubbaniy, Aktham Maghyereh, Walid Cheffi, and Ali Awais Khalid. Dynamic connectedness, portfolio performance, and hedging effectiveness of the hydrogen economy, renewable energy, equity, and commodity markets: Insights from the COVID-19 pandemic and the russia-ukraine war. *Journal of Cleaner Production*, page 142217, 2024.

[82] Perry Sadorsky. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics*, 34(1):248–255, 2012.

[83] Francesco Scotti, Andrea Flori, Riccardo Crescenzi, and Fabio Pammolli. Demand-pull and technology-push environmental innovation: A policy mix analysis on EU ETS and EU Cohesion Policy. *Climate Policy*, pages 1–18, 2024.

[84] Syed Jawad Hussain Shahzad, Elie Bouri, David Roubaud, and Ladislav Kristoufek. Safe haven, hedge and diversification for G7 stock markets: Gold versus Bitcoin. *Economic Modelling*, 87:212–224, 2020.

[85] Rajesh Sharma, Muhammad Shahbaz, Pradeep Kautish, and Xuan Vinh Vo. Diversified imports as catalysts for ecological footprint: examining the brics experience. *Environment, Development and Sustainability*, 25(4):3153–3181, 2023.

[86] Erkan Ustaoglu. Diversification, hedge, and safe-haven properties of gold and bitcoin with portfolio implications during the Russia–Ukraine war. *Resources Policy*, 84:103791, 2023.

[87] Joonas Vaissalo, Anupam Dutta, Elie Bouri, and Nehme Azoury. Carbon emission allowances and nordic electricity markets: Linkages and hedging analysis. *Energy Reports*, 12:2845–2854, 2024.

[88] Jin Boon Wong and Qin Zhang. Impact of carbon tax on electricity prices and behaviour. *Finance Research Letters*, 44:102098, 2022.

[89] Lu Yang and Shigeyuki Hamori. The role of the carbon market in relation to the cryptocurrency market: Only diversification or more? *International Review of Financial Analysis*, 77:101864, 2021.

[90] Ellen Pei-yi Yu, Bac Van Luu, and Catherine Huirong Chen. Greenwashing in environmental, social and governance disclosures. *Research in International Business and Finance*, 52:101192, 2020.

[91] Hua Zhang, Jinyu Chen, and Liuguo Shao. Dynamic spillovers between energy and stock markets and their implications in the context of COVID-19. *International Review of Financial Analysis*, 77:101828, 2021.

[92] Pengfei Zhu, Tuantuan Lu, Yue Shang, Zerong Zhang, and Yu Wei. Can China's national carbon trading market hedge the risks of light and medium crude oil? A comparative analysis with the European carbon market. *Finance Research Letters*, 58:104291, 2023.

A Nomenclature table

Table A1: Nomenclature table listing all the abbreviations and parameters of the models used throughout the manuscript.

Symbol abbreviation	Description
GHGs	Greenhouse gases
SDGs	Sustainable Development Goals
CO_2	Carbon dioxide
EU ETS	European Union Emissions Trading System: A cap-and-trade system
EUAs	European Union Allowances: Tradable units in the EU ETS
ESG	Environmental, Social, and Governance score
COP	Conference of Parties
VIX	CBOE Volatility Index: Measures market volatility
ERIX	European Renewable Energy Index
CEA	China's carbon emission allowance
ECO	WilderHill Clean Energy Index
OVX	CBOE Crude Oil Volatility Index
BTC	Bitcoin
MSCI EM	MSCI Emerging Markets Eastern Europe ex Russia
Gov Bond	Government bonds
Corp Bond	Corporate bonds
Std. dev.	Standard deviation
SR	Sharpe ratio
DCC-GARCH	Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity model
r_t	$N \times 1$ vector of asset returns at time t
$\mu_t(\theta)$	$N \times 1$ mean vector of asset returns
u_t	$N \times 1$ vector of standardized residuals
H_t	$N \times N$ conditional covariance matrix of asset returns
D_t	$N \times N$ diagonal matrix of square root conditional variances
R_t	$t\frac{N(N-1)}{2}$ time-varying conditional correlation matrix
Q_t	$N \times N$ symmetric positive-definite matrix of standardized residuals
q_{ijt}	Time-varying conditional correlations between asset i and asset j at time t
h_{ijt}	Conditional covariance between asset i and asset j at time t
HR (δ_{ijt})	Hedge ratio: the cost of hedging a €1 long position in asset i with a €δ_{ijt} short position in asset j at time t
OW (w_{ijt})	Optimal weight of asset i in a portfolio with asset j at time t
HE_i	Hedge effectiveness: Percentage reduction in the variance of the unhedged portfolio due to asset i
Var_{unhedged}	Variance of the unhedged portfolio
Var_{hedged}	Variance of the hedged portfolio using hedge ratios or optimal weights

B EU ETS description

Table B1: The descriptive statistics about the accounting and emissions variables set at the firm level collected in the dataset are shown. Data related to emissions are expressed in tCO_2 eq.

	Q1	median	Q3	mean	Source
Total assets	418,249,500	2,213,109,587	10,514,985,776	16,264,014,345	Refinitiv
Market cap	238,602,097	1,117,600,000	7,935,555,423	10,026,957,735	Refinitiv
ESG score	49	64	77	61	Refinitiv
Scope 1 emissions	300,480	1,238,041	3,918,582	10,687,470	Refinitiv
Scope 2 emissions	231,769	545,235	1,726,128	1,584,348	Refinitiv
Total verified emissions	18,540	69,633	487,368	975,640	EUTL

C EU ETS index construction

Table C1: List of the ten largest EU ETS-listed companies in decreasing order by total assets for each phase and overall.

Phase I	Phase II	Phase III	Phase IV	Total
Mercedes Benz Group AG	Electricite De France SA	Volkswagen AG	Volkswagen AG	Volkswagen AG
Electricite De France SA	Volkswagen AG	Bayerische Motoren Werke AG	Mercedes Benz Group AG	Electricite De France SA
Volkswagen AG	E ON SE	Eni SpA	Bayer AG	Mercedes Benz Group AG
E ON SE	Mercedes Benz Group AG	Equinor ASA	E ON SE	Bayerische Motoren Werke AG
Eni SpA	Bayerische Motoren Werke AG	Bayer AG	BASF SE	E ON SE
Bayerische Motoren Werke AG	ArcelorMittal SA	ArcelorMittal SA	ArcelorMittal SA	Eni SpA
ArcelorMittal SA	Equinor ASA	BASF SE	EnBW Energie Baden Wuerttemberg AG	Equinor ASA
BASF SE	BASF SE	GSK plc	Compagnie de Saint Gobain SA	Bayer AG
Compagnie de Saint Gobain SA	GSK plc	AstraZeneca PLC	Merck KGaA	ArcelorMittal SA
GSK plc	Compagnie de Saint Gobain SA	Compagnie de Saint Gobain SA	CEZ as	BASF SE

D Portfolio asset classes

Table D1: The description of assets as defined in Thomson Reuters Eikon.

Asset	Contract	Description
Bitcoin	CUSDBTC	USD to Bitcoin Crypto
Brent Oil	LCOc1	ICE - Brent Oil TRc1
Corporate Bond	SPEZICE	S&P Eurozone Investment Grade Corporate Bond Index
EUA	CFI2Zc1	ICE ENDEX - European Union Allowance
Gold	NGCC.01	CMX-Gold 100 Ounce TRC1
Government Bond	SPSFIEZ	S&P Eurozone Developed Sovereign Bond Index
Green Bond	SPGREUR	S&P Green Bond Index
MSCI Eastern Europe ex Russia	MSEEXR$	MSCI EM Eastern Europe excluding Russia USD
MSCI Europe	MSEROP$	MSCI Europe USD
Renewable Energy	RENEEEU	European Renewable Energy Index

E Empirical Results

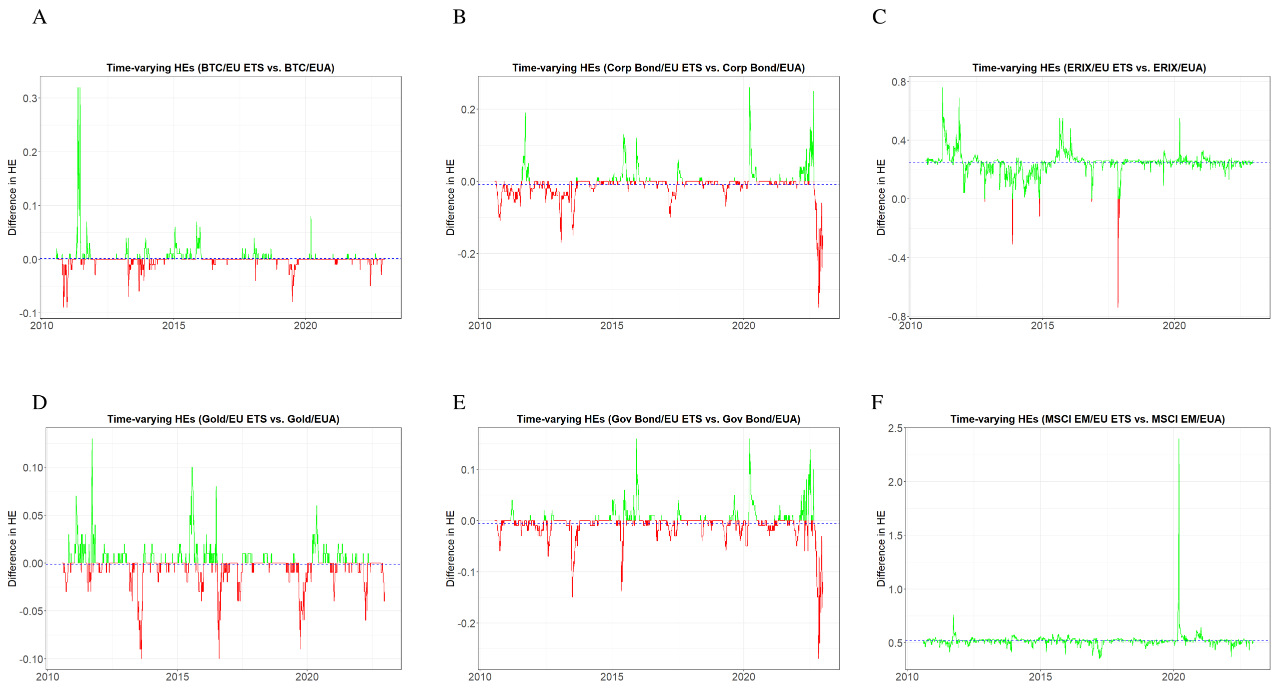

Figure E1: Difference in the time-varying HEs of the EU ETS index vs. other assets and EUA vs. other assets. The plot illustrates the difference in time-varying HE between EU ETS indices and other assets (including Bitcoin, corporate bonds, ERIX, government bonds, gold, and MSCI EM), and between EUA and other assets. A positive difference, indicating that the EU ETS index provides superior hedge effectiveness compared to EUA, is highlighted in green, while a negative difference is shown in red. The dashed horizontal blue line represents the mean of the HE difference over time.