Portfolio hedging through a novel equity index based on the verified emissions of EU ETS-regulated firms

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Abstract

We build an equity index based on EU ETS-regulated listed firms. The weights of our index reflect the cross-sectional heterogeneity in the firms' environmental performances measured in terms of verified rather than estimated or self-reported emissions. By using a DCC-GARCH model, we estimate optimal weights and assess the hedge effectiveness of the EU ETS index across multiple asset classes. The index provides robust hedging benefits, particularly during Phases III and IV of the EU ETS, aligning with stricter environmental policies. Portfolio optimization techniques show that incorporating the EU ETS index enhances risk-adjusted performance. Our findings offer actionable insights for investors seeking to minimize financial risks.

Keywords: EU ETS index; verified emissions; optimal weights; hedge effectiveness; portfolio strategies.

1 Introduction

Significant investments are necessary to drive the green transition. Consequently, market participants are increasingly allocating capital to firms developing clean technologies that support carbon abatement. This shift toward low-carbon markets helps investors limit technological risks linked to stranded assets (Campiglio, 2016) and manage climate risk influencing stock returns (Ardia et al., 2023). However, despite the growing interest in sustainable investments, carbon-intensive assets still represent a substantial portion of investors' portfolios (Monasterolo and De Angelis, 2020).

Moreover, investors tend to avoid significant portfolio rebalancing or complete asset liquidation within short-term horizons, therefore a viable solution to manage climate risks involves the identification of assets that offer sufficient hedging properties. Investors typically rely on ESG scores to identify sustainable firms (Lins et al., 2017, Albuquerque et al., 2019). Nevertheless, this choice brings attention to the reliability issues of the ESG scores. First, ESG agencies have developed their rating systems with specific characteristics that are not fully disclosed and often provide conflicting evaluations on the same companies (Billio et al., 2021), particularly regarding the environmental dimension (Gibson Brandon et al., 2021).

Second, greenwashing issues can affect ESG scores (Yu et al., 2020). Lastly, historical analyses based on recent ESG scores may not be reliable due to frequent recalculations[1]

In response to these challenges, our paper introduces a novel equity index capturing the cross-sectional heterogeneity of firms' environmental performance. Our index includes listed stocks of companies regulated by the European Union Emissions Trading System (EU ETS), which covers carbon-intensive industries, such as manufacturing, energy, mining, and quarrying. We weight stocks in our index proportionally to firms' environmental performance, calculated as the negative logarithm of the ratio between their verified emissions during a compliance period and total assets.

We focus on the EU ETS for several reasons. First, the EU ETS is the cornerstone of the European policy to enhance carbon abatement, covering around 40-45% of total greenhouse gas emissions in Europe (European Commission, 2023), and whose trade of carbon allowances accounts for approximately 90% of global carbon market trading as of 2020.[2]

Second, the EU ETS includes large emitters expected to respond actively to environmental-related events, making them a relevant sample for testing market reactions. For instance, EU ETS firms have been shown to effectively reduce emissions (Bayer and Aklin, 2020) and drive innovation in cleaner technologies (Haites et al., 2024). However, some inefficiencies contribute to their cross-sectional heterogeneity, such as the role of investment and carbon leakage (De Beule et al., 2022), episodes of carbon price bubbles related to energy and environmental policy announcements (Creti and Joëts, 2017), market spillovers from energy commodities (Flori, 2024), and the limited firm participation in allowance trading for certain sectors (Betz and Schmidt, 2016) or during surrendering months when compliance is immediate and prices are predictably high (Borri et al., 2024).

Lastly, EU ETS firms must disclose their emissions data, which are verified by third parties. This approach contrasts with other companies, whose emissions data (e.g., Scope 1, 2, and 3) are typically self-reported or estimated by external data vendors, each presenting notable limitations. Self-reported data are often produced voluntarily without a consistent legal framework, raising concerns about their accuracy and reliability (Benchora and Galanti, 2024). Similarly, emissions estimates from alternative data vendors often show only moderate correlation, highlighting concerns about the validity of these proprietary estimation methods, which heavily rely on assumptions related to business models and industry-level factors (Busch et al., 2022). In addition, analyses based on unscaled emissions could lead to misleading conclusions, as they might not accurately represent firms' true environmental performances (Aswani et al., 2024), fueling a heated debate. For example, some studies indicate that unscaled vendor-estimated emissions and emissions growth (Bolton and Kacperczyk, 2021, 2023), as well as toxic emission intensity (Hsu et al., 2023), are positively correlated with stock returns. However, the forward-looking nature of these emissions estimates tends to overstate the carbon premium in ex-ante returns. When adjustments are made to account for the data release lag and emissions are scaled by sales, the relationship with stock returns becomes globally insignificant and turns negative in the US market (Zhang, 2024). Similarly, unscaled verified emissions data have been linked to

[1]For instance, Eikon recomputes ESG scores weekly, and changes in values for any of the previous five years are expected: `https://www.lseg.com/content/dam/data-analytics/en_us/documents/methodology/lseg-esg-scores-methodology.pdf`.

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

negative stock returns among EU ETS firms (Benchora and Galanti, 2024).

We leverage the EU ETS index by calculating its optimal weights and evaluating its hedge effectiveness within a diversified portfolio. Our approach is informed by prior research demonstrating that low-carbon assets offer effective hedges against climate risk (Andersson et al., 2016, Cepni et al., 2022, Dutta et al., 2023, Li et al., 2023). Further, we assess how the hedging properties of our index have varied across different Phases of EU ETS (Phase II (2008-2012), III (2013-2020), and IV (2021-2030)) characterized by progressively more stringent environmental requirements. To do so, we consider several financial approaches to estimate the risk-adjusted performance of equally-weighted, mean-variance, minimum connectedness, and maximum decorrelation portfolios (Broadstock et al., 2022), either including all assets or excluding our EU ETS index. The results indicate that incorporating the EU ETS index generally offers hedging opportunities and improves risk-adjusted performance, especially during Phases II and IV.

2 Data

We collected data from the European Union Transaction Log, providing annual verified emissions data for EU ETS installations. Each installation is required to have an operator holding account (OHA) to manage allowances and meet emissions verification and surrender obligations. OHAs are linked to Account Holders, namely the firms owning and managing the installations. Our analysis consolidates data at the account holder level, resulting in a dataset of 203 listed companies (Table A2 reports the largest ones in terms of total assets). We integrate financial and accounting data based on Refinitiv Eikon to build a novel dataset covering both the financial and environmental performances of listed EU ETS-regulated firms (see Table A1 for descriptive statistics). As shown in Figure 1, the index is largely dominated by manufacturing firms (77%), but it is noteworthy to highlight the growing presence of energy firms over time (from 14% to 20%). This shift is largely driven by increasingly stringent EU ETS regulations targeting the energy sector, which have contributed to its expanding share within our index. The weight of other industries (e.g., mining) remains constant at about 7%.

To test the hedging properties of the EU ETS index, we examined the natural logarithmic returns of various asset classes, including European developed (MSCI Europe), emerging (MSCI Emerging Markets Eastern Europe), and green (ERIX) stocks; European government and corporate bonds; a green bond index; commodities (Brent oil and gold); Bitcoin; and European Union Allowances (EUAs). Table A3 lists the specific contracts. Our sample period spans from July 20, 2010, to December 31, 2022.

Table 1 presents the descriptive statistics and results of several statistical tests. The return distribution for these assets is left-skewed, and with the exception of green bonds, the data exhibit a leptokurtic distribution. Additionally, returns are non-normal and stationary, with significant serial autocorrelations.

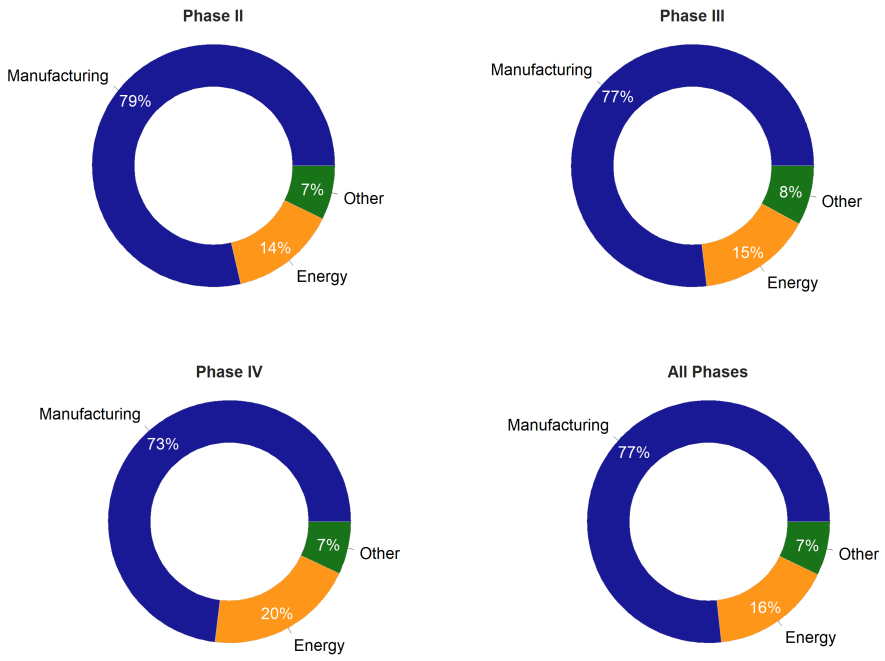

Figure 1: Sector composition of the EU ETS index divided by EU ETS phases.

	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

Table 1: JB and SW rows report the p-value of Shapiro-Wilk and Jarque Bera tests. ADF and PP denote the p-value of the Augmented Dickey-Fuller and Phillips-Perron unit root tests. LB (l) is the Ljung-Box p-value for up to the l^{th} order serial correlation.

3 Methodology

Following previous studies (e.g., Sadorsky 2012, Basher and Sadorsky 2016, Ahmad et al. 2018), we employ a DCC-GARCH (1,1) to study time-varying correlations between returns.

We estimate the optimal portfolio weights as in Kroner and Ng (1998). Precisely, w_{ijt} is the weight of the asset i in a €1 portfolio of assets i and j, computed as:

$$w_{ijt} = \frac{h_{jjt} - h_{ijt}}{h_{iit} - 2h_{ijt} + h_{jjt}} \tag{1}$$

with h_{ijt} being the conditional covariance of assets i and j as estimated from the DCC-GARCH (1,1) model. We impose that only long positions are allowed.

We employ Ederington (1979)'s method to estimate the hedge effectiveness (HE_i) of the optimal weights in relation to asset i, which represents the percentage reduction in the variance of the unhedged portfolio. In formula:

$$HE_i = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{2}$$

with $Var_{unhedged}$ denoting the variance of the unhedged strategy, while Var_{hedged} indicating the variance of the hedged portfolio.

4 Empirical results

Figure 2 illustrates the time-varying optimal weights (OWs) for pairs of assets including the EU ETS index, while Table 2 reports the corresponding average OWs and hedge effectiveness (HE). Notably, optimal weights are event-dependent. For instance, we observe a significant spike in the weight of gold (0.920) in March 2020, coinciding with the implementation of COVID-19 restrictions in Europe.

Optimal portfolios tend to overweight bonds, but the HE is particularly low or slightly negative. The weight of the EU ETS index against bonds increases during significant events, such as the Russia-Ukraine war and the United Nations Climate Change Conferences (COP). For instance, the weights of green bonds tend to decrease during COP19 and COP21 (Paris Agreement), while those of Government bonds during COP21, COP22, and COP25.

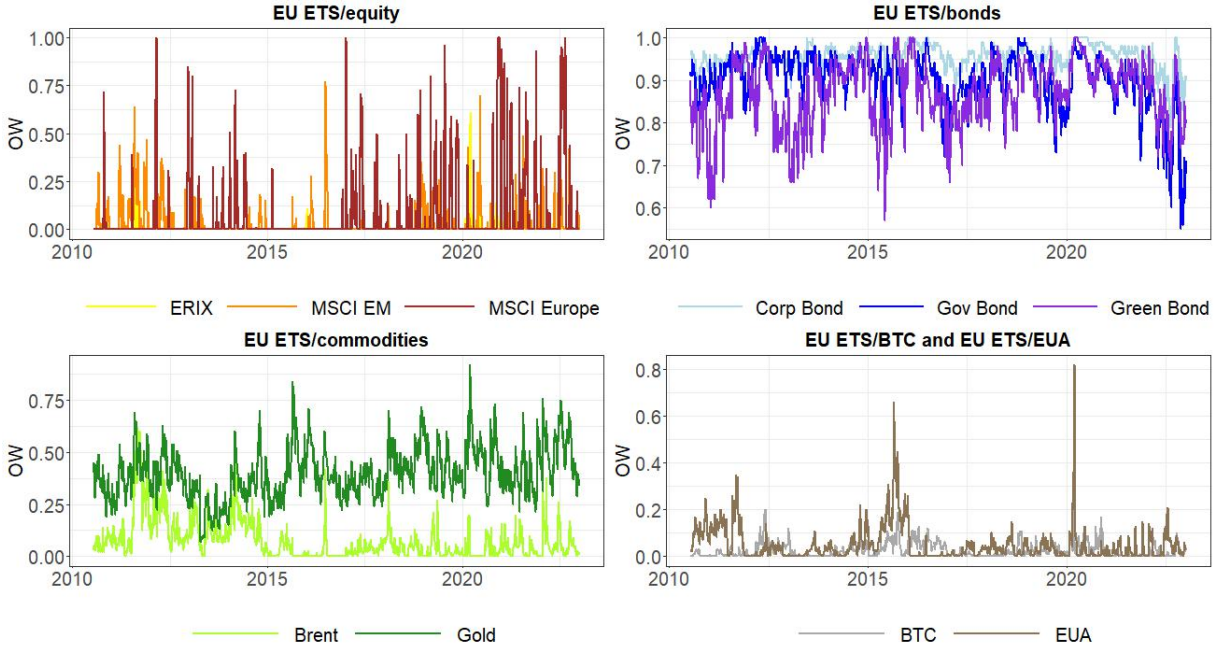

Figure 2: Time-varying OWs.

Conversely, the optimal weight of the EU ETS index rises when dealing with more volatile asset classes. For instance, the Bitcoin/EU ETS portfolio has an overage OW of 0.025, with the portfolio providing effective hedging (HE: 0.980). For instance, previous studies show how low-carbon markets offer hedging potential for Bitcoin (Naeem and Karim, 2021). Notably, the MSCI Europe/EU ETS portfolio shows the highest variations among all pairs, ranging from 0.033 (Phase II) to 0.157 (Phase

IV). Our EU ETS index may also be overweighted when considering a green equity index, such as ERIX (OW: 0.006; HE: 0.838).

	Phase II		Phase III		Phase IV		Total	
	OW	HE	OW	HE	OW	HE	OW	HE
Brent/EU ETS	0.153 [0.143, 0.163]	0.836	0.058 [0.055, 0.061]	0.862	0.054 [0.049, 0.059]	0.864	0.076 [0.073, 0.079]	0.857
BTC/EU ETS	0.024 [0.021, 0.026]	0.979	0.029 [0.028, 0.030]	0.980	0.011 [0.01, 0.013]	0.980	0.025 [0.024, 0.026]	0.980
Corp Bond/EU ETS	0.949 [0.948, 0.950]	-0.002	0.964 [0.963, 0.965]	0.005	0.940 [0.936, 0.943]	-0.059	0.957 [0.956, 0.958]	-0.007
ERIX/EU ETS	0.007 [0.005, 0.009]	0.838	0.005 [0.004, 0.007]	0.839	0.011 [0.009, 0.014]	0.838	0.006 [0.005, 0.008]	0.838
EUA/EU ETS	0.075 [0.069, 0.08]	0.922	0.046 [0.043, 0.050]	0.923	0.032 [0.029, 0.035]	0.929	0.049 [0.047, 0.052]	0.923
Gold/EU ETS	0.387 [0.380, 0.394]	0.566	0.390 [0.385, 0.396]	0.551	0.448 [0.437, 0.459]	0.558	0.399 [0.395, 0.403]	0.555
Gov Bond/EU ETS	0.921 [0.918, 0.924]	0.052	0.912 [0.910, 0.914]	0.039	0.833 [0.825, 0.841]	-0.106	0.901 [0.899, 0.903]	0.018
Green Bond/EU ETS	0.842 [0.835, 0.849]	-0.044	0.875 [0.872, 0.879]	0.009	0.873 [0.868, 0.879]	0.019	0.868 [0.866, 0.871]	0.000
MSCI EM/EU ETS	0.061 [0.053, 0.069]	0.583	0.019 [0.016, 0.022]	0.594	0.035 [0.028, 0.042]	0.590	0.030 [0.027, 0.033]	0.591
MSCI Europe/EU ETS	0.033 [0.022, 0.043]	0.341	0.061 [0.054, 0.068]	0.334	0.157 [0.134, 0.18]	0.305	0.071 [0.065, 0.077]	0.330

Table 2: OW represents the average weight the left asset should be assigned in the portfolio with the EU ETS index (95% confidence intervals are in square brackets). HE is the average hedge effectiveness of the EU ETS index.

The HEs tend to slightly increase for most pairs during Phase III compared to Phase II due to progressively more stringent carbon requirements. For instance, during Phase III auctioning became the default method for allocating allowances (57% of total allocations), replacing the grandfathering approach. Additionally, during this phase, a "back-loading" mechanism was employed to address the surplus of allowances, while a linear reduction factor of 1.74% was established, aimed at achieving a minimum 20% reduction in emissions by 2020 compared to 1990 levels. Similar patterns are observed even in Phase IV, when more stringent regulatory changes concerned the growth of the annual linear reduction factor of allowances raised to 2.2% and the implementation of the Market Stability Reserve in January 2019 aiming to neutralize the surplus of allowances.

The variations in the portfolio variances discussed in Table 2 include both the systematic and idiosyncratic components of variability. We show in Table 3 how the proposed hedging strategies do not systematically alter the systematic component. Specifically, for each asset class, we consider the hedged and unhedged portfolios and compute the differences in the betas of the Fama-French Five-Factor European Equity Model (Fama and French, 2016), interpreted as the exposures to the systematic, non-diversifiable components of risk. Panel A shows the results related to regression models including only the Fama-French factors. In Panel B, we also control for the VSTOXX, the Deutsche Bank G10 Currency Trade Index, the EURIBOR 1M, 3M, 6M, 12M, the Interest Rate Swap 1Y, 2Y, 5Y, 10Y, the S&P GSCI Precious Metal, the S&P GSCI Energy, and the Credit Default Swap iTraxx Europe 5Y.

The inclusion of the EU ETS index alters the factor loadings, either amplifying or diminishing the sensitivities, depending on the asset class and factor. For instance, the sensitivity to overall market movements is reduced for ERIX and MSCI Europe, while it increases for Brent oil, gold, bonds, and MSCI EM. Similar patterns are observed for the other risk factors. Although the hedged portfolios (except those with bonds) are associated with improved hedge effectiveness (Table 2), such varying effects suggest that the hedging strategies must be tailored to the unique characteristics and goals of each portfolio. Indeed, changes in the variance of the hedged portfolios result from the combined effects on idiosyncratic variability and exposures to multiple systematic risk components.

Portfolio managers can use previous insights to optimize hedging strategies. We investigate the

	Panel A					Panel B				
	MKT	SMB	HML	RMW	CMA	MKT	SMB	HML	RMW	CMA
Brent/EU ETS	0.203***	-0.033	-0.909***	-0.988***	-0.165	0.130	-0.276*	-0.878***	-0.928***	-0.116
	(0.077)	(0.133)	(0.168)	(0.224)	(0.228)	(0.088)	(0.145)	(0.165)	(0.215)	(0.208)
BTC/EU ETS	0.184	-0.429	0.775**	0.697	-0.100	0.185	-0.379	0.807**	0.784	0.020
	(0.171)	(0.290)	(0.341)	(0.503)	(0.556)	(0.195)	(0.294)	(0.344)	(0.504)	(0.555)
Corp Bond/EU ETS	0.021***	-0.001	0.008	-0.005	-0.007*	0.018***	0.001	0.008	-0.004	-0.008**
	(0.002)	(0.003)	(0.005)	(0.008)	(0.004)	(0.002)	(0.003)	(0.005)	(0.008)	(0.004)
ERIX/EU ETS	-0.360***	-0.153*	0.651***	0.891***	0.481***	-0.377***	-0.192**	0.656***	0.894***	0.482***
	(0.043)	(0.086)	(0.127)	(0.177)	(0.176)	(0.047)	(0.094)	(0.127)	(0.177)	(0.174)
EUA/EU ETS	0.036	-0.271*	-0.306*	0.244	0.439	0.0002*	-0.206	-0.307*	0.226	0.424
	(0.061)	(0.146)	(0.179)	(0.277)	(0.280)	(0.068)	(0.148)	(0.177)	(0.274)	(0.281)
Gold/EU ETS	0.336***	-0.043	0.134***	-0.169**	0.005	0.287***	-0.023	0.157***	-0.141**	-0.008
	(0.023)	(0.037)	(0.050)	(0.073)	(0.072)	(0.023)	(0.039)	(0.049)	(0.072)	(0.071)
Gov Bond/EU ETS	0.048***	0.010	0.029**	0.019	0.004	0.042***	0.017	0.029**	0.020	0.001
	(0.005)	(0.007)	(0.013)	(0.020)	(0.009)	(0.005)	(0.007)	(0.013)	(0.019)	(0.009)
Green Bond/EU ETS	0.063***	0.013	0.021**	-0.009	0.009	0.052***	0.011	0.024**	-0.004	0.007
	(0.006)	(0.008)	(0.011)	(0.017)	(0.011)	(0.006)	(0.008)	(0.010)	(0.016)	(0.010)
MSCI EM/EU ETS	0.126***	0.331***	-0.001	0.208**	0.268***	0.195***	0.253***	-0.022	0.182*	0.283***
	(0.040)	(0.049)	(0.063)	(0.103)	(0.088)	(0.041)	(0.049)	(0.059)	(0.096)	(0.084)
MSCI Europe/EU ETS	-0.077***	0.586***	0.280***	0.129***	-0.052*	-0.073***	0.558***	0.281***	0.130***	-0.051*
	(0.013)	(0.027)	(0.028)	(0.041)	(0.030)	(0.014)	(0.024)	(0.027)	(0.038)	(0.031)

Table 3: Difference in the Fama and French (2016) Five Factors European Equity Model's betas (Hedged vs. Unhedged portfolios). *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

performance of portfolio optimization strategies alternatively applied to all assets or excluding the proposed EU ETS index (see Table B1 for details on assets' performance). The results are summarized in Table 4.

During Phase II, portfolios that comprise our EU ETS index show better return and risk-adjusted indicators in three cases out of four. Specifically, the mean-variance (MV) portfolio is the one whose performance in terms of Sharpe ratio (SR) and Omega ratio benefits the most. Notably, the complete maximum decorrelation (Max Dec) portfolio achieves the highest SR (1.142) and Omega (123.711%), while the MV significantly reduces value at risk (VaR), expected shortfall (ES), maximum drawdown (DD), and pain index (PI).

In Phase III, the inclusion of the EU ETS index enhances the MV portfolio's SR and Omega, whereas the risk-adjusted performance of other portfolios experiences a slight decline. Still, the complete portfolios ensure lower VaR, ES, and PI (excluding the Max Dec portfolio).

During Phase IV, the complete portfolios generally show higher SR and Omega, except for the Max Dec portfolio. For instance, the SRs for the equally-weighted (EW) and minimum connectedness (Min Conn) strategies increase from 0.109 and 0.186, to 0.127 and 0.239, respectively. Similarly, the MV portfolio's Omega increases from 68.426% to 68.706% while also reducing the VaR (from -0.402% to -0.400%) and PI (from 5.574% to 5.449%). Importantly, the MV portfolios display negative returns as they assign a higher weight to bond indices, adversely affected by the European Central Bank's aggressive tightening cycle during 2022.

Phase	Strategy	Mean (%)	Median (%)	Std. dev. (%)	SR	VaR (%)	ES (%)	DD (%)	Omega (%)	PI (%)
Phase II	EW	0.051	0.027	0.958	0.845	-1.518	-2.435	34.589	116.125	17.283
	EW (without ETS)	0.056	0.020	1.010	0.873	-1.578	-2.505	35.373	116.783	17.886
	Min Conn	0.085	0.058	1.302	1.031	-1.937	-2.914	41.404	120.619	22.706
	Min Conn (without ETS)	0.080	0.059	1.306	0.968	-1.983	-3.088	42.541	119.093	23.092
	Max Dec	0.102	0.098	1.414	1.142	-2.144	-3.565	44.169	123.711	22.839
	Max Dec (without ETS)	0.102	0.091	1.418	1.141	-2.148	-3.554	44.169	123.655	22.842
	MV	0.009	0.014	0.125	1.126	-0.206	-0.308	4.950	120.613	1.071
	MV (without ETS)	0.007	0.010	0.125	0.908	-0.207	-0.305	5.634	116.288	1.387
Phase III	EW	0.053	0.053	0.959	0.885	-1.575	-3.961	30.863	118.000	4.415
	EW (without ETS)	0.057	0.059	1.012	0.894	-1.642	-3.983	30.433	118.276	4.597
	Min Conn	0.077	0.089	1.290	0.949	-2.066	-4.551	33.813	119.377	6.416
	Min Conn (without ETS)	0.081	0.087	1.352	0.950	-2.124	-4.734	32.840	119.804	6.849
	Max Dec	0.090	0.097	1.425	1.001	-2.163	-4.409	31.001	121.471	6.934
	Max Dec (without ETS)	0.091	0.094	1.428	1.009	-2.168	-4.418	31.001	121.591	6.919
	MV	0.004	0.010	0.132	0.463	-0.224	-0.687	7.185	108.867	1.426
	MV (without ETS)	0.004	0.010	0.132	0.427	-0.224	-0.687	7.185	108.128	1.513
Phase IV	EW	0.006	0.048	0.812	0.127	-1.404	-2.168	21.494	102.170	6.311
	EW (without ETS)	0.006	0.029	0.838	0.109	-1.444	-2.231	21.727	101.873	6.662
	Min Conn	0.016	0.058	1.083	0.239	-1.837	-2.838	23.564	104.164	7.456
	Min Conn (without ETS)	0.013	0.048	1.103	0.186	-1.872	-2.911	24.661	103.223	8.027
	Max Dec	0.011	0.019	0.981	0.177	-1.653	-2.440	22.579	103.003	6.638
	Max Dec (without ETS)	0.012	0.019	0.988	0.191	-1.663	-2.448	22.579	103.247	6.645
	MV	-0.030	-0.005	0.227	-2.084	-0.400	-0.617	15.967	68.706	5.449
	MV (without ETS)	-0.030	-0.009	0.228	-2.118	-0.402	-0.613	16.282	68.426	5.574
Total	EW	0.045	0.047	0.937	0.770	-1.534	-3.467	34.589	115.082	7.627
	EW (without ETS)	0.048	0.044	0.985	0.781	-1.595	-3.499	35.373	115.386	7.936
	Min Conn	0.069	0.076	1.262	0.866	-1.999	-4.004	41.404	117.221	10.366
	Min Conn (without ETS)	0.070	0.078	1.305	0.847	-2.049	-4.216	42.541	117.041	10.744
	Max Dec	0.080	0.086	1.361	0.927	-2.065	-4.012	44.169	119.308	10.411
	Max Dec (without ETS)	0.080	0.086	1.365	0.934	-2.071	-4.016	44.169	119.405	10.403
	MV	-0.001	0.009	0.150	-0.061	-0.258	-0.633	15.967	98.883	2.004
	MV (without ETS)	-0.001	0.008	0.151	-0.127	-0.259	-0.629	16.282	97.691	2.142

Table 4: Odd rows represent the performance of the considered portfolio strategies built including all assets. Even rows summarize the performance of the same strategies on portfolios excluding the EU ETS index.

5 Conclusions

The shift toward a low-carbon economy requires extensive structural adjustments, especially impacting companies in carbon-intensive industries whose assets are likely to become stranded. This underscores the importance of identifying financial assets that enable investors to hedge their portfolios effectively without the need for extensive rebalancing or liquidation.

This paper introduces a novel equity index based on the environmental performance of EU ETS-regulated firms. Our index demonstrates high HE against various financial assets, particularly during Phases III and IV.

By penalizing firms with poor environmental performance, our index can be a valuable tool for managing portfolio decisions in the transition to a low-carbon economy, as it may help mitigate risks associated with stranded assets. Notably, including the EU ETS index in investment portfolios tends to improve risk-adjusted performance and reduce VaR, ES, DD, and PI across various optimization strategies.

Declaration of Interest

'Declarations of interest: none'.

References

Ahmad, W., P. Sadorsky, and A. Sharma (2018). Optimal hedge ratios for clean energy equities. *Economic Modelling 72*, 278–295.

Albuquerque, R., Y. Koskinen, and C. Zhang (2019). Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science 65*(10), 4451–4469.

Andersson, M., P. Bolton, and F. Samama (2016). Hedging climate risk. *Financial Analysts Journal 72*(3), 13–32.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht (2023). Climate change concerns and the performance of green vs. brown stocks. *Management Science 69*(12), 7607–7632.

Aswani, J., A. Raghunandan, and S. Rajgopal (2024). Are carbon emissions associated with stock returns? *Review of Finance 28*(1), 75–106.

Basher, S. A. and P. Sadorsky (2016). Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. *Energy Economics 54*, 235–247.

Bayer, P. and M. Aklin (2020). The european union emissions trading system reduced co2 emissions despite low prices. *Proceedings of the National Academy of Sciences 117*(16), 8804–8812.

Benchora, I. and S. Galanti (2024). Verified carbon emissions and stock returns in the eu emissions trading system. *Energy Policy 193*, 114264.

Betz, R. and T. Schmidt (2016). Transfer patterns in Phase I of the EU Emissions Trading System: a first reality check based on cluster analysis. *Climate Policy 16*(4), 474–495.

Billio, M., M. Costola, I. Hristova, C. Latino, and L. Pelizzon (2021). Inside the ESG ratings:(dis) agreement and performance. *Corporate Social Responsibility and Environmental Management 28*(5), 1426–1445.

Bolton, P. and M. Kacperczyk (2021). Do investors care about carbon risk? *Journal of Financial Economics 142*(2), 517–549.

Bolton, P. and M. Kacperczyk (2023). Global pricing of carbon-transition risk. *The Journal of Finance 78*(6), 3677–3754.

Borri, N., Y. Liu, A. Tsyvinski, and X. Wu (2024). Inefficiencies of carbon trading markets.

Broadstock, D. C., I. Chatziantoniou, and D. Gabauer (2022). Minimum connectedness portfolios and the market for green bonds: Advocating socially responsible investment (SRI) activity. In *Applications in energy finance: The energy sector, economic activity, financial markets and the environment*, pp. 217–253. Springer.

Busch, T., M. Johnson, and T. Pioch (2022). Corporate carbon performance data: Quo vadis? *Journal of Industrial Ecology 26*(1), 350–363.

Campiglio, E. (2016). Beyond carbon pricing: The role of banking and monetary policy in financing the transition to a low-carbon economy. *Ecological Economics 121*, 220–230.

Cepni, O., R. Demirer, and L. Rognone (2022). Hedging climate risks with green assets. *Economics Letters 212*, 110312.

Creti, A. and M. Joëts (2017). Multiple bubbles in the european union emission trading scheme. *Energy Policy 107*, 119–130.

De Beule, F., F. Schoubben, and K. Struyfs (2022). The pollution haven effect and investment leakage: The case of the eu-ets. *Economics Letters 215*, 110536.

Dutta, A., E. Bouri, T. Rothovius, and G. S. Uddin (2023). Climate risk and green investments: New evidence. *Energy 265*, 126376.

Ederington, L. H. (1979). The hedging performance of the new futures markets. *Journal of Finance 34*(1), 157–170.

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

Fama, E. F. and K. R. French (2016). Dissecting anomalies with a five-factor model. *The Review of Financial Studies 29*(1), 69–103.

Flori, A. (2024). 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.

Gibson Brandon, R., P. Krueger, and P. S. Schmidt (2021). ESG rating disagreement and stock returns. *Financial Analysts Journal 77*(4), 104–127.

Haites, E., P. Bertoldi, M. König, C. Bataille, F. Creutzig, D. Dasgupta, S. de la rue du Can, S. Khennas, Y.-G. Kim, L. J. Nilsson, et al. (2024). Contribution of carbon pricing to meeting a mid-century net zero target. *Climate Policy 24*(1), 1–12.

Hsu, P.-H., K. Li, and C.-Y. Tsou (2023). The pollution premium. *The Journal of Finance 78*(3), 1343–1392.

Kroner, K. F. and V. K. Ng (1998). Modeling asymmetric comovements of asset returns. *The Review of Financial Studies 11*(4), 817–844.

Li, H., E. Bouri, R. Gupta, and L. Fang (2023). Return volatility, correlation, and hedging of green and brown stocks: is there a role for climate risk factors? *Journal of Cleaner Production*, 137594.

Lins, K. V., H. Servaes, and A. Tamayo (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *Journal of Finance 72*(4), 1785–1824.

Monasterolo, I. and L. De Angelis (2020). Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. *Ecological Economics 170*, 106571.

Naeem, M. A. and S. Karim (2021). Tail dependence between bitcoin and green financial assets. *Economics Letters 208*, 110068.

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

Yu, E. P.-y., B. Van Luu, and C. H. Chen (2020). Greenwashing in environmental, social and governance disclosures. *Research in International Business and Finance 52*, 101192.

Zhang, S. (2024). Carbon returns across the globe. *The Journal of Finance*.

A Data

	Q1	median	Q3	mean	Source
Total assets	418,249,500	2,213,109,587	10,514,985,776	16,264,014,345	Refinitiv
Total verified emissions	18,540	69,633	487,368	975,640	EUTL

Table A1: Descriptive statistics of total assets and emissions at the firm level.

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

Table A2: List of the ten largest companies in our sample in decreasing order by total assets.

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 East Europe ex Russia	MSEEXR$	MSCI EM Eastern Europe excluding Russia USD
MSCI Europe	MSEROP$	MSCI Europe USD
Renewable Energy	RENEEEU	European Renewable Energy Index

Table A3: The description of the asset classes as defined in Reuters Eikon.

B Portfolios

	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
SR (ann)	0.046	0.902	-0.448	0.091	0.277	0.270	0.299	-0.318	-0.102	-0.052	0.240
VaR (%)	-3.504	-9.043	-0.269	-3.446	-1.456	-4.911	-1.566	-0.416	-0.508	-2.287	-1.748
ES (%)	-6.598	-9.043	-0.655	-5.778	-4.090	-10.388	-3.061	-0.647	-0.775	-5.463	-4.101
DD (%)	90.844	97.158	19.358	85.413	42.292	91.209	38.767	24.705	20.634	54.983	38.143
Omega (%)	100.873	121.729	91.933	101.609	105.264	105.115	105.532	94.396	98.260	99.092	104.495
PI (%)	47.571	67.534	3.628	46.570	9.959	60.283	17.537	5.686	6.567	23.156	9.213

Table B1: Performance of single assets.