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Hedging Carbon Price Risk in Carbon-Intensive Sectors: Evidence from EU ETS-Regulated and Non-EU ETS-Regulated Firms

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Abstract

The EU Emissions Trading System (EU ETS) is the main carbon market in Europe and a key part of EU climate policy. As the European Union Allowance (EUA) prices increased over time, carbon price risk became more relevant for firms operating in carbon-intensive sectors. This has strengthened the interaction between carbon markets, energy markets, and industrial equity returns, making carbon price risk an increasingly important factor for both firms and investors.

This thesis examines the dynamic hedging relationships of EU ETS-regulated and non-EU ETS-regulated firms with EUA futures and sector-specific energy commodities within and across the following carbon-intensive sectors: Electricity, Gas, Steam and Air Conditioning Supply (NACE 35), Manufacture of Basic Metals (NACE 24), Manufacture of Other Non-Metallic Mineral Products (NACE 23), and Manufacture of Chemicals and Chemical Products (NACE 20). The analysis also examines how these relationships change across different market environments, including the introduction of the Market Stability Reserve (MSR), the COVID-19 pandemic, the 2022 European energy crisis, and the Carbon Border Adjustment Mechanism (CBAM).

A bivariate DCC-GARCH(1,1) model with Student-t innovations is estimated for thirty-two sector-asset pairs over the period from 1 January 2013 to 30 April 2026. Dynamic hedge ratios, optimal portfolio weights, and hedge effectiveness measures are obtained using the hedging assets EUA futures, TTF natural gas futures, Brent crude oil futures, Rotterdam coal futures, and gold.

The results show that carbon-equity hedging generally has limited effectiveness, but is highly regime-dependent. EU ETS-regulated sector portfolios require larger hedge ratios than non-EU ETS-regulated portfolios. The Electricity and Chemicals sectors have the highest hedge effectiveness with Brent crude oil, while the Basic Metals and Non-Metallic Minerals sectors have the highest hedge effectiveness with EUA in the full sample. Hedging relationships considerably strengthen during the COVID-19 period and coal and gold provide little hedge effectiveness throughout the sample.

The results indicate that carbon-equity hedging relationships depend on sector characteristics, EU ETS regulation, and prevailing market conditions. As carbon markets continue to expand, understanding these differences is becoming increasingly relevant for firms and investors who are exposed to carbon-intensive sectors.

Keywords: EU ETS, EUA futures, Carbon Border Adjustment Mechanism (CBAM), DCC-GARCH, Carbon hedging, Hedge effectiveness, European industrial sectors.

Abstract in Italiano

L'EU Emissions Trading System (EU ETS) è il principale mercato del carbonio in Europa e una componente importante della politica climatica dell'UE. Con l'aumento nel tempo dei prezzi delle European Union Allowances (EUA), il rischio legato al prezzo del carbonio è diventato più rilevante per le imprese operanti nei settori ad alta intensità di carbonio. Questo ha rafforzato l'interazione tra i mercati del carbonio, i mercati energetici e i rendimenti azionari industriali, rendendo il rischio legato al prezzo del carbonio un fattore sempre più importante sia per le imprese sia per gli investitori.

Questa tesi esamina le relazioni dinamiche di copertura delle imprese regolamentate e non regolamentate dall'EU ETS con le EUA e le commodity energetiche specifiche per ciascun settore all'interno e tra i seguenti settori ad alta intensità di carbonio: Electricity (NACE 35), Basic Metals (NACE 24), Non-Metallic Minerals (NACE 23) e Chemicals (NACE 20). L'analisi esamina inoltre come tali relazioni cambino in diversi contesti di mercato, tra cui l'introduzione della Market Stability Reserve (MSR), la pandemia di COVID-19, la crisi energetica europea del 2022 e il Carbon Border Adjustment Mechanism (CBAM).

Un modello bivariato DCC-GARCH(1,1) con innovazioni Student-t viene stimato per trentadue coppie settore-attività nel periodo compreso tra il 1° gennaio 2013 e il 30 aprile 2026. I rapporti di copertura dinamici, i pesi ottimali di portafoglio e le misure di efficacia della copertura sono ottenuti utilizzando come attività di copertura EUA futures, TTF natural gas futures, Brent crude oil futures, Rotterdam coal futures e oro.

I risultati mostrano che la copertura tra carbonio e azioni presenta generalmente un'efficacia limitata, ma dipende fortemente dal regime di mercato. I portafogli settoriali regolamentati dall'EU ETS richiedono rapporti di copertura più elevati rispetto alle loro controparti non regolamentate dall'EU ETS. I settori Electricity e Chemicals presentano la maggiore efficacia di copertura con il Brent crude oil, mentre i settori Basic Metals e Non-Metallic Minerals presentano la maggiore efficacia di copertura con le EUA nell'intero campione. Le relazioni di copertura si rafforzano significativamente durante il periodo del COVID-19, mentre il carbone e l'oro offrono un contributo limitato all'efficacia della copertura nell'intero campione.

I risultati evidenziano il ruolo delle caratteristiche settoriali, della regolamentazione dell'EU ETS e delle condizioni di mercato prevalenti nel determinare le relazioni di copertura tra carbonio e azioni. Con la continua espansione dei mercati del carbonio, comprendere queste differenze diventa sempre più rilevante per le imprese e gli investitori esposti a settori ad alta intensità di carbonio.

Parole chiave: EU ETS, EUA futures, Carbon Border Adjustment Mechanism (CBAM), DCC-GARCH, copertura del rischio del carbonio, efficacia della copertura, settori industriali europei.

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Introduction

Climate change has become a central issue in international policy discussions, particularly following global agreements such as the Paris Agreement, which emphasize the need to limit temperature increases and reduce greenhouse gas emissions [1]. In Europe, this has led to the adoption of market-based policy instruments aimed at reducing emissions. Consequently, the European Union Emissions Trading System (EU ETS) was established under Directive 2003/87/EC [2], and it has been operational since 2005. Through a market-based mechanism, the EU ETS aims to reduce greenhouse gas emissions by regulating facilities operating in the industrial and energy sectors [2]. It is one of the largest carbon market systems globally, comprising over 10,000 facilities and covering approximately 40% of the total greenhouse gases emitted by the European Union [3, 4].

Under the EU ETS, regulated facilities must surrender one allowance for every tonne of CO_2 emitted. As a result, firms are directly exposed to changes in EUA prices [2]. However, in the early phases of the EU ETS, the system suffered from structural imbalances due to the over-allocation of allowances [5]. To improve these imbalances and strengthen the carbon price signal, the system underwent several structural reforms. One of the main reforms was the establishment of the Market Stability Reserve (MSR), which was agreed in 2015 and officially started operating in 2019 [6]. The purpose of the MSR was to provide resilience against shocks within the carbon market through the withdrawal of surplus allowances when supply exceeds a certain threshold [7, 8]. This contributed to consistent growth in EUA prices, which rose from below €10 to above €90 from early 2018 to the beginning of 2022 [9, 10]. Such a sharp rise transformed carbon allowances into a substantive monetary risk factor for firms operating under the EU ETS [11]. Empirical evidence suggests that the effects of EUA price movements are transmitted into the equity valuations of firms in carbon-intensive sectors [12, 11]. Moreover, significant risk spillovers between carbon and energy markets are documented, with carbon price volatility affecting the returns of energy-intensive industries [13, 14]. This volatility is dependent on a set of macroeconomic drivers, including fossil fuel prices [15], financial market conditions [9], and regulatory announcements [10, 16], which directly affect the EUA prices.

Firms' exposure to carbon price risk under the EU ETS varies significantly across industrial sectors [11, 5]. The facilities regulated by the EU ETS are obliged to comply and bear the full cost of EUAs, while the unregulated companies fall outside of this scope and do not bear the costs of their emissions [2, 17]. This regulatory asymmetry causes the EU ETS-regulated and non-EU ETS-regulated listed firms operating within the same sector to exhibit different risk profiles [11]. However, the existing literature mostly examines the link between carbon prices and the stock market on a broader sector basis [14, 18] without differentiating between EU ETS-regulated and non-EU ETS-regulated firms within a given sector.

The increasing liquidity of carbon and commodity derivative markets has opened new avenues to manage sectoral financial risk [18, 13]. Demiralay et al. [18] show that dynamic risk management strategies using EUA futures decrease portfolio variances significantly and improve risk-adjusted returns. At the same time, carbon price risk cannot be solely attributed to EUA prices. For energy-intensive sectors, the equity performance depends simultaneously on the production inputs and the fossil fuel price movements, which affect EUA prices [15, 19]. This suggests that effective risk management strategies should account for the sector-specific energy cost structures alongside carbon price exposure.

This thesis contributes to the literature in several ways. First, to examine whether regulatory exposure affects hedging outcomes, separate portfolios are constructed for EU ETS-regulated and non-EU ETS-regulated firms within the same sectors. These sectors are Electricity, Gas, Steam and Air Conditioning Supply (NACE 35), Manufacture of Basic Metals (NACE 24), Manufacture of Other Non-Metallic Mineral Products (NACE 23) and Manufacture of Chemicals and Chemical Products (NACE 20), which have been chosen according to their emission shares and EU ETS activity coverage indicated in Annex I of Directive 2003/87/EC [2] [1]. The main analysis is based on a monthly rebalanced equal-weighted index approach [2]. To assess the robustness of the results, two alternative index construction approaches are also implemented, namely a stable equal-weighted index and a yearly rebalanced market-capitalization-weighted index. Second, the Dynamic Conditional Correlation GARCH (DCC-GARCH) framework is applied [20] to estimate time-varying hedge ratios and optimal portfolio weights [21] between the sector portfolios and a tailored set of hedging assets comprising the EUA futures, two sector-specific energy commodities selected based on each sector's primary production inputs, and gold as a placebo asset. Third, hedging performance is evaluated through a set of portfolio risk and performance measures. In addition to the variance-reduction criterion [22], the analysis considers Sharpe and Sortino ratios, Value-at-Risk, Expected Shortfall, Maximum Drawdown, and the Omega and Pain measures, extending the portfolio evaluation framework of Demiralay et al. [18]. This enables a direct comparison of hedging outcomes across sectors and between listed

[1] The sector selection procedure is discussed in detail in Section 3.3

[2] The sector index construction approaches are explained in detail in Section 3.4

EU ETS-regulated and non-EU ETS-regulated firms. The findings highlight that EU ETS-regulated portfolios generally require larger EUA hedge positions than comparable non-EU ETS-regulated portfolios, but this difference is less clear when hedge effectiveness is considered. The results also show that different hedging assets perform better in different sectors and periods.

This study analyzes the period from 1 January 2013 to 30 April 2026, which encompasses the entire Phase III period and a substantial portion of Phase IV of the EU ETS [23, 24]. Specifically, the analysis is conducted across six sub-periods: the Phase III Low Price period (January 2013-December 2018), the Post-MSR period (January 2019-February 2020), the COVID-19 period (March-December 2020), the Phase IV High Price period (January 2021-December 2022), the Phase IV Normalization period (January-September 2023), and the CBAM Transitional period (October 2023-April 2026) [25]. This sub-period decomposition allows the analysis of how hedging relationships evolve across different regulatory regimes and market conditions. The results reveal substantial differences in hedging relationships across sectors, hedging assets, and market regimes. It suggests that hedge effectiveness is highly influenced by sector characteristics and the current market environment.

The remaining sections of this thesis are organized as follows: Chapter 1 provides an overview of the EU ETS, including its institutional structure, historical evolution as well as the development of carbon price risk as a financial concern. Chapter 2 presents the existing academic literature on carbon market dynamics, sector-level equity exposure, and the application of multivariate GARCH models for hedging. Chapter 3 details the data sources, sector and firm selection procedures, and index construction approach. Chapter 4 presents the econometric framework, including the DCC-GARCH specification, hedge effectiveness and hedge ratio derivation, and portfolio performance metrics. Chapter 5 presents the empirical results, comparing the hedging metrics between EU ETS-regulated and non-EU ETS-regulated firms, across different hedging assets within each sector, and across the four sectors. Chapter 6 concludes the thesis with a summary of the main findings, a discussion of the study's contributions and limitations, and suggestions for future research.

Chapter 1

The EU Emissions Trading System

1.1 Overview and Design

The EU Emissions Trading System (EU ETS) has a fundamental role in the European Union's climate policy and constitutes one of the largest carbon markets globally. It was founded in 2003 with the adoption of Directive 2003/87/EC and started operating on 1 January 2005 [2]. The EU ETS operates as a cap-and-trade system, which is designed to reduce greenhouse gas emissions by setting a limit on the total emissions and allowing firms to trade emission allowances [2, 4].

Under this framework, a cap is set for the regulated installations' total amount of greenhouse gas emissions. Within this cap, firms receive or purchase emission allowances (EUAs), which grant the holder the right to emit one tonne of carbon dioxide equivalent. If firms can reduce their emissions below the amount of allowances they have bought, they can sell the excess allowances. On the contrary, the firms that emit more than their allowances are required to purchase additional allowances from the market [2].

The activities covered by the EU ETS are defined in Annex I of the Directive, and the scope of the system has been gradually expanded through legislative reforms [2, 26]. It includes combustion installations above 20 MW thermal capacity, mineral oil refineries, iron and steel production, cement, glass, ceramics, and pulp and paper manufacturing [2]. Commercial aviation within the European Economic Area has also been included in the scope since 2012 [27]. In addition, maritime transport was included in the EU ETS scope recently, with a phased implementation procedure starting from 2024 [26]. Installations that exceed the capacity thresholds specified in Annex I are required to participate in the system. However, firms with installations operating below the specified thresholds for their operations are outside the scope of the EU ETS and are not subject to compliance obligations. The installations covered by the EU ETS account for around 40% of the total emissions in the EU [3, 28].

Throughout the EU ETS's history, the allowance allocation system has undergone substantial changes. In the early stages, allowances were distributed through National Allocation Plans that were submitted by the member states [5]. This approach resulted in an over-allocation of the allowances and generated excess profits for firms without decreasing the amount of their emissions as intended [5, 4]. To address this issue, the system was changed and auctioning was introduced in Phase III through Directive 2009/29/EC [23], which became the main allocation method [29]. This change strengthened the carbon pricing signal by increasing the cost of emissions and improving the internalization of environmental externalities. Consequently, the design of the emissions allocation mechanism and the strictness of the emissions limit play a key role in shaping the dynamics of EUA pricing and the overall efficiency of the system.

1.2 Historical Evolution

The EU ETS, which became operational in 2005, has evolved through four phases, and each phase has been designed to improve upon the previous one, addressing the previous structural weaknesses. The analysis of this evolution is essential for interpreting the carbon market dynamics. The effectiveness of the EU ETS as a pricing mechanism and its relevance as a risk factor for the firms vary across these four phases [30, 31]. Figure 1.1 illustrates the evolution of EUA prices over different phases of the EU ETS and highlights the key events that influence these dynamics.

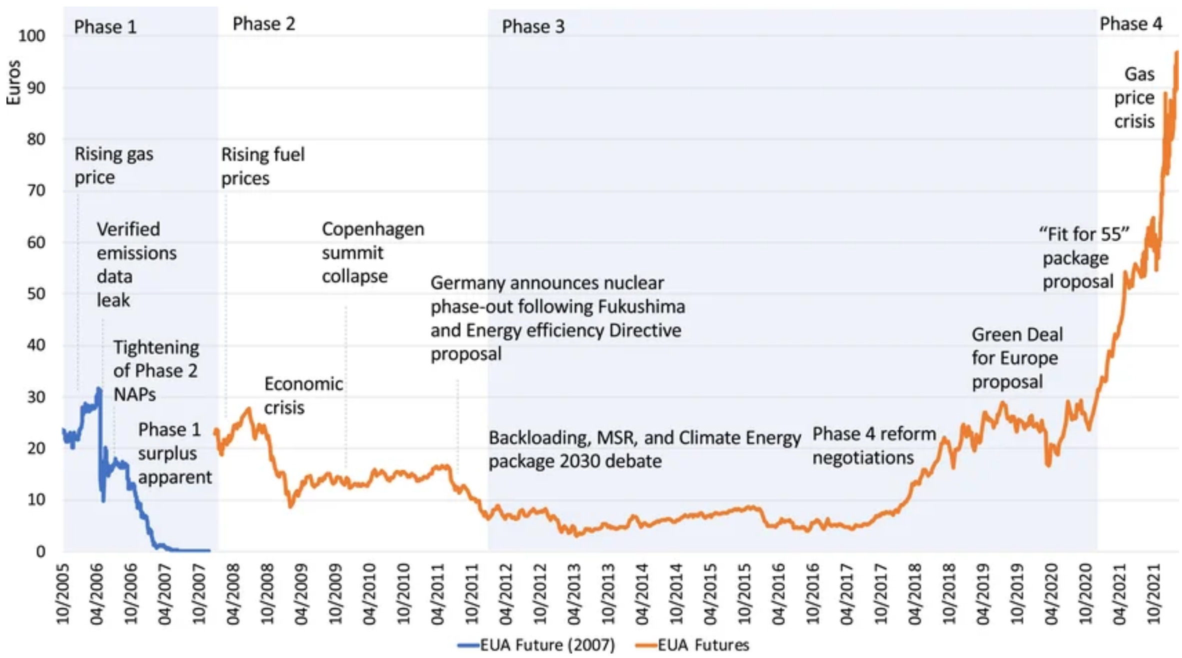

Figure 1.1: EUA futures price evolution across EU ETS trading phases. Source: Adapted from [32]. Original data from European Energy Exchange (EEX), EEA, ICAP Allowance Price Explorer and Ember.

Phase I: The primary goal of the first trading phase (2005–2007) was to test the design and the operational aspects of the EU ETS rather than prioritizing having significant emission reductions [33]. Through National Allocation Plans (NAPs) by the Member State, most of the allowances were distributed for free. Besides, the lack of reliability for the installation level emission data and the political pressure from the regulated industries caused the overestimation of actual emissions [34, 33]. When 2005 emissions data was published in April-May 2006, it was identified that the aggregate allocations actually exceeded the total emissions by approximately 3%, which caused EUA prices to collapse to nearly zero within days from the level of €30/tonne [34, 33]. While transitioning from Phase I to Phase II, banking allowances from Phase I were prohibited. Therefore, the market participants have anticipated that the surplus allowances would become worthless in the future, which triggered the carbon prices to collapse. As a result, by mid-2007, the EU ETS price signal had failed to provide effective incentives for emissions abatement [33, 19]. Despite these shortcomings, the role of Phase I was crucial as a pilot phase that established the monitoring, reporting, and verification (MRV) framework that gave rise to the effectiveness of the subsequent phases [5].

Phase II: In Phase II (2008–2012), stricter limits on the number of allowances and the inclusion of Norway, Iceland and Liechtenstein [35] represented progress, but structural problems were exacerbated by two simultaneous shocks. One of these was the 2008 financial crisis, which led to a significant drop in industrial activity and consequently emissions across the European Union, resulting in an allowance surplus [31]. In addition, a large amount of international offset credits were allowed for compliance through the Clean Development Mechanism (CDM) and Joint Implementation (JI), contributing to a decrease in the EUA prices [5]. Prices remained relatively low for most of the time, and the surplus reached approximately 2 billion tonnes of CO2 equivalent at the start of Phase III [5]. Whether such a price structure would provide sufficient incentive to reduce emissions in the future was still unclear [31, 33].

Phase III: Phase III (2013–2020) witnessed major structural changes: the decentralized NAP approach was replaced by a uniform cap on an EU-wide level; auctioning became the main allocation method for allocating allowances and the Linear Reduction Factor (LRF) of 1.74% per year was introduced to bring about a 21% cut in covered emissions by 2020 from 2005 levels [23]. However, the surplus created during the previous phase kept the EUA prices at under €10/tonne for a considerable time during Phase III, which is an amount deemed insufficient to induce any investment in decarbonization [8]. To address the persistent surplus and weak price signal, a short-term back-loading measure was implemented, which postponed the auctioning of 900 million allowances. It provided a temporary price support without eliminating the structural surplus [36]. Finally, the Market Stability Reserve (MSR) was established by Decision (EU) 2015/1814, which came into effect from 1 January 2019. It withdrew the allowances exceeding a certain level from the market and permanently canceled a portion of the withheld ones [6, 24]. EUA prices began a steady rise since then, increasing by almost fourfold in less than two years between January 2018 and the end of 2019 [8].

Phase IV: Phase IV (2021–2030) was defined by Directive (EU) 2018/410 and later revised through the *Fit for 55* package with Directive (EU) 2023/959 [24, 26]. This phase is characterized by a significant increase in the stringency of the EU ETS. The Linear Reduction Factor (LRF) was raised to 2.2% per year since 2021 [24] and then increased again to 4.3% during 2024–2027 and 4.4% thereafter, with the aim of a reduction in greenhouse gas emissions of 62% by 2030, taking 2005 as the base year [26]. Furthermore, international offset credits were no longer eligible for compliance, thereby tightening the allowance supply [24]. Over this phase, EUA prices increased drastically, reaching over €90 per tonne by early 2022. The reasons behind this price rise included tightening of allowance supplies, recovery of industrial activity after the COVID-19 pandemic, and the energy crisis resulting from Russia's war with Ukraine [9]. In total, it was a tenfold increase in comparison with the previous years and it was a fundamental transformation in the growing financial importance of the EU ETS for regulated firms [10].

1.3 Market Stability Reserve and Recent Reforms

The continuous surplus of allowances resulting from Phase I and Phase II represented a fundamental challenge for the ability of the EU ETS to create a proper price signal. Although back-loading provided a temporary solution by deferring the sale of 900 million allowances, it could not fix the problem of excess supply over demand. The long-term solution was achieved through the Market Stability Reserve (MSR), provided by Decision (EU) 2015/1814, that became operational from 1 January 2019 [6]. It established a rule-based mechanism to rebalance the supply and demand for the EUAs in the market over the long term [6, 24].

The MSR operates through a quantity trigger system known as Total Number of Allowances in Circulation (TNAC). In case the TNAC surpasses the upper limit of 1,096 million allowances, a certain share is automatically withdrawn from auctions and placed in the reserve, thus limiting the short-term supply. When the TNAC falls below the lower threshold of 400 million allowances, 100 million allowances are reintroduced to the market to avoid any excessive price rises [6]. The intake rate was first fixed at 12% of the TNAC but was later increased to 24% within the period of 2019-2023 following the revisions in 2018 in response to the need for more urgent absorption of the inherited surplus [24]. One of the key attributes that sets the MSR apart from the other policy measures is its cancellation mechanism: the surplus allowance stocks exceeding the number of annual auctions were no longer valid from 2023 onwards [8, 24]. The long-run price effects of the strengthened MSR design were examined ex-ante by Bruninx et al. [8]. They explain the increase in EUA prices after 2018 by the combined effect of the strengthened MSR, including its cancellation provision and the increase in the Linear Reduction Factor (LRF) from 1.74% to 2.2%. Their simulations show that approximately 40% of the implicit long-term emission reduction is due to the increase in LRF and 60% to the cancellation provision. Notably, without the increase in LRF, the cancellation provision alone would have led to significantly lower emission reductions. This highlights that the interaction between these two design parameters is an essential factor for the long-term EUA price trajectory [8].

Market effects of the MSR were felt even before its implementation. The anticipation of tightened allowance supply led to a rapid increase in the price of EUAs, going from around €7 per tonne in January 2018 to above €25 per tonne by the end of 2019, resulting in an almost fourfold price increase in two years [8]. According to Bruninx et al. [8], this development is due to the tightening of both the strengthened MSR and the Linear Reduction Factor (LRF), which moved from 1.74% to 2.2% in Phase IV. The combination of these developments signals a structural tightening of the EUA supply. However, Sitarz et al. point out that the significant increase in EUAs' prices from 2017 until 2021, at which point the price reached almost tenfold of its value in 2017, surpassing the €80 per tonne level, cannot be attributed to supply tightening alone [10]. It is a result of a change in the behavior of market players who have become more forward-looking because of the increased credibility of long-term EU climate targets [10].

The price of EUAs remained on an upward trajectory in the beginning of Phase IV, crossing the threshold of €50 per tonne in the middle of 2021 and exceeding €90 per tonne in early 2022 [9]. According to the European Central Bank, three main factors contributed to this acceleration of growth. The announcement of the legislative *Fit for 55* package reinforced market expectations of tighter emission constraints for the future. In addition, the start of Phase IV with new MSR parameters and a reduction in auctioned volumes triggered a shift towards coal power generation and led to an increase in demand for emission allowances [9]. Lastly, the energy crisis that followed the Russia-Ukraine war in February 2022 further intensified these pressures [37], driving EUA prices to their historical peak before a partial correction was made later in the year [9].

The Phase IV Normalization Period (January-September 2023)

After reaching its highest levels during the European energy crisis, EUA prices decreased in 2023 as the crisis conditions gradually eased. However, while carbon prices became more stable, the EU ETS continued to undergo important regulatory reforms. As part of the European Green Deal and the *Fit for 55* package, the EU ETS was revised in 2023 to align the system with the EU's updated climate targets [28, 26]. The revision strengthened the MSR, increased the Linear Reduction Factor to 4.3% from 2024 and 4.4% from 2028, and established the legal framework for the CBAM Transitional Phase that started in October 2023 [26, 28]. Therefore, 2023 is a transition period between the energy-crisis environment of 2021-2022 and the CBAM Transitional Phase that followed. Although EUA prices were lower than during the energy crisis, the EU ETS continued to move toward stricter emission reduction targets.

1.4 The Carbon Border Adjustment Mechanism

The Carbon Border Adjustment Mechanism (CBAM) was introduced under the *Fit for 55* package to address emissions associated with imports of selected carbon-intensive products [26, 38]. It applies to imports of cement, iron and steel, aluminum, fertilizers, electricity, and hydrogen [28, 38].

The CBAM Transitional Phase started on 1 October 2023. During this phase, importers were required only to submit quarterly reports on the emissions of their imports and were not subject to financial obligations [28, 38]. The Definitive Phase started on 1 January 2026 and introduced financial compliance through the surrender of CBAM certificates [28]. In parallel with the introduction of CBAM, free allocation under the EU ETS is scheduled to be gradually reduced for the sectors covered by the mechanism between 2026 and 2034. The share of free allowances is expected to decline from 97.5% in 2026 to 51.5% in 2030 and to 14% in 2033 [28].

For the sectors examined in this thesis, the CBAM Transitional Phase represents an important regulatory development. Because importers were only required to report emissions during the Transitional Phase and they were not subject to financial obligations, its direct impact on EUA demand was limited. Nevertheless, the mechanism increased the attention given to carbon costs in carbon-intensive industries. For this reason, the period from October 2023 to April 2026 is analyzed together as a separate sub-period in the empirical analysis presented in Chapter 5.

The need for market stability and subsequent regulatory reforms, along with significant macroeconomic shocks, have shaped the price dynamics of the allowances. These developments lead to six distinct economic periods, central to the analysis developed in

Chapter 5. These sub-periods are the Phase III Low Price period (2013–2018), the Post-MSR period (January 2019–February 2020), the COVID-19 period (March–December 2020), the Phase IV High Price period (2021–2022), the Phase IV Normalization period (January–September 2023), and the CBAM Transitional period (October 2023–April 2026). Each represents a separate carbon price regime with distinct implications for hedging dynamics and portfolio risk management in the sectors examined in this thesis.

1.5 Carbon Price as a Financial Risk Factor

The maturation of the EU ETS as a high-priced, liquid market has led to a shift in the way EUA prices are perceived by the market participants. At an earlier stage, while EUA prices rarely exceeded €10 per tonne and where a persistent surplus limited the strength of the carbon price signal, EUAs were considered primarily as a regulatory instrument rather than a financial variable [31]. This perception changed from 2018 onwards due to the implementation of the MSR, the changes implemented in Phase IV, and the *Fit for 55* package, resulting in significant cost exposures for the regulated firms [10]. Today, EUA price risk is regarded as a distinct financial risk category for the regulated energy-intensive sectors [11].

EUAs are actively traded through futures contracts available on the Intercontinental Exchange (ICE) [39]. The underlying determinants of pricing in these contracts are mainly driven by energy market fundamentals, macroeconomic indicators, and regulatory policies [9]. As the EUA futures market is highly liquid, any shifts in carbon policies, including limits on emissions and changes in the MSR mechanism, lead to EUA price variations. Consequently, the anticipated cost of compliance among the regulated firms are affected [11]. According to Hengge et al. [11], the use of high-frequency data related to more than 2,000 European public companies in the period from 2011 to 2021 demonstrates that any unexpected changes in carbon policies, leading to price rises in EUAs, negatively affect the returns of carbon-intensive companies. Additionally, it was shown that the effect of rising prices due to policy factors is almost three times greater than the impact of price decreases.

The effect of EUA price variations on the firms' equity returns operates through two distinct channels. First, there is the *cost channel*. If the firm regulated by the EU ETS is a net buyer of allowances, rising carbon prices will raise the variable production costs, resulting in narrower profit margins. Under conditions where the firm is unable to transfer these additional costs because of competition, this channel is expected to reduce equity returns [11, 5]. Second, there is the *risk channel*. Even for companies that do not buy EUAs currently, the volatility of carbon prices will affect their business indirectly through changes in the prices of inputs, energy prices, and valuation multiples within the industry [14, 11]. Aslan and Posch [14] study the dynamics of connections between the EUA futures price and nine FTSEurofirst300 sector indices between January 2013 and June 2022 using the connectedness network framework. According to their findings, the EUA price is mostly a net receiver of volatility from European stock sectors, mainly from financials, energy production, and energy-intensive industries, including basic materials and utilities [14]. Notably, the intensity of this connection is magnified under market turmoil circumstances. In the case of the European energy crisis resulting from the Russia-Ukraine war, the intensity of the volatility transmission increases, whereby the EUA price receives spill-over effects from all sectors at once. In summary, the findings suggest that EUA price risk is systemic rather than company-specific for energy-intensive industries.

For installations in energy-intensive industries regulated by the EU ETS, such as electricity production, metal production, non-metallic mineral industries, and chemicals manufacturing, EUA price risk is direct and structural. Firms in these industries that produce above the activity levels specified in Annex I of Directive 2003/87/EC must surrender enough allowances to cover their verified annual emissions [2]. For power-generating installations, full auctioning has been applied since Phase III, meaning that every tonne of CO_2 emitted carries a direct market cost [5]. For energy-intensive sectors like metal, non-metal, and chemical industries, the risk of being affected by EUA price is not limited only to those compliance requirements but also indirectly from the energy cost, which is affected by EUA price changes [15, 19]. Oberndorfer [40] shows that EUA price risk plays a significant role in influencing stock prices in the European electricity sector. This finding has since been extended to a broader set of energy-intensive industries [11, 14].

This financial materiality provides the motivation for the hedging analysis developed in the next chapters of this thesis. EUA price movements systematically affecting the equity valuations of the regulated firms illustrate that the EUA futures represent a natural hedging instrument [11]. Therefore, the construction of the hedging analysis for sector returns and EUA becomes a directly relevant question for portfolio risk management. In this context, the distinction between EU ETS-regulated and non-EU ETS-regulated listed firms within the same sector is particularly important. While both groups are exposed to some degree of carbon-related cost risk through energy prices, only EU ETS-regulated firms face a direct compliance obligation. As a result, EU ETS-regulated firms face a structurally more immediate and differentiated exposure to EUA price movements [11, 17].

Chapter 2

Literature Review

2.1 Carbon Markets and Financial Risk

Over the years, there have been significant changes in the EUA allocation process within the EU ETS. In the initial phases, allowance allocation was mainly determined by the National Allocation Plan (NAP) prepared by the individual member states [41]. As a result of decentralization in the allowance allocation process, permits were issued excessively, which increased the availability of allowances and therefore decreased EUA prices [34]. Therefore, the firms had less incentive to reduce their emissions [41, 5]. To address this issue, Phase III underwent structural reforms for EUA allocation. Auctioning became the main allocation method, although free allocation was still preserved for sectors with the carbon leakage risk. Auctions increased the effectiveness of the carbon price signal by increasing the cost of pollution and improving the internalization of environmental externalities [29]. Consequently, the nature of the allocation process and the stringency level of the emission caps became critical for the changes in EUA price levels and the performance of the system [23, 5]. Subsection 2.1.1 addresses the price dynamics and market fundamentals of EUAs, Subsection 2.1.2 assesses the impact of EUA price on equity market returns, Subsection 2.1.3 discusses the distinction between the EU ETS-regulated and non-EU ETS-regulated companies, and Subsection 2.1.4 analyzes the effects of crisis periods and regime changes for the carbon market dynamics.

2.1.1 EUA Price Dynamics and Market Fundamentals

There are two main elements that affect the EUA price dynamics. Firstly, EUA prices highly depend on the energy market. Mansanet-Bataller et al. [42] illustrate that energy prices, especially natural gas and coal, and weather-related variables are one of the main short-run determinants of EUA prices during Phase I of the EU ETS. Alberola et al. [19] extend this idea, demonstrating that EUA prices were reacting to energy price forecast errors and unexpected temperature shocks. Secondly, these relationships are structurally unstable in different regulatory and financial crisis periods. Since fuel switching technologies in the energy sectors depend on economic conditions, the marginal abatement cost curve, and therefore the equilibrium allowance prices shift across phases [33]. This is quantified by Aatola et al. [15], where approximately 40% of EUA forward price fluctuations are found to be explained by German electricity, gas, and coal prices estimated between 2005 and 2010.

The EUA price decrease during Phase II is due to a different set of drivers. According to Koch et al. [31], the decrease in EUA prices from 2008 to 2013 can only be attributed partially to factors related to the cost of reducing emissions, as they account for approximately 10% of the variance. However, the effect of international offset credits is found to be limited, and the deployment of the renewable energy sources, macroeconomic factors are identified as the key reasons for this reduction [31]. Moreover, Hintermann et al. [43] illustrate that although there is a broad consensus that fuel prices and abatement-relevant variables impact EUA prices, the relationship is actually fragile because the relevant technologies depend on market conditions. Therefore, a static price model would fail to capture evolving market dynamics. Sanin et al. [16] complements this view by modeling the volatility dynamics directly and identifies that the phase transitions, regulation announcements, and banking decisions are the drivers of volatility clustering in the EUA return series.

A major structural development observed after 2018 is the significant price increase of EUA after the implementation of the MSR. However, the post-reform EUA price behavior cannot be explained only by the contemporaneous supply-side reactions because of MSR and the regulatory changes. Sitarz et al. [10] demonstrate that higher allowance price levels can be explained better with a farsighted market structure than by supply-side factors because they capture the impact of the future policy credibility expectations using the structural energy systems model. Their findings suggest that EUA prices reflect the forward-looking expectations and the current abatement costs. Thus, the policy credibility and the expectations are highly important for forming carbon prices during Phase IV of the EU ETS.

After the extreme price movements observed during the European energy crisis, EUA prices stabilized during 2023. According to the European Commission, the highest EUA price seen in 2023 was €96.33 per tonne, while the average price for the year was €83.60 per tonne [44]. While carbon prices were much higher than before 2021, the rapid increases seen during crises were not observed during this period.

Major regulatory developments have also become an important consideration in EUA price formation. One of the most important recent examples is the Carbon Border Adjustment Mechanism (CBAM), which was introduced in October 2023 [25]. CBAM extends carbon pricing to importers of cement, iron and steel, aluminum, fertilizers, electricity, and hydrogen [38]. The introduction of CBAM further highlights the importance of regulatory expectations in addition to energy-market fundamentals and current abatement costs when analyzing EUA price dynamics [10].

Table 2.1 summarizes the main empirical findings on EUA price determinants across the literature.

Table 2.1: Evolution of Dominant EUA Price Drivers Across EU ETS Phases and Sub-Periods

EU ETS Phase / Regime	**Dominant Price Drivers**	**Representative Literature**
Phase I (2005-2007)	Fuel-switching behavior, weather conditions, and allowance over-allocation	Mansanet-Bataller et al. [42]; Alberola et al. [19]; Ellerman & Buchner [34]; Hintermann [33]
Phase II (2008-2013)	Macroeconomic slowdown, renewable energy expansion, and volatility clustering	Aatola et al. [15]; Koch et al. [31]; Sanin et al. [16]; Hintermann et al. [43]
Phase III Low Price (2013-2018)	Persistent allowance surplus, low carbon prices, and weak policy credibility	Bayer & Aklin [45]; Joltreau & Sommerfeld [5]
Post-MSR (Jan 2019-Feb 2020)	Structural tightening through the MSR and expectations of future allowance scarcity	Bruninx et al. [8]; Sitarz et al. [10]
COVID-19 Shock (Mar 2020-Dec 2020)	Pandemic demand shock, increased volatility connectedness with equity markets, and accelerated financialisation of the EUA market	Aslan & Posch [14]; Adekoya & Oliyide [46]; Kanamura [47]
Phase IV High Price (Jan 2021-Dec 2022)	Fit-for-55 reforms, Russia-Ukraine energy crisis, fuel-switching toward coal, and EUA prices exceeding €90	Ampudia et al. [9]; Liu et al. [48]; Sitarz et al. [10]
Phase IV Normalization (Jan 2023-Sep 2023)	Post-crisis price stabilization, moderation from the extreme price levels observed during the energy crisis, and a transition toward a more stable carbon-market environment	European Commission [44]
CBAM Transitional (Oct 2023-Apr 2026)	Extension of carbon pricing to selected imports and increasing importance of regulatory expectations in discussions of future carbon costs	European Union [25]; European Commission [38]; Sitarz et al. [10]

Notes: The table summarizes how the dominant drivers of EUA prices evolved across the EU ETS phases and sub-periods analyzed in this thesis. The CBAM Transitional row covers the official CBAM Transitional Phase (Oct 2023 - Dec 2025) and the first four months of the CBAM Definitive Phase (Jan - Apr 2026).

2.1.2 Carbon Prices and Equity Market Returns

The transmission of EUA price movements into equity valuations occurs through two channels. The first channel is the direct compliance channel, operating through the production costs. For net buyers of EUAs, an increase in prices reduces profit margins depending on how much the price increase can be reflected to the output prices [11, 49]. The second channel is the indirect channel that works through the energy prices, so that even for firms receiving free allocation, the carbon price premium embedded in electricity and fuel prices affects the input costs [15, 19]. Oberndorfer [40] shows the strong positive relationship between EUA price changes and the equity returns of European power firms and extends this finding to other sectors and time periods.

Oestreich and Tsiakas find a large and statistically significant carbon premium during EU ETS Phases I and II. This premium reaches 17% per year and can be attributed to two mechanisms. First, there is a cash-flow effect arising from the free allocation of allowances. It generates windfall profits through the opportunity cost of permits and firms' ability to pass through higher marginal costs into output prices. Second, there is uncertainty for future EUA prices, so the leading carbon-emitting firms expect higher returns. However, this premium largely disappears after March 2009, when the transition toward auctioning in Phase III became certain [49]. These effects show that regulation by the EU ETS is an important factor determining the stock market performance.

The transmission of carbon-related shocks to the equity returns is also examined. Hengge et al. [11] conduct a study to assess the influence of carbon policy shocks on equity performance by employing a proxy using the regulation-induced changes in the EUA market. Their findings suggest that carbon policy shocks result in statistically significant negative abnormal returns for firms operating in high-carbon industries. In addition, carbon policy shocks that are associated with the EUA price increase generate approximately three times larger effects compared to shocks causing the EUA price decrease. Building on this idea, Benchora and Galanti [50] employ the verified emissions data obtained from the European Union Transaction Log (EUTL) and document that green firms outperform brown firms in terms of their annual return performance by 6.6-7.9% within the EU ETS. This finding implies that the EU ETS influences the risk and return profiles of regulated firms.

The relationship between carbon and equity markets can also be examined within a broader framework of financial risk transmission. Using a Markov regime-switching DCC-GARCH model, Balcilar et al. [13] show that contagion among energy derivatives (electricity, natural gas, coal), and their risk spillovers with EUAs are significant, time-varying, and change significantly across the EU ETS phases. Extending this work to the equity-carbon connection, Aslan and Posch [14] document that the price of EUAs is *net receiver* of volatility from European equity sectors, and the intensity of this transmission intensifies during the 2022 European energy crisis. Table 2.2 presents the empirical research related to carbon prices and equity returns by grouping them according to their equity sample focus and market scope.

Table 2.2: Summary of Key Studies on Carbon Prices and Equity Returns, Grouped by Equity Sample Focus

Study	**Sample**	**Method**	**Key Finding**
Single-sector study (electricity)			
Oberndorfer [40]	EU electricity firms	OLS	EUA price changes positively affect power-sector stock returns
Multi-sector index studies			
Aslan & Posch [14]	9 FTSEurofirst300 sector indices, 2013-2022	Connectedness analysis	EUA is a net receiver of volatility from European equity sectors, and the intensity of volatility transmission intensifies under market stress
Cross-sector firm-level studies			
Oestreich & Tsiakas [49]	German emitting vs. non-emitting firms, 2003-2012	Factor model	Significant carbon premium during Phases I-II driven by free allocation and carbon risk
Brouwers et al. [12]	368 listed EU ETS firms, 2006-2013	Event study	Stock price reactions to verified emissions differ according to firms' allowance positions and pass-through ability
Hengge et al. [11]	2,000+ EU firms across 38 sectors, 2011-2021	Event study	Carbon policy shocks generate negative abnormal returns; price increases create substantially stronger effects
Benchora & Galanti [50]	EU ETS firms during Phases III-IV	Panel regression	Green firms outperform brown firms by approximately 6.6-7.9% annually
Carbon-energy market spillover studies			
Balcilar et al. [13]	EUA spot/futures and energy derivatives	MS-DCC-GARCH	Carbon-energy risk spillovers are time-varying and regime-dependent across EU ETS phases

Notes: Studies are classified based on the type of equity sample. The single-sector category includes studies conducted exclusively for the electricity sector. The multi-sector index studies use pre-defined pan-European sector indices. The cross-sector firm-level studies analyze firm-level data across multiple sectors. Finally, the carbon-energy market studies examine the EUA market together with energy derivatives instead of equities. MS = Markov-switching; DCC = dynamic conditional correlation. Within each category, studies are listed chronologically by their sample period.

2.1.3 Carbon Price Risk and the EU ETS-Regulated vs. Non-EU ETS-Regulated Distinction

The third strand of research questions focuses on the heterogeneity in risk exposures due to differences in carbon price risk between firms that have a different regulatory status. This includes investigating whether firms regulated by the EU ETS in the same industry have different risk characteristics than other non-EU ETS-regulated firms in the same industry. This research question is explored from two angles. First, from the perspective of the firm-level effects, where the effects of regulatory exposure on firms and second, from the perspective of the financial markets, investigating how these differences are reflected in asset prices and risk transmission dynamics.

Empirical evidence suggests that the effects of the EU ETS on firms are heterogeneous, dependent on sectoral characteristics, allocation rules, and firms' ability to pass through carbon costs [17]. Recent studies using causality analysis through matching methods that leverage installation-level inclusion thresholds demonstrated that the EU ETS led to a 10% decrease in carbon emissions between 2005 and 2012 without negatively affecting the economic performance of regulated firms. On the contrary, it is documented that it caused around a 15% increase in the revenues and 8% increase in fixed assets of the EU ETS-regulated firms [4]. These results suggest that participation in the EU ETS leads to financial and operational gains for regulated firms relative to non-EU ETS-regulated firms within the same sector. However, this divergence did not cause widespread competitiveness losses during Phase I and Phase II, as over-allocation and cost pass-through prevented most regulated firms from having the full burden of compliance costs [5]. As these factors are progressively reduced under Phase IV, the financial distinction between EU ETS-regulated and non-EU ETS-regulated firms becomes more relevant for the sample period examined in this thesis.

Relationships between environmental and financial performance of firms operating within the EU ETS have also been explored using the panel quantile regression method. Findings show that lower emission intensity is associated with higher financial performance, particularly for firms located at the lower end of the financial performance distribution [51]. Furthermore, firm-level trading network centrality analysis highlights that firms that are more actively involved in the EUA market exhibit better environmental-financial performance [51]. This suggests that participation in the carbon market may shape how environmental performance is reflected in firms' financial outcomes.

The differences of the EU ETS-regulated and non-EU ETS-regulated firms in terms of carbon cost exposure and regulatory obligations are driven by distinct risk channels. Hengge et al. [11] demonstrate that both the EU ETS-regulated and non-EU ETS-regulated firms are affected by carbon policy shocks in structurally different ways. EU ETS-regulated firms face direct exposure to compliance costs, while the non-EU ETS-regulated firms are influenced due to transition risks linked to the transition towards a low-carbon economy. The empirical findings also point out that the reactions of these two regulatory groups to carbon policy shocks are asymmetric. An increase in the price of EUAs generates significantly higher returns compared to declines in prices, mostly because of the direct compliance cost for the EU ETS-regulated firms [11]. Oestreich and Tsiakas [49] further demonstrate that free allocation generated a significant carbon premium effect for the regulated firms. In summary, the existing literature suggests that carbon price risks affect EU ETS-regulated and non-EU ETS-regulated companies in different ways, which might generate different returns and hedging dynamics between them.

2.1.4 Crisis Periods and Regime-Dependent Carbon Market Dynamics

The relationship between the EUA prices, equity returns, and energy commodities is not consistent across different market conditions. The EU ETS is highly regime-dependent as both EUA price levels and volatility transmission patterns vary significantly over time. Sanin et al. [16] suggest this by showing that the institutional events trigger time-varying volatility clustering in EUA returns. It is also demonstrated that the relationship between electricity and carbon markets becomes much stronger, and short-term spillovers exhibit a stronger response compared to long-term ones [52]. Additionally, carbon markets shifted from net recipients of information in Phase II to being net transmitters of information in Phase IV, and the volatility spillover and correlation indices changed significantly during politically uncertain and economic stress periods [48]. These findings suggest that hedging relationships will vary through the sample period examined in this thesis, with changing market conditions and stress periods.

The COVID-19 pandemic caused a substantial exogenous shock to the carbon market. The lockdown across Europe starting from March 2020 led to the shutdown of the energy-intensive facilities. Consequently, industrial production was significantly reduced, and the EUA demand decreased [14]. EUA futures prices, which were around €24 per tonne in late February 2020 fell below €17 per tonne by mid-March 2020 and subsequently recovered during the second half of the year. However, still, the price level at the end of 2020 was above pre-shock levels [10, 9]. The price decline was less sharp and short-lived than the price collapse in earlier phases due to the implementation of MSR together with the increased Linear Reduction Factor. These reforms shifted market expectations toward long-term allowance scarcity. It prevented a more severe price collapse by reinforcing confidence in the future tightness of the EU ETS [8, 10]. The total volatility connectedness between EUA futures and European equity sectors reached its highest level between March 2020 and 2021 at around 82%, revealing the increased dependence of carbon and equity markets under economic crises [14]. The increased stress spillover across carbon and energy markets is also demonstrated by Kanamura [47], who documents that the impact of carbon prices on energy prices significantly differs in pre- and post-COVID-19 periods, using EUA, Brent crude oil, Rotterdam (ARA) coal, and NBP natural gas prices. COVID-19 was an important factor that drove connectedness in both commodity and financial markets by creating volatility spillovers between assets that previously had a weaker link [46].

The energy crisis triggered by Russia's invasion of Ukraine in February 2022 caused another major shock through a distinct transmission channel. A shortage in the natural gas supply from Russia caused the switch to coal-powered electricity production in Europe. Thus, the demand for emissions allowances increased, and the EUA prices exceeded €90 per tonne in early 2022 [9]. Over this time, the transmission of the volatility spillover into the EUA became stronger across all of the European sectors, which indicates that the energy crisis affected the carbon market through a system-wide mechanism [9, 14]. Therefore, the post-2022 environment represents a high-price, high-volatility regime where carbon markets are more closely integrated with energy and equity markets than in previous periods of the EU ETS.

After the disruptions caused by the European energy crisis, the EU carbon market entered a period that differed from both the high-volatility conditions of 2021-2022 and the subsequent CBAM transitional phase. According to the European Commission, the temporary rise in EU ETS emissions in 2022 was mainly caused by the energy crisis and increased aviation activity. However, emissions began to decline again in 2023 [53]. This made the January–September 2023 period a transition phase between the European energy crisis and the CBAM transitional period.

The CBAM transitional period began on 1 October 2023, which required reporting of imports of certain goods with carbon-intensive production and carbon-leakage risk. These goods include cement, iron and steel, aluminum, fertilizers, electricity, and hydrogen [38]. During this transitional period, financial compliance was not required, but starting from January 2026, facilities had to purchase CBAM certificates for the embedded emissions of their imports [54]. As a result, the period from October 2023 to April 2026 is analyzed in this thesis as the CBAM transitional phase includes both the introductory phase of the CBAM with reporting requirements and a portion of the definitive phase with financial compliance obligations for the importer firms.

The dynamics of different regulatory and market regimes are likely to influence hedging performance. Estimating hedge ratios and hedging effectiveness over the full sample may therefore hide the important differences between different periods. Previous studies show that the role of the EU ETS has evolved over time. While Bayer and Aklin [45] find that the system continued to generate meaningful emission reductions even during the low-price Phase III period, Liu et al. [48] shows that the carbon market's interaction with other financial and energy markets changed substantially across phases. These findings suggest that the relationship between carbon prices and industrial equity returns is not constant over time, providing a strong motivation for the sub-period analysis conducted in this thesis.

Six sub-periods are analyzed in this paper, namely the Phase III Low Price environment, the Post-MSR recovery, the COVID-19 shock, the Phase IV High Price regime, the Phase IV Normalization window, and the CBAM Transitional period, which represent distinct carbon price regimes driven by regulatory, behavioral, and macroeconomic factors. As a result, they provide a framework for comparing hedging effectiveness.

By taking the factors discussed in Section 2.1.4 into account, the EU ETS literature can be grouped into phases, crisis periods, and regulatory regimes. Table 2.3 summarizes the main research themes for each period.

Table 2.3: Summary of the Literature by EU ETS Phases and Sub-Periods

Phase / Regime	**Key References**	**Main Topics Studied**
Phase I (2005-2007)	Mansanet-Bataller et al. [42]; Alberola et al. [19]; Hintermann [33]; Ellerman & Buchner [34]	Initial EUA price formation, the role of fuel-switching in electricity generation, and the consequences of over-allocation of allowances
Phase II (2008-2013)	Aatola et al. [15]; Koch et al. [31]; Sanin et al. [16]; Hintermann et al. [43]; Joltreau & Sommerfeld [5]	The effects of allowance oversupply after the 2008 financial crisis, declining EUA prices, and changing relationships between carbon prices and market fundamentals
Phase III Low-Price Environment (2013-2018)	Bayer & Aklin [45]; Brouwers et al. [12]; Joltreau & Sommerfeld [5]	Whether the EU ETS remained effective under persistently low carbon prices and how carbon information was reflected in equity markets
Post-MSR Recovery (2019-Feb 2020)	Bruninx et al. [8]; Sitarz et al. [10]	The impact of the Market Stability Reserve on market tightening and expectations about future EUA prices
COVID-19 Shock (Mar-Dec 2020)	Aslan & Posch [14]; Adekoya & Oliyide [46]; Kanamura [47]; Naeem et al. [52]	How the COVID-19 shock affected carbon markets through lower demand, stronger market interconnectedness, and closer links with financial and energy markets
Phase IV High-Price Regime (2021-2022)	Ampudia et al. [9]; Sitarz et al. [10]; Liu et al. [48]; Aslan & Posch [14]	The effects of the energy crisis and Fit-for-55 reforms on carbon prices, volatility, and market behavior
Phase IV Normalization (Jan-Sep 2023)	European Commission [53]; European Commission [44]; Kanamura [47]	Market developments between the European energy crisis and the introduction of the CBAM transitional phase, including the return of EU ETS emissions to their longer-term declining trend and changing carbon market conditions relative to 2021-2022
CBAM Transitional (Oct-2023-Apr-2026)	Regulation (EU) 2023/956 [25]; European Commission [38]; ICAP [54]	Introduction of CBAM reporting requirements, transition to financial compliance from January 2026, and implications for carbon-intensive sectors

Notes: The reviewed literature is classified by EU ETS phase and sub-period according to the main contribution of each paper. Studies covering multiple periods are classified by their main focus. EU ETS phase boundaries follow Directive 2003/87/EC and its revisions [23, 24, 26].

2.2 Sector-Level Exposure to Carbon Price Risk

The existing studies illustrate that the EUA price fluctuations have varying effects on financial risk depending on the allocation methods, abatement flexibility, and firms' ability to pass compliance costs to output prices. The following sections discuss the main results related to the level of carbon price risk exposure, focusing on the electricity sector, energy-intensive manufacturing industries, and the implications of regulatory participation within sectors.

2.2.1 Carbon Price Transmission in the Electricity Sector

The electricity sector was subject to full auctioning starting from Phase III, so that each tonne of CO_2 emitted by an EU ETS-regulated electricity facility had an associated market cost [5]. However, in the electricity sector, the firms are able to reflect the cost of carbon emissions into the price of electricity. Sijm et al. [55] estimate CO_2 cost pass-through rates of between 60% and 100% for Germany and the Netherlands. The nearly complete transmission of the prices is also confirmed by using structural estimation based on Spanish electricity auction data, and this is attributed to high-frequency auctions and relatively inelastic demand [56].

Consequently, EU ETS-regulated electricity producers could pass their carbon compliance cost through output prices during the free allocation phases of the EU ETS so they were able to accrue windfall profits [55, 5]. A statistically significant positive correlation between changes in EUA prices and stock returns in European electricity firms are found [40]. On this basis, Brouwers et al. [12] expand on this work by applying an event study approach to 368 listed firms regulated by the EU ETS. From their study, it is found that stock price reactions following the disclosure of carbon emissions depend on the price level of carbon and expectations regarding the scarcity of allowances. They also demonstrate that companies unable to achieve the pass-through effect have higher negative responses when facing shortages of allowances. It shows that the influence of EUA price changes on firms' equity returns depends on the relationship among carbon pricing, allowance allocations, and firms' ability to transfer compliance costs.

2.2.2 Carbon Price Risk in Energy-Intensive Manufacturing

The carbon price exposure for energy-intensive manufacturing firms is more heterogeneous based on their differing abilities to reduce emissions, international exposures, and industry cost structures. The lack of negative effects in Phases I and II can be explained by the combined presence of free allocation and pass-through, which became limited in Phase IV as the allocation regime tightened [5]. The results of the analysis indicate that pass-through capacity varies across sectors. The power generation and oil-related industries have relatively high pass-through capacity, whereas the iron and steel industry has moderate capacity. On the contrary, other energy-intensive industries with high trade exposure, such as Non-Metallic Minerals and Chemicals manufacturing, have relatively low pass-through capacity [5, 55].

Demailly and Quirion [57] indicate that the competitiveness loss in the iron and steel industry is limited despite the sector's high emission intensity. This suggests that emission intensity alone is not sufficient to explain the economic impact of carbon regulation, so it should be elaborated together with factors such as cost pass-through ability, free allowance allocation, and market structure. The financial effects of the EU ETS are larger in industries with high direct emission intensity, low pass-through capacity, and technological flexibility [17]. This is especially true for the non-metallic minerals sector, where a considerable portion of CO_2 emissions are from limestone calcination, which is an inherently unavoidable chemical process that cannot be offset through fuel switching [58]. Therefore, it constitutes an irreducible component of compliance costs independent of EUA price levels [2, 5].

Apart from the direct compliance cost, manufacturing companies are indirectly subject to carbon prices because of their energy requirements. The price of fossil fuel sources such as natural gas and coal is a significant factor that affects the price of EUAs in the short run [42, 19]. As a result, energy-intensive industries are simultaneously affected by the two factors, that is, the direct compliance cost and the input prices of the fossil fuels when there is a rise in EUA prices. This effect is particularly relevant for sectors such as chemicals and basic metals, where fossil fuels play a central role in production.

2.3 DCC-GARCH Models in Financial Hedging

The heterogeneity in carbon risk exposure, together with the system-dependent dynamics of the EU ETS in both crisis and non-crisis periods, necessitates a dynamic hedging framework to account for time-varying correlations and volatility transfer among carbon, equity, and energy markets. Models that impose constant correlations or restrict the joint distribution of returns to a static structure are insufficient to solve the empirical problem addressed in this thesis.

The Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model introduced by Engle [20] provides such a framework and has become one of the most widely used methods to estimate dynamic hedge ratios and portfolio weights. In previous studies on hedge ratios, CCC or OLS regression models were widely used, that assume certain constraints on the covariance processes of returns that do not take into account persistence and time-varying volatility in financial markets [59]. The DCC-GARCH model is estimated in two steps. In the first step, the univariate GARCH models are fitted to return series to estimate conditional variances, and the standardized residuals are extracted. After that, the time-varying conditional correlation matrix is estimated from these residuals, which captures the dynamic changes of cross-asset dependencies over time. This ordered structure reduces the dimensionality of the estimation problem compared to fully flexible multivariate frameworks such as the Baba-Engle-Kraft-Kroner (BEKK) specification [20, 59]. In addition, it simplifies the model use in applications with multiple bivariate combinations, as in this analysis.

The DCC-GARCH model has been widely used in hedging analysis in commodity and energy markets. In particular, Chang et al. [60] investigate the performance of various multivariate GARCH models, such as the Constant Conditional Correlation (CCC), VARMA-GARCH, Dynamic Conditional Correlation (DCC), BEKK, and diagonal-BEKK models in modeling the return series of the spot and futures prices of crude oil in the Brent and West Texas Intermediate markets. They highlight that all these dynamic models lead to significant variance reduction compared to static models, with the diagonal-BEKK model having the result with the highest variance reduction. Moreover, extensive out-of-sample analysis was performed between BEKK, generalized orthogonal GARCH, and DCC models for hedging equity index futures. It is reported that the multivariate GARCH specifications perform better than the static OLS hedge, with the rank of dynamic models' performance depending on the level of volatility in the analysis period, where all improvements are mainly obtained during times of high market volatility levels [59]. The analysis is extended by showing the presence of time and frequency connectedness among carbon, electricity, clean energy and oil markets. It is observed that connectedness tends to increase significantly during crisis periods and concentrate in short-run frequencies, which directly implies the need for the design of dynamic hedging strategies operating on a daily basis [52].

Within the carbon market, some studies employed the DCC-GARCH methodology to study hedging dynamics of EUAs. For example, Balcilar et al. [13] estimate a Markov-switching DCC-GARCH model by using the spot and futures returns of EUAs with a set of energy derivatives. From the analysis, it is concluded that the conditional correlations and hedge ratios vary across regimes, and regime-conditional hedging strategies are superior to unconditional strategies. Demiralay et al. [18] also employ the DCC-GARCH method to estimate dynamic hedge ratios between carbon credit futures contracts and sector-specific stock index series, and report that the addition of carbon futures to equity portfolios leads to substantial risk reduction and enhanced risk-adjusted performance, especially when carbon prices are highly volatile. Finally, Liu et al. [48] estimate a DCC-MVGARCH model by connecting the European carbon market with coal, oil, natural gas, and renewable energy markets. They reveal that the minimum variance hedge ratios vary across time and reach their maximum during economic stress periods. The volatility correlations show distinct phase dependence as the carbon market shifts from being a net volatility recipient during Phase II to becoming a net volatility transmitter during Phase IV. Further proof of connectedness provided by Aslan and Posch [14] demonstrates that the contagion effect between EUA futures and the European equity sector increases significantly during crises such as the COVID-19 pandemic and the 2022 energy crisis.

This thesis adopts the DCC-GARCH model due to the theoretical and empirical considerations indicated. First, the two-step process involved in estimating the model is applicable in the bivariate case as employed in this study. Second, the model can handle the structural changes in conditional correlations as identified through different phases of the EU ETS and crisis periods. Lastly, because of its parsimonious nature compared to multivariate models, the model is unlikely to suffer from over-parameterization problems, given the sample size is available for each sub-period analysis. The bivariate form of the DCC-GARCH model will be estimated for each pair of sector portfolio and hedging asset, producing the time-varying conditional variances and covariances from which hedge ratios and optimal portfolio weights are derived in Chapter 4.

2.4 Hedging Effectiveness Measures

To evaluate hedging performance, both theoretical and empirical tools are needed to find the best hedging positions and to measure their effectiveness. This section reviews key methods that are important for analyzing hedging effectiveness in this thesis.

The fundamental concept in the hedging literature is the minimum-variance hedge ratio, which represents the portfolio allocation that minimizes the variance of a hedged position consisting of a spot exposure offset by a futures position. The theoretical foundation of this concept is provided by Ederington [22], who suggests the use of the variance reduction criterion as the basis for the hedging effectiveness measure. It is defined as the amount of variance reduction in the portfolio return achieved by the hedged position relative to the unhedged position. This performance measure has been used as the main benchmark for hedging literature, and it is widely used in carbon market applications [13, 18, 48].

The extension of this static framework into time-varying hedge ratios is established by Kroner and Sultan [61], who derive the optimal hedge ratio as the ratio of the conditional covariance of spot and futures returns to the conditional variance of futures returns. This approach adopted in this thesis ensures that the hedge ratio is updated each period according to the evolving estimated conditional covariance matrix, therefore capturing the relationship between the hedged and the hedging asset that changes dynamically through time. The formula for determining the optimal portfolio weights, which describes the proportion that each stock should receive in a two-asset portfolio to minimize risk for a given rate of return, is developed by Kroner and Ng [21] based on the conditional covariance structure of the GARCH model. Both specifications have been widely used in multivariate GARCH hedging literature [60, 18, 48], and are used in this thesis to provide complementary insights on optimal hedging positions.

The measure of variance reduction alone is insufficient to assess the hedging performance because it does not account for the impact of hedging on the risk-adjusted return profile or the tail behavior of the portfolios. Lai [59] provides a framework for evaluating multivariate GARCH-based hedging strategies across multiple performance dimensions, demonstrating that rankings of various strategies obtained using variance reduction and risk-adjusted return metrics can yield different hedging strategies. Furthermore, Demiralay et al. [18] combine the variance reduction criterion with a range of portfolio performance metrics, including the Sharpe ratio, the Sortino ratio, Value at Risk, Expected Shortfall, and document that adding carbon to a stock portfolio improves both downside risk metrics and risk-adjusted returns.

2.5 Identified Gaps and Research Question

The research on carbon market dynamics, transmission of equity risk, and hedging effectiveness has evolved within the last decade. The literature has further developed the existing knowledge about the factors that determine the dynamics of EUA price changes [19, 16, 31, 10]; investigated the effect of carbon policy shocks to firms' equity valuations [40, 49, 12, 11, 50]; and examined the dynamic relation between EUA price and energy commodity returns during macroeconomic stress periods [14, 47, 48, 46, 52]. In parallel, the multivariate GARCH model has become one of the most widely used frameworks for studying time-varying hedging relationships and estimating dynamic hedge ratios across different financial asset classes [20, 60, 59, 13, 18].

Among these contributions, three strands of literature have largely evolved in parallel rather than in combination. The main empirical contribution of this thesis is to combine these different strands into a unified research framework. These three strands and their combined application in the present study are discussed in the following section.

2.5.1 Regulatory Distinction Within Sectors

Comparison between EU ETS-regulated and non-EU ETS-regulated companies has been widely addressed in the broader EU ETS effects. Hengge et al. [11] show that EU ETS-regulated and non-EU ETS-regulated European companies respond through different transmission channels to carbon policy shocks, which are the direct compliance cost channel or the transition risk channel. Oestreich and Tsiakas [49] show that the returns between carbon-emitting and non-emitting German firms significantly differ during the initial stages of the EU ETS. Moreover, Calel [62] compares EU ETS-regulated companies and matches control companies according to their innovation responses, whereas Dechezleprêtre et al. [4] design an installation-level threshold for identification purposes in their difference-in-differences framework, focusing on the impact of the EU ETS on emissions and business outcomes for regulated firms. Furthermore, Brouwers et al. [12] and Benchora and Galanti [50] analyze the EU ETS-regulated firms and highlight their heterogeneity in carbon-related stock market effects.

Although these findings demonstrate that regulatory involvement is an important determinant of carbon risk exposure, the majority of the hedging studies have been conducted at an aggregate level that does not perform this differentiation. Whether the regulatory separation identified above for carbon emissions, returns, abnormal returns, and innovation responses creates a meaningful difference in dynamic hedge ratios, optimal portfolio weights, and hedging effectiveness remains an open research area.

2.5.2 Cross-Sector Comparison with Sector-Specific Design

The carbon-equity hedging literature has progressively expanded in scope over time. Initially, research was concentrated on the electricity sector, which analyzed the carbon equity transmission mechanisms [40, 55, 56]. However, later on, the research scope was broadened to multi-portfolio and multi-sector settings. For example, Demiralay et al. [18] analyze the benefits of carbon credit futures in hedging regional equity portfolios, including the MSCI Asia Pacific, MSCI Europe, MSCI North America, and NASDAQ green stock portfolios, while Aslan and Posch [14] assess volatility interdependence among EUA futures and FTSEurofirst300 sector indices.

Nevertheless, there are some common structural elements that persist in the existing literature. First, the equity unit of analysis tends to be analyzed via general indices that cover entire regions or industry sectors as opposed to creating a portfolio of firms belonging to the energy-intensive industrial sector itself. Second, hedging asset structures tend to be used similarly for all equity portfolios and not adjusted based on the characteristics of production in particular sectors. Nevertheless, the results presented in Section 2.2 clearly demonstrate that carbon risks associated with electricity generation, basic metals, non-metallic minerals, and chemical industries differ from one another when taking into account the ability to adjust production, passing costs through, and use fossil fuels for production [5, 57, 17, 55, 56]. Therefore, a comparative hedging framework that combines sector-specific portfolios with hedging assets selected according to the production inputs of different sectors has received limited attention in the literature.

2.5.3 Regime-Dependent Multi-Asset Hedging

Another aspect of the literature that requires further attention is the analysis of multiple hedging instruments while accounting for both sectoral composition and carbon market regimes. EUA price is affected by the price of sector-specific energy commodities [15, 19], and this relationship varies across regulatory and macroeconomic regimes. However, current hedging strategies predominantly focus on EUA futures for the hedging analysis [13], or they study the carbon-energy relationship separately [18, 52]. Consequently, more attention should be given to comparing the hedging effectiveness of EUA futures and sector-specific energy commodities across different carbon price regimes, particularly in combination with the sectoral and regulatory dimensions described above.

2.5.4 Research Question and Contribution

The combination of these three literature gaps motivates the following research question:

> *Do EU ETS-regulated and non-EU ETS-regulated firms within carbon-intensive sectors exhibit systematically different dynamic hedging relationships with EUA futures and sector-relevant energy commodities, and how do these differences vary across sectors and market regimes?*

Building on the mentioned identified gaps, this thesis contributes to the literature in four different ways:

First, in the empirical analysis, a regulatory distinction is made within sectors, and the effects of regulatory status on firms' dynamic financial risk management are analyzed using carbon-related hedging strategies. To make the distinction, separate equal-weighted portfolios for EU ETS-regulated and non-EU ETS-regulated listed firms were formed across four selected carbon-intensive sectors. Within the two regulatory groups, the differences between dynamic hedge ratios, optimal portfolio weights, and hedging effectiveness are analyzed.

Second, the analysis is performed simultaneously across four energy-intensive industrial sectors, which are Electricity, Gas, Steam and Air Conditioning Supply (NACE 35), Manufacture of Basic Metals (NACE 24), Manufacture of Other Non-Metallic Mineral Products (NACE 23), and Manufacture of Chemicals and Chemical Products (NACE 20). These sectors have different carbon risk profiles, pass-through capacities, abatement flexibilities, and energy input structures [5, 57, 55, 56]. This contributes to the carbon-equity hedging literature, which has focused largely on the electricity sector [40, 55] or has used aggregated pan-European indices without making sectoral distinctions [14, 18].

Third, hedging assets are selected according to each sector's primary production inputs rather than applying all the assets across all the portfolios. EUA futures are combined with two assets that are relevant for the sector's cost structure and gold is included for each sector as a placebo asset to check the validity of the analysis. By using EUA and a set of assets according to their relevance with the production inputs of the sectors, the linkages between energy commodities and EUA prices are assessed [15, 19, 47] and their dynamics in different market conditions are analyzed [48, 14].

Fourth, the analysis is divided into six sub-periods to analyze the effects of the crisis and regime changes discussed in Section 2.1.4. These six periods are the Phase III Low Price environment (January 2013 - December 2018), the Post-MSR recovery (January 2019 - February 2020), the COVID-19 shock (March 2020 - December 2020), the Phase IV High Price regime (January 2021 - December 2022), the Phase IV Normalization window (January 2023 - September 2023), and the CBAM Transitional period (October 2023 - April 2026). This sub-period analysis assesses whether hedging relationships estimated under more stable market conditions remain consistent across regime changes, crisis periods, and the introduction of new regulatory channels during 2013-2026.

Methodologically, these contributions are assessed by applying the DCC-GARCH model introduced by Engle [20], with dynamic hedge ratios derived based on the methodology established by Kroner and Sultan [61] and optimal portfolio weights following Kroner and Ng [21]. The efficiency of hedging strategies is measured using two different variance reduction criteria, which are the HR-based hedging effectiveness developed by Ederington [22], and the OW-based hedging effectiveness derived from the Kroner-Ng [21] optimal portfolio composition. Then, the hedged portfolios constructed from the estimated hedge ratios and optimal portfolio weights are evaluated using the set of risk-adjusted performance metrics developed by Demiralay et al. [18] and Lai [59]. The robustness of the main estimates is also assessed in two dimensions. First, the univariate specification was re-estimated using an AR(1) mean equation and an asymmetric GJR-GARCH(1,1) variance equation to account for residual autocorrelation and sign-bias effects. Second, sector portfolios were reconstructed using the stable equal-weighted and the yearly rebalanced market-capitalization-weighted methods to test whether the results depended on the index construction methodology. Hedging effectiveness measures (HR-based and OW-based) were reported for both methods.

Table 2.4 summarizes how the empirical findings and methodologies reviewed in this chapter are used for the analytical and design choices of this thesis.

Table 2.4: Literature Findings and Their Implications in the Empirical Design

Literature Finding	**Methodological / Analytical Choice in this Thesis**
EU ETS-regulated and non-EU ETS-regulated firms respond to carbon-price shocks through different transmission channels, and their sensitivities to carbon-market developments may change [11, 49, 4]	Separate equal-weighted portfolios for EU ETS-regulated and non-EU ETS-regulated firms are constructed within each sector to test the effects of EU ETS regulation.
Pass-through capacity, abatement flexibility, and energy input structure differ across carbon-intensive sectors [5, 55, 56, 17, 57, 58]	The analysis is performed across four NACE sectors (NACE 35, 24, 23, and 20) with sector-specific structural characteristics rather than aggregate sectoral indices.
Energy commodity prices (natural gas, oil, and coal) drive EUA price dynamics, and the relevance of each commodity varies across sectors [15, 19, 42, 47]	EUA futures are combined with sector-relevant energy commodities (oil for Electricity and Chemicals, coal for Basic Metals and Non-Metallic Minerals, and gas for all sectors), while gold is included as a placebo asset.
Carbon-market dynamics are regime-dependent and shift across EU ETS phases, crisis periods, and regulatory changes [16, 48, 52, 14, 9]	The 2013-2026 sample is divided into six sub-periods (Phase III Low Price, Post-MSR, COVID-19, Phase IV High Price, Phase IV Normalization, and CBAM Transitional) to compare regime-dependent hedging behavior.
CBAM introduces reporting requirements for selected carbon-intensive imports and requires financial compliance from January 2026 [25, 38, 54]	The CBAM Transitional period (Oct 2023-Apr 2026) is treated as a separate regulatory regime within the sub-period analysis.
Time-varying conditional correlations and volatility persistence are essential for dynamic hedging analysis [20, 13, 48]	A bivariate DCC-GARCH(1,1) model is estimated for each of the 32 sector-asset pairs to extract time-varying hedge ratios and optimal portfolio weights.
The variance-reduction criterion alone is insufficient to evaluate hedging strategies; risk-adjusted return and downside-risk metrics provide complementary information [59, 18]	In addition to HE, the hedged portfolios are evaluated using the Sharpe ratio, Sortino ratio, annualized volatility, value-at-risk, and maximum drawdown.
Both HR-based and OW-based hedging effectiveness measures provide complementary views of hedging performance under long-only constraints [61, 21, 63]	Both HE and $\mathrm{HE}_{\mathrm{OW}}$ are reported throughout the analysis.
Residual autocorrelation and asymmetric volatility responses can affect DCC-GARCH hedge estimates [64, 65]	Robustness checks include re-estimation with an AR(1) mean equation and a GJR-GARCH(1,1) variance equation [64].
The choice of equity-portfolio construction methodology may influence the estimated hedging relationships [66, 67]	Robustness checks include reconstruction of the sector portfolios under the stable equal-weighted method and the yearly market-cap-weighted method.

Notes: Table shows how the key findings from the literature are reflected in the empirical design of this thesis.

2.6 Hypotheses

Based on the literature reviewed and the empirical design of the thesis, the following hypotheses are formulated.

H1 EUA futures are expected to show higher hedging effectiveness and stronger dynamic hedging relationships with EU ETS-regulated portfolios than non-EU ETS-regulated portfolios within the same sector.

H2 The hedging effectiveness of EUA futures and sector-relevant energy commodities is expected to vary across sectors, as firms differ in their emissions intensity, production structure, cost pass-through capacity, and energy dependence.

H3 Hedging effectiveness and dynamic hedge ratios are expected to change across different EU ETS regulatory regimes, including the introduction of new regulatory channels such as CBAM, and across macroeconomic crisis periods.

Chapter 3

Data

This chapter explains the dataset construction processes used in the empirical analysis. The dataset consists of sectoral equity portfolios constructed from stocks of EU ETS-regulated and non-EU ETS-regulated firms across four energy-intensive sectors, using five hedging assets. The hedging assets selected for the analysis are the EUA futures, TTF natural gas futures, Brent crude oil futures, Rotterdam coal futures, and gold. The following sections, Sections 3.2 to 3.4, describe the construction of the firm-level dataset, the sector selection process, the classification of EU ETS-regulated and non-EU ETS-regulated firms, and the construction of sector indices.

3.1 Sample Period and Scope

3.1.1 Temporal Coverage

The empirical analysis consists of daily data spanning from 1 January 2013 to 30 April 2026, providing approximately 3,400 trading days per asset and equity portfolio. These periods coincide with the beginning of Phase III of the EU ETS, implemented after the changes brought by Directive 2009/29/EC [23] and extend into Phase IV, defined by Directive (EU) 2018/410 [24] and later revised by Directive (EU) 2023/959 [26] under the *Fit for 55* package.

The sample period starts from 2013, which is the beginning of Phase III, excluding Phase I (2005-2007) and Phase II (2008-2012), which have undergone substantial structural and regulatory changes. In these early phases, over-allocation of allowances [34], restriction of Phase I to Phase II carry-forward, and the 2008 global economic crisis caused price behavior patterns that do not accurately reflect the later structure of the EU ETS [5, 31]. Analyzing Phase III and Phase IV provides a relatively more consistent regulatory framework, such as an EU-wide cap, auctioning as the default allocation mechanism, and the implementation of the Linear Reduction Factor system [23]. Thus, the chosen sample better represents the EU ETS following significant changes introduced during Phases III and IV, while covering the period when the relevance of EUA prices as a financial risk factor increased substantially.

This time period includes six different regulatory and macro-financial regimes with distinctive characteristics, which provides a basis for the analysis by sub-periods in Chapter 5: the Phase III Low Price period (2013–2018); the Post-MSR period (January 2019–February 2020); the COVID-19 period (March–December 2020); the Phase IV High Price period (2021–2022); the Phase IV Normalization period (January–September 2023); and the CBAM Transitional period (October 2023–April 2026), during which importers were required to report embedded emissions on a quarterly basis. The economic rationale for this decomposition is developed in Section 2.1.4.

3.1.2 Sectoral Coverage

The empirical analysis focuses on four 2-digit NACE sectors:

- **NACE 35** — Electricity, gas, steam and air conditioning supply
- **NACE 24** — Manufacture of basic metals
- **NACE 23** — Manufacture of other non-metallic mineral products
- **NACE 20** — Manufacture of chemicals and chemical products

These four sectors account for 68.01% of the total Scope 1 CO_2-equivalent emissions represented in the sector-selection database, further explained in Section 3.2.1. The database consists of firms headquartered and traded within the EU-27 countries, with a minimum market capitalization threshold of €50 million, subject to LSEG Workspace's data extraction limits. Sectoral emission shares were calculated by first computing each firm's average reported Scope 1 CO_2-equivalent emissions over 2013-2024, and then aggregating these values at the two-digit NACE sector level. Therefore, the reported percentage reflects the composition of the sector-selection database. The selected sectors directly include activities covered by Annex I of the EU ETS Directive (Directive 2003/87/EC) [2]. The methodology used in the sector selection process is presented in Section 3.3.

3.2 Firm-Level Sample Construction

Firm-level data retrieved from LSEG Workspace were used in two different stages of the empirical analysis. First, during the sector selection process described in Section 3.3, the extracted firm-level data were aggregated to calculate the 2-digit NACE-level sectoral CO_2 emission shares. Second, a broader firm universe was used to obtain the identifiers of the companies in EU ETS-regulated and non-EU ETS-regulated lists within the selected sectors as described in Section 3.3.3, which is later used to construct sectoral indices.

3.2.1 LSEG Workspace Data Extraction and Filtering

The empirical analysis starts from a sample of listed firms within the EU Member States to ensure that the geographic boundaries correspond to those of the EU ETS. This is performed by limiting the "Country of Headquarters" filter to 27 countries included in the EU Member States. Moreover, "Country of Exchange" was also limited to the 27 countries included in the EU Member States, to ensure that the selected firms operate and are traded within a common regulatory and financial environment shaped by the EU ETS.

For the sector-selection stage, an additional market capitalization threshold of €50 million was applied due to the size of extraction and retrieval limitations of LSEG Workspace, as Scope 1 CO_2-equivalent emissions and corresponding 2-digit NACE classifications had to be retrieved simultaneously for a large universe of European listed firms over the 2013-2025 period. This threshold was only used for the sector-selection stage. For the construction of the EU ETS-regulated and non-EU ETS-regulated firm lists, the market capitalization threshold was not applied; only the first two previously mentioned filters were implemented, and a firm list was extracted for each of the four selected 2-digit NACE-level sectors.

The analysis was conducted at the 2-digit NACE level because it is detailed enough to distinguish between industries with different production structures and carbon profiles, and it is able to provide meaningful comparisons across sectors.

Sectoral CO_2 shares were computed using Scope 1 CO_2-equivalent emissions, as they reflect firms' direct operational emissions and therefore provide a measure of exposure to EU ETS compliance obligations.

To reduce the influence of year-specific emission fluctuations, Scope 1 CO_2 equivalent emissions were retrieved over the 2013-2024 period and averaged at the firm level before sector aggregation. This period covers the part of the data sample where Scope 1 CO_2-equivalent emissions data are reported, including both Phase III and a significant portion of Phase IV of the EU ETS. By calculating average emissions across the whole sample period, the impact of year-to-year changes is reduced and a better sense of firms' long-term emissions is obtained. This method also helps limit the effects of short-term events such as the COVID-19 pandemic and the 2022 European energy crisis on sector-level emission estimates. As a result, it provides a more complete picture of emissions shares across NACE 2-digit sectors.

3.3 Sector Selection

The sectors were selected in two stages. First, an initial screening based on the NACE classification was conducted. Then, the sectors were selected based on their emission shares and direct activity mapping to the EU ETS.

3.3.1 NACE-Based Relevance Filter

According to the NACE Rev. 2 classification [68], all economic activities were first evaluated based on their relevance to the EU ETS activity scope. All six broad NACE categories that are highly involved in carbon-based production were selected based on their economic relevance to the EU ETS: Mining and Quarrying (B); Manufacturing (C); Electricity, Gas, Steam and Air Conditioning Supply (D); Water Supply and Waste Management (E); Construction (F); and Transportation and Storage (H). This filtering process allowed the analysis to focus on sectors where the EU ETS is more directly linked to production activities and carbon-related financial exposure.

3.3.2 Two-Criterion Selection

From the eligible NACE 2-digit sectors, four final sectors were selected based on two jointly applied criteria:

1. **CO_2 share.** Each sector's contribution to total Scope 1 CO_2-equivalent emissions was calculated within the filtered LSEG Workspace firm-level dataset described in Section 3.2.1. This criterion was used to identify sectors with high carbon exposure in the sample. The analysis showed that emissions were concentrated in a few NACE 2-digit sectors, while other sectors had significantly low emission shares in the sample. These results suggest that a small group of industries has a significant impact on the sample's overall emissions profile.

2. **Direct EU ETS activity mapping.** The chosen sectors had to meet the condition that their activities were directly regulated by Annex I of Directive 2003/87/EC [2]. The sectors that experience carbon pricing as a result of upstream energy costs, downstream linkages, or broader supply-chain effects were excluded, even if they are economically affected by the EU ETS [5].

The manufacture of coke and refined petroleum products (NACE 19) sector had the third-highest emissions share, at 7.61%, and strong alignment with EU ETS Annex I activities. However, compared to other sectors with the highest emissions shares, it had a limited number of firms and an inadequate balance between EU ETS and non-EU

ETS observations. Since the empirical analysis requires constructing separate EU ETS and non-EU ETS firm portfolios, a sufficiently broad set of firms is essential for each portfolio. Due to its limitations in this manner, the manufacture of coke and refined petroleum products (NACE 19) was excluded from the sample of selected sectors.

After excluding the manufacture of coke and refined petroleum products (NACE 19) sector, the final sample consisted of four sectors with the highest CO_2 emission shares that satisfied both criteria. These sectors are reported in Table 3.1, together with their CO_2 shares and the corresponding Annex I activities.

Table 3.1: Selected sectors and EU ETS activity mapping

NACE	Sector	CO_2 Share	Annex I Activity
35	Electricity, gas, steam and air conditioning supply	42.69%	Combustion of fuels in installations with rated thermal input > 20 MW
24	Manufacture of basic metals	12.83%	Production of pig iron, steel, and processing of ferrous metals
23	Manufacture of other non-metallic mineral products	7.52%	Cement clinker, lime, glass, and ceramic production
20	Manufacture of chemicals and chemical products	4.98%	Production of bulk organic chemicals, ammonia, nitric acid, and adipic acid
	Total	**68.01%**	

Notes: CO_2 shares are computed from Scope 1 CO_2-equivalent emissions of the firms included in the LSEG Workspace-listed company database used in this study. Annex I activity descriptions follow Directive 2003/87/EC [2].

3.3.3 EU ETS-Regulated vs. Non-EU ETS-Regulated Classification

The classification of firms by their EU ETS regulatory status is based on the procedure developed and validated by Chiappari et al. [63]. To obtain the list of EU ETS-regulated listed firms, installation-level records from the European Union Transaction Log (EUTL) are linked to parent companies through ORBIS, and it is matched with the LSEG Workspace listed-firm universe using firm identifiers such as ISINs, LEIs, and Tickers. The resulting dataset provides a validated list of EU ETS-regulated listed firms.

After identifying EU ETS-regulated listed firms, their 2-digit NACE classifications are retrieved from LSEG Workspace using the firms' Refinitiv Identifier Codes (RICs). Since all the financial data for the empirical analysis and NACE 2-digit sectoral level

Scope 1 emissions are also extracted from LSEG Workspace, using a single platform ensures dataset consistency. This helps to ensure that firms are assigned to the same sectors throughout the analysis.

Once the final sector sample had been established, firms were separated into EU ETS and non-EU ETS groups through the cross-matching procedure. This resulted in two portfolios for each sector:

- **EU ETS-Regulated Firms:** listed firms that were matched to the EU ETS company list and are classified as EU ETS-regulated firms.
- **Non-EU ETS-Regulated Firms:** listed firms present in the LSEG Workspace extraction with country of headquarters and exchange limited to EU-27 countries but absent from the EU ETS-regulated firms list, which represent the group of European firms operating in the same 2-digit NACE sector but without direct compliance obligations.

This classification was performed for each of the four sectors, yielding eight firm portfolios in total.

3.4 Sector Index Construction

A sector index was created daily for each of the eight firm groups using daily closing prices from 1 January 2013 to 30 April 2026, retrieved from LSEG Workspace. The primary index is constructed as a monthly rebalanced equal-weighted portfolio. Additionally, two alternative index constructions are implemented as robustness checks, which are the stable equal-weighted and a yearly rebalanced market-capitalization-weighted indices. The three portfolio constructions differ in how portfolios are rebalanced, how firms are weighted within each period, and how data-quality issues are addressed.

3.4.1 Coverage Thresholds and Data-Quality Filters

A common set of data quality rules is applied to all three index construction approaches to consistently handle missing observations and variations in firms' trading histories across the sample. Daily closing prices are forward-filled for up to five consecutive trading days. Firms with longer missing price gaps or fewer than 200 valid trading observations are excluded from the analysis when analyzing the full sample period.

The coverage threshold depends on the index construction method. For monthly rebalanced equal-weighted and yearly rebalanced market-capitalization-weighted indices, firms must have valid price data for at least 80% of trading days over the sample period.

This threshold is chosen to ensure enough firms are included in the sample while maintaining high data quality. If stricter requirements are imposed, the number of eligible firms would decrease substantially, especially in smaller sector portfolios. However, the gain in data completeness would be low. Using the 80% threshold provides enough data and helps keep each sector portfolio broad and representative. In addition, firms must have at least 200 valid trading observations, and missing daily prices are forward-filled for up to 5 consecutive trading days. This approach retains short interruptions in trading records but excludes firms with extended periods of missing data from the sample. The stable equal-weighted index has a stricter coverage requirement. Firms must meet the 90% coverage threshold over the full sample. This stricter rule is necessary because the stable equal-weighted index uses the same set of companies throughout the analysis period. Unlike indices that are updated monthly or yearly based on market capitalization, it cannot include or exclude companies over time. As a result, companies with large gaps in price data are excluded to keep the panel consistent and balanced.

3.4.2 Coverage Threshold Sensitivity Analysis

The choice of the coverage threshold is more important for the stable equal-weighted robustness specification as it requires a balanced panel of firms with overlapping observations throughout the sample period. To evaluate the trade-off between firm retention and common trading-day availability for the stable equal-weighted index, a sensitivity analysis is conducted separately for the EU ETS-regulated and non-EU ETS-regulated portfolios within each sector at thresholds of 70%, 75%, 80%, 85%, 90%, and 95%. The results are summarized in Table 3.2.

Table 3.2: Coverage threshold sensitivity analysis (1 January 2013 - 30 April 2026)

Sector portfolio	**Init.**	**70%**		**75%**		**80%**		**85%**		**90%**		**95%**	
		Firms	Days	Firms	Days	**Firms**	**Days**	Firms	Days	Firms	Days	Firms	Days
Electricity (ETS)	41	29	1957	29	1957	29	1957	26	2614	26	2614	23	2966
Electricity (Non-ETS)	101	47	1066	45	1081	40	1404	37	1518	29	2535	26	3047
Basic Metals (ETS)	17	10	2931	10	2931	10	2931	10	2931	10	2931	9	3222
Basic Metals (Non-ETS)	43	31	1640	30	2050	30	2050	28	2255	26	2432	23	2798
Non-Metallic Minerals (ETS)	19	10	1843	9	2475	8	3227	8	3227	8	3227	8	3227
Non-Metallic Minerals (Non-ETS)	35	10	1930	10	1930	8	3133	8	3133	8	3133	7	3189
Chemicals (ETS)	25	19	2586	19	2586	19	2586	19	2586	18	2841	16	3166
Chemicals (Non-ETS)	107	44	1107	40	1503	36	1794	34	1864	29	2262	22	2944

Notes: For each coverage threshold, "Firms" reports the number of firms with available data, and "Days" reports the number of common trading days available under a strict balanced-panel restriction. Firm groups are labeled according to the NACE 2-digit sector classification and regulatory status. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

According to the sensitivity analysis, a 90% threshold was retained for the stable equal-weighted index to maintain sufficiently long common trading windows for the firms with available data.

3.4.3 Primary Method: Monthly Rebalanced Equal-Weighted Index

The primary index is constructed as a monthly rebalanced equal-weighted portfolio. On the first trading day of each month, the equal rebalancing weight $w_{i,t}^{\text{reb}} = 1/n_t$ is assigned to every firm with a valid closing price, where n_t denotes the number of active firms at the rebalancing date. Between balancing dates, the weights are adjusted with the changes in stock price movements. Firms whose daily closing prices have increased since the beginning of the month have a larger weight in the portfolio, while firms whose prices have decreased have a smaller weight. The weight of firm i on trading day d within month t is therefore determined by its initial rebalancing weight and its cumulative price performance since the most recent rebalancing date. The portfolio level on trading day d within month t is given by

$$V_d = V_{\text{reb}(t)} \cdot \frac{1}{n_t} \sum_{i \in A_t} \frac{P_{i,d}}{P_{i,\text{reb}(t)}}, \tag{3.1}$$

where A_t is the active firm set in month t, $P_{i,\text{reb}(t)}$ is firm i's closing price on the rebalancing date, and $V_{\text{reb}(t)}$ is the portfolio level on that date. The daily sector log return is then

$$r_d^{\text{sector}} = \ln\left(\frac{V_d}{V_{d-1}}\right). \tag{3.2}$$

The time-varying weight of firm i on day d within month t is

$$w_{i,d} = \frac{P_{i,d}/P_{i,\text{reb}(t)}}{\sum_{j \in A_t} P_{j,d}/P_{j,\text{reb}(t)}}, \tag{3.3}$$

The weight equals $1/n_t$ on the rebalancing date and adjusts during the month based on realized firm-level returns. At each monthly rebalancing, the constituent set is updated, and weights are reset to $1/n_{t+1}$. The sector index level is set to 100 at the start of the sample.

Giving each firm equal weight at every rebalancing date helps avoid concentrating the portfolio in just a few large companies. This approach also makes sure that all firms contribute equally at the start of each month. By rebalancing every month, the portfolio can adjust when firms join or leave the sample, which helps the index remain representative of the sector during the analysis period.

3.4.4 Robustness Methods

Two alternative index constructions are implemented to validate the robustness of the empirical results to the choice of the weighting scheme.

Stable Equal-Weighted Index. The stable equal-weighted index allocates a constant weight of $1/N$ to each firm within a fixed, balanced panel of N firms that meet the full-sample 90% coverage threshold described in Section 3.4. In contrast to the primary specification, the composition of the firm universe remains constant over the sample period, and no rebalancing occurs. Consequently, daily portfolio log returns are computed as the cross-sectional mean of the constituent firms' log returns.

$$r_t^{\text{stable}} = \frac{1}{N}\sum_{i=1}^{N} \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right). \tag{3.4}$$

Since both the firm set and the weight vector are fixed over time, this approach provides a strict benchmark against which the primary monthly rebalanced index can be compared [67]. However, the simplicity of this method leads to a reduced number of firms in the sample and fewer usable trading days, as only firms that meet the full-sample coverage criterion are included.

Yearly Rebalanced Market-Capitalization-Weighted Index. The yearly rebalanced market-capitalization-weighted index assigns to each firm a weight proportional to its market capitalization obtained from LSEG Workspace. The firm universe is subject to the same data-quality filters applied in the primary specification, including a maximum forward-fill limit of five consecutive trading days, a minimum data coverage ratio of 80%, and at least 200 available trading observations. To reduce the impact of year-end and New Year public holidays, market capitalization values are retrieved during the first trading week of January in each calendar year.

For each year y, firm weights are defined as

$$w_{i,y}^{MC} = \frac{MC_{i,y}}{\sum_{j=1}^{N_y} MC_{j,y}}, \tag{3.5}$$

where $MC_{i,y}$ denotes the market capitalization of firm i at the annual rebalancing date and N_y is the number of firms included in the portfolio during year y. Daily portfolio returns are then computed as

$$r_t^{MC} = \sum_{i=1}^{N_y} w_{i,y}^{MC} \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right). \tag{3.6}$$

Weights remain fixed throughout each calendar year and are updated at the beginning of the following year using the firms' market capitalizations. This construction allows larger firms to have a greater influence on index performance. As a result, the index provides a useful robustness check for assessing whether the findings are sensitive to the monthly rebalanced equal-weighted index adopted as the primary approach.

3.5 Hedging Asset Data

3.5.1 Asset Data

The hedging asset set consists of five instruments selected based on their relevance to the production input structure of the four selected sectors and the availability of their price data over the full sample period. The instruments and their RICs are reported in Table 3.3.

Table 3.3: Hedging assets and LSEG Workspace identifiers

Asset	**Description**	**Currency**	**RIC**
EUA	EU Emission Allowance Futures	EUR	FEUAc1
Gas	TTF Natural Gas Futures	EUR	TRNLTTFMc1
Oil	Brent Crude Oil Futures	EUR	LCOc1
Coal	Rotterdam Coal Futures	EUR	ATWMc1
Gold	Gold Spot Price	EUR	GCc1

Notes: EUA futures are the primary carbon market instrument used in the empirical analysis. Brent crude oil is selected as the European-relevant crude oil benchmark [52], TTF gas as the principal European wholesale natural gas benchmark [48, 47], and Rotterdam coal futures as the European thermal coal benchmark [48, 47]. Gold is included as a placebo asset.

3.5.2 Sector-Asset Pairing Rationale

The pairing of hedging assets with the sector portfolios is based on the sectors' production and energy-input structures and their exposure to energy and carbon markets [47, 9]. This keeps the analysis focused on the sector-asset combinations expected to be most relevant from an economic perspective. The resulting sector-asset mapping is reported in Table 3.4, and its rationale is discussed below.

EU Allowance (EUA) futures - all four sectors EUA futures are paired with all sector portfolios because the four NACE sectors considered in this study (Electricity (35), Basic Metals (24), Other Non-Metallic Mineral Products (23), and Chemicals

(20)) are included in Annex I of the EU ETS Directive and are therefore directly exposed to carbon-pricing costs [2]. As firms have financial compliance obligations, changes in EUA prices affect their production costs and profitability. Previous studies also identify carbon prices as an important driver of firm value and stock returns in EU ETS-regulated industries [14, 18]. Therefore, EUA futures are included for all the sector portfolios and provide a benchmark across sectors. Additionally, their relevance for the non-EU ETS-regulated portfolios is also examined, since carbon costs may affect these firms indirectly through channels such as electricity prices, input costs, and supply-chain relationships [5, 9].

TTF natural gas futures - all four sectors Natural gas is relevant for all four sectors considered in this study. In the Electricity sector, it affects the generation costs and wholesale electricity prices [9]. It is also linked to carbon prices, as electricity producers may switch between gas and coal when relative fuel prices change [15, 42]. In Basic Metals and Non-Metallic Minerals sectors, natural gas is a source of process heat in energy-intensive production activities, including steel, cement, and glass manufacturing [69, 70]. In the Chemicals sector, it is both an energy input and a feedstock for products such as ammonia, methanol, and hydrogen [71, 72]. Due to its importance for all four sectors, TTF natural gas futures are included for all sector portfolios.

Brent crude oil futures - Electricity and Chemicals only Brent crude oil futures are paired only with the Electricity (35) and Chemicals (20) sectors. For the Electricity sector, oil prices are historically linked to electricity prices through energy markets and fuel costs [73, 74, 47]. In the Chemicals sector, crude oil is particularly important because it is one of the main production inputs of many petrochemical products derived from oil-based feedstocks such as naphtha [71, 72]. In contrast, oil is less directly connected to the production structure of the Basic Metals (24) and Other Non-Metallic Mineral Products (23) sectors. Consequently, Brent crude oil futures are included only for the Electricity and Chemicals portfolios.

Rotterdam coal futures - Basic Metals and Non-Metallic Minerals only Coal futures are paired only with the Basic Metals (24) and Other Non-Metallic Mineral Products (23) sectors. Coal is still widely used in steel production, especially for the blast-furnace process, where coal is coked [69]. It is also an important energy source in cement production and other non-metallic mineral activities [70, 75].

The importance of coal in European electricity generation declined considerably during the sample period, as coal-fired generation was gradually reduced in many countries [76, 10]. Therefore, coal is not selected as a hedging asset for the Electricity sector. Coal is also not paired with the Chemicals sector, since it is not commonly used as a major production input or feedstock [71].

Gold - all four sectors Gold is included as a validity check for all the sectors, as it has no direct economic link with the selected sectors. It is established as a safe-haven asset for equity and energy market stocks [77, 78] and it is separated from the examined carbon-energy channel. Therefore, comparing the hedge effectiveness of gold for each sector portfolio with the results obtained for EUA futures and energy commodities provides a useful benchmark for interpreting the findings. If the hedge effectiveness of gold is similar to that of the other assets, the results are more likely to reflect general portfolio diversification rather than the specific role of carbon and energy markets.

Table 3.4: Sector-relevant hedging asset mapping

NACE	Sector	EUA	Gas	Oil	Coal	Gold
35	Electricity, gas, steam and air conditioning supply	✓	✓	✓		✓
24	Manufacture of basic metals	✓	✓		✓	✓
23	Manufacture of other non-metallic mineral products	✓	✓		✓	✓
20	Manufacture of chemicals and chemical products	✓	✓	✓		✓

Notes: Asset selection depends on the production inputs of the selected sectors. Gold is included for all sectors as a placebo asset.

Gold is included as a placebo asset for all four sectors. As there is no direct production link between the chosen industries and gold, hedge effectiveness with respect to gold will indicate any specification error and provide a validity check on the empirical design [77, 78].

Figure 3.1 presents the historical price movements and daily log returns of the five hedging assets used in the analysis. Examining these series provides a clearer picture of how the assets evolved over the sample period and highlights important market events that may have influenced their relationship with sector portfolio returns.

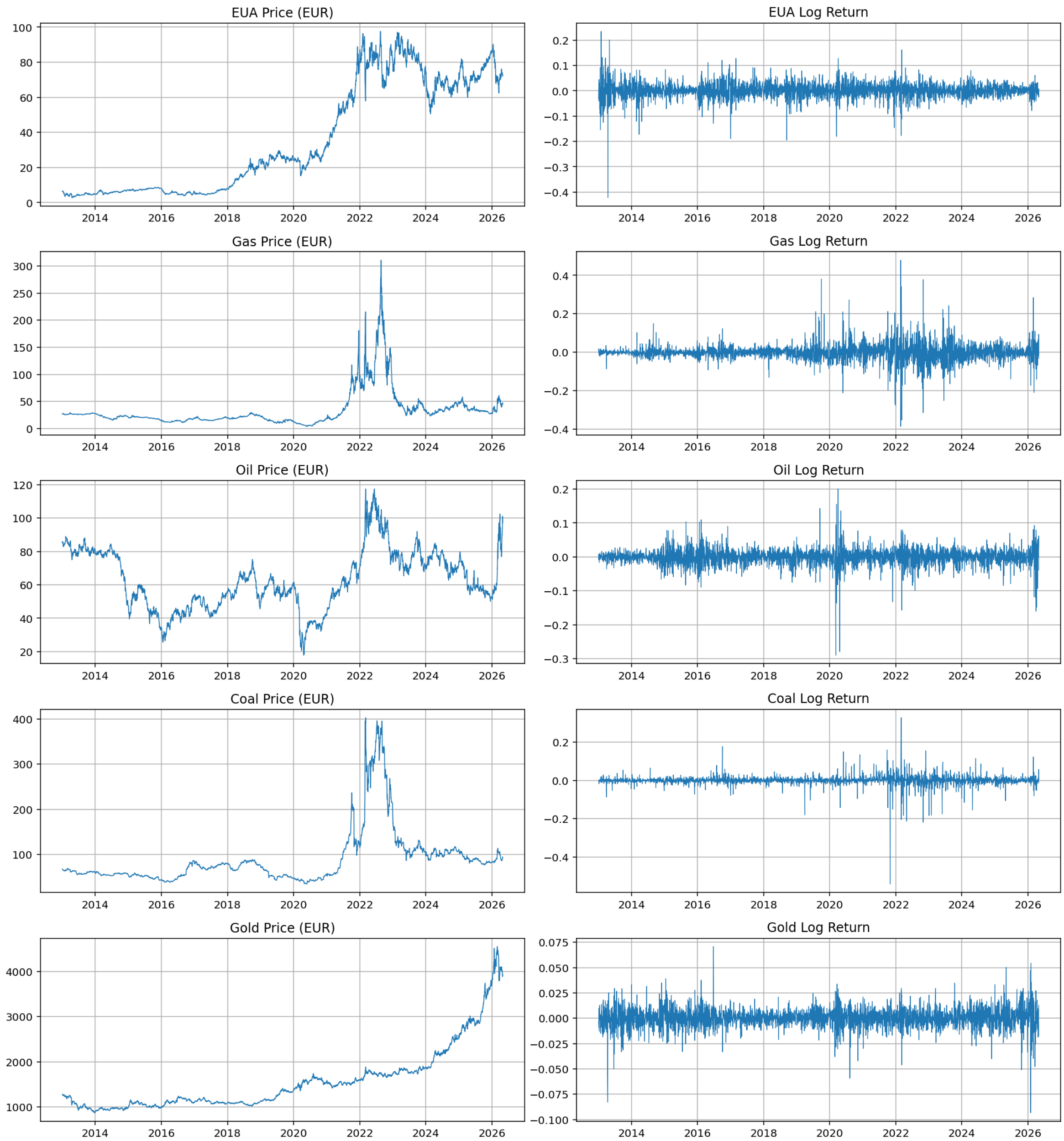

Figure 3.1: Price dynamics and daily log returns of the hedging assets, January 2013-April 2026

Figure 3.1 presents the historical price series and daily log returns of the five hedging assets used in the analysis: European Union Allowances (EUA), TTF Natural Gas Futures, Brent Crude Oil Futures, Rotterdam Coal Futures, and Gold. The price series shows clear differences in how markets behave across different assets.

The figure shows that gold follows a stable upward trend, while EUA and energy-related commodities undergo significant fluctuations. Especially during the 2021-2022 energy crisis period, natural gas and coal prices increased sharply and gradually declined as market conditions normalized. EUA prices also significantly rose during the transition period to Phase IV of the EU ETS. Differences in price behavior across assets indicate they capture distinct dimensions of the market, which is important for assessing their potential as hedging instruments for the analyzed sectors.

3.5.3 Market and Policy Context of the Hedging Assets

The six sub-periods defined in Section 5.3 were designed to capture major regulatory, economic, and energy-market developments that affected European carbon and commodity markets between 2013 and 2026. Since the hedging assets used in this thesis are closely connected to energy markets, industrial activity, and climate policy, many of these developments are reflected in their price movements. Therefore, they have to be analyzed alongside these wider market movements. This subsection therefore provides a brief overview of the main events affecting each asset and establishes the economic background for the empirical results presented in Chapter 5.

EU Allowance (EUA) Futures: Changes in EUA prices during the sample period mostly followed major regulatory shifts in the EU ETS. In Phase III, the persistent surplus of allowances kept carbon prices low and the EUA prices stayed under €10 per tonne for most of 2013 to early 2018 [9, 45]. This situation gradually changed following the adoption of the Market Stability Reserve (MSR) in 2015, which became operational in January 2019 and was designed to reduce the surplus of allowances in circulation [6, 8, 28]. Together with the strengthened Linear Reduction Factor introduced under Directive (EU) 2018/410, the MSR contributed to an increase in carbon prices after 2018 [24, 10].

Carbon prices increased even further during 2021 and 2022. A few key factors led to this increase. These include the announcement of the Fit for 55 package, a stricter emissions cap in Phase IV, and the European energy crisis following Russia's invasion of Ukraine. As a result, EUA futures were traded above €90 per tonne in early 2022 in a brief period [9, 10]. Another important development during the later part of the sample was the introduction of the CBAM transitional phase in October 2023. Because the transitional period only required importers to report emissions and did not impose financial obligations until January 2026, its direct effect on EUA demand was limited. Nevertheless, CBAM reinforced expectations that carbon costs would remain an increasingly important consideration for carbon-intensive industries [38, 28]. These developments show how regulatory changes and market conditions influenced EUA price trends during the sample period.

The developments discussed above demonstrate the significant influence of regulatory reforms and the concurrent economic conditions on the EUA market during the sample period. As a result, carbon prices evolved within a market environment that differed substantially across the sub-periods considered in this thesis.

TTF Natural Gas Futures: Dutch TTF natural gas futures are the main reference point for the natural gas prices in Europe. Between 2013 and the beginning of 2020, TTF natural gas prices remained relatively low and stable compared to their levels observed during the energy crisis, as displayed in Figure 3.1. At the beginning of the COVID-19 pandemic, the decline in economic and industrial activities led to a global decrease in energy demand [76] and therefore reached their lowest sample-period levels. But this period with low natural gas prices was short-lived. In early 2021, lower natural gas storage levels and increasing LNG demand in Asia contributed to a surge in natural gas prices [79]. After the 2022 energy crisis, concerns over the gas supply led to peak levels in TTF natural gas prices, and the prices increased around tenfold compared to their level before the crisis [10]. As shown in Figure 3.1, most of this increase occurred between February and August 2022. In 2023, storage levels recovered, and the European gas market became more stable. Policy measures such as REPowerEU, joint gas purchasing initiatives, and demand-reduction measures contributed to improving supply security across the region [37, 80].

Previous studies highlight a close relationship between gas and carbon markets. One of the main reasons for this is the change in electricity prices depending on the fuel type utilized. For instance, when natural gas prices increase, producers tend to use alternative sources such as coal, and this affects carbon emissions and therefore the EUA demand [9, 48]. This relation is especially apparent during the 2022 European energy crisis. Exceptional price movements in the natural gas market not only impacted the energy prices but also the carbon market. The market conditions observed during the 2022 European energy crisis help explain the stronger hedging performance of TTF futures reported in the sub-period analysis presented in Section 5.3.

Brent Crude Oil Futures: Brent crude oil prices were largely influenced by global supply-demand balances and significant economic events throughout the examined sample period. During the first half of Phase III, oil prices remained on a downward trend for several years due to oversupply in the global oil market [81]. However, prices partially recovered as OPEC+ countries began to restrict production. In March-April 2020, the slowdown in economic activity and the collapse of transportation demand due to the COVID-19 pandemic led to a drop in global oil demand. As a result, oil-related CO_2 emissions also decreased significantly [76, 46]. While demand recovered with the resumption of economic activity, supply concerns arising after Russia's invasion of Ukraine caused oil prices to rise again in 2022. In 2023 and 2024, oil prices became less volatile as global demand growth slowed, while OPEC+ continued to support prices through production cuts [82, 83].

The oil market is linked to the EU carbon market through several channels. Changes in oil prices can affect energy and production costs in some sectors, such as petrochemicals and refining. In addition, previous studies show that shocks in the energy and commodity markets can spill over into carbon markets, especially during market stress periods [48, 52, 46]. Therefore, developments in the oil market are particularly relevant for sectors with high energy and production costs. This may also help explain why oil provides relatively strong hedging benefits for some of the sector portfolios examined later in Section 5.2.

Rotterdam Coal Futures: Coal demand in Europe mainly declined through the sample period as coal gradually lost its role in electricity generation. By 2021, coal accounted for less than 14% of EU electricity production [76]. This decline was temporarily reversed during the 2022 energy crisis as some electricity producers shifted back toward coal-fired generation when gas prices increased sharply. This led to higher demand for both coal and emission allowances for a short period [9]. From late 2022 onwards, coal prices gradually declined as energy markets in Europe became more stable after the peak of the energy crisis [80]. Although previous studies document interactions between carbon and energy commodity markets [48, 52], the results presented later in the thesis show that coal provided almost no hedging benefits. This is consistent with the weaker relationship between coal prices and sectoral equity returns observed toward the end of the sample period.

Gold: Gold is included in the analysis as a placebo asset because it does not have a direct connection to the production processes of the four selected sectors. During the sample period, gold prices generally followed an upward trend. Gold prices especially increased during the COVID-19 period and remained relatively high in the following years. Previous studies identify gold as a hedge and safe-haven asset, while also showing that its effectiveness varies across market regimes [77, 78]. Because gold is mostly separate from the carbon and energy markets studied here, it serves as a useful benchmark for comparing the other assets.

Figure 3.2 summarizes the full data construction procedure used in this study, from the selection of carbon-intensive sectors and the classification of firms by EU ETS regulatory status, through the construction of sector portfolios, the pairing with sector-relevant hedging assets, and the resulting 32 sector–asset pairs used in the empirical analysis.

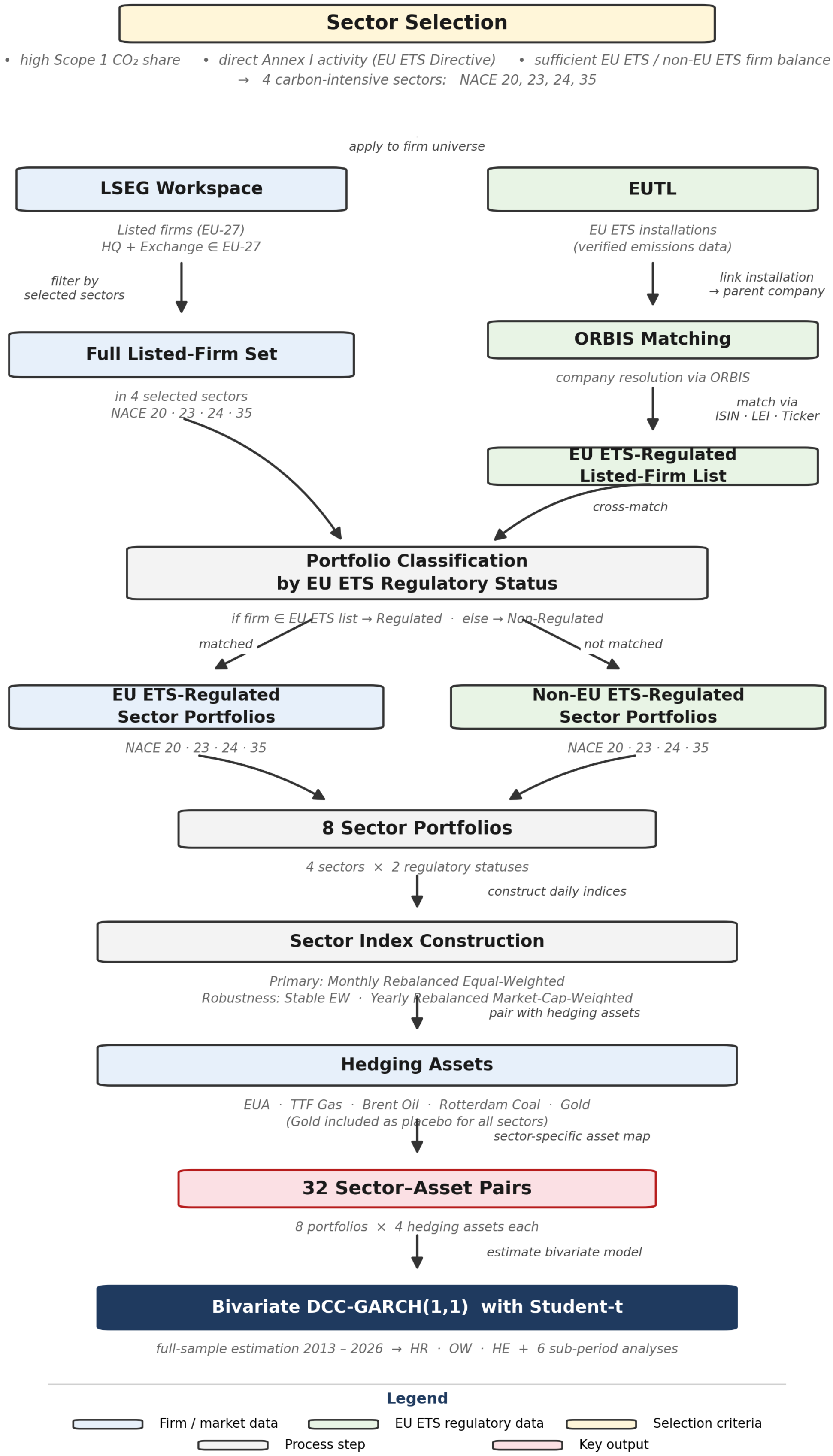

Figure 3.2: Data construction procedure

The analysis begins with the selection of four carbon-intensive NACE sectors according to the criteria mentioned in Section 3.3. For each sector, the data of listed firms are extracted from LSEG Workspace. EU ETS-regulated listed firms are classified using the EUTL and ORBIS databases. Then, non-EU ETS-regulated firms are identified by subtracting the EU ETS-regulated listed firms from the full listed firm set obtained from LSEG Workspace for each sector. This leads to eight sector portfolios in total, one EU ETS-regulated and one non-EU ETS-regulated for each sector. These portfolios are subsequently matched with EUA futures, gold, and two sector-specific hedging assets, resulting in 32 sector-asset pairs that are estimated using the bivariate DCC-GARCH(1,1) model presented in Chapter 4.

3.6 Preliminary Analysis and Model Adequacy

Before presenting the DCC-GARCH method estimations, the main characteristics of the return distributions are examined. Table 3.5 reports the descriptive statistics together with three main diagnostic tests. The standard deviation (SD) measures the volatility, skewness (Skew) evaluates the asymmetry and the excess kurtosis (Ex. Kurt) captures the extreme returns of the series. The Jarque-Bera (JB) test is used to assess normality of the distributions; the Augmented Dickey-Fuller (ADF) test measures stationarity, and the Ljung-Box test on squared returns, LB(Q^2), detects volatility clustering. These diagnostics provide the preliminary evidence required to apply the DCC-GARCH model.

The sector indices reported in Panel B are constructed using the Monthly Rebalanced Equal-Weighted (Monthly EW) index method. On the first trading day of each month, each active firm receives the rebalancing weight $1/n_t$, where n_t denotes the number of firms with available price data at the rebalancing date. Weights are adjusted within the month based on the firm's daily closing price changes and are reset to $1/n_{t+1}$ at the next rebalancing date. The model is tested with two alternative index construction methods, namely the stable equal-weighted (Stable EW) and yearly market-cap-weighted (YMCW) methods, and the results are documented in Section 5.5. The sample time is consistent across all of the return series (1 January 2013 to 30 April 2026). Differences in the number of observations across the equity indices (3,410 to 3,456) are mainly due to differences in IPO and delisting dates among the firms.

Table 3.5: Descriptive statistics of daily log returns. Sector equity indices in Panel B are constructed using the monthly rebalanced equal-weighted index method described in Section 3.4.

Series	N	**Mean (%)**	**SD (%)**	**Min (%)**	**Max (%)**	**Skew**	**Ex. Kurt**	**JB** p	**LB**(Q^2) p	**ADF** p
Panel A. Hedging assets										
EUA Futures	3,377	0.071	3.022	-42.23	23.47	-0.93	16.01	<0.001	<0.001	<0.001
TTF Natural Gas Futures	3,422	0.016	4.394	-38.54	47.89	0.77	17.66	<0.001	<0.001	<0.001
Brent Crude Oil Futures	3,439	0.004	2.447	-29.00	20.05	-0.98	16.44	<0.001	<0.001	<0.001
Rotterdam Coal Futures	3,423	0.009	2.499	-54.08	32.67	-2.51	93.53	<0.001	<0.001	<0.001
Gold	3,355	0.033	1.025	-11.05	6.96	-0.71	10.07	<0.001	<0.001	<0.001
Panel B. Sector equity indices (Monthly EW; NACE rev. 2)										
Electricity (ETS)	3,456	0.021	0.835	-11.71	8.95	-1.24	21.87	<0.001	<0.001	<0.001
Electricity (Non-ETS)	3,438	0.040	0.859	-12.65	5.41	-1.17	17.58	<0.001	<0.001	<0.001
Basic Metals (ETS)	3,431	0.030	1.699	-16.20	8.63	-0.43	5.38	<0.001	<0.001	<0.001
Basic Metals (Non-ETS)	3,410	0.029	1.049	-12.22	8.37	-0.67	10.97	<0.001	<0.001	<0.001
Non-Metallic Minerals (ETS)	3,440	0.039	1.116	-12.18	6.92	-0.72	7.52	<0.001	<0.001	<0.001
Non-Metallic Minerals (Non-ETS)	3,438	0.027	1.111	-9.53	12.92	0.22	10.57	<0.001	<0.001	<0.001
Chemicals (ETS)	3,429	0.010	1.080	-12.62	5.16	-0.93	8.94	<0.001	<0.001	<0.001
Chemicals (Non-ETS)	3,432	0.030	0.962	-11.67	6.28	-1.03	11.41	<0.001	<0.001	<0.001

Notes: N denotes the number of observations, SD denotes standard deviation, Ex. Kurt denotes excess kurtosis, JB refers to the Jarque-Bera normality test, LB(Q^2) refers to the Ljung-Box test on squared returns with 10 lags, and ADF refers to the Augmented Dickey-Fuller unit-root test. Values below 0.001 are reported as < 0.001. The sample period is from 1 January 2013 to 30 April 2026. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

According to the results, assets mainly differ in terms of their volatilities. Gold is the least volatile asset (SD = 1.025%). TTF natural gas futures (4.394%), EUA futures (3.022%), Rotterdam coal futures (2.499%), and Brent crude oil futures (2.447%) exhibit higher volatility characteristic of energy and emissions markets. Compared to the commodity assets, the equity indices have a lower range of volatility, as their standard deviations vary from 0.835% to 1.699%. Basic Metals ETS companies' portfolio (NACE 24, SD = 1.699%) has the highest volatility, and Electricity ETS companies' (NACE 35, SD = 0.835%) is the most stable portfolio. These results indicate that the sectors exhibit different volatility traits as the industries respond differently to market conditions.

All thirteen series exhibit extreme observations compared to the normal distribution. Across asset series, excess kurtosis varies from 10.07 (gold) to 93.53 (coal) across assets, and from 5.38 (Basic Metals ETS) to 21.87 (Electricity ETS) across sector indices. Rotterdam coal returns exhibit the largest extreme observations among the hedging assets, as its daily returns range from -54.08% to +32.67%. The TTF natural gas futures have positive skewness (+0.77), suggesting that large positive returns tend to be more pronounced than large negative returns. Skewness is negative for the metals, chemicals, and electricity sectors, as well as for EUA, oil, coal, and gold, showing that negative return observations occur more frequently than positive return observations. The Jarque-Bera test rejects normality for all series. In addition, the

Augmented Dickey-Fuller test rejects the null hypothesis of a unit root, and the Ljung-Box test on squared returns provides evidence of volatility clustering across all series. These characteristics motivate the use of the DCC-GARCH framework described in Chapter 4.

The dataset described above is the foundation for the econometric analysis presented in Chapter 4 and the empirical results in Chapter 5.

Chapter 4

Methodology

This chapter presents the methodology used to estimate the dynamic hedging relationships between sector portfolios and hedging assets. Building on the conceptual framework discussed in Sections 2.3 and 2.4, the estimation procedure of the DCC-GARCH model, the construction of dynamic hedged portfolios, and the evaluation of hedging performance using the dataset developed in Chapter 3 are discussed in detail.

4.1 Empirical Design and Estimation Scope

The empirical analysis is conducted separately for each sector portfolio s and the hedging asset a within the bivariate DCC-GARCH framework. First, the DCC-GARCH model is estimated for different return series pairs $(r_{s,t}, r_{a,t})$, which produces the time-varying conditional variances $h_{s,t}$, $h_{a,t}$, and the conditional covariances $h_{sa,t}$. These estimated conditional variances and covariances are then used to compute the dynamic hedge ratio HR_t, and the optimal portfolio weight $w_{s,t}$. This allows the estimated covariance dynamics to be used to construct a dynamic hedging strategy. A dynamic model is particularly suitable for this analysis as the sample period encompasses major regulatory changes and crisis periods, including the transition from Phase III to Phase IV of the EU ETS, the COVID-19 pandemic, the 2022 European energy crisis, and the introduction of the CBAM transitional phase. These events influence both asset volatility and the correlations between assets and sectors over time. Therefore, a static hedging framework may not capture these evolving relationships, so a dynamic approach is better suited to the objectives of this study.

The methodology is applied across the full sample period and in the sub-period analysis. While analyzing the full sample period, each sector portfolio is paired with EUA, two sector-relevant assets and gold. The hedging assets for each sector portfolio are indicated in Table 3.4. Since each sector consists of two separate portfolios, including the EU ETS-regulated firms and non-EU ETS-regulated firms, and each portfolio is hedged with four assets, $8 \times 4 = 32$ bivariate estimations are performed.

To assess whether hedging relationships remain stable across different regulatory regimes and market environments, the results are examined in six different sub-periods.

For the sub-period analysis, first, the DCC-GARCH(1,1) parameters are estimated using the full sample for each sector-asset pair. After that, the hedge ratios, optimal weights, and hedging effectiveness measures are computed separately for each sub-period. This method prevents estimation problems that can occur when re-estimating DCC-GARCH models on short sub-periods, as a large number of observations are needed for reliable parameter estimates.

The selected breakpoints for the sub-period analysis reflect key developments in the EU carbon and energy markets. The Phase III Low Price period (2013 to 2018) represents the years before the Market Stability Reserve (MSR) was introduced. The Post-MSR period (January 2019 to February 2020) highlights the strengthening of the carbon price signal after the reform. The COVID-19 pandemic period (March to December 2020) highlights the market disruption due to the pandemic. The Phase IV High Price period (January 2021 to December 2022) covers both the rapid increase in EUA prices and the exceptional market conditions due to the 2022 European energy crisis. The Phase IV Normalization period (January to September 2023) marks when energy and carbon markets stabilized after the crisis. The final period (October 2023 to April 2026) covers the CBAM Transitional period, which brought important regulations for carbon-intensive industries. The effects of different market regimes on the hedging relationship between the sector portfolio and the hedging asset are evaluated through the estimated hedge ratios, optimal portfolio weights, and hedge effectiveness measures.

Furthermore, the estimated dynamic hedge ratios are used to construct daily hedged portfolio return series for each sector portfolio and hedging asset pair. This step allows the direct comparison between the hedged return series and the unhedged sector portfolio returns. The resulting hedged portfolio return is compared with the unhedged portfolio return to evaluate the effectiveness of the hedging strategy in providing portfolio performance improvement and risk reduction. The comparison is conducted for the full-sample period using a set of hedge-effectiveness, risk-adjusted return, downside risk, and tail-risk measures. Each sector portfolio and hedging asset combination is analyzed independently within the bivariate DCC-GARCH framework to preserve parameter stability and estimation reliability. The performance and risk measures used in the evaluation are presented in Section 4.5.

In addition, to examine whether the empirical results depend on the method used to construct sector portfolios, the analysis is repeated using three alternative index-construction methods as described in Section 3.4. A monthly rebalanced equal-weighted index is used as the primary method, in which all firms with valid price data at the beginning of each month receive equal portfolio weights. During the month, weights change according to the firms' relative returns and are reset to equal weights at the beginning of the next month. A stable equal-weighted index is also constructed, in which equal weights are set at the beginning of the sampling period and both the weights and the set of firms remain unchanged throughout the sample. Additionally, a yearly rebalanced market-capitalization-weighted index is constructed, in which firms' relative market capitalizations are measured at the beginning of each year. These market capitalization values are kept constant throughout the year and are updated at the next annual rebalancing date. Daily index returns are then calculated using these fixed annual weights. The monthly rebalanced equal-weighted index is used as the primary method, while the stable equal-weighted and yearly market-capitalization-weighted indices are used as robustness checks. Therefore, in total, $8 \times 4 \times 3 = 96$ bivariate DCC-GARCH estimations are made for the full sample period.

4.2 Bivariate DCC-GARCH Framework

This section describes the econometric framework used to estimate the time-dependent volatility and correlation dynamics between sector portfolios and selected hedging assets. Since the aim is to model conditional variances and dynamic correlations simultaneously, the two-variable DCC-GARCH model proposed by Engle [20] is used in the analysis.

The estimation procedure involves two stages. First, univariate GARCH models are estimated for each return series to capture volatility clustering and obtain standardized residuals. In the second stage, the Dynamic Conditional Correlation (DCC) specification is used to estimate the time-dependent correlations between sector portfolio returns and hedging asset returns.

4.2.1 Univariate GARCH Specification

For each return series $i \in \{s, a\}$, the conditional mean and variance are specified as

$$r_{i,t} = \mu_i + \varepsilon_{i,t}, \qquad \varepsilon_{i,t} = \sqrt{h_{i,t}}\, z_{i,t}, \tag{4.1}$$

$$h_{i,t} = \omega_i + \alpha_i\, \varepsilon_{i,t-1}^2 + \beta_i\, h_{i,t-1}, \tag{4.2}$$

$$z_{i,t} \sim t_{\nu_i}(0, 1), \tag{4.3}$$

where μ_i is the constant mean, $h_{i,t}$ is the conditional variance that follows the GARCH(1,1) specification [84], and $z_{i,t}$ is a standardized innovation term that follows a Student-t distribution with ν_i degrees of freedom. For non-negativity of the conditional variance, the constraints $\omega_i > 0$, $\alpha_i \geq 0$, and $\beta_i \geq 0$ must be satisfied, and for covariance stationarity, $\alpha_i + \beta_i < 1$ must hold. The Student-t innovation distribution is used to capture the heavy-tailed characteristics frequently observed in financial return series and to provide a more flexible representation of extreme return outcomes than the normal distribution.

4.2.2 Dynamic Conditional Correlation Specification

The standardized residual vector $\mathbf{z}_t = (z_{s,t}, z_{a,t})'$ is obtained from the estimated univariate models. In the DCC framework, the time-varying conditional correlation process is determined using the following parameters [20]:

$$Q_t = (1 - a - b)\,\bar{Q} + a\,\mathbf{z}_{t-1}\mathbf{z}_{t-1}' + b\,Q_{t-1}, \tag{4.4}$$

$$R_t = \text{diag}(Q_t)^{-1/2}\,Q_t\,\text{diag}(Q_t)^{-1/2}, \tag{4.5}$$

with $a \geq 0$, $b \geq 0$ and $a + b < 1$, where $\bar{Q}$ is the unconditional covariance matrix of the standardized residuals and R_t is the time-varying conditional correlation matrix. The 2×2 conditional covariance matrix is given by

$$H_t = D_t\,R_t\,D_t, \qquad D_t = \text{diag}\Big(\sqrt{h_{s,t}},\ \sqrt{h_{a,t}}\Big), \tag{4.6}$$

from which the time-varying conditional covariance terms are obtained. Consistent with the univariate specifications, the standardized residuals are assumed to follow a multivariate Student-t distribution.

4.2.3 Estimation Procedure and Implementation Choices

The DCC-GARCH model is estimated in two steps. In the first step, the univariate GARCH parameters $(\mu_i, \omega_i, \alpha_i, \beta_i, \nu_i)$ are obtained separately for each return series. In the second step, the two DCC parameters (a, b) are estimated by maximizing the conditional correlation log-likelihood conditional on the first-step standardized residuals. All estimations are carried out in `R` using the `rugarch`, `rmgarch`, `ConnectednessApproach`, and `PerformanceAnalytics` packages. Numerical optimization in the DCC-GARCH model is performed using the `solnp` sequential quadratic programming solver.

Several implementation approaches are adopted to enhance the stability of the estimations. Firstly, the daily log returns are multiplied by 100 before the estimation to prevent numerical optimization problems due to small return values. Rescaling does not affect conditional correlations or hedge ratios, as these metrics are not dependent on scaling. Secondly, the minimum number of observations is set to 200 trading days for full-sample DCC-GARCH estimation. Thirdly, the unconditional covariance matrix $\bar{Q}$ under the DCC model is initialized using the sample covariance matrix of the standardized residuals.

The adequacy of each estimated model is evaluated using three diagnostic tests. First, the Ljung-Box [85] test is applied to standardized residuals to detect any remaining autocorrelation after specifying the mean equation. The test is then applied to squared standardized residuals to determine whether the GARCH(1,1) specification adequately captures volatility dynamics. Finally, the Engle-Ng [86] sign bias test is used to identify asymmetric volatility effects not captured by the symmetric GARCH(1,1) model. Sector-asset pairs that do not meet these criteria are identified and analyzed in Chapter 5.

4.3 Robustness Checks

To examine whether the main results depend on the specification of the conditional mean and variance equations, two additional robustness checks are performed. The first robustness check replaces the baseline constant-mean equation in the model with an AR(1)-GARCH(1,1) specification to account for possible autocorrelation in returns. The second replaces the standard GARCH(1,1) variance equation with a GJR-GARCH(1,1) specification, which allows negative and positive shocks to affect volatility differently. The results obtained from these alternative specifications are compared with the baseline results to determine whether the conclusions are affected by the choice of model specification.

4.3.1 AR(1)-GARCH Robustness Specification

Although daily financial returns generally have weak serial dependence, residual autocorrelation may remain in some return series. To evaluate whether the estimated hedging relationships are sensitive to the conditional mean specification, an AR(1)-GARCH(1,1) model is estimated as a robustness check.

The conditional mean equation is specified as

$$r_{i,t} = \mu_i + \phi_i r_{i,t-1} + \varepsilon_{i,t}, \qquad \varepsilon_{i,t} = \sqrt{h_{i,t}}\, z_{i,t}, \tag{4.7}$$

where ϕ_i captures first-order autocorrelation in returns. The conditional variance equation remains identical to the baseline GARCH(1,1) specification presented in Equation (4.2). All remaining elements of the DCC-GARCH model are unchanged.

The resulting dynamic correlations, hedge ratios, optimal portfolio weights, and hedging effectiveness measures are compared with the baseline model to assess the robustness of the empirical findings.

4.3.2 GJR-GARCH Robustness Specification

Financial return series may exhibit asymmetric volatility responses, where negative shocks have a larger effect on future volatility than positive shocks with the same magnitude. To account for this possibility, an additional robustness analysis is conducted using the GJR-GARCH(1,1) model proposed by Glosten, Jagannathan and Runkle [64].

The conditional variance equation is given by

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \gamma_i I_{t-1} \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \tag{4.8}$$

where

$$I_{t-1} = \begin{cases} 1, & \text{if } \varepsilon_{i,t-1} < 0, \\ 0, & \text{otherwise.} \end{cases} \tag{4.9}$$

The parameter γ_i measures the additional impact of negative shocks on conditional volatility. A positive γ_i indicates the presence of asymmetric volatility effects. The conditional mean equation is identical to the baseline model, and all other elements of the DCC-GARCH framework are unchanged.

The resulting dynamic correlations, hedge ratios, optimal portfolio weights, and hedging effectiveness measures are compared with the baseline method's outputs to evaluate the stability of the main results.

4.4 Dynamic Hedging Strategy

The DCC-GARCH model provides time-varying conditional variances and covariances between the sector portfolio and a hedge asset. The estimated covariance dynamics are then transformed into a hedging framework by constructing hedge ratios, optimal portfolio weights, and historical returns of the hedged portfolio. This approach allows the evaluation of whether the time-varying relationships identified by the DCC-GARCH model can be used to improve portfolio risk management and overall portfolio returns over time.

4.4.1 Dynamic Hedge Ratio

To form an effective hedging strategy from the estimated covariance dynamics, a time-varying hedge ratio is constructed for each portfolio-asset pair. The time-varying minimum-variance hedge ratio for a long position in the sector portfolio offset by a short position in the hedging asset is calculated as follows:

$$HR_t = \frac{h_{sa,t}}{h_{a,t}}. \tag{4.10}$$

$\mathrm{HR_t}$ is the number of units of the hedging asset that have to be sold short for each unit of long position in the sector portfolio to minimize the conditional variance of the resulting position. For each sector portfolio and asset pair, dynamic hedge ratios are computed, reporting the mean, standard deviation, and the 5th and 95th percentiles to evaluate both the average hedge position and its variation over time.

4.4.2 HR-Based Hedged Portfolio Construction

The estimated hedge ratios are subsequently applied to the observed return series to construct dynamically hedged portfolios. Given the dynamic hedge ratio in Equation (4.10), the daily return of the hedged portfolio is

$$r_{\mathrm{H},t} = r_{s,t} - HR_t\, r_{a,t}, \tag{4.11}$$

where $r_{s,t}$ and $r_{a,t}$ represent the daily log returns of the sector portfolio and the hedging asset, respectively. The HR is time-varying because it depends on the conditional covariance and variance estimated by the DCC-GARCH model. As the conditional covariance and variance change over time, the HR also changes and it is applied to the daily returns to construct the hedged portfolio. This allows the construction of hedged portfolio returns and the evaluation of the resulting risk reduction.

4.4.3 HR-Based Hedging Effectiveness

HR-based hedge effectiveness ($\mathrm{HE_{HR}}$) [22] quantifies the proportional reduction in portfolio return variance relative to the unhedged benchmark:

$$\mathrm{HE_{HR}} = 1 - \frac{\mathrm{Var}(r_{\mathrm{H},t})}{\mathrm{Var}(r_{s,t})}, \tag{4.12}$$

where $r_{\mathrm{H},t}$ denotes the dynamically hedged portfolio return constructed in Section 4.4.2. While the hedge ratio determines the size of the hedge position, HR-based hedging effectiveness evaluates how much portfolio risk is reduced relative to the unhedged sector portfolio.

$\mathrm{HE_{HR}} = 1$ corresponds to perfect variance elimination, $\mathrm{HE_{HR}} = 0$ to no improvement over the unhedged position, and $\mathrm{HE_{HR}} < 0$ to a hedge that increases portfolio variance. For gold, as in the second case, $\mathrm{HE_{HR}}$ values close to 0 are expected, since it has no economic connection to the selected sectors. If gold provides comparable $\mathrm{HE_{HR}}$ to other hedging assets, this would suggest that the results are not entirely driven by sector-specific exposures.

In addition to the full-sample and sub-period results, the time-varying $\mathrm{HR_t}$ and $\mathrm{HE_t}$ are also examined to observe how the strength of the hedging relationship changes over time. $\mathrm{HE_t}$ represents the time-varying $\mathrm{HE_{HR}}$ and is obtained as the squared DCC conditional correlation:

$$\mathrm{HE}_t = \rho_t^2, \tag{4.13}$$

where ρ_t is the conditional correlation between the sector portfolio and the hedging asset at time t obtained from the fitted DCC-GARCH model. Higher values indicate a stronger hedging relationship at a given point in time.

4.4.4 Optimal Portfolio Weight

In addition to hedge ratios, optimal portfolio weights are estimated to evaluate the time-varying allocation between the sector portfolio and the hedging asset. It is calculated using the estimated conditional variances and covariances [21] as described below:

$$w_{s,t} = \frac{h_{a,t} - h_{sa,t}}{h_{s,t} + h_{a,t} - 2\,h_{sa,t}}, \tag{4.14}$$

with $w_{s,t} \in [0,1]$ and the complementary weight $1 - w_{s,t}$ is allocated to the hedging asset. A value of $w_{s,t} = 0$ indicates full allocation to the hedging asset, whereas $w_{s,t} = 1$ indicates full allocation to the sector portfolio. Similar to the hedge ratio analysis, the time-varying portfolio weights are evaluated using their mean, standard deviation, and 5th and 95th percentile values over the sample period.

4.4.5 OW-Based Hedging Effectiveness

In addition to the HR-based hedging effectiveness, the variance reduction achieved by the optimal portfolio weight strategy is also examined. The corresponding minimum-variance portfolio return at time t is given by

$$r_{\mathrm{OW},t} = w_{s,t}\,r_{s,t} + (1 - w_{s,t})\,r_{a,t}, \tag{4.15}$$

which allocates $w_{s,t}$ of the portfolio to the sector and the complementary weight $1-w_{s,t}$ to the hedging asset at each point in time. The OW-based hedging effectiveness is then defined as

$$\mathrm{HE}_{\mathrm{OW}} = 1 - \frac{\mathrm{Var}(r_{\mathrm{OW},t})}{\mathrm{Var}(r_{s,t})}. \tag{4.16}$$

While $\mathrm{HE}_{\mathrm{HR}}$ in Equation (4.12) measures the variance reduction obtained by the dynamic hedge ratio strategy, $\mathrm{HE}_{\mathrm{OW}}$ measures the variance reduction obtained by the long-only minimum-variance portfolio. Because the two measures are based on different portfolio constructions, they may lead to different conclusions regarding hedging performance.

4.5 Portfolio Performance Evaluation

After constructing the dynamically hedged portfolios, the effectiveness of the hedging strategy is evaluated by comparing the HR-based hedged and unhedged portfolio return series across several performance and risk metrics that are variance reduction, risk-adjusted performance, downside risk, tail risk, and drawdown-based measures.

4.5.1 Risk-Adjusted Return Metrics

The risk-adjusted return performance of each portfolio is summarized by the annualized Sharpe [87] and Sortino [88] ratios:

$$\mathrm{SR} = \sqrt{252}\,\frac{\bar{r}_p - r_f}{\sigma_p}, \qquad \mathrm{Sortino} = \sqrt{252}\,\frac{\bar{r}_p - r_f}{\sigma_{p,\mathrm{down}}}, \tag{4.17}$$

where $\bar{r}_p$ is the mean daily return, σ_p is the unconditional standard deviation, and $\sigma_{p,\mathrm{down}}$ is the standard deviation computed only on negative returns. The annualization factor is $\sqrt{252}$ that corresponds to the number of trading days per year. The risk-free rate r_f is set to zero. This assumption simplifies the comparison across sectors while preserving the relative performance differences between hedged and unhedged portfolios within each sector.

The Omega ratio [89] compares the expected gain above a threshold L with the expected loss below the same threshold:

$$\Omega(L) \;=\; \frac{\int_L^{\infty} \big(1 - F(r)\big)\,dr}{\int_{-\infty}^{L} F(r)\,dr} \;=\; \frac{\mathbb{E}[(r_p - L)^+]}{\mathbb{E}[(L - r_p)^+]}, \tag{4.18}$$

where $F(\cdot)$ is the empirical cumulative distribution function of r_p and $(x)^+ = \max(x, 0)$. In this study, the threshold is set to $L = 0$. Thus, values above one indicate that gains outweigh losses. Because the Omega ratio is based on the entire return distribution, it takes into account asymmetry and tail behavior in the return series.

4.5.2 Downside, Tail, and Drawdown Risk Measures

Tail-risk exposure is demonstrated by historical Value-at-Risk (VaR) [90] and by the Expected Shortfall (ES) [91] at the 95% level:

$$\mathrm{VaR}_{0.95} = -\,\mathrm{quantile}_{0.05}(r_p), \tag{4.19}$$

$$\mathrm{ES}_{0.95} = -\,\mathbb{E}\big[r_p \,\big|\, r_p \leq -\mathrm{VaR}_{0.95}\big]\,. \tag{4.20}$$

The Maximum Drawdown (MDD) measures the largest decline from a peak in cumulative portfolio value $V_t = \exp\big(\sum_{\tau\leq t} r_{p,\tau}\big)$ over the sample period, defined as:

$$\mathrm{MDD} = \max_{t\in[0,T]} \left(\frac{\max_{\tau\leq t} V_\tau - V_t}{\max_{\tau\leq t} V_\tau} \right). \tag{4.21}$$

The Pain Index (PI) [92] measures the average drawdown over the sample period:

$$\mathrm{PI} \;=\; \frac{1}{T}\sum_{t=1}^{T} \frac{M_t - V_t}{M_t}. \tag{4.22}$$

The PI is calculated from all drawdowns observed during the sample period and therefore reflects the overall drawdown of the portfolio.

The Pain Ratio (PR) [92] relates the mean excess return of the portfolio to its Pain Index:

$$\mathrm{PR} \;=\; \frac{\bar{r}_p - r_f}{\mathrm{PI}}. \tag{4.23}$$

Higher values indicate more return per unit of drawdown. The risk-free rate is again set to $r_f = 0$ for consistency with Equation (4.17).

VaR and ES focus on downside risk over a single day, MDD and PI focus on portfolio drawdowns, while the Omega ratio and the Pain Ratio provide alternative perspectives on risk-adjusted performance.

The methodology described in this chapter is applied to the full-sample period from January 2013 to April 2026 and subsequently to the six sub-periods defined in Section 3.1. The sub-period analysis allows the evaluation of how the hedging relationships change across different regulatory and market regimes. The full-sample analysis includes the complete portfolio performance evaluation, while the sub-period analysis focuses primarily on hedge ratios, optimal portfolio weights, and hedging effectiveness measures. The empirical findings are reported and discussed in Chapter 5.

Chapter 5

Empirical Results

This chapter presents the empirical findings from the application of the bivariate DCC-GARCH(1,1) model outlined in Chapter 4. The discussion contains six sections. Section 5.1 examines the estimated univariate volatility and DCC dynamic-correlation parameters. Section 5.2 reports the hedge ratios (HR), HR-based hedging effectiveness ($\mathrm{HE}_{\mathrm{HR}}$), optimal portfolio weights (OW), and OW-based hedging effectiveness ($\mathrm{HE}_{\mathrm{OW}}$) for the full sample period for the 32 sector–asset pairs. Section 5.3 analyzes the dynamic behavior of these metrics across six different sub-periods (Phase III Low Price, Post-MSR, COVID-19, Phase IV High Price, Phase IV Normalization, and CBAM Transitional). Section 5.4 evaluates the realized risk-adjusted performance of the hedged portfolios. Section 5.5 presents the robustness checks based on alternative model specifications. It also compares results across alternative index construction approaches, including monthly rebalanced equal-weighted, stable equal-weighted, and yearly rebalanced market-capitalization-weighted. Section 5.6 relates the findings to the three hypotheses (H1–H3) introduced in Section 2.6.

5.1 Volatility and Correlation Dynamics

5.1.1 Univariate GARCH(1,1)-t Parameter Estimates

Table 5.1 reports the estimated parameters for the univariate GARCH(1,1)-t models. The ARCH parameter (α_1) reflects how new shocks affect volatility, while the GARCH parameter (β_1) shows how much past volatility continues over time. Adding these two metrics ($\alpha_1+\beta_1$) gives a measure of how persistent volatility is. When this sum is closer to one, it means that volatility shocks fade more slowly. The parameter ν represents the degrees of freedom for the Student-t innovation distribution. Lower ν values mean the distribution has heavier tails, so extreme returns are more likely.

Table 5.1: Univariate GARCH(1,1)-t parameter estimates

Series	α_1	β_1	$\alpha_1 + \beta_1$	ν
Electricity (ETS)	0.106	0.843	0.949	5.71
Electricity (Non-ETS)	0.162	0.725	0.887	5.83
Basic Metals (ETS)	0.043	0.945	0.988	6.02
Basic Metals (Non-ETS)	0.088	0.856	0.943	6.07
Non-Metallic Min. (ETS)	0.107	0.839	0.945	6.17
Non-Metallic Min. (Non-ETS)	0.127	0.753	0.881	6.05
Chemicals (ETS)	0.083	0.886	0.968	7.77
Chemicals (Non-ETS)	0.120	0.836	0.955	5.96
EUA Futures	0.097	0.894	0.991	5.97
TTF Natural Gas Futures	0.137	0.862	0.999	5.41
Brent Crude Oil Futures	0.103	0.889	0.992	5.32
Rotterdam Coal Futures	0.312	0.687	0.999	2.39
Gold	0.044	0.944	0.988	4.64

Notes: α_1 and β_1 denote the ARCH and GARCH parameters, respectively. ν denotes the degrees-of-freedom parameter of the Student-t innovation distribution. Returns are scaled by 100 before estimation. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

All the estimated persistence measures are below one, so the GARCH model's stationarity condition is met. Persistence levels vary between sectors and hedging assets. Among the sector portfolios, the Basic Metals EU ETS-regulated portfolio has the highest persistence ($\alpha_1 + \beta_1 = 0.988$), which means that high volatility tends to last longer in this sector. On the contrary, the Non-Metallic Minerals and Electricity non-EU ETS-regulated portfolios have lower persistence (0.881 and 0.887, respectively), meaning that they can adjust back quickly after shock periods. Among hedging assets, TTF natural gas and Rotterdam coal futures both exhibit the highest persistence (0.999). Rotterdam coal futures also have the lowest estimated degrees of freedom ($\nu = 2.39$), suggesting that extreme returns occur more frequently than in the other series.

5.1.2 Residual Diagnostics

Table 5.2 reports diagnostic tests based on the standardized residuals $\hat{z}_t$. If the GARCH specification provides a good description of the return series, the standardized residuals should not contain any systematic patterns. The Ljung-Box test on $\hat{z}_t$ checks for any autocorrelation remaining in the standardized residuals after estimation. Its null hypothesis is that no autocorrelation remains. The Ljung-Box test on $\hat{z}_t^2$ checks for volatility clustering after fitting the GARCH model, with the null hypothesis that there is no autocorrelation in the squared residuals. The sign-bias column reports the p-value of the Engle-Ng joint test. It examines whether positive and negative return shocks have the same effect on future volatility. The null hypothesis is that volatility responds in the same way to positive and negative shocks.

Table 5.2: Univariate residual diagnostics

Series	$\mathbf{LB}_{10}(\hat{z})$	$\mathbf{LB}_{10}(\hat{z}^2)$	$\mathbf{JB}(\hat{z})$	**Sign-bias**
Electricity (ETS)	0.213	0.926	**<0.001**	**0.013**
Electricity (Non-ETS)	0.088	0.660	**<0.001**	**0.003**
Basic Metals (ETS)	**0.003**	**0.004**	**<0.001**	**<0.001**
Basic Metals (Non-ETS)	**<0.001**	0.667	**<0.001**	**0.028**
Non-Metallic Min. (ETS)	0.069	0.564	**<0.001**	**<0.001**
Non-Metallic Min. (Non-ETS)	**0.001**	0.802	**<0.001**	**0.044**
Chemicals (ETS)	**<0.001**	**0.003**	**<0.001**	**<0.001**
Chemicals (Non-ETS)	**0.026**	0.130	**<0.001**	**<0.001**
EUA Futures	0.640	0.894	**<0.001**	0.345
TTF Natural Gas Futures	0.271	0.781	**<0.001**	0.419
Brent Crude Oil Futures	0.938	0.864	**<0.001**	0.180
Rotterdam Coal Futures	0.772	1.000	**<0.001**	0.676
Gold	**0.003**	0.064	**<0.001**	**0.041**

Notes: $\text{LB}_{10}(\hat{z})$ and $\text{LB}_{10}(\hat{z}^2)$ denote the Ljung-Box statistics on the standardized residuals and their squares with 10 lags. $\text{JB}(\hat{z})$ refers to the Jarque-Bera test on $\hat{z}$. The sign-bias column reports the p-value of the Engle and Ng [86] joint test for asymmetric volatility response. Bold numbers indicate rejection of the null hypothesis at the 5% level. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

The Ljung-Box test on $\hat{z}_t$ rejects the null hypothesis of no residual autocorrelation at the 5% significance level for six of the thirteen series, mainly among the manufacturing sector portfolios. Since residual autocorrelation may indicate that the constant-mean specification does not fully capture short-run return dynamics, the models were re-estimated with an Autoregressive Model of Order 1 (AR(1)) mean equation, which allows current returns to depend on the previous day's return. The number of series rejecting the Ljung-Box test decreased from six to two. Despite this improvement, the hedge-ratio estimates remained qualitatively unchanged. Therefore, the constant-mean specification was retained throughout the analysis. The results with the AR(1) mean equation for the rejected series are reported in Section 5.5.

In eleven out of thirteen series, the Ljung-Box test on $\hat{z}_t^2$ does not reject the null hypothesis at the 5% significance level. This indicates that the GARCH specification captures volatility dynamics reasonably well for most series. However, the null hypothesis is rejected for Basic Metals and Chemicals EU ETS-regulated portfolios, suggesting that some volatility clustering remains in these portfolios.

The Jarque-Bera test rejects the null hypothesis of normality for all thirteen standardized residual series at the 5% significance level. This means the residuals are still non-normal after estimation. When combined with the descriptive statistics and the estimated degrees-of-freedom parameters, these findings support the use of Student-t innovations.

In the sign-bias test that reports the p-value of the Engle-Ng, the null hypothesis of symmetric volatility responses is rejected at the 5% significance level for all sector portfolios and for gold. However, the null hypothesis is not rejected for EUA, TTF natural gas, Brent crude oil, or Rotterdam coal futures. This means that volatility reacts differently to positive and negative return shocks in the sector portfolios and in gold. Nevertheless, the symmetric GARCH specification is retained because the analysis focuses on the comparative performance of hedging assets across sector portfolios. Applying a common specification to all sector-asset pairs ensures that differences in hedge estimates are not driven by model selection. To assess whether asymmetric volatility affects the results, the models were also re-estimated using a GJR-GARCH specification, which allows negative shocks to have a different impact on volatility than positive shocks. As reported in Section 5.5, the resulting hedge ratios and hedging effectiveness measures remain qualitatively unchanged.

5.1.3 DCC Parameter Estimates

The DCC parameters are estimated for each of the 32 sector-asset pairs. Two DCC parameters (a, b) and a multivariate Student-t degrees of freedom parameter ν_{MVT} are reported in Table A.1 in Appendix A. The parameter a captures the effect of new shocks on correlations and b reflects the influence of past correlations. Their sum $(a+b)$ measures the persistence of the conditional correlation process, with values closer to 1 indicating that shocks to correlations tend to persist longer. The parameter ν_{MVT} provides information about the tail behavior of the joint return distribution.

The DCC parameter estimates are similar for the sector-asset pairs. In all cases, the effect of past correlations dominates the effect of new shocks, as the estimated values of b (0.892-0.994) are considerably larger than the values of a (0.005-0.034). Consequently, the persistence measure $(a + b)$ ranges from 0.921 to 1.000, indicating that conditional correlations are generally highly persistent.

The main exception is the Rotterdam coal pairs. In these cases, the estimated degrees-of-freedom parameter is 4.0, and two coal pairs have persistence values of 1.000. These are the highest persistence values observed among all sector-asset pairs. Coal also exhibits the highest excess kurtosis among all hedging assets, as shown in Table 3.5, which may contribute to these unusually persistent estimates.

5.1.4 Implications for the Hedging Analysis

The results indicate that the DCC-GARCH model is suitable for this thesis. Most diagnostic tests show that the model adequately captures the main features of the data. Although some series still exhibit residual autocorrelation or asymmetric volatility effects, these issues do not materially affect the suitability of the DCC-GARCH framework.

To examine whether these findings affect the hedging results, additional robustness checks are performed using an AR(1) mean specification and a GJR-GARCH model. As discussed in Section 5.5, the main results from the hedging analysis are largely unchanged. Therefore, the Student-t DCC-GARCH model is implemented as the main approach for the hedging analysis in the following sections.

5.2 Full-Sample Hedge Ratios, Optimal Weights, and Hedge Effectiveness

Table 5.3 and Figures 5.1 to 5.4 report the full-sample (1 January 2013-30 April 2026) DCC-GARCH(1,1) outputs for the 32 sector-asset pairs under the Monthly EW index methodology. In Table 5.3, the average conditional hedge ratio (HR) measures the size of the position in the hedging asset required to hedge a €1 long position in the sector portfolio. SD, Q5, and Q95 report the standard deviation and the 5th and 95th percentiles of the daily hedge ratio series. Hedge effectiveness based on the HR (HE_{HR}) [22], computes the percentage reduction in the sector portfolio's variance. Optimal weight (OW) measures the optimal allocation to the sector portfolio to achieve minimum variance. OW SD, OW Q5, and OW Q95 report the standard deviation and the 5th and 95th percentiles of the daily optimal portfolio weight allocated to the sector portfolio. HE_{OW} measures the percentage variance reduction of the portfolio formed by allocating the optimal weight to the sector portfolio and the remaining weight to the hedging asset, relative to holding the sector portfolio alone.

Table 5.3: Full-sample hedge ratios, hedging effectiveness, and optimal portfolio weights (Monthly EW, 1 January 2013 - 30 April 2026).

Sector	**Hedging Asset**	**HR**	**SD$_{\text{HR}}$**	**Q5$_{\text{HR}}$**	**Q95$_{\text{HR}}$**	**HE$_{\text{HR}}$**	**OW**	**OW SD**	**OW Q5**	**OW Q95**	**HE$_{\text{OW}}$**
35 ETS	EUA	0.05	0.03	0.02	0.10	0.05	0.95	0.08	0.84	1.00	0.09
35 Non-ETS		0.04	0.02	0.01	0.08	0.04	0.93	0.07	0.81	1.00	0.03
35 ETS	Gas	0.02	0.04	-0.03	0.10	0.02	0.91	0.11	0.65	1.00	0.14
35 Non-ETS		0.01	0.02	-0.01	0.04	0.01	0.88	0.13	0.60	0.99	0.14
35 ETS	Oil	0.07	0.05	0.01	0.15	0.08	0.92	0.08	0.77	1.00	0.05
35 Non-ETS		0.06	0.04	0.01	0.13	0.07	0.89	0.10	0.70	1.00	0.05
35 ETS	Gold	0.02	0.07	-0.07	0.10	0.02	0.62	0.13	0.39	0.82	0.46
35 Non-ETS		0.03	0.06	-0.05	0.11	0.01	0.59	0.14	0.35	0.82	0.45
24 ETS	EUA	0.11	0.07	0.02	0.24	0.06	0.73	0.15	0.47	0.95	0.21
24 Non-ETS		0.06	0.04	0.02	0.12	0.06	0.90	0.09	0.72	0.99	0.06
24 ETS	Coal	0.02	0.07	-0.07	0.13	0.00	0.59	0.16	0.33	0.89	0.29
24 Non-ETS		0.02	0.05	-0.04	0.13	-0.01	0.79	0.11	0.62	0.95	0.08
24 ETS	Gas	0.04	0.09	-0.06	0.19	0.02	0.71	0.22	0.27	0.96	0.27
24 Non-ETS		0.02	0.05	-0.04	0.10	0.03	0.85	0.14	0.55	0.99	0.15
24 ETS	Gold	0.06	0.16	-0.25	0.27	0.01	0.26	0.12	0.12	0.50	0.74
24 Non-ETS		0.01	0.11	-0.18	0.15	0.01	0.49	0.14	0.29	0.76	0.55
23 ETS	EUA	0.06	0.04	0.02	0.13	0.07	0.88	0.11	0.66	0.99	0.07
23 Non-ETS		0.04	0.03	0.01	0.09	0.03	0.87	0.10	0.69	0.98	0.12
23 ETS	Coal	0.01	0.06	-0.05	0.12	0.01	0.77	0.12	0.55	0.95	0.17
23 Non-ETS		0.00	0.03	-0.05	0.05	0.00	0.77	0.12	0.57	0.95	0.24
23 ETS	Gas	0.00	0.06	-0.07	0.10	0.04	0.82	0.16	0.49	0.98	0.21
23 Non-ETS		0.00	0.04	-0.06	0.05	0.01	0.82	0.16	0.49	0.99	0.24
23 ETS	Gold	-0.05	0.15	-0.30	0.15	0.02	0.46	0.13	0.26	0.68	0.59
23 Non-ETS		-0.02	0.10	-0.18	0.12	0.02	0.47	0.13	0.28	0.70	0.57
20 ETS	EUA	0.06	0.04	0.01	0.14	0.06	0.89	0.10	0.71	0.99	0.07
20 Non-ETS		0.05	0.04	0.01	0.12	0.07	0.91	0.09	0.76	1.00	0.03
20 ETS	Oil	0.10	0.07	-0.01	0.22	0.10	0.85	0.10	0.67	1.00	0.08
20 Non-ETS		0.06	0.06	-0.01	0.16	0.08	0.87	0.10	0.67	0.99	0.10
20 ETS	Gas	0.01	0.07	-0.06	0.14	0.04	0.84	0.15	0.54	0.99	0.17
20 Non-ETS		0.01	0.04	-0.04	0.07	0.03	0.87	0.13	0.60	0.99	0.11
20 ETS	Gold	-0.04	0.15	-0.31	0.17	0.03	0.48	0.14	0.26	0.73	0.58
20 Non-ETS		0.01	0.12	-0.18	0.17	0.02	0.55	0.15	0.30	0.80	0.51

Notes: Results are based on the full-sample DCC-GARCH(1,1) model under the Monthly EW methodology. HR denotes the average dynamic hedge ratio, representing the average hedging cost of a 1 EUR long position in the sector portfolio with a short position in the corresponding hedging asset. SD, Q5, and Q95 denote the standard deviation, 5th percentile, and 95th percentile of the time-varying hedge ratio series, respectively. HE$_{\text{HR}}$ denotes the average hedging effectiveness of the HR-based hedged portfolio. OW denotes the average optimal portfolio weight allocated to the sector portfolio in a minimum-variance portfolio. OW SD, OW Q5, and OW Q95 denote the standard deviation, 5th percentile, and 95th percentile of the time-varying optimal weight series, respectively. HE$_{\text{OW}}$ denotes the average hedging effectiveness of the OW-based portfolio. EUA futures and TTF natural gas futures are paired with all sectors. Brent crude oil futures are paired only with Electricity (NACE 35) and Chemicals (NACE 20), while Rotterdam coal futures are paired only with Basic Metals (NACE 24) and Non-Metallic Minerals (NACE 23), reflecting the primary production inputs of these sectors. Gold is paired with all the sectors as it is included as a placebo asset. Sector definitions: 35 = Electricity, Gas, Steam and Air Conditioning Supply; 24 = Manufacture of Basic Metals; 23 = Manufacture of Other Non-Metallic Mineral Products; 20 = Manufacture of Chemicals and Chemical Products. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

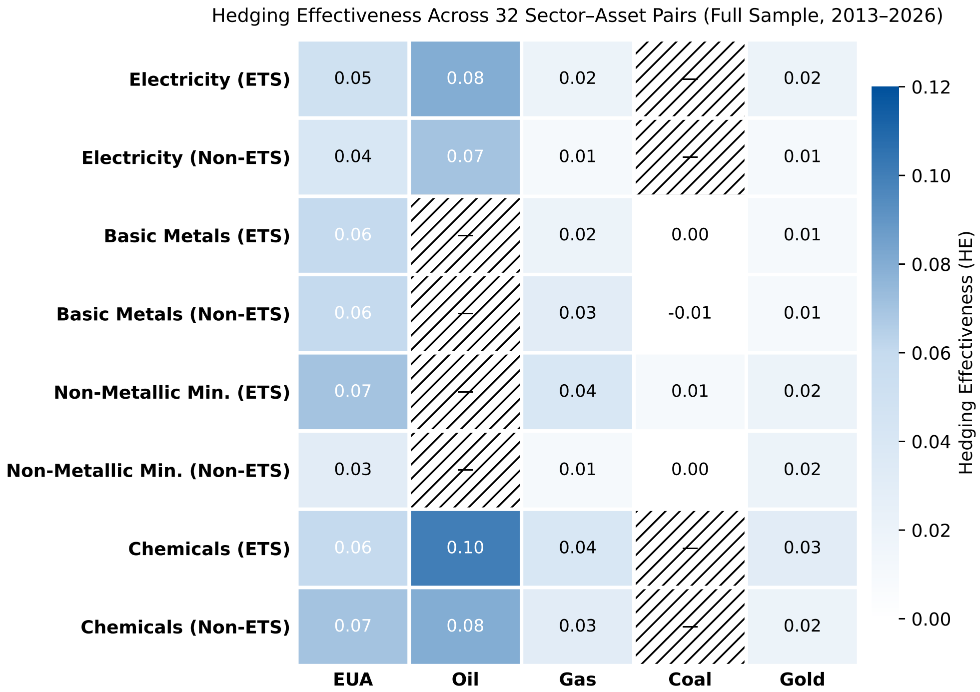

Figure 5.1: Hedging effectiveness across 32 sector-asset pairs, full sample 1 January 2013 - 30 April 2026, monthly rebalanced equal-weighted index methodology. Hatched cells represent sector-asset combinations not estimated by design: coal is excluded for Electricity and Chemicals, and Brent crude oil is excluded for Basic Metals and Non-Metallic Minerals. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

Key Findings From the Full-Sample Analysis

The results in Table 5.3 are analyzed in four ways. First, the EUA hedge is evaluated for eight sector portfolios to identify the differences in the sectors' carbon price sensitivities. Second, EU ETS-regulated and non-EU ETS-regulated portfolios are compared within each sector. Third, the five hedging assets in each sector are compared. Fourth, the optimal portfolio weights and the HE_{OW} values are examined to understand the minimum-variance composition implied by the hedging strategies.

EUA Hedging Results

Among the four sectors selected for this thesis, Electricity, Gas, Steam and Air Conditioning Supply have the largest direct Scope 1 emissions, followed by Basic Metals, Non-Metallic Minerals, and Chemicals (Table 3.1). The EUA HR does not follow this ordering. The largest mean HR (0.11) belongs to the Basic Metals EU ETS-regulated portfolio, while the Electricity EU ETS-regulated portfolio has the smallest (0.05). Chemicals and Non-Metallic Minerals EU ETS-regulated portfolios are in between these two extremes (both at 0.06). Direct emissions levels alone, therefore, do not explain the hedging relationship between sector returns and EUA futures.

Cost pass-through may help explain part of these results. Electricity producers can pass through much of the EUA costs on to consumers, which implies higher EUA prices have less effect on their profit margins [55, 56]. Although the Electricity sector has the highest direct emissions, its returns do not respond as strongly to changes in the EUA price. Manufacturing sectors face different challenges, as they generally have less ability to pass on carbon costs because of international competition [5, 32]. Expectations related to Fit-for-55 and the Carbon Border Adjustment Mechanism (CBAM) may already be reflected in industrial stock prices [10]. In addition, process emissions are particularly important in Basic Metals and cement production, where emissions cannot be reduced through fuel switching [58]. These factors may help explain why Electricity exhibits the lowest EUA HR despite having the highest direct emissions, while Basic Metals requires the largest hedge position.

However, one common pattern for all the sector portfolios is higher EUA HR in the EU ETS-regulated portfolios compared to the non-EU ETS-regulated portfolios. The largest difference is observed in the Basic Metals sector. A €1 long position in the EU ETS-regulated portfolio requires a €0.11 short position in EUA, compared with €0.06 for the non-EU ETS-regulated portfolio. The other sectors exhibit a similar pattern, as Non-Metallic Minerals has HRs of 0.06 and 0.04, while the Electricity sector has 0.05 and 0.04 and the Chemicals sector has 0.06 and 0.05 for the EU ETS-regulated and non-EU ETS-regulated portfolios, respectively. These results indicate that a larger EUA position is required to hedge the EU ETS-regulated sector portfolio.

The HE_{HR} results show a different pattern when comparing EU ETS-regulated and non-EU ETS-regulated portfolios. The largest difference between the EU ETS-regulated and non-EU ETS-regulated portfolios is observed in the Non-Metallic Minerals sector, with $\text{HE}_{HR} = 0.07$ for the EU ETS-regulated portfolio and 0.03 for the non-EU ETS-regulated portfolio. Electricity EU ETS-regulated portfolio also has a slightly higher HE_{HR} than the non-EU ETS-regulated portfolio (0.05 compared to 0.04). In Basic Metals, both groups have the same HE_{HR} value (0.06) and for Chemicals the non-EU ETS-regulated portfolio has a slightly higher HE_{HR}. These results suggest that larger HR do not necessarily translate into higher HE_{HR} and the higher HRs observed for EU ETS-regulated portfolios do not always result in greater variance reduction.

The relatively small differences between EU ETS-regulated and non-EU ETS-regulated portfolios observed in the Basic Metals and Chemicals sectors may be explained by two structural factors. First, non-EU ETS-regulated firms are still indirectly affected by EUA prices because of energy input costs and price competition from regulated firms in the same markets [5]. Second, the fact that many large European industrial groups have both EU ETS-regulated and non-EU ETS-regulated facilities within the same listed company may hinder the regulatory distinction to some extent in these portfolios. These effects are likely to be more significant in industrial sectors than in the electricity sector, where the regulatory boundary is clearer.

Looking at HR and HE_{HR} together also helps to identify the trade-off between hedging costs and the resulting variance reduction. The HR-to-HE_{HR} ratio ranges from 0.71 for Chemicals non-EU ETS-regulated to 1.83 for Basic Metals EU ETS-regulated portfolio. Basic Metals EU ETS-regulated portfolio has the highest ratio (1.83), indicating that a relatively large hedge position is needed to obtain a HE_{HR} of only 0.06. In contrast, the Chemicals non-EU ETS-regulated portfolio has the lowest ratio (0.71) with EUA, as it achieves a higher HE_{HR} with a smaller hedge ratio. Most of the remaining EUA portfolios have ratios close to one. Consequently, the Basic Metals EU ETS-regulated portfolio appears to be the least cost-efficient EUA hedge, whereas Chemicals non-EU ETS-regulated and Non-Metallic Minerals EU ETS-regulated have higher HE_{HR} relative to the size of the hedge position.

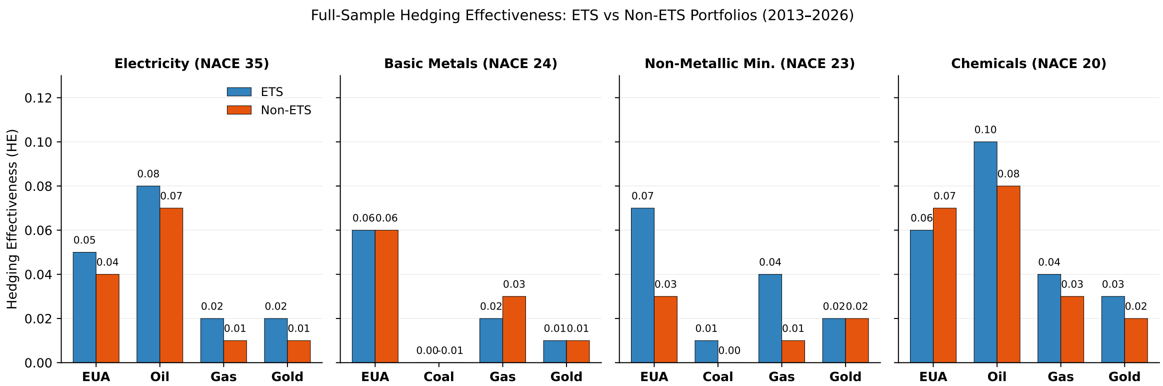

Figure 5.2: Full-sample average HE based on HR for the 32 sector-asset pairs, separated into EU ETS-regulated (blue) and non-EU ETS-regulated (orange) portfolios within each NACE sector. Sector indices are constructed using the monthly rebalanced equal-weighted index methodology.

EU ETS-Regulated versus Non-EU ETS-Regulated Sector Return Series

For EUA futures, EU ETS-regulated portfolios generally exhibit higher HR than non-EU ETS-regulated portfolios, although the differences in HE_{HR} are less consistent. The following results examine whether a similar relationship can also be observed for TTF natural gas, Brent crude oil, Rotterdam coal, and gold.

Natural gas results are similar to those obtained for EUA futures. In most sectors, the EU ETS-regulated portfolios require larger HRs than the non-EU ETS-regulated portfolios. The largest difference is observed in Basic Metals, where the average HR is 0.04 for the EU ETS-regulated portfolio and 0.02 for the non-EU ETS-regulated portfolio. However, larger HRs do not always lead to higher HE_{HR}. In Basic Metals, the non-EU ETS-regulated portfolio achieves a slightly higher $\mathrm{HE}_{\mathrm{HR}}$ despite requiring a smaller hedge position. Non-Metallic Minerals shows the strongest difference between the two regulatory groups, with $\mathrm{HE}_{HR} = 0.04$ for the EU ETS-regulated portfolio and 0.01 for the non-EU ETS-regulated portfolio. Electricity and Chemicals also have slightly higher $\mathrm{HE}_{\mathrm{HR}}$ values in the EU ETS-regulated portfolios. Therefore, similar to the EUA results, the EU ETS-regulated portfolios generally require larger hedge positions, but these larger positions do not always generate greater variance reduction.

Brent crude oil has a clearer distinction between the two regulatory groups. In both Electricity and Chemicals, the EU ETS-regulated portfolios have higher HR and higher $\mathrm{HE}_{\mathrm{HR}}$ than the non-EU ETS-regulated portfolios. The largest difference is observed in Chemicals, where the EU ETS-regulated portfolio has a HR of 0.10 compared to 0.06 for the non-EU ETS-regulated portfolio. The corresponding HE_{HR} values are 0.10 and 0.08. A similar pattern is observed in Electricity, although the differences are smaller. Unlike the EUA and natural gas results, the higher HRs observed in the EU ETS-regulated portfolios are also accompanied by higher $\mathrm{HE}_{\mathrm{HR}}$. These results suggest that Brent crude oil price risk is more closely linked to the returns of EU ETS-regulated firms in these sectors.

Unlike EUA, natural gas, and oil, the coal results do not indicate a systematic difference between EU ETS-regulated and non-EU ETS-regulated portfolios in terms of either HR or $\mathrm{HE}_{\mathrm{HR}}$. The $\mathrm{HE}_{\mathrm{HR}}$ values are close to zero for both regulatory groups. In Basic Metals, the EU ETS-regulated portfolio has a $\mathrm{HE}_{\mathrm{HR}}$ of 0.00, while the non-EU ETS-regulated portfolio has a slightly negative value (-0.01). A similar pattern is observed in Non-Metallic Minerals, where the EU ETS-regulated and non-EU ETS-regulated portfolios have $\mathrm{HE}_{\mathrm{HR}}$ values of 0.01 and 0.00, respectively. Unlike the other hedging assets, coal provides almost no variance reduction for either regulatory group. This is consistent with the previous findings, where coal exhibited very high volatility and weak hedging performance across the sector portfolios. The declining role of coal in the European energy mix may also have reduced its relationship with sector returns over time.

A different picture emerges for gold. There is no clear distinction between EU ETS-regulated and non-EU ETS-regulated portfolios in terms of their average HR and $\mathrm{HE}_{\mathrm{HR}}$. In addition, several portfolios have negative average HR values, including Non-Metallic Minerals EU ETS-regulated (-0.05), Non-Metallic Minerals non-EU ETS-regulated (-0.02), and Chemicals EU ETS-regulated (-0.04) portfolios. Negative HR values imply a long position in gold, but the $\mathrm{HE}_{\mathrm{HR}}$ values still remain close to zero, showing that gold has limited hedging benefits. Gold therefore provides almost no variance reduction for either regulatory group. The results are consistent with gold's role as a placebo asset since it does not show any systematic patterns across sectors and regulatory groups.

Hedging Assets Compared Within Sectors

Comparing the five hedging assets in each sector shows which commodity markets have the biggest impact on sector equity returns. In the Electricity sector, Brent crude oil provides the highest HE_{HR}, 0.08 for the EU ETS-regulated and 0.07 for non-EU ETS-regulated portfolio, followed by EUA (0.05 and 0.04). TTF natural gas and gold provide almost no variance reduction. Similarly, for the Chemicals sector, Brent crude oil has the largest HE_{HR} (0.10 for the EU ETS-regulated and 0.08 for non-EU ETS-regulated portfolio), and EUA is still fairly effective (0.06 and 0.07). For Basic Metals and Non-Metallic Minerals, EUA is the main hedging asset. TTF natural gas has a smaller effect, and Rotterdam coal offers almost no variance reduction, even though it has a high importance for steel and cement production.

A notable feature of the results is the behavior of gold. Across all sectors, gold generates some of the highest HE_{OW} values despite very low HE_{HR} values. For example, Basic Metals EU ETS-regulated portfolio reports $HE_{HR} = 0.01$ but $HE_{OW} = 0.74$. Chemicals EU ETS-regulated portfolio reports $HE_{HR} = 0.03$ and $HE_{OW} = 0.58$. Gold is also the least volatile asset in the sample. These results suggest that gold contributes more through diversification than through direct hedging.

Evaluating HR and HE_{HR} together provides additional insight into which asset is more effective for a sector, so that it enables a higher portfolio variance reduction with a lower allocation to the asset. Figure 5.3 plots the full-sample HR and HE_{HR} values for all 32 sector-asset pairs.

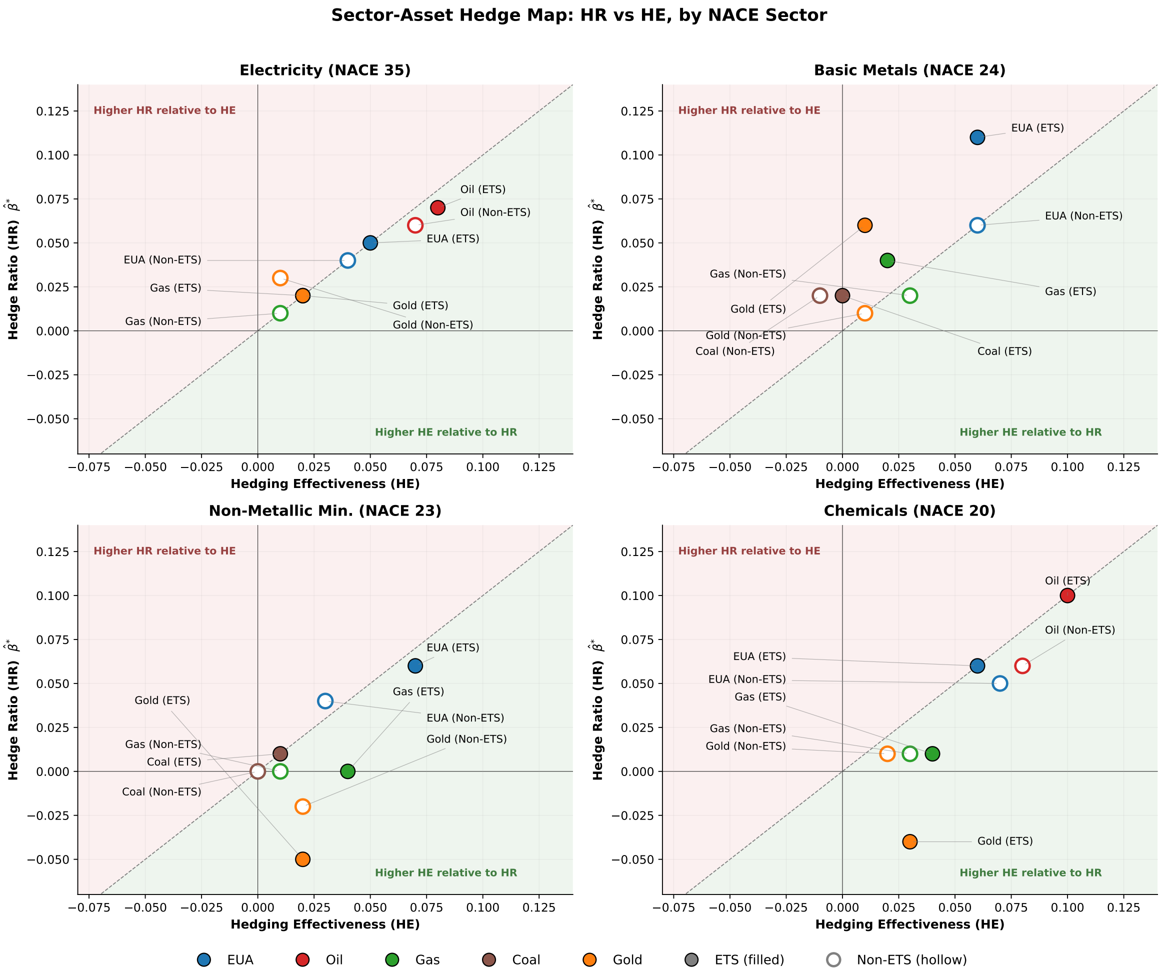

Figure 5.3: The horizontal axis shows hedging effectiveness (HE_{HR}), and the vertical axis shows the average dynamic hedge ratio (HR) for 32 sector–asset pairs over the full sample period from 1 January 2013 to 30 April 2026, using a Monthly Rebalanced Equal-Weighted method. Each point represents a sector–asset pair. Different colors indicate the hedging asset, and filled or hollow markers show whether the portfolio is EU ETS-regulated or not. The dashed diagonal line marks where HR is equal to HE. Pairs in the lower-right corner have high variance reduction with a small hedge position, while those in the upper-left need larger hedge positions for only limited variance reduction.

Figure 5.3 demonstrates the heterogeneity between the sector portfolios and the hedging assets. In the Electricity and Chemicals sectors, Brent crude oil has a favorable position as it has a higher HE_{HR} compared to its moderate average HR. In contrast, EUA is a strong hedging asset for carbon-intensive manufacturing sectors. The highest HE_{HR} is achieved by EUA futures for the Non-Metallic Minerals EU ETS-regulated portfolio (0.07), while requiring a significantly smaller HR than the Basic Metals EU ETS-regulated portfolio (0.06 versus 0.11). Furthermore, hedging with TTF natural gas achieves relatively high HE_{HR} in the Non-Metallic Minerals sector despite an average HR close to zero. This suggests that the dynamic hedge ratio fluctuates around zero over time. Nevertheless, the positive HE_{HR} values indicate that TTF natural gas can still contribute to risk reduction in this sector. HE_{HR} values for Rotterdam coal are near zero for Basic Metals and Non-Metallic Minerals sectors, which shows that it is not an effective hedging asset in reducing portfolio risk. Finally, gold exhibits a different pattern than the other hedging assets. Several sector-gold pairs have negative average hedge ratios, conveying that gold requires a long position rather than a short to minimize the portfolio variance. Although gold has very limited HE_{HR}, its high HE_{OW} values suggest that it has diversification benefits to the portfolio.

Hedge Stability and Optimal Portfolio Weights

Table 5.3 also provides insight into the stability of the dynamic HRs. The EUA and Brent crude oil pairs generally exhibit the narrowest Q5-Q95 ranges, and their HRs remain positive across almost the entire distribution. In contrast, most TTF natural gas, Rotterdam coal, and gold pairs have wider percentile ranges that span both negative and positive values. This implies that the dynamic HR changes sign across different market conditions. The Basic Metals EU ETS-regulated-gold pair exhibits the widest HR range ($[-0.25, 0.27]$), suggesting that the relationship between gold and the sector portfolio varies considerably over time. Figure 5.4 illustrates these patterns for all 32 sector-asset pairs.

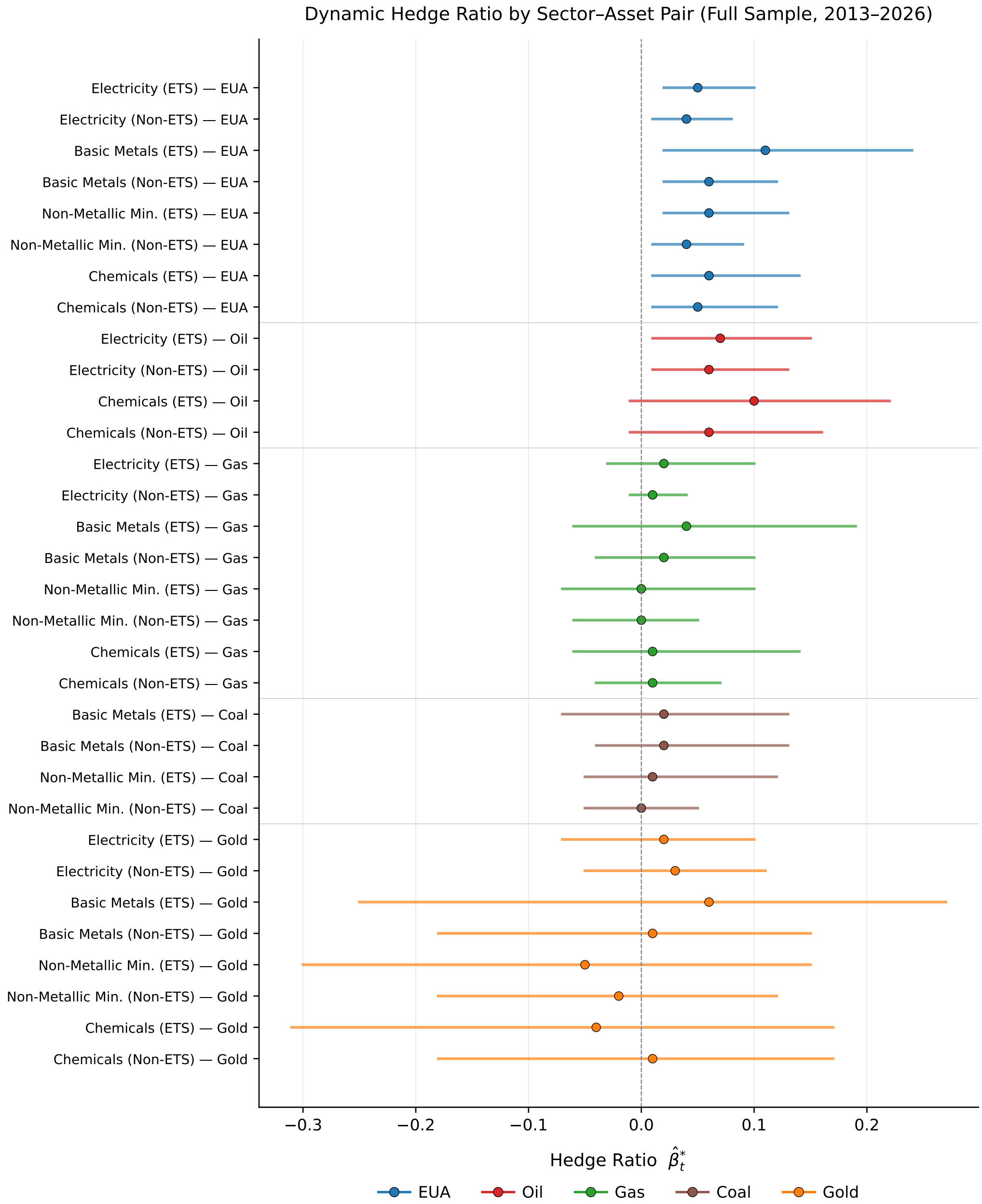

Figure 5.4: Dynamic hedge ratio ($\mathrm{HR_t}$) by sector-asset pair, full sample 1 January 2013 - 30 April 2026. Markers show the time-series mean, and horizontal bars represent the 5th-95th percentile range. Pairs are grouped by hedging asset. Monthly rebalanced equal-weighted index methodology is used. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

The optimal sector weights are generally high across the sample. For most EUA, TTF natural gas, Brent crude oil, and Rotterdam coal pairs, the minimum-variance portfolio allocates between 80% and 95% of the weight to the sector portfolio. This indicates that only a limited portion is allocated to the hedging asset to achieve the highest variance reduction as the hedging asset series are mostly more volatile than the sector returns. The main exceptions are the Basic Metals and gold pairs, where the optimal sector weights are substantially lower. For example, Basic Metals EU ETS-regulated portfolio-EUA has an OW of 0.73, while the Basic Metals EU ETS-regulated portfolio-gold has the lowest OW in the sample (0.26). This is partly driven by the low volatility of the gold series, so that a higher allocation to gold results in greater variance reduction. Overall, the OW results complement the HR and HE measures by showing how the minimum-variance portfolio balances risk between the sector and the hedging asset.

Bridge to Sub-Period Analysis

In summary, the full-sample analysis demonstrates that Brent crude oil provides the strongest hedging performance for the Electricity and Chemicals sectors. For the Basic Metals and Non-Metallic Minerals sectors, EUA is the preferred hedging asset. The findings also show that the EU ETS-regulated portfolios generally require larger hedge positions than the non-EU ETS-regulated portfolios, conveying that they are more sensitive to carbon price changes.

These conclusions are for the full sample period from 1 January 2013 to 30 April 2026 that contains several distinct regulatory and market regimes. The next section examines whether the carbon and energy hedging relationships remain stable across the Phase III Low Price period, the Post-MSR period, the COVID-19 shock, the Phase IV High Price period, the Phase IV Normalization period, and the CBAM Transitional period.

5.3 Sub-Period Analysis

The full-sample averages reported in Section 5.2 do not show the effects of economic crisis and regime changes. To examine how hedge dynamics change across these periods, the 1 January 2013 - 30 April 2026 window is divided into six sub-periods:

- **Phase III Low Price** (2013-01 - 2018-12): the low EUA price period before the Market Stability Reserve (MSR).
- **Post-MSR** (2019-01 - 2020-02): the price-recovery period after the activation of the MSR.
- **COVID-19** (2020-03 - 2020-12): the pandemic shock period.
- **Phase IV High Price** (2021-01 - 2022-12): the Fit-for-55 reform package and the 2022 European energy crisis.
- **Phase IV Normalization** (2023-01 - 2023-09): the stabilization period after the 2022 European energy crisis.

- **CBAM Transitional** (2023-10 - 2026-04): the CBAM regulatory period began with quarterly emissions reporting requirements for importers of cement, iron and steel, aluminum, fertilizers, electricity, and hydrogen.[1]

5.3.1 The Carbon Hedge Across Regimes

Tables 5.4-5.5 report the sub-period statistics of the EUA hedge for the eight sector portfolios. For each portfolio and period, the table lists the mean conditional hedge ratio (HR), the 5th and 95th percentiles of the daily HR series, the HR-based hedging effectiveness (HE_{HR}), optimal weight (OW), and the hedging effectiveness based on optimal portfolio weight (HE_{OW}). Sub-period results for TTF natural gas, Brent crude oil, Rotterdam coal, and gold are reported in Appendix B.

[1] The CBAM Transitional Phase ran from 1 October 2023 to 31 December 2025. The period analyzed here also covers the first four months of the CBAM Definitive Phase (January - April 2026), when the regime shifted from reporting-only to financial compliance through certificate purchases. The two phases are merged because the carbon-leakage signal priced into industrial equities was already in place when the Transitional Phase began.

Table 5.4: Sub-period EUA hedge ratio, hedging effectiveness, and optimal portfolio weight statistics across the Phase III Low Price, Post-MSR, and COVID-19 periods. Bold rows highlight the COVID-19 amplification period.

	HR statistics					OW statistics				
Sector portfolio	**HR**	**Std. dev.**	**5%**	**95%**	**HE_{HR}**	**OW**	**Std. dev.**	**5%**	**95%**	**HE_{OW}**
Panel A. Phase III Low Price (1 Jan 2013 - 31 Dec 2018)										
Electricity (ETS)	0.04	0.03	0.02	0.10	0.04	0.96	0.06	0.82	1.00	0.03
Electricity (Non-ETS)	0.03	0.02	0.01	0.07	0.01	0.93	0.08	0.78	1.00	0.07
Basic Metals (ETS)	0.09	0.07	0.02	0.26	0.04	0.76	0.18	0.31	0.98	0.24
Basic Metals (Non-ETS)	0.05	0.03	0.01	0.11	0.03	0.91	0.09	0.70	1.00	0.08
Non-Metallic Min. (ETS)	0.05	0.03	0.01	0.12	0.02	0.88	0.12	0.63	1.00	0.11
Non-Metallic Min. (Non-ETS)	0.04	0.03	0.01	0.09	0.01	0.88	0.11	0.66	0.99	0.16
Chemicals (ETS)	0.04	0.03	0.01	0.12	0.03	0.90	0.11	0.66	1.00	0.11
Chemicals (Non-ETS)	0.03	0.03	0.00	0.09	0.02	0.92	0.09	0.75	1.00	0.08
Panel B. Post-MSR (1 Jan 2019 - 29 Feb 2020)										
Electricity (ETS)	0.05	0.04	0.02	0.14	0.01	0.94	0.16	0.63	1.00	0.50
Electricity (Non-ETS)	0.03	0.02	0.02	0.05	0.03	0.94	0.05	0.88	0.98	0.02
Basic Metals (ETS)	0.11	0.05	0.05	0.18	0.05	0.72	0.11	0.52	0.87	0.21
Basic Metals (Non-ETS)	0.06	0.02	0.02	0.09	0.05	0.93	0.04	0.87	0.98	0.01
Non-Metallic Min. (ETS)	0.05	0.03	0.02	0.08	0.05	0.90	0.06	0.81	0.97	0.04
Non-Metallic Min. (Non-ETS)	0.03	0.02	0.00	0.05	0.02	0.90	0.06	0.80	0.95	0.05
Chemicals (ETS)	0.06	0.03	0.03	0.10	0.04	0.89	0.06	0.79	0.97	0.05
Chemicals (Non-ETS)	0.04	0.03	0.01	0.07	0.04	0.92	0.06	0.83	0.98	0.05
Panel C. COVID-19 (1 Mar 2020 - 31 Dec 2020)										
Electricity (ETS)	**0.08**	**0.05**	**0.04**	**0.18**	**0.13**	**0.93**	**0.15**	**0.49**	**1.00**	**-0.02**
Electricity (Non-ETS)	**0.07**	**0.05**	**0.04**	**0.15**	**0.13**	**0.93**	**0.14**	**0.60**	**1.00**	**-0.03**
Basic Metals (ETS)	**0.22**	**0.07**	**0.13**	**0.32**	**0.18**	**0.69**	**0.15**	**0.44**	**0.88**	**0.17**
Basic Metals (Non-ETS)	**0.12**	**0.06**	**0.06**	**0.19**	**0.18**	**0.88**	**0.14**	**0.62**	**0.99**	**0.02**
Non-Metallic Min. (ETS)	**0.13**	**0.06**	**0.06**	**0.23**	**0.25**	**0.91**	**0.14**	**0.55**	**1.00**	**-0.08**
Non-Metallic Min. (Non-ETS)	**0.07**	**0.05**	**0.03**	**0.15**	**0.13**	**0.90**	**0.12**	**0.67**	**0.99**	**-0.05**
Chemicals (ETS)	**0.14**	**0.06**	**0.07**	**0.21**	**0.15**	**0.88**	**0.14**	**0.58**	**0.99**	**0.02**
Chemicals (Non-ETS)	**0.12**	**0.07**	**0.07**	**0.23**	**0.20**	**0.90**	**0.15**	**0.54**	**1.00**	**-0.07**

Notes: Results are reported for EUA futures only. HR denotes the average hedge ratio within each sub-period, and HE_{HR} denotes the hedge-ratio-based hedging effectiveness. OW denotes the average optimal portfolio weight, and HE_{OW} denotes the optimal-weight-based hedging effectiveness. The Std. dev., 5%, and 95% columns under HR and OW report the standard deviation and the 5th and 95th percentiles of the daily HR and OW series within each sub-period. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios. This table reports the Phase III Low Price period, the Post-MSR period following the introduction of the Market Stability Reserve, and the COVID-19 shock period. The Phase IV High Price, Phase IV Normalization, and CBAM Transitional periods are reported in Table 5.5. Comprehensive sub-period results for all 32 sector-asset pairs and all five hedging assets are reported in Appendix B.

Table 5.5: Sub-period EUA hedge ratio, hedging effectiveness, and optimal portfolio weight statistics across the Phase IV High Price, Phase IV Normalization, and CBAM Transitional periods.

	HR statistics					**OW statistics**				
Sector portfolio	**HR**	**Std. dev.**	**5%**	**95%**	**HE_{HR}**	**OW**	**Std. dev.**	**5%**	**95%**	**HE_{OW}**
Panel A. Phase IV High Price (1 Jan 2021 - 31 Dec 2022)										
Electricity (ETS)	0.05	0.02	0.03	0.08	0.04	0.96	0.04	0.88	1.00	0.00
Electricity (Non-ETS)	0.04	0.02	0.02	0.09	0.03	0.94	0.04	0.85	0.99	0.02
Basic Metals (ETS)	0.12	0.05	0.05	0.20	0.02	0.74	0.11	0.53	0.92	0.18
Basic Metals (Non-ETS)	0.08	0.03	0.04	0.12	0.04	0.91	0.06	0.82	0.99	0.00
Non-Metallic Min. (ETS)	0.07	0.02	0.03	0.10	0.04	0.90	0.07	0.77	0.98	0.01
Non-Metallic Min. (Non-ETS)	0.04	0.02	0.01	0.08	0.03	0.90	0.06	0.77	0.98	0.02
Chemicals (ETS)	0.08	0.03	0.04	0.13	0.05	0.92	0.06	0.82	1.00	0.01
Chemicals (Non-ETS)	0.06	0.02	0.03	0.11	0.04	0.92	0.06	0.81	0.99	-0.01
Panel B. Phase IV Normalization (1 Jan 2023 - 30 Sep 2023)										
Electricity (ETS)	0.06	0.02	0.03	0.08	0.02	0.94	0.04	0.87	0.99	0.04
Electricity (Non-ETS)	0.04	0.01	0.03	0.06	0.01	0.93	0.03	0.87	0.97	0.02
Basic Metals (ETS)	0.12	0.02	0.09	0.15	0.02	0.70	0.09	0.59	0.84	0.21
Basic Metals (Non-ETS)	0.06	0.01	0.04	0.08	0.00	0.88	0.05	0.79	0.94	0.09
Non-Metallic Min. (ETS)	0.05	0.01	0.03	0.07	-0.01	0.87	0.06	0.76	0.94	0.11
Non-Metallic Min. (Non-ETS)	0.04	0.02	0.02	0.07	0.00	0.85	0.06	0.76	0.94	0.11
Chemicals (ETS)	0.06	0.02	0.03	0.09	0.01	0.85	0.06	0.75	0.94	0.11
Chemicals (Non-ETS)	0.04	0.01	0.02	0.06	-0.01	0.90	0.05	0.81	0.96	0.08
Panel C. CBAM Transitional (1 Oct 2023 - 30 Apr 2026)										
Electricity (ETS)	0.06	0.02	0.03	0.10	0.03	0.93	0.05	0.84	0.99	0.05
Electricity (Non-ETS)	0.05	0.02	0.03	0.07	0.02	0.91	0.06	0.80	0.98	0.06
Basic Metals (ETS)	0.12	0.05	0.04	0.21	0.04	0.69	0.13	0.49	0.90	0.25
Basic Metals (Non-ETS)	0.08	0.03	0.03	0.13	0.03	0.85	0.11	0.69	0.97	0.14
Non-Metallic Min. (ETS)	0.07	0.04	0.01	0.14	0.03	0.82	0.10	0.62	0.95	0.15
Non-Metallic Min. (Non-ETS)	0.05	0.04	0.00	0.10	0.01	0.82	0.11	0.62	0.93	0.26
Chemicals (ETS)	0.07	0.03	0.01	0.12	0.03	0.84	0.07	0.72	0.95	0.11
Chemicals (Non-ETS)	0.07	0.04	0.03	0.14	0.05	0.88	0.09	0.73	0.98	0.11

Notes: Results are reported for EUA futures only. HR, HE_{HR}, OW, and HE_{OW} are defined as in Table 5.4. The Std. dev., 5%, and 95% columns under HR and OW report the standard deviation and the 5th and 95th percentiles of the daily HR and OW series within each sub-period. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios. This table reports the Phase IV High Price period, the Phase IV Normalization period, and the CBAM Transitional period. Comprehensive sub-period results for all 32 sector-asset pairs and all five hedging assets are reported in Appendix B.

During Phase III Low Price period, the average HR and HE_{HR} have relatively low values. HR values range from 0.03 to 0.09 across the eight portfolios, and HE_{HR} values are between 0.01 and 0.04. These results suggest that EUA futures provided only limited hedging benefits during the low-price phase of the carbon market. In the post-MSR period, HE_{HR} values improve for most of the sector portfolios compared to the Phase III Low Price period. This coincides with the recovery in EUA prices after the implementation of the MSR and suggests a stronger relationship between sector returns and carbon prices than in the earlier years of the sample.

In the COVID-19 sub-period, the largest deviations from the full-sample results are displayed. Basic Metals EU ETS-regulated portfolio has an HR of 0.22, more than twice its Phase III level, and the Non-Metallic Minerals EU ETS-regulated portfolio has the highest HE_{HR} value in the sample (0.25). All eight portfolios have HE_{HR} values at or above 0.13, compared to values generally below 0.07 in the full-sample analysis. The Q5-Q95 range also substantially widens. EUA HR with the Basic Metals EU ETS-regulated portfolio fluctuates between 0.13 and 0.32 within this period. The strongest increase in HE_{HR} values is observed during the COVID-19 period. This period was also characterized by large movements in both carbon and energy markets. As discussed in Section 2.1.4, the increase in HE_{HR} values across all portfolios is consistent with the stronger carbon-equity relationships often observed during periods of market stress.

The Phase IV High Price period shows a moderation relative to the extreme COVID-19 period. HR values fall back into the 0.04-0.12 range, and the HE_{HR} values return to the levels between 0.02-0.05. However, HR levels do not fully return to their Phase III levels for the manufacturing sectors. Basic Metals EU ETS-regulated portfolio has an HR of 0.12 throughout Phase IV, against 0.09 in the Phase III Low Price period and 0.11 in the Post-MSR period. Chemicals and Non-Metallic Minerals sectors also mainly have higher HR values during Phase IV compared to Phase III. Results show that the relationship between EUA and the manufacturing portfolios remains stronger than in the pre-2020 period.

The Phase IV Normalization period has the lowest HE_{HR} values in the entire panel for five of the eight portfolios and tied for the lowest in two others. During that period, HE_{HR} values collapse to between -0.01 and 0.02. HRs stayed high possibly because EUA conditional volatility is higher than in Phase III, but the conditional correlation with the sector portfolios weakens after the 2022 European energy crisis subsides. Then, in the CBAM Transitional period, HE_{HR} values increase back to similar levels to their levels at Phase IV High Price period, but HR values stay similar to Phase IV Normalization period. The hedge has a better performance in this period, as a similar amount of the hedging asset is needed to hedge a €1 long position in the sector portfolio, but a higher portfolio variance reduction is achieved.

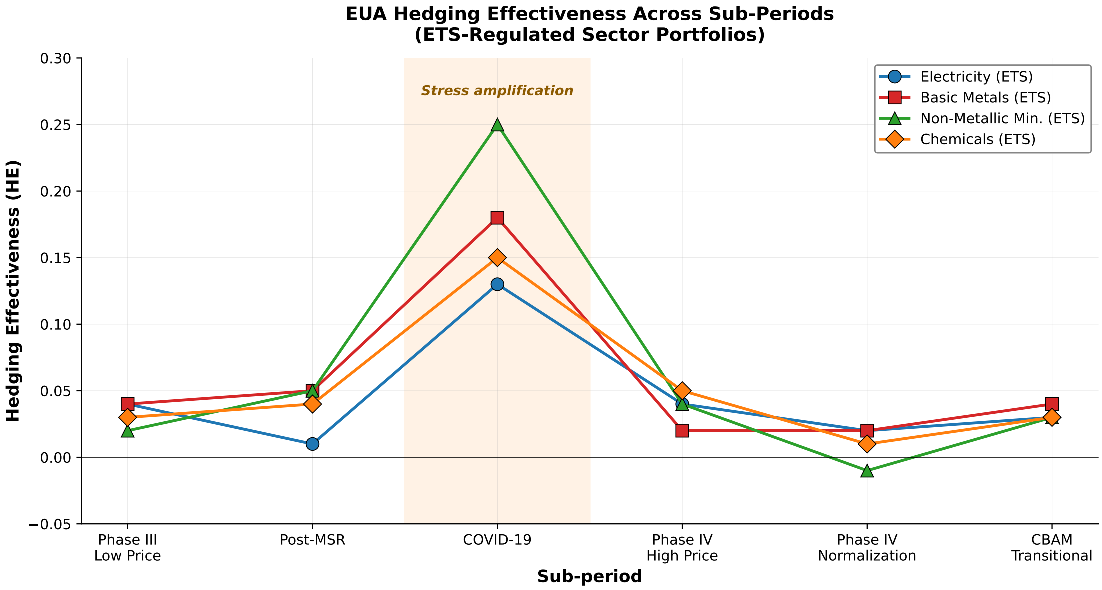

Figure 5.5: This figure shows EUA average HE_{HR} for the four EU ETS-regulated sector portfolios across six sub-periods. The shaded area highlights the COVID-19 stress period, when HE_{HR} values rise sharply and Non-Metallic Min. (ETS) reaches the maximum value 0.25. After this, HE_{HR} values decrease during Phase IV High Price period and reach their lowest point in the Phase IV Normalization period, before recovering slightly in the CBAM Transitional period.

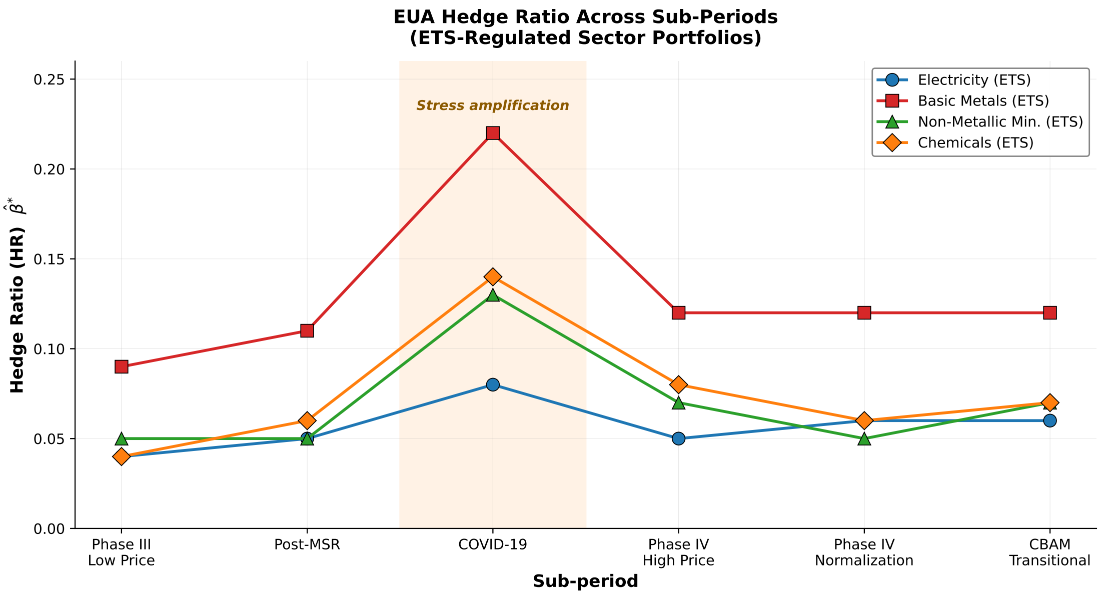

Figure 5.6: The average HR was measured for EUA across six sub-periods for four sector EU ETS-regulated portfolios. Basic Metals (ETS) has the highest HR in every period and it reaches 0.22 during the COVID-19 period. Unlike HE_{HR}, HR values remain high for the manufacturing portfolios during Phase IV. This implies that larger hedge positions did not necessarily result in greater variance reduction after COVID-19.

Figures 5.5 and 5.6 together show that the HE_{HR} and HR have regime-dependent patterns. The COVID-19 period is the only time when both average HR and HE_{HR} reach their highest levels across all four EU ETS-regulated portfolios. Starting from the Phase IV High Price period, HR for the manufacturing portfolios stay relatively high (Basic Metals EU ETS-regulated portfolio at 0.12, Chemicals EU ETS-regulated portfolio at 0.06 to 0.08, Non-Metallic Minerals EU ETS-regulated portfolio at 0.05 to 0.07), but HE_{HR} values drop to between -0.01 and 0.05. Especially during the Phase IV Normalization period, the lowest HE_{HR} values are observed. This suggests that the EUA hedge becomes less efficient as a relatively large hedge position is required while delivering limited variance reduction. During the CBAM Transitional period, HE_{HR} recovers slightly, but this is not matched by a similar rise in HR.

5.3.2 Time-Varying Hedging Across Assets

The sub-period averages presented above provide only a summary of the underlying time-varying relationships. Therefore, to show how these relationships evolve within each sub-period, the dynamic behavior of the hedging assets is also examined. Figures 5.7-5.11 show the time-varying HR_t and HE_t measures obtained from the full-sample DCC-GARCH estimations. As described in Section 4.4.3, HE_t represents the time-varying HE_{HR}. The results are reported separately for EUA futures, TTF natural gas, Brent crude oil, Rotterdam coal, and gold. For each asset, the EU ETS-regulated portfolios are shown in the left column and the non-EU ETS-regulated portfolios in the right column. The six sub-periods discussed in Section 5.3 are indicated in the background to compare the dynamic hedging results of different sub-periods. More detailed sub-period statistics are reported in Tables 5.4 and 5.5 for EUA and in Appendix B for the remaining hedging assets.

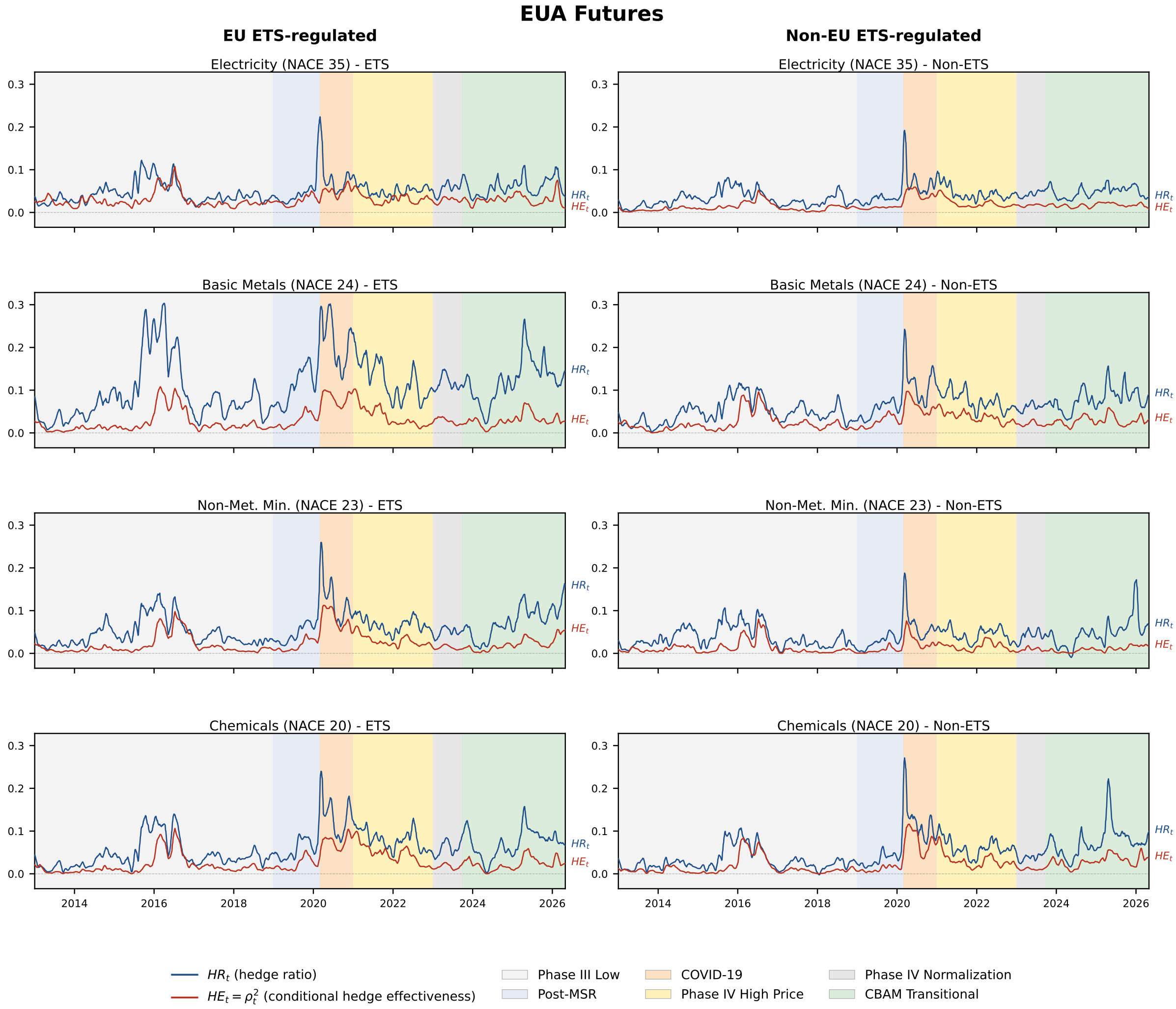

Figure 5.7: EUA futures: $\mathrm{HR_t}$ and $\mathrm{HE_t}$ for the eight sector portfolios. Results are grouped by sector; each row shows the results for one of the four selected NACE sectors. The blue lines represent $\mathrm{HR_t}$ and the red lines represent $\mathrm{HE_t}$. The left column reports the EU ETS-regulated portfolios and the right column reports the non-EU ETS-regulated portfolios. Background shading indicates the six sub-periods used in the empirical analysis.

EUA: The sub-period analysis identified the COVID-19 pandemic as the period with the strongest average EUA hedging relationships. Figure 5.7 shows that this pattern is not uniform over time and reveals additional periods with high $\mathrm{HE_t}$. Higher values are also observed in the later part of the Phase III Low Price period, especially from the beginning of 2016 until the middle of 2017. The increase around 2016 and 2017 coincides with an important period for the EU ETS. Although this increase is clearly visible in the estimates, it is less apparent in the Phase III Low Price sub-period averages because it covers only a limited part of the six-year period. The Market Stability Reserve was approved in 2015 [6] and became operational on 1 January 2019. However, the reform process and the expected reduction in future allowance supply were already being incorporated into market expectations before its implementation. After the European Council decision of 28 February 2017, which redirected a larger share of excess allowances to the MSR and introduced a cancellation mechanism for Phase IV, EUA prices increased from €5.15 per tonne at the start of 2017 to €11.06 by January 2018 [93]. As the legislative details became clearer, EUA prices started to recover from the allowance surplus that had accumulated after the 2008 global financial crisis [28, 10]. This may explain the higher $\mathrm{HE_t}$ values observed across several portfolios. Moreover, an increase in $\mathrm{HE_t}$ during the Phase IV High Price period is visible, although it is not as pronounced as during the COVID-19 period. Compared with the COVID-19 period, the increase is generally smaller and confined to shorter periods across the sector portfolios.

The dynamic results give more insight into the differences between HR and $\mathrm{HE_{HR}}$ observed in the sub-period analysis. During the increase observed between 2016 and mid-2017, $\mathrm{HR_t}$ and $\mathrm{HE_t}$ increase at the same time in several portfolios. This is consistent with the regulatory developments described above, as the expected tightening of EUA supply increased both the size of the hedge position required and the variance reduction it delivered. Moreover, during the COVID-19 period, both measures increase sharply across most portfolios. Lockdowns during the COVID-19 pandemic reduced industrial activity and energy demand across Europe. Carbon prices and the stock returns of carbon-intensive firms responded to the same economic environment, which strengthened their relationship. Thus, higher $\mathrm{HR_t}$s are required and a higher variance reduction is achieved during this period. However, after the COVID-19 pandemic period, the two measures do not always move together. For several manufacturing portfolios, $\mathrm{HE_t}$ still remains relatively high during 2021 and 2022, despite the lower $\mathrm{HR_t}$ values compared to the COVID-19 period. The Basic Metals and Chemicals portfolios show this behavior. Furthermore, during the Phase IV Normalization period, for all the sector portfolios, higher $\mathrm{HR_t}$ values are observed with lower $\mathrm{HE_t}$ values. This shows that larger hedge positions are still required, but they do not generate the same reduction in portfolio variance observed during earlier periods. This is likely because the effects of the 2022 European energy crisis are gradually decreasing. Although EUA prices continued to fluctuate, sector returns were no longer driven by the same market conditions as during the crisis.

There are also certain periods where the difference between EU ETS-regulated and non-EU ETS-regulated portfolios is better observed. During the increase observed between 2016 and mid-2017, EU ETS-regulated portfolios generally have higher $\mathrm{HE_t}$. This indicates that the developments affecting the EU carbon market during this period were reflected more strongly in the returns of EU ETS-regulated firms. Once the market started to expect a tighter supply of allowances, changes in EUA prices were reflected more strongly in the returns of EU ETS-regulated firms than in non-EU ETS-regulated firms.

Figure 5.8: TTF natural gas futures: $\mathrm{HR_t}$ and $\mathrm{HE_t}$ for the eight sector portfolios. Results are grouped by sector; each row shows the results for one of the four selected NACE sectors. The blue lines represent $\mathrm{HR_t}$ and the red lines represent $\mathrm{HE_t}$. The left column reports the EU ETS-regulated portfolios and the right column reports the non-EU ETS-regulated portfolios. Background shading indicates the six sub-periods used in the empirical analysis.

TTF Natural Gas: The plots for TTF natural gas display much stronger sectoral differences. The strongest increase in $\mathrm{HE_t}$ during the earlier years of the sample is observed for Electricity and Chemicals EU ETS-regulated portfolios between mid-2015 and mid-2017. The $\mathrm{HR_t}$s have a similar increase pattern among the EU ETS-regulated sector portfolios in this period, although higher $\mathrm{HE_t}$s are observed for Electricity and Chemicals sectors compared to Basic Metals and Non-Metallic Minerals. The substantial movements in gas prices during this period, including the sharp price declines of 2014-2015 and a partial recovery following that, may have made the link between gas prices and gas-intensive sector returns more visible. Since natural gas is an important input for electricity generation and chemical production, changes in gas prices have a higher impact on these sectors [94, 95], as shown in increasing $\mathrm{HR_t}$ and $\mathrm{HE_t}$. This increase is also reflected, but with a smaller magnitude for the Basic Metals and the Non-Metallic Minerals sectors. Furthermore, unlike with the other assets, a clear increase in $\mathrm{HE_t}$ together with negative $\mathrm{HR_t}$ values are observed from 2014 to 2015 for Electricity, Non-Metallic Minerals and Chemicals portfolios. This indicates that the relationship between natural gas prices and sector returns became stronger during this period, but in a direction that implied negative $\mathrm{HR_t}$s. A possible explanation is the sharp decline in energy prices during 2014 and 2015. As gas prices declined, production costs became lower for gas-intensive sectors. This may have contributed to the inverse relationship observed between gas returns and sector returns, resulting in a negative HR [96, 97]. There is also a substantial difference from the beginning of 2022 until 2023, likely due to the 2022 European energy crisis. During this period, the largest increases in $\mathrm{HE_t}$ are observed for the Non-Metallic Minerals and Chemicals EU ETS-regulated portfolios. This coincides with a period of severe disruptions in European natural gas supply following the rise in geopolitical tensions and the Russia-Ukraine war, which led to increases in gas prices across Europe [98]. The stronger increase observed for the Chemicals and Non-Metallic Minerals portfolios is consistent with the high dependence of these sectors on natural gas as both an energy source and a production input [95, 99].

Furthermore, while $\mathrm{HE_t}$ values increase during the 2022 European energy crisis, $\mathrm{HR_t}$ turns negative for most sector portfolios, particularly for the EU ETS-regulated portfolios. This indicates a reversal in the sign of the hedging relationship. During this period, several portfolios require a long rather than a short position in natural gas to minimize portfolio variance. This is due to the fact that natural gas prices rose substantially during the 2022 European energy crisis and therefore increased the production costs. As a result, the increase in natural gas prices decreased sector returns and caused the HRs to turn negative [100, 101].

Outside these periods, the relationship weakens again and $\mathrm{HE_t}$ returns to relatively low levels for most portfolios. The increase observed between 2015 and 2017 gradually disappears afterwards. The decline after 2017 is particularly visible for the Electricity EU ETS-regulated portfolio, which experienced one of the strongest increases in the earlier years of the sample. A similar pattern can be observed after the 2022 European energy crisis. HE_t values gradually fell from their 2022-2023 levels. However, HE_t begins to increase again towards the end of the sample, especially for the Chemicals EU ETS-regulated and Non-Metallic Minerals EU ETS-regulated portfolios, while a smaller increase can also be observed for the Basic Metals EU ETS-regulated portfolio. This increase overlaps with the later stages of the CBAM Transitional period and the introduction of the CBAM definitive phase [54]. As the CBAM definitive phase approached, the sectors covered by the CBAM may have become more sensitive to carbon and energy market developments as regulatory requirements gradually tightened.

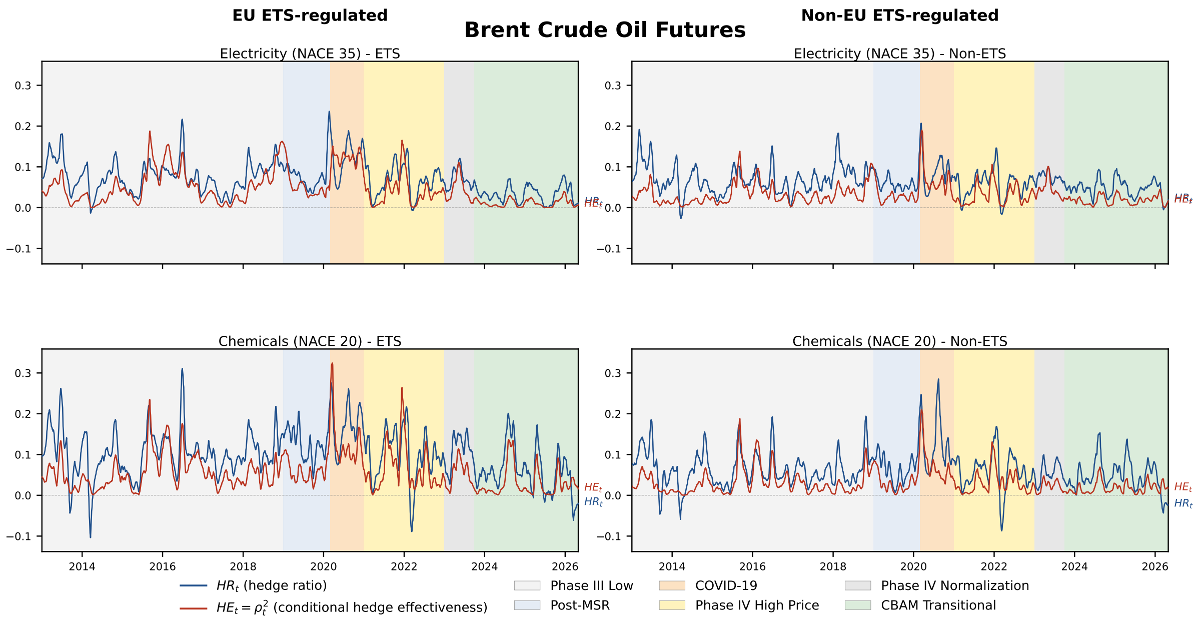

Figure 5.9: Brent crude oil: HR_t and HE_t for the Electricity (NACE 35) and Chemicals (NACE 20) portfolios. The blue lines represent HR_t and the red lines represent HE_t. The left column reports the EU ETS-regulated portfolios and the right column reports the non-EU ETS-regulated portfolios. Background shading indicates the six sub-periods used in the empirical analysis.

Brent Crude Oil: The sub-period analysis showed that Brent crude oil provides the highest average HE_t values for the Electricity and Chemicals portfolios, especially during the Phase III Low Price, Post-MSR, and COVID-19 periods. The dynamic estimates display these results clearly for Phase III Low Price and COVID-19 periods, but it also conveys that higher values for the Post-MSR period in the average metrics are driven by shorter intervals of higher HR_t and HE_t, rather than by a persistent increase throughout the period. For the Electricity sector, HE_t increases simultaneously between 2015-2017 inside the Phase III Low Price period, between middle 2018 and middle 2019, covering a small portion of the Post-MSR period and during the COVID-19 pandemic. Likewise, the Chemicals sector also exhibits an increase in $\mathrm{HR_t}$ and $\mathrm{HE_t}$ during 2015-2017 and the COVID-19 period, but the co-movement between $\mathrm{HR_t}$ and $\mathrm{HE_t}$ is less pronounced.

The increase observed between 2015 and 2017 is particularly strong for the Chemicals portfolios. This is consistent with the importance of oil-based feedstocks, such as naphtha, in chemical production, which creates a closer link between oil prices and sector profitability [71, 72]. A second increase is observed during the COVID-19 period across all portfolios. This was a period when oil prices and the Electricity and Chemicals sectors were influenced by the slowdown in economic activity due to the COVID-19 pandemic. Thus, the relationship between them got stronger, and $\mathrm{HE_t}$ for both sector portfolios increased when hedged with Brent crude oil [102]. This period has the highest $\mathrm{HE_t}$ values observed for the pairs with Brent crude oil.

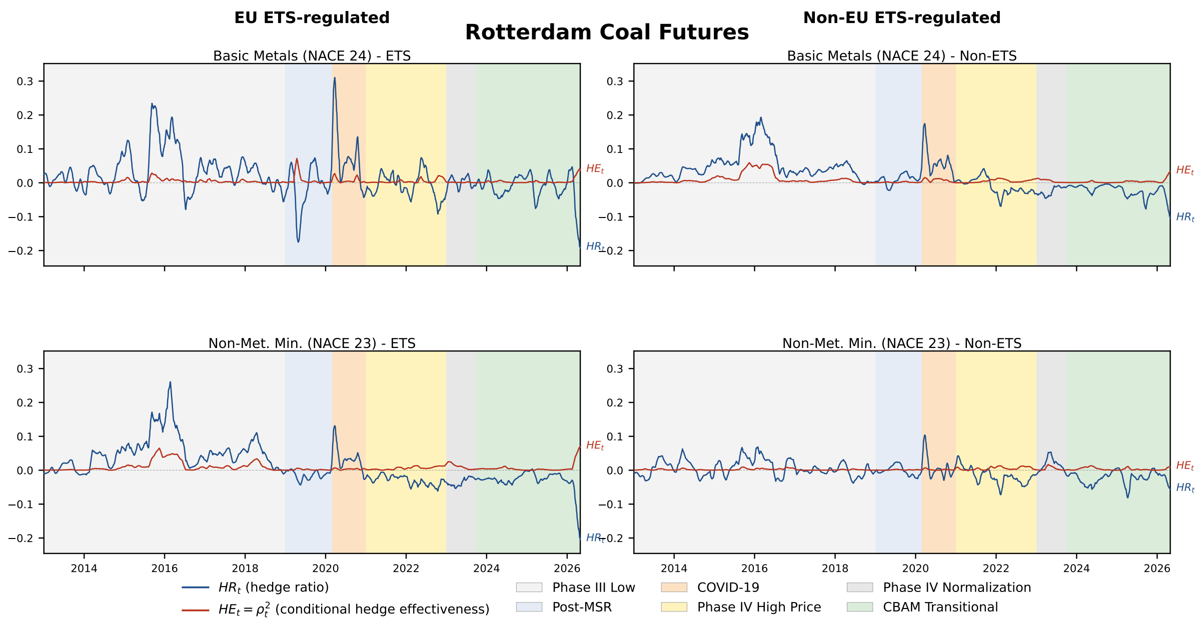

Figure 5.10: Rotterdam Coal: $\mathrm{HR_t}$ and $\mathrm{HE_t}$ for the Basic Metals (NACE 24) and Non-Metallic Minerals (NACE 23) portfolios. The blue lines represent $\mathrm{HR_t}$ and the red lines represent $\mathrm{HE_t}$. The left column reports the EU ETS-regulated portfolios and the right column reports the non-EU ETS-regulated portfolios. Background shading indicates the six sub-periods used in the empirical analysis.

Rotterdam Coal:

Rotterdam coal differs considerably from the other energy-related assets. $\mathrm{HE_t}$ remains close to zero for most of the sample, and only small increases can be observed, mainly between 2015 and 2017, especially for the Non-Metallic Minerals portfolio. Even during the COVID-19 period, when EUA, natural gas, and Brent crude oil experience noticeable increases in $\mathrm{HE_t}$, it stays near zero for coal.

While $\mathrm{HE_t}$ still stays near zero for the majority of the sample, there are some trends that can be observed for the $\mathrm{HR_t}$. It increases from 2015 to 2017, especially for the EU ETS-regulated portfolios, and decreases over the subsequent period. The increase from 2015 to 2017 coincides with a period in which the market for coal is extremely volatile as a result of Chinese supply-side reforms and disruptions in major exporters, which led to a rise in the price of Rotterdam coal from less than USD 70 per tonne at the beginning of 2017 to around USD 95 per tonne in September 2017 [103]. These market conditions may have contributed to the higher $\mathrm{HR_t}$s observed during this period, although they did not result in a noticeable improvement in $\mathrm{HE_t}$.

Furthermore, after 2021, particularly for the Non-Metallic Minerals EU ETS-regulated portfolio, $\mathrm{HR_t}$ becomes negative. The other portfolios also experience periods of negative $\mathrm{HR_t}$, although the sign change is less persistent and it alternates with positive values over time. The years after 2021 were unusual for coal markets, as coal prices reached record levels after the supply disruptions and changes in international trade during the 2022 European energy crisis [104]. The sign reversal in $\mathrm{HR_t}$ observed after 2021 coincides with the same period of coal market disruptions. A similar shift in the sign of $\mathrm{HR_t}$ is also observed for TTF natural gas during the 2022 European energy crisis, suggesting that the relationship between energy commodity prices and equity returns of carbon-intensive sectors changed during this period.

Coal is an important input for both steel and cement production [69, 70]. Nevertheless, movements in Rotterdam coal prices appear to have only a limited relationship with portfolio risk. This finding is consistent with the full-sample results, where coal exhibited very low $\mathrm{HE_t}$ despite its high price volatility. The declining role of coal in the European industrial and power sectors may also contribute to the weak hedging relationships observed throughout the sample period.

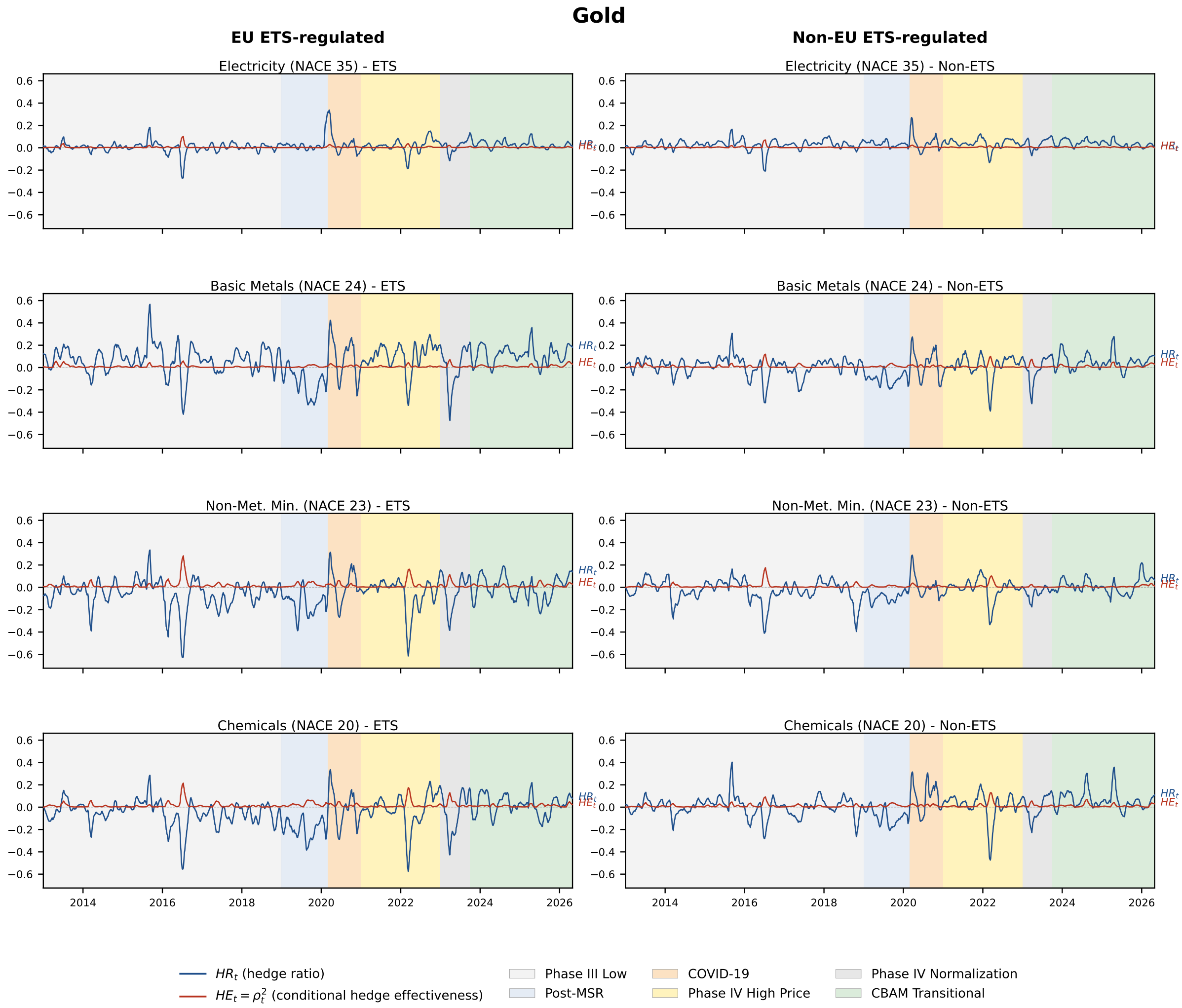

Figure 5.11: Gold: $\mathrm{HR_t}$ and $\mathrm{HE_t}$ for the eight sector portfolios. Results are grouped by sector; each row shows the results for one of the four selected NACE sectors. The blue lines represent $\mathrm{HR_t}$ and the red lines represent $\mathrm{HE_t}$. The left column reports the EU ETS-regulated portfolios and the right column reports the non-EU ETS-regulated portfolios. Background shading indicates the six sub-periods used in the empirical analysis.

Gold:

Gold does not have a consistent pattern over time. Between 2015 and 2017, $\mathrm{HE_t}$ increases for all portfolios, especially for the Non-Metallic Minerals and Chemicals sectors. At the same time, $\mathrm{HR_t}$ values turn negative during this period, which shows that the improvement in $\mathrm{HE_t}$ is often accompanied by a long position in gold. After 2017, the portfolios begin to follow more distinct paths. Higher $\mathrm{HE_t}$ values can still be observed, particularly for the Chemicals and Non-Metallic Minerals portfolios during the Phase IV High Price period. Similar to the earlier periods, these increases are often accompanied by negative $\mathrm{HR_t}$ values, indicating that gold takes a long position in the hedge.

Gold is often referred to as a safe-haven asset during market uncertainty periods [77, 78]. This may help explain some of the temporary increases in $\mathrm{HE_t}$ observed throughout the sample. However, the increases occur in different portfolios and periods, making it difficult to identify a common pattern across sectors or regulatory groups.

The previous figures show that the largest increases in $\mathrm{HR_t}$ and $\mathrm{HE_t}$ are generally observed during the COVID-19 period. The next subsection examines this period in more detail and discusses the factors behind the stronger hedging relationships observed during the COVID-19 pandemic.

5.3.3 Hedge Dynamics During COVID-19

The increase in both $\mathrm{HE_{HR}}$ and HR during COVID-19 reflects three mechanisms. First, the collapse and recovery in industrial activity pushed demand for EUAs in line with European stock market returns and increased the conditional covariance between EUAs and European stock market returns. Second, the financialization of EUA markets accelerated in 2020 [105], so it further synchronized carbon prices with wider stock market dynamics. Third, the sharp increase in energy market uncertainty strengthened the link between oil, natural gas, and coal prices.

Another important feature of the COVID-19 period is that while the average $\mathrm{HE_{HR}}$ increases across the eight portfolios, $\mathrm{HE_{OW}}$ becomes negative in five of them. The portfolios with negative $\mathrm{HE_{OW}}$ allocate only around 7%-10% of their weight to EUA. However, three portfolios with positive $\mathrm{HE_{OW}}$ allocate at least 12%. It suggests that a small EUA allocation is not sufficient to generate diversification benefits during the highly volatile COVID-19 period. Therefore, the minimum-variance portfolio often did not reduce risk, although the $\mathrm{HE_{HR}}$ was high.

5.3.4 The CBAM Transitional Period

The transition from the Phase IV Normalization period to the CBAM Transitional period mainly affects the manufacturing sectors. The Electricity sector is mostly unaffected at the equity level. Table 5.6 compares the EUA hedge statistics across the two periods.

Table 5.6: Change in the EUA hedge statistics between the Phase IV Normalization period (Norm., January - September 2023) and the CBAM Transitional period (CBAM, October 2023 - April 2026). Sectors are ordered by their direct exposure to CBAM scope.

	HR		**HE_{HR}**		**OW**		**HE_{OW}**	
Sector portfolio	**Norm.**	**CBAM**	**Norm.**	**CBAM**	**Norm.**	**CBAM**	**Norm.**	**CBAM**
Panel A. Sectors directly within CBAM scope								
Basic Metals (ETS)	0.12	0.12	0.02	0.04	0.70	0.69	0.21	0.25
Basic Metals (Non-ETS)	0.06	0.08	0.00	0.03	0.88	0.85	0.09	0.14
Non-Metallic Min. (ETS)	0.05	0.07	-0.01	0.03	0.87	0.82	0.11	0.15
Non-Metallic Min. (Non-ETS)	0.04	0.05	0.00	0.01	0.85	0.82	0.11	0.26
Chemicals (ETS)	0.06	0.07	0.01	0.03	0.85	0.84	0.11	0.11
Chemicals (Non-ETS)	0.04	0.07	-0.01	0.05	0.90	0.88	0.08	0.11
Panel B. Sectors outside CBAM scope (imported electricity only)								
Electricity (ETS)	0.06	0.06	0.02	0.03	0.94	0.93	0.04	0.05
Electricity (Non-ETS)	0.04	0.05	0.01	0.02	0.93	0.91	0.02	0.06

Notes: Norm. refers to the Phase IV Normalization period (1 January - 30 September 2023) after the 2022 European energy crisis; CBAM refers to the CBAM Transitional period (1 October 2023 - 30 April 2026). Basic Metals corresponds to iron, steel, and aluminum producers directly subject to CBAM. Non-Metallic Minerals correspond to cement and lime producers, also directly affected by the CBAM. Chemicals contain fertiliser producers (CBAM-subject) and their downstream users. Electricity is within the CBAM scope only through imported electricity, which is a small fraction of the activity of the listed European firms in this thesis. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

There is only a slight change between the HR values from Phase IV Normalization to CBAM Transitional periods. In contrast, HE_{HR} values improve considerably across the manufacturing sectors. For example, Basic Metals EU ETS-regulated portfolio increases from 0.02 to 0.04, Chemicals non-EU ETS-regulated portfolio from -0.01 to 0.05, and Non-Metallic Minerals EU ETS-regulated portfolio from -0.01 to 0.03. The Electricity portfolios have much smaller changes. This suggests that the EUA hedge becomes more effective for manufacturing sectors during the CBAM period, even though the size of the required hedge position remains largely unchanged.

5.3.5 Sign Reversals in Phase IV: TTF Natural Gas and Rotterdam Coal Futures

Table 5.7 shows the change in gas and coal hedging between the Phase III Low Price (2013-2018) and Phase IV High Price (2021-2022) periods, which is not visible in the full-sample averages. The TTF natural gas hedge ratio changes direction for gas-intensive manufacturing sectors and Rotterdam coal also changes sign, mainly in the Basic Metals and Non-Metallic Minerals sectors.

Table 5.7: Sign reversals of the gas and coal hedge ratios between the low-price period of Phase III (2013-2018) and the high-price period of Phase IV (2021-2022). All values are sub-period means of the hedge ratio HR_t. Negative values are shown in **bold**.

	HR			**HE_{HR}**		
Sector portfolio	**2013-2018**	**2021-2022**	**Δ**	**2013-2018**	**2021-2022**	**Δ**
Panel A. TTF natural gas front-month futures						
Chemicals (ETS)	0.03	**-0.01**	-0.04	0.05	0.08	+0.03
Chemicals (Non-ETS)	0.01	**-0.01**	-0.02	0.03	0.05	+0.02
Non-Metallic Min. (ETS)	0.01	**-0.02**	-0.03	0.02	0.10	+0.08
Non-Metallic Min. (Non-ETS)	0.00	**-0.01**	-0.01	0.01	0.03	+0.02
Basic Metals (ETS)	0.06	0.00	-0.06	0.02	0.02	0.00
Basic Metals (Non-ETS)	0.03	0.00	-0.03	0.03	0.04	+0.01
Electricity (ETS)	0.02	0.00	-0.02	0.04	0.02	-0.02
Electricity (Non-ETS)	0.01	0.00	-0.01	0.01	0.01	0.00
Panel B. Rotterdam API2 coal front-month futures						
Basic Metals (ETS)	0.04	**-0.01**	-0.05	0.01	0.00	-0.01
Basic Metals (Non-ETS)	0.05	**-0.01**	-0.06	0.01	**-0.04**	-0.05
Non-Metallic Min. (ETS)	0.05	**-0.03**	-0.08	0.01	0.00	-0.01
Non-Metallic Min. (Non-ETS)	0.01	**-0.02**	-0.03	0.00	**-0.01**	-0.01

Notes: The 2013-2018 column reports the Phase III low EUA price regime before the MSR became operational. The 2021-2022 column reports the Phase IV high price regime that includes the Fit-for-55 reforms and the European energy crisis. The intermediate Post-MSR and COVID-19 results are reported in Appendix B. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

In the Phase III Low Price period, TTF natural gas prices and sector equity returns are positively correlated, so they have small positive hedge ratios. By the Phase IV High Price period, the gas hedge ratios become negative in four of the manufacturing portfolios with the highest gas intensity (Chemicals (ETS), Chemicals (Non-ETS), Non-Metallic Min. (ETS), Non-Metallic Min. (Non-ETS)). For the other sector portfolios, HR converges to zero. The 2021-2022 energy crisis raised TTF natural gas prices from below €20/MWh in early 2021 to above €300/MWh in August 2022. Additionally, over the same period, the equity returns of industrial firms declined as energy input costs reduced their profit margins. The dynamic hedge for the gas-intensive sectors, therefore, requires a long position in TTF natural gas to offset the equity-side exposure, which is the opposite of the pre-crisis direction. The HE_{HR} values also increase in the sectors where the HR changes sign. Non-Metallic Minerals EU ETS-regulated portfolio has the largest improvement (from 0.02 to 0.10), followed by the Chemicals EU ETS-regulated portfolio (from 0.05 to 0.08).

Rotterdam coal shows a similar but less pronounced change. Before the crisis, hedge ratios in the four coal-related portfolios are low but positive. By Phase IV High Price period, all four coal hedge ratios become slightly negative, while their hedge effectiveness values remain close to zero. Basic Metals (Non-ETS) stands out with a clearly negative hedge effectiveness of -0.04. In this case, hedging with coal increases portfolio variance rather than reducing it. Overall, the results demonstrate that coal has little practical value as a hedge for the manufacturing sectors during this period.

5.4 Risk-Adjusted Portfolio Performance

The realized performance of the hedged portfolio is evaluated with respect to overall returns and downside risk. The hedged sector portfolio, $r_{H,t} = r_{s,t} - HR_t\, r_{a,t}$, is compared with the unhedged sector portfolio, $r_{s,t}$, using the annualized Sharpe ratio [87], Sortino ratio [88], annualized volatility, one-day 95% historical Value at Risk (VaR) [90], one-day 95% Expected Shortfall (ES) [91], and the cumulative maximum drawdown (MDD) over the 1 January 2013 - 30 April 2026 sample period. The Sharpe ratio measures risk-adjusted returns using total volatility, the Sortino ratio focuses only on downside volatility. Volatility captures the overall variability of returns, VaR measures the loss threshold at the 95% confidence level, ES measures the average loss beyond that threshold, and MDD measures the largest cumulative loss from a portfolio peak to a subsequent trough over the sample period. Table 5.8 reports these metrics for all 32 sector-asset pairs and the HR-based and OW-based hedging effectiveness values. HE and the risk-adjusted performance metrics are calculated from the HR-based dynamic hedge portfolio. $\mathrm{HE_{OW}}$ is reported separately as the variance reduction obtained from the minimum-variance portfolio formed by the optimal portfolio weights and it is added as a reference.

Table 5.8: Risk-adjusted performance of hedged and unhedged portfolios across all 32 sector-asset pairs (Monthly EW, full sample 1 Jan 2013 - 30 Apr 2026, annualized where applicable). H denotes hedged; U denotes unhedged.

Sector portfolio	Hedge	HE_{HR}	HE_{OW}	Sharpe H	Sharpe U	Sortino H	Sortino U	Vol H	Vol U	VaR_{95} H	VaR_{95} U	ES_{95} H	ES_{95} U	MaxDD H	MaxDD U
Electricity (ETS)	EUA	0.05	0.09	0.33	0.33	0.033	0.033	0.131	0.134	-0.012	-0.012	-0.019	-0.020	0.37	0.39
	Gas	0.02	0.15	0.33	0.33	0.033	0.033	0.133	0.134	-0.012	-0.012	-0.020	-0.020	0.39	0.39
	Oil	0.08	0.05	0.39	0.33	0.038	0.033	0.129	0.134	-0.012	-0.012	-0.019	-0.020	0.32	0.39
	Gold	0.01	0.51	0.31	0.33	0.032	0.033	0.133	0.134	-0.012	-0.012	-0.020	-0.020	0.37	0.39
Electricity (Non-ETS)	EUA	0.04	0.03	0.64	0.64	0.061	0.060	0.135	0.137	-0.013	-0.013	-0.019	-0.020	0.37	0.35
	Gas	0.01	0.14	0.64	0.64	0.060	0.060	0.137	0.137	-0.013	-0.013	-0.020	-0.020	0.35	0.35
	Oil	0.07	0.05	0.76	0.64	0.071	0.060	0.132	0.137	-0.013	-0.013	-0.018	-0.020	0.38	0.35
	Gold	0.01	0.51	0.64	0.64	0.060	0.060	0.137	0.137	-0.013	-0.013	-0.020	-0.020	0.36	0.35
Basic Metals (ETS)	EUA	0.06	0.21	0.08	0.13	0.018	0.023	0.264	0.272	-0.026	-0.027	-0.038	-0.040	0.73	0.72
	Gas	0.02	0.27	0.16	0.13	0.026	0.023	0.269	0.272	-0.026	-0.027	-0.039	-0.040	0.72	0.72
	Coal	0.00	0.28	0.14	0.13	0.024	0.023	0.272	0.272	-0.027	-0.027	-0.040	-0.040	0.73	0.72
	Gold	0.01	0.77	0.12	0.13	0.023	0.023	0.271	0.272	-0.027	-0.027	-0.040	-0.040	0.70	0.72
Basic Metals (Non-ETS)	EUA	0.06	0.06	0.33	0.34	0.036	0.036	0.162	0.167	-0.015	-0.015	-0.023	-0.024	0.53	0.58
	Gas	0.03	0.15	0.34	0.34	0.036	0.036	0.165	0.167	-0.015	-0.015	-0.024	-0.024	0.56	0.58
	Coal	0.00	0.08	0.31	0.34	0.034	0.036	0.168	0.167	-0.015	-0.015	-0.024	-0.024	0.58	0.58
	Gold	0.01	0.60	0.35	0.34	0.037	0.036	0.167	0.167	-0.015	-0.015	-0.024	-0.024	0.56	0.58
Non-Met. Min. (ETS)	EUA	0.07	0.06	0.44	0.44	0.045	0.044	0.173	0.179	-0.017	-0.017	-0.025	-0.027	0.41	0.41
	Gas	0.04	0.21	0.45	0.44	0.045	0.044	0.175	0.179	-0.017	-0.017	-0.026	-0.027	0.40	0.41
	Coal	0.01	0.16	0.41	0.44	0.042	0.044	0.178	0.179	-0.018	-0.017	-0.026	-0.027	0.41	0.41
	Gold	0.02	0.64	0.48	0.44	0.048	0.044	0.177	0.179	-0.017	-0.017	-0.026	-0.027	0.39	0.41
Non-Met. Min. (Non-ETS)	EUA	0.03	0.12	0.32	0.31	0.037	0.036	0.174	0.177	-0.016	-0.016	-0.024	-0.025	0.53	0.55
	Gas	0.01	0.24	0.33	0.31	0.037	0.036	0.176	0.177	-0.016	-0.016	-0.025	-0.025	0.55	0.55
	Coal	0.00	0.23	0.33	0.31	0.037	0.036	0.177	0.177	-0.016	-0.016	-0.025	-0.025	0.55	0.55
	Gold	0.03	0.61	0.32	0.31	0.036	0.036	0.175	0.177	-0.016	-0.016	-0.025	-0.025	0.52	0.55
Chemicals (ETS)	EUA	0.06	0.07	0.01	0.02	0.008	0.009	0.168	0.173	-0.017	-0.017	-0.025	-0.026	0.56	0.55
	Gas	0.04	0.17	0.05	0.02	0.011	0.009	0.169	0.173	-0.017	-0.017	-0.025	-0.026	0.54	0.55
	Oil	0.09	0.07	0.06	0.02	0.013	0.009	0.165	0.173	-0.017	-0.017	-0.024	-0.026	0.51	0.55
	Gold	0.02	0.63	0.05	0.02	0.012	0.009	0.171	0.173	-0.017	-0.017	-0.026	-0.026	0.52	0.55
Chemicals (Non-ETS)	EUA	0.07	0.03	0.37	0.34	0.038	0.035	0.148	0.154	-0.015	-0.015	-0.022	-0.024	0.51	0.51
	Gas	0.03	0.12	0.36	0.34	0.037	0.035	0.151	0.154	-0.015	-0.015	-0.023	-0.024	0.51	0.51
	Oil	0.08	0.10	0.41	0.34	0.041	0.035	0.148	0.154	-0.015	-0.015	-0.022	-0.024	0.54	0.51
	Gold	0.01	0.56	0.33	0.34	0.034	0.035	0.153	0.154	-0.015	-0.015	-0.023	-0.024	0.52	0.51

Notes: H = hedged portfolio; U = unhedged sector portfolio. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios. Volatility is the annualized standard deviation of daily returns. VaR_{95} is the one-day historical Value at Risk at the 95% confidence level, expressed as a fraction of portfolio value. ES_{95} is the one-day historical Expected Shortfall at the 95% confidence level, i.e. the mean loss conditional on returns falling below VaR_{95}. MaxDD is the cumulative peak-to-trough maximum drawdown over the sample. HE_{HR} and HE_{OW} are the Ederington [22] and Kroner-Ng [21] optimal-weight effectiveness measures, reported for reference. All values are computed from the Monthly EW DCC-GARCH(1,1) hedge series. Sub-period results are reported in Appendix C.

Four main points are indicated by the results. First, the pairs with higher HE_{HR} are generally associated with better risk-adjusted performance. The Electricity non-EU ETS-regulated portfolio-oil pair shows the greatest improvement, increasing the annualized Sharpe ratio from 0.64 to 0.76 with $HE_{HR} = 0.07$. The Chemicals non-EU ETS-regulated portfolio-oil hedge increases the Sharpe ratio from 0.34 to 0.41, the Chemicals EU ETS-regulated portfolio-oil pair from 0.02 to 0.06, and the Chemicals non-EU ETS-regulated portfolio-EUA pair from 0.34 to 0.37. The Sortino ratio moves in the same direction as the Sharpe ratio across the panel, except for the Basic Metals EU ETS-regulated portfolio-EUA pair (Sortino falls from 0.023 to 0.018). This suggests that the improvement in risk-adjusted performance is generally not limited to reductions in total volatility but is also reflected in downside risk measures.

Second, the downside-risk measures also imply similar conclusions. Annualized volatility falls by around 2-5% for the EUA hedges and by 3-5% for the strongest oil hedges. Changes in daily VaR_{95} and ES_{95} are generally small across the sample. The reduction is more visible in maximum drawdown values. For example, the Electricity EU ETS-regulated portfolio-oil hedge lowers the maximum drawdown from 0.39 to 0.32, the Chemicals EU ETS-regulated portfolio-oil hedge from 0.55 to 0.51, and the Basic Metals non-EU ETS-regulated portfolio-EUA hedge from 0.58 to 0.53.

Third, some hedge pairs yield conflicting results. Hedging the Basic Metals EU ETS-regulated portfolio with EUA reduces volatility from 0.272 to 0.264, but at the same time it lowers the Sharpe ratio from 0.13 to 0.08. This is due to the EUA position decreasing realized portfolio return by more than the amount that the variance reduction increases it. Hedging the Electricity non-EU ETS-regulated portfolio with oil increases the Sharpe ratio from 0.64 to 0.76 but also increases the maximum drawdown from 0.35 to 0.38. These cases show that improvements in one performance measure do not necessarily lead to improvements in all performance measures.

Fourth, for portfolios hedged with EUA and Brent crude oil, the difference between $\mathrm{HE}_{\mathrm{HR}}$ and $\mathrm{HE}_{\mathrm{OW}}$ is generally low. The main exception is the Basic Metals EU ETS-regulated portfolio-EUA pair, where the $\mathrm{HE}_{\mathrm{OW}}$ value of 0.21 is significantly higher than $\mathrm{HE}_{\mathrm{HR}}$ of 0.06. This is also the pair with the lowest OW (0.73), indicating that a larger portion is allocated to EUA than in the other portfolios.

On the other hand, the values of $\mathrm{HE}_{\mathrm{HR}}$ and $\mathrm{HE}_{\mathrm{OW}}$ yield different results for gold and several gas and coal pairs. For gold, $\mathrm{HE}_{\mathrm{OW}}$ values range from 0.45 to 0.74 while $\mathrm{HE}_{\mathrm{HR}}$ values are below 0.03. There is a similar pattern for several gas and coal pairs, where $\mathrm{HE}_{\mathrm{OW}}$ ranges from 0.08 to 0.29 and $\mathrm{HE}_{\mathrm{HR}}$ values are near-zero. These results suggest that gold, gas, and coal contribute more to variance reduction within the minimum-variance portfolio than through the HR-based hedging strategy.

5.4.1 Distribution-Based and Drawdown-Based Risk Metrics

The metrics in Table 5.8 provide a comprehensive view of the hedged portfolios. Nevertheless, they focus primarily on volatility, downside risk, and tail risk. To assess portfolio performance from additional perspectives, the Omega ratio of Keating and Shadwick [89] and the Pain Index of Bacon [92] are also examined.

The Omega ratio considers both positive and negative returns. As a zero-return threshold is used, values above one indicate that gains exceed losses. Comparing the Omega ratios of the hedged and unhedged portfolios provides an additional perspective on portfolio performance beyond volatility reduction.

The Pain Index measures the average drawdown throughout the sample period. Unlike maximum drawdown, it also captures long periods of smaller losses. The Pain Ratio relates portfolio returns to the Pain Index and can be interpreted as a drawdown-based version of the Sharpe ratio.

Table 5.9: Omega ratio, Pain Index, and Pain Ratio across all 32 sector-asset pairs. H denotes hedged and U denotes unhedged portfolios.

		Omega		**Pain Index**		**Pain Ratio**	
Sector portfolio	**Hedge**	**H**	**U**	**H**	**U**	**H**	**U**
Electricity (ETS)	EUA	1.080	1.081	0.071	0.072	0.657	0.676
	Gas	1.073	1.073	0.076	0.080	0.549	0.532
	Oil	1.086	1.077	0.069	0.076	0.734	0.589
	Gold	1.065	1.067	0.082	0.081	0.447	0.475
Electricity (Non-ETS)	EUA	1.138	1.139	0.117	0.101	0.803	0.939
	Gas	1.132	1.132	0.113	0.114	0.789	0.784
	Oil	1.157	1.138	0.121	0.106	0.873	0.878
	Gold	1.111	1.111	0.116	0.115	0.633	0.640
Basic Metals (ETS)	EUA	1.040	1.051	0.313	0.244	0.083	0.169
	Gas	1.052	1.048	0.239	0.253	0.180	0.146
	Coal	1.049	1.047	0.266	0.255	0.146	0.138
	Gold	1.034	1.036	0.276	0.270	0.056	0.066
Basic Metals (Non-ETS)	EUA	1.077	1.081	0.135	0.132	0.425	0.466
	Gas	1.077	1.077	0.129	0.136	0.438	0.423
	Coal	1.073	1.077	0.140	0.137	0.379	0.421
	Gold	1.071	1.069	0.141	0.140	0.364	0.357
Non-Met. Min. (ETS)	EUA	1.098	1.100	0.087	0.082	0.937	1.029
	Gas	1.099	1.098	0.088	0.085	0.928	0.958
	Coal	1.094	1.098	0.088	0.082	0.879	0.994
	Gold	1.105	1.096	0.077	0.079	1.140	1.004
Non-Met. Min. (Non-ETS)	EUA	1.077	1.078	0.206	0.207	0.291	0.291
	Gas	1.069	1.067	0.216	0.223	0.238	0.223
	Coal	1.076	1.071	0.199	0.211	0.293	0.255
	Gold	1.065	1.064	0.201	0.206	0.239	0.225
Chemicals (ETS)	EUA	1.020	1.024	0.215	0.174	0.022	0.046
	Gas	1.025	1.022	0.182	0.195	0.056	0.036
	Oil	1.032	1.025	0.187	0.186	0.089	0.050
	Gold	1.018	1.014	0.193	0.214	0.015	-0.007
Chemicals (Non-ETS)	EUA	1.091	1.088	0.150	0.150	0.426	0.411
	Gas	1.085	1.084	0.170	0.168	0.345	0.346
	Oil	1.101	1.091	0.169	0.154	0.419	0.412
	Gold	1.081	1.082	0.151	0.151	0.365	0.372

Notes: Computed on daily hedged returns from the full-sample DCC-GARCH(1,1)-t fit, full sample 1 Jan 2013 - 30 Apr 2026 ($\sim$ 3,400 trading days per pair). Same row order as Table 5.8. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

According to the results, while the main conclusions are mostly unchanged, several differences are observed across sectors and regulatory groups. In some cases, portfolios with relatively strong volatility reduction do not exhibit similarly strong Omega and Pain metrics.

Electricity: For the Electricity EU ETS-regulated portfolio, the additional metrics lead to the same conclusion as the previous performance measures. Brent crude oil remains the strongest hedge, with a higher Omega ratio (1.086 against 1.077), a lower Pain Index (0.069 against 0.076), and a higher Pain Ratio (0.734 against 0.589). On the contrary, the changes for EUA, gas, and gold relative to the unhedged portfolios are very low.

The Electricity non-EU ETS-regulated portfolio presents a slightly different picture. Brent crude oil again has the highest Omega ratio (1.157 against 1.138), but at the same time, it has a higher Pain Index (0.121 against 0.106). A similar pattern can also be observed for the EUA hedge. While the Omega ratio remains close to the unhedged portfolio, the Pain Index increases from 0.101 to 0.117, and the Pain Ratio declines from 0.939 to 0.803. Therefore, although the portfolio benefits from a more favorable gain–loss profile, it does not improve its drawdown profile.

Overall, the results for the Electricity sector point to Brent crude oil as the strongest hedge across the performance measures considered. For the non-EU ETS-regulated portfolio, the Omega and Pain metrics do not move in the same direction.

Basic Metals: For the Basic Metals EU ETS-regulated portfolio, the additional metrics lead to a different conclusion than HE_{HR}. The EUA hedge, which is the strongest hedge according to HE_{HR}, produces a lower Omega ratio (1.040 against 1.051), a higher Pain Index (0.313 against 0.244), and a lower Pain Ratio (0.083 against 0.169). The reduction in variance is therefore accompanied by a clear deterioration in the drawdown profile. The gas hedge moves in the opposite direction across all three measures, with a slightly higher Omega ratio (1.052 against 1.048), a lower Pain Index (0.239 against 0.253), and a higher Pain Ratio (0.180 against 0.146). All three measures therefore improve relative to the unhedged portfolio. Coal and gold remain close to the unhedged portfolio.

The Basic Metals non-EU ETS-regulated portfolio presents the same pattern in a less pronounced way. The EUA hedge slightly lowers the Omega ratio (1.077 against 1.081) and the Pain Ratio (0.425 against 0.466), while the gas hedge again delivers the best Pain Index value (0.129 against 0.136). The differences are smaller than those observed for the EU ETS-regulated portfolio, but the direction is the same.

Overall, the results for the Basic Metals sector point to the gas hedge as the strongest one when distribution and drawdown measures are considered alongside variance reduction. The EUA hedge improves HE_{HR} but worsens the drawdown profile of the EU ETS-regulated portfolio.

Non-Metallic Minerals: For the Non-Metallic Minerals EU ETS-regulated portfolio, the differences between the hedged and unhedged values are smaller than for the other sectors. The most notable observation is the gold hedge, which produces the highest Omega ratio (1.105 against 1.096), the lowest Pain Index (0.077 against 0.079), and the highest Pain Ratio (1.140 against 1.004). This is the only portfolio in the sample where the gold placebo behaves like an effective hedge. One possible explanation is the input-cost sensitivity of the cement, lime, and glass sub-sectors that anchor this sector and gold's role as a long-term inflation hedge [77]. The EUA, gas, and coal hedges remain close to the unhedged portfolio across all three measures.

The Non-Metallic Minerals non-EU ETS-regulated portfolio does not display the same gold pattern. The four hedges produce very small changes in the Omega ratio and the Pain Index. This is consistent with the low HE_{HR} values reported for this portfolio in the previous sections.

Overall, the Non-Metallic Minerals sector shows the smallest changes in the additional risk-adjusted measures relative to the other sectors. Gold is the only hedge that produces a meaningful improvement, and only for the EU ETS-regulated portfolio.

Chemicals: For the Chemicals EU ETS-regulated portfolio, the additional metrics do not point to a single strongest hedge. Brent crude oil produces the highest Omega ratio (1.032 against 1.025), while gas has the lowest Pain Index (0.182 against 0.195) and the highest Pain Ratio (0.056 against 0.036). The EUA hedge follows a similar pattern to the Basic Metals EU ETS-regulated portfolio. The Pain Index increases from 0.174 to 0.215, and the Pain Ratio declines from 0.046 to 0.022. Although the EUA hedge improves HE_{HR}, the drawdown profile becomes less favorable.

The Chemicals non-EU ETS-regulated portfolio is closer to the conclusion suggested by HE_{HR}. Brent crude oil has the highest Omega ratio (1.101 against 1.091), and the EUA hedge slightly improves the Omega ratio (1.091 against 1.088) and the Pain Ratio (0.426 against 0.411). For gas and gold, the three measures are close to the unhedged portfolio.

Overall, the results for the Chemicals sector do not point to a single strongest hedge. Brent crude oil performs best in terms of Omega, whereas gas produces the most favorable Pain metrics for the EU ETS-regulated portfolio. The EUA hedge follows the same pattern observed for Basic Metals EU ETS-regulated portfolio, improving HE_{HR} while worsening the drawdown profile.

EU ETS-regulated versus non-EU ETS-regulated Sector Portfolios: For the heavy-industry sectors, Basic Metals and Chemicals, the EUA hedge produces higher HE_{HR} values for the EU ETS-regulated portfolios, but is also associated with a higher Pain Index and a lower Pain Ratio. The same pattern is much less visible for the corresponding non-EU ETS-regulated portfolios. One possible explanation is the partial cost pass-through documented for EU ETS-regulated firms by Joltreau and Sommerfeld [5]. Since part of the carbon cost can be passed on to downstream consumers, equity returns may not fully reflect changes in EUA prices. This may partly explain why the improvement in HE_{HR} is not matched by similar improvements in the Pain metrics for the EU ETS-regulated portfolios.

These results suggest that variance and drawdown reduction do not necessarily coincide for the EU ETS-regulated portfolios in the heavy-industry sectors. For the Basic Metals EU ETS-regulated portfolio, the gas hedge improves both dimensions simultaneously. For the Chemicals EU ETS-regulated portfolio, Brent crude oil has the highest Omega ratio, whereas gas has the most favorable Pain metrics. For the Electricity EU ETS-regulated portfolio, Brent crude oil stands out across HE_{HR}, Sharpe, Omega, and Pain measures. Across all four sectors, gold contributes little to risk reduction outside the Non-Metallic Minerals EU ETS-regulated portfolio discussed above.

5.5 Robustness Checks

The robustness analysis is conducted along two dimensions. First, the DCC-GARCH model is re-estimated using an AR(1) mean equation to account for the possible autocorrelation in returns and the GJR-GARCH(1,1) specification [64] is implemented to capture asymmetries in volatility.

Since the Ljung-Box test on $\hat{z}_t$ rejects the null hypothesis of no residual autocorrelation at the 5% significance level for six out of thirteen series (Section 5.1.2), the model is re-estimated using an AR(1) mean equation instead of the AR(0) mean specification used in the main analysis. This robustness check tests whether the estimated hedge ratios and hedging effectiveness measures change depending on the mean specification. Moreover, as the null hypothesis of symmetric volatility responses is rejected at the 5% significance level for the sector portfolios and for gold in the sign-bias test reporting the p-value of the Engle-Ng model [86], the models were also re-estimated using a GJR-GARCH specification. It allows negative shocks to have a different impact on volatility than positive shocks, and therefore, it provides a useful check for the baseline model.

Second, the results are tested under alternative portfolio construction methods. The sector portfolios are reconstructed using a stable equal-weighted approach with a 90% full-sample coverage threshold (Stable EW) and a yearly rebalanced market-capitalization-weighted method with a 80% data coverage threshold for each year (YMCW). The rationale for the coverage thresholds is explained in Section 3.4.2. These robustness checks are performed using the same DCC-GARCH(1,1) framework over the full sample period.

5.5.1 Alternative Univariate Specifications

Table 5.10 shows the full-sample HR, HE_{HR}, OW, and HE_{OW} values for the 32 sector-asset pairs using the DCC-GARCH(1,1) model, the AR(1)-mean DCC-GARCH(1,1), and the DCC-GJR-GARCH(1,1). The AR(1) specification produces values identical to the main model at 2-decimal points for all 32 pairs. The GJR-GARCH model also yields the same results for most of the sector-asset pairs. Only for some of the pairs, it produces a maximum absolute difference of 0.01 in HR and HE_{HR}, 0.02 in HE_{OW}, and 0.01 in OW. These small deviations are concentrated in the pairs where the asymmetric volatility adjustment of the GJR-GARCH specification slightly shifts the conditional variance estimate. The robustness checks show that the main conclusions remain unchanged under the AR(1) and GJR-GARCH specifications. Therefore, residual autocorrelation and sign-bias effects explained in Section 5.1.2 do not have significant effects on the HR, HE_{HR}, and OW values, supporting the use of the symmetric DCC-GARCH(1,1) model with constant mean as the main framework.

Table 5.10: Cross-specification robustness of full-sample HR, HE_{HR}, OW, and HE_{OW} values across the baseline DCC-GARCH(1,1) specification (Main), the AR(1)-mean DCC-GARCH(1,1) specification (AR1), and the DCC-GJR-GARCH(1,1) specification (GJR). All values are based on the Monthly EW sector indices over the 1 January 2013 - 30 April 2026 sample period.

	HR			$\mathbf{HE_{HR}}$			**OW**			$\mathbf{HE_{OW}}$		
Pair	**Main**	**AR(1)**	**GJR**	**Main**	**AR(1)**	**GJR**	**Main**	**AR(1)**	**GJR**	**Main**	**AR(1)**	**GJR**
20 ETS / EUA	0.06	0.06	0.06	0.06	0.06	0.06	0.89	0.89	0.89	0.07	0.07	0.06
20 ETS / Gas	0.01	0.01	0.01	0.04	0.04	0.04	0.84	0.84	0.85	0.17	0.17	0.17
20 ETS / Gold	-0.04	-0.04	-0.04	0.03	0.03	0.03	0.48	0.48	0.49	0.58	0.58	0.59
20 ETS / Oil	0.10	0.10	0.09	0.10	0.10	0.10	0.85	0.85	0.85	0.08	0.08	0.06
20 Non-ETS / EUA	0.05	0.05	0.05	0.07	0.07	0.07	0.91	0.91	0.91	0.03	0.03	0.03
20 Non-ETS / Gas	0.01	0.01	0.01	0.03	0.03	0.04	0.87	0.87	0.87	0.11	0.11	0.11
20 Non-ETS / Gold	0.01	0.01	0.02	0.02	0.02	0.01	0.55	0.55	0.55	0.51	0.51	0.51
20 Non-ETS / Oil	0.06	0.06	0.06	0.08	0.08	0.08	0.87	0.87	0.87	0.10	0.10	0.09
23 ETS / Coal	0.01	0.01	0.01	0.01	0.01	0.01	0.77	0.77	0.77	0.17	0.17	0.18
23 ETS / EUA	0.06	0.06	0.06	0.07	0.07	0.07	0.88	0.88	0.88	0.07	0.07	0.06
23 ETS / Gas	0.00	0.00	0.00	0.04	0.04	0.04	0.82	0.82	0.82	0.21	0.21	0.22
23 ETS / Gold	-0.05	-0.05	-0.05	0.02	0.02	0.02	0.46	0.46	0.46	0.59	0.59	0.59
23 Non-ETS / Coal	0.00	0.00	0.00	0.00	0.00	0.00	0.77	0.77	0.77	0.24	0.24	0.23
23 Non-ETS / EUA	0.04	0.04	0.04	0.03	0.03	0.03	0.87	0.87	0.87	0.12	0.12	0.12
23 Non-ETS / Gas	0.00	0.00	0.00	0.01	0.01	0.01	0.82	0.82	0.82	0.24	0.24	0.24
23 Non-ETS / Gold	-0.02	-0.02	-0.02	0.02	0.02	0.02	0.47	0.47	0.47	0.57	0.57	0.57
24 ETS / Coal	0.02	0.02	0.02	0.00	0.00	0.00	0.59	0.59	0.59	0.29	0.29	0.30
24 ETS / EUA	0.11	0.11	0.11	0.06	0.06	0.06	0.73	0.73	0.73	0.21	0.21	0.21
24 ETS / Gas	0.04	0.04	0.04	0.02	0.02	0.02	0.71	0.71	0.71	0.27	0.27	0.28
24 ETS / Gold	0.06	0.06	0.07	0.01	0.01	0.01	0.26	0.26	0.26	0.74	0.74	0.74
24 Non-ETS / Coal	0.02	0.02	0.02	-0.01	-0.01	0.00	0.79	0.79	0.79	0.08	0.08	0.09
24 Non-ETS / EUA	0.06	0.06	0.06	0.06	0.06	0.07	0.90	0.90	0.90	0.06	0.06	0.05
24 Non-ETS / Gas	0.02	0.02	0.02	0.03	0.03	0.03	0.85	0.85	0.85	0.15	0.15	0.15
24 Non-ETS / Gold	0.01	0.01	0.01	0.01	0.01	0.01	0.49	0.49	0.49	0.55	0.55	0.55
35 ETS / EUA	0.05	0.05	0.05	0.05	0.05	0.05	0.95	0.95	0.95	0.09	0.09	0.08
35 ETS / Gas	0.02	0.02	0.02	0.02	0.02	0.02	0.91	0.91	0.91	0.14	0.14	0.14
35 ETS / Gold	0.02	0.02	0.02	0.02	0.02	0.02	0.62	0.62	0.62	0.46	0.46	0.47
35 ETS / Oil	0.07	0.07	0.07	0.08	0.08	0.08	0.92	0.92	0.91	0.05	0.05	0.04
35 Non-ETS / EUA	0.04	0.04	0.04	0.04	0.04	0.04	0.93	0.93	0.93	0.03	0.03	0.03
35 Non-ETS / Gas	0.01	0.01	0.01	0.01	0.01	0.01	0.88	0.88	0.88	0.14	0.14	0.15
35 Non-ETS / Gold	0.03	0.03	0.03	0.01	0.01	0.00	0.59	0.59	0.59	0.45	0.45	0.46
35 Non-ETS / Oil	0.06	0.06	0.06	0.07	0.07	0.07	0.89	0.89	0.89	0.05	0.05	0.05

Notes: The Main column corresponds to the baseline DCC-GARCH(1,1) specification with the symmetric sGARCH(1,1) variance equation and a constant mean. AR(1) adds a first-order autoregressive term to the mean equation. GJR replaces the symmetric sGARCH(1,1) with the asymmetric GJR-GARCH(1,1) of Glosten et al. [64]. NACE divisions: 20 = Chemicals; 23 = Other non-metallic mineral products; 24 = Basic metals; 35 = Electricity, gas, steam and air conditioning supply. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

5.5.2 Alternative Index Construction Methods

To measure the effects of the index construction methods on the hedging metrics, Table 5.11 compares the full-sample HR, HE_{HR}, OW, and HE_{OW} values between the baseline monthly rebalanced equal-weighted index and stable equal-weighted, yearly rebalanced market-capitalization-weighted methods.

According to the results, first, the HR and HE_{HR} values are similar across the three methods. The maximum absolute difference in HR is 0.14 (Basic Metals non-EU ETS-regulated portfolio-gold), but the typical difference stays between 0.01 and 0.03. The maximum absolute difference in HE_{HR} is 0.03 across the 32 pairs. Second, the asset-level rankings are preserved: Brent crude oil is the most effective hedging asset for Electricity and Chemicals across all three methods; EUA is the most effective asset in terms of HE_{HR} for the Basic Metals and Non-Metallic Minerals sectors; Rotterdam coal and gold have near-zero HE_{HR} values regardless of the index construction method. The mean HE_{HR} by asset is also similar across methods. Third, the OW values move in a clear direction across the three methods. The mean OW decreases when moving from Monthly EW to Stable EW and decreases further under YMCW. For example, the mean OW for the EUA pairs decreases from 0.88 under Monthly EW to 0.85 under Stable EW and to 0.80 under YMCW. A similar pattern is observed for the other assets. The largest individual OW differences are observed for the Basic Metals non-EU ETS-regulated portfolio: the OW for gold drops from 0.49 under Monthly EW to 0.19 under YMCW, and the OW for coal drops from 0.79 to 0.54. Fourth, the HE_{OW} values move in the opposite direction of OW. The largest spreads are observed for the YMCW method, where the mean HE_{OW} reaches 0.69 for gold pairs and 0.25 for coal pairs, while it is 0.56 and 0.20 under Monthly EW, respectively. The largest difference is in the Basic Metals non-EU ETS-regulated portfolio-coal pair, where HE_{OW} increases from 0.08 under Monthly EW to 0.33 under YMCW.

The differences in OW and HE_{OW} are consistent with the volatility-substitution mechanism discussed in Section 5.2. The YMCW portfolios are generally less volatile than the equal-weighted portfolios, which affects the minimum-variance allocation and often leads to lower OW values and higher HE_{OW} values. The effect is particularly visible for gold and coal, where HE_{OW} is more sensitive to changes in portfolio volatility. As a result, part of the variation in OW and HE_{OW} is likely driven by the index construction method rather than by changes in the underlying hedging relationship.

The comparison between the methods indicates that the sectoral and asset-level patterns of HR and HE_{HR} are similar across different index construction approaches. The OW and HE_{OW} values should be interpreted within the chosen index construction method, as they mainly reflect the volatility substitution mechanism in different index construction methods rather than the carbon-equity hedging signal.

Table 5.11: Cross-method robustness of full-sample HR, HE_{HR}, OW, and HE_{OW} values across the three index construction methods: Monthly EW (Main), Stable EW (Stable), and yearly rebalanced market-capitalization-weighted (YMCW). All values are based on the baseline DCC-GARCH(1,1) model over the 1 January 2013 - 30 April 2026 sample period.

	HR			**HE_{HR}**			**OW**			**HE_{OW}**		
Pair	**Main**	**Stable**	**YMCW**	**Main**	**Stable**	**YMCW**	**Main**	**Stable**	**YMCW**	**Main**	**Stable**	**YMCW**
20 ETS / EUA	0.06	0.06	0.06	0.06	0.04	0.04	0.89	0.85	0.86	0.07	0.10	0.11
20 ETS / Gas	0.01	0.01	0.01	0.04	0.03	0.02	0.84	0.81	0.82	0.17	0.21	0.17
20 ETS / Gold	-0.04	-0.03	-0.04	0.03	0.02	0.02	0.48	0.42	0.40	0.58	0.62	0.63
20 ETS / Oil	0.10	0.10	0.09	0.10	0.08	0.07	0.85	0.80	0.80	0.08	0.11	0.10
20 Non-ETS / EUA	0.05	0.06	0.05	0.07	0.04	0.06	0.91	0.86	0.87	0.03	0.10	0.08
20 Non-ETS / Gas	0.01	0.00	0.01	0.03	0.02	0.02	0.87	0.86	0.83	0.11	0.19	0.17
20 Non-ETS / Gold	0.01	0.05	0.00	0.02	0.01	0.02	0.55	0.45	0.42	0.51	0.59	0.63
20 Non-ETS / Oil	0.06	0.05	0.09	0.08	0.06	0.08	0.87	0.80	0.82	0.10	0.10	0.08
23 ETS / Coal	0.01	0.01	0.01	0.01	0.01	0.00	0.77	0.72	0.63	0.17	0.24	0.24
23 ETS / EUA	0.06	0.07	0.07	0.07	0.07	0.04	0.88	0.84	0.75	0.07	0.10	0.20
23 ETS / Gas	0.00	0.00	0.00	0.04	0.04	0.03	0.82	0.79	0.73	0.21	0.24	0.26
23 ETS / Gold	-0.05	-0.06	-0.08	0.02	0.02	0.02	0.46	0.41	0.28	0.59	0.64	0.78
23 Non-ETS / Coal	0.00	0.01	0.00	0.00	0.00	0.00	0.77	0.74	0.76	0.24	0.23	0.16
23 Non-ETS / EUA	0.04	0.03	0.05	0.03	0.02	0.05	0.87	0.84	0.87	0.12	0.12	0.06
23 Non-ETS / Gas	0.00	-0.01	0.00	0.01	0.01	0.02	0.82	0.81	0.83	0.24	0.21	0.18
23 Non-ETS / Gold	-0.02	0.02	-0.02	0.02	0.03	0.02	0.47	0.41	0.42	0.57	0.60	0.61
24 ETS / Coal	0.02	0.01	0.03	0.00	0.00	0.00	0.59	0.60	0.54	0.29	0.38	0.28
24 ETS / EUA	0.11	0.11	0.12	0.06	0.05	0.06	0.73	0.73	0.67	0.21	0.22	0.27
24 ETS / Gas	0.04	0.02	0.06	0.02	0.02	0.01	0.71	0.70	0.68	0.27	0.30	0.26
24 ETS / Gold	0.06	0.06	0.09	0.01	0.01	0.01	0.26	0.26	0.20	0.74	0.74	0.81
24 Non-ETS / Coal	0.02	0.01	0.02	-0.01	0.00	0.01	0.79	0.78	0.54	0.08	0.21	0.33
24 Non-ETS / EUA	0.06	0.06	0.10	0.06	0.05	0.03	0.90	0.87	0.68	0.06	0.09	0.28
24 Non-ETS / Gas	0.02	0.00	0.03	0.03	0.03	0.01	0.85	0.84	0.67	0.15	0.21	0.30
24 Non-ETS / Gold	0.01	-0.02	0.12	0.01	0.01	0.02	0.49	0.44	0.19	0.55	0.60	0.79
35 ETS / EUA	0.05	0.04	0.07	0.05	0.05	0.06	0.95	0.93	0.89	0.09	0.05	0.06
35 ETS / Gas	0.02	0.01	0.03	0.02	0.02	0.02	0.91	0.88	0.84	0.14	0.16	0.19
35 ETS / Gold	0.02	0.01	0.02	0.02	0.01	0.02	0.62	0.55	0.45	0.46	0.49	0.60
35 ETS / Oil	0.07	0.08	0.08	0.08	0.08	0.06	0.92	0.90	0.83	0.05	0.01	0.08
35 Non-ETS / EUA	0.04	0.04	0.06	0.04	0.03	0.03	0.93	0.89	0.84	0.03	0.09	0.16
35 Non-ETS / Gas	0.01	0.01	0.02	0.01	0.01	0.01	0.88	0.89	0.82	0.14	0.15	0.15
35 Non-ETS / Gold	0.03	0.06	0.09	0.01	0.01	0.01	0.59	0.48	0.38	0.45	0.54	0.67
35 Non-ETS / Oil	0.06	0.06	0.09	0.07	0.05	0.05	0.89	0.86	0.79	0.05	0.07	0.15
Mean across EUA pairs (8)	**0.059**	**0.059**	**0.072**	**0.055**	**0.044**	**0.046**	**0.882**	**0.851**	**0.804**	**0.085**	**0.109**	**0.152**
Mean across Oil pairs (4)	**0.073**	**0.073**	**0.087**	**0.083**	**0.068**	**0.065**	**0.883**	**0.840**	**0.810**	**0.070**	**0.073**	**0.103**
Mean across Gas pairs (8)	**0.014**	**0.005**	**0.020**	**0.025**	**0.022**	**0.018**	**0.837**	**0.823**	**0.777**	**0.179**	**0.209**	**0.210**
Mean across Coal pairs (4)	**0.013**	**0.010**	**0.015**	**0.000**	**0.003**	**0.003**	**0.730**	**0.710**	**0.618**	**0.195**	**0.265**	**0.253**
Mean across Gold pairs (8)	**0.002**	**0.011**	**0.022**	**0.018**	**0.015**	**0.018**	**0.490**	**0.427**	**0.343**	**0.556**	**0.603**	**0.690**

Notes: Monthly EW (Main) is the baseline monthly rebalanced equal-weighted index method with an 80% coverage threshold. Stable refers to the stable equal-weighted method with a 90% full-sample coverage threshold. YMCW is the yearly rebalanced market-cap-weighted method with an 80% coverage threshold. ETS denotes EU ETS-regulated portfolios and Non-ETS denotes non-EU ETS-regulated portfolios.

5.6 Hypothesis Assessment and Discussion

Chapter 2 proposed three hypotheses related to carbon-price risk transmission and the effectiveness of carbon-instrument hedging. The results presented in Sections 5.2-5.4 allow these hypotheses to be evaluated.

H1: EUA futures are expected to show higher hedging effectiveness and stronger dynamic hedging relationships with EU ETS-regulated portfolios than non-EU ETS-regulated portfolios within the same sector.

Result: Partially confirmed. The HE_{HR} results provide mixed evidence. For the Electricity and Non-Metallic Minerals sectors, EU ETS-regulated portfolios have higher hedging effectiveness. In Basic Metals, the HE_{HR} is equal, while in Chemicals, it is slightly higher for the non-EU ETS-regulated portfolio. The highest difference is in the Non-Metallic Minerals sector, where HE_{HR} is 0.07 for the EU ETS-regulated portfolio and 0.03 for the non-EU ETS-regulated portfolio.

The HR results are more consistent. The average EUA HR is higher for the EU ETS-regulated portfolios than for the non-EU ETS-regulated portfolios in all four sectors. The highest difference is observed in the Basic Metals sector, where the average HR for the EU ETS-regulated portfolio is 0.11 compared to 0.06 for the non-EU ETS-regulated portfolio. Smaller differences are also observed in the Electricity, Non-Metallic Minerals, and Chemicals sectors. The results show that EU ETS-regulated firms have a stronger link with EUA price movements, which aligns with their exposure to carbon pricing. The small HE_{HR} differences with non-EU ETS-regulated firms also suggest that carbon-price developments are not entirely confined to firms directly regulated under the EU ETS and may affect non-EU ETS-regulated firms through indirect channels [5].

The time-varying findings reinforce the same conclusion. The higher HRs for the EU ETS-regulated portfolios are not limited to any specific sub-period and can be seen during several sub-periods in the sample period. Moreover, the portfolio performance metrics show similar findings for the two regulatory regimes. In most cases, the EUA hedge reduces volatility and improves tail-risk measures such as VaR and ES but the effects on the drawdown metrics are less consistent. Thus, the EUA hedge usually improves volatility and tail-risk measures, but these improvements are not always greater for EU ETS-regulated portfolios. The evidence for H1 is therefore strongest in the HR results, while the realized portfolio performance metrics do not show consistent distinctions between the two regulatory groups when hedged with EUA.

H2: The hedging effectiveness of EUA futures and sector-relevant energy commodities is expected to vary across sectors, as firms differ in their emissions intensity, production structure, cost pass-through capacity, and energy dependence.

Result: Confirmed. According to the results, HE_{HR} of EUA and sector-specific energy commodities differ across sectors. In terms of HE_{HR}, the dominant hedging asset for the Electricity and Chemicals sectors is Brent crude oil futures, and EUA futures offer the highest HE_{HR} in the Basic Metals and Non-Metallic Minerals sectors. These findings are consistent with the different sources of risk faced by each sector. Oil price fluctuations appear to be more strongly correlated with the returns of the Electricity and Chemicals sectors. At the same time, the Basic Metals and Non-Metallic Minerals sectors are directly exposed to carbon prices and have low cost-pass-through capacity. Therefore, the influence of EUA prices on returns is greater, and EUA futures represent the most effective hedging asset for these sectors.

For the Electricity sector, although it has the largest emission share, EUA does not generate the highest HE_{HR} values. This can be attributed to the relative ability of the electricity producers to pass through the costs of carbon to the prices of electricity [55, 56]. As a result, changes in EUA prices may be less directly reflected in equity returns, reducing the covariance between sector returns and EUA futures.

Evaluating HR together with HE_{HR} gives additional insights into the trade-off between hedging cost and effectiveness. For example, Brent crude oil is the strongest hedging asset for the Electricity sector because the increase in HE_{HR} relative to EUA is larger than the increase in the required hedge ratio. In the Basic Metals sector, EUA futures provide the highest HE_{HR} but also require the largest hedge ratios in the sample. Similarly, in the Chemicals sector, Brent crude oil has the highest HE_{HR}, but TTF natural gas is able to achieve meaningful variance reduction with a smaller hedge position. These results suggest that sectoral differences are reflected not only in the level of hedging effectiveness but also in the amount of hedging position required to obtain it.

For the pairs with Rotterdam coal, despite coal's historical importance for steel and cement production [69, 70], the HE_{HR} values are close to zero. This finding is consistent with the declining role of coal in European energy-intensive industries discussed in Section 2.1.4. TTF natural gas shows stronger results, but mainly during specific market conditions. According to the sub-period analysis, its most significant hedging benefits are observed during the Phase IV High Price period, particularly in the Chemicals and

Non-Metallic Minerals sectors, where natural gas is both an important energy source and a production input.

The placebo asset gold also mostly exhibits near-zero HE_{HR} values across all sectors. Unlike EUA, oil, or gas, gold has no direct economic connection with the sectors. However, several sector pairs generate relatively high HE_{OW} values when hedged with gold. This result is largely driven by the low volatility of gold and the mechanics of the minimum-variance portfolio rather than a strong hedging relationship with sector returns.

H3: Hedging effectiveness and dynamic hedge ratios are expected to change across different EU ETS regulatory regimes, including the introduction of new regulatory channels such as CBAM, and across macroeconomic crisis periods.

Result: Strongly confirmed. The sub-period analysis in Section 5.3 provides clear evidence for H3. During the COVID-19 period, the EUA hedge ratios for the manufacturing portfolios reach values that are approximately two to four times their Phase III averages, and the HE_{HR} values rise by a factor of approximately fivefold or more on average. The Basic Metals EU ETS-regulated portfolio reaches an HR of 0.22 (against 0.09 in Phase III), and the Non-Metallic Minerals EU ETS-regulated portfolio reaches the highest HE_{HR} in the sample of 0.25. All eight portfolios deliver HE_{HR} values at or above 0.13 in this period. The time-varying analysis in Section 5.3.2 provides additional context for these findings. The higher HE_{HR} values observed during the COVID-19 period in the sub-period analysis can also be seen in the estimates of EUA futures, Brent crude oil, and, to a lesser extent, TTF natural gas. This shows that the sub-period results are driven by distinct periods of stronger hedging relationships.

During the CBAM Transitional period, the HE_{HR} values rise from near zero in the Phase IV Normalization window to between 0.01 and 0.05 in the CBAM Transitional window for the sectors directly within CBAM scope (Basic Metals, Non-Metallic Minerals, and Chemicals). The HR values remain close to their values during the Phase IV Normalization period. This implies that the increase in hedging effectiveness is driven by a stronger link between the sector portfolios and the hedging assets rather than by a larger required hedge position. The Electricity sector portfolios, which are exposed to CBAM only through imported electricity, show much smaller changes. The time-varying analysis supports this interpretation. For the manufacturing portfolios, the increase in EUA HE_{HR} after the start of the CBAM Transitional period develops gradually over time rather than appearing as an immediate shift in October 2023. A similar pattern is visible for TTF natural gas in the Chemicals and Non-Metallic

Minerals sectors towards the end of the sample, suggesting that the stronger hedging relationships observed during the CBAM Transitional period emerged progressively over time.

The Phase IV results for gas and coal further support H3. In four manufacturing sector portfolios, the TTF natural gas hedge ratio changes from positive in Phase III to negative in Phase IV. At the same time, for the sector-asset pairs that change sign, HE_{HR} values increase significantly. For example, HE_{HR} increases from 0.02 to 0.10 in the Non-Metallic Minerals EU ETS-regulated portfolio and from 0.05 to 0.08 in the Chemicals EU ETS-regulated sector portfolios. Several coal pairs show a similar sign reversal, but their HE_{HR} values are mostly close to zero throughout the period. Unlike gas, the sign change does not lead to a meaningful hedging benefit. The gas-coal substitution mechanism in EU electricity generation discussed by Ampudia et al. [9] provides one possible explanation for the gas results. When natural gas prices increase substantially, electricity generation can shift back towards coal, changing the relationship between gas prices and the returns of gas-intensive manufacturing firms. The time-varying results in Section 5.3.2 show that the negative gas HRs observed for the manufacturing portfolios continue throughout most of 2022 and 2023. This suggests that the change in the hedging relationship was not temporary but persisted during much of the 2022 European energy crisis period.

Taken together, the results show that both regulatory developments and major macroeconomic shocks can substantially alter HRs and HE_{HR}, supporting H3 across multiple assets and market environments.

Chapter 6

Conclusion

This thesis has examined the hedging of carbon-price risk in European sectoral equity indices using a bivariate Student-t DCC-GARCH(1,1) framework over the 1 January 2013 - 30 April 2026 sample period. The empirical analysis covers 32 sector-asset pairs constructed from eight sector portfolios (Electricity, Basic Metals, Non-Metallic Minerals, and Chemicals, each split into EU ETS-regulated and non-EU ETS-regulated portfolios) and five hedging assets (EUA futures, TTF natural gas futures, Brent crude oil futures, Rotterdam coal futures, and gold as a placebo). The hedge ratio (HR), HR-based hedging effectiveness ($\mathrm{HE}_{\mathrm{HR}}$), Kroner-Ng optimal portfolio weights (OW), and OW-based hedging effectiveness ($\mathrm{HE}_{\mathrm{OW}}$) are estimated at the full-sample level and across six regulatory and macroeconomic sub-periods (Phase III Low Price, Post-MSR, COVID-19, Phase IV High Price, Phase IV Normalization, and CBAM Transitional). The evolution of the hedging relationships over time is further examined through the time-varying estimates of HR and $\mathrm{HE}_{\mathrm{HR}}$. The realized performance of the hedged portfolios is evaluated using both traditional risk-adjusted performance measures and downside-risk metrics, including the Sharpe ratio, Sortino ratio, annualized volatility, Value-at-Risk (VaR), Expected Shortfall (ES), Maximum Drawdown (MDD), Omega ratio, Pain Index, and Pain Ratio. The robustness of the results is tested along two dimensions. Alternative univariate specifications are implemented, including an AR(1) mean equation and a GJR-GARCH variance equation. Sector portfolio indices are reconstructed with alternative index construction methods, namely the stable equal-weighted and yearly rebalanced market-capitalization-weighted approaches.

This chapter summarizes the main empirical findings, discusses their contribution to the literature on carbon-equity hedging, draws out the policy and practical implications, acknowledges the limitations of the analysis, and outlines directions for future research.

6.1 Summary of the Main Findings

Six main results emerge from the empirical analysis presented in Chapter 5.

EUA hedging effectiveness is limited on average but varies across market regimes. Looking at the full sample period, EUA futures have only limited hedging benefits for the sector portfolios. However, the sub-period analysis shows that the effectiveness of the hedge changes considerably over time. The highest results are observed during the COVID-19 period. Both HR and HE_{HR} increase across all eight sector portfolios. HE_{HR} values increase more compared to HRs during this period, which makes EUA more favorable as a hedging asset. During Phase IV, these effects weaken, but HE_{HR} values generally are above the levels observed during the Phase III Low Price period. The CBAM Transitional period shows slightly higher HE_{HR} values than the preceding Phase IV Normalization period for the sectors covered by CBAM. While HRs remain at similar levels, HE values move from near-zero levels to positive values in most cases.

EU ETS-regulated portfolios require larger EUA hedge positions. For hedging with EUAs, EU ETS-regulated portfolios require larger hedge positions than their non-EU ETS-regulated counterparts in all four sectors. The largest difference is observed in Basic Metals, where the average HR is 0.11 for the EU ETS-regulated portfolio and 0.06 for the non-EU ETS-regulated portfolio. Similar but smaller differences are also observed in the Electricity, Non-Metallic Minerals, and Chemicals sectors. On the other hand, the differences in HE_{HR} are generally smaller, and there are no clear distinctions between the two regulatory groups, unlike the HR measures. The highest difference between the two portfolios is observed for the Non-Metallic Minerals sector, where HE_{HR} reaches 0.07 for the EU ETS-regulated portfolio compared with 0.03 for the non-EU ETS-regulated portfolio. A smaller difference is also observed in the Electricity sector, with HE_{HR} values of 0.05 for the EU ETS-regulated and 0.04 for the non-EU ETS-regulated portfolios. In Basic Metals and Chemicals, this pattern is less clear and the HE_{HR} values remain very similar across the two regulatory groups.

Different sectors benefit from different hedging assets. No single asset provides the best hedging performance across all sectors. EUA is the most effective hedging asset for the Basic Metals and Non-Metallic Minerals sectors, which is consistent with their relatively high carbon intensity. In contrast, Brent crude oil produces the strongest hedging results in Electricity and Chemicals. For the Chemicals sector, this strong Brent crude oil hedging relationship also persists throughout much of the Phase IV High Price period (2021-2022), which reinforces its role as the dominant hedging asset for this sector. Natural gas has relatively low HE_{HR} values for the full-sample period, but its performance improves during Phase IV for gas-intensive manufacturing sectors. For coal, although it was an important input in steel and cement production, sector portfolios hedged with coal yield HE_{HR} values that are close to zero. Gold also delivers very limited HE_{HR}. The higher OW-based results for gold show that it provides diversification benefits as a low-volatility asset rather than meaningful hedging benefits against carbon-related equity risk.

The role of gas and coal changes across market regimes. Hedging with TTF natural gas and Rotterdam coal shows important findings in the sub-period analysis. Between the Phase III Low Price and the Phase IV High Price periods, the hedge ratios change from positive to negative for some of the sector-asset pairs with TTF natural gas. Also, hedging effectiveness increases, especially for TTF natural gas pairs with the Non-Metallic Minerals EU ETS-regulated sector portfolio. A similar sign change is also seen for hedge ratios with Rotterdam coal as the hedging asset. However, HE values with Rotterdam coal stay close to zero throughout the analysis period, unlike with TTF natural gas. Overall, the results show that the 2022 European energy crisis changed the relationship between energy and industrial stock returns. This change is particularly clear for TTF natural gas, while coal does not offer any practical hedging benefit in either period.

Portfolios' optimal weight differs substantially among hedging assets. In most of the EUA, TTF natural gas, Brent crude oil, and Rotterdam coal pairs, sector portfolios' OW are high and lie within the range of 0.80 to 0.95. For sector portfolios paired with gold and the Basic Metals EU ETS-regulated portfolio, the allocated OWs are mostly lower. OW for gold pairs range from 0.26 to 0.62, showing the lower volatility of gold relative to the sector portfolios. Basic Metals EU ETS-regulated portfolio has a similar pattern, as it has relatively low OW values of 0.59 for coal, 0.71 for gas, and 0.73 for EUA. Compared with the other sector portfolios, the Basic Metals EU ETS-regulated portfolio has higher volatility, which reduces the weight assigned to the sector portfolio in the minimum-variance allocation.

In terms of HE_{OW}, a similar pattern is observed. Gold pairs reach HE_{OW} values of up to 0.74, while the Basic Metals EU ETS-regulated portfolio hedged with EUA reaches 0.21. However, these results should be interpreted together with the HR-based measures. Although gold generates some of the highest HE_{OW} values in the sample, its HE_{HR} values remain close to zero. This suggests that the high HE_{OW} values are mainly related to the low volatility of gold rather than a particularly strong relationship with sector returns.

The time-varying analysis reveals several patterns that are not fully visible in the full-sample or sub-period results. The time-varying analysis identifies another period where HR and HE_{HR} increase specifically, especially for the EU ETS-regulated portfolios across most of the sectors, which is not visible from the average sub-period metrics. This increase is observed from 2016 to mid-2017, within the Phase III Low Price period. This period also coincides with the 2017 MSR reform measures aimed at reducing the surplus of emission allowances and tightening future allowance supply. These developments were followed by an increase in EUA prices [93]. This implies that the expectations of changes in allowance scarcity may have influenced hedging relationships even before the formal implementation of the reform. Moreover, the increasing HR and HE_{HR} values during the COVID-19 period observed in the sub-period analysis are also evident in the time-varying estimates. Furthermore, the strengthening of the hedging relationships during the CBAM Transitional period emerges gradually and mainly for the manufacturing sectors directly covered by CBAM. Additionally, the negative TTF natural gas hedge ratios observed during the 2022 European energy crisis continue throughout most of 2022 and 2023, suggesting that the energy crisis altered the relationship between gas prices and manufacturing-sector returns for an extended period. Finally, an earlier increase in TTF natural gas HE_{HR} is also observed during 2014-2015, together with negative HR, suggesting that the link between energy prices and sector returns became stronger during that period when European energy prices declined.

The risk-adjusted performance analysis in Section 5.4 shows that the strongest HE-based hedges also lead to clear improvements in the Sharpe ratio, the Sortino ratio, and the maximum drawdown. For example, the Electricity non-EU ETS-regulated portfolio hedged with Brent crude oil increases the annualized Sharpe ratio from 0.64 to 0.76. The Chemicals EU ETS-regulated portfolio hedged with Brent crude oil reduces the maximum drawdown by four percentage points and the Basic Metals non-EU ETS-regulated portfolio-EUA pair by five percentage points. However, some pairs have mixed results. The Basic Metals EU ETS-regulated portfolio-EUA pair lowers volatility from 0.272 to 0.264, but it also reduces the Sharpe ratio from 0.13 to 0.08. In this case, the improvement in risk is outweighed by the reduction in returns. These examples show that reducing variance is necessary, but not sufficient to improve portfolio performance.

The Omega ratio and the Pain measures in Section 5.4.1 point to a similar result. For the Basic Metals EU ETS-regulated portfolio-EUA pair, variance decreases, but the Pain Index increases from 0.244 to 0.313 and the Pain Ratio declines from 0.169 to 0.083. Therefore, the lower volatility is not accompanied by an improvement in drawdown performance. A different picture emerges for the Electricity EU ETS-regulated portfolio-oil hedge. In this case, volatility, Omega ratio, Pain Index, and Pain Ratio all improve, making it one of the most consistently performing hedges in the sample.

The robustness checks in Section 5.5 support all of the main conclusions. The results are mainly the same across different model specifications and index construction methods. The AR(1) mean equation provides the same HR, HE_{HR}, OW, and HE_{OW} values to two decimal places for all 32 pairs. The DCC-GJR-GARCH(1,1) specification produces the same results for most sector-asset pairs. Only small differences are observed for some pairs, which do not change the main conclusions. Moreover, the stable equal-weighted and yearly rebalanced market-capitalization-weighted index construction approaches also produce similar results and preserve the findings with the monthly rebalanced equal-weighted index construction method. The OW-based results vary more across methodologies, especially under the yearly rebalanced market-capitalization-weighted method, but the overall interpretation of the results remains the same.

6.2 Discussion and Contributions

This thesis aims to contribute to the literature in several ways. First, this thesis compares carbon-equity hedging effectiveness between EU ETS-regulated and non-EU ETS-regulated firms within the same sector. The existing literature mostly examines sectors as a whole with more aggregate sector indices without distinguishing the regulatory statuses of the firms. By introducing this distinction, the effects of the EU ETS on the hedging outcomes are assessed while keeping sector-specific characteristics constant. The results show that EU ETS-regulated firm portfolios generally exhibit higher hedge ratios, although the differences are less pronounced for hedging effectiveness. These findings provide a more detailed view of how carbon pricing is transmitted to equity markets and extend the existing sector-level evidence.

In addition, this thesis assesses the impact of EU ETS regulation by dividing the sample period into six sub-periods and examines the Phase III Low Price period, the Post-MSR period, the COVID-19 period, the Phase IV High Price period, the Phase IV Normalization period, and the CBAM Transitional period. The results show that various hedging relationships change considerably across the different market and regulatory regimes. Several patterns that are not visible in the full-sample averages emerge in the sub-period analysis, including the substantial increase in EUA hedging effectiveness during the COVID-19 period, the sign reversals observed for natural gas and coal hedge ratios during Phase IV, and differences in EUA hedging performance across the later Phase IV and CBAM periods. Consequently, the findings suggest that the hedging relationships depend heavily on the market and regulatory environment. In addition to the sub-period analysis, the dynamic hedging relationships are also examined using time-varying estimates of HR and HE_{HR}. This approach allows the observation of dynamics within the sub-periods, which is not directly visible in the sub-period averages. The combination of sub-period averages and time-varying estimates provides a more complete view of the changing hedging relationships in response to different market and regulatory developments.

Another contribution of this thesis is its sectoral design. The study focuses on four NACE 2-digit sectors with high shares of Scope 1 CO_2-equivalent emissions and activities directly covered by the EU ETS. These sectors vary in their production processes, energy use, and ability to pass on costs. This approach allows for an examination of hedging relationships across industries with different structures. In addition, the hedging assets are selected based on each sector's main production inputs rather than applying the same set of assets across all portfolios. This makes it possible to capture sector-specific hedging relationships with carbon and energy commodities. The findings highlight that both carbon exposure and the sectors' structural features affect hedging outcomes. Differences in production methods, energy dependence, and cost pass-through capacity contribute to the variation in hedging relationships between sectors. For example, EUA futures provide the highest variance reduction in the Basic Metals and Non-Metallic Minerals sectors, while Brent crude oil is more effective in the Electricity and Chemicals sectors, reflecting the different cost structures and energy dependencies of these industries.

Finally, unlike most previous studies that evaluate hedge performance mainly through variance reduction, this thesis also examines the realized performance of the hedged portfolios using a broad set of portfolio performance measures. Sharpe ratio, Sortino ratio, annualized volatility, Value-at-Risk, Expected Shortfall, maximum drawdown, Omega ratio, Pain Index, and Pain Ratio are used to assess the implications of the hedging strategies. While the strongest hedges in terms of $\mathrm{HE}_{\mathrm{HR}}$ generally also improve portfolio performance, this relationship is not always straightforward. In some cases, a reduction in portfolio volatility is accompanied by weaker risk-adjusted returns. For example, the Basic Metals EU ETS-regulated portfolio hedged with EUA reduces volatility, but it decreases the Sharpe ratio and increases the Pain Index. These findings show that a hedge can reduce risk without necessarily improving overall portfolio performance and highlight the importance of evaluating hedging strategies with multiple portfolio performance measures rather than only relying on variance reduction.

6.3 Implications for EU ETS-Regulated Firms, Policymakers, and Investors

The findings of this thesis have practical implications for EU ETS-regulated firms, policymakers, and investors in the European carbon and equity markets. The implications discussed below explain how EU ETS-regulated firms can use the results to form hedging strategies, how policymakers can interpret them when assessing the financial impact of the regulations in the carbon market, and how investors can take these findings into account when investing in carbon-intensive sectors.

For EU ETS-regulated firms in the four sectors examined, the findings indicate that the management of carbon price risk should not fully rely on EUA futures. The hedging instrument with the highest performance varies among sectors. Although EUA futures are the best hedging instrument in terms of variance reduction in Basic Metals and Non-Metallic Minerals sectors, Brent crude oil is more effective for the Electricity and Chemicals sectors. This suggests that firms may benefit from choosing hedging instruments that better match the characteristics of their sector, rather than relying only on EUA futures.

The findings also indicate that the hedge with the maximum $\mathrm{HE}_{\mathrm{HR}}$ is not necessarily the most practical one to implement. For instance, in the case of the Basic Metals sector, although EUA futures lead to the highest $\mathrm{HE}_{\mathrm{HR}}$, they also require one of the largest hedge positions in the sample. The same applies to the Chemicals industry, in which Brent crude oil achieves the greatest variance reduction, but TTF natural gas can deliver smaller but still meaningful variance reduction with relatively smaller hedge positions. This difference may be particularly relevant for firms that are more concerned about hedging costs, since larger hedge positions are generally more expensive to maintain. Thus, when choosing a hedging asset, firms should take into account both the extent of risk reduction and the size of the hedge needed to achieve it.

Furthermore, hedge positions should not be treated as fixed over time. The results show that both the effectiveness of the hedge and, in some cases, even its direction can change as market conditions change. The COVID-19 pandemic and the 2022 European energy crisis show this clearly. During the COVID-19 period, EUA became a more effective hedging asset for most of the carbon-intensive sectors. During the 2022 European energy crisis, the sign of the HR changed, and several portfolios required a long position in TTF natural gas instead of a short one. This implies that a hedging asset that works well under normal market conditions may no longer work during periods of market stress. Thus, firms may benefit from reviewing their hedge positions from time to time, especially around major regulatory or macroeconomic events, instead of keeping the same hedging strategy for several years.

Finally, reducing volatility does not always lead to the best overall portfolio performance. For some pairs, such as the EU ETS-regulated Electricity portfolio hedged with Brent crude oil, high variance reduction is achieved together with improvements across the portfolio performance measures. This makes Brent crude oil a good choice for EU ETS-regulated firms operating in the Electricity sector that want a single hedging instrument performing well across different performance measures. In other cases, however, the picture is less clear because the portfolio measures do not all point in the same direction. For the Basic Metals EU ETS-regulated portfolio, EUA futures provide the strongest variance reduction but worsen the drawdown-based measures, while TTF natural gas reduces variance and improves drawdown measures at the same time for the same portfolio, although the variance reduction is smaller than with EUA. An

EU ETS-regulated Basic Metals firm mainly concerned with volatility may still prefer EUA futures, whereas a firm that is more focused on limiting drawdowns may find TTF natural gas more suitable. A similar pattern can be observed for the Non-Metallic Minerals EU ETS-regulated portfolio, where gold is more attractive as a hedging asset when drawdown-based measures are considered, although it has no direct economic link with the sector. Overall, these results suggest that firms with different objectives may not benefit from the same hedging strategy, even when they operate in the same sector. When the priority is variance reduction, EUA futures remain the best choice for the Basic Metals EU ETS-regulated portfolio; when the priority is limiting drawdown risk, TTF natural gas becomes more relevant for the same portfolio, and gold for the Non-Metallic Minerals EU ETS-regulated portfolio.

In terms of the implications for policymakers, the results suggest that carbon-market regulation is becoming increasingly reflected in equity valuations. This is consistent with the evolution of the EUA market over time. While in the earlier phases of the EU ETS, EUA futures were traded mainly for compliance purposes, their financial role became more prominent during Phase III and Phase IV of the EU ETS, supported by the growing participation of financial investors and the development of derivatives markets [9, 105]. The consistently higher HRs observed for the EU ETS-regulated portfolios, compared with non-EU ETS-regulated portfolios, are consistent with this development.

The results also suggest that the effects of carbon-market regulation may become visible in financial markets before they are fully reflected in firms' operations. One example is the increase in $\mathrm{HE}_{\mathrm{HR}}$ during 2016–2017, before the MSR became operational in 2019, when measures aimed at tightening the future supply of emission allowances were introduced and EUA prices started to recover. After the European Council's decision of 28 February 2017 to strengthen the MSR framework and introduce a Phase IV cancellation mechanism, EUA prices more than doubled within a year despite no immediate change in firms' compliance obligations [93]. This suggests that expectations about future carbon market conditions can influence the relationship between carbon prices and equity returns well before the direct effects of the regulation are reflected in firms' actual carbon costs.

Finally, the findings highlight the close interaction between carbon and energy markets. The changes observed during the 2022 European energy crisis show that developments in energy markets can alter the relationship between carbon prices and sector returns. For policymakers, this suggests that the financial impact of carbon-market reforms should be assessed together with the conditions in energy markets. The same reform may lead to different outcomes depending on the energy market environment in which it is introduced.

For investors holding European industrial equities, investing in different carbon-intensive sectors does not mean that the same hedge will work equally well for the whole portfolio. Since the sectors respond differently to changes in carbon and energy markets, different parts of the portfolio may require different hedging instruments. For example, EUA futures provide better protection in the Basic Metals and Non-Metallic Minerals portfolios, while Brent crude oil works better in the Electricity and Chemicals portfolios. Taking these sectoral differences into account may therefore lead to more effective portfolio hedging.

Another implication concerns the role of gold. Throughout the analysis, gold has low $\mathrm{HE}_{\mathrm{HR}}$, despite being one of the best-performing assets in the minimum-variance portfolios because of its low volatility. For investors, this means that $\mathrm{HE}_{\mathrm{HR}}$ alone may not be sufficient when selecting a hedging asset, since low-volatility assets can still improve overall portfolio performance. A good example is the Non-Metallic Minerals EU ETS-regulated portfolio, where gold outperforms the other hedging assets according to the Omega and Pain measures despite its relatively low $\mathrm{HE}_{\mathrm{HR}}$. For investors, this suggests that assets without a direct economic link to the underlying source of risk may still be included in the portfolio if they contribute to overall portfolio performance.

An important dimension to consider for investors is the regulatory differences among firms. In general, EU ETS-regulated portfolios require larger positions in EUAs than non-EU ETS-regulated portfolios inside the same sector. This implies that despite the similar level of exposure to a particular industry, two portfolios will react to carbon price changes in different ways depending on their regulatory status under the EU ETS. Thus, for investors building exposure to carbon-intensive industries, regulatory status can be just as important as sector selection. A portfolio consisting of EU ETS-regulated firms is more closely linked to movements in EUA prices, while the non-EU ETS-regulated firms are indirectly affected. As a result, two portfolios inside the same sector may still respond differently to developments in carbon markets. This may be particularly relevant for investors who expect future changes in European carbon-market regulation to affect asset prices. Investors seeking greater direct exposure to carbon-price movements may prefer EU ETS-regulated portfolios within a carbon-intensive sector, and those seeking lower direct exposure may prefer non-EU ETS-regulated portfolios.

6.4 Limitations

The interpretation of the results presented in this thesis is subject to four limitations.

First, the analysis is based on a bivariate DCC-GARCH framework, where the relationship between one sector portfolio and one hedging asset is estimated at a time.

This design choice enables a direct comparison of the hedging effectiveness of EUA futures, TTF natural gas, Brent crude oil, Rotterdam coal, and gold across sectors and market regimes. However, it does not capture the effects of multiple hedging assets simultaneously. As a result, the analysis cannot fully account for spillover effects among the different commodity and carbon markets. A multivariate framework could identify hedging strategies involving combinations of assets and may lead to higher hedging effectiveness than the single-asset hedges considered in this thesis.

Second, the optimal portfolio weights are calculated using a long-only constraint and assume frictionless rebalancing. In addition, the analysis does not take into account transaction costs, financing costs for futures positions, or margin requirements. Because of this, the actual performance of the hedging strategies may differ from the results reported in the thesis, especially if portfolios need to be rebalanced often.

Third, the sector portfolios are constructed from listed European firms only and may not be representative of the full sectoral universe. The distinction between the EU ETS-regulated and non-EU ETS-regulated portfolios is made at the company level based on the available EU ETS coverage information. However, many large European industrial firms operate both EU ETS-regulated and non-EU ETS-regulated facilities together, which makes the separation between the two groups less clear. A possible extension to address this limitation would be to identify the Global Ultimate Owners of unlisted EU ETS-regulated firms. Many of these firms are subsidiaries of listed European or non-European parent companies. Since the equity returns of the listed parents reflect the activities of their subsidiaries, including these parents in the sample could partially capture the EU ETS exposure of unlisted firms and help generalize the results beyond firms that are directly listed.

Fourth, the sub-period analysis has a trade-off between capturing the real effects of each period and maintaining sufficient sample length for sub-periods to preserve the precision of the DCC-GARCH model. The periods are selected to reflect different market conditions and regulatory regimes, such as the COVID-19 shock, the Phase IV High Price period, and the CBAM Transitional period. This approach avoids overlap between the effects of adjacent regimes. As a result, some sub-periods are too short for estimating the DCC-GARCH model. Therefore, conditional correlations and hedge ratios are calculated using the full-sample DCC-GARCH estimation and then assessed within each sub-period. Longer sub-periods would have allowed separate model estimation, but they would also have mixed the effects of different market and regulatory regimes, which would make the results harder to interpret.

6.5 Directions for Future Research

The empirical evidence presented in this thesis suggests several directions for future research.

The analysis could be extended by examining multiple hedging assets simultaneously for each sector portfolio. The current analysis is based on a bivariate DCC-GARCH framework and therefore examines each sector-asset pair separately. This allows the hedging performance of the different assets to be compared using a consistent modeling approach. However, in practice, firms and investors often combine carbon and energy assets to manage risk. A multivariate framework could therefore provide a better understanding of how these assets interact with each other and whether combinations of assets can achieve stronger hedging performance than the individual hedges examined in this thesis.

Another area for future research is the transmission of carbon-price shocks across sectors. Examining how these relationships change under different market and regulatory conditions could improve the understanding of how carbon markets interact with different industries. This could be explored using network or spillover models that capture the links between sectors.

Furthermore, the analysis could be extended by including a broader set of hedging assets. Some sustainability-related financial assets may be added to the analysis, such as green bonds, transition-focused equity indices, renewable energy stocks, and carbon investment products. The inclusion of these assets would add a new dimension to the study by allowing their hedging performance to be examined across different sectors and phases of the EU ETS.

The findings in this thesis that depend on different regimes could be reviewed again as more data becomes available. The CBAM analysis could be improved when longer-term data from the CBAM Definitive Phase is available. This would show whether the patterns seen during the CBAM Transitional period continue over time or are just part of the policy's early phase.

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Appendix A

DCC-GARCH Parameter Estimates

Table A.1 presents the DCC-GARCH parameter estimates for all 32 sector-asset pairs discussed in Section 5.1. The parameter a captures the short-run impact of new shocks on conditional correlations and b reflects the persistence of past correlation dynamics. Their sum $(a+b)$ reflects how persistent the conditional correlation process is over time. The parameter ν_{MVT} represents the degrees-of-freedom parameter of the multivariate Student-t distribution and provides information about the tail behavior of the return distribution.

Table A.1: DCC-GARCH parameter estimates for all sector-asset pairs.

Sector Portfolio	**Regulatory Group**	**Asset**	a	b	$a+b$	ν_{MVT}
Electricity	ETS	EUA	0.0083	0.9694	0.9777	6.66
	ETS	Gas	0.0127	0.9779	0.9906	6.38
	ETS	Oil	0.0171	0.9682	0.9853	6.30
	ETS	Gold	0.0200	0.9051	0.9251	5.66
	Non-ETS	EUA	0.0047	0.9869	0.9916	6.92
	Non-ETS	Gas	0.0062	0.9808	0.9870	6.50
	Non-ETS	Oil	0.0248	0.9213	0.9461	6.28
	Non-ETS	Gold	0.0174	0.9051	0.9225	5.57
Basic Metals	ETS	EUA	0.0089	0.9825	0.9915	6.99
	ETS	Gas	0.0109	0.9818	0.9927	6.47
	ETS	Coal	0.0179	0.9615	0.9794	4.00
	ETS	Gold	0.0221	0.9384	0.9605	5.52
	Non-ETS	EUA	0.0082	0.9811	0.9893	6.78
	Non-ETS	Gas	0.0273	0.9356	0.9629	6.37
	Non-ETS	Coal	0.0057	0.9943	1.0000	4.00
	Non-ETS	Gold	0.0274	0.9245	0.9520	5.58
Non-Metallic Minerals	ETS	EUA	0.0077	0.9844	0.9921	7.15
	ETS	Gas	0.0134	0.9771	0.9905	6.42
	ETS	Coal	0.0069	0.9931	1.0000	4.00
	ETS	Gold	0.0311	0.9311	0.9622	5.49
	Non-ETS	EUA	0.0097	0.9731	0.9829	7.00
	Non-ETS	Gas	0.0282	0.8924	0.9205	6.51
	Non-ETS	Coal	0.0102	0.9787	0.9890	4.00
	Non-ETS	Gold	0.0214	0.9419	0.9634	5.81
Chemicals	ETS	EUA	0.0086	0.9833	0.9919	7.78
	ETS	Gas	0.0195	0.9674	0.9870	7.04
	ETS	Oil	0.0335	0.9283	0.9617	7.04
	ETS	Gold	0.0296	0.9323	0.9619	5.99
	Non-ETS	EUA	0.0091	0.9825	0.9916	6.81
	Non-ETS	Gas	0.0262	0.9212	0.9475	6.37
	Non-ETS	Oil	0.0277	0.9303	0.9581	6.32
	Non-ETS	Gold	0.0275	0.9341	0.9616	5.40

Notes: All estimates are obtained under the monthly rebalanced equal-weighted index method over the 1 January 2013-30 April 2026 sample period. ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios.

Appendix B

Sub-Period Hedging Results for Non-EUA Hedging Assets

This appendix reports the detailed sub-period results for the four non-EUA hedging assets: TTF natural gas futures, Brent crude oil futures, Rotterdam coal futures, and gold. For each sector-asset pair, the hedge ratio (HR), HR-based hedging effectiveness (HE_{HR}), optimal portfolio weight (OW), and OW-based hedging effectiveness (HE_{OW}) are reported across the six sub-periods analyzed in Section 5.3. The EUA results are presented in Tables 5.4 and 5.5 in the main text. The results are organized by NACE division: Table B.1 reports the Electricity sector, Table B.2 the Basic Metals sector, Table B.3 the Non-Metallic Minerals sector, and Table B.4 the Chemicals sector.

Table B.1: Sub-period hedge ratio, hedging effectiveness, and optimal portfolio weight results across the six sub-periods for Electricity, Gas, Steam and Air Conditioning Supply (NACE 35). The EUA results are reported in Tables 5.4 and 5.5 of the main text.

		HR statistics					**OW statistics**				
Asset	**Reg.**	**HR**	**SD**	**Q5**	**Q95**	**HE_{HR}**	**OW**	**SD**	**Q5**	**Q95**	**HE_{OW}**
Panel A. Phase III Low Price (1 Jan 2013 - 31 Dec 2018)											
TTF natural gas futures	ETS	0.02	0.06	-0.05	0.13	0.04	0.84	0.12	0.61	0.98	0.12
	Non-ETS	0.01	0.02	-0.03	0.05	0.01	0.80	0.14	0.53	0.97	0.20
Brent crude oil futures	ETS	0.08	0.04	0.01	0.15	0.10	0.91	0.08	0.74	1.00	0.04
	Non-ETS	0.07	0.04	0.02	0.14	0.06	0.87	0.12	0.63	1.00	0.11
Gold	ETS	0.00	0.06	-0.07	0.07	0.01	0.63	0.12	0.42	0.83	0.42
	Non-ETS	0.02	0.06	-0.05	0.10	0.01	0.59	0.14	0.34	0.81	0.48
Panel B. Post-MSR (1 Jan 2019 - 29 Feb 2020)											
TTF natural gas futures	ETS	0.01	0.01	0.00	0.04	-0.02	0.95	0.10	0.83	1.00	0.36
	Non-ETS	0.00	0.01	0.00	0.02	-0.01	0.95	0.05	0.86	0.99	0.01
Brent crude oil futures	ETS	0.08	0.05	0.03	0.19	0.02	0.93	0.14	0.79	1.00	0.37
	Non-ETS	0.06	0.03	0.03	0.11	0.08	0.91	0.09	0.71	0.99	-0.09
Gold	ETS	0.03	0.08	-0.03	0.09	0.01	0.57	0.15	0.21	0.72	0.73
	Non-ETS	0.03	0.04	-0.02	0.09	-0.03	0.52	0.12	0.28	0.67	0.44
Panel C. COVID-19 (1 Mar 2020 - 31 Dec 2020)											
TTF natural gas futures	ETS	0.02	0.02	0.01	0.06	0.01	0.90	0.15	0.53	1.00	0.24
	Non-ETS	0.02	0.02	0.00	0.05	0.01	0.91	0.14	0.64	0.99	0.25
Brent crude oil futures	ETS	0.12	0.05	0.05	0.21	0.23	0.96	0.08	0.84	1.00	-0.17
	Non-ETS	0.09	0.05	0.03	0.19	0.20	0.94	0.07	0.78	1.00	-0.05
Gold	ETS	0.04	0.13	-0.09	0.30	0.04	0.58	0.17	0.18	0.76	0.51
	Non-ETS	0.05	0.11	-0.06	0.24	0.01	0.60	0.18	0.24	0.81	0.53
Panel D. Phase IV High Price (1 Jan 2021 - 31 Dec 2022)											
TTF natural gas futures	ETS	0.00	0.02	-0.03	0.03	0.02	0.97	0.02	0.93	1.00	0.06
	Non-ETS	0.00	0.01	-0.01	0.01	0.01	0.97	0.02	0.93	0.99	0.05
Brent crude oil futures	ETS	0.07	0.04	0.00	0.13	0.01	0.91	0.07	0.80	1.00	0.07
	Non-ETS	0.06	0.04	0.00	0.12	0.03	0.90	0.09	0.74	1.00	0.07
Gold	ETS	0.02	0.07	-0.09	0.13	0.02	0.56	0.13	0.35	0.75	0.51
	Non-ETS	0.04	0.05	-0.04	0.11	0.00	0.54	0.12	0.34	0.72	0.49
Panel E. Phase IV Normalization (1 Jan 2023 - 30 Sep 2023)											
TTF natural gas futures	ETS	0.00	0.01	-0.02	0.01	-0.01	0.98	0.03	0.92	1.00	0.01
	Non-ETS	0.00	0.00	0.00	0.01	-0.01	0.98	0.02	0.94	1.00	0.03
Brent crude oil futures	ETS	0.07	0.03	0.03	0.13	0.03	0.93	0.05	0.85	1.00	0.03
	Non-ETS	0.07	0.02	0.04	0.11	0.07	0.92	0.06	0.83	0.99	-0.03
Gold	ETS	0.01	0.07	-0.11	0.09	0.03	0.57	0.08	0.45	0.70	0.47
	Non-ETS	0.04	0.06	-0.06	0.11	0.03	0.56	0.09	0.42	0.73	0.42
Panel F. CBAM Transitional (1 Oct 2023 - 30 Apr 2026)											
TTF natural gas futures	ETS	0.02	0.02	0.00	0.07	0.02	0.96	0.03	0.88	1.00	-0.03
	Non-ETS	0.01	0.01	-0.01	0.02	0.00	0.94	0.05	0.84	0.99	0.01
Brent crude oil futures	ETS	0.03	0.02	0.00	0.08	-0.02	0.91	0.06	0.79	0.98	0.08
	Non-ETS	0.05	0.03	0.00	0.09	-0.03	0.90	0.07	0.77	0.98	0.09
Gold	ETS	0.03	0.04	-0.02	0.10	0.01	0.70	0.11	0.53	0.87	0.15
	Non-ETS	0.04	0.04	-0.01	0.10	0.01	0.68	0.14	0.46	0.93	0.23

Notes: ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. HR is the mean dynamic hedge ratio. SD, Q5, and Q95 report the standard deviation and the 5th and 95th percentiles of the daily HR (or OW) series within each sub-period. HE_{HR} is the HR-based hedging effectiveness. OW is the mean Kroner-Ng optimal sector weight and HE_{OW} is the OW-based hedging effectiveness. Negative HE_{OW} values indicate that the OW-based portfolio variance exceeds the variance of the unhedged sector portfolio during the period. EUA results for this sector are reported in Section 5.3.

Table B.2: Sub-period hedge ratio, hedging effectiveness, and optimal portfolio weight results across the six sub-periods for Manufacture of Basic Metals (NACE 24). The EUA results are reported in Tables 5.4 and 5.5 of the main text.

		HR statistics					**OW statistics**				
Asset	**Reg.**	**HR**	**SD**	**Q5**	**Q95**	**HE_{HR}**	**OW**	**SD**	**Q5**	**Q95**	**HE_{OW}**
Panel A. Phase III Low Price (1 Jan 2013 - 31 Dec 2018)											
TTF natural gas futures	ETS	0.06	0.11	-0.07	0.29	0.02	0.55	0.21	0.21	0.87	0.44
	Non-ETS	0.03	0.06	-0.05	0.12	0.03	0.76	0.14	0.50	0.95	0.18
Rotterdam coal futures	ETS	0.04	0.06	-0.04	0.17	0.01	0.55	0.14	0.31	0.78	0.55
	Non-ETS	0.05	0.05	0.00	0.15	0.01	0.79	0.08	0.65	0.92	0.25
Gold	ETS	0.07	0.14	-0.15	0.25	0.01	0.27	0.12	0.12	0.51	0.74
	Non-ETS	0.01	0.10	-0.18	0.12	0.01	0.51	0.14	0.31	0.77	0.51
Panel B. Post-MSR (1 Jan 2019 - 29 Feb 2020)											
TTF natural gas futures	ETS	0.03	0.02	0.00	0.07	0.00	0.82	0.11	0.62	0.96	0.09
	Non-ETS	0.01	0.02	-0.01	0.05	-0.01	0.94	0.05	0.84	1.00	0.03
Rotterdam coal futures	ETS	-0.01	0.07	-0.14	0.08	0.00	0.53	0.12	0.36	0.79	0.46
	Non-ETS	0.01	0.02	-0.02	0.04	0.00	0.80	0.08	0.68	0.94	0.12
Gold	ETS	-0.14	0.14	-0.36	0.07	0.02	0.18	0.04	0.12	0.26	0.87
	Non-ETS	-0.11	0.08	-0.22	0.01	-0.03	0.43	0.08	0.27	0.53	0.64
Panel C. COVID-19 (1 Mar 2020 - 31 Dec 2020)											
TTF natural gas futures	ETS	0.08	0.05	0.03	0.17	0.02	0.73	0.21	0.35	0.96	0.30
	Non-ETS	0.05	0.05	0.00	0.16	0.04	0.85	0.16	0.54	0.99	0.21
Rotterdam coal futures	ETS	0.08	0.11	-0.04	0.33	0.00	0.46	0.21	0.14	0.86	0.39
	Non-ETS	0.06	0.05	0.00	0.19	-0.01	0.67	0.21	0.28	0.96	0.29
Gold	ETS	0.09	0.21	-0.27	0.40	0.02	0.21	0.06	0.11	0.29	0.78
	Non-ETS	0.04	0.16	-0.20	0.29	0.00	0.44	0.15	0.13	0.63	0.63
Panel D. Phase IV High Price (1 Jan 2021 - 31 Dec 2022)											
TTF natural gas futures	ETS	0.00	0.03	-0.05	0.06	0.02	0.88	0.08	0.73	0.97	0.14
	Non-ETS	0.00	0.03	-0.03	0.06	0.04	0.95	0.04	0.88	1.00	0.10
Rotterdam coal futures	ETS	-0.01	0.04	-0.07	0.06	-0.02	0.68	0.17	0.41	0.96	-0.31
	Non-ETS	-0.01	0.03	-0.06	0.03	-0.04	0.83	0.11	0.64	0.98	-0.44
Gold	ETS	0.10	0.14	-0.14	0.29	0.01	0.20	0.07	0.09	0.33	0.81
	Non-ETS	0.02	0.12	-0.17	0.17	0.03	0.42	0.09	0.27	0.57	0.62
Panel E. Phase IV Normalization (1 Jan 2023 - 30 Sep 2023)											
TTF natural gas futures	ETS	0.00	0.01	-0.02	0.01	0.00	0.92	0.08	0.75	0.99	0.04
	Non-ETS	0.00	0.01	-0.01	0.01	-0.02	0.97	0.03	0.91	1.00	0.00
Rotterdam coal futures	ETS	0.00	0.02	-0.03	0.03	-0.01	0.73	0.15	0.51	0.96	-0.31
	Non-ETS	-0.02	0.02	-0.06	-0.01	-0.03	0.86	0.08	0.72	0.97	-0.32
Gold	ETS	-0.01	0.22	-0.45	0.23	0.04	0.22	0.04	0.16	0.30	0.82
	Non-ETS	-0.01	0.14	-0.26	0.13	0.03	0.44	0.07	0.32	0.55	0.62
Panel F. CBAM Transitional (1 Oct 2023 - 30 Apr 2026)											
TTF natural gas futures	ETS	0.01	0.04	-0.06	0.07	0.02	0.81	0.12	0.55	0.95	0.16
	Non-ETS	0.01	0.04	-0.05	0.06	0.04	0.90	0.09	0.74	0.98	0.13
Rotterdam coal futures	ETS	-0.01	0.05	-0.09	0.04	0.01	0.64	0.13	0.46	0.88	0.31
	Non-ETS	-0.02	0.02	-0.06	0.00	0.01	0.79	0.11	0.62	0.94	0.18
Gold	ETS	0.11	0.10	-0.06	0.25	0.03	0.35	0.13	0.19	0.61	0.49
	Non-ETS	0.05	0.09	-0.08	0.17	0.01	0.56	0.17	0.29	0.88	0.38

Notes: ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. HR is the mean dynamic hedge ratio. SD, Q5, and Q95 report the standard deviation and the 5th and 95th percentiles of the daily HR (or OW) series within each sub-period. HE_{HR} is the HR-based hedging effectiveness. OW is the mean Kroner-Ng optimal sector weight and HE_{OW} is the OW-based hedging effectiveness. Negative HE_{OW} values indicate that the OW-based portfolio variance exceeds the variance of the unhedged sector portfolio during the period. EUA results for this sector are reported in Section 5.3.

Table B.3: Sub-period hedge ratio, hedging effectiveness, and optimal portfolio weight results across the six sub-periods for Manufacture of Other Non-Metallic Mineral Products (NACE 23). The EUA results are reported in Tables 5.4 and 5.5 of the main text.

		HR statistics					**OW statistics**				
Asset	**Reg.**	**HR**	**SD**	**Q5**	**Q95**	**HE$_{HR}$**	**OW**	**SD**	**Q5**	**Q95**	**HE$_{OW}$**
Panel A. Phase III Low Price (1 Jan 2013 - 31 Dec 2018)											
TTF natural gas futures	ETS	0.01	0.07	-0.10	0.14	0.02	0.72	0.16	0.42	0.94	0.28
	Non-ETS	0.00	0.06	-0.08	0.08	0.01	0.71	0.17	0.41	0.93	0.35
Rotterdam coal futures	ETS	0.05	0.05	-0.01	0.16	0.01	0.75	0.12	0.54	0.92	0.34
	Non-ETS	0.01	0.03	-0.03	0.05	0.00	0.73	0.11	0.54	0.90	0.41
Gold	ETS	-0.06	0.15	-0.29	0.14	0.02	0.46	0.13	0.26	0.69	0.60
	Non-ETS	-0.03	0.11	-0.25	0.12	0.02	0.46	0.12	0.27	0.67	0.61
Panel B. Post-MSR (1 Jan 2019 - 29 Feb 2020)											
TTF natural gas futures	ETS	0.00	0.01	-0.02	0.02	-0.01	0.92	0.06	0.80	0.98	0.04
	Non-ETS	0.00	0.02	-0.03	0.02	0.00	0.93	0.06	0.81	0.99	0.02
Rotterdam coal futures	ETS	-0.01	0.01	-0.04	0.01	-0.01	0.77	0.10	0.59	0.92	0.16
	Non-ETS	0.00	0.02	-0.02	0.02	0.00	0.79	0.08	0.68	0.94	0.14
Gold	ETS	-0.15	0.13	-0.40	0.06	-0.04	0.40	0.07	0.26	0.51	0.65
	Non-ETS	-0.08	0.06	-0.18	0.01	-0.01	0.42	0.07	0.27	0.52	0.54
Panel C. COVID-19 (1 Mar 2020 - 31 Dec 2020)											
TTF natural gas futures	ETS	0.04	0.04	0.00	0.14	0.04	0.87	0.16	0.53	1.00	0.21
	Non-ETS	0.00	0.03	-0.03	0.07	0.00	0.87	0.13	0.61	0.99	0.26
Rotterdam coal futures	ETS	0.04	0.04	-0.03	0.15	-0.01	0.70	0.20	0.24	0.95	0.33
	Non-ETS	0.01	0.04	-0.03	0.10	0.00	0.72	0.17	0.33	0.96	0.33
Gold	ETS	0.03	0.18	-0.26	0.35	0.00	0.47	0.15	0.14	0.68	0.58
	Non-ETS	0.02	0.13	-0.12	0.25	0.05	0.51	0.15	0.17	0.73	0.55
Panel D. Phase IV High Price (1 Jan 2021 - 31 Dec 2022)											
TTF natural gas futures	ETS	-0.02	0.02	-0.05	0.02	0.10	0.94	0.03	0.88	0.99	0.19
	Non-ETS	-0.01	0.02	-0.03	0.02	0.03	0.95	0.04	0.87	0.99	0.08
Rotterdam coal futures	ETS	-0.03	0.02	-0.06	-0.01	0.00	0.82	0.11	0.63	0.98	-0.37
	Non-ETS	-0.02	0.03	-0.06	0.02	-0.01	0.84	0.11	0.64	0.98	-0.28
Gold	ETS	-0.05	0.16	-0.42	0.11	0.08	0.42	0.11	0.22	0.57	0.70
	Non-ETS	-0.01	0.10	-0.22	0.13	0.04	0.44	0.10	0.27	0.61	0.62
Panel E. Phase IV Normalization (1 Jan 2023 - 30 Sep 2023)											
TTF natural gas futures	ETS	-0.01	0.01	-0.03	0.00	0.00	0.96	0.03	0.89	0.99	0.02
	Non-ETS	0.00	0.01	-0.01	0.01	-0.01	0.96	0.03	0.91	1.00	-0.01
Rotterdam coal futures	ETS	-0.03	0.02	-0.07	-0.01	-0.03	0.85	0.08	0.69	0.97	-0.28
	Non-ETS	0.02	0.02	-0.01	0.06	0.00	0.87	0.09	0.71	0.99	-0.35
Gold	ETS	-0.04	0.17	-0.38	0.20	0.08	0.43	0.08	0.28	0.56	0.62
	Non-ETS	-0.05	0.07	-0.13	0.03	0.01	0.43	0.08	0.31	0.57	0.61
Panel F. CBAM Transitional (1 Oct 2023 - 30 Apr 2026)											
TTF natural gas futures	ETS	-0.02	0.04	-0.09	0.03	0.05	0.88	0.08	0.71	0.96	0.19
	Non-ETS	0.00	0.03	-0.04	0.03	0.01	0.88	0.09	0.73	0.97	0.17
Rotterdam coal futures	ETS	-0.03	0.03	-0.06	0.00	0.02	0.76	0.10	0.57	0.92	0.28
	Non-ETS	-0.02	0.02	-0.06	0.01	0.00	0.77	0.11	0.59	0.93	0.30
Gold	ETS	-0.01	0.12	-0.21	0.17	0.00	0.52	0.14	0.31	0.81	0.43
	Non-ETS	0.01	0.08	-0.10	0.13	0.02	0.54	0.16	0.30	0.85	0.46

Notes: ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. HR is the mean dynamic hedge ratio. SD, Q5, and Q95 report the standard deviation and the 5th and 95th percentiles of the daily HR (or OW) series within each sub-period. HE$_{HR}$ is the HR-based hedging effectiveness. OW is the mean Kroner-Ng optimal sector weight and HE$_{OW}$ is the OW-based hedging effectiveness. Negative HE$_{OW}$ values indicate that the OW-based portfolio variance exceeds the variance of the unhedged sector portfolio during the period. EUA results for this sector are reported in Section 5.3.

Table B.4: Sub-period hedge ratio, hedging effectiveness, and optimal portfolio weight results across the six sub-periods for Manufacture of Chemicals and Chemical Products (NACE 20). The EUA results are reported in Tables 5.4 and 5.5 of the main text.

		HR statistics					**OW statistics**				
Asset	**Reg.**	**HR**	**SD**	**Q5**	**Q95**	**HE$_{HR}$**	**OW**	**SD**	**Q5**	**Q95**	**HE$_{OW}$**
Panel A. Phase III Low Price (1 Jan 2013 - 31 Dec 2018)											
TTF natural gas futures	ETS	0.03	0.09	-0.10	0.20	0.05	0.76	0.16	0.45	0.96	0.22
	Non-ETS	0.01	0.05	-0.05	0.08	0.03	0.80	0.14	0.53	0.97	0.19
Brent crude oil futures	ETS	0.10	0.07	0.01	0.21	0.11	0.85	0.11	0.66	1.00	0.06
	Non-ETS	0.06	0.05	0.00	0.16	0.09	0.87	0.10	0.68	0.99	0.07
Gold	ETS	-0.05	0.12	-0.28	0.11	0.02	0.51	0.13	0.29	0.74	0.56
	Non-ETS	0.00	0.10	-0.17	0.13	0.01	0.58	0.13	0.35	0.80	0.45
Panel B. Post-MSR (1 Jan 2019 - 29 Feb 2020)											
TTF natural gas futures	ETS	0.02	0.02	-0.01	0.05	-0.01	0.92	0.06	0.80	0.99	0.05
	Non-ETS	0.01	0.02	-0.01	0.03	0.01	0.95	0.05	0.85	0.99	0.03
Brent crude oil futures	ETS	0.13	0.05	0.04	0.23	0.10	0.84	0.11	0.60	0.95	0.02
	Non-ETS	0.07	0.05	0.00	0.15	0.11	0.88	0.08	0.73	0.99	-0.01
Gold	ETS	-0.20	0.11	-0.38	-0.03	0.01	0.38	0.08	0.23	0.49	0.74
	Non-ETS	-0.09	0.09	-0.22	0.05	-0.05	0.47	0.10	0.29	0.60	0.61
Panel C. COVID-19 (1 Mar 2020 - 31 Dec 2020)											
TTF natural gas futures	ETS	0.05	0.04	0.01	0.14	0.02	0.84	0.16	0.51	1.00	0.20
	Non-ETS	0.03	0.06	-0.03	0.15	0.04	0.85	0.15	0.57	0.98	0.05
Brent crude oil futures	ETS	0.17	0.07	0.08	0.30	0.20	0.89	0.09	0.73	1.00	-0.01
	Non-ETS	0.13	0.08	0.05	0.29	0.19	0.86	0.19	0.47	1.00	0.03
Gold	ETS	0.00	0.20	-0.30	0.27	0.03	0.41	0.11	0.19	0.62	0.63
	Non-ETS	0.10	0.18	-0.13	0.46	0.01	0.45	0.17	0.10	0.68	0.56
Panel D. Phase IV High Price (1 Jan 2021 - 31 Dec 2022)											
TTF natural gas futures	ETS	-0.01	0.03	-0.05	0.03	0.08	0.95	0.03	0.89	0.99	0.16
	Non-ETS	-0.01	0.02	-0.03	0.02	0.05	0.96	0.03	0.90	0.99	0.13
Brent crude oil futures	ETS	0.10	0.07	-0.02	0.20	0.06	0.86	0.10	0.68	1.00	0.13
	Non-ETS	0.06	0.05	-0.03	0.14	0.04	0.86	0.10	0.67	0.99	0.18
Gold	ETS	-0.02	0.16	-0.30	0.19	0.08	0.43	0.12	0.23	0.62	0.66
	Non-ETS	0.01	0.14	-0.26	0.17	0.06	0.47	0.12	0.29	0.67	0.62
Panel E. Phase IV Normalization (1 Jan 2023 - 30 Sep 2023)											
TTF natural gas futures	ETS	0.00	0.01	-0.02	0.01	-0.01	0.96	0.04	0.87	1.00	0.02
	Non-ETS	0.00	0.01	-0.02	0.01	-0.01	0.98	0.02	0.94	1.00	0.02
Brent crude oil futures	ETS	0.11	0.05	0.02	0.19	0.05	0.85	0.07	0.71	0.95	0.06
	Non-ETS	0.05	0.03	0.01	0.11	0.01	0.89	0.06	0.78	0.98	0.02
Gold	ETS	-0.05	0.21	-0.40	0.21	0.10	0.41	0.07	0.28	0.51	0.68
	Non-ETS	0.00	0.12	-0.19	0.15	0.06	0.52	0.10	0.37	0.67	0.52
Panel F. CBAM Transitional (1 Oct 2023 - 30 Apr 2026)											
TTF natural gas futures	ETS	-0.01	0.03	-0.06	0.04	0.02	0.90	0.06	0.77	0.97	0.11
	Non-ETS	0.01	0.03	-0.03	0.07	0.04	0.92	0.07	0.79	0.99	0.07
Brent crude oil futures	ETS	0.06	0.06	-0.03	0.18	-0.01	0.83	0.08	0.66	0.95	0.19
	Non-ETS	0.05	0.05	-0.02	0.12	-0.02	0.86	0.08	0.69	0.96	0.19
Gold	ETS	0.02	0.11	-0.16	0.19	0.00	0.55	0.15	0.32	0.85	0.38
	Non-ETS	0.06	0.10	-0.07	0.22	0.00	0.61	0.16	0.34	0.89	0.37

Notes: ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. HR is the mean dynamic hedge ratio. SD, Q5, and Q95 report the standard deviation and the 5th and 95th percentiles of the daily HR (or OW) series within each sub-period. HE$_{HR}$ is the HR-based hedging effectiveness. OW is the mean Kroner-Ng optimal sector weight and HE$_{OW}$ is the OW-based hedging effectiveness. Negative HE$_{OW}$ values indicate that the OW-based portfolio variance exceeds the variance of the unhedged sector portfolio during the period. EUA results for this sector are reported in Section 5.3.

Appendix C

Sub-Period Risk-Adjusted Portfolio Performance

This appendix reports the realized risk-adjusted performance of the hedged and unhedged portfolios across the six sub-periods analyzed in the thesis, complementing the full-sample results presented in Section 5.4. For each sector-asset pair, Tables C.1 to C.6 report the annualized Sharpe and Sortino ratios, annualized volatility, one-day 95% historical Value-at-Risk (VaR), and cumulative maximum drawdown for both the hedged (H) and unhedged (U) portfolios. The variance-reduction column (VarRed) reports the realized variance reduction achieved by the hedge within each sub-period and provides a comparison with the HR- and HE-based results discussed in Section 5.3. The hedged return series is constructed using the time-varying hedge ratios obtained from the full-sample DCC-GARCH(1,1) estimation. Annualized measures are calculated using the $\sqrt{252}$ convention and a zero risk-free rate.

Table C.1: Risk-adjusted performance of hedged (H) and unhedged (U) portfolios during the Phase III Low Price period (1 Jan 2013-31 Dec 2018).

Sector portfolio	**Hedge**	**Sharpe**		**Sortino**		**Vol**		**VaR_{95}**		**MaxDD**		**VarRed**
		H	U	H	U	H	U	H	U	H	U	
Electricity (ETS)	EUA	0.21	0.25	0.023	0.026	0.109	0.111	-0.011	-0.011	0.23	0.26	0.04
	Gas	0.24	0.24	0.025	0.025	0.108	0.110	-0.011	-0.011	0.22	0.26	0.04
	Oil	0.38	0.24	0.037	0.025	0.104	0.110	-0.011	-0.011	0.23	0.26	0.10
	Gold	0.15	0.15	0.017	0.017	0.110	0.110	-0.011	-0.011	0.24	0.25	0.01
Electricity (Non-ETS)	EUA	0.91	0.95	0.087	0.090	0.128	0.128	-0.013	-0.013	0.14	0.14	0.01
	Gas	0.94	0.95	0.090	0.090	0.127	0.128	-0.012	-0.013	0.13	0.14	0.01
	Oil	1.09	0.96	0.103	0.091	0.124	0.128	-0.012	-0.013	0.14	0.15	0.06
	Gold	0.81	0.78	0.078	0.075	0.126	0.126	-0.013	-0.013	0.13	0.14	0.01
Basic Metals (ETS)	EUA	-0.15	-0.12	-0.003	0.001	0.247	0.252	-0.025	-0.026	0.51	0.52	0.04
	Gas	-0.06	-0.08	0.005	0.004	0.248	0.251	-0.025	-0.026	0.49	0.50	0.02
	Coal	-0.11	-0.13	0.001	-0.000	0.250	0.251	-0.026	-0.026	0.51	0.52	0.01
	Gold	-0.18	-0.21	-0.006	-0.008	0.251	0.252	-0.026	-0.026	0.51	0.52	0.01
Basic Metals (Non-ETS)	EUA	0.17	0.21	0.021	0.025	0.139	0.141	-0.015	-0.015	0.39	0.36	0.03
	Gas	0.20	0.23	0.024	0.026	0.139	0.140	-0.015	-0.015	0.38	0.37	0.03
	Coal	0.18	0.21	0.022	0.024	0.140	0.140	-0.015	-0.015	0.37	0.37	0.01
	Gold	0.21	0.19	0.024	0.023	0.140	0.141	-0.015	-0.015	0.36	0.35	0.01
Non-Met. Min. (ETS)	EUA	0.71	0.72	0.067	0.067	0.163	0.165	-0.016	-0.017	0.29	0.28	0.02
	Gas	0.76	0.76	0.070	0.070	0.162	0.164	-0.017	-0.017	0.31	0.28	0.02
	Coal	0.73	0.73	0.068	0.068	0.163	0.164	-0.016	-0.017	0.30	0.30	0.01
	Gold	0.79	0.72	0.073	0.066	0.163	0.164	-0.017	-0.017	0.29	0.29	0.02
Non-Met. Min. (Non-ETS)	EUA	0.39	0.40	0.045	0.045	0.178	0.180	-0.015	-0.015	0.38	0.36	0.01
	Gas	0.39	0.42	0.044	0.046	0.177	0.178	-0.015	-0.015	0.36	0.36	0.01
	Coal	0.42	0.41	0.047	0.046	0.178	0.178	-0.015	-0.015	0.36	0.36	0.00
	Gold	0.32	0.31	0.038	0.037	0.177	0.178	-0.015	-0.015	0.37	0.37	0.02
Chemicals (ETS)	EUA	0.43	0.43	0.043	0.043	0.145	0.147	-0.015	-0.015	0.33	0.30	0.03
	Gas	0.52	0.47	0.050	0.046	0.143	0.146	-0.015	-0.015	0.31	0.30	0.05
	Oil	0.62	0.48	0.059	0.047	0.138	0.146	-0.014	-0.015	0.27	0.30	0.11
	Gold	0.42	0.40	0.042	0.041	0.145	0.147	-0.015	-0.015	0.30	0.30	0.02
Chemicals (Non-ETS)	EUA	0.82	0.78	0.075	0.071	0.123	0.124	-0.012	-0.013	0.22	0.20	0.02
	Gas	0.72	0.78	0.067	0.071	0.122	0.124	-0.012	-0.013	0.21	0.20	0.03
	Oil	0.89	0.80	0.081	0.073	0.118	0.123	-0.012	-0.013	0.18	0.20	0.09
	Gold	0.74	0.71	0.069	0.065	0.123	0.124	-0.012	-0.013	0.21	0.20	0.01

Notes: H = hedged portfolio; U = unhedged sector portfolio. ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. Vol is the annualized standard deviation. VaR_{95} is the one-day 95% historical Value-at-Risk reported as a fraction of portfolio value. MaxDD is the cumulative peak-to-trough maximum drawdown over the sub-period. VarRed is the realized HR-based variance reduction within the sub-period, $1 - \text{Var}(r^H)/\text{Var}(r_s)$. All quantities are computed from the daily realized hedged and unhedged return series, with $\hat{\beta}_t^*$ extracted from the full-sample DCC-GARCH(1,1) conditional covariance matrix.

Table C.2: Risk-adjusted performance of hedged (H) and unhedged (U) portfolios, Post-MSR period (1 Jan 2019-29 Feb 2020).

Sector portfolio	**Hedge**	**Sharpe**		**Sortino**		**Vol**		**VaR$_{95}$**		**MaxDD**		**VarRed**
		H	U	H	U	H	U	H	U	H	U	
Electricity (ETS)	EUA	0.09	0.07	0.016	0.014	0.170	0.171	-0.010	-0.010	0.21	0.20	0.01
	Gas	0.16	0.07	0.022	0.014	0.172	0.170	-0.010	-0.010	0.20	0.20	-0.02
	Oil	0.04	0.07	0.011	0.014	0.168	0.170	-0.010	-0.010	0.19	0.20	0.02
	Gold	-0.04	0.05	0.004	0.012	0.171	0.172	-0.010	-0.010	0.22	0.21	0.01
Electricity (Non-ETS)	EUA	3.04	2.92	0.258	0.244	0.117	0.119	-0.009	-0.010	0.11	0.12	0.03
	Gas	2.88	2.91	0.242	0.244	0.119	0.119	-0.010	-0.010	0.12	0.12	-0.01
	Oil	3.28	2.89	0.284	0.242	0.113	0.118	-0.009	-0.010	0.09	0.12	0.08
	Gold	2.31	2.59	0.195	0.219	0.121	0.119	-0.010	-0.010	0.12	0.12	-0.03
Basic Metals (ETS)	EUA	-0.53	-0.57	-0.038	-0.042	0.273	0.280	-0.030	-0.030	0.37	0.37	0.05
	Gas	-0.46	-0.58	-0.030	-0.042	0.279	0.279	-0.030	-0.030	0.36	0.37	-0.00
	Coal	-0.59	-0.57	-0.043	-0.042	0.279	0.278	-0.031	-0.030	0.37	0.37	-0.00
	Gold	-0.63	-0.64	-0.048	-0.049	0.279	0.281	-0.031	-0.030	0.36	0.37	0.02
Basic Metals (Non-ETS)	EUA	0.08	-0.00	0.013	0.006	0.133	0.136	-0.014	-0.013	0.15	0.15	0.05
	Gas	0.11	0.00	0.015	0.006	0.137	0.136	-0.013	-0.013	0.15	0.15	-0.01
	Coal	0.04	0.00	0.009	0.006	0.136	0.136	-0.013	-0.013	0.15	0.15	-0.00
	Gold	-0.25	-0.25	-0.016	-0.016	0.138	0.136	-0.014	-0.013	0.17	0.16	-0.03
Non-Met. Min. (ETS)	EUA	0.55	0.46	0.051	0.043	0.144	0.148	-0.016	-0.016	0.14	0.15	0.05
	Gas	0.49	0.45	0.046	0.043	0.148	0.147	-0.015	-0.015	0.14	0.15	-0.01
	Coal	0.41	0.45	0.039	0.042	0.147	0.147	-0.015	-0.015	0.15	0.15	-0.01
	Gold	0.38	0.42	0.036	0.040	0.152	0.148	-0.015	-0.016	0.17	0.14	-0.04
Non-Met. Min. (Non-ETS)	EUA	-0.66	-0.69	-0.053	-0.055	0.125	0.126	-0.011	-0.011	0.17	0.18	0.02
	Gas	-0.77	-0.69	-0.062	-0.055	0.125	0.126	-0.011	-0.011	0.18	0.18	0.00
	Coal	-0.74	-0.69	-0.059	-0.055	0.126	0.125	-0.011	-0.011	0.18	0.18	-0.00
	Gold	-0.69	-0.73	-0.054	-0.058	0.127	0.126	-0.011	-0.011	0.16	0.16	-0.01
Chemicals (ETS)	EUA	-0.48	-0.55	-0.035	-0.041	0.169	0.172	-0.017	-0.017	0.26	0.27	0.04
	Gas	-0.48	-0.55	-0.035	-0.041	0.172	0.171	-0.017	-0.017	0.27	0.27	-0.01
	Oil	-0.58	-0.55	-0.044	-0.041	0.163	0.171	-0.017	-0.017	0.24	0.27	0.10
	Gold	-0.53	-0.66	-0.039	-0.051	0.172	0.173	-0.018	-0.017	0.27	0.29	0.01
Chemicals (Non-ETS)	EUA	1.14	0.98	0.095	0.082	0.133	0.136	-0.012	-0.012	0.13	0.14	0.04
	Gas	1.05	0.97	0.088	0.082	0.135	0.135	-0.012	-0.012	0.14	0.14	0.01
	Oil	1.11	0.97	0.094	0.082	0.127	0.135	-0.012	-0.012	0.10	0.14	0.11
	Gold	0.78	0.86	0.066	0.073	0.140	0.136	-0.012	-0.012	0.16	0.14	-0.05

Notes: H = hedged portfolio; U = unhedged sector portfolio. ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. Vol is the annualized standard deviation. VaR$_{95}$ is the one-day 95% historical Value-at-Risk reported as a fraction of portfolio value. MaxDD is the cumulative peak-to-trough maximum drawdown over the sub-period. VarRed is the realized HR-based variance reduction within the sub-period, $1 - \text{Var}(r^H)/\text{Var}(r_s)$. All quantities are computed from the daily realized hedged and unhedged return series, with $\hat{\beta}_t^*$ extracted from the full-sample DCC-GARCH(1,1) conditional covariance matrix.

Table C.3: Risk-adjusted performance of hedged (H) and unhedged (U) portfolios, COVID-19 period (1 Mar 2020-31 Dec 2020).

Sector portfolio	**Hedge**	**Sharpe**		**Sortino**		**Vol**		**VaR$_{95}$**		**MaxDD**		**VarRed**
		H	U	H	U	H	U	H	U	H	U	
Electricity (ETS)	EUA	0.86	0.58	0.073	0.051	0.224	0.240	-0.019	-0.020	0.24	0.26	0.13
	Gas	0.41	0.40	0.040	0.039	0.238	0.239	-0.021	-0.019	0.26	0.26	0.01
	Oil	1.02	0.48	0.085	0.045	0.210	0.239	-0.018	-0.019	0.19	0.26	0.23
	Gold	0.34	0.32	0.035	0.034	0.235	0.240	-0.020	-0.020	0.24	0.26	0.04
Electricity (Non-ETS)	EUA	1.90	1.41	0.139	0.104	0.231	0.247	-0.018	-0.019	0.25	0.28	0.13
	Gas	1.31	1.25	0.099	0.095	0.243	0.244	-0.019	-0.019	0.27	0.28	0.01
	Oil	2.42	1.36	0.173	0.102	0.219	0.245	-0.015	-0.019	0.18	0.28	0.20
	Gold	1.28	1.13	0.100	0.088	0.244	0.246	-0.018	-0.019	0.25	0.28	0.01
Basic Metals (ETS)	EUA	0.69	0.74	0.069	0.073	0.394	0.435	-0.036	-0.037	0.35	0.38	0.18
	Gas	0.73	0.57	0.073	0.062	0.428	0.434	-0.035	-0.037	0.38	0.38	0.02
	Coal	0.69	0.61	0.071	0.065	0.433	0.433	-0.038	-0.037	0.40	0.38	-0.00
	Gold	0.63	0.63	0.067	0.066	0.432	0.436	-0.039	-0.037	0.35	0.38	0.02
Basic Metals (Non-ETS)	EUA	0.95	0.66	0.084	0.062	0.282	0.312	-0.026	-0.029	0.26	0.35	0.18
	Gas	0.70	0.51	0.066	0.052	0.306	0.312	-0.028	-0.029	0.33	0.35	0.04
	Coal	0.49	0.54	0.051	0.054	0.313	0.311	-0.029	-0.029	0.36	0.35	-0.01
	Gold	0.61	0.55	0.060	0.055	0.314	0.314	-0.029	-0.029	0.34	0.35	-0.00
Non-Met. Min. (ETS)	EUA	0.79	0.55	0.070	0.052	0.249	0.288	-0.023	-0.027	0.22	0.30	0.25
	Gas	0.63	0.37	0.058	0.040	0.280	0.286	-0.024	-0.027	0.29	0.30	0.04
	Coal	0.41	0.40	0.042	0.042	0.287	0.286	-0.026	-0.027	0.31	0.30	-0.01
	Gold	0.31	0.29	0.036	0.033	0.286	0.287	-0.026	-0.027	0.29	0.30	0.00
Non-Met. Min. (Non-ETS)	EUA	2.48	2.02	0.191	0.152	0.248	0.266	-0.020	-0.022	0.21	0.26	0.13
	Gas	1.89	1.73	0.147	0.135	0.264	0.264	-0.023	-0.022	0.26	0.26	0.00
	Coal	1.94	1.86	0.147	0.143	0.264	0.264	-0.022	-0.022	0.27	0.26	0.00
	Gold	1.66	1.68	0.132	0.132	0.260	0.266	-0.023	-0.022	0.24	0.26	0.05
Chemicals (ETS)	EUA	0.77	0.64	0.071	0.060	0.285	0.309	-0.025	-0.027	0.25	0.30	0.15
	Gas	0.79	0.58	0.071	0.056	0.304	0.307	-0.028	-0.027	0.30	0.30	0.02
	Oil	1.21	0.61	0.105	0.058	0.276	0.307	-0.026	-0.027	0.19	0.30	0.20
	Gold	0.55	0.55	0.054	0.054	0.305	0.309	-0.027	-0.027	0.27	0.30	0.03
Chemicals (Non-ETS)	EUA	3.23	2.53	0.209	0.164	0.258	0.288	-0.023	-0.025	0.20	0.25	0.20
	Gas	3.07	2.64	0.193	0.170	0.282	0.287	-0.024	-0.025	0.24	0.25	0.04
	Oil	3.95	2.69	0.245	0.172	0.258	0.287	-0.021	-0.025	0.15	0.25	0.19
	Gold	2.48	2.55	0.166	0.166	0.288	0.289	-0.025	-0.025	0.25	0.25	0.01

Notes: H = hedged portfolio; U = unhedged sector portfolio. ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. Vol is the annualized standard deviation. VaR$_{95}$ is the one-day 95% historical Value-at-Risk reported as a fraction of portfolio value. MaxDD is the cumulative peak-to-trough maximum drawdown over the sub-period. VarRed is the realized HR-based variance reduction within the sub-period, $1 - \mathrm{Var}(r^H)/\mathrm{Var}(r_s)$. All quantities are computed from the daily realized hedged and unhedged return series, with $\hat{\beta}_t^*$ extracted from the full-sample DCC-GARCH(1,1) conditional covariance matrix.

Table C.4: Risk-adjusted performance of hedged (H) and unhedged (U) portfolios, Phase IV High Price period (1 Jan 2021-31 Dec 2022).

Sector portfolio	**Hedge**	**Sharpe**		**Sortino**		**Vol**		**VaR$_{95}$**		**MaxDD**		**VarRed**
		H	U	H	U	H	U	H	U	H	U	
Electricity (ETS)	EUA	0.25	0.42	0.028	0.043	0.139	0.141	-0.015	-0.015	0.21	0.21	0.04
	Gas	0.35	0.40	0.036	0.041	0.140	0.141	-0.015	-0.015	0.22	0.22	0.02
	Oil	0.20	0.42	0.024	0.043	0.140	0.141	-0.015	-0.015	0.24	0.21	0.01
	Gold	0.54	0.47	0.053	0.047	0.140	0.142	-0.015	-0.015	0.21	0.21	0.02
Electricity (Non-ETS)	EUA	-0.74	-0.55	-0.060	-0.043	0.144	0.147	-0.016	-0.015	0.28	0.25	0.03
	Gas	-0.63	-0.63	-0.050	-0.050	0.146	0.146	-0.016	-0.015	0.27	0.27	0.01
	Oil	-0.73	-0.55	-0.059	-0.043	0.144	0.146	-0.015	-0.015	0.30	0.25	0.03
	Gold	-0.56	-0.62	-0.044	-0.049	0.146	0.147	-0.015	-0.015	0.25	0.26	0.00
Basic Metals (ETS)	EUA	0.14	0.41	0.024	0.047	0.294	0.298	-0.031	-0.031	0.38	0.38	0.02
	Gas	0.28	0.37	0.036	0.043	0.295	0.298	-0.030	-0.031	0.36	0.38	0.02
	Coal	0.41	0.41	0.047	0.046	0.299	0.297	-0.031	-0.031	0.40	0.38	-0.02
	Gold	0.33	0.31	0.040	0.039	0.297	0.298	-0.031	-0.031	0.38	0.38	0.01
Basic Metals (Non-ETS)	EUA	0.28	0.52	0.031	0.051	0.181	0.186	-0.019	-0.020	0.28	0.29	0.04
	Gas	0.32	0.48	0.035	0.047	0.181	0.185	-0.020	-0.020	0.29	0.29	0.04
	Coal	0.54	0.53	0.053	0.051	0.189	0.185	-0.021	-0.020	0.30	0.29	-0.04
	Gold	0.65	0.56	0.061	0.054	0.184	0.186	-0.021	-0.020	0.28	0.28	0.03
Non-Met. Min. (ETS)	EUA	-0.25	-0.07	-0.014	0.003	0.191	0.195	-0.021	-0.021	0.40	0.40	0.04
	Gas	-0.20	-0.14	-0.010	-0.004	0.185	0.195	-0.021	-0.021	0.40	0.41	0.10
	Coal	-0.07	-0.07	0.002	0.002	0.194	0.195	-0.021	-0.021	0.39	0.40	0.00
	Gold	-0.03	-0.08	0.006	0.001	0.186	0.194	-0.020	-0.021	0.35	0.37	0.08
Non-Met. Min. (Non-ETS)	EUA	-0.88	-0.75	-0.070	-0.058	0.169	0.172	-0.020	-0.020	0.47	0.48	0.03
	Gas	-0.81	-0.86	-0.063	-0.067	0.168	0.171	-0.020	-0.020	0.49	0.50	0.03
	Coal	-0.66	-0.75	-0.051	-0.058	0.172	0.171	-0.020	-0.020	0.46	0.48	-0.01
	Gold	-0.64	-0.65	-0.048	-0.049	0.167	0.170	-0.019	-0.020	0.45	0.45	0.04
Chemicals (ETS)	EUA	-0.13	0.11	-0.003	0.017	0.180	0.185	-0.020	-0.020	0.25	0.25	0.05
	Gas	-0.02	0.04	0.006	0.011	0.177	0.185	-0.020	-0.020	0.26	0.27	0.08
	Oil	-0.16	0.09	-0.006	0.016	0.178	0.184	-0.020	-0.020	0.30	0.26	0.06
	Gold	0.13	0.02	0.018	0.010	0.177	0.185	-0.019	-0.020	0.21	0.24	0.08
Chemicals (Non-ETS)	EUA	-0.43	-0.25	-0.031	-0.014	0.172	0.175	-0.020	-0.019	0.38	0.38	0.04
	Gas	-0.37	-0.34	-0.025	-0.022	0.170	0.175	-0.019	-0.019	0.40	0.40	0.05
	Oil	-0.45	-0.25	-0.032	-0.014	0.171	0.175	-0.019	-0.019	0.41	0.38	0.04
	Gold	-0.28	-0.35	-0.017	-0.023	0.168	0.174	-0.019	-0.019	0.35	0.37	0.06

Notes: H = hedged portfolio; U = unhedged sector portfolio. ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. Vol is the annualized standard deviation. VaR$_{95}$ is the one-day 95% historical Value-at-Risk reported as a fraction of portfolio value. MaxDD is the cumulative peak-to-trough maximum drawdown over the sub-period. VarRed is the realized HR-based variance reduction within the sub-period, $1 - \mathrm{Var}(r^H)/\mathrm{Var}(r_s)$. All quantities are computed from the daily realized hedged and unhedged return series, with $\hat{\beta}_t^*$ extracted from the full-sample DCC-GARCH(1,1) conditional covariance matrix.

Table C.5: Risk-adjusted performance of hedged (H) and unhedged (U) portfolios, Phase IV Normalization period (1 Jan 2023-30 Sep 2023).

Sector portfolio	**Hedge**	**Sharpe**		**Sortino**		**Vol**		**VaR_{95}**		**MaxDD**		**VarRed**
		H	U	H	U	H	U	H	U	H	U	
Electricity (ETS)	EUA	0.14	0.09	0.018	0.013	0.109	0.110	-0.012	-0.012	0.07	0.08	0.02
	Gas	-0.39	-0.30	-0.030	-0.022	0.108	0.108	-0.012	-0.012	0.09	0.08	-0.01
	Oil	-0.21	-0.13	-0.014	-0.007	0.107	0.108	-0.012	-0.012	0.09	0.08	0.03
	Gold	0.00	-0.05	0.005	0.001	0.108	0.110	-0.011	-0.012	0.07	0.08	0.03
Electricity (Non-ETS)	EUA	-0.77	-0.82	-0.063	-0.067	0.105	0.105	-0.011	-0.011	0.15	0.15	0.01
	Gas	-0.97	-1.00	-0.080	-0.082	0.104	0.103	-0.011	-0.011	0.14	0.14	-0.01
	Oil	-1.22	-1.05	-0.103	-0.087	0.099	0.103	-0.009	-0.011	0.16	0.15	0.07
	Gold	-0.99	-0.99	-0.081	-0.082	0.102	0.103	-0.011	-0.011	0.13	0.14	0.03
Basic Metals (ETS)	EUA	-0.32	-0.33	-0.018	-0.019	0.228	0.231	-0.024	-0.024	0.25	0.25	0.02
	Gas	-0.55	-0.53	-0.039	-0.037	0.230	0.230	-0.024	-0.024	0.27	0.26	-0.00
	Coal	-0.46	-0.46	-0.030	-0.031	0.231	0.229	-0.024	-0.024	0.25	0.25	-0.01
	Gold	-0.41	-0.42	-0.026	-0.027	0.227	0.231	-0.023	-0.024	0.23	0.23	0.04
Basic Metals (Non-ETS)	EUA	1.67	1.65	0.146	0.144	0.141	0.141	-0.012	-0.012	0.14	0.14	-0.00
	Gas	1.43	1.43	0.126	0.125	0.141	0.140	-0.012	-0.012	0.14	0.14	-0.02
	Coal	1.12	1.43	0.100	0.126	0.141	0.139	-0.012	-0.012	0.15	0.14	-0.03
	Gold	1.32	1.22	0.119	0.108	0.138	0.140	-0.012	-0.012	0.15	0.14	0.03
Non-Met. Min. (ETS)	EUA	1.81	1.74	0.158	0.150	0.140	0.139	-0.014	-0.014	0.09	0.09	-0.01
	Gas	1.39	1.57	0.121	0.137	0.139	0.139	-0.014	-0.014	0.09	0.09	-0.00
	Coal	1.20	1.57	0.107	0.137	0.140	0.138	-0.014	-0.014	0.09	0.09	-0.03
	Gold	1.97	1.70	0.169	0.146	0.133	0.139	-0.013	-0.014	0.09	0.09	0.08
Non-Met. Min. (Non-ETS)	EUA	-0.13	-0.18	-0.005	-0.010	0.142	0.142	-0.014	-0.014	0.19	0.20	-0.00
	Gas	-0.20	-0.24	-0.012	-0.015	0.143	0.142	-0.014	-0.014	0.20	0.20	-0.01
	Coal	-0.12	-0.26	-0.004	-0.017	0.141	0.141	-0.014	-0.014	0.18	0.20	-0.00
	Gold	-0.41	-0.48	-0.032	-0.038	0.138	0.138	-0.014	-0.014	0.18	0.19	0.01
Chemicals (ETS)	EUA	-1.36	-1.38	-0.116	-0.118	0.155	0.156	-0.017	-0.017	0.26	0.27	0.01
	Gas	-1.61	-1.58	-0.139	-0.136	0.155	0.154	-0.017	-0.017	0.27	0.27	-0.01
	Oil	-1.76	-1.57	-0.153	-0.135	0.148	0.153	-0.017	-0.017	0.29	0.27	0.05
	Gold	-1.64	-1.62	-0.141	-0.140	0.146	0.154	-0.017	-0.017	0.26	0.26	0.10
Chemicals (Non-ETS)	EUA	-1.28	-1.35	-0.110	-0.115	0.118	0.118	-0.013	-0.013	0.19	0.19	-0.01
	Gas	-1.61	-1.63	-0.137	-0.139	0.116	0.115	-0.013	-0.013	0.20	0.20	-0.01
	Oil	-1.72	-1.58	-0.147	-0.134	0.114	0.114	-0.013	-0.013	0.21	0.19	0.01
	Gold	-1.53	-1.53	-0.131	-0.130	0.111	0.114	-0.012	-0.013	0.17	0.18	0.06

Notes: H = hedged portfolio; U = unhedged sector portfolio. ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. Vol is the annualized standard deviation. VaR_{95} is the one-day 95% historical Value-at-Risk reported as a fraction of portfolio value. MaxDD is the cumulative peak-to-trough maximum drawdown over the sub-period. VarRed is the realized HR-based variance reduction within the sub-period, $1 - \mathrm{Var}(r^H)/\mathrm{Var}(r_s)$. All quantities are computed from the daily realized hedged and unhedged return series, with $\hat{\beta}_t^*$ extracted from the full-sample DCC-GARCH(1,1) conditional covariance matrix.

Table C.6: Risk-adjusted performance of hedged (H) and unhedged (U) portfolios, CBAM Transitional period (1 Oct 2023-30 Apr 2026).

Sector portfolio	**Hedge**	**Sharpe**		**Sortino**		**Vol**		**VaR$_{95}$**		**MaxDD**		**VarRed**
		H	U	H	U	H	U	H	U	H	U	
Electricity (ETS)	EUA	0.81	0.77	0.071	0.066	0.114	0.115	-0.010	-0.011	0.11	0.12	0.03
	Gas	0.76	0.77	0.066	0.067	0.114	0.115	-0.011	-0.011	0.12	0.12	0.02
	Oil	0.75	0.77	0.065	0.067	0.115	0.114	-0.011	-0.011	0.12	0.12	-0.02
	Gold	0.62	0.71	0.055	0.062	0.115	0.115	-0.010	-0.011	0.14	0.14	0.01
Electricity (Non-ETS)	EUA	0.59	0.59	0.057	0.056	0.113	0.114	-0.010	-0.010	0.12	0.12	0.02
	Gas	0.54	0.54	0.052	0.052	0.113	0.113	-0.010	-0.010	0.13	0.12	0.00
	Oil	0.63	0.59	0.060	0.056	0.114	0.113	-0.010	-0.010	0.12	0.12	-0.03
	Gold	0.33	0.46	0.033	0.045	0.112	0.112	-0.010	-0.010	0.13	0.11	0.01
Basic Metals (ETS)	EUA	1.02	0.96	0.096	0.091	0.224	0.229	-0.021	-0.021	0.22	0.24	0.04
	Gas	1.02	0.98	0.095	0.092	0.226	0.228	-0.021	-0.021	0.24	0.24	0.02
	Coal	0.96	0.96	0.090	0.091	0.226	0.228	-0.021	-0.020	0.24	0.24	0.01
	Gold	0.73	0.91	0.073	0.086	0.226	0.229	-0.021	-0.021	0.28	0.24	0.03
Basic Metals (Non-ETS)	EUA	0.32	0.29	0.037	0.035	0.158	0.161	-0.013	-0.014	0.17	0.18	0.03
	Gas	0.36	0.31	0.041	0.037	0.157	0.160	-0.013	-0.014	0.18	0.18	0.04
	Coal	0.27	0.30	0.033	0.035	0.159	0.160	-0.014	-0.014	0.17	0.18	0.01
	Gold	0.10	0.19	0.017	0.026	0.160	0.161	-0.014	-0.014	0.20	0.19	0.01
Non-Met. Min. (ETS)	EUA	0.19	0.19	0.026	0.025	0.169	0.172	-0.016	-0.016	0.20	0.20	0.03
	Gas	0.18	0.22	0.024	0.028	0.167	0.172	-0.016	-0.016	0.20	0.20	0.05
	Coal	0.17	0.20	0.023	0.026	0.169	0.171	-0.016	-0.016	0.20	0.20	0.02
	Gold	0.22	0.21	0.028	0.027	0.172	0.172	-0.017	-0.016	0.19	0.19	0.00
Non-Met. Min. (Non-ETS)	EUA	1.02	1.04	0.102	0.103	0.167	0.169	-0.015	-0.015	0.15	0.16	0.01
	Gas	0.87	0.85	0.088	0.086	0.170	0.171	-0.015	-0.016	0.16	0.16	0.01
	Coal	0.85	0.86	0.085	0.086	0.170	0.170	-0.015	-0.016	0.16	0.16	0.00
	Gold	0.91	0.88	0.089	0.088	0.170	0.171	-0.015	-0.016	0.16	0.16	0.02
Chemicals (ETS)	EUA	-0.33	-0.36	-0.023	-0.025	0.157	0.159	-0.016	-0.017	0.26	0.26	0.03
	Gas	-0.37	-0.33	-0.026	-0.023	0.157	0.159	-0.016	-0.016	0.26	0.26	0.02
	Oil	-0.26	-0.34	-0.016	-0.024	0.159	0.158	-0.017	-0.016	0.25	0.26	-0.01
	Gold	-0.41	-0.36	-0.030	-0.025	0.159	0.159	-0.016	-0.016	0.30	0.29	-0.00
Chemicals (Non-ETS)	EUA	-0.36	-0.35	-0.026	-0.026	0.146	0.150	-0.015	-0.014	0.24	0.25	0.05
	Gas	-0.38	-0.36	-0.029	-0.027	0.146	0.149	-0.014	-0.014	0.25	0.25	0.04
	Oil	-0.28	-0.32	-0.019	-0.023	0.151	0.149	-0.015	-0.014	0.25	0.25	-0.02
	Gold	-0.39	-0.27	-0.030	-0.018	0.149	0.150	-0.014	-0.014	0.28	0.25	0.00

Notes: H = hedged portfolio; U = unhedged sector portfolio. ETS denotes EU ETS-regulated portfolios; Non-ETS denotes non-EU ETS-regulated portfolios. Vol is the annualized standard deviation. VaR$_{95}$ is the one-day 95% historical Value-at-Risk reported as a fraction of portfolio value. MaxDD is the cumulative peak-to-trough maximum drawdown over the sub-period. VarRed is the realized HR-based variance reduction within the sub-period, $1 - \mathrm{Var}(r^H)/\mathrm{Var}(r_s)$. All quantities are computed from the daily realized hedged and unhedged return series, with $\hat{\beta}_t^*$ extracted from the full-sample DCC-GARCH(1,1) conditional covariance matrix.

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