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The Impact of Emissions on Stock Returns: A Multi-Factor Model Approach and Hedging with EUA Futures

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Abstract

This study investigates the co-movements of European stock returns, EU Allowances (EUA's) and carbon price intensity factors based on weekly data from 2018-2023. For this investigation we use a multi-factor model to analyze the relationship. In addition, the paper presents an analysis of cross-hedging carbon risk in European equity portfolios using EUA futures. Hedging ratios are found by using an OLS estimator and a DCC-GARCH model. To evaluate the effect from the hedge ratios they are tested out-of-samples using rolling windows. Our results from the multi-factor analysis show that there is a positive and significant relationship between stock returns, EUA returns and the carbon price intensity factors for free, scope 2 and hedged emissions. Furthermore, the carbon price intensity reflecting firms' paid emissions have a negative and significant relationship with stock returns. The results from analyzing hedging strategies find a short position in the EUA futures to be appropriate for variance reduction. The realized hedging effectiveness from the two approaches yields a positive result using the OLS approach and a negative result using the DCC approach. Furthermore, one out of the four hedged portfolios with OLS-based hedge ratios see an increase in annualized return, while all the hedged portfolios with the DCC-based hedge ratios see an increase in annualized return.

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Abbreviations

CBAM	Carbon Border Adjustment Mechanism
CER	Certified Emission Reduction
CI	Carbon Price Intensity
CO2e	Carbon dioxide equivalents
DCC-GARCH	Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity
DG CLIMA	The Directorate-General for Climate Action
ES	Eurostoxx
EU ETS	European Union Emission Trading System
EUA	European Union Allowance
EUTL	European Union Transaction Log
EW	Equally Weighted
EWMA	Exponentially Weighted Moving Average
GHG	Greenhouse gas
HE	Hedging effectiveness
HR	Hedge ratios
LSEG	London Stock Exchange Group
MLE	Maximum Likelihood Estimation
MM	Multi-factor model
MSR	Market Stability Reserve
N2O	Nitrous oxide
OHR	Optimal Hedging Ratio
OLS	Ordinary Least Squares
PFC	Perfluorocarbons
QML	Quasi-Maximum Likelihood
RHE	Realized Hedging Effectiveness
tCO2e	Tons of carbon dioxide equivalents
CBAM	Carbon Border Adjustment Mechanism

1 Introduction

A substantial body of asset pricing literature investigates the variability in stock returns by examining their connections to overarching risk factors. In recent years, CO_2 emissions have emerged as an increasingly important and studied risk factor. Several studies have found that there is an added carbon risk premium in stock prices for carbon-intensive firms (Bolton & Kacperczyk, 2021; Monasterolo & de Angelis, 2020; Trinks et al., 2022; Witkowski et al., 2021). Other studies have focused on analyzing co-movements with the objective of measuring the impact of changes in carbon price on stock performance (Millischer et al., 2023; Tian et al., 2016).

Intensified regulatory initiatives to reduce CO_2 emissions have raised questions about the risk this represents for investors. In this study we ask whether we can establish a relationship between the price of EU Allowances (EUA) and European stocks participating in the EU emission trading system (ETS). To test this, we use the method proposed by Millischer et al. (2023) where they investigate the effect from EUAs and carbon price intensities on stock returns. Building on their work, which differentiates between paid and free carbon price intensity, we further explore the effects of hedged, banked, and scope 2 carbon price intensities. To the best of our knowledge, this extended analysis represents a new contribution to the research on carbon price risk. Stock co-movements with carbon prices has consequences not only for energy-intensive companies but also for portfolio managers.

Carbon risk introduces a new type of risk when assessing the long-term sustainability and profitability of investments. Given this context, our objective is to investigate whether hedging can effectively mitigate the risk associated with carbon prices. Different strategies for reducing carbon risk have been studied. Some approaches focus on asset allocation within equity portfolios, and select stocks based on characteristics (Andersson et al., 2016; Engle et al., 2020).

Another strategy for reducing carbon risk in equity portfolios, is to incorporate EUA futures as an asset (Ahmad et al., 2018; Demiralay et al., 2022). This solution of internalizing the carbon cost is a proposed strategy from the Norwegian insurer Gjensidige.[1] Using EUA futures as a hedging instrument to reduce carbon risk in equity portfolios is a form of cross-hedging. The use of EUA futures has emerged because there are trade-offs between emissions and essential goods and services. The approach allows investors to punish

[1] Case study: Gjensidige applies basic economics to net-zero :: Insurance Asset Risk

carbon intensive firms by increasing their cost of equity while also having the opportunity to retain quality assets in their investment universe (Huck, 2023).

In this study we want to test if EUA futures can be used to hedge carbon risk in European equity portfolios. We find hedge ratios using an ordinary least squared (OLS) estimator and a Dynamic Conditional Correlation (DCC) model to test the ratios out-of-sample and evaluate hedging effectiveness. This approach is inspired by Ahmad et al. (2018). The focus in their study is to hedge market risk in a clean energy index with a variety of hedge instruments, one of them being EUA futures contracts. In this study we want to hedge carbon risk in energy-intensive stock portfolios covered by the EU ETS only using EUA futures as the hedging instrument.

An EU Allowance (EUA) is a contract that give the right to emit one ton of CO_2-equivalents under the EU ETS. There are various types of EUA contracts, including spot, futures and options (EEX, 2020). EUA futures, which is the product type we will focus on in this study, are traded across multiple exchanges. The major exchanges are the European Energy Exchange (EEX) and Intercontinental Exchange (ICE).

Investments in energy-intensive sectors can potentially carry an increased risk due to regulatory changes and shifts in market demand towards low-carbon alternatives. Consequently, investors may face heightened volatility in these sectors, which demands a more cautious approach and possibly a re-evaluation of their strategies to include risk-mitigating options. Our study aims to investigate the risk factors associated with increased regulation on carbon emissions. By analyzing the relationship between stock returns and variables related to carbon risk we can use the findings in the context of hedging. To our knowledge, the combination of these two topics has not been explored as we present in this study.

1.1 Research questions and hypotheses

To investigate the above-mentioned relationships, the analysis is separated into two main parts. In the first part we aim to investigate how the EUA returns and carbon price intensity of firms influence risk within European stock portfolios. In the second part, we seek to test the efficacy of hedging strategies, specifically through EUA futures in mitigating carbon price risk and minimizing portfolio variance.

Our first research question is: how does the return on EUA futures and carbon price intensity factors impact stock returns in the European stock market? Accordingly, the hypotheses have been defined as:

- Null hypothesis: There is no significant relationship between stock returns, the return on EUA futures or the carbon price intensity factors.
- Alternative hypothesis 1: There is a significant relationship between stock returns, the return on EUA futures and/or the carbon price intensity factors.

The second research question is: Does implementing a hedge strategy with EUA futures effectively reduce the variance in European, energy-intensive stock portfolios? The hypotheses to be tested are framed as:

- Null hypothesis: Implementing a hedge strategy using EUA futures does not reduce the variance of the stock portfolios.
- Alternative hypothesis 1: Implementing a hedge strategy using EUA futures as a hedging instrument will reduce portfolio variance and result in a positive realized hedging effectiveness.

In the subsequent chapters, we provide an examination of the EU ETS and concepts associated with carbon risk. Chapter 3 presents a review of the existing literature on carbon risk in stock markets and the outcomes of managing carbon price risk through hedging strategies. This is followed by Chapter 4 which delves into theoretical frameworks relating to risk and risk management within stock markets. Chapter 5 outlines the methodology used for the regression analyses and implementing hedging models. Chapter 6 presents the dataset used in this study alongside stylized facts to provide context for our analysis. In Chapter 7, we report the findings from our regression analyses and hedging strategies. Subsequent discussions in Chapter 8 explore the implications of these results and discuss the limitations of our analysis. The study concludes in Chapter 9, where we summarize our key findings.

2 Background

Systematic risks in financial markets capture a broad spectrum of economic, political, and market factors that impact investment portfolios, industries, and economies globally. One such increasingly recognized risk is related to climate change and the regulatory responses aimed at mitigating its effects. In this setting, regulation on greenhouse gas (GHG) emissions stands out as an example of how environmental policies are impacting financial markets and investments. Governments worldwide are implementing a variety of policies designed to reduce GHG emissions. These policies are directly affecting industries and, consequently, investments tied to these.

Reducing GHG emissions is critical to prevent irreversible changes to nature and climate. The term "social cost of carbon" (SCC) describes the external expense from carbon emissions and is a foundation for regulating and reducing emissions (Pindyck, 2013). The aim of the SCC is to quantify the marginal cost of one additional unit of carbon emissions and thus enable the integration of this cost into climate policies. In alignment with the temperature targets from the Paris Agreement, the EU has made their climate goals legally binding through the European Climate Law. The law aims to cut GHG emissions by 55 percent within 2030 and achieve net zero by 2050 (European Parliament, 2019). The EU emission trading system (ETS) is a crucial part of the binding policies.

The underlying principle of carbon pricing is that the market will seek out cost-effective strategies to reduce emissions. In a carbon tax system, reductions are incentivized up to the level where the cost of reductions exceeds the tax level. Conversely, in an ETS where there is a cap on emissions, the market price of allowances determines the threshold to which reductions are justified (Gillingham & Stock, 2018; Martin et al., 2016). The increased financial burden particularly impacts energy-intensive firms, and through this increased cost it introduces a carbon price risk.

As of 2023, 5 percent of global GHG emissions were covered by a carbon tax and 18 percent were covered by an emission trading initiative (The World Bank, 2024). The EU ETS is the world's second largest[2] cap-and-trade system for emissions. It covers about 36 percent of emissions within in the EU (European Commission, 2022b, p. 4) and covers all member states, in addition to Northern Ireland, Iceland, Liechtenstein and Norway (European Commission, n.d.-b). In the following section, we will delve into the historical context and purpose of the EU ETS.

2.1 The EU ETS

The ETS is a centerpiece in EU climate policy and is an important tool for the EU member states to reach their goal of climate neutrality by 2050 (European Commission, 2023a). The system covers three types of direct GHG emissions: CO_2, N_2O and PFCs and emissions from factories, power plants, and industrial installations. The firms covered by the EU ETS are producers of electricity and heat, cement, iron and steel, oil refining, aviation within the EU,

[2] The Chinese ETS is the world's largest and covers 4.5 Gt CO_2
[Executive summary – Enhancing China's ETS for Carbon Neutrality: Focus on Power Sector – Analysis - IEA]

and other energy intensive industries like aluminum, paper, and glass production (European Commission, n.d.-b). These companies are generally categorized as being in the utility, energy, industrial and materials sectors.

One EUA offers the right to emit one ton of CO_2e and every year firms are required to give up enough allowances to account for their European based emissions. The emission cap, expressed in emission allowances, is reduced on a yearly basis to incentivize a gradual reduction in emissions (European Commission, 2023b). The cap is pre-determined to be in line with EU climate goals and will progress according to a reduction plan. The reduction plan follows a *linear reduction factor*, and it is independent of unanticipated market outcomes such as economic shocks or advancements in low-carbon technology (European Commission, Directorate-General for Climate Action, 2021). In the European carbon market, market participants can buy, receive, and trade emission allowances on the common trading platform EEX. In 2022, the total auction volume amounted to 398 million, which resulted in € 31.696 million in revenue (EEX, 2023, p. 8). For participants with an excess of allowances, they can *bank* or sell the surplus. Furthermore, firms can also trade EUAs in the secondary market as futures (EEX, 2024; European Commission, 2023b).

Since the beginning of the EU ETS, a large portion of allowances have been allocated for free. In the ETS's trial period (2005-2007), 95 percent of allowances were distributed to firms for free, and in the second phase (2008-2012), 90 percent were allocated for free (Ellerman et al., 2015). The different sectors exposure to international competition has been emphasized when deciding the degree of free distribution. The utility sector is an example from which free allocation largely ended in 2013. This is because it is almost not subject to direct international competition, and therefore has not received as much free allocation as other sectors (Balcilar et al., 2016). In contrast, reduction for the non-electric industrial sectors have been more gradual; the gradual reduction is due to the exposure to international competition and the risk of carbon leakage (Ellerman et al., 2015). As an alternative to free allocation of allowances EU will initiate a Carbon Border Adjustment Mechanism (CBAM) in 2026 that gradually will replace free allocation. This regulation aims to limit carbon leakage by evening out price differences between EU ETS compliant firms exposed to international competition and foreign firms who are not subject to similar carbon pricing regimes (EPRS, 2023).

During the second phase of the ETS, a surplus of allowances had started to accumulate. This was primarily due to the global financial crisis which led to a downturn in the EU's economic activity, subsequently reducing carbon emissions and causing a notable decrease in the carbon price (European Commission, 2022a). The development of EUA prices can be seen in Figure 1.

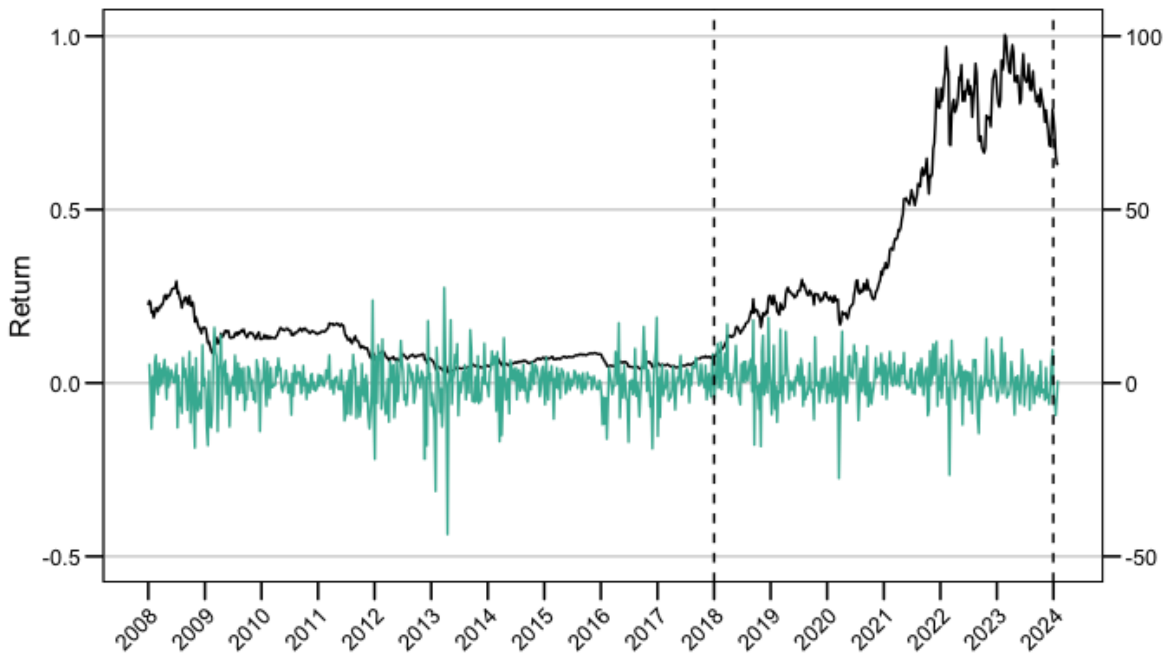

Figure 1. Illustration of the EUA price development (black, right axis) and log returns (green, left axis) from 2008-2024. The vertical, dashed lines mark the period included in the dataset for our analysis.

The third phase (2013-2020) was the first period in which auctioning, and not free allocation was the default for distributing allowances. Now there were no national caps, but a system-wide cap and an annual reduction factor of 1.74 percent. In this period, allocation rules were also harmonized for the quotas that were still allocated for free (European Commission, n.d.-a). In 2013 the surplus amounted to 2.1 billion allowances. Due to a short-term solution of back-loading allowances the surplus was reduced to 1.8 billion by 2015. Finding a permanent solution to the over-accumulation was important since the surplus undermined the function of the carbon market (European Commission, 2022a).

In the long term, the surplus of emission allowances could jeopardize emission reduction goals. This is because the low price would not effectively underpin the cost-efficient approach to emission reduction that a cap-and-trade system is intended to facilitate. The long-term solution to the allocation surplus has been the Market Stability Reserve (MSR). In addition to address the surplus, the reserve improves the ETS' flexibility to shocks by providing a mechanism for regulating the supply of allowances auctioned (European Commission, 2022a). The MSR begun operating in 2019 based exclusively on pre-established guidelines. The MSR distributes allowances from the reserve during periods of undersupply, and during periods of excess it absorbs allowances into the reserve and subsequently cancels them, depending on the total amount of allowances in circulation (European Commission, Directorate-General for Climate Action, 2021).

For the fourth phase of the system (2021-2030) the annual reduction factor has been raised from 1.74 percent to 2.2 percent (Directorate-General for Climate Action, 2020). Additionally, this phase will see the introduction of the CBAM, as a measure to reduce carbon leakage particularly from the sectors that will no longer be receiving free allocation (European Commission, 2023a). By the end of the phase, the EU ETS has hopefully made an impactful contribution toward reaching the milestone of a 55 percent reduction by 2030.

2.2 Carbon risk and asset pricing

With increasing climate policy, it becomes relevant to consider carbon risk as a new factor impacting firms' risk-premiums. Carbon risk can be referred to as a *transition risk*, which is the risk associated with the transition from a carbon dependent to a carbon-neutral society. This is to be distinguished from *physical risk*, which refers to the risk physical assets face due to climate change. This is a different type of risk, that we do not cover in this study. Transition risk, however, is a risk that materializes through increased financial, legal, and reputational risks associated with difficulty adapting to decarbonization. Trinks et al. (2022) refer to carbon risk as "the uncertain firm-level impacts of future regulatory and market actions that address the physical climate risks". A firms GHG emissions play a role in assessing the transition risk.

Within standardized reporting practices, GHG emissions have distinct classifications based on their connection with the reporting entity. The term "scope 1" is used for emissions from sources within the direct ownership or control of the entity. Conversely, "scope 2" represents indirect emissions resultant from the entity's purchase of electricity. All other indirect GHG emissions, upstream and downstream in the supply chain, are classified under "scope 3", which is an optional reporting category (The Greenhouse Gas Protocol, 2015, p. 25). To compare firms' GHG emissions, intensity ratios are commonly used. Intensity ratios often represent emissions per unit of economic output or value (The Greenhouse Gas Protocol, 2015, p. 67).

When discussing intensity ratios in this study we will refer to the ratios as the *carbon intensities*; carbon *price* intensity is the ratio we mainly will focus on. Carbon price intensity (CI) aims to reflect the firms carbon intensity multiplied by the price of EUAs and includes allowances allocated for free and allowances paid for by the firms. The goal of this metric is to illustrate the firms' cost associated with their EU ETS compliant scope 1 emissions normalized by revenue. This will be discussed further in chapter 5.1.1.1. Within the framework of the EU ETS, only scope 1 emissions are regulated and thus directly affected by the carbon price. However, because the scope 1 emissions from e.g. companies in the utility sector are affected by the carbon price, there can be secondary price effect on other sectors scope 2 emissions. Based on this price affect, we have also included a CI scope 2 term in our analysis. In the following chapter we will present a review of the literature on the relationship between stock prices and carbon emissions. Followed by a presentation of the literature on hedging carbon risk.

3 Literature review

Connecting carbon risk to the firm's total risk originates from the idea that due to an increased financial burden from regulation, GHG emissions represent future potential losses. This assumption leads to an increase in total risk which should impact the firms' cost of capital (Trinks et al., 2022). There are several papers that have examined carbon risk in equities. Carbon intensity is a common metric used in these studies. However, they differ somewhat in their approach both in the exact carbon intensity calculation, sample, and timeframe. Below we present papers that are relevant for the purpose of our research questions and analysis. In the first section we look at what others have found regarding carbon as a risk factor in equities. In the second section we present some relevant literature on hedging carbon risk and EUAs as a hedging instrument.

3.1 Carbon risk

The first article we want to present is Monasterolo and de Angelis (2020) they analyze carbon risk with a straightforward approach, with regards to the indices selection. By comparing the performance of carbon-intensive (brown) indices and low-carbon (green) indices to the market, in the EU, US, and international stock markets before and after the 2015 Paris Agreement. The low carbon indices used in the analysis consists of companies mainly in the renewable energy sector and the constituents in the carbon intensive indices are mainly in the oil and gas sector. The authors find that before the announcement of the Paris Agreement, low-carbon asset classes were perceived as riskier than the market, but after the announcement, their risk-return profile had been significantly reduced. The carbon intensive indices were perceived as equally risky as the market before the announcement, and after the announcement the risk-return profile had increased when looking at daily frequency, but not as much when looking at monthly data. Their findings show that the market viewed most low-carbon indices as less risky and, consequently, more desirable as investment options, following the announcement of the Paris Agreement.

The following articles use a more complex carbon intensity stock sample. Carbon intensity is a ratio and is defined by its numerator, representing GHG emissions and its denominator, which is a measure of output, such as revenue or sales, used to normalize the emissions.

Witkowski et al. (2021) uses carbon intensity to divide firms individual carbon risk exposure into three groups: dirty, medium, and clean. These groups are used to investigate the EU ETS's influence on 39 energy-intensive companies' carbon premium. They found a positive and statistically significant carbon premium in the period 2003–2012 and a negative carbon premium in the period 2013–2015. In the last period from 2016-2019 they did not find a statistically significant carbon premium. The portfolios are based on a *carbon risk exposure ratio,* which consists of the difference between emissions and free allocation normalized by total assets. This approach to carbon intensity mirrors the CI paid variable we used in our study, whereby deducting the free allocation, the carbon intensity reflects the actual emission costs incurred by a firm.

Bolton and Kacperczyk (2021) investigate whether investors factor in carbon risk by analyzing cross-sectional stock returns with carbon emissions and carbon intensity (total emissions / sales) as variables. They investigate 3.421 unique firms from 2005-2017 and include scope 1, 2 and 3 emissions. They find that carbon emissions have a positive impact that is statistically significant on stock returns, suggesting that investors consider carbon risk in their evaluations. However, they report that the emission intensity does not lead to a carbon premium within industries most impacted by divestment, such as oil and gas, utilities, and the automobile sector. Outside these industries, they identify a carbon premium at the individual firm level.

In an unpublished IMF working paper Hengge et al. (2023) find similar results to Bolton and Kacperczyk (2021) when looking at the interaction between carbon intensity (scope 1 and 2 / revenue) and EUA return, carbon intensive firms have an increased return, when carbon price increase. The authors then focus on how carbon policy impacts stock return on days with regulatory events. Then they find that event days resulting in higher carbon prices lead to negative returns, contrary to their first findings. The negative relationship increases with the firm's carbon intensity and is stronger for firms not included in the EU ETS. This negative relationship reflects that the transition risk is priced in by investors. The sample of this paper includes daily stock return for more than 2,000 listed European firms from 2011-2021.

While Hengge et al. (2023) uncover that higher carbon intensity is linked with increased risk, specifically for firms not compliant to the EU ETS, a contrast is found by Trinks et al. (2022). They test whether higher carbon intensity (scope 1 and 2 / net sales) commands a higher risk premium. In their study of 1,897 firms covering 50 countries, both within and outside the EU, over the years 2008-2016. Their results show carbon intensity increases the carbon premium in sectors and regions with carbon regulation, particularly the EU, compared with non-EU countries. However, when adjusting for sector-specific carbon intensity, the effect becomes less apparent.

The study by Tian et al. (2016) investigates the relationship between the EUA market and stock returns for electricity companies in the EU ETS. Their study covers the first and the second phase of the ETS, from 2005-2012 and the stock portfolio consists of 12 of the largest utility companies in the Eurozone. The results show that the impact on stock returns depend on market volatility and firms' carbon intensity. In phase I, the relationship between EUA and stock returns were positive for all producers. However, in phase II, there was a negative relationship between stock returns and EUA returns for carbon-intensive producers. The positive relationship from the first phase is in line with previous literature and is explained by periods of high volatility. The authors note that the result showing carbon-intensive producers having a negative relationship between their stock returns and the return on EUAs is in line with financial theory.

The article of Millischer et al. (2023) sets itself apart from the previously mentioned papers by distinguishing between paid and free carbon intensity within the EU ETS. The authors investigate the extent to which European stock markets consider carbon prices and carbon intensities in their valuations. The sample covers 338 listed European firms from 2013-2021. They find that the relationship between weekly carbon and stock returns is positive and significant; with higher carbon price intensity (scope 1 / revenue * EUA price) affecting stock performance during periods of increased carbon prices. However, emissions covered with free allowances do not affect this relationship, instead it is the paid carbon intensity which significantly lowers stock returns when there is a carbon price increase. The authors conclude that the relationship between changes in carbon prices and stock returns is dependent on the firms' paid carbon intensity and that the total emissions do not matter beyond the effect it has on paid carbon intensity.

In our study, we use the same method as Millischer et al. (2023). We construct a carbon price intensity term, to capture changes in the EUA price. In addition to differentiating between paid and free carbon price intensity, we further enhance our analysis by incorporating factors such as banking, hedging, and scope 2 emissions to examine the influence of EUAs and emission intensities on European stock prices. One of the differences between their study and ours is that they matched each installation from the European Union Transaction Log (EUTL) with their parent company. We have used a comparable data set from SparkChange[3] which will be presented in more detail later.

3.2 Strategies to hedge carbon risk

In the literature there are different strategies to hedge climate risk. The first strain, we categorize as a variant of positive and negative screening. These approaches are tested by Engle et al. (2020) and Andersson et al. (2016). The second strain of hedging strategies uses variations of carbon assets such as EUAs and carbon indices in a cross hedge with stocks (Ahmad et al., 2018; Batten et al., 2021; Demiralay et al., 2022; Jin et al., 2020). This is what we also do in our analysis for carbon risk reducing hedge ratios (HR).

Engle et al. (2020) use an approach based on American stock's ESG-scores to construct equity portfolios and investigate how news on climate change influences their returns. By investigating which rise and fall based on negative climate news they construct portfolios with the aim to hedge climate risk shocks. Andersson et al. (2016) present a different strategy where an investor uses a standard benchmark index and underweights companies with high carbon intensities. This new portfolio contains fewer stocks than the benchmark but with a comparable aggregate risk exposure to priced risk factors.

In the second category, we find papers using carbon derivatives in a cross hedge. Ahmad et al. (2018) test whether EUA futures and other hedging instruments can be used to hedge risk for an investment in clean energy equities and use an index[4] to benchmark the sector. Their sample covers daily data from 2008-2017 and they find low hedging effectiveness from the EUA futures. Ahmad et al. (2018) forecast one-step-ahead and test the estimated hedge ratios out-of-sample using rolling windows.

Demiralay et al. (2022) investigates if various derivatives (agriculture, energy, precious metals, and carbon futures) reduce equity market risk as hedging instruments. In contrast

[3] SparkChange is a data and analytics provider focused on the integration of carbon prices in financial markets. See more about the company at About SparkChange - SparkChange

[4] The WilderHill Clean Energy Index.

to others, they use a global carbon index[5] designed to track global carbon credits. Their data set consist of daily data from 2014-2021 and the full-sample hedging effectiveness show that adding carbon overall reduces downside risk in stock portfolios. Both papers use variations of multivariate GARCH models to obtain the conditional correlations for their hedge ratios.

The aim of the study by Ahmad et al. (2018) was to find effective hedges for investors interested in investing in clean energy. Their conclusion, based on their results, is that EUA futures are not well suited to hedge clean energy stocks. This is due to the low hedging effectiveness. Demiralay et al. (2022) find that carbon underperforms compared to precious metals and agriculture futures due to low hedging effectiveness.

In a third paper, Jin et al. (2020), takes the opposite position and investigates how a long position in EUAs can be hedged by a short position in a green bond. The context of the paper is to explore hedge instruments for carbon market risk in the period between 2008-2018. In addition to the green bond index, they also look at a volatility index, a commodity, and an energy index and use various DCC-GARCH models and an OLS estimation to construct hedge ratios. Their results show that the green bond index is the best suited hedge for carbon futures and has the highest hedging effectiveness. They also find that the OLS is outperformed by the other models.

The final paper we have looked at in this category uses energy commodities as a cross hedge for equities. Though the aim is to reduce portfolio risk, Batten et al. (2021) put the paper in the context of climate agreements and the effect these agreements can have on energy prices and consequently stock portfolios. The data set consists of monthly prices from 1990-2017 and their results show benefits from hedging with oil but with a time varying effect. As the other papers in this section, they use a DCC-GARCH model to derive the time-varying hedge ratios. They do not test their models out-of-sample.

3.2.1 EUA futures as a hedge for EUA spot price risk

To ensure that the EUA futures can be used as a proxy for the EUA price risk we have also looked at some studies examining the hedging effectiveness EUA futures has on the EUA spot. Fan et al. (2013) finds that hedging a spot position in the futures markets can significantly reduce volatility. The naïve approach, OLS estimator, and Error Correction Model are found to be the most effective in estimating the hedge ratios.

[5] IHS Markit Global Carbon Index.

In another study, Philip and Shi (2016) analyses the hedging effectiveness in the European carbon market using a Markov regime switching DCC model to hedge daily EUA spot prices with EUA futures. The period they study is from 2008-2012 and they find that the model outperforms both in-sample- and out-of-sample, compared to the other models they use, which include OLS, DCC-GARCH, and other types of models.

Lastly, Balcilar et al. (2016) investigates risk spillovers between carbon markets and electricity, natural gas, and coal futures prices. They also look at both EUAs and Certified Emission Reduction (CER) credits. Their aim is to address volatility interactions between EUA and CER spot and futures, by also including energy markets. This is done by using a Markov regime-switching DCC-GARCH model to study time variations, structural breaks, and to construct hedge ratios. They use daily prices and find significant volatility transmission from the energy markets to the EUA market.

4 Theory on risk and cross hedging

In the context of financial markets, risk refers to the concept of realized returns being different from expected returns. This difference can occur because of many different factors, from changes in firm specific information, changes in economic conditions, political changes, and even environmental changes. The capital asset pricing model (CAPM) is one of the most well-known models concerning the prediction of expected asset returns. The CAPM is based on the idea that the appropriate risk premium for an asset is defined by its contribution to the total risk of a portfolio. This is because, to an investor, portfolio risk is the critical consideration which influences the risk premiums demanded (Bodie et al., 2021, pp. 275-280).

Within the CAPM framework, risk is divided into what is referred to as systematic and unsystematic risk. Systematic risk is the variance of returns that can be assigned to the market, while unsystematic risk is firm-specific and is not affected by wider market shocks. Assets' sensitivity to the systematic risk factor are usually denoted by β and in a single-factor model, asset returns (r_i) are expressed as (Bodie et al., 2021, p. 245):

$$r_i = E(r_i) + \beta_i m + e_i \tag{1}$$

In the equation, $E(r_i)$ is the expected return, m is the market factor, β_i is the sensitivity, and e_i is the firm-specific risk. This show us that the total risk of asset r_i is comprised of two components: the systematic risk $\beta_i^2\sigma_m^2$ and the unsystematic risk $\sigma^2(e_i)$ (Bodie et al., 2021, p. 245):

$$\sigma_i^2 = \beta_i^2 \sigma_m^2 + \sigma^2(e_i) \tag{2}$$

An extension of the single factor model is the single-index model. In this model a broad market index is used as a proxy for the common market factor m. This model can be written as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + e_{i,t} \tag{3}$$

In the equation α_i is the intercept and represents expected excess return, and R_M is the excess market returns. The coefficient β_i is the sensitivity to the market index and is the rate by which the asset returns increases (decreases) for every 1 percent the index returns increase (decrease). The average beta for all the stocks in the economy is 1, as the market index would contain all the stocks in the economy. Lastly, $e_{i,t}$ is the residual, representing the firm specific returns (Bodie et al., 2021, p. 247). Additionally, in our analysis we will use a multi-factor model (MMM), which is an extension of the single-index model. This approach enables us to examine the co-movements and realized returns between independent variables for EUA returns and carbon price intensities on the dependent stock return variable. This will be presented in further detail in chapter 5.

Volatility serves as a critical measure when evaluating risk. Alexander (2008, p. 90) provides a precise definition of an assets volatility as the “annualized measure of dispersion in the stochastic process that is used to model the log returns”. In simpler terms, volatility is the standard deviation of asset returns. High volatility is an indication of high risk, and conversely low volatility is an indication of low risk. High volatility offers the opportunity to make significant gains, but also significant losses. Because of market risk components in financial markets, strategies like hedging have become popular.

The nature of commodity futures trading as stated by Johnson (1960) revolves around speculation and hedging. Futures are standardized contracts traded on an exchange, which reduces counterparty risk for the market participants. A crucial aspect of hedging is that the traders coordinate their efforts across two marketplaces; in the spot market, which reflect the original asset position, and in the futures market for the hedging instrument. There are different strategies to hedge a spot position. The simplest strategy is called naïve hedging and generally refers to holding a long position in the spot market and an equivalent short position in the futures market. Typically, the physical asset of the spot is the underlying asset of the futures contract (Kroner & Sultan, 1993).

Conventional hedging is a similar strategy and refers to the practice of running a regression between the returns on the spot and the futures prices or returns to obtain a beta; the beta indicates the number of futures contracts to hold relative to the spot position and in contrast to a naïve hedge, the ratio can be different from 1. To account for two common attributes in financial time series: 1) that the spot and the futures are cointegrated and 2) that there is non-constant risk in spot and futures markets, Kroner and Sultan (1993) made a conditional model to account for what the conventional model simplified. The calculations of hedge ratios are like the conventional method, but it accounts for time-varying risk in the spot and futures returns and therefore results in time changing hedge ratios.

A challenge emerges in hedging when there is no futures contract or other instrument available based on the same asset as the investor wants to hedge. *Cross hedging* introduced by Anderson and Danthine (1981) poses a solution to this challenge: they suggest hedging an asset position with a futures contract on a different asset. A premise for effective hedges is high correlation between the value of the asset and the instrument used for hedging (Moosa, 2003). Comparing a cross hedge to a standard hedge, the correlations between the spot and the futures may be considerably lower. This is assumed to be one of the challenges in our study, as the hedge instrument does not have the unhedged asset position as the underlying asset. Because of this relationship, it is rarely optimal to use a naïve hedge ratio for cross hedging. Rather, it is more appropriate to find the ratio that maximizes the reduction in the variance caused by changes in the carbon price, in our case.

A range of methods and models are used to study and capture the volatility characteristics of financial returns. The most common method is to look at historical volatility. Historical volatility can be useful as a benchmark, but more complex models will provide more accurate predictions. Models such as exponentially weighted moving average (EWMA) models are a bit more sophisticated and allow for weighing recent observations more than older observations. A second type of volatility model is autoregressive (AR) volatility models (Brooks, 2019, pp. 503-506).

A popular variant is the autoregressive conditional heteroscedastic (ARCH) model by Engle (1982). The usefulness of this model is that it does not assume that the variance of the standard errors is constant, which in the context of financial time series, is likely. This phenomenon is known as *heteroscedasticity*. An additional feature of this model is that it considers what is known as *volatility clustering*. This refers to the tendency that volatility is positively correlated with the preceding periods. ARCH models are used to model this phenomenon (Brooks, 2019, pp. 507-511). The most widely used volatility model is the generalized ARCH or GARCH model. Compared to the ARCH(q) process in which the conditional variance is specified as a linear function of past sample variances, the GARCH(p, q) process allows for lagged conditional variances (Bollerslev, 2023). An additional innovation in variance modelling is by Engle (2002). His dynamic conditional correlation (DCC) specification allows the correlations to be time-varying. To investigate the efficiency of EUA futures as a hedging instrument, we use a DCC-GARCH model to obtain parameter estimates for the conditional hedging ratios.

5 Method

In this chapter we will describe the methods used to answer our research questions. In the first section, we introduce the methodology behind our multi-factor analysis, examining the impact of carbon prices and carbon intensities on the returns of European stocks. In the second section, we present the variables and the approach used to obtain hedge ratios (HRs) for reducing carbon price risk in European equity portfolios. We use two approaches to obtain the HRs. The first is a time-varying OLS estimator, and the second is a DCC-GARCH model. We also present the method for estimating the realized hedging effectiveness (RHE).

5.1 Multi-factor approach

To test for the carbon and stock price relationship, we want to test for the effect of various pricing factors on the returns of stocks participating in the EU ETS by using a multi-factor model. We follow the same method as Millischer et al. (2023) and run an OLS regression on the stock returns as the dependent variable and use EUA returns, energy commodity returns and some constructed firm specific factors for the carbon price intensities. We also add three new carbon intensity variables which include scope 2 emissions, banking, and hedging for the stocks in our sample. The financial data used in our multi-factor analysis is retrieved from London Stock Exchange Group (LSEG). The emission data is from SparkChange, a provider of financial products, analytics, and carbon data to assist financial institutions in managing risks for the transition to a low-carbon economy.

Our dataset contains 112 listed firms from 8 sectors. The firms are from 18 European countries and covers a period of 6 years, spanning from 2018 – 2023. To arrive at these firms, we started with the constituents from Eurostoxx 600 and mapped them to the SparkChange database. This database consists of companies reporting emissions in accordance with the EU ETS. By using this approach 112 stocks out of the 600 Eurostoxx constituents had emissions mapped to them. The refined data set covered a diverse range of variables, including stock prices, scope 1 emissions reported to the EU, allowances received, banked allowances, hedge book positions, scope 2 emissions, ISIN, Country of origin, and the GICS sector classification for each stock, providing a comprehensive foundation for our analysis. The 112 stocks will be referred to as the EW (equally weighted) portfolio. In the following sections we go through the independent variables used as factors in the multi-factor regression before we present the full regression models.

5.1.1 Constructing the economic factors

To construct the pricing factors for the regression we calculate the natural logarithmic return for the variables ES600 (Euro Stoxx 600), EUA, oil, gas, and electricity prices. The price series have been obtained from the LSEG database. The weekly returns are denoted by the variables r_t^{ES} and r_t^{EUA}, whereas the price in week t is indicated by $ES600_t$ and EUA_t:

$$r_t^{ES} = \ln ES600_t - \ln ES_{t-1} \tag{4}$$

$$r_t^{EUA} = \ln EUA_t - \ln EUA_{t-1} \tag{5}$$

The factor r_t^{comm} is a single vector representing the log returns for oil, gas, and electricity:

$$r_t^{comm} = \begin{bmatrix} r^{OIL} \\ r^{GAS} \\ r^{EL} \end{bmatrix} = \begin{bmatrix} r_t^{OIL} = \ln OIL_t - ln\ OIL_{t-1} \\ r_t^{GAS} = \ln GAS_t - ln\ GAS_{t-1} \\ r_t^{EL} = \ln EL_t - ln\ EL_{t-1} \end{bmatrix} \tag{6}$$

We include energy commodities as controls because carbon prices have been shown to be significantly affected by the price of energy, among other economic variables and weather conditions (Balcilar et al., 2016). Including returns of commodities such as gas, oil, and electricity helps to account for the effects of external price shocks that might influence both the stock and carbon markets. In addition, because electricity producers in an ETS generally treat the imposed carbon cost as a marginal cost, the price of electricity is also impacted by the price of EUAs (IEA, 2020, p. 39). By controlling for these commodity returns, the model aims to isolate the specific effect of carbon prices on stock returns from these external shocks. Furthermore, we adjust for variability across sectors, by including sector fixed effects. To capture influence from business cycles we also use country–month interacted fixed effects (Millischer et al., 2023).

5.1.1.1 Total carbon price intensity

We follow Millischer et al. (2023) and calculate the total carbon price intensity factor CI^{total} as shown in equation (7). The factor is constructed by multiplying total scope 1 emissions (tCO_2e) by the annual average carbon price and dividing by revenue (euros). This term aims to capture the carbon price sensitivity for each stock.

$$CI_{i,Y}^{total} = \frac{E_{i,Y}^{total} \times \widehat{\mathrm{P}}_Y}{R_{i,Y}} \tag{7}$$

5.1.1.2 Free and paid carbon price intensity

To capture the dynamics in total carbon price intensity we split the term into two new components: free allowances and paid allowances. The sum of these two terms is equal to total emissions. This results in the two new terms CI^{free} and CI^{paid} shown in the equation below:

$$CI_{i,Y}^{total} = \frac{\left(E_{i,Y}^{free} + E_{i,Y}^{paid}\right) \times \widehat{\mathrm{P}}_Y}{R_{i,Y}} = \frac{E_{i,Y}^{free} \times \widehat{\mathrm{P}}_Y}{R_{i,Y}} + \frac{E_{i,Y}^{paid} \times \widehat{\mathrm{P}}_Y}{R_{i,Y}} = CI_{i,Y}^{free} + CI_{i,Y}^{paid} \tag{8}$$

5.1.1.3 Additional carbon price intensity factors

In addition to total carbon price intensity as an explanatory factor we include three additional terms: banked, hedged and scope 2 carbon price intensities. We include these terms to test if they can provide additional explanations on risk contributions to the stock returns.

The first term we have included in banking. We have chosen to include this factor because firms participating in the EU ETS have had the opportunity bank their allowances since the second phase. It allows the firms to bank their surplus and carry them over for future use (Ellerman et al., 2015). These allowances are a result of overallocation in prior years. Because banked allowances decrease future exposure to the carbon price, this metric might capture some aspects of the risk that energy-intensive firms face. Data for banked allowances is from SparkChange and the banked carbon price intensity is calculated by multiplying total banked allowances (tCO_2e) by the annual average carbon price and dividing by revenue (euros):

$$CI_{i,Y}^{X} = \frac{E_{i,Y}^{X} \times \widehat{\mathrm{P}}_{Y}}{R_{i,Y}} \tag{9}$$

The second factor is hedged carbon price intensity. Firms compliant with the EU ETS can hedge their future emissions. This risk management strategy is often done by buying allowances in advance and planning for compliance in future years. In practice this is very similar to banking, however, hedging refers to allowances the firms have paid for and is not the result of previous over-accumulation of free allowances. The firms in our sample that hedge receive a small number of free allowances compare to the firms that have banked allowances. Data for each firm's "hedge book" is from SparkChange, and the hedged carbon price intensity is calculated by multiplying hedge book allowances (tCO_2e) by the annual average carbon price and dividing by revenue (euros).

The last factor we look at is scope 2 emissions. These emissions are estimations of the firms' scope 2 emissions that are affected by the EU ETS price. Data for scope 2 emissions is from SparkChange, and the scope 2 carbon price intensity is calculated by multiplying total scope 2 emissions (tCO_2e) by the annual average carbon price and dividing by revenue (euro). As for the two other additional factors this is calculated as shown in equation (9).

5.1.2 Regression models for the relationship between carbon and stock returns

In this section we present the regressions models used in our analysis, following the method presented in Millischer et al. (2023). The objective is to analyze the co-movement between stock returns and changes in the carbon price. To achieve this, we use a multi-factor model approach and run a regression by ordinary least squares (OLS). We regress stock returns on carbon price returns and other variables that we will go through in the following sections.

Equation (10) shows the dependent variable of the weekly stock returns $r_{i,t}^{stock}$ and the independent variables r_t^{ES} which are weekly returns for ES600; $CI_{i,Y}$ which is the total carbon price intensity for stock i in year $Y-1$, presented in more detail in equation (7); $r_{i,t}^{EUA}$ is the weekly return on carbon futures; r_t^{comm} represents weekly returns for the commodities (oil, gas and electricity); and lastly, $FE_{i,t}$ are sector and country × month fixed effects (FE).

$$r_{i,t}^{stock} = \beta_1 r_t^{ES} + \left[\beta_2 + \beta_3 CI_{i,Y}\right] r_{i,t}^{EUA} + \beta_4 r_t^{comm} + FE_{i,t} + \varepsilon_{i,t} \tag{10}$$

When we use the CI term from equation (8), equation (10) becomes:

$$r_{i,t}^{stock} = \beta_1 r_t^{ES} + \left[\beta_2 + \beta_3^{free} CI_{i,Y}^{free} + \beta_3^{paid} CI_{i,Y}^{paid}\right] r_{i,t}^{EUA} + \beta_4 r_t^{comm} + FE_{i,t} + \varepsilon_{i,t} \tag{11}$$

The inclusion of banked, hedged and scope 2 CI terms are added individually in addition to the paid and free CI factors. A generalized presentation of the equation is below. Where $\beta_5^X CI_{i,Y}^X$ represents the terms from equation (9).

$$r_{i,t}^{stock} = \beta_{1 r_t^{ES}} + \left[\beta_2 + \beta_3^{free} CI_{i,Y}^{free} + \beta_3^{paid} CI_{i,Y}^{paid} + \beta_5^X CI_{i,Y}^X\right] r_{i,t}^{EUA} + \beta_4 r_t^{comm} + FE_{i,t} + \varepsilon_{i,t} \tag{12}$$

To test the relationships between the multi-factor terms, a 5 % significance level ($\alpha = 0.05$) is adopted.

5.2 Carbon risk hedging

For effective hedging, it is necessary to forecast the returns of both the original asset and the hedged portfolio. This process involves finding optimal hedging ratios (OHRs) by estimating the future performance of the assets (Bloznelis, 2018). To do this we model the conditional mean vector and conditional variance matrix for the returns of the indices and the futures returns. This is done using a Dynamic Conditional Correlation (DCC), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. We have included the OLS estimator for comparative purposes as the hedge ratios can be more useful due to their stability compared to more complicated GARCH models (Ku et al., 2007). The models are estimated using rolling windows of 204 weeks (January 2018 - December 2021) to obtain out-of-sample forecasts. Out-of-sample data is used to estimate forecast accuracy which is used to evaluate hedging effectiveness.

We use weekly price series data from LSEG to model and estimate hedge ratios. This price data encompasses four sector portfolios and prices for 1- and 2-month EUA futures contracts. In our analysis we use two specific Eurostoxx sector indices: ES Industry and ES Energy. ES Industry is the Euro Stoxx Industrials E index consisting of 64 constituents and uses a free-float market cap weighting. ES Energy is the Euro Stoxx Energy E index consisting of 13 constituents and uses a free-float market cap weighting. In addition to the ES portfolios, we have also constructed two equally weighted (EW) portfolios for the same sectors. They are constructed based on the GICS sector classification of the 112 stocks from the EW portfolio. EW Industry is an equally weighted portfolio consisting of the 16 industry firms and EW Energy is the equally weighted portfolio consisting of 11 energy firms from the EW portfolio.

Initially, we attempted to model hedge ratios for ten sector portfolios. Our initial group included sector portfolios covered by the EU ETS, e.g. materials, utilities, and the EW portfolio. However, we faced issues with the DCC-GARCH model - specifically, getting the hedge ratios to work correctly. As a result, we excluded some portfolios. We decided to exclude any portfolio if it failed to converge more than five times. This cutoff was decided because the next highest number of failures was twelve, indicating a clear separation. We selected the four ES and EW Industry and Energy portfolios for our final analysis due to these limitations to ensure our model worked properly.

When building our models, we forecast one month ahead. Due to the nature of the price series of futures contracts, we construct the return series, so we get the correct returns for our time series. This process is necessary because prices for futures get recorded on different continuous time series. Therefore, while the physical contract might be for December 2024, its returns get recorded on different continuous time series (e.g. F2 in October and F1 in November). Therefore, the hedge consists of buying a 2-month futures contract at time t-4 and selling a 1-month futures contract at time t. The futures return series is calculated as follows:

$$f_t = log(F1_t) - \log(F2_{t-4}) \tag{13}$$

As a robustness test, we also made a return series for a one week forecast. This return series is constructed in a somewhat different manner. For most weeks the returns are calculated on the 1-month futures contract. However, in the week of expiry for the 1-month contract, we buy a 2-month futures contract and sell a 1-month futures contract.

5.2.1 Ordinary Least Squares estimator

The first model we use to find hedge ratios is a conditional OLS estimator. This approach takes the time-varying properties of the spot and the futures into consideration. In the equation below, s_t is the log return of the stock portfolio and f_t is the log return of the futures contract; b_t^* is the position in the futures contract. The sign in front of b_t^* indicates whether it is a short (-) or a long (+) position. The first method we use to find hedge ratios is a conditional model taking the time-varying properties of the spot and the futures into consideration. The approach is follows Kroner and Sultan (1993). The return on the hedged portfolio x_t is:

$$x_t = s_t - b_t^* * f_t$$

$$(14)$$

Furthermore, the formula for calculating the OLS conditional hedge ratios b_t^* can be written as:

$$b_t^* = \frac{\sigma_t(s_{t+1}, f_{t+1})}{\sigma_t^2(f_{t+1})} \tag{15}$$

Here, the time-varying covariance of the stock portfolio and futures returns are divided by the time-varying variance of the futures returns. We have included the OLS estimator for comparative purposes as the hedge ratios these models produce can be more useful due to their stability compared to GARCH models (Ku et al., 2007).

5.2.2 DCC-GARCH model

The second model we use to find hedge ratios is a DCC-GARCH(1,1) model. We use this model with the aim of capturing the volatility dynamics of the returns for the stock portfolios and the futures. This is because there is little evidence for constant correlation for stock returns (Brooks, 2019, p. 554). Because of time-varying correlations, the DCC model by Engle (2002) is widely used in the field and is the one we use as well. When specifying the equations we use a similar notation as Ahmad et al. (2018) and Ku et al. (2007).

$$r_t = \mu_t + \varepsilon_t \,, \qquad \varepsilon_t | \Omega_{t-1} \sim N(0, h_t) \tag{16}$$

$$z_t = \frac{\varepsilon_t}{\sqrt{H_t}} \tag{17}$$

The conditional mean equation of r_t is specified as shown in equation (16), where the expected return is denoted by μ_t and the error term by ε_t. The conditional distribution of the error term ε_t is described by the information set Ω_{t-1}, with a normal distribution, a mean of zero and a variance of h_t. The standardized residuals z_t are obtained by dividing the error term by the conditional standard deviations. H_t represents the conditional variance-covariance (VCV) matrix. It consists of the time-varying correlation matrix R_t and a leading diagonal matrix D_t containing the conditional standard deviations.

$$H_t = D_t R_t D_t = \begin{bmatrix} h_{s,t} & h_{sf,t} \\ h_{sf,t} & h_{f,t} \end{bmatrix} \tag{18}$$

Furthermore, the specifications of the conditional variance equations for the spot and the futures returns can be written as:

$$h_{s,t} = \alpha_{0s} + \alpha_{1s}\varepsilon_{s,t-i}^2 + \beta_{1s}h_{s,t-j} \tag{19}$$

$$h_{f,t} = \alpha_{0f} + \alpha_{1f}\varepsilon_{f,t-i}^2 + \beta_{1f}h_{f,t-j} \tag{20}$$

$$h_{sf,t} = \rho_{sf,t}\sqrt{h_{s,t}}\sqrt{h_{f,t}} \tag{21}$$

The conditional variances of the spot and futures return are represented by $h_{s,t}$ and $h_{f,t}$. The equations illustrate a one period estimate, where the first term can be interpreted as a function weighted by a long-term average value, the second term shows the volatility from the preceding period, and the last term shows the fitted variance derived from the previous period based on the model estimates (Brooks, 2019, p. 512). It is by solving $h_{sf,t}$ we can obtain the OHRs. But to do this we must first find the estimates for $\rho_{sf,t}$, the dynamic conditional correlations, for the spot and the futures returns:

$$\rho_{sf,t} = \frac{q_{sf,t}}{\sqrt{q_{ss,t}q_{ff,t}}} \tag{22}$$

To find the parameters for conditional variance and covariance we use Maximum Likelihood Estimation (MLE). This involves optimization techniques which iterate over different parameter values to find the optimal solution, maximizing the likelihood function to best fit the data (Brooks, 2019, pp. 515-517). In cases like ours, where the returns exhibit non-Gaussian innovations, the DCC model can be interpreted as a quasi-maximum likelihood (QLM) estimator (Engle, 2002; Engle & Sheppard, 2001). Furthermore, where the model failed to converge, we implemented a mechanism where the model would adopt the parameter value from the preceding iteration. The outcome of this process is the parameter estimates which are used for obtaining the time-varying hedge ratios b_t^*:

$$b_t^* = \rho_{sf,t}\sqrt{\frac{h_{s,t}}{h_{f,t}}} \tag{23}$$

To compare the hedge ratios obtained from the OLS and DCC model, we calculate the hedging effectiveness, HE, by taking the difference in variance of the unhedged and the hedged portfolio and dividing it by the variance of the unhedged portfolio. This is the same method used by Ku et al. (2007) to find a superior model:

$$HE = \frac{\sigma^2_{unhedged} - \sigma^2_{hedged}}{\sigma^2_{unhedged}} \tag{24}$$

5.3 Use of AI tools

While working on this study we have used different types of AI tools. The AI models we have used are ChatGPT (model 4), Copilot and QuillBot paraphrasing tool. The AI tools have been used in different stages of the process. Copilot was used to in the early stages to assist in finding sources of information. E.g. to find specific information about the EU ETS. Chat-GPT was used for data analysis to debug and improve code. It was also used to provide suggestions on structure for writing different chapters. Lastly it has been used to improve language, similarly to how we have used QuillBot. QuillBot have been used to assist in writing by finding synonyms and improve language. When using these AI-tools, we have always provided own input and we have not used Chat-GPT or other AI tools to generate text based on general prompts. Furthermore, we have not used Chat-GPT or Copilot as sources of information and therefore we have not cited any AI models. Here are some examples of prompts we have used in different contexts:

Example prompts on writing (grammar/language and structure):

- "Can you help improve this sentence as a bridge between climate change and EU climate law? [sentence]"
- "How should a theory chapter be different from a methodology chapter?"

Example prompt for data analysis and debugging:

- "In above code the return is following error: [error received in R]. Can you please provide some insight to what this error means and how I can improve the code?"
- "In R, how do I create a dataset with only observations from 01.01.2018 until 31.12.2023. The dataset is [name of dataset], and the new dataset is to be named [new name]."

6 Data and descriptive statistics

This chapter is divided into two main parts, one for the stock and carbon price intensity analysis and the other on hedging carbon risk in a stock portfolio. There are commonalities between the data used in both sections. The financial data we have used includes return series for individual stocks, indices, energy commodities, and futures contracts. The emission data we have used is from SparkChange and is only used in the first section. A summary of all variables and in which section they are used can be found in Table 1.

Table 1. Glossary, definitions, and source of the variables used in the carbon risk analysis and the hedge ratio analysis.

Variable	Definition	Source
	Multi-factor variables	
EW portfolio	Stock portfolio log-returns	112 firms included in EU ETS out of the Euro Stoxx 600 total return index
ES600	European stock index log-returns	Euro Stoxx 600 total return index
rEUA	EUA log-returns series	ICE EUA 1-month futures contract
OIL	Oil price log-returns	Europe Brent oil
GAS	Gas price log-returns	Refinitiv TTF Dutch natural gas
EL	Electricity price log-returns	EEX Phelix[6] Baseload electricity
CI (total)	Total carbon price intensity	Historical Scope 1 emissions covered by the EU ETS, multiplied by EUA price, divided by revenue
CI (paid)	Paid carbon price intensity	Historical Scope 1 emissions paid for in the EU ETS, multiplied by EUA price, divided by revenue
CI (free)	Free carbon price intensity	Free allocation multiplied by EUA price, divided by revenue
CI (hedged)	Hedge carbon price intensity	Hedge book multiplied by EUA price, divided by revenue
CI (banked)	Banked carbon price intensity	Banked allowances multiplied by EUA price, divided by revenue
CI (scope2)	Scope 2 carbon price intensity	Scope 2 emissions multiplied by EUA price, divided by revenue
	Hedging variables	
ES Energy	Energy portfolio log-returns	Euro Stoxx Energy E total return index
ES Industry	Industrials portfolio log-returns	Euro Stoxx Industrials E total return index
EW Energy	Energy portfolio log-returns	Equally weighted portfolio of the 11 Energy firms in the EW portfolio
EW Industry	Industrials portfolio log-returns	Equally weighted portfolio of the 16 Industry firms in the EW portfolio
fEUA	EUA log-return series	ICE EUA 1- and 2-month futures contract

[6] The Physical Electricity Index is the average price for electricity traded on the German/Austrian Auction. Glossary | EPEX SPOT

6.1 Variables for the multi-factor analysis of carbon risk factors on stock returns

The EW portfolio consists of firms from different European countries and sectors. The various GICS sectors are: Consumer Discretionary (8), Consumer Staples (10), Energy (11), Financials (7), Health Care (7), Industry (16), Materials (32), and Utilities (21). The sectors covered by the EU ETS generally fall into the energy, utility, materials, and industrials categories. However, because of how the database from SparkChange is constructed, GICS sectors that formally are not included in the EU ETS are assigned emissions. This is because a firm in the Health Care sector, for example, may be the parent company to a power installation. In total we have firms from 18 European countries, with the majority based in Germany (22), France (17), Great Britain (14) and Italy (8).

Figure 2 visually present the reported scope 1 emissions under the EU ETS from sectors included in our dataset. Total yearly emissions reached a top of 747 million tCO_2e in 2015 and has since had a declining trend, reaching the lowest level of 518 million tons in 2023. On average, the utilities sector has the largest number of reported emissions, followed by materials, energy, and the industrials sectors.

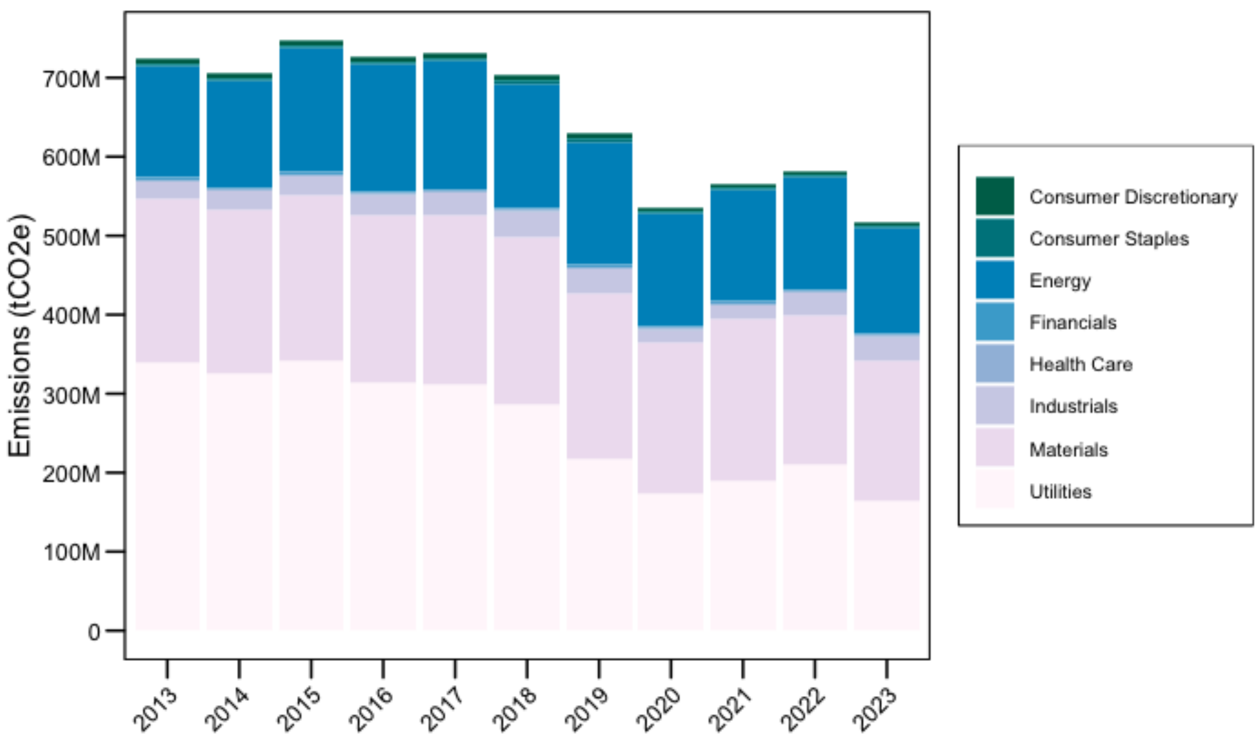

Figure 2. Illustrates scope 1 emissions covered by the EU ETS in the period 2013-2023 grouped by the sectors in our data set.

On average, firms in our sample receive 60 % of their emission allowances for free each year. As a result, they pay for the remaining 40 % of the emission allowances relative to their total emissions. The share of free allowances provided across the different sectors in the EU ETS is varied. In our sample, the firms in the utilities sector received 13 % of their total emission in free allowances. The firms in the energy, industrials and materials sector received 55 %, 64 %, and 97 % respectively. The firms in the materials sector received almost enough free allowances to cover their total emissions.

The average amount of hedged allowance in the sample period are close to 600 million tones. The average amount of banked allowances and scope 2 emissions impacted by the EUA price are 96 and 80 million tons, respectively.

Firms within the utilities sector experience the highest exposure to carbon costs in relation to their paid emissions (CI paid). On average, these costs account for 1.37 % of their revenue. The firms in the materials sector experience the lowest CI paid of 0.19 %, this is due to the large amount of free allocation to firms in this sector. The average CI paid for the firms in the industrials and energy sector is 0.31 % and 0.37 %, respectively. A plot to illustrate the development of the variable CI total for the is presented in Figure 3. This figure visualizes the price effect on the carbon intensities and can be seen in relation to Figure 1 and 2 as well as equation (7).

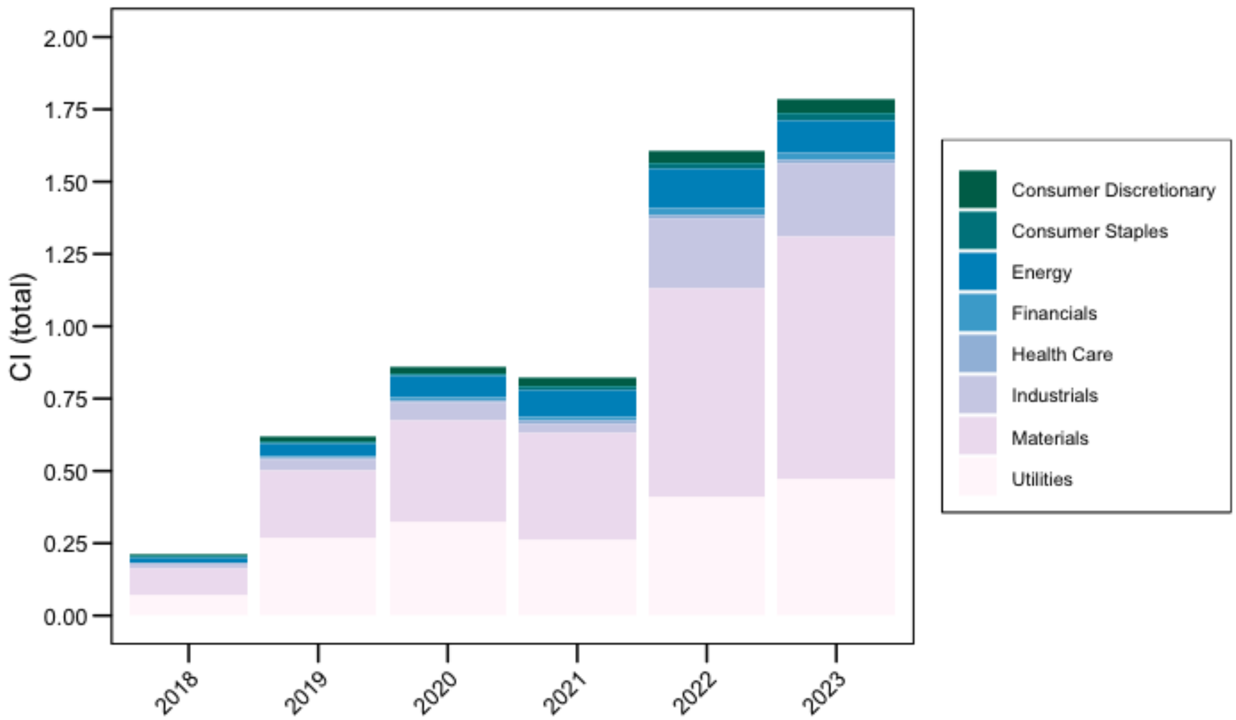

Figure 3. Illustrates the total carbon price intensities grouped by sectors for the period 2018-2023 used in our analysis. Note that there is a lag of Y-1, as explained in chapter 5.1.2.

There are noticeable differences in the hedging behavior of the firms in each sector. The difference appears to be related to the number of allowances firms in each sector receive for free, as the sectors with a high share of paid allowances also hedge more. For example, in the utilities sector, the proportion of emissions hedged exceeds total annual emissions, reaching 126 %. Notably, every firm from the utilities sector in our sample have hedged on an annual basis. In contrast, only two companies from the materials sector have hedged. The annual average hedge for those two companies is 14 % of total emissions. For the industrials sector, three firms have hedged, all are related to the airline sector. The annual average hedge for those three companies is 102 % of total emissions. Lastly, out of the firms in the energy sector, all but one firm engages in hedging. The average hedge for the energy hedgers is 46 % of total emissions.

We will now detail the variables included in the regression analysis. Summary statistics of the variables are presented in Table 2. The table provides an overview of various statistics for the weekly log returns of the variables in our dataset. This includes the EW portfolio, ES600, EUA, oil, gas, and electricity. It also covers the carbon price intensities – total, paid, free, hedged, banked, and scope 2 – calculated on an annual basis for each firm.

Specifically, it shows the mean, median, minimum, maximum, and standard deviation of these values. An overview of all the variables can be found in Table 1.

For the EW portfolio and ES600 returns, the means are comparable, although the median return for ES600 is greater. Among the energy commodities analyzed, electricity (EL) emerges as the most volatile, implying the highest risk. Out of all the return series, the EUA has the greatest mean. During the period investigated the price of EUAs has seen an exceptional price increase, as illustrated in Figure 1. When evaluating risk through standard deviations, the EUA returns exhibit the greatest variability at 6 %. This indicates that while EUAs offer higher profitability, they also entail a greater risk level than the stock portfolios, but lower than the energy commodities.

Table 2. Summary statistics for the period 2018-2023. Stocks, index, EUA, oil, gas, and electricity are weekly log returns and reported in %. CI paid, free, hedged, banked and scope 2 are annual intensities and reported in %.

Variable	Frequency	N	Mean	Median	Min.	Max.	Std.
			Full sample				
ES600	Weekly	312	0.12	0.46	-14,2	7.7	2.3
rEUA	Weekly	312	0.72	0.47	-27.5	18.8	6.0
OIL	Weekly	312	0.09	0.65	-85.9	53.9	9.2
GAS	Weekly	312	0.17	0.11	-81.5	147.7	17.7
EL	Weekly	312	0.0	0.77	-188.5	204.9	38.8
EW portfolio	Firm-weekly	34,743	0.13	0.28	-60.4	43.3	4.3
CI (total)	Firm-annual	666	0.67	0.15	-0.1	18.8	1.7
CI (paid)	Firm-annual	666	0.31	0.03	-0.6	18.1	1.3
CI (free)	Firm-annual	666	0.35	0.05	0	11.6	1.0
CI (hedged)	Firm-annual	666	0.68	0	0	91.9	6.1
CI (banked)	Firm-annual	666	0.12	0	0	7.8	0.6
CI (scope2)	Firm-annual	666	0.09	0.03	0	1.7	0.2
			Hedgers sample				
Hedgers portfolio	Firm-weekly	11,164	0.12	0.31	-60.4	32.7	4.5
CI (total)	Firm-annual	211	1.09	0.49	0	18.8	2.5
CI (paid)	Firm-annual	211	0.80	0.25	-0.5	18.1	2.2
CI (free)	Firm-annual	211	0.29	0.07	0	116	0.9
CI (hedged)	Firm-annual	211	2.14	0.28	0	91.9	10.8

Regarding the carbon intensities (CI), the data reveals the following averages: the total carbon intensity stands at 0.67, with the CI paid factor averaging 0.31 and the CI free factor at 0.35. For the additional factors, CI hedged has a high average of 0.68 while the CI banked and scope 2 are 0.12 and 0.09, respectively. The highest recorded total CI in the dataset reaches 19 %, while the maximum for CI free and CI paid is 12 % and 18 %. Looking at the CI hedged, banked, and scope 2, it's observed that the minimum values across these categories are zero, which is consistent with the nature of these factors. Furthermore, the CI hedged showcases a maximum value of 92 % and a median of 0. This is because at least half of the firms in the sample do not engage in hedging activities. However, there are notable cases of extensive hedging by some firms, as indicated by the maximum value of CI hedged.

Tests for normality and stationarity reveal that all variables deviate from normality, but exhibit stationarity. Normality was tested using a Jarque–Bera (JB) test and stationarity was tested using an Augmented Dickey-Fuller (ADF) test. The results can be found in the appendix.

6.2 Variables for the hedge ratio analysis

In this sub-chapter, we will present descriptive statistics for the variables used for modelling and estimating the hedge ratios. Table 3 shows the four sector portfolios and the EUA return series. All variables deviate from normality but exhibit stationarity. A JB test was used to test for normality and an ADF was used to test for stationarity. The results can be found in the appendix.

Table 3. Summary statistics for the period 2018-2023. All variables are weekly log returns and mean, median, min., max. and std. reported in %.

Variable	Frequency	N	Mean	Median	Min.	Max.	Std.
EW Industry	Weekly	309	0.21	3.7	-27.3	14.9	0.14
ES Industry	Weekly	309	0.17	3.1	-21.4	10.6	0.09
EW Energy	Weekly	309	0.22	3.9	-26.0	17.0	0.15
ES Energy	Weekly	309	0.20	3.6	-23.8	15.3	0.13
fEUA	Weekly	309	-0.02	0	-34.9	27.5	8.8

Table 4 displays the correlations between the sector portfolios and the EUA. The correlation between the industry portfolios and the fEUA series, varies between 0.26 and 0.24 across the entire sample (2018-2023). For the last two years (2022-2023) the correlations have changed slightly to 0.24 and 0.23. For the Energy portfolios, the correlation with fEUA stands at 0.15 for the full sample period. In the last two years, there has been a modest rise to 0.17 and 0.21.

Table 4. Correlation matrix of log returns for the periods 2018-2023 and 2022-2023.

	fEUA	***EW Industry***	***ES Industry***	***EW Energy***
		2018-2023		
EW Industry	0.26			
ES Industry	0.24	0.93		
EW Energy	0.15	0.68	0.67	
ES Energy	0.15	0.69	0.69	0.96
		2022-2023		
EW Industry	0.24			
ES Industry	0.23	0.95		
EW Energy	0.17	0.38	0.36	
ES Energy	0.21	0.44	0.40	0.93

7 Results

In this chapter the empirical results from 1) the multi-factor analysis of the relationship between EUA price returns and stock returns, and 2) the hedge ratio analysis will be presented. In the first section we present the findings from the independent carbon price intensities and EUA variables on the stock returns for firms participating in the EU ETS. In the second section we present the estimated and modelled hedge ratios for minimizing variance in four sector specific equity portfolios by using EUA futures contract as the hedging instrument. The implications from the results will be discussed in the chapter 8.

7.1 Multi-factor analysis of EUA returns and carbon price intensities on stock returns

In Table 5 the result from the Ordinary Least Squares (OLS) regression on the relationship between carbon price and stock returns is presented. There are seven different regression models, with stock returns as the dependent variable. Columns one to five provide full-sample estimates, incorporating data from 112 firms over a period of six years, spanning 52 weeks each (n = 35,056), with additional variables included in the analysis. In the initial regression model, the added carbon price intensity variable is CI total. From the second to the seventh regression models, the CI total variable is divided into CI paid and CI free. The third regression model incorporates the CI scope 2 variable, the fourth model adds the CI banked variable, and the fifth model includes the CI hedged variable.

An additional sample of firms that hedge is created. This sample incorporates 36 firms over the same period of six years, spanning 52 weeks (n=11,164). The 36 firms are from the EW portfolio and are firms who hedge a portion of their emissions. This sample is used in regression models six and seven, where model six includes CI paid and CI free and model seven also includes CI hedged. All regression models include the following independent variables: EUA return, ES600 return, gas, oil, and electricity returns. Fixed effects for sector and country-month are included for all models.

7.1.1.1 Total carbon price intensity

The first model in Table 5 shows the results for the CI total variable. The result from the EUA return variable shows a significant and positive β_2 coefficient (0.03) $(p < 0.0001)$. This result indicates that a weekly increase of the EUA price of 1 % relates to an increase in stock prices of 0.03 %. The corresponding result from the CI total shows a positive (0.1), but not significant β_3 coefficient. The ES600 has a β_1 coefficient of 1.08 $(p < 0.0001)$, showcasing that individual stock returns in our sample co-move with the market. Gas price returns are negative and significant with a beta of -0.003 $(p < 0.01)$ and the beta for electricity returns are 0. Oil price returns are statistically significant and positive with a beta of 0.03 $(p < 0.0001)$. The adjusted $R^2 = 0.34$.

Table 5. Results from regression. Column (1) – (5) are full sample estimates with added factors indicated by the left-side column. Column (6) – (7) are samples of firms that hedge emissions. Standard errors are reported in parentheses. Level of significance: *** p<0.0001, ** p<0.001, * p<0.01, '.' p<0.05

	(Model 1) Full sample		(Model 2) Full Sample		(Model 3) Full Sample		(Model 4) Full sample		(Model 5) Full sample		(Model 6) Hedgers		(Model 7) Hedgers	
$r^{carbon}(\beta_2)$	0.03	***	0.02	***	0.02	***	0.02	***	0.03	***	0.02	**	0.02	***
	(0.003)		(0.004)		(0.004)		(0,004)		(0.007)		(0.007)		(0.007)	
$CI^{total} \times r^{carbon}(\beta_3)$	0.10													
	(0.156)													
$CI^{paid} \times r^{carbon}\left(\beta_3^{paid}\right)$			-0.58	**	-0.59	**	-0.61	**	-2.06	***	-0.64	**	-2.02	**
			(0.219)		(0.159)		(0.221)		(0.542)		(0.243)		(0.680)	
$CI^{free} \times r^{carbon}\left(\beta_3^{free}\right)$			1.13	***	1.22	***	1.25	***	1.25	***	3.01	***	2.96	***
			(0.275)		(0.219)		(0.303)		(0.278)		(0.604)		(0.605)	
$CI^{Scope2} \times r^{carbon}(\beta_3^{Scope2})$					0.24	*								
					(0.102)									
$CI^{banked} \times r^{carbon}(\beta_3^{banked})$							-0.49							
							(0.499)							
$CI^{hedged} \times r^{carbon}(\beta_3^{hedged})$									0.36	**			0.33	*
									(0.124)				(0.150)	
$ES600\ (\beta_1)$	1.08	***	1.08	***	1.08	***	1.08	***	1.08	***	1.00	***	1.00	***
	(0.009)		(0.009)		(0.009)		(0.009)		(0.009)		(0.017)		(0.016)	
Gas return	-0.003	*	-0.003	*	-0.003	*	-0.003	*	-0.003	*	0.005	*	0.004	*
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.002)		(0.002)	
Oil Return	0.03	***	0.03	***	0.03	***	0.03	***	0.03	***	0.05	***	0.05	***
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.005)		(0.005)	
Electricity return	0		0		0		0		0		0		0	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
N	35 056		35 056		35 056		35 056		35 056		11 164		11 164	
Sector FE	✓		✓		✓		✓		✓		✓		✓	
Country/Month FE	✓		✓		✓		✓		✓		✓		✓	
R^2	0.34		0.34		0.34		0.34		0.34		0.31		0.31	
Adj. R^2	0.34		0.34		0.34		0.34		0.34		0.30		0.30	

7.1.1.2 Free and paid carbon price intensity

In model two, the β_3^{paid} coefficient is negative (-0.58) and statistically significant $(p < 0.001)$. This indicates that an increase in EUA prices negatively affects the stock returns of firms that pays for their emissions. The β_3^{free} coefficient is positive (1.13) and significant $(p < 0.0001)$. This suggests that for firms that receive emission allowances for free, there is a positive effect on the stock return when EUA prices increase. The coefficient β_2 for the EUA price returns decrease slightly in size (0.02) but remain significant $(p < 0.0001)$. Co-movements for the stock returns with the other variables, ES600, oil, gas and electricity price returns remain unchanged, compared to the results in model one.

If we focus on the relationship between stock return, $r_{i,t}^{stock}$, and the EUA return, $r_{i,t}^{EUA}$, from equation (11), i.e. by including only the terms that depend on the EUA return, we get the following coefficient for $r_{i,t}^{EUA}$ (based on model 2): $\beta_2 + \beta_3^{free} CI_{i,Y}^{free} + \beta_3^{paid} CI_{i,Y}^{paid}$. By inserting the values for the estimated coefficients from Table 5 (model two) and the mean values for $CI_{i,Y}^{paid}$ and $CI_{i,Y}^{free}$ from Table 2 , we get the following coefficient value:

$$\beta_2 + \beta_3^{paid} CI_{i,Y}^{paid} + \beta_3^{free} CI_{i,Y}^{free} = 0.02 - 0.58 * 0.31 + 1.13 * 0.35 = 0.24$$

The positive value of this coefficient shows that for the EW portfolio, an increase in the EUA returns will in fact result in an increase in the stock returns. One implication of this positive relationship is that if one wants to reduce the volatility in stock returns via hedging the EW portfolio with future contracts on the EUA, one needs to use short positions in the futures contracts, see further discussion of hedging below.

It should however be noted that since the estimated coefficient for CI paid, β_3^{paid} , is negative, the separate impact on stock returns from paid EUAs is negative, i.e. an increase in EUA returns will lead to a reduction in stock returns. This negative impact will be stronger with a larger $CI_{i,Y}^{paid}$, i.e. for firms with a larger number of paid emission allowances, and it will be larger if the price of the EUAs increase, (see also the definition in equation (7).

7.1.1.3 Hedged carbon price intensity

On average, 29 % of total annual emissions for the full sample are hedged each year. Out of the 112 firms, 36 participate in hedging. For these 36 firms, the annual average of their emissions hedged relative to their total emissions is 92 %. Model five shows the result for the CI hedged variable for the full sample. The β_3^{hedged} coefficient is positive (0.36) and significant $(p < 0.001)$. When the CI hedged variable is included a noteworthy change in the

β_3^{paid} occurs, the coefficient decreases from -0.58 $(p < 0.001)$ to -2.06 $(p < 0.0001)$. There is also a small change in the β_3^{free} coefficient which increases from 1.13 $(p < 0.0001)$, to 1.25 $(p < 0.0001)$.

If we for model five focuses on the relationship between stock returns and EUA returns, corresponding to the calculations in section 7.1.1.2, we get the following coefficient value for $r_{i,t}^{EUA}$:

$$\beta_2 + \beta_3^{paid} CI_{i,Y}^{paid} + \beta_3^{free} CI_{i,Y}^{free} + \beta_3^{hedged} CI_{i,Y}^{hedged}$$
$$= 0.03 - 2.06 * 0.31 + 1.25 * 0.35 + 0.33 * 0.68 = 0.05$$

The positive value of this coefficient shows that for the EW portfolio an increase in the EUA returns will result in an increase in the stock returns. An implication of this is that if one wants to reduce the volatility in stock returns via hedging the EW portfolio with EUA futures contracts, a short position in the futures contract must be used. The short position is however smaller compared to the ratio indicated by model two.

Due to the significant results shown in model five and the large change in the β_3^{paid} coefficient, a new sample of the firms that hedge is made to further investigate the relationship. The result from the sample of hedgers is shown in model six and seven. In model six, the CI paid, and free variables are included. In model seven the CI hedged variable is also used. When comparing the two models we see that the β_3^{free} coefficient is very similar in size $(3.01; 2.96)$ and significant $(p < 0.0001)$. The β_3^{paid} coefficient is however quite different in size. In model six it is -0.64 and in model seven it is -2.02, the significance level is however the same $(p < 0.01)$. The β_3^{hedged} coefficient in model seven is positive (0.33) and significant $(p < 0.01)$.

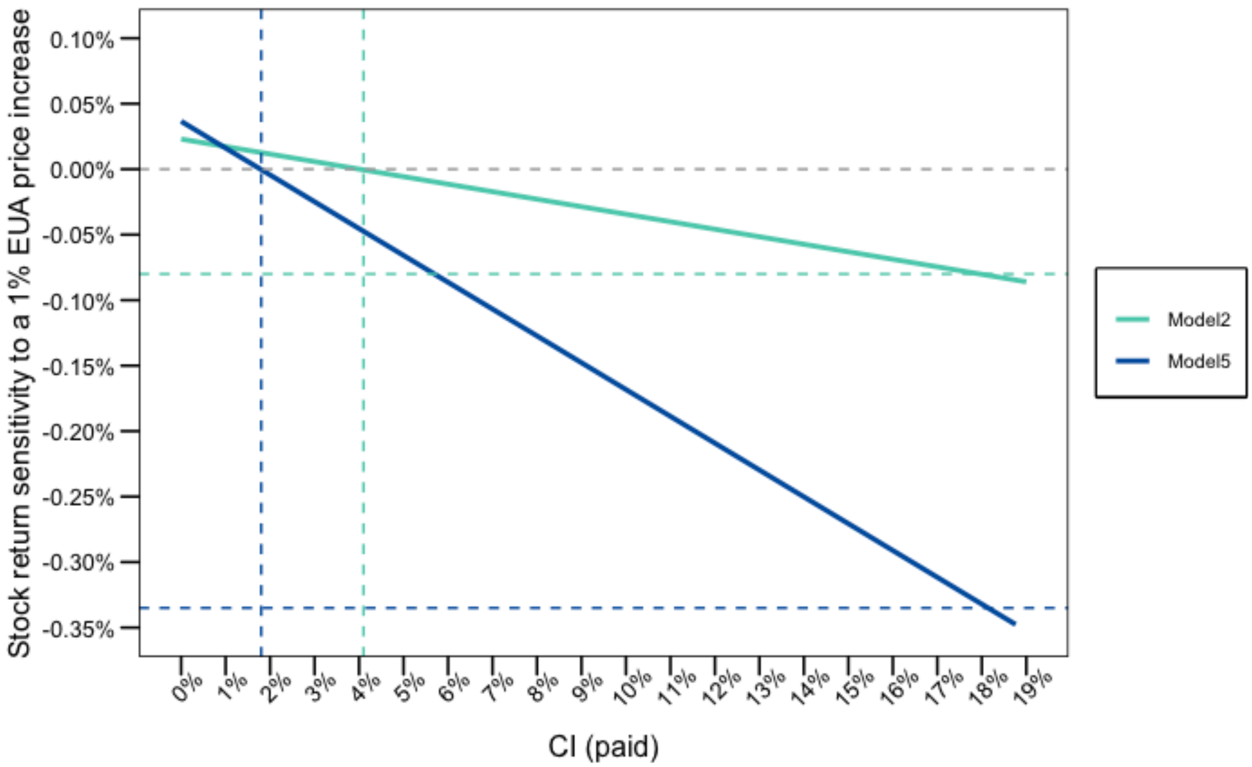

Figure 4. The plot shows an illustration of stock return sensitivity to a 1 percent change in EUA return as a function of paid carbon intensity. The values for CI free and CI hedged is set equal to the average values for the EW portfolio (see table 2). The figure shows the result from model 2 (green) and 5 (blue). Firms that see a negative effect on stock prices (if there is an increase in the EUA price) are to the right of the dashed, vertical lines. The horizontal lines (green and blue) indicate the largest stock price sensitivity and (grey) marks the point for a negative (right) or positive (left) impact.

As seen in Figure 4, stock return sensitivity to an EUA price increase affects individual firms differently depending on the firms paid carbon intensity. The model choice also impacts the sensitivity. Model two (green) shows that stock returns are less sensitive to changes in the CI paid than model five (blue). Looking closer at model five, the plot illustrates that it is only firms with a CI paid larger than 1.8 % that see a decrease in their returns if the EUA price increases by 1 %. Furthermore, if there is a 1 % increase in the EUA price, the stock in our sample with the highest paid carbon price intensity (18 %) will have a 0.34 % reduction in stock return. Based on model two (green), firms with a CI paid larger than 4.1 % will get a reduction in stock return. If there is a 1 % increase in the EUA price, the stock in our sample with the highest paid carbon price intensity (18 %) will get a 0.08% reduction in stock return based on model two.

7.1.1.4 Scope 2 carbon price intensity

Regression model three includes the CI scope 2 variable as an addition to the CI paid and free variables. Scope 2 emission impacted by carbon pricing amounts to 13 % of total scope 1 emissions. The β_3^{scope2} coefficient has a value of 0.24 and is statistically significant $(p < 0.01)$. The coefficient of β_3^{paid} is negative -0.59 and statistically significant $(p < 0.001)$ which is the same as for model two. The β_3^{free} coefficient is positive (1.22) and significant $(p < 0.0001)$. Including the independent CI scope 2 variable resulted in changes in the coefficients, slightly magnifying the size of CI paid and free.

7.1.1.5 Banked carbon price intensity

There are 34 firms in the full sample who bank allowances. Banked emission amounts to 15 % of total scope 1 emissions. In model four, the results for the CI banked variable are presented. The results reveal a negative (-0.49) but not significant β_3^{banked} coefficient. The β_3^{paid} coefficient is negative (-0.61) and statistically significant $(p < 0.001)$ and the β_3^{free} coefficient is positive (1.25) and significant $(p < 0.0001)$. Including the independent CI banked variable did not lead to any significant changes in the coefficients.

7.1.1.6 Conclusion

The results from the multi-factor analysis show that there is positive and statistically significant co-movement between the returns on EUAs, CI free, hedged, scope 2 and the stocks in our EW portfolio. We have also found a negative and significant relationship between the CI paid variable and the stock returns. In model six and seven, which focuses on the hedgers sample, the relationships found in model two and five, referring to the full sample, continues to hold. The independent variables related to banked allowances did not generate significant results. We speculate that the impact of banked allowances may be reflected indirectly in the dynamics of free allowances. The results from the independent CI paid, free, scope 2 and hedge variables will be discussed further in chapter 8. Because we have been able to identify a relationship between said variables, we now want to investigate risk management strategies aimed at reducing carbon price risk. In the next section we calculate hedge ratios and test hedging effectiveness on European stock portfolios using EUA futures contracts as a hedging instrument.

7.2 Hedging carbon risk with EUA futures

In this chapter we present the results from the estimated and modelled hedge ratios. The aim of the hedge is to reduce carbon price risk in European equity portfolios, with EUA futures contracts as the hedging instrument. The hedge ratios (HRs) are estimated and modelled on in-sample data and tested on the out-of-sample data. The results are based on a monthly (12 times/year) hedge over a period of 6 years. As a robustness check for the hedge ratios and effectiveness is also calculated from a continuous weekly hedge on the same sample. The ratios and effectiveness are presented the following chapters.

7.2.1.1 Hedging ratios

The time varying hedge ratios from the monthly DCC model and OLS estimates are presented in Figure 5 and 6. The hedge ratios represent the proportion of the position in EUA futures compared to the portfolio position. There is a difference between the stability and size of the ratios from the two models. However, a consistent result from both is to go short in the EUA futures. This is true for both the OLS estimates and DCC models, and for all four portfolios. The ES and EW Energy portfolios have HRs moving somewhat similarly. This is the case for the ES and EW Industry portfolios, as well. The HRs exhibit only slight variations in the OLS model, whereas the HRs from the DCC model are much more varying.

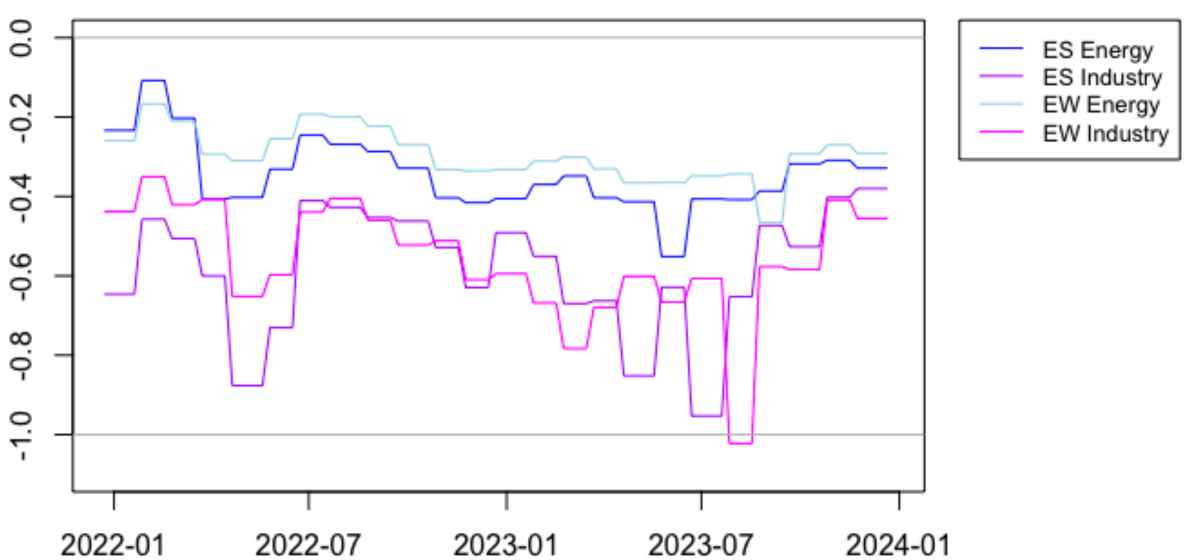

Figure 5. Optimal hedging ratios from monthly hedging of energy and industry indices obtained from rolling window estimations. The OHRs are obtained from a DCC-GARCH model.

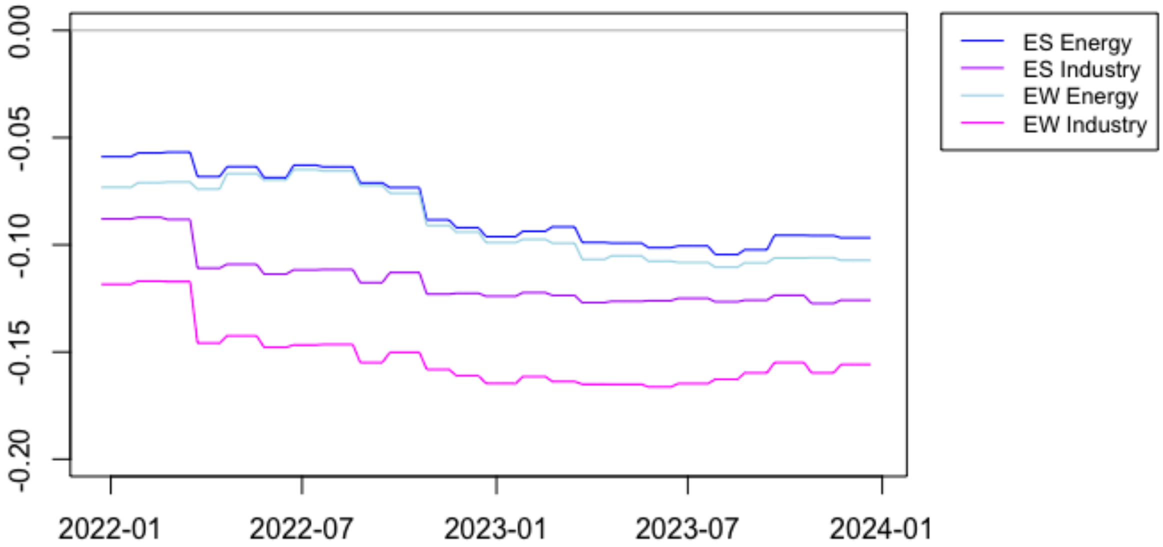

Figure 6. Optimal hedging ratios from monthly hedging of energy and industry indices obtained from rolling window estimations. The OHRs are obtained from OLS estimations.

The results from the DCC model indicate that the industry portfolios require a larger number of short positions in EUA futures for their HRs than the energy portfolios. The ES industry portfolio has an average HR of -0.59 and the EW industry portfolio has an average of -0.56. The ES energy portfolio has an average HRs of -0.35 and the EW energy portfolio -0.29.

On the other hand, for the OLS estimates, the ES Industry portfolio has a mean HR of -0.12 and the EW Industry portfolio has a mean of -0.15. The ES Energy portfolio has an average HR of -0.08 and the EW Energy portfolio has an average of -0.09. The results from the OLS estimates indicate that the industry and energy portfolios require similar and a more stable number of EUA futures for their HRs compare to the HRs from the DCC.

Table 6. An Overview of results from the analysis on hedging. In Panel A the average hedge ratios are reported. Panel B and C display the RHE and the change in variance from the out-of-sample OLS and DCC results. Correlation and annualized variance are reported for the full sample as well as in- and out-of-sample in panel D and E. Panel F shows changes in out-of-sample returns for the hedged portfolios using the OLS and DCC hedging ratios.

	EW Industry	ES Industry	EW Energy	ES Energy
Panel (A)	Mean Hedge Ratio			
OLS	-0.15	-0.12	-0.09	-0.08
DCC	-0.56	-0.59	-0.29	-0.35
Panel (B)	Realized Hedging Effectiveness			
OLS	0.08	0.05	0.09	0.11
DCC	-0.77	-1.23	-0.21	-0.44
Panel (C)	Δ Variance			
OLS	-0.005	-0.003	-0.004	-0.004
DCC	0.05	0.06	0.01	0.02
Panel (D)	Correlation with EUA			
Full sample	0.26	0.24	0.15	0.15
In-sample	0.27	0.26	0.15	0.13
Out-of-sample	0.23	0.21	0.17	0.19
Panel (E)	Annualized variance for the unhedged portfolios			
Full sample	0.07	0.05	0.08	0.07
In-sample	0.08	0.05	0.10	0.08
Out-of-sample	0.06	0.05	0.05	0.04
Panel (F)	Δ Annualized return			
Hedged OLS portfolio	-0.04	0.00	-0.02	0.03
Hedged DCC portfolio	0.01	0.04	0.01	0.07

7.2.1.2 Hedging effectiveness

The hedge ratios from the OLS estimates result in positive realized hedging effectiveness (RHE) for all four portfolios. The ES industry portfolio has a RHE of 0.05 and the EW industry portfolio has a RHE of 0.08. The ES energy portfolio has a RHE of 0.11 and the EW Energy portfolio has a RHE of 0.09, these results are visualized in Figure 7. The OLS approach led to a reduction in annualized variance by 0.005 and 0.003 for the EW and ES industry portfolios, and a reduction of 0.004 for both the energy portfolios. These results are presented panel C in Table 6. The only hedged portfolio with an increased annualized return is the ES energy portfolio. The annualized return for the hedged EW and ES industry portfolios is reduced compared to the unhedged stock portfolios. There is no change in the return for the hedged ES industry portfolio.

Figure 8 displays the RHE derived from the DCC model for the four hedged portfolios. Applying the HRs from the DCC produced negative out-of-sample hedging effectiveness for all portfolios under consideration. Specifically, the figure highlights that the ES industry portfolio exhibits an RHE of -1.23, while the EW portfolio records an RHE of -0.77. Moreover, the analysis reveals that the ES energy portfolio presents an RHE of -0.44, and the EW energy portfolio demonstrates an RHE of -0.21.

The analysis reveals that employing ratios from the DCC model led to an increase in the variance across all hedged portfolios. Notably, the ES industry portfolio experienced the most significant rise in variance, with an increase of 0.06. In contrast, the EW energy portfolio saw the most modest rise, with an increase of 0.01. Additionally, ratios derived from the DCC model resulted in an increase in annualized returns for all portfolios. The largest increase was observed in the ES energy portfolio, which saw returns increase by 0.07. The ES industry portfolio had an increase of 0.04. Meanwhile, both EW portfolios, the energy and industry, recorded the smallest change in returns, each increasing by 0.01.

As a robustness check, we also calculate hedge ratios for a one week forecast. The results from this analysis showed similar results as we found in the one month forecast. The positive RHE from the OLS and the negative RHE from the DCC was consistent for the robustness check as well. This is illustrated in Figure 7 and 8. An overview of the results from the robustness check analysis can be found in the appendix.

The results from the hedge analysis show that EUA futures can be employed to minimize variance in stock portfolios containing firms from the energy and industry sector, especially when using a simple OLS estimator to obtain hedge ratios for out-of-sample hedging. Conversely, when modelling the hedge ratios with a DCC-GARCH model, an increase in variance was observed for the same equity portfolios. Notably, the increase in variance was accompanied by an increase in annualized returns for some of the portfolios. Although both the OLS estimator and the DCC-GARCH model recommended adopting a short position in EUA futures, the hedge ratios calculated through the DCC-GARCH model were larger and exhibited greater volatility compared to those estimated via the OLS approach.

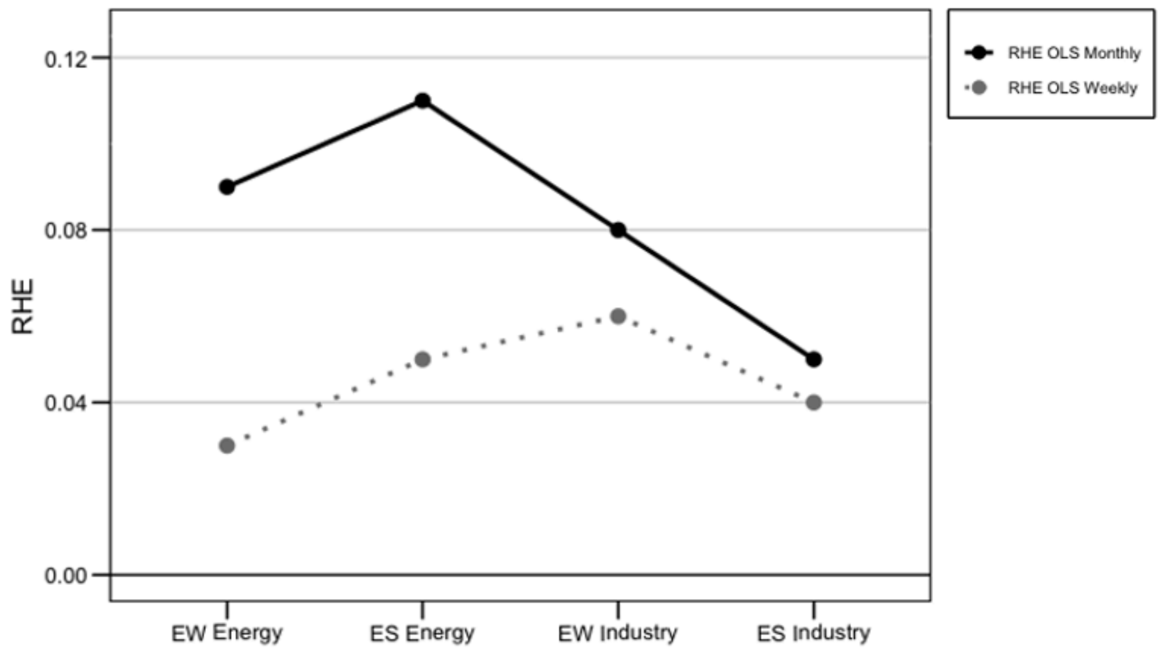

Figure 7. Realized hedging effectiveness for the four portfolios with optimal hedge ratios (OHRs) from OLS estimates.

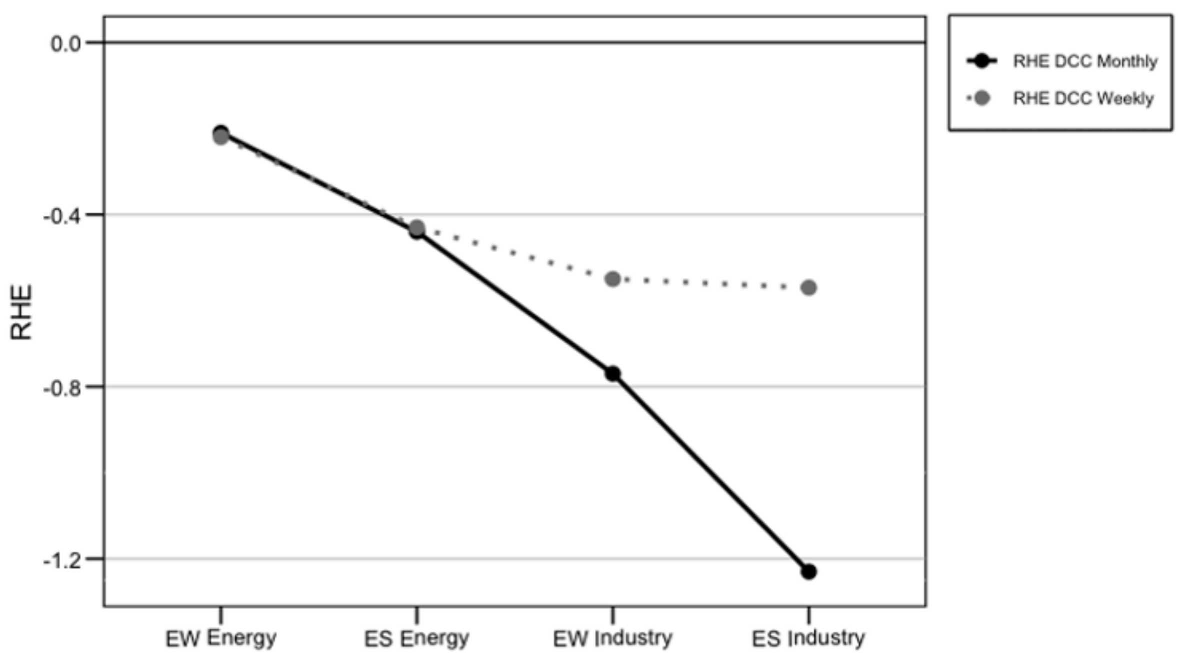

Figure 8. Realized hedging effectiveness (RHE) for the four hedged portfolios with optimal hedge ratios (OHRs) from the DCC-GARCH model.

8 Discussion

In this this chapter, the results from our analyses are compiled and discussed. The analysis of this study has been separated into two main parts. In the first part, we studied the relationship between the dependent variable of European stock returns and independent variables for the return on EU allowances, carbon price intensities (CI) and other control variables for the period 2018-2023. In the second part, we estimated and modelled hedge ratios with the goal of reducing carbon price risk in European stock portfolios. The results from our analyses are presented in relation to our hypothesizes as well as the results from similar studies. Furthermore, we discuss the implications of our results, as well as methodological and data limitations. Finally, we suggest directions for further analyses.

8.1 Multi-factor analysis

The findings from our multi-factor analysis show a positive and a statistically significant relationship between the return on the EUA variable and the stock return in our EW portfolio. Furthermore, the coefficient for independent variable CI total is found to be non-significant. However, splitting it into the two independent terms CI paid and CI free, reveals both components to be significant, although with differing directional relationships with the stock returns. Specifically, CI free exhibits a positive relationship, whereas CI paid reveals a negative relationship with the stock returns. This finding add insight into the non-significant coefficient from variable CI total.

Our results from the CI paid coefficient are consistent with those of Millischer et al. (2023). However, our results differ by identifying a significant, positive correlation for CI free, contrasting with their non-significant findings for this variable. Our result parallels the results of Hengge et al. (2023), who suggest a possible explanation for the positive correlation between carbon intensity and stock returns. E.g., if there's more demand for products made by high-emitting companies, these companies might produce more and earn higher profits. This increase in production would increase the need for carbon allowances, leading to higher carbon price. The firms in our sample that receive free allowances could end up making a profit due to over allocation. This dynamic might explain the positive impact on their stock price in response to rising allowance prices.

When incorporating regulatory events to model demand shocks, Hengge et al. (2023) observe that rising carbon prices negatively affect stock returns. In the context of our analysis, we believe that the inclusion of shocks, is similar to the effect we find from the variable CI paid. Millischer et al. (2023) also investigates the impact of regulatory events and find that the coefficient for CI paid is negative and significant on both event and non-event days. Furthermore, on event days impacting the allocation of free allowances, they find that the coefficient for CI free is negative and significant. This is the only time they find significant results for this variable.

Another key finding in our study is the effect from including the independent variable CI scope 2 and CI hedge. The inclusion of the CI scope 2 variable has a small effect on the CI free and paid variables, by slightly increasing the size of both coefficients. We interpret the results from including CI scope 2 in the context of the regulatory structure of the EU ETS. Even though the carbon price has no direct effect on scope 2 emissions, as only firms' scope 1 emissions are included in the system, there is an indirect effect through power prices. This is because utility firms' scope 1 emissions are other firms' scope 2 emissions. Therefore, the indirect impact on firm's scope 2 related costs can explain the existence of co-movements with the stock returns.

When the CI hedge variable is included in the regression model, the estimated coefficient from CI paid has a stronger negative relationship with the stock returns. To our knowledge, the inclusion of a variable to account for firms' own hedging behavior (CI hedge), has not been explored in previous literature. Consequently, the estimated coefficient we find for CI paid, when including the CI hedge variable, has a larger negative impact on stock returns than what Millischer et al. (2023) finds in their study.

Our interpretation of the results from including the CI hedged variable is that we capture a more comprehensive representation of the relationship between firm's carbon price intensity and stock returns, because we account for the firm's risk management strategies. This result suggests that the market views the imposed carbon cost (CI paid) as indicative of high emissions, potentially leading to significant costs because of climate regulation. Conversely, a self-imposed carbon cost through emissions hedging (CI hedge) is rewarded. Thus, distinguishing between a voluntary carbon cost (CI hedge) and an imposed carbon cost (CI paid) reveals a differentiation between risk management and compliance.

The adjusted r-squared value for our regression models based on the full sample is 0.34. This indicates that the variables we chose explain a part of the relationship we're exploring. However, there are still other factors affecting stock returns that we haven't included in our analysis. The outcomes of our study are influenced by the specific period and sample examined. Since the EU ETS began, the price of EUA futures was initially low but has seen an exceptional rise in the last four years. Furthermore, the development of the EUA price impacts the carbon price intensities used in our analysis.

In conclusion, in our examination of European stocks, we find evidence supporting our alternative hypothesis. There is a significant relationship between the dependent stock return variable, the independent EUA returns, and the carbon price intensity variables free, paid, scope 2 and hedged. For the independent carbon price intensity variable banked the null hypothesis is not rejected. In the next section we will discuss the results from our analysis on hedging strategies.

8.2 Hedging strategies

In our analysis of carbon risk mitigation within European stock portfolios, we have used EUA futures contracts as a hedging instrument. For the calculation of hedge ratios (HRs), we used a Dynamic Conditional Correlation (DCC) model and an Ordinary Least Squares (OLS) estimation. Four distinct portfolios were included in our analysis: Eurostoxx (ES) Energy, ES Industry, Equally Weighted (EW) Energy, and EW Industry. To evaluate the effect of the estimated HRs, we tested them out-of-sample using rolling windows.

For all four portfolios the estimated coefficients confirmed a short position in the EUA futures to be the most effective for reducing variance. The DCC hedge ratios for the two energy portfolios were quite stable, while the industry ratios were more varying. The energy ratios ranged between -0.1 and -0.5 and the industry hedge ranged between -0.4 and -1. Furthermore, the estimated hedge ratios from the OLS estimator gave more stable ratios. Here the EUA ratio for the energy portfolios ranged between -0.06 and -0.1. The ratios for the industry portfolios were also more varying when estimated with OLS, between -0.08 and -0.16. This indicates that minimizing variance with EUAs are more expensive in the industry portfolios than the energy portfolios. Furthermore, it means that following a hedging strategy based on the DCC estimates are more costly.

Moreover, our analysis identified a positive realized hedging effectiveness (RHE) across the four portfolios when applying OLS estimations. With this method, the values ranged between 5 percent and 11 percent. Conversely, the application of the DCC model resulted in negative RHE for all portfolios.

The OLS method resulted in a reduction of annualized variance for all portfolios. This is expected for hedged portfolios with a positive RHE. When the DCC model was applied all hedged portfolios showed an increase in variance, but also an increase in annualized returns.

The results derived from the DCC model support the null hypothesis. The hypothesis states that using EUA futures contracts as a hedging instrument does not lead to a reduction in variance for the stock portfolios in question.

The DCC model is known for its ability to capture and adapt to changes in correlations. However, the absence of observed hedging effectiveness could come from multiple issues. Specifically, the DCC model's handling of time-varying correlations might introduce complications. This is potentially due to overfitting or misinterpretations of fluctuations in the correlations between the EUA returns and the stock portfolio returns. Consequently, this approach fell short in delivering the anticipated hedging benefits.

The results from the OLS estimations support for the alternative hypothesis. This hypothesis states that implementing a hedge strategy using EUA futures as a hedging instrument reduces portfolio variance and results in a positive hedging effectiveness.

The OLS estimation is a more straightforward method that, when combined with the rolling windows, can indirectly accommodate time-varying correlation. The hedge ratios are recalculated over successive, overlapping time windows. Instead of a direct application of the changing correlations, the OLS estimation indirectly captures the changes in correlation between the stock portfolio and the EUAs. Our results show that this approach resulted in a variance reduction and positive hedging effectiveness.

To our knowledge, Ahmad et al. (2018) is the only study estimating out-of-sample HRs and RHE with EUA futures as a hedge instrument for stocks. In their analysis, they find positive HRs between the Clean Energy Index and the EUA futures contracts. The average HRs are 10 percent from both the OLS estimator and the DCC model. Using the DCC ratios, they get positive HE of 0.02. When using the estimated ratios from the OLS, they get negative HE of -0.05. In our analysis we find the opposite result. We identify positive HE when using the OLS estimations and negative HE when using the DCC model.

Our findings are unexpected, particularly the negative outcomes produced by the DCC model. Given its sophistication compared to the OLS estimator and the results by Ahmad et al. (2018), we expected it would lead to a reduction in variance and positive hedging effectiveness. The contrary results thus present a surprising deviation from our assumptions.

There are however differences between our and their study. First, Ahmad et al. (2018) use a ten-year period which ends when ours start. Second, they look at clean energy stocks and we look at energy-intensive firms in the EU ETS. Third, they use daily frequency for their return series, and we use weekly. Our decision to use a weekly frequency differs from other studies and is deliberately chosen to align closer with the preferences of investors who engage in hedging. The approach acknowledges that investors tend to avoid frequent alterations to their hedging strategies, instead selecting an approach for a longer-term view.

8.2.1 Model limitations for hedging

The negative hedge effectiveness (HE) raises several questions. Initially, it's possible that the model's estimation lacks precision. The HRs for the industry portfolios show more variation than the energy portfolios. It is also the energy portfolio where we observe that the HE outcomes are more favorable than those for the industry portfolios.

Further inspection into the model fitting supports this observation: the energy portfolios have fewer convergence issues. The EW energy portfolio has one failure, and the ES energy portfolio has two failures. Conversely, the industry portfolios have a higher rate of convergence issues. The EW industry portfolio has five failures, and the ES industry portfolio has four. These disparities can explain some of the observed differences in the HE, emphasizing why the energy portfolios exhibit better HE. It also suggests that the convergence issues might have impacted the results.

Another explanation for the observed negative effectiveness may be the time inconsistent behavior in the time series, resulting in an ineffective forecast. This explanation is strengthened by a simple examination of the underlying data. We find that the out-of-sample hedged portfolio has a positive correlation with the predicted variances from the DCC model. The predicted variances are used as a proxy for the realized portfolio variance. The positive correlation indicates that the model's forecasts are not inherently flawed. Consequently, this leads us to infer that there may be inconsistencies within the data that limit the effectiveness of our DCC model.

An alternative perspective is to consider the results from our multi-factor analysis. The results from model two revealed the relationship within the carbon risk factors to be complex. The analysis aimed to determine whether EUA returns, and carbon intensity variables co-moved with European stocks. However, a challenge emerges when we consider that these variables display different effects on stock returns. Specifically, while the EUA and CI free variable displays a positive relationship with stock returns, the CI paid variable demonstrates a negative relationship.

This difference presents a challenge in the context of hedging. On one hand, the positive correlation between stock returns and EUA returns would imply a strategy favoring short positions in EUA futures. Conversely, the negative influence attributed to the CI paid variable, suggests taking long positions in EUAs. Our analyses in preceding sections have recommended short positions. However, examining the risk factors discussed in this section, it's obvious that the interactions are more complex than what is reflected in the method used to obtain HRs. Our position is that the simplification, which focuses solely on EUA returns, may have weakened the hedge's effectiveness.

8.3 Data limitations

For our multi-factor analysis, we used data from 112 companies. We arrive at this selection by mapping the constituents from the Eurostoxx 600 index to a data set from SparkChange. The common key is ISIN. The method for selecting the firms is therefore not random, but first dependent on the Eurostoxx 600 and then on the database from SparkChange. This results in a small sample consisting of mainly large European stocks.

Our samples are not representative because they were not chosen randomly. As a result, the findings, and conclusions we've drawn apply only to our specific sample, not to the broader population or market. This limitation means our sample doesn't accurately reflect the overall stock market or its various sectors, making it inappropriate to generalize our results.

Given the relatively small number of companies covered, we were unable to perform meaningful analysis on specific industries such as energy and utilities. We had hoped to run regression analyses on these various sectors to gain deeper insights, but this was not feasible with the sample size.

There are also issues with the carbon price intensity variables. Specifically, the CI paid variable shows a low average but a very high maximum. This suggest there are a few cases with extremely high paid carbon price intensities. Hence, we need to be cautious when interpreting the results displayed in Figure 4.

In essence, our findings cannot reliably inform definite conclusions. Further research is necessary to provide solid recommendations. Moreover, the outcomes we observed are tied to the specific period of our study. A look at previous literature confirms that results can vary significantly across different periods.

8.4 Future research

If we were to study this subject further, we would explore how different time periods affect the relationship between stock returns and the independent carbon variables. Specifically, we would want to split our sample period into smaller frames to better understand the effect from the EUA price. It would also be interesting to extend the total period to investigate ETS phases and introduction of regulation like the MSR.

Additionally, an extension of the sample size would also be an avenue we would want to explore. The database from SparkChange contains many more firms than we could include, based on our restrictions. Therefore, not limiting the sample size by the 600 constituents from the Eurostoxx index, we would want to do a broader analysis including stocks impacted by other ETS's in addition to the EU ETS.

For further exploration of the relationship between stock returns, EUA returns and carbon price intensities we would also want to test different methods. One of the directions we would be interested in exploring is if there is a non-linear relationship between the variables. We would want to do this by squaring the independent variables.

Related to the hedge strategies, there's an opportunity to refine more complex models to more accurately reflect the volatility patterns observed in the return series. We would want to extend the bivariate DCC-GARCH model to a multi-variate model, by including other futures contract e.g. oil and gas, to isolate the volatility effect from the EUA futures. Furthermore, we would also look at more indices. The indices could be constructed based on e.g. carbon intensities. We believe a more comprehensive understanding is crucial for effective hedging strategies. Better strategies could help tackle the nuanced challenges of carbon risk, leading to improved risk mitigation techniques for investment portfolios.

The research on the subjects presented in this study is highly dependent on the relatively new regulatory framework in which carbon risk and carbon prices exist. The EU ETS, which began in 2008, initially gave out most allowances for free and set a high emission cap. This resulted in low prices and a small impact on company costs. However, with the emission cap decreasing over time, it will probably play a more significant role in the future. Therefore, it's important to continue research in the coming years to better understand how carbon risk factors influence stock returns.

9 Conclusion

The main purpose of this study has been 1) to investigate carbon risk as a risk factor in the European stock market and 2) to analyze if this risk can be hedged with EUA futures. The period studied is from 2018-2023. We have investigated the relationship between 112 stocks and the price of EUA futures as well as the stocks' carbon price intensities. The stocks in our sample are in the EU ETS. In addition, we have examined if EUA futures can be used as a cross hedge in stock portfolios to reduce risk.

Investigating the co-movements between the dependent stock returns and the independent EUA return and carbon price intensity variables was done using a multi-factor approach. The carbon price intensities for each stock were calculated based on their normalized emission costs. Multiple intensities have been investigated. The most relevant for our results were free, paid, scope 2 and hedged carbon price intensity. For these variables the null hypothesis stating that there was no relationship between stock prices and carbon price intensity variables was rejected.

To evaluate the effect from hedging with EUA futures, we tested the hedge ratios out-of-sample using rolling windows. The hedge ratios used for the portfolios were estimated and modelled using an OLS estimator and a DCC-GARCH model.

In our sample, we find a positive and significant relationship between the return on EUA futures, and the carbon price intensities free, and hedged. For the paid carbon price intensity, we find a negative and significant relationship with the stock returns. One of our contributory findings is that when we include the variable for hedged, the value of the paid variable increases.

The results from using the OLS estimated hedge ratios was reduced volatility and a positive hedging effectiveness for all four portfolios. One of the hedged portfolios saw an increase in annualized return. The results from using the DCC modelled hedge ratios was increased volatility and a negative hedging effectiveness for all four portfolios. However, these hedged portfolios saw an increase in annualized return.

Our study reveals some interesting results. However, our conclusion is that the results are highly dependent on the sample and cannot be generalized to the broader population. Because of this we cannot provide any clear recommendations, but only share what our results can encourage for future investigations.

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Appendix

1.1.1 Variable testing

The results of the Augmented Dickey-Fuller (ADF) unit root test and the Jarque-Bera (JB) test for normality are presented in Table 1.

Table 1. ADF test results for stationarity, lag = 10. Jarque-Bera test for normality. P-values in square brackets.

Variables	ADF	JB
EW portfolio	7.9 [0.00]	124 643 [0.00]
ES600	-11.5 [0.00]	800.75 [0.00]
rEUA	-6.8 [0.00]	116.2 [0.00]
CI (total)	-4.3 [0.00]	116.2 [0.00]
CI (free)	-5.3 [0.00]	69 315 [0.00]
CI (paid)	-7.4 [0.00]	135 844 [0.00]
CI (banked)	-10.0 [0.00]	287 174 [0.00]
CI (Hedged)	-17.9 [0.00]	197 865 [0.00]
CI (Scope2)	-3.6 [0.00]	750 869 [0.00]
Oil	-7.4 [0.00]	116.2 [0.00]
Gas	-8.6 [0.00]	14 726 [0.00]
El	-7.9 [0.00]	4215.1 [0.00]
EW Industry	-10.3 [0.00]	1688.2 [0.00]
ES Industry	-11.6 [0.00]	1292 [0.00]
ES Energy	-12.8 [0.00]	1710.9 [0.00]
EW Energy	-11.1 [0.00]	1382.8 [0.00]
fEUA	-11.5 [0.00]	21.8 [0.00]

The ADF test indicate that all return series are stationary and reject the existence of a unit root. The Jarque–Bera (JB) test indicates that all sample variables are deviating from normality. The results of the preliminary test show that all the return series are stationary but deviate from normality. The variables are suitable for additional modelling in accordance with our research objectives.

1.1.2 Robustness check for hedging

To test the monthly hedge for robustness, a simpler forecast was attempted for a one-step forecast. Table 2 show the results from weekly hedging for the four indices. The results from weekly hedging seem to be consistent with the monthly hedging.

Table 2. An Overview of results from the analysis on weekly hedging. In Panel A the average hedge ratios are reported. Panel B and C display the RHE and the change in variance from the out-of-sample OLS and DCC results. Correlation and annualized variance are reported for the full sample as well as in- and out-of-sample in panel D and E. Panel F shows changes in out-of-sample returns for the hedged portfolios using the OLS and DCC hedging ratios.

	EW Industry	ES Industry	EW Energy	ES Energy
Panel (A)	Mean Hedge Ratio			
OLS	-0.26	-0.19	-0.17	-0.15
DCC	-0.53	-0.57	-0.33	-0.40
Panel (B)	Realized Hedging Effectiveness			
OLS	0.05	0.04	0.03	0.04
DCC	-0.36	-0.35	-0.24	-0.45
Panel (C)	Δ Variance			
OLS	-0.003	-0.002	-0.002	-0.002
DCC	0.02	0.02	0.01	0.02
Panel (D)	Correlation with EUA			
Full sample	0.30	0.26	0.20	0.19
In-sample	0.29	0.26	0.21	0.18
Out-of-sample	0.31	0.27	0.20	0.24
Panel (E)	Annualized variance for the unhedged portfolios			
Full sample	0.07	0.05	0.08	0.07
In-sample	0.08	0.05	0.09	0.08
Out-of-sample	0.06	0.05	0.05	0.04
Panel (F)	Δ Annualized return			
Hedged OLS portfolio	0.08	0.01	0.13	0.10
Hedged DCC portfolio	0.12	0.12	0.12	0.12

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