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MASTER'S THESIS

AN EVENT STUDY OF THE EFFECTS OF CARBON PRICING SHOCKS ON FIRMS

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ABSTRACT

Carbon pricing has become an important topic in finance and economics, making it essential to quantify its effects for policy evaluation and corporate decision-making. As financial markets increasingly price in carbon risk, firms must adapt to evolving regulation and transition towards greener operations. For investors and regulators, understanding how markets respond to carbon price shocks provides valuable insight. Carbon pricing can affect firms' stock performance, which in turn can influence both the systematic risk of the firm and its cost of capital. To assess systematic carbon risk at the firm level, I estimated carbon betas by regressing stock returns on emission allowance futures returns for each firm in my sample. Carbon-intensive firms show the highest sensitivity, with a median carbon beta of 0.13, while renewable firms show the lowest (0.075). Energy firms fall in between. The results do not provide strong evidence that carbon risk is fully reflected in asset prices in this small sample. Analysis of the weighted average cost of capital (WACC) over the 2015–2025 period further indicates that carbon-intensive firms have historically faced the highest financing costs, while energy firms have faced the lowest. The core of this thesis applies an event study methodology to examine the market reaction of European firms to a significant increase in carbon prices. The empirical analysis, complemented by machine learning models, evaluates abnormal returns across three subgroups: carbon-intensive firms, energy firms, and renewable firms. Results indicate a slight decline in average abnormal returns for carbon-intensive firms and a slight increase for energy and renewable firms on the event day. However, cumulative average abnormal returns are statistically insignificant for carbon-intensive and energy firms, while, for renewable firms, cumulative average abnormal returns are negative and significant over the full event window. When the analysis is split into pre- and post-event periods, statistical significance appears only in the pre-event period. An important aspect of this thesis is the evaluation of machine-learning techniques within the event study framework. Across all firm groups, linear regression outperforms alternative models on average, producing the lowest root mean square error when two explanatory variables are included in the market model.

KEYWORDS: carbon pricing, event study, machine learning, econometrics, emission trading scheme, carbon risk, abnormal returns, linear regression, cumulative average abnormal returns, volatility

SUSTAINABLE DEVELOPMENT GOALS

POVZETEK

Zaračunavanje emisij ogljika je postalo pomembna tema v financah in ekonomiji, zato je ključno kvantificirati njegove učinke za oblikovanje politik in poslovnih odločitev podjetij. Ker finančni trgi vse bolj upoštevajo tveganja, povezana z emisijami, se morajo podjetja prilagajati razvijajoči se regulativi in postopoma preusmerjati v bolj trajnostno delovanje. Za vlagatelje in regulatorje razumevanje odziva trgov na cenovne šoke emisij ogljika predstavlja dragocen vpogled v delovanje trga. Zaračunavanje emisij ogljika vpliva na donose delnic, kar lahko posledično vpliva tudi na sistematično tveganje podjetja in stroške kapitala. Za zajem sistematičnega ogljičnega tveganja sem na ravni posameznih podjetij ocenil ogljične bete z regresijo donosov delnic na donose emisijskih terminskih pogodb. Podjetja z visoko emisijsko intenzivnostjo izkazujejo največjo občutljivost z mediano ogljične bete 0,13, medtem ko imajo podjetja obnovljivih virov najnižjo občutljivost (0,075). Energetska podjetja se nahajajo med tema dvema skupinama. Rezultati ne ponujajo močnih dokazov, da je ogljično tveganje v celoti vključeno v cene delnic na tem majhnem vzorcu. Analiza tehtanega povprečnega stroška kapitala (WACC) za obdobje 2015–2025 kaže, da so podjetja z visoko emisijsko intenzivnostjo zgodovinsko imela najvišje stroške financiranja, energetska podjetja pa najnižje. Jedro magistrske naloge predstavlja uporaba metodologije študije dogodkov za preučevanje odziva evropskih podjetij na večje zvišanje cen emisijskih kuponov. Empirična analiza, dopolnjena z modeli strojnega učenja, ocenjuje abnormalne donose treh podskupin podjetij: podjetij z visoko emisijsko intenzivnostjo, energetskih podjetij in podjetij, ki delujejo na področju obnovljivih virov energije. Rezultati kažejo rahel padec povprečnih abnormalnih donosov za podjetja z visoko emisijsko intenzivnostjo ter rahel porast za energetska podjetja in podjetja obnovljivih virov na dan dogodka. Kljub temu so kumulativni povprečni abnormalni donosi za podjetja z visoko emisijsko intenzivnostjo in energetska podjetja statistično neznačilni, medtem ko so za podjetja obnovljivih virov negativni in statistično značilni skozi celotno obdobje dogodka. Ob ločitvi analize na obdobje pred dogodkom in po njem se statistična značilnost pojavi le v pred-dogodkovnem obdobju. Pomemben del magistrske naloge predstavlja tudi ocena uporabnosti metod strojnega učenja v okviru študije dogodkov. Za vse skupine podjetij se je pokazalo, da v povprečju linearni regresijski model deluje bolje od alternativnih, saj dosega najnižjo vrednost, merjeno s korenom srednje kvadratne napake, kadar sta v model vključeni dve pojasnjevalni spremenljivki.

KLJUČNE BESEDE: zaračunavanje emisij ogljika, študija dogodkov, strojno učenje, ekonometrija, sistem EU za trgovanje z emisijami, ogljično tveganje, abnormalni donosi, linearna regresija, kumulativni povprečni abnormalni donosi, volatilnost

CILJI TRAJNOSTNEGA RAZVOJA

7 CENOVNO DOSTOPNA IN ČISTA ENERGIJA

9 INDUSTRIJA, INOVACIJE IN INFRASTRUKTURA

12 ODGOVORNA PORABA IN PROIZVODNJA

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LIST OF ABBREVIATIONS

sl. – Slovene
AAR – (sl. povprečni abnormalni donosi); Average Abnormal Returns
BMG – Brown-minus-Green
CAAR – (sl. kumulativni povprečni abnormalni donosi); Cumulative Average Abnormal Returns
CAC – (sl. zapovedno-nadzorni sistem); Command and Control
CBAM – (sl. mehanizem za ogljično prilagoditev na mejah); Carbon Border Adjustment Mechanism
CO_2 – (sl. ogljikov dioksid); Carbon Dioxide
CPU – (sl. negotovost glede podnebne politike); Climate Policy Uncertainty
CV – (sl. navzkrižno preverjanje); Cross-Validation
EAP – (sl. Okoljski akcijski program); Environmental Action Programme
EEX – (sl. Evropska energetska borza); European Energy Exchange
ESG – (sl. okolje, družba, upravljanje); Environmental, Social, Governance
ETS – (sl. Emisijska trgovalna shema); Emission Trading Scheme
EU – (sl. Evropska unija); European Union
GHG – (sl. toplogredni plin); Greenhouse Gas
ICE – (sl. interkontinentalna borza); Intercontinental Exchange
IID – (sl. neodvisno in enako porazdeljeni); Independent and Identically Distributed
IXC – (sl. globalni energetski indeks); IShares Global Energy ETF
LCP – (sl. velike kurilne naprave); Large Combustion Plants
LGBM – Light Gradient Boosting Machine
ML – (sl. strojno učenje); Machine Learning
MSR – (sl. rezerva za stabilnost trga); Market Stability Reserve

NLP – (sl. obdelava naravnega jezika); Natural Language Processing
NSPS – New Source Performance Standards
SEA – (sl. Enotni evropski akt); Single European Act
STAR – (sl. gladki prehodni avto-regresijski model); Smooth Transition Autoregressive Model
TVP-VAR – (sl. vektorska avto-regresija s časovno spremenljivimi parametri); Time-Varying Parameter Vector Autoregression
VGK – (sl. evropski delniški indeks); Vanguard FTSE Europe ETF
WACC – (sl. tehtani povprečni strošek kapitala); Weighted Average Cost of Capital
WCED – (sl. Svetovna komisija za okolje in razvoj); World Commission on Environment and Development
XGBOOST – Extreme Gradient Boosting

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1 INTRODUCTION

Environmental pollution has become a major global issue, affecting air, water, and soil, and posing risks to human health. Although natural disasters such as floods and volcanic eruptions contribute to pollution, industry, transport and agriculture remain the primary sources, causing serious environmental and economic impacts. Preventive environmental management and policy are crucial; however, enforcement varies across countries, many of which lack effective regulation. Pollution can be reduced through cleaner production, waste reduction, emission limits, sustainable transport, environmental monitoring, and international cooperation (Awewomom et al., 2024). While pollution affects both developed and developing economies, developed economies contribute to a greater extent in protecting the environment (Ukaogo et al., 2024).

Key challenges associated with environmental policy include national sovereignty concerns and economic pressures. Effective pollution control requires strong institutional frameworks, collaborative global policies, and continuous environmental innovation (Awewomom et al., 2024). Environmental policies, while essential for sustainability, may result in higher costs for businesses and consumers, reduced industrial competitiveness, and potential job losses in pollution-intensive sectors, thereby presenting economic challenges alongside environmental benefits (Dechezleprêtre & Sato, 2017).

The introduction of environmental regulations in the 1970s raised concerns about their economic impact. Policymakers feared that stricter rules would encourage pollution-intensive industries to relocate to countries with looser standards, distorting trade and disadvantaging early adopters of climate policies. Two main hypotheses seek to explain this effect: the pollution haven hypothesis, which links higher costs to firm relocation, and the Porter hypothesis, which argues that strict regulation can boost competitiveness through efficiency and innovation (Dechezleprêtre & Sato, 2017).

As concerns regarding the impact of environmental policies on competitiveness increased, Jaffe et al. (1995) examined this relationship and found little evidence that environmental policies disrupt competitiveness, as compliance costs are small compared to other production costs. However, their results may differ in the current context, given the availability of more extensive data and more comprehensive environmental policies. The research also emphasised that there was little evidence to suggest that environmental policies stimulate innovation. In a more recent study, Iraldo et al. (2021) investigated the extent and conditions under which environmental regulations exert negative or positive effects on competitiveness. The results indicate that these effects can be attributed to the forms of regulation and firms' responses.

Environmental measures comprise a set of policies, laws, and other actions aimed at limiting pollution and can be classified into three subgroups. Command-and-control (hereinafter

CAC) measures refer to direct actions, such as laws that permit or prohibit certain environmentally relevant behaviours. Market-based measures use economic tools to regulate business activities, including taxation and emissions trading schemes (hereinafter ETS). Voluntary measures involve commitments and agreements to achieve specific environmental goals (Xing et al., 2023).

Pollution taxes and emissions trading systems, such as the European Union (hereinafter EU) ETS, are market-based environmental measures designed to reduce emissions. While both systems allow firms to choose cost-effective compliance methods, they differ in their design. Under a pollution tax system, emitters pay a fixed fee per unit of emissions, whereas under an ETS, emitters receive tradable allowances covering a set amount of emissions. Firms that exceed their allocation must purchase additional allowances from more efficient peers. Unlike taxes, ETS ensure an overall emissions cap; however, prices fluctuate with market conditions, creating cost uncertainty for firms (Portney, 2007).

CAC measures consist of laws and regulations that impose restrictions on economic activities responsible for environmental pollution. These policies directly set emission limits and impose technical requirements on polluters. Historically, CAC measures faced several challenges, which were addressed over time. One such challenge was the “grandfathering effect”, whereby older facilities were exempt from emission limits, allowing less efficient and more polluting plants to continue operating. The New Source Performance Standards (hereinafter NSPS) in the United States, introduced in 1970, and the EU's Large Combustion Plants (LCP) Directive of 1988 addressed this issue. CAC systems were favoured in the past, and the number of CAC policies increased steadily after 1950. Despite the development of market-based and voluntary measures, CAC policies continue to account for a substantial share of the overall portfolio of environmental measures (Singhal, 2018).

Financial markets play a vital role in environmental policy by reallocating capital towards greener activities. Green bonds, environmental, social and governance (hereinafter ESG) investment funds and sustainable finance regulations facilitate direct investment into clean technologies and low-carbon projects. As noted by Xia and Zulaica (2022), such financial support is crucial for accelerating the transition to a sustainable economy.

The development of environmental policies, particularly carbon pricing, influences firms’ stock returns. Studies indicate that firms respond differently to carbon pricing depending on the industry in which they operate. Millischer et al. (2023) find that carbon-intensive firms underperform during periods of rising carbon prices, demonstrating a strong link between stock returns and changes in emission allowance prices. Hengge et al. (2023) further support this finding, showing that regulatory events leading to higher carbon prices lead to negative stock returns for carbon-intensive firms. In contrast, Oberndorfer (2009) identified a positive and symmetric relationship between the stock returns of European electricity providers and emission allowance returns.

The objective of this thesis is to examine the impact of carbon price shocks on firms within the EU using an event study analysis. Firms are categorised as carbon-intensive firms, renewable energy producers, and energy firms to assess potential differences in market reactions. Additionally, the research integrates machine learning models to predict normal returns. This analysis highlights the potential of machine learning in financial research and evaluates its effectiveness in analysing financial variables compared to traditional econometric methods.

The sample, consisting of European firms, is divided into three subsamples in the event study analysis to examine potential heterogeneous effects. The analysis addresses the following questions:

- Do carbon-intensive firms experience negative abnormal stock returns following a significant increase in carbon prices due to higher operating costs and decreasing investor confidence?
- Do renewable energy-producing firms exhibit positive abnormal stock returns in response to a carbon price increase as they become more competitive?
- Do energy firms involved in both carbon-intensive and renewable energy production experience insignificant abnormal returns following a carbon price increase due to offsetting effects between increased costs and investor interest in renewables?
- Does linear regression outperform machine-learning techniques due to the simplistic nature of the market model?

The structure of this thesis is as follows. The first section outlines the history of environmental policy in the EU, followed by the development of the EU ETS. This is followed by an assessment of the efficiency of the EU ETS and an examination of the functioning and modelling of emission allowances as financial products. Subsequently, the existing literature on the effects of carbon pricing is reviewed. The methodology is then presented, beginning with a discussion of the differences between machine learning and econometric approaches to modelling and how these approaches can be combined. The results of the event study are then presented and interpreted. The final two sections address the effect on firms' financials and methods for hedging against carbon risk.

The key literature for this master's thesis comprises several works that form its theoretical and empirical foundations. Känzig (2021) provides key insights into the macroeconomic effects of carbon pricing, while Park et al. (2024) expand the understanding of emissions trading by analysing the Korean ETS. Hengge et al. (2023) directly examine the relationship between carbon policy and stock returns, closely aligning with the empirical part of this study. Bolton and Kacperczyk (2021) investigate how carbon emissions affect stock returns and provide insight into the existence of a carbon premium. Benz and Trueck (2006) conceptualise emission allowances as an asset class, thereby laying the foundation for treating carbon allowances as financial instruments. From a methodological perspective, López de Prado (2018) presents an overview of recent advances in financial machine learning, supporting the implementation of specialised techniques to ensure the appropriate use of machine learning models. Finally, De Jong and De Goeij (2007) provide the event study methodology that underpins the empirical analysis of this thesis, guiding the estimation and measurement of average abnormal and cumulative average abnormal returns.

2 EUROPEAN ENVIRONMENTAL POLICY DEVELOPMENT

European environmental policy began to develop in response to increasing global environmental concerns. A key catalyst was the 1972 United Nations Conference on the Human Environment in Stockholm, which prompted the European Commission to begin formulating a Community-wide environmental policy. This led to the adoption of the First Environmental Action Programme (hereinafter EAP) in November 1973, based on European commitments made earlier that year (Hey, 2005).

2.1 The Foundations: 1973–1986

The First EAP (1973–1976) recognised the close link between economic growth, prosperity, and environmental protection. It focused on preventing and reducing environmental damage while promoting the rational use of natural resources (Hey, 2005). Although the European Parliament lacked legislative powers at the time, it played an important role in placing environmental issues on the Community agenda. In the absence of a strong legal framework, environmental action followed a three-phase strategy: first addressing water pollution, then air quality, and later waste management, thereby laying the foundation for future directives (Meyer, 2024).

The Second EAP (1977–1982) built on these initial efforts by expanding existing objectives and introducing stricter standards for drinking water quality, while also increasing attention to air pollution. The Third EAP (1982–1986) marked a notable shift from quality-based to emission-based regulation, aiming to harmonise standards to preserve competitiveness within the Internal Market. Emission limits were introduced for factories, power plants, vehicles, and ships. German environmental policies, strongly influenced by the Green Party, played a crucial role in promoting EU-wide emission controls to prevent market distortions arising from differing national standards (Hey, 2005).

2.2 Legal Integration and Strategic Shift: 1987–1992

A major turning point came with the Single European Act (hereinafter SEA) of 1987, which for the first time formally integrated environmental protection into European Community law. This established a legal foundation for more comprehensive and enforceable environmental policies (Meyer, 2024). At the same time, the Fourth EAP (1987–1992) continued to align environmental goals with the development of the Internal Market while recognising the shortcomings of earlier approaches. It emphasised “high-level harmonisation” of environmental standards to prevent distortions of competition, promoted integrated pollution prevention, and encouraged greater efficiency alongside emission reduction. Furthermore, it introduced market-based instruments such as emission taxes and tradable allowances (Hey, 2005).

At the global level, the publication of the Brundtland Report by the World Commission on Environment and Development (hereinafter WCED) in 1987 provided the political and conceptual foundation for the modern understanding of sustainable development. The report defined sustainable development as “development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (WCED, 1987, p. 43). It identified four essential dimensions: long-term environmental protection, the fulfilment of basic human needs, and fairness within and between generations (Holden et al., 2014).

2.3 Towards Co-legislation and Sectoral Integration: 1992–1997

The Fifth EAP (1992–1999) marked a further strengthening of EU environmental policy through more strategic planning. It introduced a sectoral approach, requiring the integration of environmental considerations into key high-impact areas such as transport, agriculture and energy. Moving away from traditional “end-of-pipe” solutions, it promoted structural changes that encouraged public transport, energy efficiency and waste prevention, relying increasingly on market-based and voluntary measures (Hey, 2005).

The Treaty of Maastricht (1992) further reinforced the EU’s environmental role by embedding environmental protection within the broader framework of economic and social policy. It promoted non-inflationary growth while ensuring that environmental concerns were systematically taken into account. The principle of subsidiarity allowed the EU to act only when its interventions would be more effective than those of individual Member States, enabling environmental policy to evolve beyond national limitations. Although new legislative procedures were expected to slow decision-making, the introduction of qualified majority voting in the Council of Ministers accelerated progress by removing the ability of individual states to veto proposals (Wilkinson, 1992).

The Treaty of Maastricht granted the European Parliament co-legislative powers in environmental policy, later extended to other areas by the Lisbon Treaty. This change provided the Parliament equal negotiating authority with the Council of the European Union, further centralising decision-making at the EU level and reducing the influence of individual Member States. The Parliament also highlighted several key instruments that later became central to European Community environmental policy (Meyer, 2024).

While the expansion of the Parliament’s powers improved the democratic balance within the EU, it also made the legislative process more time-consuming. The Maastricht Treaty strengthened the role of the European Court of Justice by authorising it to fine Member States that failed to comply with EU law. It also elevated environmental protection to the same level of importance as economic objectives. To assist Member States facing financial constraints in implementing new environmental rules, the Cohesion Fund was established. The Treaty reiterated the “polluter pays” principle from the Single European Act, although it still lacked a clear framework for its implementation (Wilkinson, 1992).

Despite overall progress in EU environmental policymaking, the 1992 United Nations Conference on Environment and Development (UNCED) represented a setback for the Environmental Action Programme. The conference prioritised industrial competitiveness and advocated the decentralisation of environmental governance, an approach that resonated with several Member States. Led by Germany and the United Kingdom, they pushed to re-nationalise environmental policy under the subsidiarity principle, arguing for greater national flexibility. These developments exposed the European Commission’s overestimation of Member State support for an integrated, supranational environmental policy (Hey, 2005).

2.4 Amsterdam Treaty and the Limits of Sustainable Development (1997)

The Amsterdam Treaty (1997) marked another shift in EU environmental policy. Article 2 included a reference to non-inflationary growth with respect for the environment, signalling that sustainable development was once again gaining political acceptance among Member States. This trend likely stemmed from previously strengthened commitments to sustainability. However, the practical implementation of environmental goals remained uncertain. As noted in Greening the Treaty 2, principles of sustainable development would only be implemented effectively if recognised as a primary objective and prioritised over economic goals. The Amsterdam Treaty failed to achieve this, and sustainable development remained a symbol rather than a legally prioritised objective. Nevertheless, the formal recognition of sustainability helped to consolidate its position as a Community objective (Poostchi, 1998).

2.5 The Cardiff Process and Sectoral Integration Challenges

Following the Amsterdam Treaty, the Cardiff Process was launched to integrate environmental considerations into EU sectoral policies. Sector-specific Councils were expected to identify priorities, set goals, and coordinate actions (Hey, 2005). However, the results submitted varied greatly. A key problem with sector-specific Councils was their differing levels of motivation for environmental action (Kraemer, 2001). As a result, the strategies were often weak and lacked political support. Voluntary measures also fell short of expectations. In response, the EU modernised its legislation and shifted towards market-based instruments, such as Environmental Impact Assessment and the Carbon Dioxide (hereinafter CO_2) Emission Trading Directive, while also enhancing civil society rights, including access to information, participation, and justice in environmental matters (Hey, 2005).

2.6 The Sixth Environmental Action Programme (2002–2012) and Lisbon Treaty (2009)

The Sixth EAP introduced a more cautious and less ambitious approach compared to its predecessors. Rather than setting concrete targets, it focused on broad themes, such as climate change, biodiversity loss, and resource consumption, using thematic strategies to guide action. It also marked a shift towards cooperative governance, emphasising voluntary agreements, standardisation, and collaboration with industry and expert groups. The role of the European Commission evolved from legislative initiator to policy manager, making environmental governance more technical and process-oriented. While innovative, this model often lacked momentum. In particular, Member States with limited expertise or negotiation capacity struggled to implement these strategies effectively, resulting in mixed outcomes (Hey, 2005). [1]

The Lisbon Treaty, signed in 2007 and in force since 2009, merged the EU and the European Community into a single legal entity. It reaffirmed the Union's commitment to sustainable development, environmental protection and the improvement of environmental quality. Although the Lisbon Treaty introduced few changes to environmental policy, it strengthened the external dimension by embedding environmental objectives in EU foreign relations. It also linked environmental protection more explicitly to technological advancement and economic development (Vedder, 2010). Furthermore, the Treaty emphasised the EU's responsibility to contribute to global peace and security, and placed renewed attention on animal welfare, which must be considered in the formulation and implementation of EU policies (Benson & Jordan, 2010).

3 EUROPEAN UNION AND EMISSIONS TRADING SCHEME DEVELOPMENT

Initially, the EU was sceptical about the use of international emissions trading as a mechanism to reduce greenhouse gas (hereinafter GHG) emissions. However, only three years after the Kyoto Protocol was adopted, the European Commission proposed the world's first emissions trading system. This system targeted large industrial CO_2 emitters (Skjaerseth & Wettestad, 2009). Portney (2007) argues that the EU announced the adoption of a cap-and-trade system to control carbon dioxide as it struggled to comply with the terms of the Kyoto Protocol.

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[1] For an overview of the 7th and 8th Environmental Action Programmes, see Pindaru et al. (2023).

3.1 The Kyoto Protocol and Early European Union Commitments

The issue of carbon emissions was formally addressed by the Kyoto Protocol, adopted on 11 December 1997. Following ratification, it entered into force on 16 February 2005. The Protocol aimed to commit industrialised countries and economies in transition to reducing carbon emissions through individually defined targets. However, it binds only developed countries, recognising them as primarily responsible for the current high levels of GHG emissions (UNFCCC, n.d.-a).

Under the Kyoto Protocol, the 15 EU Member States at the time agreed to a joint emissions reduction target of 8%. This was achieved through the “bubble” mechanism, which allowed each country to have different individual targets, provided that their combined efforts met the overall 8% reduction goal. Even before the Protocol entered into force, the EU had already decided how to distribute these targets among its Member States (UNFCCC, n.d.-b).

3.2 Development of the European Union Emissions Trading Scheme

In March 2000, the European Commission presented a Green Paper introducing the initial concepts for the EU ETS. The purpose of this document was to provide a foundation for stakeholder discussions, which ultimately helped shape the final system (European Commission, 2021a).

3.2.1 Phase 1 (2005–2007): The Trial Period

The EU ETS was developed in four phases. The first phase (2005–2007) was considered a pilot phase, during which most emission allowances were allocated to businesses free of charge. Initially, it covered only CO_2 emissions from power generators and energy-intensive industries. The penalty for non-compliance was set at €40 per tonne of CO_2 emissions (European Commission, 2021a).

The primary aim of the first period, also known as the “trial period”, was to develop the necessary infrastructure and gain experience for the subsequent implementation of a full-scale ETS. This initial phase was not intended to achieve significant emissions reductions, but rather to prepare for the 2008 Kyoto Protocol commitment period. The development process was complex, and additional requirements emerged, including the need for market institutions, monitoring, and compliance mechanisms. Despite these challenges, the EU ETS performed well during the first phase. Notable achievements from this period include the establishment of a transparent market price for allowances, the creation of a liquid trading market, and the encouragement of several industries to incorporate carbon pricing into their business decisions (Ellerman & Joskow, 2008).

3.2.2 Phase 2 (2008–2012): Kyoto Commitment Period

The period from 2008 to 2012 marked the first commitment period under the Kyoto Protocol, during which targets for the reduction of GHG emissions were set. At the time, GHGs covered included carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, and sulphur hexafluoride. During the commitment period, each country was allocated what was known as an assigned amount, which was determined individually for each country (UNFCCC, n.d.-b).

During the same period (2008–2012), the EU launched the second phase, which featured a lower cap on allowances, specifically a cap 6.5% lower than in 2005. Several new countries joined the system, and some countries also began auctioning allowances. The proportion of free allocation fell to approximately 90%. The penalty for non-compliance with the allowance was increased to €100 per tonne. In 2012, the aviation sector was incorporated into the system; however, flights to and from non-European countries were suspended. (European Commission, 2021a).

3.2.3 Phase 3 (2013–2020): Market Maturity

The third phase, which ran from 2013 to 2020, introduced substantial changes to the system compared to the first and second phases. In this phase, a single EU-wide cap on emissions was introduced, replacing national caps. Auctioning became the default method for allocating allowances, replacing the predominance of free allocation. Several additional sectors and gases were included during this phase. Three hundred million allowances were set aside as a reserve, mainly to fund innovative renewable energy technologies, carbon capture and storage programmes. This mechanism was implemented under the NER300 (European Commission, 2021a).

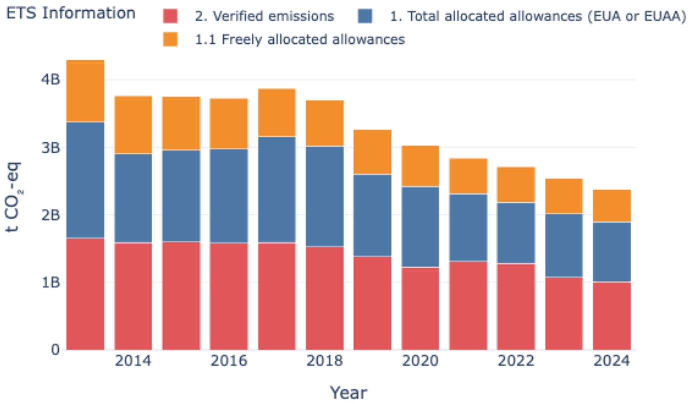
During the third phase, on 22 January 2014, the European Commission presented the 2030 Climate and Energy Framework, outlining energy policy objectives for the 2020–2030 period. Its purpose was to address issues such as the reduction of GHG emissions, the EU's vulnerability to future energy price increases (such as oil and gas), dependence on energy imports, the need to upgrade existing energy infrastructure and the establishment of a GHG emissions reduction target for 2030. A target of a 40% reduction in GHG emissions relative to 1990 was set. Renewable energy production was required to account for at least 27% of total energy consumption, and improved energy efficiency was one of the three main objectives (Council of the European Union, n.d.-a).

3.2.4 Phase 4 (2021–2030): Green Deal Alignment

Phase four, covering the current period (2021–2030), focuses on meeting the updated EU climate targets for 2030 and includes the European Green Deal. It also strengthened the MSR to address oversupply issues and introduced a steeper annual cap reduction, increasing linearly from 2.2% to above 4%. The functioning of the auctioning system was enhanced, while free allocation was phased out for additional sectors. The Innovation Fund and the Modernisation Fund were reinforced to increase funding and support for low-carbon innovation and the energy transition (European Parliament, n.d.).

Figure 1 shows the historical tightening of the carbon cap, reflected in a reduction in allocated allowances and lower emissions. It should be noted that the COVID-19 period affected overall economic activity.

Figure 1: Historical Emissions and Allocated Allowances under EU ETS (EU27)



Source: Own work based on data from the European Environment Agency (n.d.).

3.3 The European Green Deal and Fit for 55

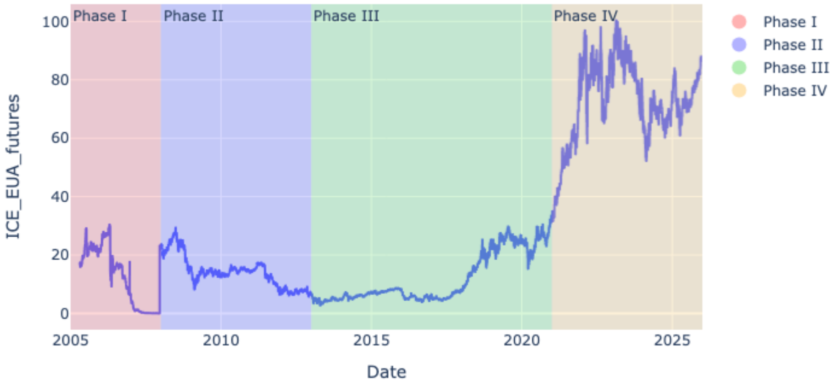
Building on the foundations of the EU ETS and its carbon pricing framework, subsequent initiatives such as the European Green Deal and the Fit for 55 package further deepened and expanded the EU's climate policy ambitions. The Fit for 55 package was introduced in the second half of 2021 and was designed to achieve the objectives of the European Climate Law: climate neutrality by 2050 and the increased target of a 55% reduction in GHG emissions by 2030 relative to 1990. It included six new legislative proposals and revisions to 13 existing climate laws. The package played a significant role in the evolution of the EU ETS by creating a separate ETS covering buildings and transport fuels. Several additional targets were also set, including increasing renewable energy production by 2030 and strengthening energy efficiency rules. Two major new systems were introduced: the Carbon Border Adjustment Mechanism (hereinafter CBAM), designed to price carbon on imports, and the Social Climate Fund, intended to support vulnerable households (European Parliament, 2024).

The European Green Deal, introduced in 2019, marked a major shift in EU climate policy, aiming for climate neutrality by 2050 and positioning the EU as a global climate leader (Oberthür & von Homeyer, 2022). A central element of the Green Deal is the 2050 climate neutrality goal. The transition is financed in various ways, involving both citizens and firms in the process. Member States provide subsidies to support households in transitioning to renewable energy sources. At the investment level, countries and firms can issue green bonds, which are used exclusively to fund environmental and sustainable projects. The European Investment Bank also provides loans to finance environmental objectives (Janda & Sajdikova, 2022).

While previous EU climate efforts focused on carbon pricing, the Green Deal expanded the policy toolkit to include regulations limiting emissions in specific sectors, subsidies to promote the adoption of green technologies and public support measures aimed at citizens and businesses. By integrating carbon pricing, regulation, funding and innovation, the Green Deal aligns all sectors with climate goals. It has transformed the EU climate policy from a single-tool approach into a broader and more inclusive strategy for achieving a just and effective green transition (Oberthür & von Homeyer, 2022).

In Figure 2, we observe the historical price development of the most liquid Emission Allowance futures series. The most notable price movement occurred at the end of 2007, marking the end of Phase 1. Due to overallocation resulting from incomplete emissions data and political allocation decisions, allowances exceeded demand and the price collapsed to nearly zero. The allowances themselves were also not permitted to be banked for Phase 2. Banking of allowances and lowering the cap contributed to price stabilisation. While the second phase was based on data from the first phase, an important challenge emerged: the 2008 financial crisis led to emissions reductions that were significantly greater than expected, resulting in a surplus of allowances and making it difficult to isolate the impact of the scheme on emissions reductions (European Commission, 2021a).

Figure 2: Emission Allowance Futures Price Development Throught the First Four Phases of Emission Trading Scheme Development



Source: Own work based on data from Refinitiv (2026).

4 EMISSIONS TRADING SCHEME EFFICIENCY AND EMISSION ALLOWANCES

One key aspect of the original EU ETS Directive concerned the allocation of emission allowances. A central question was whether governments should sell the allowances or distribute them free of charge. Auctioning allowances offers many benefits. Through revenue recycling, it can address competitiveness issues. Auctioning can also stabilise prices if Member States coordinate auctions and set a price floor. In addition, auctions can strengthen environmental effectiveness (Hepburn et al., 2006). [2]

4.1 Carbon Emission Market Microstructure and Its Efficiency

Initially, the EU emissions allowance market was centred around eight major exchanges, including BlueNext, Nord Pool, and the European Energy Exchange (hereinafter EEX). Among these, EEX quickly became the dominant trading venue, accounting for the majority of trading volume by 2009 (Mizrach & Otsubo, 2014).

Over time, improvements in liquidity and trading infrastructure enhanced market efficiency. Benz and Hengelbrock (2008) observed a significant reduction in bid–ask spreads during the first phase of the EU ETS, indicating a more competitive and liquid market. Price discovery increasingly shifted to the futures segment, where higher liquidity, lower spreads, and more frequent trading enabled futures prices to respond more rapidly to new information. Spreads also fluctuated with information flow, narrowing after regulatory announcements and widening during periods of uncertainty (Mizrach & Otsubo, 2014).

To better understand these dynamics, Mizrach and Otsubo (2014) applied the Madhavan et al. (1997) model, which decomposes bid–ask spreads into adverse selection and liquidity provision costs. Their results showed that by December 2009, emission allowance spreads were tight and primarily driven by information asymmetry, emphasising the institutional nature of the market.

In addition, Ibikunle et al. (2016) assessed efficiency at the Intercontinental Exchange (hereinafter ICE), the largest secondary market for allowances, using short-term return predictability as a proxy. Their findings revealed that as spreads narrowed, predictability diminished, implying increasing efficiency. During Phase II (2008–2012), emission allowance futures prices followed a random walk, confirming that the market had matured and was characterised by high liquidity, reduced transaction costs and improved informational efficiency.

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[2] For a technical overview of the functioning of the EU ETS, see Appendix 3.

4.2 Emission Allowances as Financial Instruments

Emission allowances can be regarded as determinants of permitted plant utilisation. Firms with an allowance deficit must either improve efficiency or reduce emissions unless they purchase additional allowances. Conversely, firms emitting below their cap can sell surplus allowances, making allowances both assets and liabilities. Unlike stocks, whose value reflects profit expectations, allowance prices are driven by supply and demand and have defined expiration dates. The EU classifies emission allowances as intangible assets, although countries determine whether trading allowances constitutes a financial service. Emission allowances can also be considered production factors, as firms must hold a sufficient number of allowances to operate (Benz & Trueck, 2006).

Under MiFID II, the EU categorised emission allowances as financial instruments. Since then, the development of financial products related to allowances has progressed significantly. Financial products such as carbon options, futures, swap contracts, funds, and bonds are now available. In 2020, carbon futures represented the largest carbon asset, accounting for 88% of the trading volume in the EU ETS. Recent studies suggest that emission allowance futures provide policymakers with a basis for assessing carbon market efficiency. They are also viewed as risk management tools for firms seeking to control emissions and offer opportunities for financial investors to gain exposure through speculative and arbitrage activities (Lu et al., 2024).

4.3 Modelling of Emission Allowances

To trade and develop trading strategies for asset classes such as commodities or emission allowances, it is essential to understand price dynamics and their determinants. Knowledge of key price determinants is also crucial for effective risk management and policymaking (Benz & Trueck, 2006).

4.3.1 Deterministic versus Stochastic Indicators

When discussing indicators, it is necessary to distinguish between stochastic and deterministic indicators (Benz & Trueck, 2006). The key difference lies in the treatment of uncertainty. Deterministic models compute future values without incorporating randomness, whereas stochastic models explicitly account for uncertainty in their inputs. As a result, stochastic models may produce different outputs when estimated multiple times, yielding a range of possible values (Robins, 2020).

4.3.2 Predictive Power and Machine Learning Approaches

As emission allowances are closely linked to the energy sector, weather features, which can be considered deterministic indicators, can influence allowance price dynamics. Using the machine learning (hereinafter ML) technique, Extreme Gradient Boosting (hereinafter XGBoost), Eslahi and Mazza (2023) found that weather conditions and electricity demand play important roles in predicting carbon prices during the first three phases of EU ETS development. Air temperature and electricity demand were identified as the most important features for predicting carbon prices, whereas total precipitation and relative humidity were the least important variables. A key finding of the study is that weather and emission allowance prices exhibit a non-linear relationship, which can be effectively captured by methods such as XGBoost, a tree-based ML model.

4.3.3 Linkage with Other Markets and Risk Spillovers

There is increasing evidence from studies showing co-movements between carbon emission allowance futures and various commodity futures, such as energy, metals, agriculture, and other energy-related futures, particularly during periods of extreme market developments. However, this evidence tends to vary across different time spans, frequencies, methodologies and assets used (Lu et al., 2024).

Evidence from a study employing the GARCH-jump model suggests that time-varying jumps in emission allowance prices are present but largely insignificant. Emission allowances were found to be highly sensitive to the implied volatility of oil markets, with heterogeneous impacts. This information is particularly useful for investors, as crude oil volatility (OVX) can be used to predict uncertainty in the emission allowance market. Crude oil futures transmit risk to carbon allowance futures, indicating that oil markets exert a stronger influence on emission allowance prices than vice versa (Dutta, 2018).

A similar risk spillover effect was observed between carbon allowance futures and agricultural futures, mainly corn and soybean futures, under extreme market conditions. Using a TVP-VAR model, a one-way risk spillover was identified. As in the previously mentioned study, carbon allowance futures were found to be receivers of spillovers. The results further indicate that spillover effects among oil, carbon and agricultural commodity futures are stronger during periods of extreme market movements. From the perspective of futures investors, carbon futures are identified as an effective hedging tool, with the potential to improve the performance of oil and agricultural portfolios (Wei et al., 2023).

4.3.4 Economic Uncertainty and Co-movements

Using linear Granger causality tests, Lu et al. (2024) found that economic policy uncertainty significantly drives extreme co-movements between CO_2 emission allowances and other commodity markets. Under the influence of economic policy uncertainty, both markets generally move in the same direction.

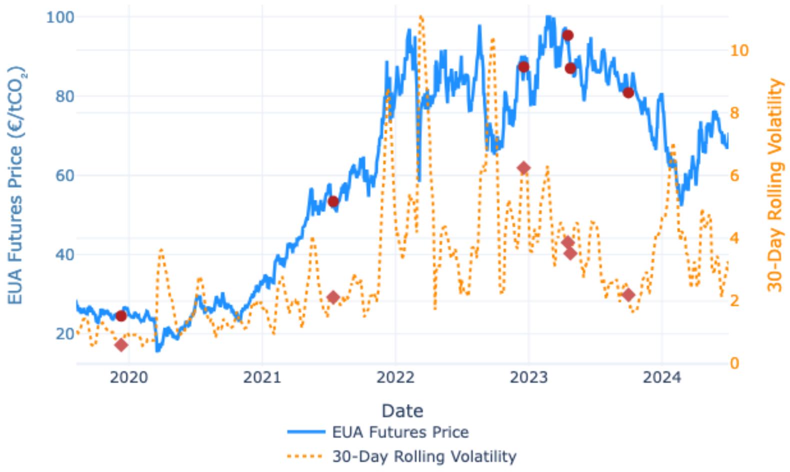
Table 1 presents the pre-event and post-event volatility of emission allowance futures prices for the documented events. As post-event volatility does not increase significantly, I can conclude that these events do not have a significant impact on the volatility of the price series. However, this does not imply a change in the relationship between emission allowance futures and other commodities, as documented by Lu et al. (2024). The time series of emission allowance futures prices and volatility is shown in Figure 3, with events marked by dotted lines.

Table 1: Key Environmental Policy Events and Corresponding Market Volatility, Calculated as the 5-day Average of the 30-day Rolling Volatility before and after Each Event

Event	**Date**	**Pre-event volatility**	**Post-event volatility**
European Green Deal announced	2019-12-11	0.6573	0.5604
Fit for 55 package published	2021-07-14	2.1586	1.9496
Fit for 55 provisional agreement	2022-12-18	6.1290	6.2628
EP adopts key climate target laws	2023-04-18	3.8773	3.6142
Council adopts key legislation	2023-04-25	3.4865	3.7065
CBAM reporting phase starts	2023-10-01	2.3722	1.9389

Source: Own work based on data and official press releases from the European Commission (2019, 2021b, 2023); European Parliament (2023); Council of the European Union (2023, n.d.-b); Refinitiv (2025).

Figure 3: Emission Allowance Futures Prices and Volatility with Corresponding Policy Events



Source: Own work based on data from Refinitiv (2025).

5 IMPACT OF EMISSIONS TRADING SCHEMES ON THE ECONOMY, FIRMS, AND FINANCIAL MARKETS

With the development of comprehensive environmental policy frameworks, an important question arises: how do economies, firms, and financial markets respond to the implementation of these policies? In addition, do firms operating in different sectors respond differently to carbon pricing?

5.1 Pricing Carbon Risk

In their paper Carbon Risk, Görgen et al. (2020) analysed how carbon risk affects global equity markets. They constructed the Brown-Green Score (BGS) to measure firms' exposure to transition risk and developed a Brown-minus-Green (hereinafter BMG) factor-mimicking portfolio. Their findings show that, while brown firms earn higher average returns, firms that become browner experience lower announcement returns. The authors find no evidence of a carbon risk premium, attributing this outcome to carbon risk being largely associated with unpriced cash-flow news rather than discount-rate news. Notably, the BMG factor is uncorrelated with other factors, indicating that it captures unique risk content. When included in standard asset pricing models, it increased their explanatory power.

5.2 Macroeconomic Impact of Carbon Pricing

In terms of macroeconomic impact, Känzig (2021) examined the economic consequences of introducing a carbon price. His analysis focused on the effectiveness of climate policies in reducing emissions and their side effects for individuals and firms. He studied the effects across various population groups and found that carbon pricing reduces emissions and effectively encourages firms to cut pollution. However, it also increases energy prices and negatively affects economic activity in the short term. Lower-income households are more affected than wealthier households, as higher energy prices have a greater impact on them because a relatively large proportion of their income is spent on energy bills. Based on his findings, Känzig proposed making carbon pricing more equitable by having governments provide targeted support for lower-income groups.

5.3 Firm-Level Effects of Carbon Pricing

Several academic studies have examined the effects of carbon ETS on the financial performance of listed firms participating in such schemes, as well as on financial markets in general. As ETS are being developed in economies outside the EU, the literature on these systems continues to expand. ETS are being introduced in both developed and emerging markets, which may influence their effects on firms. South Korea, an emerging market, developed its own ETS, which yielded the following results for the firms examined: treated firms did not reduce emissions, even though their environmental ratings improved. The ETS increased firms' profitability but decreased their market value. It also increased the systematic risk of the examined firms, indicating that investors price in future carbon risks (Park et al., 2024).

5.4 Carbon Risk and Stock Returns

In their analysis of carbon emissions in a cross-section, Bolton and Kacperczyk (2021) conducted a cross-sectional study that included carbon emissions as a firm-level characteristic. They found that higher emissions are associated with higher stock returns, suggesting that investors price in carbon risk. This so-called carbon premium remained robust even after accounting for the “sin stock” divestment effect, although carbon intensity itself was not significantly related to the premium. The authors proposed several hypotheses to explain carbon risk pricing: the carbon risk premium hypothesis (investors demand compensation for holding high-emission stocks), the inefficient pricing hypothesis (carbon risk is underpriced), the carbon alpha hypothesis (low-emission portfolios generate positive abnormal returns), and the divestment hypothesis (sin stocks earn higher returns to attract investors).

5.5 Carbon Risk and Debt Markets

In contrast to equity instruments, Xia and Zulaica (2022) conducted a panel analysis of U.S. corporate bonds, examining the existence of a carbon premium through two channels. The preference channel refers to investors’ stronger preferences for environmentally responsible firms, resulting in a required premium for firms perceived as environmentally unfriendly. The second channel is the risk channel, in which environmentally unfriendly firms are viewed as more likely to default due to higher transition risks. The authors found a positive and statistically significant carbon premium through both channels, with the effect being larger for energy firms. They also identified a positive relationship between firms' carbon emissions and their probability of default.

On the lending side, banks incorporate a carbon risk premium when issuing loans; however, this premium remains relatively modest compared to the implied credit risk. The premium, measured using carbon intensity defined as CO_2 emissions relative to firm revenue, has become statistically significant since the signing of the Paris Agreement in late 2015. The risk premium varies both within and across industries. Interestingly, the so-called green banks, often self-identified as such, do not appear to price carbon risk differently from conventional banks (Ehlers et al., 2022).

5.6 Asset Performance and the Paris Agreement

One way to assess the performance of low-carbon versus carbon-intensive assets is to compare their returns before and after the 2015 Paris Agreement, a key milestone in global climate policy. An analysis of EU, United States and global market indices showed that, prior to the agreement, low-carbon assets were perceived as equally risky as the broader market. Following the agreement, their risk–return profile improved significantly, with declining risk levels and higher overall performance. The correlation of low-carbon indices fell to near zero, while that of carbon-intensive indices remained high. Similarly, the beta of low-carbon indices decreased, resulting in higher optimal portfolio weights under the Markowitz optimisation (Monasterolo & de Angelis, 2020).

5.7 Firms' Heterogeneous Responses to Carbon Pricing

The existing literature on carbon pricing indicates that firms' responses to changes in emission allowance prices depend on their sector. Moreno and Pereira da Silva (2016) analysed the impact of the EU ETS on stock market returns. Using an econometric panel data model for Spanish firms, they found that sectors respond differently to changes in emission allowance prices. The effect of emission allowance returns on firms' stock returns is both positive and negative, statistically significant and sector-dependent during Phase 2 and Phase 3. Stock returns also responded differently to decreases in emission allowance prices compared to increases.

Oberndorfer (2009) analysed the relationship between emission allowance price developments and the stock returns of European electricity providers. He found that this relationship is positive and symmetric, indicating that the energy stocks do not react differently to increases or decreases in emission allowance prices. The study suggests that increases in emission allowance prices resulted in higher market valuations for electricity providers covered by the EU ETS.

These findings are further addressed in a study by Tian et al. (2016), who suggest that during the first two phases of EU ETS development, the relationship between emission allowance returns and the stock returns of electricity providers was driven by market shocks, reflecting higher volatility in those periods. However, this relationship depends on whether the impacts of such market shocks are controlled. When controlled, the relationship varies according to the carbon intensity of electricity providers. Stock returns of carbon-intensive providers are negatively affected by increases in emission allowance prices, while the effect is reversed for less carbon-intensive providers. These results are consistent with financial theory, which suggests that carbon-intensive providers are adversely affected by stock market reactions to their carbon-intensive activities.

Furthermore, Zhu et al. (2018) examined the impact of carbon pricing in the EU on carbon-intensive firms using a panel quantile regression framework. The results indicate a positive effect of emission allowance price changes in low-return markets and a negative effect in normal and high-return markets during the first phase. In the second phase, a positive impact of emission allowance prices on stock returns was observed in normal and high-return markets. In the third phase, the relationship is less clear, as the emission allowance prices declined significantly. Regarding the symmetry of stock return responses to changes in emission allowance prices, asymmetry is observed only in the second phase, which coincided with a period of economic instability.

In line with the focus of this master's thesis, Millischer et al. (2023) analysed stock returns during periods of rising carbon prices. The authors found a strong and statistically significant relationship between stock prices and changes in emission allowance prices, driven by firms' carbon intensity. Carbon-intensive firms experienced weaker stock performance during periods of increasing carbon prices. The authors argue that carbon pricing plays a crucial role in enabling stock markets to influence the transition to a low-carbon economy. When analysing subsamples, the empirical results indicate that the relationship between stock prices and carbon prices is driven by firms with high carbon costs. This relationship may be less evident across all groups, as carbon costs remain relatively small compared to revenues for most firms, leading investors to discount their importance. In addition, carbon emissions data are published annually and with delays, reducing their immediate relevance for investors.

Carbon pricing shocks are often driven by regulatory events. In their study "Carbon Policy and Stock Returns: Signals from the Financial Markets," Hengge et al. (2023) report that regulatory events under the EU ETS that result in higher carbon prices are associated with negative realised stock returns. This effect is more pronounced for firms with higher carbon emissions. Interestingly, the correlation between carbon-intensive stocks and emission allowance prices remains positive and robust even after controlling for country-sector-time fixed effects and firm-year-quarter fixed effects. The authors conclude that this positive correlation may be driven by an endogenous shock.

6 ECONOMETRIC AND MACHINE LEARNING APPROACHES TO MODELLING

While ML techniques have a long history, they have become particularly attractive in recent years, as high-dimensional data have become more widely available and computational power has become less costly. The success of these methods in finance and economic forecasting stems from their flexibility, which allows them to capture non-linear relationships in the data (Babii et al., 2023). In contrast, econometrics has faced criticism for its slower pace of development relative to ML methods (López de Prado, 2018).

6.1 Key Methodological Differences

Despite this criticism, it is important to clarify the distinction between the two fields. Econometrics is a discipline that combines mathematics, statistics and economics. The objectives of econometric models and ML models differ significantly. While econometrics relies on statistical models specifically designed to address economic questions, ML models are not explicitly programmed to solve a specific problem (Perez et al., 2021).

When comparing ML with the econometric toolbox, supervised ML models are primarily applied to prediction tasks, with little emphasis on statistical inference. In contrast, econometric models are used to identify causal relationships between variables, allowing for more intuitive interpretation. ML models are generally more powerful in analysing and capturing complex, non-linear patterns in data. As a result, ML models are mainly applied to prediction tasks rather than to parameter estimation for interpretative purposes (Mullainathan & Spiess, 2017).

Although econometrics and ML differ in their primary areas of application, the increasing availability of data has led to growing demand for more flexible ML models in finance and economics (Zheng et al., 2017). When referring to ML models in comparison with econometric models, this thesis focuses on supervised ML models, which are trained on labels and features, corresponding to dependent and independent variables in econometric methodology (Perez et al., 2021).

Econometricians and ML practitioners also differ in their approaches to data analysis. Econometricians typically begin with theory-based models grounded in economic assumptions, whereas ML practitioners adapt data-driven approaches and computational techniques to build models (Judge, 2016).

6.2 Non-Linearity in Financial Time Series

The popularity of ML techniques has increased largely because of their ability to capture non-linear relationships. Econometric approaches, in many applications, often rely on linear estimators such as ordinary least squares, which can be problematic given that financial time series frequently exhibit non-linearity (López de Prado, 2018, p. 15). Financial time series are non-linear in nature, as returns and volatility behave differently across various regimes. Franses and van Dijk (2000) tested linear models for forecasting and found that such models do not consistently yield reliable results. They further argue that financial time series display asymmetric behaviour, which has increased interest in non-linear models. This asymmetry is evident in the fact that large negative returns in stock markets occur more frequently than large positive returns. Moreover, following significant negative returns, volatility tends to increase more than it does after significant positive returns. This phenomenon is commonly referred to as asymmetric volatility. Several econometric models have been developed to account for this behaviour, including asymmetric ARCH models (see Wu, 2001).

Business cycles are also known to exhibit seasonal and cyclical non-linearities (Swanson & Franses, 1999). Neglecting these features of time series data may result in invalid statistical inference and inaccurate forecasts (Franses & van Dijk, 2000).

Interest in non-linear models has also extended to macroeconomic analysis. Using a Markov switching dynamic bi-factor model, Chauvet and Jiang (2023) identified significant regime-switching patterns in three stock indices (Dow Jones Industrial Average, S&P 500, NASDAQ Composite) and three monetary policy variables (the federal funds rate, Divisia M4 and consumer credit), further reinforcing the relevance of non-linear modelling.

6.3 Non-Linear Econometric Models

Although econometric models are often regarded as primarily linear, reflecting the traditional focus on linear regression techniques, non-linear modelling in econometrics has expanded as advances in technology have made the computational estimation of non-linear models more feasible and as high-dimensional data have become widely available. For example, stochastic unit root (STUR) models have been developed in econometrics, in which unit roots in autoregressive processes are allowed to vary (Swanson & Franses, 1999). Other non-linear econometric models include threshold autoregressive models (Tong, 1983, 1990), bilinear models (Granger & Andersen, 1978), smooth transition autoregressive (STAR) models (Luukkonen et al., 1988; Granger & Teräsvirta, 1993), and Markov switching models (Hamilton, 1989, 1994). Further classes of non-linear models include random parameter models and time-varying parameter models (Swanson & Franses, 1999).

The question is whether using more complex non-linear models leads to better modelling of economic behaviour. This does not have a simple answer, but it can be examined by comparing the out-of-sample predictive power of simple and more complex modelling approaches (Swanson & Franses, 1999).

6.4 Complementarity Between Machine Learning and Econometrics

Based on their research, Perez et al. (2021) conclude that econometric and ML models may converge in certain activities, such as investment and research, where ML models have outperformed econometric models. However, there is no guarantee of consistent outperformance of ML over econometric models in prediction tasks.

The true value, however, lies in the complementary use of econometrics and ML. There are several ways in which the two approaches can be combined. ML techniques can be used to extract valuable features from image data, video or text, which can then serve as variables in econometric models to study causal relationships. Econometric tools can also be employed to enhance ML models, and vice versa (Zheng et al., 2017).

In economics, the primary objective is often the estimation of parameters, although econometric procedures also include prediction tasks. In this sense, econometric and ML models can complement one another in economic research rather than stand in conflict (Mullainathan & Spiess, 2017). Techniques drawn from ML can also be applied within econometric models, such as cross-validation (hereinafter CV), not only to obtain estimates, but also to further assess their out-of-sample predictive power and conduct robustness checks (Zheng et al., 2017).[3]

7 EVENT STUDY ANALYSIS METHODOLOGY

This chapter outlines the methodology and procedures of an event study analysis conducted to examine abnormal returns in response to a carbon price shock. The study employs both a traditional linear regression model and ML techniques to estimate normal returns. Three subgroups of firms were analysed separately: carbon-intensive firms, energy firms and renewable energy-producing firms. The sample sizes for each group were 8, 10 and 6, respectively. A detailed list of the firms included in the sample is provided in Appendix 1. The explanatory variables, referred to as features in ML terminology, are the Vanguard FTSE Europe ETF (hereinafter VGK) and the iShares Global Energy ETF (hereinafter IXC).

7.1 Introduction to Event Studies

The empirical analysis of the research questions is based on a common framework in economics and finance known as event study analysis, an empirical method used to capture the effects of economic events on a firm's market value. The simplicity of the method lies in the assumption that a given economic event will have an immediate impact on stock prices, given the rational nature of financial markets. In economics and finance, event study analysis has been widely applied to assess the effects of earnings, acquisitions, and other announcements on stock prices. Owing to its simplicity, the method can also be used to examine the effects of changes in environmental regulatory measures on a firm's value (MacKinlay, 1997).

7.2 Dataset Segmentation and Time Windows

The dataset is divided into three distinct time windows:

- The estimation window, spanning from January 2015 to 31 October 2021, is used to train the models. The dataset consists primarily of daily observations, although some gaps remain due to the removal of missing values.

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[3] For those interested in the intersection of machine learning and econometrics, see Gaillac and L'Hour (2025).

- The testing window, covering November 2021, is used to evaluate model performance and to identify the best-performing model for each stock.
- The event window is defined symmetrically around the event date, encompassing five trading days before and five trading days after the event (i.e., from 3 January 2022 to 18 January 2022). This window is used to analyse the short-term market reaction to the event.

7.3 Defining an Event of Interest

Figure 4 shows the price dynamics of carbon allowances from 2012 to 2023. Positive and negative price shocks are indicated by green and red dots, respectively. Shocks are identified using a 1% threshold based on daily returns, calculated as the percentage change in carbon allowance prices. Days on which returns fall below the 1st percentile or exceed the 99th percentile are classified as negative and positive shocks, respectively.

Figure 4: Carbon Prices and Identified Positive and Negative Price Shocks

Source: Own work based on data from the European Energy Exchange (2025).

With the threshold set at 1%, a challenge arises from the clustering of multiple positive and negative shocks within the same calendar period, making it difficult to isolate the effect of a specific shock. To address this, I selected the price increase on 10 January 2022 as the event of interest, during which carbon prices rose from €74 to €82. Notably, no other significant positive or negative shocks occurred in the months immediately before or after this date, allowing for a clearer analysis. For the analysis of the immediate effects of emission allowance price changes on asset prices, it is important that the relevant stock exchanges are open at the time of the shock. In this case, the most relevant exchanges were open, with their trading hours shown in Appendix 2.

A different approach to identifying carbon price shocks was used in the study most closely related to this thesis, where Hengge et al. (2023), show that regulatory events increasing carbon prices are associated with negative realised stock returns for carbon-intensive firms. However, as empirical results in financial time series analysis can vary substantially depending on sample selection, data frequency, and the time period considered, this thesis adopts a different methodological approach. Unlike Hengge et al. (2023), carbon price shocks are not linked to specific regulatory or macroeconomic events, as is often the case in studies on commodity price shocks, but are identified in a more data-driven manner to allow comparison with existing studies.

7.4 Ramsey's Regression Equation Specification Error Test for Functional Form Misspecification

A common method for assessing the functional form of the data is the Ramsey regression equation specification error test. This test involves estimating the model using the explanatory variables in their original form and adding their non-linear forms, such as squares or cubes. An F-test is then used to determine whether these non-linear variables have predictive power. If the null hypothesis, which states that the non-linear variables are jointly equal to zero, is rejected, the model is considered to be misspecified (Christodoulou-Volos & Tserkezos, 2023).

7.5 Modelling Approaches

To estimate normal returns, several modelling approaches were employed, including linear regression and a range of ML techniques: lasso regression, decision trees, light gradient boosting machine (hereinafter LGBM), random forests and feedforward neural networks. Predicting normal returns with different models allows for a comparison of their relative performance.

7.5.1 Machine Learning Models

Decision trees provide a structured representation in the form of a tree, consisting of paths that lead to terminal nodes, where the prediction is given by the mean of the target variable for all observations that fall into that node. Trees are built from top to bottom, with features split into binary branches based on criteria such as minimising the residual sum of squares, maximising gain, or other desired metrics. Ideally, splitting continues until the leaf or terminal nodes contain the most homogeneous partitions of the target variable (Darveau, 2023). In finance, decision trees are particularly popular because they are simple to implement and interpret. They are commonly used for forecasting stock price movements, evaluating credit risk, optimising portfolios, and similar applications (Baruah & Huque, 2024).

Random forest is a powerful non-linear ML model that combines multiple decision trees into a so-called forest. Two key aspects distinguish random forests from individual decision trees.

First, the sample used to train each tree is drawn as a subsample from the full dataset using methods such as bootstrapping. For prediction, the most common class (in classification) or the average label (in regression) is taken across all trees (Zheng et al., 2024).

Lasso regression is a linear model with an additional term that shrinks the sum of the absolute values of the coefficients. As it can shrink some coefficients to zero, it has two favourable properties: those of subset selection and ridge regression (Tibshirani, 1996). The shrinking of coefficients, often called regularisation, is useful when dealing with many explanatory variables or when it is unclear which variables are good predictors. In such cases, ordinary least squares may overfit or even fail if the number of observations is smaller than the number of variables. It is important to note that lasso, which uses the L1 regularisation norm, is best used for out-of-sample forecasting but is not suitable for interpretation, as regularisation makes it a biased estimator (Hauck & Woutersen, 2024).

In Formula 3, lasso regression is very similar to linear regression. The difference lies in the addition of the lambda (regularisation term) to the minimisation of the residual sum of squares (Hauck & Woutersen, 2024).

$$\gamma_{LASSO} = \arg\min_{\gamma} \sum_i (Y_i - \alpha - \gamma X_i)^2 + \lambda|\gamma|, \quad \lambda > 0 \tag{3}$$

Neural networks are an information-processing framework that mimics the human brain. They are applied to many pattern recognition problems, which can be useful in analysing financial time series. They are used in security trading systems, pricing financial instruments, predicting merger targets, and other applications. Neural networks consist of multiple interconnected layers, referred to as neurons (Swamy et al., 2000).

In this case, feedforward neural networks are used. These consist of an input layer at the beginning, followed by hidden layers and an output layer. They are referred to as feedforward neural networks because information moves in one direction, from input to output, without cycles. Neural networks also combine many different functions.

We may have functions

$$f(x) = f^{(3)}\left(f^{(2)}\left(f^{(1)}(x)\right)\right) \tag{4}$$

connected in a chain, which results in the composition

$$f^{(1)},\ f^{(2)},\ f^{(3)} \tag{5}$$

By adding non-linear activation functions to the hidden layers, neural networks are well suited for capturing complex, non-linear relationships in data. However, this non-linearity results in a non-convex loss function. Therefore, neural networks are optimised using gradient-based optimisers, which update the weights to minimise the loss function (Goodfellow et al., 2016).

LGBM is an advanced ML model that offers both flexibility and efficiency. While some modelling techniques, such as neural networks, require significant computational power, LGBM, when applied correctly, achieves high accuracy with lower computational demands. As the name suggests, the LGBM model uses gradient boosting, where the first tree produces a base prediction and each subsequent tree corrects the current ensemble's residuals. For each subsequent tree, the final prediction is the previous prediction plus the predicted error, scaled by the learning rate hyperparameter. The forecast at each point is also scaled by a regularisation term (Bisdoulis, 2024).

LGBM is also becoming popular for predicting financial time series. In their study, Sajid et al. (2023) used LGBM to predict crude oil prices. Compared to other popular methods such as decision trees, random forests and lasso regression, LGBM showed the best performance, producing the lowest error.

LGBM incorporates several features that enhance its efficiency. Gradient-based One-Side Sampling retains all high-gradient observations and a subset of low-gradient observations after computing gradients for each observation. This reduces the number of samples used in subsequent trees, improving speed without sacrificing accuracy. Histogram-based binning groups continuous feature values into discrete bins, which speeds up computation and improves robustness to outliers. Unlike models such as XGBoost or random forest, LGBM grows tree’s leaf-wise by splitting only the leaf that maximises loss reduction, rather than expanding all leaves at the same depth, resulting in higher efficiency and accuracy (Bisdoulis, 2024). [4]

7.5.2 Hyperparameter Tuning

As all models used in the analysis include configuration variables, known as hyperparameters, which control the behaviour of ML models, special care must be taken in their selection. The choice of hyperparameters in modelling significantly affects overall model performance. As a manual search for optimal hyperparameters is often not feasible, an algorithm must be used to identify the best values. The main techniques include random search, quasi-random search, grid search, gradient-based approaches and others (Franceschi et al., 2024).

The most used methods are grid search and random search, both of which present challenges in industrial-scale applications. A popular approach today is to identify the optimal hyperparameter values using a method called Optuna, which is based on sequential model-

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[4] Additional figures illustrating the machine learning model architectures are provided in Appendix 6.

based optimisation, also known as Bayesian optimisation. In each trial, Optuna employs a sampler (such as the Tree-structured Parzen Estimator) to suggest a set of hyperparameters based on previous trial results and the predefined search space. Compared to grid and random search, this algorithm is faster and less computationally demanding. The method also does not assume any specific functional form. The algorithm aims to identify the maximum or minimum value of an objective function (Hanifi et al., 2024).

7.5.3 Cross-Validation

The purpose of CV is to determine the parameters of ML models that best fit the data. When building ML models, the model learns the general structure of the data to make future predictions. If we test ML models on the same data on which they were trained, we obtain excellent results. However, such results do not provide any information about the model’s predictive power or the extent of overfitting (López de Prado, 2018).

7.5.3.1 Traditional Cross-Validation Approaches

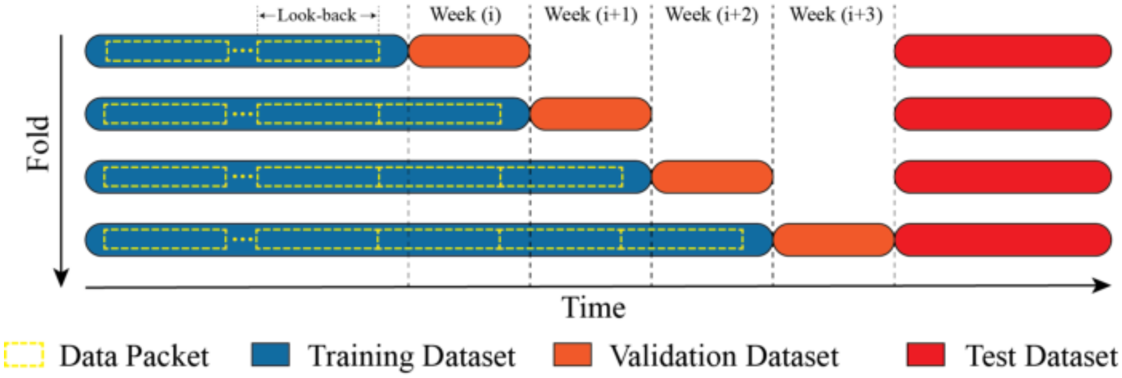
The standard train-test split is used to assess models for overfitting or underfitting. However, this approach has limitations, as a model may fit the training data particularly well while the test set contains structural changes, resulting in poor predictions, or vice versa. For this reason, traditional CV approaches, such as k-fold CV, are used. These approaches employ splits that randomly select observations from the dataset and assign them to training and testing data. The iterative process selects observations *n* times and builds and tests the model on randomly assigned observations, which are assumed to be independent and identically distributed (hereinafter IID). In finance, CV is used for backtesting strategies and parameter tuning (López de Prado, 2018).

7.5.3.2 Time Series Cross-Validation

Traditional CV approaches, such as k-fold CV, are often not suitable for sequential data, such as time series, which exhibit serial correlation and non-stationarity. For this reason, practitioners use alternative approaches to address this issue (Bergmeir et al., 2018).

One such approach is rolling CV. It starts with a smaller training sample, which expands over time. The model is then validated on validation data that are shifted forward in time, as shown in Figure 5 (Hyndman & Athanasopoulos, 2021).

Figure 5: Expanding Window Approach Used in Time Series Cross-Validation



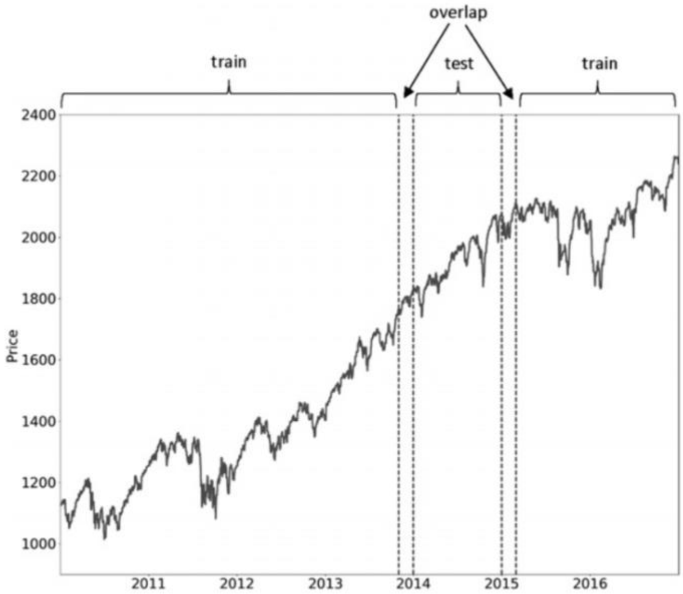
Source: Kumar (2023).

7.5.3.3 Combinatorial Purged Cross-Validation

Two challenges arise when applying CV to financial data. First, observations cannot be assumed to be drawn from an IID process due to time dependence in financial time series. A less obvious issue, which is underemphasised in academic papers, is data leakage. Data leakage occurs when the training set contains information that is also directly or indirectly present in the test set. In finance, data leakage arises due to serial correlation, whereby features or labels allow information to leak from the training to the test set, leading to overoptimistic performance estimates. A solution to this problem is combinatorial purged CV, which removes part of the data between the training and test sets, thereby reducing the effect of data leakage caused by serial correlation (López de Prado, 2018).

Figure 6 demonstrates the imposition of bins between the training and testing sets, whereby certain timestamps between the two sets are excluded from the training set to reduce or eliminate data leakage. The process then iterates over the entire dataset using the same logic (López de Prado, 2018). As I apply ML models to financial data in this master's thesis, I use purged CV and the Optuna algorithm within the estimation window to identify the optimal hyperparameters for each model and firm.

Figure 6: Purged Cross-Validation, which Creates Gaps in the Time Series



Source: Mazza (2023).

7.6 Model Selection

For each stock, the best-performing model was selected based on the lowest mean square error in the testing window. Linear regression was included in the comparison, and if it outperformed the ML models, it was used to estimate normal returns.

7.7 Constructing the Test Statistic

The construction of the test statistic requires the estimation of abnormal returns for each firm. These are then entered into a matrix, allowing for the calculation of the necessary components of the test statistics, as described in this section.

Normal returns were estimated twice for each stock: once using linear regression and once using the selected best-performing model. For linear regression, normal returns were estimated using Formula 6:

$$NR_{it} = \alpha + \beta_1 \cdot VGK_t + \beta_2 \cdot IXC_t + e \tag{6}$$

It is important to note that for ML models, such as neural networks or tree-based methods, the parametric form of the linear model does not apply; however, the same explanatory variables are used.

Abnormal returns are defined as the difference between realised returns and estimated normal returns, as shown in Formula 7 (De Jong & De Goeij, 2007):

$$AR_{it} = R_{it} - NR_{it} \tag{7}$$

Abnormal returns for each firm were organised into matrices to facilitate subgroup analysis. For each subgroup (e.g., carbon-intensive, energy, and renewable firms), average abnormal returns (hereinafter AAR) were calculated by averaging abnormal returns across firms at each point in time, as shown in Formula 8, where *i* denotes the firm and *t* the point in time (De Jong & De Goeij, 2007). Separate figures of AAR were generated: one based on normal returns estimated using the linear regression model, and the other based on normal returns estimated using the best-performing model. This procedure was carried out separately for each subgroup.

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it} \tag{8}$$

Statistical tests for cumulative average abnormal returns (hereinafter CAAR) are conducted to determine whether the estimated CAAR in the event window is statistically different from zero. These tests assess the significance of the market's reaction to the carbon price shock. The statistical tests are based on the standard assumption that abnormal returns are IID across firms. The null hypothesis states that CAAR equals zero, while the alternative hypothesis states that CAAR differs from zero, resulting in a two-sided test. The calculations used in the study are described in Formulas 9–14 (De Jong & De Goeij, 2007).

$$H_0\colon E[CAAR] = 0 \qquad H_1\colon E[CAAR] \neq 0 \tag{9}$$

$$\text{where } CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_i \tag{10}$$

$$the\ test\ statistic\ is\colon TS = \frac{\sqrt{N}\,CAAR}{s} \sim N(0,1) \tag{11}$$

$$with\ the\ sample\ standard\ deviation\colon s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(CAR_i - CAAR)^2} \tag{12}$$

where $$CAR_i = \sum_{t=t_1}^{t_2} AR_{it} \tag{13}$$

and $$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it} \tag{14}$$

Note that the test statistic follows a normal distribution in large samples, but in smaller samples it follows a *t*-distribution, as shown in Formula 15 (De Jong & De Goeij, 2007):

$$TS = \frac{\sqrt{N}\,CAAR}{s} \sim t_{N-1} \tag{15}$$

7.8 Potential Issues with the Test

As stated above, all formulas rely on the assumption that returns are not correlated across firms. If this assumption is violated, the resulting test statistic is biased.

7.8.1 Changing Variance of Abnormal Returns and Event Volatility

Another assumption for a valid test is that abnormal returns have constant variance in both event and non-event periods. If variance increases during the event period, while the variance used in hypothesis testing is estimated from a different period, the variance of abnormal returns will be underestimated. This phenomenon is known as event-induced variance, whereby return volatility typically increases during the event period. As a result, the test statistic becomes upward biased, leading to overly frequent rejection of the null hypothesis (Boehmer et al., 1991). To address this issue, a cross-sectional estimator of standard errors can be employed. Event volatility represents an additional potential concern, as firms included in the analysis have different volatilities in stock returns, which is not explicitly accounted for in the standard test statistic (De Jong & De Goeij, 2007).

7.8.2 Event Clustering and Crude Adjustment Method

Event clustering, or cross-sectional dependence, occurs when the event windows of several firms overlap in calendar time, causing abnormal returns to be correlated. This violates the assumption of independent abnormal returns. In the present case, this applies to all firms, as the analysis examines a shock that occurs on the same calendar date for all firms in the sample. This violation renders the test statistic for CAAR invalid, as the usual variance estimator underestimates the variance of the AAR due to positive correlations between events, resulting in upward-biased test statistics (Brown & Warner, 1980).

Possible solutions include averaging all stocks into a single portfolio and performing a single time-series regression, often referred to as the calendar-time approach. Another method is to apply a crude adjustment, which is used in this analysis (De Jong & De Goeij, 2007).

Crude adjustment is a method used to correct for cross-sectional heteroscedasticity, which can invalidate test statistics in event studies. It involves estimating the variance of abnormal returns for each firm during the estimation window. The individual variances are then summed across all firms and divided by N^2 to obtain the variance of the AAR. The square root of this value yields the standard deviation, which is used in the denominator of the test statistics for AAR or CAAR. The correction is described in Formulas 16–21 (De Jong & De Goeij, 2007).

Firm-specific variances of abnormal returns from the estimation window:

$$\overline{AR_i} = \frac{1}{T_2 - T_1 + 1} \sum_{t=T_1}^{T_2} AR_{it} \tag{16}$$

$$\widehat{s_i^2} = \frac{1}{T_2 - T_1} \sum_{t=T_1}^{T_2} (AR_{it} - \overline{AR_i})^2 \tag{17}$$

The adjusted variance of AAR is computed as:

$$s_{AAR}^2 = \frac{1}{N^2} \sum_{i=1}^{N} \widehat{s_i^2} \tag{18}$$

Now, the adjusted test statistics for AARt and CAAR are:

$$TS = \frac{AAR_t}{\sqrt{s_{AAR}^2}} \sim N(0,1) \tag{19}$$

$$TS = \frac{CAAR}{\sqrt{T} \cdot s_{AAR}} \sim N(0,1) \tag{20}$$

where

$$T = t_2 - t_1 + 1 \tag{21}$$

As usual, the test statistic follows a standard normal distribution in large samples. In smaller samples, it follows a *t*-distribution with $N - 1$ degrees of freedom (De Jong & De Goeij, 2007).

8 EMPIRICAL RESULTS

In the following section, I begin by specifying the data used in the event study. More specifically, I examine the relationship between returns and the explanatory variables included in the study. I then present and interpret the empirical results.

8.1 Testing for Model Specifications Using Ramsey's Regression Equation Specification Error Test

To test the joint significance of the non-linear forms of the explanatory variables, I reduce the dimensionality of the data by constructing three portfolios: renewable, carbon-intensive, and energy. I calculate the time series of portfolio returns using weighted average returns, with market capitalisation serving as the weight for each stock in the portfolio. To avoid look-ahead bias, I lag the market capitalisation of each firm by one period. In this context, I use monthly data. The portfolio returns are useful later when calculating correlations between the three portfolios in the discussion on hedging carbon risk.

Figure 7 compares residuals and fitted values for each of the linear regressions applied to the three portfolios. Each portfolio's returns are regressed on VGK and IXC, which are also used in the event study. For the carbon-intensive portfolio, I observe large spikes in residuals during the global financial crisis, as well as large spikes in fitted values during the COVID-19 period, suggesting the potential presence of volatility clustering. The renewable portfolio shows less pronounced volatility clusters. For the energy portfolio, I observe a large spike in fitted values during the COVID-19 period.[5]

Figure 7: Fitted and Residual Values for Each Portfolio, Estimated Using Ordinary Least Squares

Source: Own work based on data from Yahoo Finance (2025); S&P Global (2025).

Based on the test statistics in Table 2, I cannot reject the null hypothesis for the renewable and energy portfolios, which provides evidence that the model specification is appropriate for the returns of these two portfolios. For the carbon-intensive portfolio, however, I reject the null hypothesis, indicating poor model specification. This issue could potentially be addressed by adding additional explanatory variables or incorporating non-linear terms.

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[5] Portfolio return distributions are displayed in Appendix 5.

Table 2: Test Statistic for the Functional Form of the Data Using the Ramsey Regression Equation Specification Error Test

Portfolio	**F-statistics**	**P-value**	**Null hypothesis**
Renewable	0.6906	0.5994	Not rejected
Carbon-intensive	5.4912	0.003	Rejected
Energy	0.3438	0.8481	Not rejected

Source: Own work based on data from Yahoo Finance (2025); S&P Global (2025).

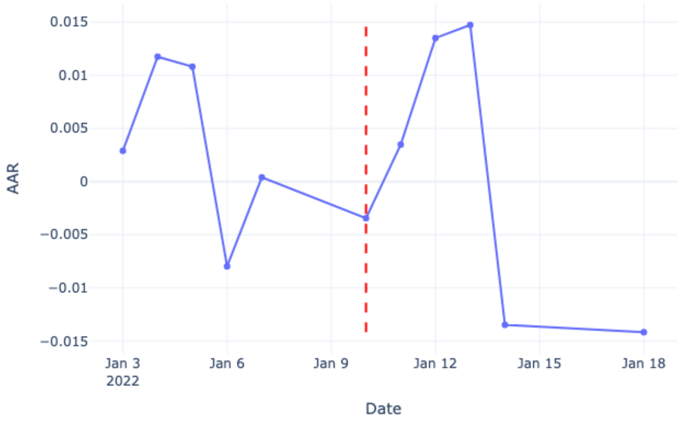
8.2 Average Abnormal Returns in the Event Window

Averaging abnormal returns allows me to test their statistical significance. In addition, I can use them for visualisation purposes to intuitively observe how carbon price shocks affect combined stock performance.

8.2.1 Category 1: Carbon-Intensive Firms

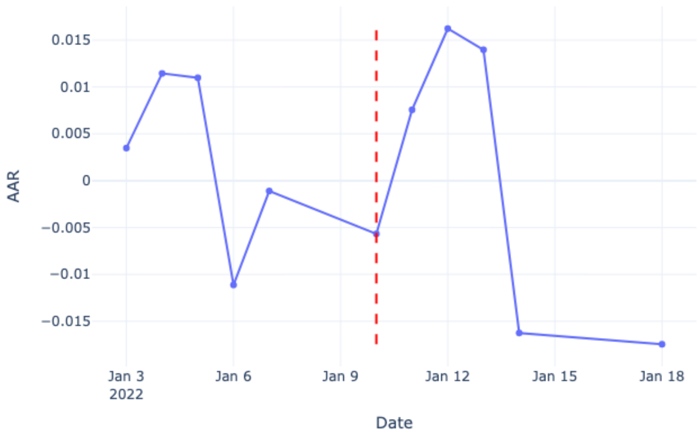
In Figures 8 and 9, which present the AAR for carbon-intensive firms, I observe a slight decrease in AAR on the event day. The minimal difference between the two figures can be attributed to two factors. First, due to superior performance in the testing window, linear regression is predominantly used to estimate normal returns in both cases. Second, linear regression and other ML models produce very similar prediction values.

Figure 8: Average Abnormal Returns over Time – Linear Model for Carbon-Intensive Firms



Source: Own work based on data from Yahoo Finance (2025).

Figure 9: Average Abnormal Returns over Time – Best Model for Carbon-Intensive Firms

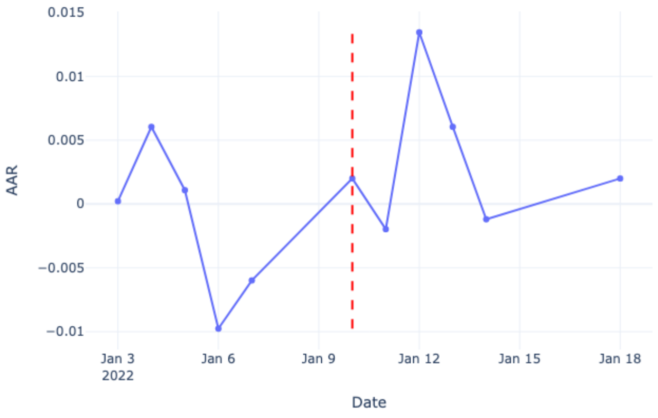


Source: Own work based on data from Yahoo Finance (2025).

8.2.2 Category 2: Energy Firms

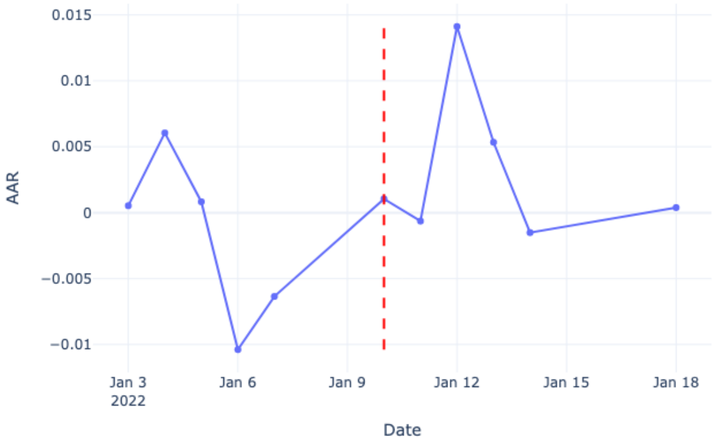
In Figures 10 and 11, I observe a slight increase in the AAR of energy firms on the event day. The two figures appear identical, either because linear regression performs well compared to other ML models or because the predictions from the linear model and the best-performing model are very similar. A minor difference between the figures is visible on the day following the event.

Figure 10: Average Abnormal Returns over Time – Linear Model for Energy Firms



Source: Own work based on data from Yahoo Finance (2025).

Figure 11: Average Abnormal Returns over Time – Best Model for Energy Firms

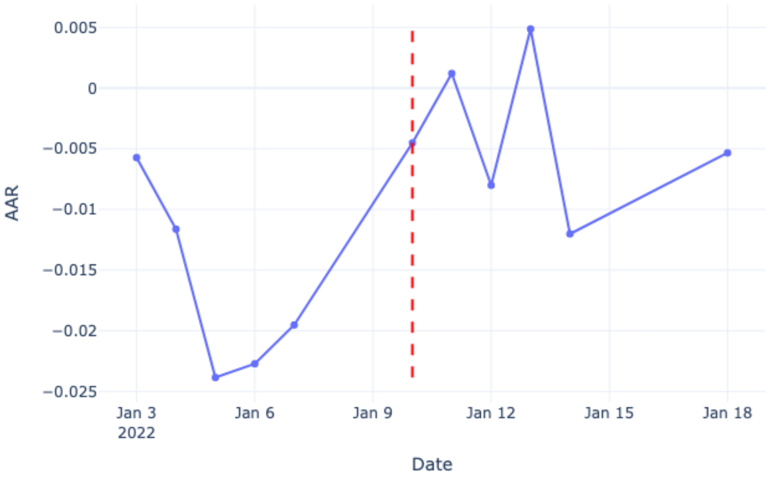


Source: Own work based on data from Yahoo Finance (2025).

8.2.3 Category 3: Renewable Firms

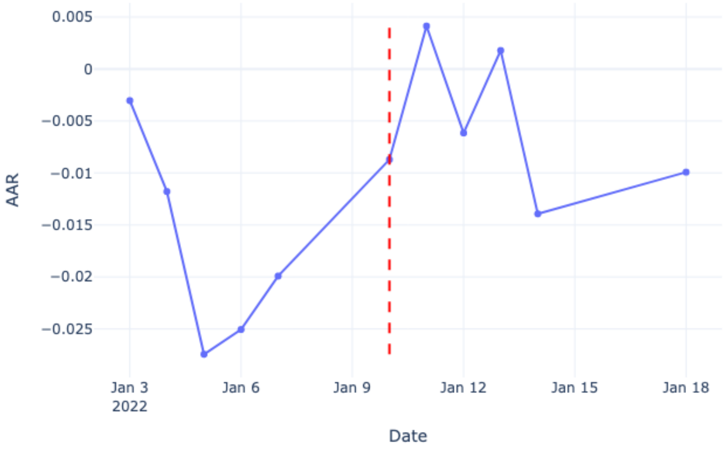
Figures 12 and 13 show an increase in AAR on the event day for renewable firms. As with the other two firm types, only a very small difference is observed between the linear and best-performing model estimates. Compared to energy firms, the increase appears steeper.

Figure 12: Average Abnormal Returns over Time – Linear Model for Renewable Firms



Source: Own work based on data from Yahoo Finance (2025).

Figure 13: Average Abnormal Returns over Time – Best Model for Renewable Firms



Source: Own work based on data from Yahoo Finance (2025).

8.3 Test Statistics for Cumulative Average Abnormal Returns

Based on the results in Table 3, I conclude that over the entire event window, the test statistics for CAAR are positive but statistically insignificant for carbon-intensive and energy firms. For renewable firms, the test statistic is negative and statistically significant. It should be noted that AAR are negative throughout almost the entire event window for renewable firms. For this reason, I further divide the event window into pre-event and post-event periods.

Table 3: Test Statistics for Cumulative Average Abnormal Returns for the Entire Event Window

Model and firm type	**Test statistics**	**Critical value**
Linear model – carbon-intensive	1.05	2.365
Best model – carbon-intensive	0.61	2.365
Linear model – energy firm	0.67	2.262
Best model – energy firm	0.59	2.262
Linear model – renewable firm	–3.0	2.571
Best model – renewable firm	–2.99	2.571

Source: Own work based on data from Yahoo Finance (2025).

Table 4 reports the results after splitting the event window into two sub-periods: pre-event and post-event. For carbon-intensive firms, the test statistic declines in the post-event period. Under the linear model, it decreases from 1.18 to 0.27, and under the best model from 0.88 to 0.22. This reduction is driven by a lower CAAR in the post-event period, as the standard deviation (calculated from the estimation window) remains unchanged. For energy firms, the test statistic increases substantially in both cases. Using the linear model, it increases from -0.67 to 1.46, while using the best model it increases from -0.67 to 1.39. For renewable firms, the test statistic increases from -3.3 to -0.76 when using the linear model, and from -3.22 to -0.72 when using the best model.

Table 4: Test Statistics for Cumulative Average Abnormal Returns, Separated into before and after The Event

Model and firm type	**Event period**	**Test statistics**	**Critical value**
Lin model – carbon-intensive	Pre-event	1.18	2.365
Lin model – carbon-intensive	Post-event	0.27	2.365
Best model – carbon-intensive	Pre-event	0.88	2.365
Best model – carbon-intensive	Post-event	0.22	2.365
Lin model – energy firms	Pre-event	–0.67	2.262
Lin model – energy firms	Post-event	1.46	2.262
Best model – energy firms	Pre-event	–0.67	2.262
Best model – energy firms	Post-event	1.39	2.262
Lin model – renewable firms	Pre-event	–3.3	2.571
Lin model – renewable firms	Post-event	–0.76	2.571
Best model – renewable firms	Pre-event	–3.22	2.571
Best model – renewable firms	Post-event	–0.72	2.571

Source: Own work based on data from Yahoo Finance (2025).

8.4 Performance of the Models in the Test Window

The fourth research question concerns the test-window performance of the models. In this section, I present model performance by firm type. For this purpose, test root mean square errors are averaged for each model and each firm type (i.e. energy, renewable, and carbon-intensive). As shown in Table 5, the linear model performs best for carbon-intensive firms, with the neural network ranking second. Based on these results, I conclude that, among the ML approaches, the neural network provides the most precise estimates for computing normal returns for carbon-intensive firms.

Table 5: Average Model Performance for Carbon-Intensive Firms

Model	**Test root mean square error**
Linear model	0.013850
Neural network	0.014087
Best neural network	0.014087
Random forest	0.014325
LGBM	0.014425
Decision tree	0.014787
Lasso model	0.016475

Source: Own work based on data from Yahoo Finance (2025).

Table 6 reports the results for energy firms, for which the linear model yields the lowest error rate. This indicates that, despite its simplicity, the linear model outperforms the ML alternatives in the testing window.

Table 6: Average Model Performance for Energy Firms

Model	**Test root mean square error**
Linear model	0.01409
Neural network	0.01415
Best neural network	0.01415
Random forest	0.01434
LGBM	0.01454
Decision tree	0.01497
Lasso model	0.01779

Source: Own work based on data from Yahoo Finance (2025).

For renewable firms, LGBM outperforms the other models, with the linear model ranking a close second. Across all models, the error is slightly higher than for carbon-intensive and energy firms. The results are shown in Table 7.

Table 7: Average Model Performance for Renewable Firms

Model	**Test root mean square error**
LGBM	0.025367
Linear model	0.025700
Neural network	0.025717
Best neural network	0.025717
Random forest	0.025883
Lasso model	0.025950
Decision tree	0.026050

Source: Own work based on data from Yahoo Finance (2025).

Regarding overall model performance across firm categories, the results are summarised in Table 8. On average, the linear model outperforms other models, suggesting that it provides the most precise estimates overall. The neural network ranks second across all firms.

Table 8: Overall Average Model Performance (Root Mean Square Error)

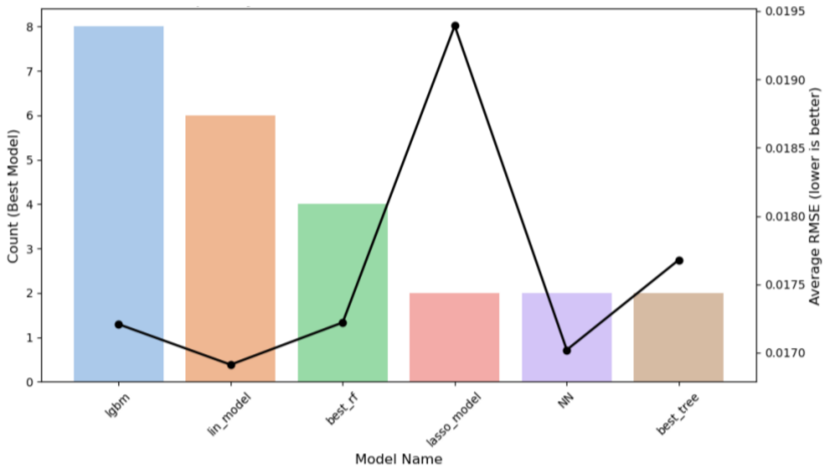
Model	**Test root mean square error**
Linear model	0.016913
Neural network	0.017021
Best neural network	0.017021
Random forest	0.017208
LGBM	0.017221
Decision tree	0.017679
Lasso model	0.019392

Source: Own work based on data from Yahoo Finance (2025).

As stated in the methodology, normal returns were estimated twice for each firm: once using linear regression and once using the best-performing model among linear regression, lasso regression, decision trees, random forests, LGBM, neural networks, and early-stopped neural networks.

Figure 14 illustrates the frequency with which each model is selected as the best-performing approach for predicting normal returns, along with the corresponding root mean square errors. Results show that LGBM has the highest selection frequency, being used eight times to estimate normal returns. The linear model ranks second, having been selected six times as the best-performing model, followed by the random forest, which is selected four times. The results suggest that although some models, such as neural networks, perform well on average, they are selected less frequently than LGBM. This may indicate that LGBM performs well in most cases but underperforms in others.

Figure 14: Frequency of Models Used and their Root Mean Square error



Source: Own work based on data from Yahoo Finance (2025).

Based on these results, I conclude that linear regression remains a valuable tool for small-scale modelling in settings where only a few variables are used as inputs (in our case, only two). If more variables are added, ML models may outperform linear regression due to their greater flexibility and ability to capture non-linear relationships. [6]

8.5 Carbon Betas

To quantify the systematic carbon risk of firms, I estimated a carbon beta for each firm by regressing firm stock returns on emission allowance futures. To address potential autocorrelation and heteroscedasticity, which could affect the statistical significance of the estimated betas, I employed Newey-West standard errors. As shown in the boxplot, carbon

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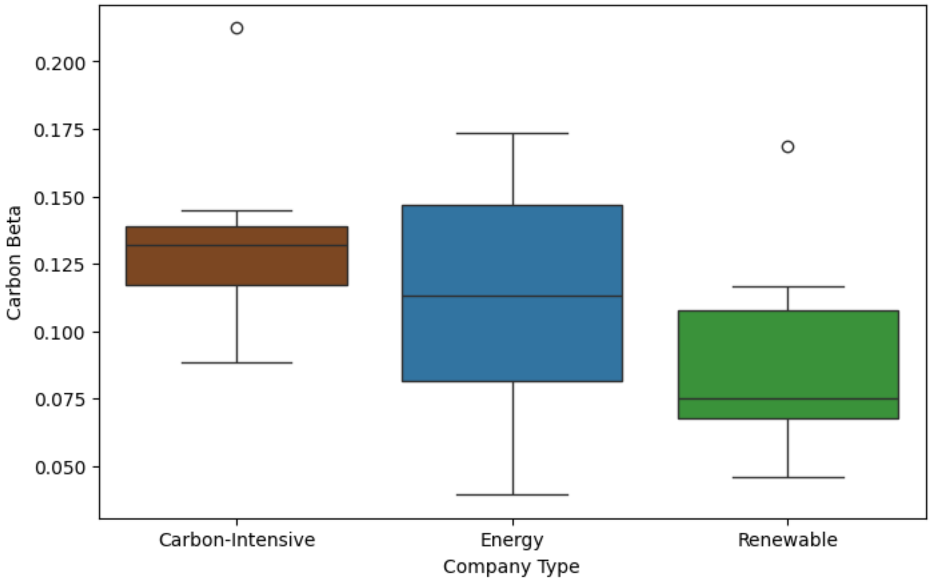
[6] The results of the event study are further supported by a robustness check using different event dates, as shown in Appendix 4.

betas range from 0.04 to 0.22 across all firms. Carbon-intensive firms exhibit the highest carbon sensitivity, with a median carbon beta of 0.13. In contrast, renewable firms display the lowest sensitivity, with a median carbon beta of 0.075. Energy firms have a median beta of 0.11, placing them between the most sensitive carbon-intensive firms and the least sensitive renewable energy firms. Overall, the obtained results do not provide strong evidence that carbon risk is reflected in asset prices for this sample. Figure 15 illustrates the dispersion of carbon betas by firm type.

Figure 15: Carbon Betas by Firm Type, Estimated Using Ordinary Least Squares on Daily Data from 2015 to 2022



Source: Own work based on data from Yahoo Finance (2025); Investing.com (2025).

8.6 Firms' Weighted Average Cost of Capital

Figure 16 presents the time series of the weighted average cost of capital (hereinafter WACC) for each subsample considered in the analysis. Carbon-intensive firms appear to have the highest WACC.

Figure 16: Average Monthly Weighted Average Cost of Capital for Each Subsample

Source: Own work based on data from Refinitiv (2025). Data observed from January 2015 to October 2025.

Table 9 reports WACC averaged over time by firm type. Carbon-intensive firms have the highest average WACC, at 8.9%. Renewable firms lie in between, with an average WACC of 6.7%, while energy firms exhibit the lowest average WACC, at 5.8%.

Table 9: Average Weighted Cost of Capital by Firm Type and Date

Firm type	**WACC**
Carbon-intensive	0.0885
Energy	0.0578
Renewable	0.0667

Source: Own work based on data from Refinitiv (2025).

9 EFFECT ON FIRMS' FINANCIALS AND DECISION MAKING

As carbon pricing affects stock performance, it may also influence firms' financials and decision-making, given that stock performance impacts firms' investment decisions. In their analysis, Zaigham et al. (2019) examined the impact of stock price performance on firms' investment and the reverse effect. The analysis was conducted using a random-effects model on Chinese manufacturing firms from 2002 to 2016. The results show a significant negative relationship between stock prices and investment expenditures, with stock prices exerting a stronger effect on investment expenditures than vice versa. An additional insight is that information asymmetry has a positive impact on stock price sensitivity to investment and investment sensitivity to stock prices.

Carbon shocks can also increase the volatility of stock returns. Dessaint et al. (2019) examined how noisy stock prices are reflected in corporate investments. They found that managers consider both their own and their peers’ stock performance when making investment decisions. Empirical results indicate that when peers' stock prices fall due to noise, firms reduce investment.

9.1 Carbon Shocks and the Cost of Capital

One channel through which a carbon shock can affect a firm's financials is through its beta and required return on equity. The cost of capital is central to firm valuation and is commonly estimated using the WACC. While the cost of equity can be estimated using several methods, such as the CAPM or Fama-French models, the CAPM remains a standard approach (Olson & Pagano, 2023).

In the CAPM, the cost of equity is defined as:

$$R_e = R_f + \beta \cdot \left(R_m - R_f\right) \tag{22}$$

where R_f represents the risk-free rate and $R_m - R_f$ denotes excess market returns.

The WACC then combines the cost of equity and the cost of debt to estimate the overall cost of capital:

$$r_{WACC} = r_e w_e + r_d(1 - t_c)w_d \tag{23}$$

where w_d and w_e represent the relative weights of equity and debt in total capital, and t_c represents the corporate tax rate.

A higher beta increases the cost of equity and, consequently, the WACC, making investments less attractive. Importantly, carbon shocks can increase firms' betas if stock prices fall more than the overall market, thereby raising the cost of capital (Damodaran, 2012). Firms' emissions are also directly linked to their cost of capital. Evidence from studies on US firms shows that firms with higher emissions tend to have a higher cost of capital, just like this study on EU firms (Kim & Pouget, 2023).

9.2 Effect on Firms' Profitability

Carbon emissions can affect a firm's profitability. They may increase costs, but they can also generate revenue through free permit allocations. The cost of carbon emissions is given by the product of the per-unit emissions price and the emissions rate. When accounting for free allocations of emissions credits, Formula 24 can be used to estimate the firm's net profits. In this formulation, q denotes the firm's output, $P(Q)$ is the market price as a function of total output Q, $C(q, \omega)$ is the cost function dependent on output and input prices ω, τ denotes the carbon price, and A is the allocation of free emissions permits. The term $\tau \cdot r \cdot q$ represents the firm's cost of emissions at a given production level (Bushnell et al., 2009).

$$\pi = P(Q) \cdot q - C(q, \omega) + \tau A - \tau_r q \tag{24}$$

9.3 Strategic Responses

One way for carbon-intensive firms to reduce the impact of environmental measures and carbon price shocks is by fostering innovation to make processes cleaner. Firms can pursue this strategy in two ways. First, they can manage pollution more intelligently and minimise their environmental impact, thereby reducing compliance costs. Second, they can improve the affected products or related processes in an environmentally friendly manner, thus promoting industrial innovation. Product offsets enhance product performance, increase quality, and improve safety, while production offsets involve reducing waste, increasing resource productivity, and improving the utilisation of by-products (Porter & van der Linde, 1995).

9.4 Capital Allocation

Strategic response is one way firms react to carbon pricing. Another expected response is improved capital allocation. Strategic capital allocation is essential for firm growth and profitability. A study using data from 2010 to 2021 found that ETS can mitigate capital misallocation. The authors conclude that macro-level environmental regulations contribute to improvements in micro-level organisational capital efficiency. These findings are consistent with the strategic response, as innovation also promotes more efficient capital allocation (Wang et al., 2024).

10 HEDGING CARBON RISK

In 2005, risk management began to play a significant role in the work of energy portfolio managers. Energy utilities, such as electricity providers, regard carbon regulation as a serious financial risk. As power plants and their associated infrastructure are designed for long operational lifetimes, often spanning several decades, it is unrealistic to assume that carbon emissions will remain unregulated throughout that period. To address this uncertainty, utilities include carbon cost estimates into their planning processes and select resource options that minimise both cost and risk. The objective is to avoid investments in carbon-intensive assets in anticipation of potential carbon pricing (Bokenkamp et al., 2005). Since then, carbon risk has gained recognition in investment and related fields, as the question of whether carbon emissions present material risk for investors has become more prominent (Bolton & Kacperczyk, 2021). Growing investor awareness of the effects of climate change on financial markets has further increased demand for financial products that can hedge climate-related risks (Cao et al., 2024).

10.1 Types of Climate Risk

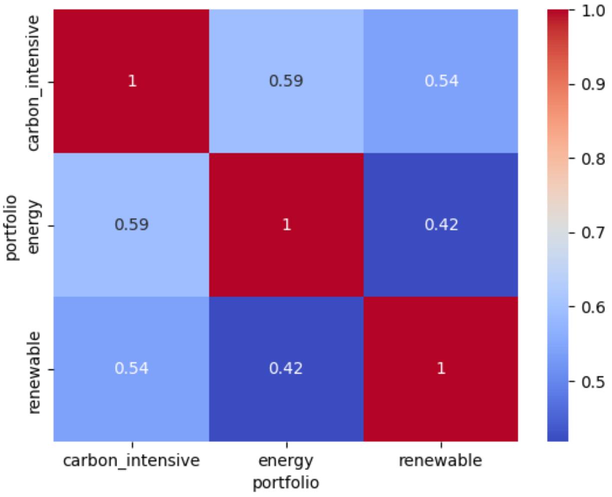
To further investigate the hedging of climate risk, I first distinguish between two main types of climate risks. Physical climate risk refers to the disruptive effects of climate-related events on business operations and firms' cash flows. This type is largely independent of firm-specific characteristics or industry. Transition risk, on the other hand, relates to firms' adjustment to climate regulations as they decarbonise their processes to comply with policy regulations. This type of risk has a greater effect on energy-intensive industries and firms that rely heavily on fossil fuels (Cepni et al., 2022).

10.2 Equity Markets

In equity markets, green and brown stocks typically exhibit negative correlations, positioning green stocks as potential hedging instruments against climate risk. Volatility spillovers between the two groups are bidirectional, and both correlation and spillover effects intensify during periods of carbon policy change. This suggests that green and brown stocks may serve as complementary tools within climate hedging strategies (Kim & Eom, 2024).

In Figure 17, I present the correlations across the three portfolios constructed from the sample, using lagged market capitalisation as the weight for each firm within the portfolios. Renewable and carbon-intensive firms display a positive correlation of 0.54, which contrasts with the findings of Kim and Eom (2024), who report a negative correlation between these two groups.

Figure 17: Correlation Heatmap of Carbon-Intensive, Renewable, and Energy Portfolio



Source: Own work based on data from Yahoo Finance (2025); S&P Global (2025).

10.3 Constructing Hedging Portfolios

As climate risk exerts negative effects on assets over long horizons, financial derivatives and specialised insurance markets are not available to hedge these long-term risks. For this reason, investors must construct portfolios to hedge against climate risk (Engle et al., 2020). While it is possible to construct an efficient hedging portfolio using a carbon factor, doing so using ESG scores as a risk factor is more challenging due to their overly broad definition (Azzone et al., 2025).

Engle et al. (2020), in their paper "Hedging Climate Change News", developed a methodology for constructing climate risk news hedging portfolios. These dynamic portfolios are based on asset pricing theory and draw on the work of Black-Scholes and Merton. The portfolios consist of equities selected based on their short-term return responses to climate-related news, thereby hedging long-term climate risk exposure over time. To construct the mimicking portfolio, the authors used firm-level ESG characteristics, taking long positions in portfolios with high ESG scores and short positions in portfolios with low ESG scores. Their empirical results show superior in-sample and out-of-sample performance relative to industry-based or naive factor-based hedges.

In their research, Cao et al. (2024) proposed a new method for constructing hedging portfolios against climate risk by analysing real-time market reactions to climate-related discussions during corporate earnings calls. Using natural language processing (NLP) techniques and ChatGPT-4, they identified conversations focused on climate risks and build a long–short portfolio, taking long positions in stocks with positive reactions and short positions in stocks with negative reactions. The portfolio is rebalanced quarterly to reflect changes in firms' climate risk exposure. This approach overcomes limitations associated with traditional hedging methods based on ESG scores or historical betas and achieves stronger out-of-sample correlations with aggregate climate shock measures, thereby demonstrating superior hedging performance.

10.4 Estimating Carbon Risk Exposure Using Carbon Beta – A Market-Based Measure

A firm's carbon risk sensitivity can be estimated using either fundamental or market-based measures. Carbon beta, a market-based measure, is a key financial metric as it reflects carbon-related systematic risk. It provides valuable information for trading and risk management by reflecting the extent to which carbon risk is priced by financial markets (Roncalli et al., 2020). Carbon beta can therefore serve as an indicator for climate hedging, enabling the construction of hedging portfolios that deliver higher returns during periods of climate stress. A key advantage of this approach is that carbon betas can be estimated even for firms for which emissions data are unavailable (Huij et al., 2023).

Carbon risk can be interpreted as either relative or absolute. Relative carbon risk focuses on directional exposure to climate risk and reflects a preference for green over brown firms by targeting stocks with negative carbon beta, those that benefit from the climate transition, while avoiding stocks with positive carbon betas. This approach incorporates investors' moral values. Absolute carbon risk, by contrast, is more risk-oriented and treats extreme carbon betas, whether negative or positive, as indicative of risky stocks. The aim is to reduce overall exposure to climate-sensitive stocks, irrespective of whether the firms are green or brown. This represents a more risk-averse strategy that is not motivated by ethical preferences (Roncalli et al., 2020).

In a study by Huij et al. (2023), empirical evidence shows that stocks with high carbon betas yield lower returns during months in which climate change is frequently discussed in the news, as measured by the Climate Policy Uncertainty (hereinafter CPU) Index, during months with abnormally high temperatures, and during exceptionally dry months. The results indicate a modest annual return of 1.15% for each one-unit increase in the standard deviation of carbon beta, suggesting a positive carbon risk premium. Carbon betas also distinguish firms according to their exposure to CPU, helping to identify green firms that may serve as hedges against sudden climate-related risks. Similarly, investors may hedge against extreme weather events by holding stocks with low or negative carbon betas, as high carbon beta stocks yield lower returns during such periods, when investors are more aware of climate risks.

10.5 Carbon-Related Financial Instruments

With the development of comprehensive climate policies, numerous debt instruments have been introduced to support firms in transitioning towards a greener and more socially responsible economy. Firms can use these instruments to facilitate the shift to cleaner business operations (Feldhütter et al., 2024). Green bonds were initially issued by the European Investment Bank and the World Bank; however, corporations now account for two-thirds of global green bond issuance. Firms issue green bonds to secure lower-cost financing, while investors are willing to accept lower yields in exchange for environmental benefits (Caramichael & Rapp, 2022). It is important to note that green bonds expose investors to the same default risk as conventional bonds (Zerbib, 2016).

While green bonds finance environmentally friendly projects, blue bonds are used to fund initiatives related to ocean sustainability, and social bonds support socially beneficial projects. Sustainability-linked bonds, by contrast, tie proceeds to one or more ESG-related key performance indicators. These instruments are less restrictive regarding the use of proceeds than the aforementioned ESG debt instruments, but they impose a penalty on the firm if the specified key performance metrics are not met (Feldhütter et al., 2024). Unlike green bonds, which finance specific projects, sustainability-linked bonds link the cost of capital to ESG performance, thereby making the issuer financially accountable for sustainability outcomes (Kölbel & Lambillon, 2023).

10.6 Sustainability-Linked Bonds and Green Bonds Premium

In their paper "Pricing of Sustainability-Linked Bonds," Feldhütter et al. (2024) found a statistically significant negative ESG premium, concluding that sustainability-linked bonds could serve as a hedge against ESG risk. In contrast, evidence on the green bond premium, based on matching methods combined with fixed-effects regression, reveals a small but statistically significant negative premium of approximately 2 basis points. This premium, defined as the yield difference between a green bond and a conventional bond after controlling for liquidity, is influenced by both sector and credit rating. Notably, the financial sector and lower-rated bonds exhibit a larger negative premium. These findings suggest that investors are willing to accept slightly lower returns in exchange for the environmental benefits associated with green bonds (Zerbib, 2016). Similar results are reported by Caramichael and Rapp (2022), who, using U.S. corporate bond data, found a green bond premium of 8 basis points, further supporting the notion of lower borrowing costs for issuers.

10.7 Hedging Climate Risk with Sustainability Linked and Green Bonds

Sustainability-linked bonds are tied to specified ESG targets. If these targets are not met, penalties are applied, usually in the form of a higher coupon rate, which can serve as a hedge for investors. Sustainability-linked bonds thus indirectly hedge transition risk, as they incentivise issuers to improve their ESG performance (Feldhütter et al., 2024). Regarding green bonds, evidence suggests that they may serve as an even more effective hedge than many traditional assets, including gold. Green bonds exhibit a consistent, positive, and time-varying correlation with both physical and transition climate risk indices (Cepni et al., 2022).

11 CONCLUSION

To conclude this master's thesis, I reflect on the findings, highlight the limitations, and outline the contribution of this research. When examining the three AAR figures, it is evident that the differences between the linear model and the best-performing ML model are minimal. This provides confidence that, despite differences in estimation methods, both approaches yield very similar results.

Question 1 concerns abnormal stock returns of carbon-intensive firms. According to the results, Figures 7 and 8 show a small decrease in AAR for carbon-intensive firms on the event day, followed by an increase on the next day. Regarding the statistical significance of CAAR, the evidence indicates no statistical significance, as reported in Tables 3 and 4.

Question 2, which focuses on renewable firms, shows a negative AAR on the event day, although AAR increases relative to previously observed values. The results also indicate a statistically significant negative CAAR for the full event window (Table 3); however, when the event window is split into pre- and post-event periods, statistical significance is present only in the pre-event period (Table 4). The disappearance of significance in the post-event period suggests that the event itself does not convey additional information beyond what may already be priced in. The presence of statistical significance indicates a potential trading anomaly, such as information leakage or anticipatory trading, whereby market participants adjust their expectations prior to the event.

Question 3 addresses the possibility of offsetting effects for energy firms. On the event day, AAR turns positive (Figures 9 and 10), although it turns negative again on the following day. The increase on the event day is, however, smaller than that observed for renewable firms. Tests of CAAR show no statistical significance (Tables 3 and 4). While the slight increase in AAR may be indicative of offsetting effects, the lack of statistically significant CAAR implies that the results do not provide sufficient evidence to conclude that such effects are present.

As none of the results showed meaningful statistical significance, I conducted a robustness check by selecting an alternative event day that also featured a significant jump in the emission allowance price series. The robustness check, presented in Appendix 4, shows a pattern of AAR behaviour similar to that observed for the primary event date. This leads me to conclude that firms' stock prices do, in fact, react differently to increases in emission allowance prices, depending on whether the firms are carbon-intensive, energy firms, or renewable energy firms. The observed pattern across the three firm types suggests that market participants lose confidence in carbon-intensive firms following an increase in emission allowance prices, whereas energy and renewable firms are affected differently, with investors exhibiting stronger preferences for their stocks.

Question 4 compares machine learning models with linear regression in terms of predictive accuracy, measured by the root mean square error in the test window. On average, the linear model performs best (Table 8). It is important to note that the market model includes only two explanatory variables. With more variables included, machine learning models may perform better, as is often the case in other applications. For carbon-intensive firms (Table 5) and energy firms (Table 6), the linear model performed best, whereas LGBM performed best for renewable firms (Table 7). Figure 13 further illustrates model usage, showing that the linear model was selected six times in total under the best-model approach. The only model used more frequently was LGBM, indicating that linear regression performs consistently well, combining the lowest average error with the second-highest usage frequency.

As carbon pricing influences stock performance and may further translate into systematic carbon sensitivity and changes in the cost of capital, I also estimate carbon betas for all firms in the sample. The results show that carbon-intensive firms exhibit the highest median carbon beta, at approximately 0.13, while renewable firms display the lowest, at approximately 0.075. Energy firms fall between these two groups. The results do not provide strong evidence that carbon risk is fully reflected in asset prices in this small sample. Regarding the WACC, carbon-intensive firms historically show the highest average values, whereas energy firms have the lowest.

The main limitation of this study is the sample size. As the analysis focuses on European publicly traded firms, the three subgroups are not sufficiently large to produce fully robust statistical results. Future research could address this limitation by expanding the sample to include firms from other ETSs, such as those in the United States or Asia. Overall, this thesis contributes to the literature by enhancing the understanding of how carbon pricing affects stock performance and by demonstrating how machine learning can be applied alongside traditional econometric methods within an event study framework.

It is important to note that despite differences in estimation techniques, the results remain highly consistent with existing literature and research, supporting the robustness of the relationship between increases in carbon prices and negative stock returns for carbon-intensive firms.

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APPENDICES

Appendix 1: List of Firms

This sample was obtained using information from Capital IQ Pro. I filtered out publicly traded EU firms with sufficient history and no missing values in returns on Yahoo Finance for the period of analysis and obtained the results. From these, I excluded firms whose business operations are not primarily based in the EU, based on publicly available information for each firm. I grouped the firms into the defined subsamples by industry. I placed steel, chemical, cement, and building materials firms into one subsample. For energy firms, I selected the largest firm in each major EU country, as market conditions in the EU typically result in one major energy firm per country involved in various activities related to energy and gas supply. My renewable sample consists of firms involved in renewable energy generation or the production of renewable energy solutions, as investors may view this as a safe haven during periods of carbon price shocks. Plug Power Inc. is an exception, as it is a US company, but due to major business operations in the EU, I included it in the analysis.

Carbon-Intensive Firms

1. **SSAB-B.ST – SSAB AB** (Sweden): Major steel manufacturer.
2. **MT.AS** – ArcelorMittal: Steel production firm, based in Luxembourg.
3. **BAS.DE** – BASF: Chemical manufacturing giant, Germany.
4. **SOLB.BR** – Solvay: Chemicals producer, based in Belgium.
5. **AKZA.AS** – Akzo Nobel: Dutch multinational in chemicals and coatings.
6. **HEI.DE** – Heidelberg Materials: Cement production firm, Germany.
7. **CRH.L** – CRH plc: Cement and building materials firm, Ireland.
8. **SIE.DE** – Siemens AG: Industrial manufacturing conglomerate, Germany.

Energy Firms

1. **TTE.PA** – TotalEnergies: French multinational energy producer.
2. **ENI.MI** – ENI: Italian oil and gas firm.
3. **REP.MC** – Repsol: Energy and petrochemical producer, Spain.
4. **SHEL** – Shell plc: Oil and gas firm, UK/Netherlands.
5. **GALP.LS** – Galp Energia: Portuguese energy firm.
6. **RWE.DE** – RWE: German utilities firm focused on fossil fuels.
7. **ENGI.PA** – Engie: French multinational utility and energy provider.
8. **PGE.WA** – Polska Grupa Energetyczna: Polish energy group.
9. **CEZ.PR** – CEZ Group: Czech energy producer and distributor.
10. **EDP.LS** – EDP: Portuguese utilities and energy firm.

Renewable Energy Firms

1. **VWS.CO** – Vestas Wind Systems: Danish leader in wind energy solutions.
2. **EDPR.LS** – EDP Renováveis: Portuguese renewable energy subsidiary of EDP.
3. **IBE.MC** – Iberdrola: Spanish renewable energy and utilities firm.

4. **FORTUM.HE** – Fortum Oyj: Finnish clean energy corporation.
5. **EOAN.DE** – E.ON: German energy firm transitioning to renewables.
6. **PLUG** – Plug Power Inc.: US firm specializing in hydrogen and fuel cell solutions. Although it is a US firm, it has a strong presence in the EU.

Appendix 2: Capturing the Immediate Effect of Carbon Price Increase on Stock Returns

Table 1 shows the closing hours (CEST) of relevant stock exchanges to investigate whether exchange operating hours allow for immediate (same-day) transmission of carbon price shocks to stock returns.

As the bidding window for emission allowances usually closes at 11:00 a.m. CET, during active trading hours, it is possible to capture the immediate (same-day) effect of carbon price shocks on stock returns (EEX, n.d.).

Table 1: Closing hours of relevant stock exchanges

Exchange	**Country**	**Closing time**
Euronext Paris	France	17:30
Euronext Amsterdam	Netherlands	17:30
Euronext Brussels	Belgium	17:30
Euronext Lisbon	Portugal	17:30
Euronext Dublin	Ireland	17:30
Euronext Milan (Borsa Italiana)	Italy	17:30
Euronext Oslo	Norway	17:30
Xetra (Frankfurt)	Germany	17:30
London Stock Exchange (LSE)	United Kingdom	16:30
Six Swiss Exchange	Switzerland	17:20
Warsaw Stock Exchange (WSE)	Poland	16:50
Nasdaq Stockholm	Sweden	17:30
Nasdaq Copenhagen	Denmark	16:55
Nasdaq Helsinki	Finland	16:55
Luxembourg Stock exchange	Luxembourg	17:30

Source: Own work based on data from Euronext (n.d.), Deutsche Börse Xetra (n.d.), London Stock Exchange (n.d.), Nasdaq (n.d.), and TradingHours.com (n.d.).

Appendix 3: Auction Mechanism, Clearing Price Formation, and Functioning of the Primary and Secondary Markets for Allowances

Primary market for Emission Allowances

The market for carbon allowances is divided into primary and secondary markets. The primary market, organised by the German trading venue EEX, allows entities such as investment firms, commodity trading firms, and credit institutions to participate alongside compliance entities, including power plants, industrial facilities, and airlines operating under the EU ETS (European Securities and Markets Authority [ESMA], 2022).

Non-compliance participants must meet regulatory criteria to ensure fairness, openness, and the integrity of the auction process. One requirement is that non-compliance entities must be based in the EU (European Securities and Markets Authority [ESMA], 2022).

Entities must also open an account in the Union registry and appoint a bidder's representative. Stricter rules apply to traders such as investment banks and credit institutions that trade on behalf of clients. The clients they represent must be eligible persons and have a contractual relationship with the representative. EEX imposes additional requirements, requiring bidders to demonstrate a certain level of reliability and professional qualification, such as experience or knowledge in trading and risk management (European Securities and Markets Authority [ESMA], 2022). If a firm has a surplus of allowances, it may sell them or save them if permitted (Benz and Trueck, 2006).

Secondary Market for Allowances

A secondary market for allowances exists. Currently, secondary market trading occurs on three provider platforms: EEX in Germany, ICE in the Netherlands, and Nasdaq Oslo in Norway. ICE is the largest provider, holding 85% of total gross positions; EEX holds 15%, while Nasdaq Oslo's market share is negligible (ESMA, 2022).

The contracts available for trading on these venues include spot (daily expiry) futures, longer-maturity futures, and options on futures. All derivatives are standardised, with each contract representing 1,000 emission allowances. Market participants can place buy or sell orders in the exchange’s order book, and a transaction occurs when matching orders from opposite sides are submitted (ESMA, 2022).

Transactions may also occur outside the regulated platform. Two parties can exchange allowances and their derivatives over the counter (OTC). To enter such a transaction, a participant may have compliance obligations or not. Participants have freedom over contractual terms, but the delivery of allowances still takes place through the Union Registry (ESMA, 2022).

Auction Mechanism and Clearing Price Formation

The EU ETS plays a key role in reducing greenhouse gas emissions at the lowest possible economic cost. EEX acts as a common auction platform for the EU ETS and conducts auctions on Mondays, Tuesdays, and Thursdays from 9:00 to 11:00 Central European Time (EEX, n.d.). The auction clearing price is determined at the end of the bidding window (11:00 CET) and published on the EEX website, making it available to the public (EEX, n.d.).

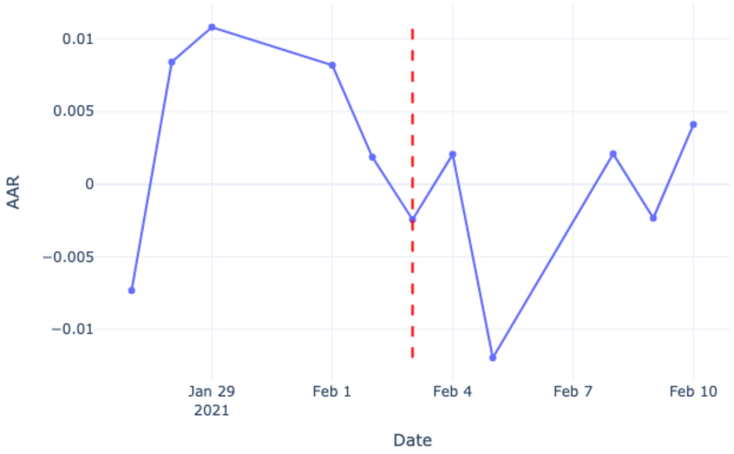
The clearing price is the price of emission allowances determined by supply and demand at the auction. It is a uniform price at which all firms can buy or sell emission allowances. This ensures that every successful bidder pays the same price for an allowance, regardless of their bid amounts. A successful bidder is one who submits a bid at or above the auction clearing price. Allowances are delivered to them the next day via their EEX account (EEX, n.d.).

Successful bidders receive their allowances in their EU Registry accounts. This is managed through the Central Clearing Party and central clearing accounts, where internal accounting adjustments reflect the credits and debits between auctioneers and buyers. Finally, upon receipt of payment, allowances are transferred from the Central Clearing Party accounts into buyers' registry accounts (European Securities and Markets Authority [ESMA], 2022).

Appendix 4: Robustness Check

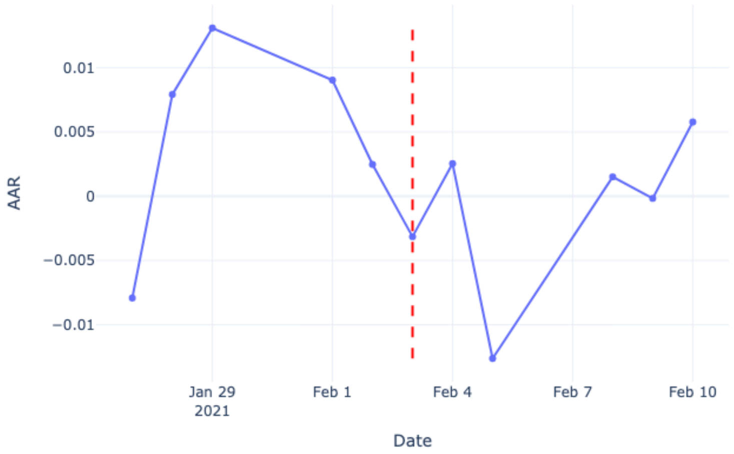
To assess the robustness of the results, the analysis was repeated using different dates. Another non-overlapping shock occurred on 3 February 2021, making it suitable for robustness analysis.

Figure 1: Average Abnormal Returns over Time – Linear Model for Carbon-Intensive Firms, Robustness Check



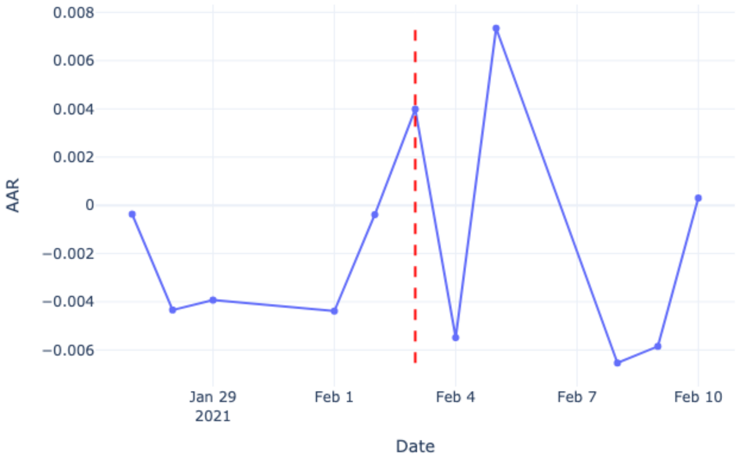
Source: Own work based on data from Yahoo Finance (2025).

Figure 2: Average Abnromal Returns over Time – Best Model for Carbon-Intensive Firms, Robustness Check



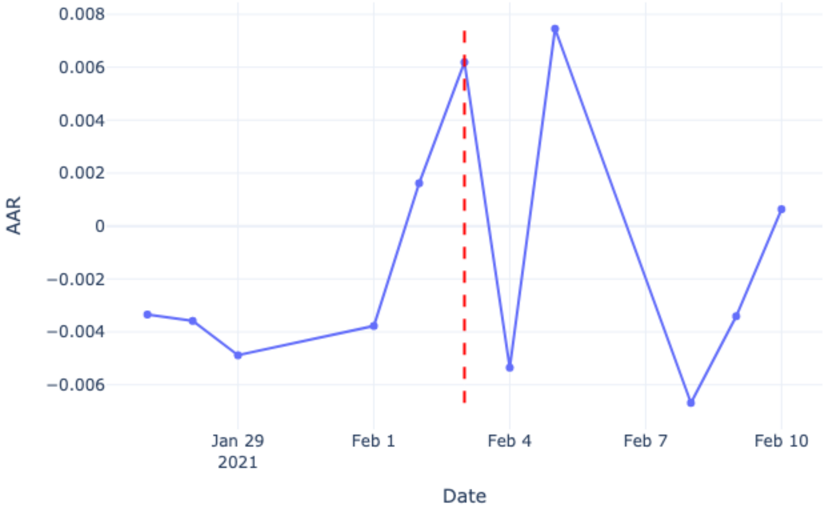
Source: Own work based on data from Yahoo Finance (2025).

Figure 3: Average Abnormal Returns over Time – Linear Model for Energy Firms, Robustness Check



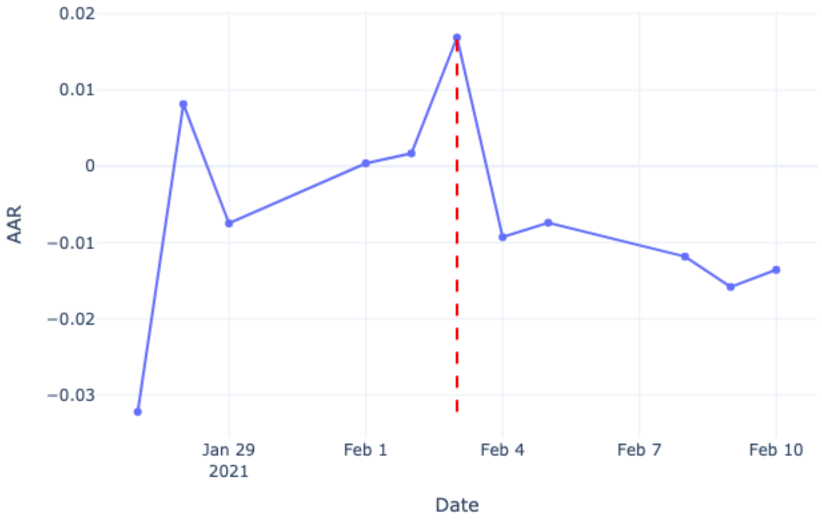
Source: Own work based on data from Yahoo Finance (2025).

Figure 4: Average Abnormal Returns over Time – Best Model for Energy Firms, Robustness Check



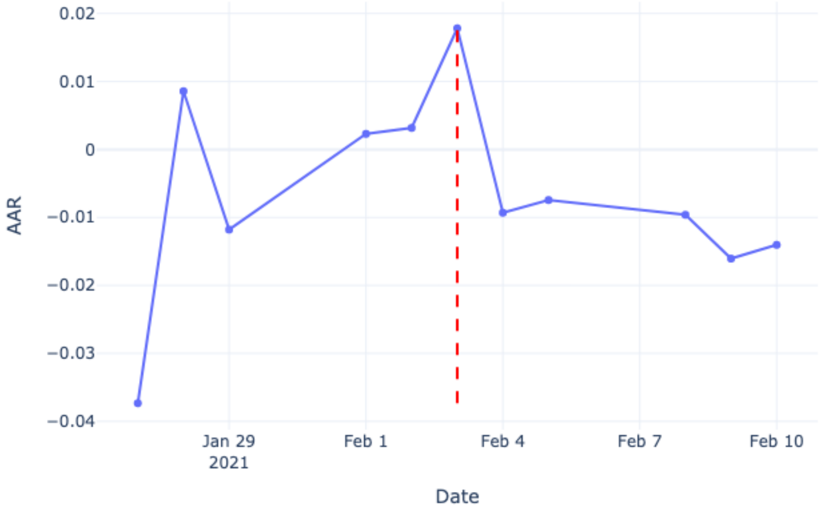
Source: Own work based on data from Yahoo Finance (2025).

Figure 5: Average Abnormal Returns over Time – Linear Model for Renewable Firms, Robustness Check



Source: Own work based on data from Yahoo Finance (2025).

Figure 6: Average Abnormal Returns over Time – Best Model for Renewable Firms, Robustness Check



Source: Own work based on data from Yahoo Finance (2025).

When observing Figures 1–6, we see similar behaviour as in the event year later. Carbon-intensive firms experience a slight decrease in AAR on the event day, while energy firms and renewable firms experience a slight increase on the event day.

Table 3: Test Statistics for Cumulative Average Abnormal Returns, Separated into Before and after The Event, Robustness Check

Model and firm type	**Event period**	**Test Statistics**	**Critical value**
Lin model – carbon-intensive	Pre-event	1.42	2.365
Lin model – carbon-intensive	Post-event	-0.39	2.365
Best model – carbon-intensive	Pre-event	1.6	2.365
Best model – carbon-intensive	Post-event	-0.19	2.365
Lin model – energy firms	Pre-event	-1.06	2.262
Lin model – energy firms	Post-event	-0.81	2.262
Best model – energy firms	Pre-event	-1.11	2.262
Best model – energy firms	Post-event	-0.58	2.262
Lin model – renewable firms	Pre-event	-1.23	2.571
Lin model – renewable firms	Post-event	-2.41	2.571
Best model – renewable firms	Pre-event	-1.46	2.571
Best model – renewable firms	Post-event	-2.35	2.571

Source: Own work based on data from Yahoo Finance (2025).

Table 4: Test Statistics for Cumulative Average Abnormal Returns for the Entire Event Window, Robustness Check

Model and firm type	**Test Statistics**	**Critical value**
Linear model – carbon-intensive	0.75	2.365
Best model – carbon-intensive	1.04	2.365
Linear model – energy firm	-1.1	2.262
Best model – energy firm	-0.85	2.262
Linear model – renewable firm	-2.07	2.571
Best model – renewable firm	-2.17	2.571

Source: Own work based on data from Yahoo Finance (2025).

Table 5: Overall Average Model Performance (Root Mean Square Error), Robustness Check

Model	**Test root mean square error**
Linear Model	0.023123
Random Forest	0.023991
Lgbm	0.024574
Neural Network	0.024740
Best Neural Network	0.024740
Decision Tree	0.026891
Lasso Model	0.029049

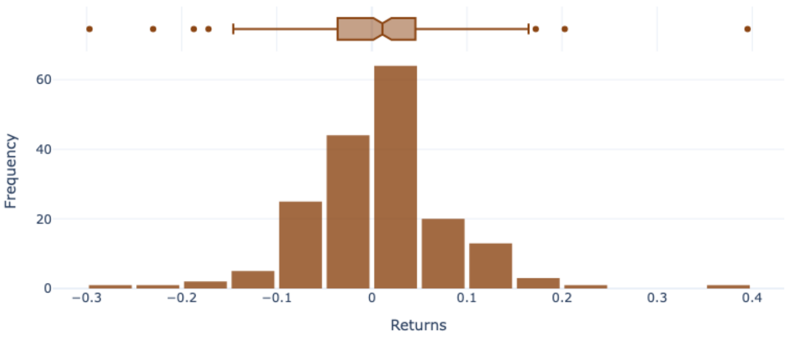
Source: Own work based on data from Yahoo Finance (2025).

We also observe very similar behaviour in estimation techniques, with linear regression outperforming other models.

Appendix 5: Distributions of the Constructed Portfolio Returns

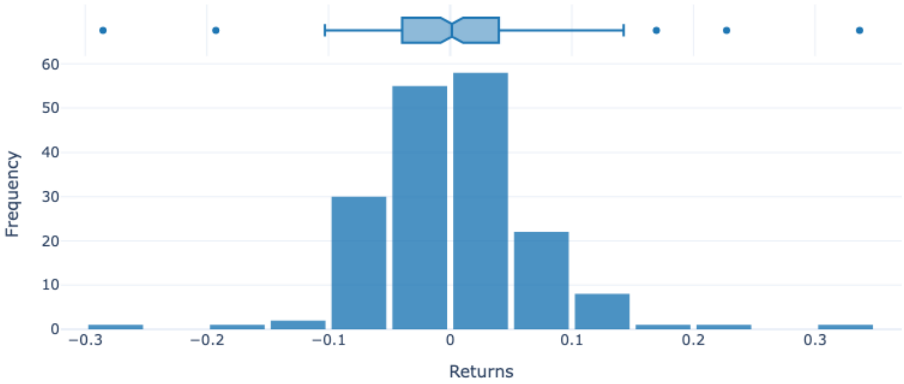
Regarding the distributions of constructed portfolio returns, energy portfolio returns appear the most balanced. All three distributions peak around zero, indicating that most returns are close to zero. Large negative and positive values are also observed, representing extreme movements. As the data used in the figures include both the financial crisis and the COVID period, with returns calculated monthly, this type of behaviour is expected.

Figure 7: Carbon-Intensive Portfolio Return Distribution, Constructed from Data



Source: Own work based on data from Yahoo Finance (2025); S&P Global (2025).

Figure 8: Energy Portfolio Return Distribution Constructed from Data



Source: Own work based on data from Yahoo Finance (2025); S&P Global (2025).

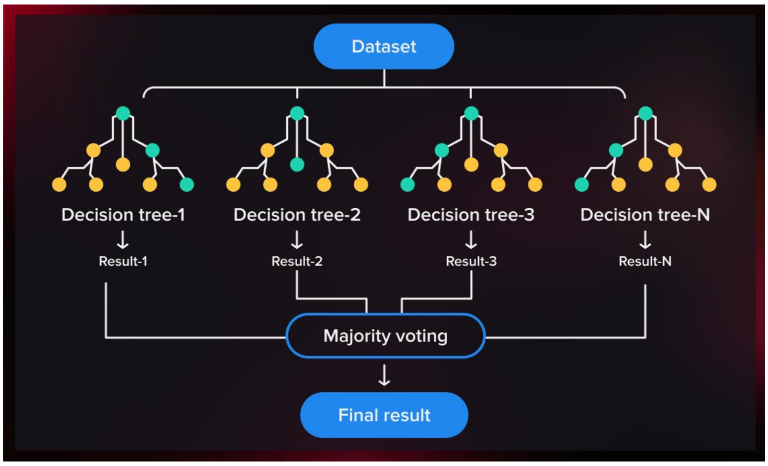
Figure 9: Renewable Portfolio Return Distribution Constructed from Data

Source: Own work based on data from Yahoo Finance (2025); S&P Global (2025).

Appendix 6: Graphical Presentation of Machine Learning Models

Figure 10 illustrates the combination of multiple decision trees into a forest-like architecture, where the final prediction is the average of all predictions from the individual trees, each built independently (Zheng et al., 2024).

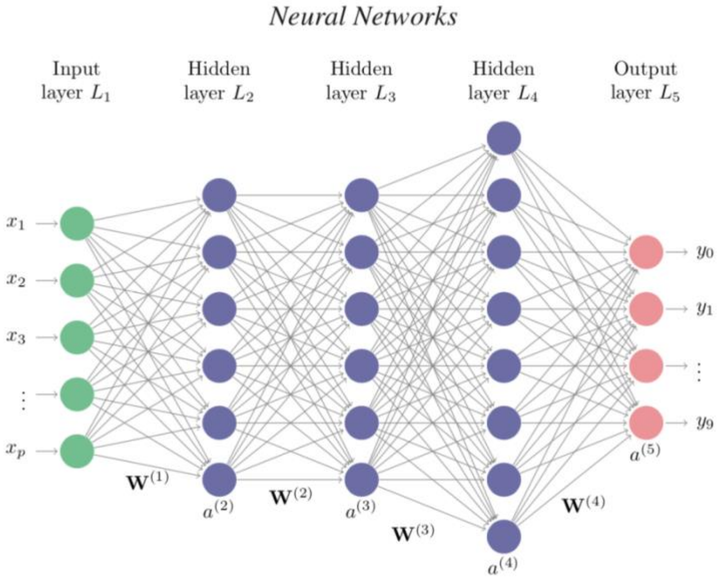
Figure 10: Illustration of the Random Forest Algorithm



Source: Serokell (2021).

Figure 11 illustrates a neural network, beginning with an input layer on the left and ending with an output layer on the right. The neurons in between are represented in hidden layers (Goodfellow et al., 2016).

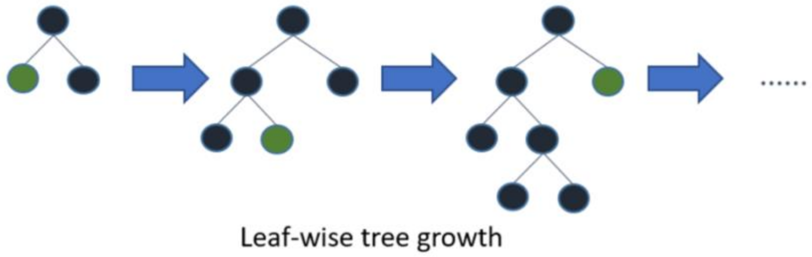
Figure 11: Visual Representation of Feedforward Neural Network



Source: Kose (2020).

Figure 12 illustrates leaf-wise growth, as opposed to level-wise growth, which is typical of other tree-based models, such as random forest, shown in Figure 12 (Bisdoulis, 2024).

Figure 12: Light Gradient Boosting Machine and Leaf-wise Growth



Source: Mandot (2020).