CHARLES UNIVERSITY

FACULTY OF SOCIAL SCIENCES

Institute of Economic Studies

Analysis of Cost Curves of Companies in Power & Heat Sector on the European Market Depending on the Carbon Allowances

Bachelor's thesis

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Year of defense: 2023

Declaration of Authorship

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Prague, May 3, 2023

Pavel Bittnar

Abstract

This thesis investigates the relationship between the profits of companies in the Power and Heat sector and the European carbon allowances. The main aim of this thesis is to determine whether the profits have a linear relationship with the number of allocated allowances. This thesis also provides insight into the European Emissions Trading System. To analyse the relationship, four different measures of profit are used. The findings show that the number of surrendered allowances, measured in Verified Emissions, is an appropriate measure for explaining the revenue, whereas the actual profits, such as profits after taxes, have a significant positive relationship with the number of allowances a company owns. The thesis concludes that there is a positive linear relationship between profits and carbon allowances. Despite certain limitations, the thesis provides a foundation for further research.

JEL Classification	D22, Q54, L94
Keywords	Cost Curves, European Market, Carbon Allowances, Power & Heat sector

Title	Analysis of Cost Curves of Companies in Power & Heat Sector on the European Market Depending on the Carbon Allowances

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Abstrakt

Tato bakalářská práce zkoumá vztah mezi zisky firem působících na Evropském trhu v energetickém sektoru v závislosti na množství emisních povolenek. Hlavním záměrem této práce je zjistit, zda je vztah mezi zisky a množstvím emisních povolenek lineární. V této práci je mimo jiné představen i Evropský systém pro obchodování s emisemi. K analýze byly použity čtyři různé závislé proměnné. Výsledky ukazují, že množství odevzdaných emisních povolenek měřeno v množství vyprodukovaných emisí je vhodnou proměnnou pro vysvětlování výnosů. Pro vysvětlování skutečných zisků, například zisků po zdanění, je však vhodné použít množství emisních povolenek, které firma vlastní. Závěrem této bakalářské práce je, že mezi zisky firmy a množstvím emisních povolenek doopravdy existuje lineární vztah. Ač tato práce čelí určitým limitacím, pokládá základní kámen pro budoucí výzkum v této oblasti.

Klasifikace JEL	D22, Q54, L94
Klíčová slova	nákladové křivky, Evropský trh, emisní povolenky, Power & Heat sektor

Název práce	Analýza nákladových křivek firem v sektoru Power & Heat v závislosti na emisních povolenkách na Evropském trhu

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Acknowledgments

The author is grateful especially to RNDr. Michal Červinka, Ph.D. for his patience. The author is also grateful to Mgr. Ing. František Zapletal, Ph.D. for providing access to the Carbon Market Database.

Typeset in FSV LaTeX template with great thanks to prof. Zuzana Havrankova and prof. Tomas Havranek of Institute of Economic Studies, Faculty of Social Sciences, Charles University. In compliance with university guidelines, we have utilised tools such as Grammarly and Chat GPT version 3.5 to expand vocabulary and improve grammar and writing style, ensuring high-quality and well-structured academic work.

Bibliographic Record
Bittnar, Pavel: *Analysis of Cost Curves of Companies in Power & Heat Sector on the European Market Depending on the Carbon Allowances.* Bachelor's thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies, Prague. 2023, pages 54. Advisor: RNDr. Michal Červinka, Ph.D.

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Acronyms

EU ETS European Emissions Trading System

IFRS International Financial Reporting System

PAT Profit After Taxes

PBT Profit Before Taxes

EBIT Earnings Before Interest and Taxes

CA Current Assets

NCA Non-current Assets

TA Total Assets

CL Current Liabilities

NCL Non-current Liabilities

TL Total Liabilities

Bachelor's Thesis Proposal

Research Question and Motivation

The main research question of this thesis is whether cost curves of individual companies can be modeled as simple polynomial functions of key factors. In particular, we plan to study the relationship between the total amount of output produced and the costs of individual company including emissions as a cost.

In the context of recent years, questions about sustainability and future start to arise more frequently. One term that is frequently used in while debating about these questions is carbon dioxide. The overall trend is to gradually decrease the amount of carbon dioxide emitted to minimum. However, many sectors of market that influence life of almost all people in the world are dependent on emitting carbon dioxide.

One of the most important sectors is Power & Heat. In the upcoming years, mankind will probably not be able to go fully sustainable in this sector. Therefore, there is a need for regulation of carbon dioxide emitted. One of the regulations is EU ETS (European Union Emissions Trading System), that allows EU to control the volume of emission via carbon allowances. Since carbon allowances are tradeable, they constitute valuable assets for any company that is emitting carbon dioxide. Hence, it is interesting to study how does owning carbon allowances reflects into cost curves, and, what are the other significant parameters that influence cost curves.

The research is based on data set from Carbon Market Database. This data set contains information about 19 sectors in Europe, such as Cement & Lime, Power & Heat, Iron & Steel, etc. The data is collected since 2005 and includes 1014 records. There are 286 records regarding the Power & Heat sector, however, we plan to take into an account just a sample of companies companies, containing roughly 65 of them, which, however, makes up for more than 80% of allocated allowances in the sector considered.

Contribution
The contribution of the thesis is twofold. We plan to confirm that cost curves can be modeled as simple polynomial functions of the input factors, i.e. of the output produced, at best as a linear or quadratic function. For this purpose we plan to employ tools of linear regression Subsequently, the results of this thesis will directly influence the structure of much more advanced models for pricing of emission allowances and illuminate differences in effectiveness of emission allowances and carbon tax systems, which however goes beyond the scope of the thesis. In addition, there is not a lot of existing literature related to this topic, and therefore, my research should contribute to development of interest in this topic.

Methodology
We use data from Carbon Market Database, more specifically European Emission Trading System (EU ETS) database for Power & Heat sector. This database provides information about parameters such as number of installations and number of allocated allowances. To include more parameters in the analysis, I will use annual reports of each individual firm and extract financial statements of the company. This part must be done manually, and the data set will include information about approximately 65 companies.

Once the construction of a data set is complete, we will consider two types of linear regression models for each individual company. In the first one, we plan to uncover the relationship between production costs as a function of output produced along with other factors available in annual reports and the Carbon Market Database. The second model is focused on uncovering the form of a technology function which links the costs for emission allowances required and the output produced.

Introduction

(a) Why the topic is interesting

(b) Introduction to carbon allowances

(c) Introduction to the Power and Heat sector

(d) Structure of the thesis

Methodology

(a) Description of the data

(b) How the tests were performed

Results

(a) Rejecting / not rejecting the hypothesis

(b) My interpretation of the results

Conclusion

(a) What are the implications that can be used in practice

Literature

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Chapter 1

Introduction

Over the last few hundred years, humankind has been producing large amounts of emissions without any significant penalisation. With the worsening situation in the late 90s of the previous century, the issue of global warming became a broadly discussed topic. In 2005, the EU decided to tackle this problem by issuing carbon allowances that should help measure and reduce the emissions produced by individual sectors in the EU. Plenty of sectors influencing our daily lives must surrender carbon allowances to compensate for the emitted CO_2 each year. The EU controls the total CO_2 emitted annually by setting the overall number of allowances. This allows for the reduction of emissions over time. The EU will shrink the amount of allowance distributed each year until it reaches the desired zero-emissions policy.

Carbon allowances do not directly affect our everyday lives. People as individuals do not have to be concerned about these allowances. However, carbon allowances represent a cost for individual companies dependent on emitting CO_2 as a side effect of their production. Carbon allowances are an additional expense with unique characteristics. They can be classified as a cost of production and also might generate additional, unexpected profits at the same time.

The crucial characteristic of carbon allowances that allows for such a behaviour is that they can be traded. Once a company acquires a surplus of carbon allowances, the surplus can be sold, which generates additional profits. However, if the company is running a deficit of allowances, the costs associated with production will increase since each company must cover its emissions with carbon allowances. Each allowance covers one ton of CO_2 or its equivalents.

This thesis aims to examine the relationship between carbon allowances and profits of a company with a focus on the Power and Heat sector. The main hypothesis is that there is a linear relationship between the number of allowances a company has and its profits. Based on company-level data, we try to describe the relationships between various measures of profit and measures of carbon allowances.

Note that we have stated in the second paragraph of this section that carbon allowances do not affect our daily lives directly. Companies, especially in the Power and Heat sector, can shift their costs associated with covering the emissions to the consumer. Hence they do not face the costs of emissions and only benefit from the profits coming from the surplus of allowances.

In fact, this was an issue that the power and heat sector faced between 2005 and 2012. Since 2013, the system of allocating allowances in the power and heat sector has changed. The structural change in the distribution of allowances that should stop companies from profiting from freely allocated allowances makes the power and heat sector the most interesting for analysis. Other sectors still receive a certain number of allowances for free, whereas free allowances are distributed in the power and heat sector only under strict conditions.

The thesis is organized as follows, Chapter 2 introduces two important topics used throughout the thesis, the European Emissions Trading System and International Financial Reporting Standards since we do not consider understanding of these two topics to be common knowledge. In Chapter 3, we provide a deeper insight into the carbon allowances market in the Power and Heat sector context. Additionally, we discuss the background of our hypothesis and look for other variables that might improve our analysis. Chapter 4 presents information about our data. This chapter discusses the adjustments made to the data and their limitations. We also provide information about individual parts of the dataset. Based on the data structure, we make an assumption about the appropriate model in Chapter 5. In addition, Chapter 5 provides mathematical reasoning for the chosen model and its limitations. The final form of models is introduced in Chapter 6. After stating the models, we discuss issues such as collinearity and formally verify our assumption from Chapter 5. We also interpret our result in Chapter 6. In Chapter 7, we make suggestions for further research and Chapter 8 summarises our findings.

Chapter 2

Key Terms

This chapter aims to familiarise a reader with the key concepts used throughout this thesis.

2.1 European Emission Trading System

As the situation with greenhouse gases was getting worse in the late 90s of the previous century, United Nations (1997) came up with a solution, Kyoto Protocol. Under Kyoto Protocol, several countries, including the members of the European Union, have committed to reducing the amounts of carbon dioxide and its equivalents emitted. The target was to reduce overall emissions by at least 5% below 1990 levels in the commitment period 2008 to 2012, United Nations (1997), Article 3/1.

The Green Paper presented by European Commission (2001) gives the first idea of the European Emissions Trading System (EU ETS). To the question of what emission trading is, European Commission (2001) provides the following answer. Emissions trading is a scheme whereby companies are allocated allowances for their emissions of greenhouse gases according to the overall environmental ambitions of their government, which they can trade subsequently with each other, (European Commission 2001). This definition has its limits. The most obvious limitation of this definition is that it reflects emission trading only at the scale of countries.

However, Article 4 of the Kyoto Protocol provides an exception for the EU. Under Kyoto Protocol, the EU has committed to decreasing the overall emission by 8% below 1990 levels, and no further restrictions are explicitly imposed on individual member states. The respective emission level allocated to each of the Parties to the agreement shall be set out in that agreement, Kyoto Protocol, Article 4, where the agreement is the joint commitment to reducing emissions.

Since the decrease is joint among all European countries, the opportunity for the trading system of the emission allowances arised. In 2003 the EU ETS Directive was issued. This document includes the rules of EU ETS and defines the key terms such as allowance or emission.

Consequently, following the rules of the EU ETS Directive, EU ETS was established on the 1st of January 2005 as Europe's reaction to the Kyoto Protocol. Since 2005 there have been four phases of EU ETS.

The system of emission allowances provides an efficient way of controlling the number of emissions emitted by a given subject (company or an individual). Each subject that is involved in the market has assigned some number of allowances. The number of allowances corresponds to the maximal amount of carbon dioxide or its equivalents that can be emitted. This number of emissions emitted must be balanced with a corresponding number of allowances at the end of a year.

After the end of each year, businesses have a four-month period during which they must give in the allowances. Under the EU ETS, one emission allowance equals one ton of carbon dioxide or its equivalent. Generally, this system is referred to as a cap-and-trade system.

Phase I, between 2005 and 2007, could be described as a learning phase. Most allowances were initially allocated for free concerning the number of installations. During this phase, the optimal price for emissions was found, and the infrastructure required for efficient controlling was developed.

Phase II covers the commitment period of the Kyoto Protocol, the period from 2008 to 2012. Heavily influenced by Phase I, the EU aimed to decrease emissions by 8% below 1990 levels. Alberola *et al.* (2009), for example, provides supporting evidence that during Phase II, the audited figures for each installation were known, and installations that initially received a substantial surplus of allowances generally received much less allowances during the second phase.

Although there might have been a decrease in allocated allowances for some businesses, the allocation was mostly free. During Phase I and Phase II, allowances were allocated by governments.

However, Phase III (2013–2020) brought centralized distribution of allowances across the EU. The principle of 'free allocation as the norm and auctioning as an option' was replaced by 'auctioning as a default and free allocation as an exception' (Verde *et al.* 2018). Phase III changed the system. Additionally, the total number of allocated allowances across the EU, the cap, decreased linearly by a factor of 1.74% a year.

In 2021 EU ETS entered Phase IV, which is projected to end in 2030. The linear factor of the decrease of the cap has increased to 2.2% per year in this phase. This amounts to a tightening of the overall cap by some 560 million tons over the duration of Phase IV (Perino & Willner 2017).

The EU controls the cap and steadily decreases emissions by shrinking the cap. Since the EU's primary concern is to reduce emissions, the distribution of allowances among individual companies does not affect the overall target. Therefore, trading these permits between companies does not disrupt the plan. Moreover, it makes allowances valuable assets. As proposed in the Green Paper, the EU is sharing the 'burden among its members'. The term burden sharing allows for trading inside the EU.

In general, there are three cases that can occur. Certain businesses can use all allocated allowances or have a surplus or deficit. The first situation is almost impossible since companies produce emissions on a large scale. Therefore estimating the exact quantity of emissions is unlikely.

Any company can generate more emissions than has allowances and thus run a deficit of allowances, given that it provides additional allowances in the upcoming four months after the end of the year. Companies with a surplus of allowances can sell their allowances to those that run a deficit; thereby, the cost of an allowance is an opportunity cost for a company.

2.2 International Financial Reporting Standards

During the process of data collection, we need to rely on the assumption of comparability of the data. Annual reports are sometimes published with the intention of attracting investors and shareholders. To do so, companies might provide data measured in the best-looking units to make their results appear more attractive. Therefore we cannot assume that all the data is comparable. To tackle the problem of a possible violation of the comparability of variables, we use consolidated financial statements reported in accordance with IFRS.

International Financial Reporting Standards (IFRS) refers to widely accepted system accounting issued by International Accounting Standards Board (IASB). With ongoing globalisation and the rise of larger markets, there is a need for efficient comparison between the performances of individual companies. Using different accounting standards does not enable investors to make apple-to-apple comparisons of companies since they need to make several adjusting accounting entries, (Hines 2007).

Harmonising accounting methods and providing more consistent reporting is not a concern of just the last few decades. In 1973 in London, the International Accounting Standards Committee (IASC) was founded with the intention of setting a widely accepted reporting standard. During the year 2001, IASC was restructured and replaced with IASB.

However, IFRS is not the only set of accounting rules, Ortega (2017) reviews the history of harmonisation of accounting standards and provides an interesting analysis of the IFRS – US GAAP convergence. The U.S. almost adopted IFRS in the period 2008–2010, however, after the year 2012, the enthusiasm for the adoption in the U.S. started to disappear, (Ortega 2017). Although the U.S. did not adopt the united accounting system yet, investors in the U.S. market commonly encounter it. The volume of trade between the EU and the U.S. is undeniable, and the difference in reporting systems generates only inefficiency.

Tweedie & Seidenstein (2005) summarises that the EU adopted a regulation that requires publicly traded companies to apply IFRS since the beginning of 2005. However, this does not imply that IFRS was not used in the EU before 2005.

Ahmed *et al.* (2013) conducted research on the mandatory implementation of IFRS. The study suggests that even when companies are forced to implement this set of accounting rules, the change increases the quality of accounting. Moreover, Horton *et al.* (2012) provide supporting evidence on the topic of mandatory implementation. IFRS adoption is likely to generate both information and comparability effects and improve the quality of information, (Horton *et al.* 2012).

United reporting standard poses a relevant tool for comparing companies. Conveniently enough, the mandatory implementation of IFRS started in the same year as the EU ETS. This ensures that the data obtained from annual reports refer to the same information across all examined companies if taken from the consolidated financial statements part of the report.

Chapter 3

Literature Review

This section provides an overview of the relevant literature regarding the relationship between profits and EU ETS in the Power and Heat sector. It is possible to differentiate between three directions in reviewing related literature.

3.1 EU ETS: Power and Heat Sector

In Chapter 2, we have introduced the EU ETS, its history and individual phases. Unlike other sectors, however, the Power and Heat sector faces slightly different settings. Since Phase III, the distribution of allowances to the Power and heat Sector forces individual companies to evaluate the costs of carbon allowances more carefully.

After the end of Phase II in 2013, Laing *et al.* (2013) published a paper that assessed the impacts of the EU ETS. Besides other topics, Laing *et al.* (2013) discusses the effects of EU ETS on product prices and profits. Two essential terms are introduced, the CO_2 price cost pass-through and windfall profits. Cost pass-through refers to the process during which a producer reflects its additional costs via price changes. Regarding carbon allowances, cost pass-through refers to adjusting prices based on the additional costs of carbon allowances. The windfall profits can be described as unexpected profits.

Laing *et al.* (2013) state that there is a general consensus in studies that windfall profits are accrued by power companies as a significant part of the costs of CO_2 emission allowances is passed through to product prices, resulting in higher electricity prices for consumers. Assuming that 100% of the cost of allowances is passed to the consumer, a company generates windfall profits equal to the price of carbon allowance times the amount of output sold to the consumers. Moreover, large companies that have acquired a surplus of allowances gather even larger windfall profits, whereas consumers must share the burden of paying the price of carbon. Verde *et al.* (2018) provides supporting evidence for Laing *et al.* (2013) conclusions. Since Phase III, electricity generation has ceased to receive free allowances (with an exception for some countries) upon clear evidence of high-cost pass-through and related windfall profits (Verde *et al.* 2018).

To tackle this problem, Phase III is shifting away from free allowances to the cap system. Since 2013, the power sector has had to acquire most of its allowances from auctions. Free allowances are distributed only as a motivation to improve the efficiency of power generators.

The efficiency of the system of free allowances can be observed in the case of Poland. Even though Poland is not a classic low-income country in the EU, Poland's dependency on fossil fuel power generators is undeniable.

In all low-income countries, the distribution of free allowances is conditional on the investment towards higher carbon efficiency. In general, this means that companies receive free allowances if they either invest in the new carbon-independent generator or modernise the existing fossil fuel generator. Since a majority of power generators using fossil fuels are owned by the government, according to Brauers & Oei (2020), the current socio-political environment in Poland still prefers coal as a source of energy. Moreover, based on forecasting methods, Manowska *et al.* (2017) suggest that coal will remain the main component of the Polish energy mix in the coming years.

The option to modernise already existing power generators weakens the goal of reducing the dependency on fossil fuels. Müller & Teixidó (2021) observed the effect of free allocation on Poland's energy mix diversity. Using aggregate data and applying the synthetic control approach, they conclude that the free allocation did not have the intended effect of reducing fossil fuel dependence and mainly acted as a subsidy to the power sector in coal-dependent countries. The suggestion is that it is less costly to modernise already existing power generators than to invest in a fossil-independent power generator.

3.2 Theoretical Background of the Hypothesis

Most of the studies conducted on the topic of the relationship between profits and carbon allowances present the perspective of the price of carbon allowances. One such study is conducted by Guo *et al.* (2020). Based on a completely unique firm-based dataset in Phases I and II, Guo *et al.* (2020) suggests that firms of higher emission abatements can acquire greater profitability for carbon allowance trading, which might result in the situation where participants with bigger trading scale intentionally or unintentionally manipulate the market.

In the period 2013–2021, we can discuss the risk aversion of companies. Since companies do not receive almost any allowances for free, they face a decision whether to buy them via auctioning or rely on the secondary market. In this decision, the risk aversion must be involved. Zapletal *et al.* (2019) conducted a case study on a single company in the steel production sector, observing the influence of emission trading on the risk aversion of producers. Based on the initial price of allowance and the problem has been solved at different significance levels. Zapletal *et al.* (2019) concludes that the production and the probability of default depend on risk aversion. Additionally, the case study presented suggests that the emission prices do influence the economic results of a company.

Zapletal *et al.* (2022) provide a more broad view than the previous case study Zapletal *et al.* (2019), which was conducted only based on one company. Unlike the previously discussed case study, Zapletal *et al.* (2022), not only discusses the risk aversion but also provides an optimal combination of futures and spot prices of carbon allowances. In terms of the company's average profit, the carbon allowance futures used together with banking are the best option for the company's emissions management, (Zapletal *et al.* 2022).

Although these findings are not Power and Heat sector specific, we can use them in our decision-making process. Companies in the Power and Heat sector in Phases III and IV face this risk aversion problem more than companies in any other sector.

Based on the studies presented in this chapter, we decided to focus on explaining the profit with measures of allocated allowances. Most of the studies capture only the perspective of carbon allowance prices, therefore, we decided to use the actual numbers of allowances and related metrics to observe their effects on profits.

3.3 Identifying Other Parameters

In the search for the relationship between profits and the number of allowances, we focused on literature to find other valuable variables. The primary focus are variables that can be retrieved from balance sheets directly or calculated from these variables.

Among others, Liargovas & Skandalis (2010) observe which variables might affect a firm's profitability. This study is based on panel regression with a sample of 102 firms listed on the Athens Stock Exchange observed from 1997 to 2004. The measure of profitability was evaluated using three measures, return on sales (ROS), return on assets (ROA) and return on equity (ROE).

It is proposed that a firm's size, measured in the number of employees, affects its profitability due to economies of scale and the power to compete. The study suggests that there is a positive relationship between profitability and the size of a firm.

Dogan (2013) provides a study with similar settings, which supports the positive relationship between a firm's size and profitability. Similarly to Liargovas & Skandalis (2010), ROA is used as a dependent variable, and the number of employees as an independent variable. Moreover, total assets and total sales are used as another measure of size, suggesting a positive relationship between the size and profits of a company.

Although substantial evidence suggests that a firm's size affects its profitability, presented, studies discussed various sectors. Fareed *et al.* (2016) use ROA as a proxy for profitability in their study, which ensures comparability with previous studies. Similarly to this thesis, annual reports are used as a source for the dataset, which includes 16 companies in the Power sector observed from 2001 to 2012. Based on panel data regression, Fareed *et al.* (2016) conclude that the firm's size measured in the total value of sales has a positive and significant relationship with the firm's profitability.

Findings of Liargovas & Skandalis (2010) and Dogan (2013) provide a piece of evidence suggesting that, in general, the profit of a company is influenced by the size of a company. Fareed *et al.* (2016) indicate that these findings are also valid in the context of Power and Heat sector.

Chapter 4

Data

4.1 Dataset Introduction

The data used for modeling purposes can be divided into two categories. The first part of the data comes from Carbon Market Data. Established in 2006, Carbon Market Data provides an accurate information about individual emissiong trading systems used around the world. The dataset we have used captures relevant information regarding the EU ETS since the beginning of Phase I in 2005 in 27 EU countries plus the UK. It covers a large variety of sectors that are dependent on emitting greenhouse gases. In the dataset, there are listed individual companies that are observed over 17 years. For each company, there are variables such as the number of allocated allowances, number of installations, and verified emissions.

The second part of the data comes from annual reports of individual companies in the Power and Heat sector. We have constructed this part of the dataset using financial information captured in balance sheets. The selection of respective companies is based on the data about allocated allowances from the first part.

Initially, only 65 companies that make up 80% of the market concerning the number of installations were considered significant. Once the companies were identified, data about financial statements were extracted from annual reports. Measures of company's profit are the most crucial parameters that must be obtained since they are used as the dependent variable in the model. Other parameters, such as the structure of assets and liabilities, were obtained since they might be significant parameters involved in explaining the profit.

However, the crucial assumption about the data is that it only concerns the European Market. Many companies in the Power and Heat have installations outside of the EU. Since the initial dataset regarding allocated allowance covers only European Market, including power plants from outside the EU is unreasonable.

Therefore before the extraction of the data from annual reports, a closer examination of the structure of assets of each company is required. One such example of a company reaching outside the EU is the energetic Spanish company Endesa. In 2008 this company was operating both in the European Market and Latin America. At the time, the share of the revenue from Latin America reached almost 40%. This fact indicates that the effect of markets outside the EU is significant and cannot be overlooked.

Additionally, the distribution of power plants must be observed each year since the assumption that a company keeps its field of action is wrong. Endesa provides an example of such behaviour. Although it was reporting revenue coming from Latin America in 2008, since 2014, no revenue has been reported from this market.

Gathering the data for the second part of the dataset requires a deeper understanding of each company. Even though the data extraction might seem straightforward, some errors must be taken into account, and the data must be adjusted accordingly.

4.2 Adjustments to the Data

In this section, we list all the adjustments done to the raw data. Moreover, we discuss possible limitations and problems that might arise from the transformation.

Companies Outside the EU

Companies operating outside the EU can be classified as a subpopulation of the initial population of companies in the Power and Heat sector. In the analysis, this subpopulation cannot be excluded from the dataset since it would violate the assumption of randomness. Therefore we have to adjust the numbers stated in the consolidated balance sheets. At first, we need to estimate each company's share of individual markets for each year. Hence, we propose two feasible approaches to estimating the share of the European market, the share of power plants distribution and the share of revenues.

On the one hand, the distribution of non-current assets might be used as a proxy for the distribution of power plants. However, there is a limitation worth mentioning. Even though companies must provide specific characteristics in accordance with IFRS, the share of non-current assets across the individual markets is not one of them. Annual reports might lack consistency of variables that are not required to be stated in accordance with IFRS. Consequently, looking for a proxy for non-current assets or using another characteristic would generate inconsistency across estimates.

On the other hand, the perspective of the dependent variable can be used. Profit after taxes is misleading since the tax rate cannot be assumed constant across all markets. Profit before taxes also suffers from inconsistency since plenty of deductions are made before reaching its value. Therefore, revenue should be used since it contains the most information.

Nevertheless, one possible limitation of this approach is that revenue needs to reflect individual operations. Revenue defined as sales might include sales of goods and services unrelated to the Power and Heat sector, which is of interest in this thesis. Without prior knowledge about individual overseas operations of a particular company, revenues might also generate biased estimates of market shares in the context of the aim of this thesis.

The first approach uses non-current assets to estimate the market share, whereas the second uses the dependent variable. In our study, it is more feasible to use the second approach since it is more straightforward and faces less severe limitations. Unlike the inconsistency generated by missing information about non-current assets, the bias of the second approach can be prevented by closer examination of the operations of individual companies.

To conclude, the dataset includes 8 companies operating outside the EU. A separate sheet with information about these companies is included in the dataset. This sheet includes the company's revenues from operations associated with the Power and Heat sector are captured for all markets the company operates at. Then the European market share is calculated, and the data obtained from balance sheets is adjusted accordingly.

Excluding Companies

Initially, we identified 65 companies that made up 80% of the market. While extracting the data from annual reports, we had to exclude certain companies from the dataset. There are two reasons for the exclusion, the absence of annual reports and subsidiary companies.

Companies can be divided into three categories based on the number of installations. Small companies are defined as companies with less than 20 installations, medium-sized companies with a number of installations ranging from 20 to 50, and large companies with more than 50 installations. To provide context, the largest energetic company in the Czech Republic, ČEZ, has 25 installations.

Firstly, we had to exclude 17 companies that did not publish their annual reports online. The dataset was supposed to include all companies with at least 10 installations. 9 small companies without traceable annual reports were excluded immediately. In other 8 cases, we tried to contact the company with the request for annual reports. Regardless of size, companies did not respond to the request, hence we also had to exclude them from the dataset.

The distribution of missing reports can be interpreted as random since we did not observe any pattern. Even though it might seem rational to assume that the number of missing reports increases as the company's size decreases, there is no evidence of such behaviour.

Secondly, during the process of extracting the data, we discovered that there are some inside relationships among certain companies. Moreover, a pattern of absence of annual reports of subsidiary companies occurred. One might suggest using the number of installations to estimate the data from missing annual reports. A parent company's annual report includes a group's balance sheet, which must contain a combination of information about subsidiary companies and the parent company. However, this scaling requires some assumptions about the size of an installation. As mentioned before, the installation size is not limited in any way. Estimates might be biased without knowledge about the company's actual share in the group.

Moreover, Wooldridge (2013) suggests that companies that went out of business or merged with another company might generate a non-random sample in subsequent periods in unbalanced panel datasets. Over the span of 17 years, there were many acquisitions and mergers among individual companies. In 2014, for example, Dalkia became a wholly-owned subsidiary of EDF.

A closer examination of subsidiary companies reveals that the exclusion does not discriminate against smaller companies. The sample of subsidiary companies includes companies from all three categories without a sign of any pattern.

Additionally, excluding 11 subsidiary companies solves the problem of independence. In this particular case, there is a possible proxy for independence, the perfect market. Under the perfect market assumption, companies should be allowed to expand across the EU to maximise their profits. However, the inside structure of a group might not allow its subsidiary companies to compete in the same countries. Since a group maximises its profits by maximising the profits of all its subsidiary companies, only the group faces the perfect market. Only a group can expand across the EU through its subsidiary companies.

To conclude, 28 companies out of the initial sample of 65 companies had to be excluded from the dataset. The absence of annual reports does not affect the randomness of the sample. Companies do not provide annual reports regardless of their size. The subsidiary companies not only causes no harm to the randomness of the sample but also strengthens the assumption of independence.

Exchange Rates

Further adjustment to the dataset is converting currencies. Most companies provide balance sheets in Euros, making Euro the most reasonable currency used as a base. Since some companies are operating in countries that have not adopted Euro as their currency, there is a need to convert these currencies to Euro.

All balance sheets provided in annual reports are given to the date 31^{st} of December each year. For this reason, we decided that instead of using the average exchange rate for the period to use the exchange rate from the date 31^{st} of December. The data was obtained from the OFX database containing information about the daily exchange rates of all required currencies.

4.3 Data Description

After all adjustments, our final dataset consists of information about 37 unique companies in the Power and Heat sector. All the financial data were collected from annual reports usually published on individual companies' websites. Once acquired, annual reports provide easily accessible financial data for a given period and the period before. This structure allows for more accurate numbers. The information about the period before is usually adjusted to its actual value. Therefore it is more reasonable to gather the data about period t from the annual report regarding the period $t + 1$. Lets say that we are extracting financial information from the 2012 annual report of a certain company. This report also includes financial statements for the year 2011, which are adjusted to their actual value. Therefore the information about the year 2011 stored in the annual report for year 2012 is more accurate than information provided in annual report for the year 2011.

We suggest using a rule of the last two digits. If the change in value from period t to period $t+1$ is captured only in the last two digits, the numbers do not need to be adjusted. Larger companies generate profits of billions and report only the billions in their annual report. This makes the values theoretically incomplete; hence, we allow this rule for more straightforward data extraction.

Due to the limited availability of annual reports, only 21 companies capture the entire duration of EU ETS, 2005–2021. For the other 16 companies, the year of the first observation varies. All companies were observed consistently over time, meaning that there are no missing values for the key variables from the first observation to the observation in 2021.

Carbon Market Dataset

Initially, the Carbon Market dataset includes a large variety of information about variables regarding allowances and yearly changes. Unfortunately, most of the variables are not time-consistent. We had to exclude all variables that were not observed during the entire EU ETS. Additionally, we have excluded all variables that captured yearly changes of our chosen variables. If necessary, these values can be recalculated.

The interpretation of this dataset requires knowledge developed in previous chapters. This dataset includes four variables, Allocated Allowances, Verified Emissions, the Excess Allowances and the Emissions-to-cap Ratio as a %. The Excess Allowances in the dataset is calculated as

$$Excess\ Allowances = Verified\ Emissions - Allocated\ Allowances.$$

This formula implies that the Excess Allowances is negative when a company has a surplus of allowances for a given period.

However, slightly more interesting information is hidden in the variable Verified Emissions. This variable captures the total emissions a company has to cover in a given period. Without loss of generality, we say that one ton of CO_2 emissions is compensated with one allowance.

The most tricky to understand is the variable Allocated Allowances. This number refers to (a) the number of allowances that a company received for free in Phases I and II, 2005–2012 or (b) the number of allowances that a company bought on the primary market via auctioning in Phases III and IV. To provide a more intuitive understanding, Tables 4.1 and 4.2 capture basic summary statistics for all companies included in the dataset in periods 2005–2012 and 2013–2021.

Period	Min.	Q1	Median	Mean	Q3	Max.
2005–2012	0.0	1,173.9	10,309.3	20,066.8	27,809.2	138,655.2
2013–2021	0.0	42.3	183.2	1,367.1	881.1	40,590.1

Table 4.1: Allocated Allowances – summary statistics in thousands of Euros

Period	Min.	Q1	Median	Mean	Q3	Max.
2005–2012	0.0	1,257.2	12,005.5	22,978.5	31,550.5	145,236.0
2013–2021	0.1	625.9	5,714.9	15,879.8	21,613.3	134,728.4

Table 4.2: Verified Emissions – summary statistics in thousands of Euros

Both Tables 4.1 and 4.2 provide an interesting insight into the Power and Heat sector. Firstly, Table 4.2 provides evidence that verified emissions have a decreasing trend. The difference between the first and second period is significant for almost all measures. This makes intuitive sense since the overall aim of the EU ETS is to decrease emission levels.

Secondly, Table 4.1 captures the effect of the transition from Phase II to Phase III. In Phase II, the Power and Heat sector companies received allowances for free, whereas Phase III introduced the auctioning system. Free allowances are distributed only to low-income countries of the EU. The distribution of free allowances is a motivation or reward for reducing the output generated by, for example, power generators that burn coal. The sharp decrease is visible even on the maximum values of allocated allowances.

For the purpose of analysis, we return to the variable Excess Allowances and calculate basic summary statistics.

Period	Min.	Q1	Median	Mean	Q3	Max.
2005–2012	-8,278.5	-177.4	368.7	2,911.6	4,227.7	58,522.5
2013–2021	-170.1	327.0	5,380.0	14,512.7	19,060.7	132,885.0

Table 4.3: Excess Allowances – summary statistics in thousands of Euros

When interpreting Table 4.3, we must remember that negative values mean a surplus of allocated allowances and vice versa. On average, during Phases I and II, companies had to cover ex-post approximately five times less emissions than in Phases III and IV. The most interesting effect can be observed on the minimum value and the first quartile. The maximum surplus decreased almost by 98%. The surplus of allowances became a relatively rare situation.

Tables 4.1, 4.2, and 4.3 highlight the inefficiency of the first two phases of the EU ETS. Moreover, numbers stated in Tables 4.1 and 4.3 provide evidence that once companies do not receive allowances for free, they are less likely to acquire them via auctioning. In the second period, between 2013 and 2021, we can use the Excess Allowances to measure allowances obtained from the secondary market. Since Excess Allowances is higher for almost all statistics provided, we conclude that the number of allowances acquired from the second market exceeds the number of allowances acquired via auctioning, the primary market. This evidence is in line with the claim that allowances were cheaper on the secondary market than on the primary market, the auctioning, in 2013–2016, (Carratù *et al.* 2020).

The conclusions presented in this section will help interpret the results of our models. However, without prior knowledge of the structure of the EU ETS, it might be suggested that the dataset contains incomplete information. The case of the company Electricity Supply Board (ESB) provides a great demonstration of possible misinterpretation. In the dataset, ESB has the number of allocated allowances ranging from 8,541,714 to 9,795,048 between 2005 and 2012. Since 2013, there have been reported values of 0. Without the knowledge of the change in the distribution structure, one might suggest that the data is missing and missing values were replaced with 0.

Moreover, the amount of ESB's verified emissions decreases over time, however, it is not equal to zero for any year recorded. This suggests that after the change in 2013, ESB stopped receiving free allowances and does not obtain them from the primary market.

Chapter 5

Methodology

5.1 Model

In this section, we give you a reason for the chosen model. Prior to the models proposed in Chapter 6, we have also tried models with different relationships between the profits and allowances-related variables. We tested not only the linear relationship but also quadratic, cubic, polynomial and cubic root relationships. Quadratic, cubic and polynomial relationships did not have significant results. Even though the cubic root relationship did prove to be significant for some of the proposed variables, the overall performance of the models was significantly lower than in the case of a linear relationship. For this reason, we use the linear relationships between profits and allowances-related variables.

Choosing the Right Model

In the dataset, there are only 21 companies that were observed over the period 2005–2021. It is less than a third of the number of initially proposed companies. We assume that time series with 17 observations would suffer from multiple limitations and, therefore, would not be effective to study.

As an alternative, we could consider the Tobit model. In order to use the Tobit model, we have to focus only on profits after and before taxes and periods with losses (negative profits) would receive zeros. Assigning zeroes to losses does not use the full potential of the dataset since we have the actual information about negative values.

After considering various possibilities, we conclude that the most appropriate would be to use panel data. Since all companies were fully observed at least in the period 2013–2021, there is an option to use a balanced panel. Moreover, this period covers the Phase III of EU ETS. Phase III brought a new system of receiving carbon allowances for the Power and Heat sector. This makes the model more consistent since it does not experience any changes in the market structure.

Otherwise, we can choose an unbalanced panel to use the full potential of the dataset. This, however, requires a broader ex-post discussion of the interpretation.

5.2 Mathematical Explanation

In this section, we would like to provide a mathematical explanation for the fixed and random effects models. We begin with the fixed effects model. Consider that the following unobserved effects models describe some population,

$$y_{it} = \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + a_i + u_{it},\ t = 1, 2, \ldots, T,\ i = 1, 2, \ldots, I. \quad (5.1)$$

For each cross-sectional unit $i = 1, 2, \ldots, I$, we take an average over all the time periods $t = 1,\ 2,\ \ldots,\ T$, obtaining the equation

$$\bar{y}_i = \beta_1 \bar{x}_{i1} + \beta_2 \bar{x}_{i2} + \cdots + \beta_k \bar{x}_{ik} + a_i + \bar{u}_i. \quad (5.2)$$

Note that a_i is fixed over all the periods $t = 1,\ 2,\ \ldots,\ T$ for all $i = 1, 2, \ldots, I$; therefore, taking an average does not affect it. To calculate averages of individual x_{ik}'s, we used the formula

$$\bar{x}_{ij} = \frac{1}{T} \sum_{t=1}^{T} x_{itj},$$

where $j = 1,\ 2,\ \ldots,\ k$. We also used this averaging formula to calculate the $\bar{y}_i$. Subtracting Equation 5.2 from Equation 5.1 we get the equation

$$y_{it} - \bar{y}_i = \beta_1 \left(x_{it1} - \bar{x}_{i1}\right) + \cdots + \beta_k \left(x_{itk} - \bar{x}_{ik}\right) + u_{it} - \bar{u}_i,\ t = 1, 2, \ldots, T,\ i = 1, 2, \ldots, I.$$

Lastly, we use a substitution $\ddot{y} = y_{it} - \bar{y}_i$, where $\ddot{y}_{it}$ is time-demeaned data on y. Similar substitutions and explanations are used for $\ddot{x}_{it}$ and $\ddot{u}_{it}$. This results in the equation

$$\ddot{y}_{it} = \beta_1 \ddot{x}_{it1} + \beta_2 \ddot{x}_{it2} + \cdots + \beta_k \ddot{x}_{itk} + \ddot{u}_{it},\ t = 1, 2, \ldots, T,\ i = 1, 2, \ldots, I. \quad (5.3)$$

Due to the time-demeaning in Equation 5.3, we eliminated the fixed effect a_i. The Equation 5.3 is estimated with a pooled OLS estimator. On the other hand, there is the Random Effects Model. The population equation is the same as Equation 5.1, we only add the intercept β_0,

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + a_i + u_{it},\ t = 1, 2, \ldots, T,\ i = 1, 2, \ldots, I.$$

The random effect assumes that the fixed variable a_i is uncorrelated with all independent variables. Therefore, a_i is included in the Random Effects Model's error term u_{it}. The $\nu_{it} = a_i + u_{it}$ is referred to as the composite error term, and we can rewrite the Equation 5.1 as

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + \nu_{it},\ t = 1, 2, \ldots, T,\ i = 1, 2, \ldots, I.$$

Since a_i is included in the ν_{it} regardless of the time period, ν_{it} are serially correlated across time. To solve the problem of autoregressive serial correlation, following GLS transformation is used,

$$\theta = 1 - \left[\sigma_u^2 / \left(\sigma_u^2 + T\sigma_a^2\right)\right]^{1/2},$$

which is between 0 and 1, $\sigma_a^2 = \mathrm{Var}(a_i)$ and $\sigma_u^2 = \mathrm{Var}(u_{it})$. Hence, the transformed equation is

$$y_{it} - \theta\bar{y}_{it} = \beta_0 (1 - \theta) + \beta_1 (x_{it1} - \theta\bar{x}_{i1}) + \cdots + \beta_k (x_{itk} - \bar{x}_{ik}) + (\nu_{it} - \theta\bar{\nu}_i),$$

for all $t = 1, 2, \ldots, T$ and $i = 1, 2, \ldots, I$. The overbar means the time average. Unlike the fixed effects transformation, random effects transformation subtracts a fraction of that time average, where the fraction depends on the σ_u^2 and σ_i^2 and the number of periods T. The methodology presented in this section was done in accordance with Wooldridge (2013).

5.3 Fixed or Random Effect Model

To help us decide whether to use the Fixed or the Random Effects model, Wooldridge (2013) suggests that the Fixed Effects model allows for arbitrary correlation between the independent variables and the unobserved effect variable a_i, while the Random Effects does not.

The dataset regarding EU ETS contains the number of installations for each company. This variable is time-independent, meaning it is not observed for each period. According to Directive 2003/87/EC of the European Parliament and of the Council, installation is defined as a stationary technical unit which could affect emissions and pollution. In the case of the Power and Heat sector, this mostly means power plants and equipment.

If assumed to be fixed, the number of installations undoubtedly correlates with possible explanatory variables such as Allocated Allowances or Verified Emissions. Allowances are bought according to some estimate about the expected production scale, and the amounts of emitted emissions also depend on the production scale. Moreover, the number of installations might also affect the dependent variable. Therefore we have to decide whether we will treat the number of installations as fixed. To do so, we propose two approaches based on the data included in the part of the dataset obtained from annual reports.

Plants and equipment are included in the balance sheets of individual companies inside the variable non-current assets. Without loss of generality, it can be assumed that a power plant is equivalent to installation according to the official definition. Additionally, plants and equipment usually make up the largest share of non-current assets. Therefore, the changes in the number of installations should be reflected in yearly changes in the values of non-current assets.

An alternative approach that can be useful for assessing the number of installations is to observe non-current liabilities. Assuming that creating a new plant, a new installation, is costly, there can be expected to be a sudden increase in non-current liabilities, which might reflect a loan required for the expansion.

However, both non-current assets and non-current liabilities are expected not to be constant over time. Therefore, the natural growth rate must be considered before making any conclusions.

To assess non-current assets, we used data for the period 2013–2021 and calculated the annual growth of non-current assets for each company as,

$$\frac{NCA_{it+1} - NCA_{it}}{NCA_{it}},$$

where $t = 1, \ldots, 9$, correspond to years 2013–2021 respectively. With these calculations, we have eight annual growth rates for each company i. Now we calculate the variable average annual growth rate for each company i. Summary statistics for variable average annual growth rate of NCA is presented in

Table 5.1.

Min	Q1	Median	Mean	Q3	Max.
-0.079	0.010	0.018	0.035	0.050	0.357

Table 5.1: Average Growth of Non-current Assets – summary statistics

Similarly, for non-current liabilities, we used the same equation to calculate yearly changes. Table 5.2 provides summary statistics for the variable average growth rate of non-current liabilities.

Min	Q1	Median	Mean	Q3	Max.
-0.134	0.004	0.041	0.066	0.080	0.822

Table 5.2: Average Growth of Non-current Liabilities – summary statistics

To conclude, the interquartile range (IQR) is only 4% for non-current assets implying relatively steady natural growth. The distribution is skewed to the right due to large outliers. This makes the median more relevant than the mean value for assessing the natural growth rate.

In the case of non-current liabilities, the IQR is 7%. Moreover, the median and the mean are larger than non-current assets. Non-current liabilities are composed of more components compared to non-current assets. This makes non-current liabilities more sensitive to changes in components. Therefore, we allow the natural growth rate of non-current liabilities to have a broader range. The distribution is skewed to the right again due to the large positive outliers.

On its own, non-current assets and non-current liabilities do not provide a clear conclusion. However, combining these two approaches helps to identify potential candidates for whom the assumption of a fixed number of installations does not hold. These are points where the increase in both observed variables was exceptionally high, suggesting violating the assumption. The conclusion requires a closer examination.

After the examination, we did not find a piece of evidence for such a conclusion that the number of installations changes over time. Some companies changed both non-current assets and liabilities significantly over one year. However, based on the percentage values, we decided that these companies are outliers and that most companies experience only natural growth.

Based on this evidence, we assume that the number of installations is fixed and included inside the a_i variable. This makes, according to Wooldridge (2013) fixed effect model more convenient than using the random effects model. Additionally, we will verify this assumption formally in Section 6.5 with the Hausman Test.

Limitations of Fixed Effect Model

In section 4.2, we introduced categories depending on the company's size. Using a dummy variable to capture the effect of larger companies might solve possible inefficiency caused by outliers. Because this categorisation was based on the number of installations, which is considered to be fixed, this characteristic is also fixed over time. Therefore it disappears in the model and we cannot use this characteristics to eliminate possible outliers.

Chapter 6

Results

In this Chapter, analyse of the used models and discuss issues and implications related to the model. The Chapter is structured as follows, firstly, we introduce the dependent and independent variables used in the model in Sections 6.1, 6.2 and 6.3. Next, we discuss the multicollinearity and test its presence in Section 6.4. In Section 6.5 we present our models, perform Hausman Test and discuss the results of our analysis. We begin the discussion with allowances-related variables, and then proceed to the discussion of other independent variables. We end the Section 6.5 with a brief summary our findings. Section 6.6 discusses the topic of outliers. Table 6.1 provides an overview of the meaning of individual variables used throughout this Chapter.

Variable	Description
PAT	Profit After Taxes
PBT	Profit Before Taxes
$EBIT$	Earnings Before Interest and Taxes
Rev	Revenue
$Verif$	Verified Emission
$ExAl$	Excess Allowances
TA	Total Assets
$CurRatio$	Current Ratio
TD	Dummy variable capturing changes in market
$EqRatio$	Equity Ratio

Table 6.1: List of used variables

6.1 Measures of Dependent Variable

We have decided to use four measures of profit, all of which refer to the company's profit, given some additional assumptions. In general, we can create a sequence of the four measures of profit as follows, Rev, $EBIT$, PBT and PAT. Each step is this sequence represents a deduction of some additional expenses. The step from Rev to $EBIT$ represents mostly the costs of production, the step from $EBIT$ to PBT represents deduction of interest and lastly the step from PBT to PAT represents the income tax.

	PAT	PBT	$EBIT$	Rev
PAT	1.00	0.83	0.65	0.29
PBT		1.00	0.83	0.45
$EBIT$			1.00	0.66
Rev				1.00

Table 6.2: Dependent variables – correlation matrix

Table 6.2 provides a correlation matrix of our dependent variables. There is a strong correlation between PAT and PBT. One might suggest that these two variables should be correlated perfectly. The variable generated by a linear transformation of another variable creates two perfectly correlated variables. However, the dataset contains companies across the EU, and the income tax differs across all European countries. Therefore the correlation should converge to 1 as the income tax for each country converges to some constant.

The same intuition can be applied to the correlation between $PBT - EBIT$. From the definition of $EBIT$, the only difference between these two variables is the interest. The same reasoning about different interests in different countries causes a strong correlation between PBT and $EBIT$. The largest deduction step is between the Rev and $EBIT$, corresponding to the weakest pairwise correlation of two consecutive variables. This is due to including costs of production to the value of Rev.

Moreover, we can observe that the pairwise correlation decreases with the increasing pairwise distance of variables in the proposed sequence, $Rev - EBIT - PBT - PAT$. The correlation between Rev and PAT is the weakest due to three deduction steps.

6.2 Measures of Allowances

In our analysis, we would like to explain the relationship between profits and the number of allowances. In the section Section 4.3, we have discussed the meaning of individual variables from the Carbon Market Database. Based on prior knowledge, we conclude that the variable Allocated Allowances does not capture the number of allowances a company must surrender at the end of each period.

We suggest using the variable Verified Emissions to measure the total amount of allowances the company has to surrender. The idea is that companies have to cover the volume of emitted emissions for the period. Hence, without loss of generality, we use the number of verified emissions as an equivalent to the number of surrendered allowances.

Moreover, the variable Excess Allowances covers the company's beliefs about its production, especially after 2013. During Phases I and II, companies usually traded, stored for the next year, or bought allowances. Since Phase III, this variable provides more interesting information. Since 2013 we can view the Excess Allowances as the number of allowances a company has to buy from the secondary market. Inevitably, this number must represent the beliefs of a company about its production and must reflect the profitability of a company for the given year.

To conclude, we use both Verified Emissions and Excess Allowances as a measure of the behaviour of a company in the context of emission allowances. Variable Verified Emissions measures to the total number of surrendered allowances. The variable Excess Allowances captures firms' beliefs about emission trading and, therefore, the assumptions about the profitability of emission trading.

6.3 Additional Variables

We also include other independent variables in models to improve their quality. Based on the literature, we included the natural logarithm of Total Assets in the model as a proxy for the company's size. Moreover, we also added the Current Ratio and Equity Ratio as measures of the company's performance.

The Current Ratio was calculated using the data from the dataset as

$$CurRatio = \frac{CA}{CL},$$

where CA refers to the Current Assets and CL refers to the Current Liabilities. Similarly, we have calculated the Equity Ratio as

$$EqRatio = \frac{EQ}{TA}.$$

EQ refers to the Total Equity, and TA refers to the Total Assets. It is important to note that we use TA as a proxy for the company's size. Although it might seem that it violates our assumption of a fixed number of installations introduced in Section 5.1, the size of a company cannot be measured with the number of installations.

The reasoning for this statement is as follows, the definition of installation provided in Section 5.1 is strictly limited only to carbon-emitting dependent power generators. However, companies might own power generators that do not emit any CO_2 or its equivalents. These power generators count towards the size of a company and, at the same time, are not included in the number of installations. Since we do not know the exact distribution of types of power plants in the company's portfolio, we can not conclude that the size of a company is measured in the number of installations.

The assumption of a fixed number of installations is, therefore, not violated. Moreover, we have a proxy variable for a company's size, which is suggested by the literature to explain the profit and observable across all periods.

Additionally, we have scaled both *CurRatio* and *EqRatio* by 100. Both variables were stated in %, therefore the interpretation would be more difficult. Now the interpretation is the same as for variables that are transformed by the natural logarithm, increase by 1% results in corresponding change.

We have also decided to add the variable TD. This variable captures the transition effect from Phase II to Phase III. TD equals zero for the years 2005–2012 and equals one for the years 2013–2021. Although no literature directly suggests including this dummy variable in the regression, there is enough evidence of the impact of the transition.

6.4 Collinearity

In this part, we analyse the relationships among independent variables. We begin with empirical analysis based on pairwise correlations. Then we use testing methods to verify our conclusions from the empirical analysis.

Empirical Verification

	$ExAl$	$Verif$	$\log(TA)$	$CurRatio$	$EqRatio$	TD
$ExAl$	1.00	0.72	0.49	-0.02	0.01	-0.14
$Verif$		1.00	0.40	-0.04	-0.07	0.29
$\log(TA)$			1.00	-0.25	0.03	-0.03
$CurRatio$				1.00	-0.03	0.07
$EqRatio$					1.00	-0.06
TD						1.00

Table 6.3: Independent variables – correlation matrix

Table 6.3 provides a correlation matrix of independent variables. Most of the correlation coefficients are close to zero. The highest correlation is between the $Verif$ and $ExAl$. Section 4.3 discusses the relationship between these two variables. Although the correlation of 0.72 is strong, we conclude that a strong correlation between these two variables is inevitable. However, from the structure of the Carbon Market Dataset, we can rule out the possibility of there two variables causing multicollinearity.

Additionally, there are two other correlation coefficients standing out. We conclude that the correlation is not strong, so we do not assume any linear relationship among our independent variables.

Testing Collinearity

Since we are using a fixed effects model, software such as R can not calculate the VIF coefficient efficiently, therefore, we have to search for other methods for testing collinearity.

Chatterjee & Hadi (2015) suggest two methods based on the analysis of the correlation matrix of independent variables, Table 6.3. Firstly, we have to obtain the eigenvalues of the correlation matrix. Based on the eigenvalues, we calculate two criteria:

1. The sum of reciprocals of the eigenvalues as

   $$\sum_{i=1}^{6} \frac{1}{\lambda_i},$$

   where λ_i's correspond to eigenvalues of our correlation matrix described in Table 6.3.

2. The condition number κ of our correlation matrix is defined as

$$\kappa = \sqrt{\frac{\max\{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6\}}{\min\{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6\}}} = \sqrt{\frac{\lambda_1}{\lambda_6}},$$

since λ_i's are ordered such that $\lambda_1 > \lambda_2 > \cdots > \lambda_6$.

Chatterjee & Hadi (2015) suggest that collinearity is present if the first criterion exceeds five times the number of independent variables. For the second criterion, Chatterjee & Hadi (2015) suggest that a condition number less than 15 indicate the absence of collinearity.

In our case, the sum of reciprocal eigenvalues is approximately 11.00, and the condition number is about 3.93. Based on the rules suggested by Chatterjee & Hadi (2015), we conclude that our findings from the empirical analysis were correct; there is no collinearity present among our independent variables.

6.5 Models

We have satisfied the first four assumptions of the fixed effect model described by Wooldridge (2013). We could not adjust the data so that the fixed effects estimator is BLUE, the best linear unbiased estimator. However, we claim that estimates of the following equations are unbiased and consistent under the first four assumptions. Due to the presence of heteroskedasticity, we had to use robust standard errors to account for it.

$$\begin{aligned} PAT_{it} = {} & \beta_1 Verif_{it} + \beta_2 ExAl_{it} + \beta_3 \log(TA_{it}) + \beta_4 CurRatio_{it} \\ & + \beta_5 TD_{it} + \beta_6 EqRatio_{it} + a_i + u_{it}, \\ & t = 1, \ldots, 17,\ i = 1, \ldots, 37, \end{aligned} \tag{6.1}$$

$$\begin{aligned} PBT_{it} = {} & \beta_1 Verif_{it} + \beta_2 ExAl_{it} + \beta_3 \log(TA_{it}) + \beta_4 CurRatio_{it} \\ & + \beta_5 TD_{it} + \beta_6 EqRatio_{it} + a_i + u_{it}, \\ & t = 1, \ldots, 17,\ i = 1, \ldots, 37, \end{aligned} \tag{6.2}$$

$$\begin{aligned} EBIT_{it} = {} & \beta_1 Verif_{it} + \beta_2 ExAl_{it} + \beta_3 \log(TA_{it}) + \beta_4 CurRatio_{it} \\ & + \beta_5 TD_{it} + \beta_6 EqRatio_{it} + a_i + u_{it}, \\ & t = 1, \ldots, 17,\ i = 1, \ldots, 37, \end{aligned} \tag{6.3}$$

$$\begin{aligned}\log\left(Rev_{it}\right) = \ & \beta_1 Verif_{it} + \beta_2 ExAl_{it} + \beta_3 \log\left(TA_{it}\right) + \beta_4 CurRatio_{it} \\ & + \beta_5 TD_{it} + \beta_6 EqRatio_{it} + a_i + u_{it}, \\ & t = 1, \dots, 17, \ i = 1, \dots, 37, \end{aligned} \tag{6.4}$$

where log denotes a natural logarithm, and variables are measured in millions. We are using the same set of independent variables for each model. This will allow for a wider interpretation and comparability of our results.

Hausman Test

Since we have specified the final form of our models, we can verify the assumption of arbitrary correlation between the independent and unobserved effect variable presented in Section 5.1. To do so, we introduce the Hausman test. Based on the Hausman test, we will determine whether it is more appropriate to use the fixed or random effects model. Based on the p-value, we either reject or accept the following null hypothesis.

$$\begin{aligned} H_0 &: \text{The random effects model is appropriate.} \\ H_1 &: \text{The fixed effect model is appropriate.} \end{aligned}$$

After running this test for all four proposed models, we obtained p-values less than 5%. Therefore, we reject the null hypothesis and accept the alternative hypothesis that the fixed effects model is appropriate for all our models. This result confirms our initial idea that the fixed effects model is appropriate for our models.

Results Interpretation

We begin our analysis with the variable $Verif$. The relationship between $Verif$ and Rev is positive and significant at the 5% level of significance. Although we use $Verif$ to measure the total number of allocated allowances, we can use the initial interpretation as the total amount of verified emissions without affecting the results. Verified emissions might provide a proxy for the total output dependent on producing CO_2. The income coming from selling this output must be reflected in Rev. Additionally, the effect of $Verif$ on other measures of profits is not significant. To obtain profits in general, we have to deduct the costs associated with producing the output. We cannot make any conclusions about profit before or after taxes based on revenue once we do not know whether the costs associated with production did or did not exceed the

	PAT	PBT	$EBIT$	$\log(Rev)$
$Verif$	-8.180	6.468	**23.153*** **	**0.005** **
	(8.660)	(7.782)	(5.883)	(0.002)
$EmCap$	**-18.026** **	**-32.029*** **	**-19.763*** **	-0.001
	(5.873)	(5.278)	(3.990)	(0.001)
$\log(TA)$	**818.462*** **	**978.532*** **	**1,075.716*** **	**0.828*** **
	(230.424)	(207.072)	(156.541)	(0.050)
$CurRatio$	0.446	-1.267	-1.182	**-0.001*** **
	(1.162)	(1.044)	(0.790)	(0.0002)
$EqRatio$	**53.726*** **	**38.084*** **	**32.754*** **	**-0.004 .**
	(9.163)	(8.234)	(6.225)	(0.002)
TD	**-519.345** **	**-454.571** **	**-439.774*** **	0.026
	(160.199)	(143.964)	(108.833)	(0.034)
R-Squared	0.133	0.199	0.249	0.415

Note: Significance levels: $^{\cdot}$p<0.1;*p<0.05; **p<0.01; ***p<0.001

Table 6.4: Models summary

sales. Therefore the insignificance of $Verif$ in Models 6.1 and 6.2 does not contradict the intuition.

However, the significance of $Verif$ in the Model 6.3 is unexpected. The results suggest a positive relationship between the $EBIT$ and $Verif$.

The other variable of our primary interest is $ExAl$. When interpreting the $ExAl$, we must remember that a positive value refers to the deficit of carbon allowances obtained from the primary market and vice versa. The results suggest that the increase in the deficit of carbon allowances decreases a company's profits. Given the setting of our models, this does not contradict the empirical theory. Increasing the deficit results in higher demand for carbon allowances at the end of the period, which results in higher expenses at the end of the period. At the same time, tightening the deficit will decrease the costs of buying additional allowances to cover all emissions for the period. Moreover, once a company has a surplus of allowances, the $ExAl$ has a negative sign and therefore, the effect on profits is positive. The Rev is not affected by the changes in $ExAl$ since it does not reflect any costs associated with production.

We begin the discussion the rest of independent variables with the dummy variable TD. Results suggest a significant negative relationship between PAT, PBT and $EBIT$. These results do not contradict the intuition and the literature. The change in the structure of the distribution of carbon allowances was supposed to tackle the problem of windfall profits. The results suggest that the transition from Phases I and II to Phase III affected the profits heavily.

Moreover, in absolute values, the effect of TD on our three measures of profit decreases as we move from the PAT, which is the final profit of a company. The revenue of a company is not affected by TD. *Rev* captures the profit before any deductions are made. Therefore, it includes the sales of goods and services before deducting their costs. Based on Table 4.2 we can clearly see that the output did not dramatically decrease.

Regrading the TA, estimated coefficients of TA are positive and largely significant for all proposed models. This perfectly aligns with the suggestions about other variables that might explain the profit presented in 6.3. Variable TA used as a measure of the size of a company was supposed to have a positive relationship with profits (Fareed *et al.* (2016), Liargovas & Skandalis (2010), Dogan (2013)).

The only notable suggestion is that, unlike other variables, the interpretation of coefficients differs in this case. The first three proposed models, 6.1, 6.2 and 6.3, should be interpreted as an increase of TA by 1% results in an increase in profits by the estimated values. In the last model, 6.4, both dependent and independent variables are transformed with the logarithm. Therefore, the interpretation changes to percentage increases. If the TA increases by 1%, *Rev* should increase by the estimated number of percentages.

Opposed to other variables, TA has significantly larger estimated parameters. To provide context, Table 6.5 provides summary statistics for the variable TA.

Min	Q1	Median	Mean	Q3	Max.
91.1	6,884.3	15,223.3	35,836.0	36,498.5	345,709.2

Table 6.5: Total Assets – summary statistics

The numbers in Table 6.5 are provided in millions of euros. For example, a 1% increase in the mean value of TA corresponds to an increase of 358.36 million euros. Assuming that a wind turbine costs around 3 million Euro, to increase the TA by 1% via the expansion of the portfolio of power generators requires approximately 119 new wind turbines. Therefore the changes in TA likely will not be as much as 1% and the estimated coefficients will receive less weight.

An efficient interpretation of the effect that $CurRatio$ has on Rev requires an understanding of the formula we used to calculate the $CurRatio$,

$$CurRatio = \frac{CA}{CL}.$$

The formula shows that an increase in the $CurRatio$ can be caused by either increase in the CA or a decrease in the CL. We provide a discussion of the first option. CA assets include the merchandise inventory and the total value of the goods in the inventory for a given year. Assuming that company generates the revenue mostly from selling goods, an increase in the inventory refers to unsold goods. Goods that are not sold decrease the hypothetical revenue that a company could have gained. Hence increase in $CurRatio$ caused by an increase in the TA decreases the revenues company could have achieved.

$CurRatio$ is not significant for the rest of the dependent variables. We can interpret this behaviour based on just the $EBIT$. PAT and PBT are obtained by deductions from $EBIT$, therefore the intuition is the same.

In general, EBIT is obtained after deducting the costs of goods. EBIT captures the profits from the goods sold. Unlike revenue, EBIT is not influenced by the hypothetical revenue that is not achieved by the merchandise inventory. Therefore $CurRatio$ should not affect $EBIT$. These arguments provide reasoning for why $CurRatio$ has a different effect on individual measures of profit.

To interpret the $EqRatio$, we use a similar approach to interpreting $CurRatio$. At the 5% level of significance, $EqRatio$ has a positive relationship with profits in models 6.1, 6.2 and 6.3. An increase in $EqRatio$ results in an increase in profits. To examine what factors cause the increase in $EqRatio$, we discuss its formula,

$$EqRatio = \frac{EQ}{TA}.$$

$EqRatio$ increases, keeping the other variable fixed, when EQ increases or TA decreases. Since we assume that there is a positive relationship between profits and TA, we do not consider the second case, the decrease of TA. EQ increases as the investors fund the company. As $EqRatio$ converges to one, the proportion of TA that are financed by investors increases. This means that a company is not using a debts to finance its assets.

Regarding the R-squared statistics, the most efficient model is the model with the dependent variable Rev. As we already mentioned, Rev includes the sales of goods and services. For the Power and Heat sector, most sales come from energy sales. Based on the percentage of fossil fuel-dependent power generators, the Rev can be approximated with the number of verified emissions. For companies with a large share of fossil fuel-dependent power generators in their portfolio, $Verif$ captures the majority of their output and, therefore, the majority of the output sales.

On the other hand, the lowest R-squared has the model with PAT as the dependent variable. The R-Squared of Models 6.2 and 6.3 is not dramatically higher. The low R-Squared suggests that there are other omitted variables that help explain the profit.

Brief Summary

We were primarily interested in the effect of variables associated with carbon allowances on a company's profits. Two measures of carbon allowances, the Excess Allowances and Verified emissions, were used. We found that the number of surrendered allowances, best measured with Verified Emissions, has a positive relationship with the Revenue. In Models 6.1 and 6.2, we did not discover any significant relationship between profits and surrendered allowances. However, it seems that EBIT has a significant positive relationship with the number of surrendered allowances. This relationship was not predicted. Except for the EBIT, these findings are consistent with the empirical theory since the Revenue does not account for any costs associated with production. Hence, an increase in allocated allowances should reflect an increase in output produced, and the Revenue should also increase.

Based on the results, the Excess Allowances has a significant negative relationship with profits in Models 6.1, 6.2 and 6.3. In fact, the interpretation of this relationship is not as straightforward as it might seem. The negative value of the Excess Allowances reflects the surplus of allowances and vice versa. A high Excess Allowances suggests that a company did not buy enough allowances to cover its emissions and therefore has to obtain them from the secondary market.

The estimated relationship is indeed in line with the hypothesis that there is a positive relationship between the number of allowances and a company's profits. Additionally, as the deficit of allowances shrinks, the variable Excess Allowances decreases the weight of the negative effect on profits. This reasoning can be applied to all three Models 6.1, 6.2 and 6.3.

We used the Total Assets as a proxy to measure the company's size. As the literature suggested, a company's size has a positive effect on its profits. In addition, we used two measures of the company's performance. We concluded that at the 5% level of significance, the Equity Ratio has a positive effect on profits in models 6.1, 6.2 and 6.3, whereas the Current Ratio affects only the revenue.

Lastly, we added the dummy variable TD that captured the change in the distribution of allowances. As suggested by the literature, the change in the system decreased all measures of profits except the Revenue. Due to the shifting of the costs of emissions to the consumers, the change did not affect production significantly, and therefore, the Revenue is not affected by this change.

6.6 Outliers

We must admit that our models suffer from the presence of outliers. There are two causes for outliers, large and subsidised companies. In the context of the size of these two groups, we could use the term sub-populations of the population of companies in the power and heat sector in the EU rather than outliers.

The first category, the large companies, was expected to be an outlier since we generated it intentionally due to the need for information about subsidiary companies. The linearity should not be heavily influenced since we assume that subsidiary companies behave similarly to others. Therefore summation should not cause large deviations from the linear relationship, only shift outliers away from the clustered companies. The second category of outliers, the subsidised companies, was not expected. In the Section 3.1, we introduced the rules for the free allocation of carbon allowances. Allowances are given to companies with a large share of fossil fuel-dependent power generators in their portfolio. Usually, this concerns small companies producing large amounts of emissions. Therefore, outliers with large emissions relative to the profit are generated. We conclude that this second type of outliers causes more severe damage to the results than the first category since it deviates from the linear relationship.

Unfortunately, we could not determine which companies suffer from this issue based on our data. Moreover, the combination of both categories can occur. Some subsidiary companies might meet the condition for free allowances, and we cannot observe it. Even though it might not affect the randomness, we cannot detect the second type of outliers and exclude them from the dataset. Hence we kept them in the sample and admitted this inefficiency.

Chapter 7

Suggestions for Further Research

Due to the limitations of the Carbon Market Database, we could not include banking in the model. Banking refers to the possibility of transferring the surplus of allowances to the next period. Information about the number of banked allowances could justify the behaviour in Phases III and IV presented in section 4.3. To maximise the potential, adding information about the number of allowances sold to other companies might also give some additional information. We suggest observing how many allowances were banked before the beginning of Phase III. Moreover, further details on the number of allowances a company received for free during Phases III and IV might help identify the outliers described in the Section 6.5. Unfortunately, we were not able to access this data since it is not published publicly and the access is costly.

Additionally, the issue of outliers caused by the subsidiary companies might be solved by using appropriate data regarding individual subsidiary companies rather than the group financial statements.

We also recommend using more accurate financial data about the companies. Annual reports are a good source but are not completely precise. Numbers in balance sheets are usually stated in billions. Therefore, we are missing the information that has disappeared due to the rounding. Using accurate data might improve the results.

Chapter 8

Conclusion

This thesis aimed to determine whether there is a linear relationship between the profits of companies in the Power and Heat sector and the European carbon allowances. Our hypothesis is that a positive linear relationship exists between the number of allowances a company has and its profits. In the thesis, we have also introduced the topic of the European Emissions Trading System and provided insight into the mechanism of distribution of allowances throughout individual phases of the EU ETS.

Our research contributed to the topic in two ways. Firstly, we created a dataset containing financial information about a relatively large share of companies in the Power and Heat sector in the EU. Further research can be conducted based on the information in the dataset. Secondly, we presented how individual measures of carbon allowances influence four different measures of profit.

To summarise our findings, we have verified our hypothesis, that there is a positive linear relationship between carbon allowances and profits of companies in the Power and Heat sector. The best carbon-related variable to capture this relationship for the actual profits, Models 6.1, 6.2 and 6.3, is the variable Excess Allowances. Whereas for explaining the Revenue, the appropriate variable regarding carbon allowances is Verified Emissions, which serves mostly as a proxy for the production. Additionally, the EBIT is influenced by both the Verified Emissions and Excess Allowances. The question of why it is so is out of the scope of this thesis, and we suggest that it is an interesting topic for further research. Although our models suffer from certain limitations, they present the foundation for further research on this topic.

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Appendix A

Content of Enclosed Supplement

- Folder 1: Dataset in the Microsoft Excel

  Microsoft Excel includes the data obtained from the annual reports, the estimated shares of revenue of companies operating outside the EU, exchange rates used for converting currencies and the Carbon Market dataset with the information about all companies in the power and heat sector in the EU.

- Folder 2: Downloaded annual reports

  All annual reports published online were downloaded and stored in separate folders. The names of folders correspond to individual companies, and the annual reports are named such that there is a name of the company and the year about which the report includes information.

- Folder 3: R source code

  The R source code includes the code required for merging the dataset obtained from annual reports and the Carbon Market dataset. Moreover, there are transformations of individual variables, scaling, tests used in the thesis and, most importantly, the models with appropriate tests.