Bachelor Thesis

European Emissions Trading Scheme (EU ETS) impact on firm economic performance

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Abstract

This bachelor thesis examines the impact of the European Union Emissions Trading System (EU ETS) Phase 3 on the short-term economic performance of manufacturing firms within the EU. Using data from the European Union Transaction Log (EUTL) and the Bureau van Dijk database (ORBIS), the study covers the period from 2014 to 2020, analysing key financial indicators such as turnover, number of employees, EBIT, total assets, and profit margin. Through the application of propensity score matching (PSM) and Difference-in-Differences (DiD) methodologies, the research aims to ascertain whether firms subjected to EU ETS regulations exhibit different economic outcomes compared to their non-regulated equivalents. The findings reveal no significant impact of the EU ETS Phase 3 on the economic performance indicators of the treated firms, suggesting that these firms were able to adapt effectively to the regulatory framework without detriment to their economic health. The study contributes to the literature on the efficacy and economic consequences of cap-and-trade systems, indicating the potential for environmental regulations to achieve policy objectives without negatively affecting firm performance.

1. Introduction

Over the past several years, environmental policies have increasingly incorporated emissions trading programs. As of 2021, the European Union's Emissions Trading System, hereinafter called EU ETS, stood out as the world's most significant cap-and-trade initiative in terms of trading volume. Initiated in 2005, the EU ETS provided tradable emission allowances to more than 12,000 industrial and power facilities across 31 nations, covering over 40% of the EU's overall greenhouse gas emissions. The European Union Emissions Trading System (EU ETS) is structured into distinct phases, each characterized by unique policy applications and consequent impacts on participants. These phases are Phase 1, spanning from 2005 to 2007; Phase 2, from 2008 to 2012; Phase 3, which extends from 2013 to 2020; and Phase 4 which started in 2021 and ends in 2030. The varying policies implemented in each phase result in differing effects on those involved in the system.

The studies on the impact of the EU ETS on firm performance from Phase 1 to Phase 2 reveal mixed outcomes (Anger, 2008; Di Maria & Jaraite, 2016; Klementsen, 2020; Marin et al. 2018). While some found no significant impact on firm competitiveness or profitability, others observed modest benefits or reduced profitability in certain phases, highlighting the effects of the EU ETS across different regions and periods. However, an analysis of Phase 3 has not yet been conducted, given that it concluded recently in 2020.

Consequently, we arrive at our research question: **How does participation in the EU ETS impact the economic performance of firms in Phase 3?**

Our study aims to determine if the EU ETS (Phase 3) affects firms economically in the short run and, if so, how. We will be looking at the following economic variables - turnover, number of employees, EBIT, total assets, and profit margin. Building on Marin et al. (2018), Di Maria and Juraite (2016), Calel and Dechezlepretre (2016), and Dechezleprêtre, Nachtigall, and Venmans (2023), we establish a causal link between the policy and outcomes. We address this task by carefully filtering data and using propensity score and matching, specifically Nearest Neighbor Matching (NNM), to align control and treated groups. We then estimate the impact of EU ETS using Average Treatment Effect on the Treated (ATT) for various outcome variables. This approach ensures a detailed analysis of the economic effects of EU ETS Phase 3 on the treated firms.

This research paper introduces novelty to this field by focusing exclusively on Phase 3 of the EU ETS, an area not analyzed at all. Firstly, we know that being under the scheme, it is environmentally sensible, since it limits actual CO2 emissions. Our paper checks whether it is economically sensible for firms to pass the thresholds set by the scheme, or is it better for them to limit their growth and thermal capacity to just stay under. Secondly, we check whether the effect of the policy is positive, negative or does it have an effect at all on chosen economic indicators. Lastly, our methodology guarantees that any spillover effects from the previous Phases are not present and during 2013-2020 there weren't any major economic shocks, thus we see the short-term effects of Phase 3.

2. Literature review

2.1. The European Union Trading Scheme: Framework, Inclusion and Compliance

The European Union Emissions Trading System (EU ETS) is a cornerstone of the EU's policy to combat climate change and a key tool for reducing greenhouse gas emissions cost-effectively. Conceptualized following the 1997 Kyoto Protocol and launched in 2005, it is the world's first major carbon market and remains the biggest one. The system covers around 10,000 installations in the energy sector and manufacturing industry, as well as airlines operating within the EU, accounting for approximately 40% of the EU's greenhouse gas emissions (European Commission, n.d.).

The EU ETS operates on a "cap and trade" principle. Essentially, there is a maximum limit (the "cap") on the total amount of greenhouse gasses that can be emitted by all the participants in the system (European Commission, n.d.). This cap is set lower than what the expected emissions would be without any restrictions. The system then distributes emissions allowances, which are essentially permits that allow the holder to emit a certain amount of greenhouse gasses. The total amount of these allowances equals the cap. Within this framework, companies can buy, sell, or trade these allowances with each other. This trading is what makes the system flexible and cost-effective for participants. The cap is crucial because it limits the number of allowances available, creating a controlled scarcity in the market (Vlachou, 2013).

The inclusion of a firm in the EU ETS is determined by several criteria. Primarily, it targets sectors with high greenhouse gas emissions, such as power and heat generation, energy-intensive industries like oil refineries, steelworks, and the production of iron, aluminum, and cement, as well as commercial aviation (European Commission, n.d.). According to the Directive 2003/87/CE, the system generally applies to companies that have installations with a rated thermal input exceeding 20 MW, although there are exceptions, such as waste installations, which are included regardless of size. Geographically, it encompasses companies operating within the 27 EU countries, Iceland, Liechtenstein, and Norway. For the aviation sector, it includes flights between these countries, covering both EU and non-EU operators (Borghesi et al., 2016). Thus, a company falls under the EU ETS if it operates in these sectors and installations exceed 20 MW thermal input threshold.

In the EU ETS, firms exceeding regulatory thresholds must undergo a multi-step process to obtain a European Union Transaction Log (EUTL) account, which is essential for managing their emissions allowances (European Commission, n.d.). Initially, firms assess their eligibility based on their activities and emissions levels. Subsequently, they apply for an account in their national registry, part of the EUTL, providing detailed information about their operations and compliance strategies. This application undergoes a thorough review and verification by the national competent authority, a process that may extend over several weeks or months. Upon approval, the firm's account is activated, enabling them to participate in the EU ETS by receiving, holding, trading EU allowances, and meeting their emissions obligations through regular monitoring, reporting, and allowance surrendering (European Commission, n.d.). This structured procedure ensures firms are properly registered and accountable within the EU's cap-and-trade system for greenhouse gas emissions.

The constraints within the EU ETS are legally binding, with strict penalties for non-compliance, and have not changed throughout the different phases. Firms are required to accurately report their emissions and surrender enough allowances to cover these emissions. For every ton of emissions that isn't matched with a timely surrendered allowance, a fine of €100 is imposed. This fine is in addition to the expenses incurred for the necessary surrendering of allowances. Furthermore, the names of the operators subject to these penalties are made public (European Commission, n.d.). This system of monitoring, reporting, and verification (MRV) ensures accountability and transparency in emissions reporting. To safeguard the integrity of the market and prevent (mis)behavior such as market manipulation, the EU ETS is regulated and monitored by competent authorities at both the national and EU levels (European Commission, n.d.).

2.2. Overview of the EU ETS Phases

EU ETS has undergone several phases, each characterised by specific regulatory adjustments and responses to emerging challenges (European Commission, n.d.).

Phase 1 (2005-2007) aimed to establish a carbon market and develop the necessary infrastructure for monitoring and reporting emissions. This phase primarily covered CO_2 emissions from power generators and energy-intensive industries, with most allowances allocated for free (European Commission, n.d.). However, due to the absence of reliable emissions data, the total allowances exceeded actual emissions, leading to a price collapse by the end of this phase (Vlachou, 2013).

Phase 2 (2008-2012) saw a tighter cap on allowances, about 6.5% lower compared to 2005 levels. This phase expanded to include more countries and sectors, with a slight reduction in free allocation and the introduction of auctions in several countries. The economic crisis of 2008, however, led to unexpected emissions reductions, resulting in a surplus of allowances and a depressed carbon price (European Commission, n.d.).

Phase 3 (2013-2020) marked a significant overhaul of the EU ETS, introducing a single EU-wide cap on emissions and making auctioning the default method for allocating allowances (European Commission, n.d.). This phase also included harmonised allocation rules and expanded the scope to more sectors and gases. Despite these changes, the system faced challenges, such as a surplus of allowances, which affected the carbon price (Borghesi, 2016).

The current phase, Phase 4 (2021-2028), aligns with the European Commission's 2021 legislative proposals under the European Green Deal, aiming for a 55% net reduction in greenhouse gas emissions by 2030 and climate neutrality by 2050. This phase is expected to see further tightening of caps and adjustments in line with the EU's climate targets (European Commission, n.d.).

The question is whether firms have any underlying incentives to take part of the program. Several authors argue that firms might be incentivized to participate in the EU ETS regulation due to the potential for environmental regulations to spur innovation in low-carbon technologies, thereby enhancing competitiveness and increasing economic growth through green innovation (Dechezleprêtre et al., 2023; Marin et al., 2018; Martin et al., 2014). On the other hand, concerns exist that the EU ETS could disadvantage European firms internationally by imposing additional costs and diverting resources from other productive activities, potentially leading to a slowdown in productivity growth and causing businesses to relocate to countries with less stringent policies (Levinson & Taylor, 2008). The following section will offer comprehensive insights into various research areas related to the policy and its outcomes.

2.3. Multifaceted Insights of EU ETS

In the expanding field of research on the European Union Emissions Trading Scheme (EU ETS), a comprehensive review by Martin et al. (2016) categorised the literature into three main themes – emission abatement, economic performance and competitiveness, and innovation. This section aims to provide an overview of the significant research contributions in these areas, setting aside the central theme of this thesis, the firm-level economic performance, which we will be focusing on in section 2.5.

The first theme revolves around emission abatement, with biggest contributions from scholars like Ellerman & Buchner (2008) and Anderson & Di Maria (2011), who have extensively analysed the effectiveness of the EU ETS in reducing emissions (Anderson & Di Maria, 2011; Bel & Joseph, 2015; Ellerman & Buchner, 2008). Their research provides a foundational understanding of the environmental impact of the EU ETS. Ellerman & Buchner (2008) offer a nuanced view, indicating a mix of over-allocation and substantial emission reductions, reflecting the complexity of the system's impact. Similarly, Anderson & Di Maria (2011) explore the pilot phase of the EU ETS, revealing modest abatement and under-allocation, highlighting the importance of reliable data and effective cap setting. Complementing these insights, Bel & Joseph (2015) conclude that the EU ETS accounted for only a minor part of emission reductions, suggesting that external economic factors, particularly the recession, played a more crucial role than the policy itself. However, their study's reliance on retrospective data might not fully capture the scheme's real-time impact, potentially influencing this conclusion.

As a response to the EU ETS, innovation constitutes another major theme. Studies by Hoffmann (2007), Schmidt (2012), Rogge (2011), and others have explored whether the scheme has spurred technological advancements and innovative practices in various sectors (Borghesi et al., 2015; Calel & Dechezlepretre, 2016; Hoffmann, 2007; Rogge et al., 2011; Schmidt et al., 2012). Hoffmann (2007) and Schmidt et al. (2012) highlight the moderate influence of the EU ETS on technological innovation and low-carbon investments, particularly noting the failure of the scheme's initial phase in driving significant innovation. Rogge et al. (2011) and Borghesi et al. (2015) acknowledge the EU ETS's role in initiating corporate climate innovation activities, yet they emphasize its insufficiency in meeting the EU's 2050 targets without complementary policies. Conversely, Calel & Dechezlepretre (2016) find a substantial impact of the EU ETS on low-carbon patenting among regulated firms, but note this effect is limited when considering the broader technological landscape. These studies collectively suggest that while the EU ETS has influenced innovation, its effectiveness varies and is often constrained by its design and external factors.

Beyond these core areas, the literature also addresses specific challenges encountered during the implementation of the EU ETS. As noted by Sijm (2005), the early phases of the scheme were marked by issues such as the over-allocation of allowances. The volatility of emission allowance prices, a critical concern for market stability, has been examined by researchers like Alberola and Medina (Alberola et al., 2008; Medina et al., 2016). Alberola's (2008) Phase 1 study showed that factors like the strictness of emission caps and energy prices significantly influenced carbon price changes, with the 2006 price collapse highlighting design flaws. In contrast, Medina's (2016) research on Phase 2 points to reduced trading costs and better information handling, but also notes a lasting decline in market quality following the 2006 collapse and financial crisis. This indicates that Phase 2, despite improvements, did not fully resolve the earlier phase's issues.

Having explored various aspects of the EU ETS and its expanding field of research, we now turn to the core of this thesis of whether participation in EU ETS affects firm-level economic performance. In the next section, we will examine and compare the findings of numerous studies to understand the financial implications for companies participating in the EU ETS.

2.4. The Effect of Participation on Firm Economic Performance

Compliance with the EU Emissions Trading System (EU ETS) poses a significant decision for companies - either invest in costly emission reduction strategies or purchase EU

Allowances (EUAs) (European Commission, n.d.). This decision is vital as it can influence a firm's financial health. Moreover, companies face the challenge of maintaining their market position against competitors not subject to the EU ETS, particularly in the case of industrial emitters operating in global markets. These firms may find it difficult to transfer the cost of carbon to their prices without risking a loss in market share. This situation could lead to a decrease in production and employment. In extreme scenarios, to evade the obligations of the EU ETS, some firms might even consider relocating their operations. Thus, a proportion of the EU ETS literature focuses on economic performance indicators, for example, turnover, profits, and employment (Martin et al., 2016).

Anger (2008) used regression analysis to assess the impact of EU ETS inclusion on German firms' competitiveness, economic performance, and employment. The study did not find evidence that EU ETS participation influenced firm-level competitiveness, revenue, or employment within the observation period. The author points out that the observed insignificant results could be attributed to limitations in accessing verified emission data from companies prior to their regulation under the EU ETS. This constraint, however, does not concern our research, as our analysis is exclusively concentrated on financial performance.

The first non-country specific study was done by Abrell (2011), where the author found modest effects on profits, employment, and added value, with firms that got over-allocated with allowances benefited from increased profit margins. The analysis period only spanned from the beginning of Phase 1 until the beginning of Phase 2, which similarly to Anger's research, loses validity due to absence of reliable emissions data (as mentioned in Section 2.2). This overlap in limitations between the two studies underscores a common challenge in evaluating the early impacts of the EU ETS, highlighting the need for more comprehensive data to fully assess its effects on firm-level performance.

Similarly to Anger (2008), a country-specific approach was used in a research paper done by Di Maria & Jaraite (2016), where the authors examined Lithuanian firms that are under EU ETS between the period of 2003-2010. Their methodology included comparing EU ETS-regulated firms with firms that are not regulated, using Nearest Neighbour (NN) and Kernel matching estimators, which matched firms based on observable characteristics and the propensity score of being regulated under the EU ETS. The study observed no significant changes in profitability during the Phase 1 of the program, but indicated a decrease in profitability for firms in 2009 and 2010.

Marin et al. (2018) examined the economic impact of the EU ETS on firms using a propensity score matching approach, focusing on firms consistently regulated under the ETS from 2005 to 2012. Analysed variables included employment, average wages, turnover, value added, gross fixed capital formation/assets, labour productivity, total factor productivity (TFP), and return on investment (ROI). Their findings suggest that regulated firms did not experience adverse effects on competitiveness and economic performance, as firms seemed to have passed costs to customers and improved labour productivity. The study also navigated challenges in evaluating new firms and accounting for firm exits, which could potentially skew the results. Furthermore, the authors recognized that the data from the pre-treatment group, being prior to Phase 1, could be subject to a spillover effect and an increase in bias, potentially impacting the study's results. Marin et al. (2018) suggested that biases observed in their analysis might originate from a breach of the Stable Unit Treatment Value Assumption (SUTVA), a topic that we will discuss further in upcoming sections.

Another country-specific study was done by Klemetsen (2020), where the author employed a Difference-in-Differences (DID) analysis and panel data regression to evaluate the impact of the EU ETS on Norwegian manufacturing plants. The study observed higher value added and productivity in Phase 2 of the EU ETS, which, in line with the findings of Marin et al. (2018), suggests that the economic performance of the firms was not harmed, but rather slightly increased.

The study by Dechezleprêtre, Nachtigall, and Venmans (2023) analysed the first two Phases of EU ETS and added to the evidence that the policy is effective in reducing carbon emissions but also in maintaining the economic performance of regulated firms on the same level as it was before treatment. The research found no adverse effects on profits, employment, or overall economic performance. Remarkably, an increase in revenues and assets was observed among these firms, indicating that adhering to EU ETS regulations might have encouraged investments in cleaner technologies and processes (Dechezleprêtre et al., 2023).

It is important to acknowledge that the impact of participating in the EU ETS is not solely or immediately reflected in financial indicators. However, within the scope of this paper, our focus is on the methodology and financial variables utilised by Marin et al. (2018) to assess tangible short-run effects. It should be noted, though, that since Phase 3 of the EU ETS concluded two years ago, there is a notable absence of scholarly papers analysing this phase. This gap in the literature could present a potential limitation for our study, as it restricts our ability to compare and contrast findings with recent research.

3. Methodology

3.1 Data and Sample

To find out what the short-run economic impact of the EU ETS is, we use data provided by the European Union Transaction Log (EUTL) to get the necessary information about the installations and firms under the EU ETS. It accounts for all allowances allocated at the installation level. An installation is subjected to the EU ETS if it fulfills two conditions: it belongs to one of the sectors mentioned in Directive 2003/87/CE (energy-intensive industry sectors, power and heat generators, commercial aviation (from Phase 2), commercial maritime transport (from Phase 3)); an installation capacity above a sector-specific threshold (European Parliament, 2023). EUTL is the register for the EU that accounts for every installation that is obligated to be included in the EU ETS. These installations account for 37% of all GHG emissions in 2022 in the European Economic Area (European Environment Agency, 2023).

In the footsteps of the literature (Marin et al., 2018), we exclude the power and energy sector and other non-tradable sectors. We solely focus on the manufacturing sector since it is exposed to international competition which makes alleviating the additional costs of EU ETS harder. Manufacturing firms are competing with each other internationally and if a firm goes just over the sector threshold, it will mean direct costs from the EU ETS allowances which raise the average cost of production, thus making the product more expensive and losing competitiveness relatively to a competitor that just falls under the threshold. Loss of competitiveness means loss of jobs in the manufacturing sector, making the economic impact quite significant. Moreover, the relocation of emission-intensive manufacturing abroad to reduce the costs of EU ETS would result in a carbon leakage - the emissions will not disappear which would only impair the effectiveness of the EU ETS (Martin et al., 2016). Lastly, the manufacturing sector was responsible for 32% of total emissions covered by the EU ETS during Phase 2 (2005-2012) and in 2019 it contributed up to 22% (European Commission, 2023).

Although participation under EU ETS is performed and recorded at the installation level, this paper analyses things from the firm's perspective. This is due to the fact that economic performance (different financial statements) is not reported on every installation, but rather every firm. To account for this, we establish a link between the EU ETS installations and the parent companies through a key identification method (BvD ID number). This allows us to match all installations to their corresponding direct owners since EUTL and Bureau van Dijk both include the BvD ID number with all installations and companies. If the ID number is missing (which was the case for only a few companies), we exclude the firm since it does not reduce our sample size significantly. This brings us to the second dataset.

Since we analyse the economic performance of firms, we need financial information to create necessary indicators. This is provided by the Bureau van Dijk database (ORBIS). It is a major publisher of business and financial information which specialises in private company data with different tools to help analyse and navigate the database (Bureau van Dijk, 2023). We extracted a significant number of firms operating in the manufacturing sector to create a large dataset of all EU27 manufacturing firms. The original dataset contained 159 710 companies and the respective yearly information of turnover, EBIT, total assets, profit margin and number of employees starting from 2012 up until 2020. The aim was to gather data for the treatment (2013-2020) and pre-treatment period (2012), since the EU ETS Phase 3 started in 2013. However, due to missing data, we had to remove almost half of the firms in the dataset (primarily missing data during 2012-2014 regarding most of the variables), which left us with a set of 89 599 active firms in the manufacturing sector with at least one employee and all the necessary financial information starting from 2014. Thus, we use 2014 as the pre-treatment period and the treated period will be from 2015 to 2020. This is justified, since the treated group's firms are filtered as such that only firms that opened their EUTL account(s) starting from 2015 up to 2020, are included. Meaning, that the treated group's firms joined the EU ETS in 2015 or later (up to 2020). Regarding the omitted firms, we initially thought that smaller firms might be missing financial data, and on further examination, it turned out to be true. A large number of dropped firms were companies with less than 20 employees, but despite that, a significant number of similar sized companies remained in the dataset since they had the necessary data available.

For the treated group, we extracted a dataset from the European Union Transaction Log (EUTL), which contained 43 019 entries of EU ETS accounts. This dataset includes all accounts opened starting from 2005 up until 2023. Furthermore, it includes the registration data of the company to which the account(s) is/are linked, BvD ID and several other variables. It is necessary to mention that a single firm can have multiple accounts/installations in the EUTL dataset, but we are exclusively interested in the firm level data. The clean-up process started with filtering out all inactive accounts that had closed their operations under EU ETS (about a third of the entries). Then we filtered out the accounts that were opened in the span of 2015-2020 (during the aforementioned treatment period), meaning we exclusively look at firms that have joined only Phase 3. Next up was removing the accounts that had no BvD ID indicated. Then we removed all duplicate values of BvD ID, since our analysis needs only the firm, to which an installation (or several) are linked. Although two thirds of the firms that match our criteria joined during 2013-2014 (Table 1), we still have a sufficient sample of the firms that joined after - 601 firms. Here, though, we are assuming that the early adopters, who joined in 2013 and 2014 are similar to those that entered later. But on the other hand, the early adopters of Phase 3 can be firms that were already under EU ETS in previous Phases, thus making the leap to Phase 3 almost instantaneously. This assumption can strengthen our analysis because we look at the effects of Phase 3 exclusively and the firms that joined early, might have spillover effects from previous Phases which would increase the bias of our results.

Table 1. Number of firms joined by year

Year	# of firms joined	% of Total
2013	963	51,64%
2014	301	16,14%
2015	106	5,68%
2016	96	5,15%
2017	99	5,31%
2018	140	7,51%
2019	129	6,92%
2020	31	1,66%
[illegible]	[illegible]	

Note: Table created by authors.

We then extracted the necessary financial information of said firms from the Bureau van Dijk database via the BvD ID and the company name, which was matched in the database itself using internal matching tools. Some of the companies were omitted since a sufficient match was not found in the Bureau van Dijk database. The filtering steps and the number of eliminated observations can be seen in Appendix B. Our final treated group consists of 431 companies and their respective yearly financial information. Lastly, we cross-matched the two datasets in order to remove EU ETS firms from the control group. This was to ensure that the EU ETS duplicates and their mother-companies were removed from the control group, thus ensuring our matching strategy worked (Section 3.2.1).

3.2 Method Description

The main goal of our paper is to find out whether the implementation of EU ETS (in Phase 3) has an economic impact on a firm or not, and if so, what are the effects in the short run. Based on the previous literature, we follow the footsteps of Marin et al. (2018), Di Maria and Juraite (2016), and Calel and Dechezlepretre (2016). The challenge of this analysis is to find a causal link between the policy and the outcome variable. As the firms that join the EU ETS are not chosen at random, they might have different characteristics compared to the firms that do not join. This would make the comparison of treated and untreated firms challenging since we do not have comparative measures. We tackle this challenge by implementing effective data filtering and using propensity score-based matching between the control group and the treated group. We use Nearest Neighbor Matching (NNM) method to find the closest match to the treated firm in terms of propensity score. We then estimate the impact of EU ETS using the average treatment effect on the treated (ATT) on the outcome variables.

3.2.1 Propensity Score Matching

Propensity Score Matching is a statistical method that is used in research settings where it is not possible to randomly assign participants to different groups. This situation often arises in observational studies where the goal is to evaluate the effects of a treatment, but can not control who receives it. It is called the issue of “dimensionality”. It involves calculating the propensity score through logistic regressions which result in the likelihood of receiving the treatment, in our case EU ETS, based on observed factors. We apply the described technique to identify the closest matching firms in the control group and match them with a corresponding firm in the treatment group. This creates a scenario where the non-ETS firms hypothetically had been subjugated to it, and this allows us to compare the economic performance between the treated firms and the similar ones that are not under EU ETS.

For the propensity score analysis, we propose a function:

$$p(X)_i = \Pr(D_i = 1|X_i), \tag{1}$$

Where $p(X)i$ is the propensity score for firm i, Di is a dummy variable that indicates whether the firm is under EU ETS or not, and Xi denotes the covariates (Janani & Valojerdi, 2018). It is mentioned by Caliendo and Kopeinig (2008) that when using PSM in a binary treatment analysis, logit and probit models usually have very similar outcomes. The score is estimated with a logit model (result of a scientific coin flip), where its value ranges from 0 to 1 as it represents the probability of falling under EU ETS.

Heinrich et al. (2010) state that there are two underlying assumptions that have to be met in order to implement this statistical method.

The first assumption is called Conditional Independence Assumption (CIA): “There is a set X of covariates, observable to the researcher, such that after controlling for these covariates, the potential outcomes are independent of the treatment status” (Heinrich et al., 2010). Or to put it in a simpler way, “after controlling for X, the treatment assignment is “as good as random”” (Heinrich et al., 2010). This assumption is also referred to as “unconfoundedness” or “selection on observables”. The CIA is essential for accurately determining EU ETS’ impact because it guarantees that, even though there are differences between the treated and untreated groups, these distinctions can be considered to minimise selection bias. This enables the untreated firms to serve as a basis for creating a comparison with the treatment group. The mathematical notation for this assumption is as follows (Rosenbaum & Rubin, 1983):

$$(Y_1, Y_0) \perp D|X \tag{2}$$

Where Y_0 and Y_1 are the outcomes of treated and control firms, D is the treatment dummy variable and X notes all the observable characteristics of firms before treatment (various economic indicators).

The second assumption is called the Common Support Condition which states: “for each value of X, there is a positive probability of being treated and untreated” (Heinrich et al., 2010). In other words it states that the probability of falling under EU ETS is in the same domain for the treated and controlled groups. It is noted mathematically as follows (Heinrich et al., 2010):

$$0 < P(D = 1 \mid X) < 1 \qquad (3)$$

This assumption is also known as the "overlap condition" because it makes sure there are enough similarities between the traits of the treated and untreated firms to ensure that a suitable match is found. When these conditions are met, the treatment assignment is "strongly ignorable" (Rosenbaum & Rubin, 1983). The various economic indicators that account for the comparable variables (X) are to be observable for both groups. This ensures that the synthesised propensity score for the treated firm is similar to the match(es) in the control group, which enables us to estimate the short-run effect of EU ETS.

Aforementioned assumptions, CIA and common support, guarantee that our sample consists of firms that are picked randomly and the subsequent assignment to control and treated groups happened also by mere chance.

The next step in PSM is the actual matching process. For our matching algorithm, we use the Nearest Neighbour Matching (NNM). The algorithm chooses a firm from the control group as the closest match to a treated unit in terms of propensity score. There are two variants of NNM - matching with replacement and without replacement. In essence, the first option allows us to use one controlled firm more than once as a match, the latter does not. Caliendo and Kopeinig (2008) mention that the first option complements data where the distribution of the propensity score is distributed very widely between the groups, thus we choose the first option. If no match is found for a treated firm, we omit it from the group. We match the firms using the pre-treatment characteristics (financial data from 2014)

When using NNM, the closest neighbour can be far away which results in bad matches. This can be avoided by using a caliper of the maximum propensity score, which is the maximum distance from the nearest match (a caliper of 0.1 means that the distance in terms of probability of being treated with the corresponding match is greater than 10%). It is a form of common support condition that increases the quality of the matches, since the nearest neighbours can still be relatively far. As Smith & Todd (2005) state that it is hard to know what caliper to use before the analysis, we intend to find the right level of tolerance during the matching process.

For additional robustness checks to assess the quality of the matching, we perform a Welch t-test before and after matching, to check whether there are any significant differences in covariate means for both groups (Rosenbaum & Rubin, 1985). We also compare the matching results using standardised mean differences and variance ratios to find out which caliper has the most balanced outcome (e.g. has the most accurate matches) (Zhang et al., 2019). After the matching process is completed, we estimate the short-run effect on the treated.

3.2.2 Average Treatment Effect on the Treated (ATT)

To find out what effect EU ETS has on the economic performance of a firm, we use the average treatment effect on the treated (ATT). It can be noted mathematically as follows:

$$\alpha_{TT} = E[Y_1 - Y_0 | D = 1] \tag{4}$$

Where the expected value (E) is the difference between expected outcome values with and without treatment for those who actually were treated. By focusing solely on the treated, this parameter gives us the gross gain from EU ETS. It helps us to determine the program's (in)effectiveness (Heckman et al., 1998). Supported by the literature (Abadie & Imbens, 2006; Marin et al., 2018), we have to account for some assumptions regarding ATT.

The validity of this difference-in-difference approach lies in its assumptions. The first assumption is that without the treatment, the trend of the treated and untreated firms' outcome variables would have been the same e.g. common trend assumption. As Marin et al. (2018) state, it cannot be explicitly tested, but it can be mitigated by using key outcome variables that account for the growth of the firm, in the propensity score estimation. This ensures that the outcome variable trend which was similar pre-treatment, would have been similar post-treatment. However, the meticulous system of the EU ETS does not allow for common support to fully hold because of the threshold. In order for the assumption to hold, a treated and control firm have to be similar. EU ETS allows the common support to hold only for the firms that are very close to the threshold, just above and just below. Thus, we do not violate the assumption fully, but it nevertheless introduces a selection bias to our results.

The second assumption is called Stable Unit Treatment Value Assumption (SUTVA), which states that the treatment has zero impact on the non-EU ETS firms. The estimation of ATT must be unbiased. This might slightly affect our empirical results of the analysis since the firms operate in the same industry, some of them in the same country, and an increase in average costs imposed by the EU ETS will impact the economic performance of firms in such an environment. The violation of this assumption can lead to opposite sign effects on turnover, firm size, and margin if we expect a zero-sum game between the two groups that operate in the same market. Given a demand function, the changes in the market share of treated firms will affect the market share in control firms (Marin et al., 2018). However, in our case, this assumption is unlikely to be violated since the market share of treated firms compared to control firms is rather small. The total turnover of treated firms in 2020 was 385 billion USD and the total turnover of the manufacturing sector in 2020 was 5,22 trillion USD (Eurostat, 2022). This makes the market share of the treated group 7,3%, which is relatively small, and does not significantly violate the assumption. Sijm et al. (2006) found a second reason why this assumption might be violated. They found that the power sector is estimated to pass through about 60-100% of CO2 to cost by increasing electricity prices. This increase is induced by the EU ETS and it will influence all manufacturing firms, including non-treated ones.

3.3 Variables

This study employs various metrics from prior research, utilizing the Propensity Score Matching (PSM) method to pair firms based on size (employees, total assets), profitability (profit margin), and performance (EBIT, turnover), as outlined in Table 2. The impact of EU ETS regulation on firm-level data is examined using the Difference-in-Differences (DiD) model, using the same variables as in PSM - changes in turnover, EBIT, total assets, employee count, and profit margin after firms cross the EU ETS threshold (see Table 2).

Table 2. Variables used in PSM and DiD analysis, sourced from previous studies.

Variables	Sources
Turnover	Anger, N. (2008); Marin et al. (2018); Martin et al. (2014)
EBIT	Dechezlepretre et al., (2023); Klemetsen et al., (2020);

	Martin et al., (2014)
Total assets	Dechezlepretre et al., (2023); Di Maria & Jaraite (2016)
Employees	Anger, N. (2008); Abrell et al., (2011); Dechezlepretre et al., (2023) Klemetsen et al., (2020); Marin et al., (2018); Martin et al., (2014);
Margin	Abrell et al., (2011); Martin et al., (2014)

Note. Created by authors.

4. Results

4.1. Descriptive Statistics

Our research delves into the effects of the European Union Emissions Trading System (EU ETS) on a selection of firms across the European Union from 2014 to 2020, with a particular emphasis on Phase 3 of the initiative. Our focus centres on firms that opened their EUTL account(s) in 2015, analysing data from 2014 to 2020 to assess the policy's impact pre- and post-implementation. The rationale behind selecting the 2014 start point is attributed to the minimal data availability for 2011 and 2012, which led us to choose a more comprehensive dataset starting from 2014. Our sample is composed of both "control firms," which operate outside the EU ETS regulation, and "treated firms," which are subject to it. The criteria for selecting firms for our study were as follows: the firm must be engaged in the manufacturing sector, as classified by the NACE Rev. 2 four-digit code; it must have more than one employee; and it must be actively operational. This methodological approach facilitates a thorough analysis of the EU policy's effects on regulated firms, providing insights into the pre-and post-treatment impacts of the EU ETS. After all the data cleaning and manipulation that was explained in

Section 3.1, we were left with 431 firms for the treatment group and 89 599 firms for the control group, totalling a sample size of 90 030.

In the span of our study, we encountered significant fluctuations in the features of our firm-level dataset. Table 3 illustrates the mean and standard deviation values, which reflect the wide range of variability across our sample. The Welch t-test before matching was applied to explicitly outline the significant differences in variables between the treatment and control groups. This analysis emphasises the diverseness of firm characteristics within our study, indicating a broad spectrum of behaviours and characteristics across the analysed firms.

Table 3. Descriptive statistics for treated and control firms (2014–2020) before matching.

	Treatment Group		**Control Group**		
Variables of interest	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*t-test*
turnover	790 085	4 662 079	3 416.43	21 969.5	***
ebit	51 653	431 801	180.7	2 531.97	***
total assets	873 554	5 232 754	3 043.39	20 681.06	***
employees	1 624	8 451.97	15.313	34.379	***
margin	3.938	12.092	3.975	11.827	*0.8475*
Number of firms	**431**		**89 599**		

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

Monetary values in thousand EUR. Welch t-test explains the difference in means between the treated and control firms

Note: Data from Bureau van Dijk (ORBIS), European Union Transaction Log (EUTL) Public. Created by authors.

Table 3 demonstrates that, with the exception of profit margin, all variables exhibit significantly higher values in the treated group compared to the control group, on average. This can be observed also from the variables' small p-values. The pronounced differences in turnover, EBIT, total assets, and the number of employees between the two groups are logically explained by the larger size and greater variance within the control group's dataset. This variability leads to lower average values for the control group. The profit margin values are strikingly similar for both the treated and control groups. This similarity can be attributed to the fact that both datasets consist exclusively of firms from the manufacturing sector, operating within the same timeframe, and sharing comparable levels of margins.

To give a better understanding of our datasets characteristics, Table 3 shows the size distributions of the analysed firms. We categorised firms based on the size determined by their workforce from 2014 through 2020, giving us our sample's overall structure. We have split them into five distinct size classes. The breakdown includes three tiers for micro firms with employee numbers spanning 1-9, 10-19, and 20-49. Then, there is a specific category for small and medium-sized enterprises (SMEs) with a workforce of 50-249, and lastly, a segment for larger firms that have 250 employees or more. The table shows that most firms in our dataset fall into the microenterprise category, with the SME size class coming in as the second biggest. It is also clear that the proportions of these size classes vary significantly between the control and treatment groups. This discrepancy highlights the need for a better matching approach to account for the unequal proportions and differences in financial variables as highlighted in Table 3 and Table 4.

Table 4. Size distribution of our sample data at the beginning of the observation period (2014).

	2014					
	Treatment Group		**Control Group**		**Total**	
Size class (number of employees)	*Count*	*Share*	*Count*	*Share*	*Count*	*Share*
1-9	6	*1,39%*	58 459	*65,25%*	58 465	*64,94%*
10-19	12	*2,78%*	18 706	*20,88%*	18 718	*20,79%*
20-49	52	*12,06%*	8 396	*9,37%*	8 448	*9,38%*
50-249	174	*40,37%*	3 565	*3,98%*	3 739	*4,15%*
250+	187	*43,39%*	473	*0,53%*	660	*0,73%*
Total	**431**		**89 599**		**90 030**	

Note: Data from Bureau van Dijk (ORBIS), European Union Transaction Log (EUTL) Public. Created by authors.

4.2. Propensity Score Matching Discussion

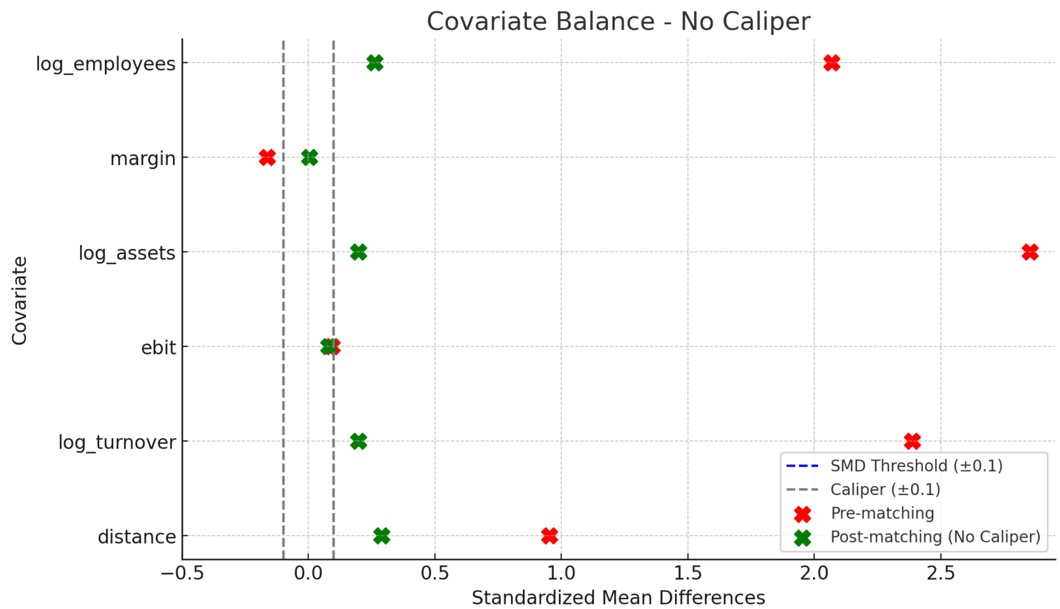
Through Propensity Score Matching (PSM), our objective is to assess the impact of the EU ETS policy. This method allows us to account for the covariates that predict whether a firm is subjected to the treatment, enabling a more accurate estimation of the policy's effect. We figure out propensity scores with logistic regression. In this model, the dependent variable shows if a firm fell under EU ETS regulations at the beginning of our observation period. This regression includes every PSM variable we detailed in Section 3.3.

We perform firm matching based on data from the year before the treatment (2014) to clear away any confounding effects from pre-treatment differences. This approach lets us factor in any impacts that might have surfaced in the year that EU ETS Phase 3 started, dodging any misleading correlations. Additionally, we used log transformation on turnover, number of employees and total assets during our analysis to tone down the variability throughout the dataset. It helps to keep the variance steady, making sure that our statistical models don't get thrown off by any extreme values or odd outliers (Dechezlepretre et al., 2023). With log transformation, we managed to even out the data distribution, which ensured the solidity and trustworthiness of our regression analysis.

Hereupon, nearest neighboring matching (NNM) is done which resulted in exactly 431 pairs, meaning all treated group's firms were matched with exactly one firm from the control group. It has to be noted that balance in matching means ensuring the treated and control groups are similar in observable traits, which helps accurately estimate treatment effects by reducing selection bias (Stuart et al., 2010).

The first matching was done without a caliper and it resulted in significant differences between the covariates of the matched and unmatched samples as seen in Figure 1. The standardized mean differences are far from the maximum threshold that indicates an adequate balance between the matched and unmatched, which is considered to be 0.1 in propensity score matching literature (Austin et al., 2007). Only EBIT and profit margin fit into the selected criteria after matching without calipers. The matching was 100% successful, no firms were omitted.

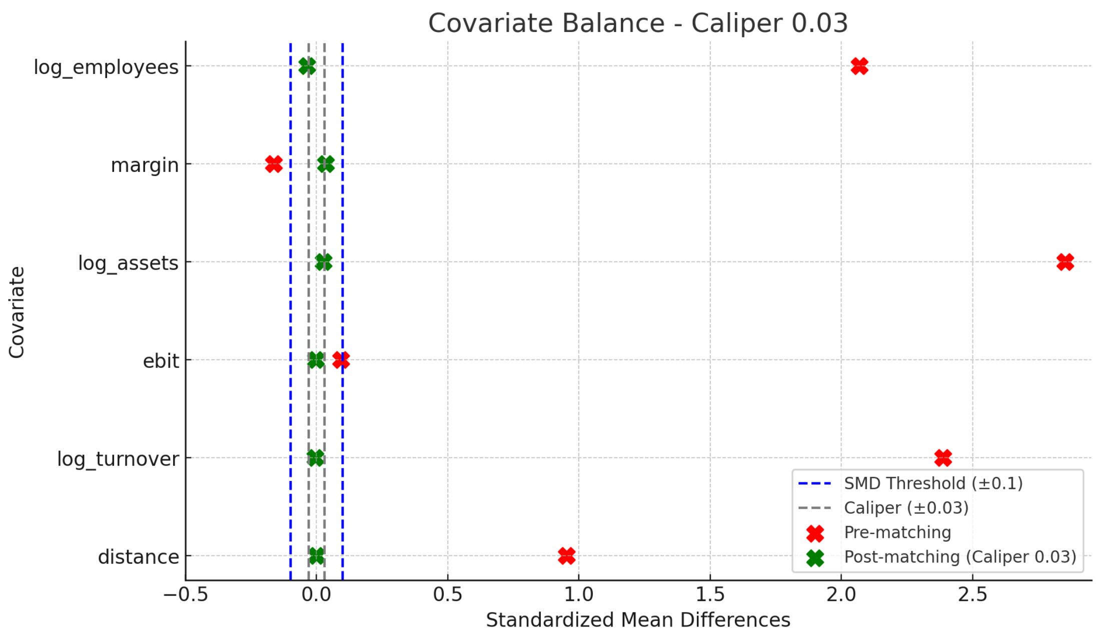
Figure 1. Standardized Mean Differences before and after nearest neighbor matching without a caliper.



Note. Created by authors

To improve the balance of our matching, we conducted matching with a caliper of 0.01, 0.02, 0.03 and 0.05 for additional robustness checks. A caliper of 0.03 yielded the best results, which are illustrated in Figure 2. This reduced the matched pairs down to 307, 124 were unmatched and omitted from the dataset because they did not fulfil the criteria of 0.1 standardised mean differences. It is because the introduced caliper sets a boundary for the maximum allowed difference between the treated and control firms. Thus, the matching was 71,22% successful. The reduction of the sample size is rather big, but the improved balance makes up for the smaller sample by increasing the validity of our matches. Matching with 0.01, 0.02 and 0.05 calipers yielded almost the same results as a caliper of 0.03 (see Appendix A), but not as sufficient. Appendix D shows that our results are sensitive to whether using a caliper or not, which improves our internal validity. This means that there is a tradeoff between external and internal validity. But it is justified by the reason that we are examining firm-level effects, and in order for the firm level results to be robust and accurate, our internal validity must be high, which is in fact improved by the inclusion of the caliper.

Figure 2. Standardised Mean Differences before and after matching using a caliper of 0.03



Note. Created by authors.

Next, we check the variance ratios of each variable. Variance ratio is a measure of the balance between the treated and control groups, comparing the variances of covariates across these groups. A variance ratio close to 1 indicates that the variances are similar, suggesting that the matching process has created comparable groups in terms of the spread of the covariate values (Austin et al., 2007). It is also mentioned in the literature that a variance ratio of two is the maximum threshold that describes sufficient balance (Zhang et al., 2019). In the analysis, we observe the outcomes of two nearest neighbor matching (NNM) techniques, one with a caliper of 0.03 and the other without any caliper. As seen in Table 4, the principle of using variance ratios as a measure of balance between matched samples is upheld here, with the ratio threshold ideally remaining below two, when using a caliper of 0.03.

Table 5 illustrates that the introduction of a 0.03 caliper significantly adjusts the variance ratios across all variables. Notably, the log_turnover ratio decreases from 1.6496 to 0.9477, ebit from 106.3045 to 0.1018, log_assets from 1.5683 to 0.8398, margin from 0.7033 to 0.5401, and log_employees from 3.0796 to 1.2208. These adjustments suggest that the calibration of the matching process with a caliper has markedly improved the comparability of the matched firms. The ratios, all falling below the threshold, indicate an acceptable balance and justify the use of a caliper to enhance the matching method's precision.

Table 5. Variance ratios of nearest neighbor matching without a caliper and with a caliper.

Variables	NN mathcing without a caliper	NN mathcing with 0.03 caliper
log_turnover	1.6496	0.9477
ebit	106.3045	0.1018
log_assets	1.5683	0.8398
margin	0.7033	0.5401
log_employees	3.0796	1.2208

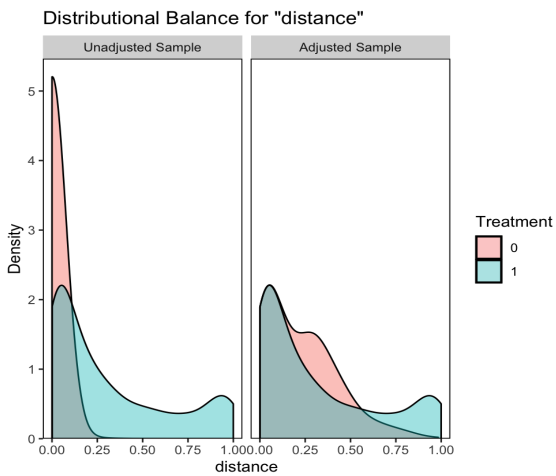
Note. Created by authors.

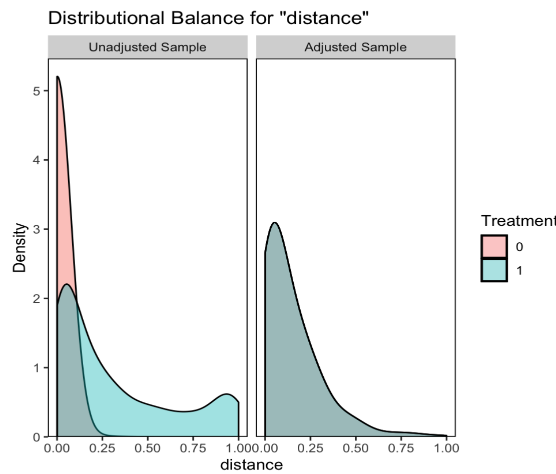
Finally, for additional overview it is important to look at the propensity score distributions in order to see the effects of matching with both caliper and without. Figure 3 illustrates the distribution of propensity scores in a study sample, comparing the unadjusted (before matching) and adjusted (after matching) scenarios, with the first figure representing matching without a caliper and the second using a 0.03 caliper.

On the left-side figure (without caliper), we see that the propensity score distributions for both treatment groups (0 and 1) are quite different in the unadjusted sample. After matching, the distributions overlap more, suggesting that the matching process has improved the balance between the two groups, although some differences remain.

On the right-side figure (with 0.03 caliper), the propensity score distributions in the unadjusted sample are similar to those in the first figure. However, after matching with the 0.03 caliper, the overlap between the two groups' distributions is much greater. This indicates that the use of a caliper in matching has resulted in a more balanced distribution between the treatment groups, thus reducing selection bias more effectively than matching without a caliper. Now, the treatment and control groups are more comparable in terms of the propensity score, which is critical for causal inference in observational studies.

Figure 3. Propensity score distributions before/after matching, without caliper (left) and with 0.03 caliper (right).





Note. Created by authors

For an additional robustness check, we conduct a t-test between the matched treated and control firms. Since the t-test highlights the difference in means between the control group and the treated group, the matching process should bring the means closer and the test should show high p-values for each variable, so as to not reject the null hypothesis. As we can see from Table 6, the means are significantly closer than pre-matching. All variables have a high p-value, except total assets, but it is still higher than before the matching process. Thus, we can conclude that the means are not significantly different between the groups, except for total assets, but when inspecting the actual number, it is still significantly close. Furthermore, the variance ratio and standardized mean differences robustness checks confirm the validity and sufficiency of the balance.

Table 6. Post-matching (caliper 0.03) Welch t-test between the control group and treated group

	Treatment Group	**Control Group**	
Variables of interest	*Mean*	*Mean*	*t-test*
log_turnover	10.519	10.438	***0.072***
ebit	5 859.14	5 209.9	***0.443***
log_total assets	10.662	10.495	***0.00002***
log_employees	4.819	4.826	***0.8276***
margin	3.779	3.211	***0.1436***

H0: true difference in means is equal to one; p-value<0.05 - we reject the null hypothesis

Note. Created by author

4.4 Difference-in-Differences Discussion

This section discusses the results of the DiD analysis applied to evaluate the impact of EU ETS policy on five different firm economic variables - turnover, number of employees, total assets, EBIT and profit margin over a period from 2014 to 2020. The analysis utilizes a longitudinal dataset, comparing pre- and post-treatment periods to infer causal effects. The results of our analysis are shown for each variable, where the "(intercept)" represents the average value of the outcome variable, all else equal; "treated" represents the difference between the treated and control group before the treatment is applied; "post_treatment" indicates the overall effects on the variable after the treatment was introduced (2015-2020) for all firms; "treated:post_treatment" is the interaction term of this regressions, which is also the variable that we are interested in. It represents the additional change for the treated group that is caused by the treatment, from which one can draw conclusions about whether there is a causal inference or not. This regression can be represented by the following formula:

$$Y = \beta_0 + \beta_1 * \text{treated} + \beta_2 * \text{post\_treatment} + \beta_3 * (\text{treated} * \text{post\_treatment}) + \varepsilon \quad (5)$$

4.4.1 Turnover

The analysis of turnover reveals that the treatment's effect is not statistically significant. Our finding that the treatment had no statistically significant impact on firms' turnover is consistent with several studies mentioned in the literature review. For instance, Anger (2008) and Di Maria and Jaraite (2016) both found no significant impact of the EU ETS on firm-level income generation during the initial phases of the program. This could be because firms are able to pass through the costs associated with the EU ETS to their customers without losing sales (Abrell et al., 2011; Marin et al., 2018; Klemetsen et al., 2020). Alternatively, the market may have already anticipated the costs associated with compliance, allowing firms to adjust their strategies in advance, thereby mitigating any negative impact on turnover (Marin et al., 2018). A study done by Dechezleprêtre et al. (2023) observed a statistically significant increase in revenues. However, this contrary result could stem from several limitations in our analysis, including a smaller sample size, fewer variables considered, and a shorter observation period compared to their study.

Table 7. DiD estimation for Turnover using NNM matching and 0.03 caliper.

Variable	Coefficient	*p-value*
Turnover		
(Intercept)	10.379	***
treated	-0.012	0.921
post_treatment	0.068	0.457
treated:post_treatment	0.1097	0.4

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

Note. Data from Bureau van Dijk (ORBIS), European Union Transaction Log (EUTL) Public. Created by authors.

4.4.2 Number of Employees

Similarly, the non-significant effect on employment levels found in our study is parallel with the findings of most of the previous literature, where authors did not observe a significant influence of the EU ETS on employment within firms (Abrell et al., 2011; Anger, N., 2008; Klemetsen et al., 2020; Marin et al., 2018; Martin et al., 2014). This consistency across different studies may indicate that firms might be optimizing other operational costs or increasing efficiency to comply with the EU ETS without reducing their workforce, meaning that adjustments to the EU ETS might not directly lead to employment changes but rather encourage firms to seek efficiencies in other areas, such as energy use or process improvements.

Table 8. DiD estimation for Number of Employees using NNM matching and 0.03 caliper.

Variable	Coefficient	*p-value*
Number of Employees		
(Intercept)	4.821	***
treated	-0.058	0.481
post_treatment	0.005	0.930
treated:post_treatment	0.06	0.501

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

Note. Data from Bureau van Dijk (ORBIS), European Union Transaction Log (EUTL) Public. Created by authors.

4.4.3 EBIT

The absence of a statistically significant effect on EBIT in our analysis aligns with the broader narrative in the literature that the EU ETS has not had a detrimental impact on firms' operational profitability (Dechezleprêtre et al., 2023; Klemetsen et al., 2020). The potential reason for this finding is that the costs associated with the EU ETS (such as purchasing allowances or investing in emissions reduction technologies) may be relatively small compared to overall operating costs, or firms may be effectively managing these costs. Additionally, the influence of external economic factors or firm-specific strategies to mitigate the impact could be at play, allowing firms to maintain their operating profits despite the treatment.

Table 9. DiD estimation for EBIT using NNM matching and 0.03 caliper.

Variable	Coefficient	*p-value*
EBIT		
(Intercept)	4827.2	**
treated	-1499.3	0.503
post_treatment	446.5	0.794
treated:post_treatment	2506.6	0.299

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

Note. Data from Bureau van Dijk (ORBIS), European Union Transaction Log (EUTL) Public. Created by authors.

4.4.4 Total Assets

The lack of a significant impact on total assets found in our study adds to the mixed findings in the literature. While not directly comparable, the absence of significant effects on assets could parallel the findings regarding turnover and employment, suggesting that the EU ETS's influence may not immediately manifest in firms' strategic asset decisions. This is in contrast to Dechezleprêtre et al. (2023), who noted an increase in revenues and assets, implying that the effect of the EU ETS on assets might vary depending on the phase of the program or the specific conditions of the firms involved. However, as discussed before, this discrepancy could stem from some of the limitations. Furthermore, assets are influenced by various factors, including strategic growth plans and external economic conditions, which may overshadow the impact of the EU ETS in the short run.

Table 10. DiD estimation of Total Assets using NNM matching and 0.03 caliper.

Variable	Coefficient	*p-value*
Total Assets		
(Intercept)	10.477	***
treated	0.046	0.661
post_treatment	0.021	0.797
treated:post_treatment	0.141	0.210

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

Note. Data from Bureau van Dijk (ORBIS), European Union Transaction Log (EUTL) Public. Created by authors.

4.4.5 Profit Margin

Finally, the initial analysis revealed a statistically significant positive effect on profit margins for all firms after the treatment was introduced. However, upon examining the interaction term, which estimates the causal effect, we observed that this effect becomes statistically insignificant. The initial significant positive effect on profit margins could be interpreted as an indication of firms improving efficiency or successfully passing through additional costs to customers (Abrell et al., 2011; Klemetsen et al., 2020; Marin et al., 2018). However, the insignificance of the interaction term, which is crucial for establishing causality, suggests that these observed improvements in profit margins may not be directly attributable to the treatment. This discrepancy could arise from factors such as variations in firm behaviour, market conditions, or external economic influences that were not fully controlled for in the initial analysis. Drawing on Abrell's (2011) insights into the benefits of over-allocation, our analysis suggests that the connection between the EU ETS and increased profit margins in affected firms is more complex than initially thought. While there's an observation of improved profitability, attributing these gains solely to the EU ETS overlooks other significant factors that could also be influencing these outcomes.

Table 11. DiD estimation for Profit Margin using NNM matching and 0.03 caliper.

Variable	Coefficient	*p-value*
Profit Margin		
(Intercept)	0.655	0.366
treated	0.462	0.652
post_treatment	2.982	***
treated:post_treatment	0.124	0.911

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

Note. Data from Bureau van Dijk (ORBIS), European Union Transaction Log (EUTL) Public. Created by authors.

5. Limitations

The primary limitation of this study was the absence of comprehensive firm-level data significantly narrows our scope, leading to a smaller sample size than initially anticipated. This limitation not only constrains the depth of our analysis but also affects the external validity of our findings, as the representativeness of our sample to the wider population of EU ETS-affected firms is limited. Furthermore, the optimal timeframe for a pre-treatment period analysis would span from 2011 to 2012, however, it was not achievable due to the aforementioned reasons. It also affects our internal validity, since the firms that started under the scheme in 2012 could be larger in output and GHG emissions. This leaves us with the sample of firms that could have entered later on purpose and were better prepared for the EU ETS inclusion, which could make the impact of Phase 3 different compared to if we had the treated sample starting from 2012.

Additionally, the framework of EU ETS does not allow for the common support assumption to fully hold. This is one of the assumptions of DiD analysis and as mentioned in Section 3.2.2, our violation of this, introduces a selection bias to the results. This does not fully hold because the comparable firms are only close to the output threshold.

Also, our analysis may not fully account for the strategic behaviors of firms not regulated by EU ETS, particularly those that might intentionally limit the size of their production installations to remain just below the threshold for EU ETS inclusion. This introduces a potential bias in assessing the performance of untreated firms, as their decisions may be influenced by the desire to avoid EU ETS costs rather than purely market-driven factors.

Lastly, our econometric methodology could be complemented or replaced by alternative methods. Although PSM is a widely used method in scientific research, it is also criticized. Several authors highlight that the weakness of PSM stems from its reliance on mimicking completely randomized experiments, increasing imbalance and bias. The authors suggest using other methods that emulate fully blocked randomized experiments, such as coarse exact matching (CEM) (Crown, 2014; King & Nielsen, 2018). Furthermore, the DiD model relies on several critical assumptions, making it sensitive to the validity of these assumptions. Violation of these assumptions can lead to biases or misleading results (Lechner, 2011). This limitation could be overcome by using alternative techniques like regression discontinuity design or instrumental variable estimation.

6. Conclusion

In our analysis of the European Union's Emissions Trading Scheme (EU ETS) Phase 3, we explore its impact on the economic performance of manufacturing firms in the short run. By using key financial indicators such as turnover, employee number, total assets, EBIT and profit margin in the time period of 2014-2020, we employed propensity score matching (PSM) and Difference-in-Differences methodologies to find out how firms under the EU ETS compared to their non-regulated counterparts in terms of economic performance. The utilized data was derived from European Union Transaction Log (EUTL) and the Bureau van Dijk database (ORBIS).

Our findings indicate no significant impact on the treated firms in EU ETS's third phase, suggesting that firms managed to navigate the regulatory environment effectively without compromising their economic situation. Our findings contribute to the broader discourse on the efficiency and economic implications of cap-and-trade systems, highlighting the adaptability of firms to environmental regulations. Our analysis reveals that despite the imposed regulations, firms in the system maintained their economic performance across the analyzed indicators. The lack of significant effects may suggest that the costs associated with the compliance were effectively managed and offset by operational activities or the costs were minor.

The methodology used is supported by the literature and ensures the robustness of our findings. The matching balance was improved by the use of a caliper, standardized mean differences test and variance ratio checks. By combining these methods, sufficiently robust matches were produced which were then analyzed by the average treatment effect on the treated (ATT) regression, to find out the short-term effects of the EU ETS on firm economic performance. Additionally, we used before and after matching t-tests, and a difference-in-differences analysis using matches without a caliper, to further check the validity and robustness of our results.

However, the scope of further research remains vast. Future studies could explore the long-term impacts of the EU ETS, particularly in terms of competitiveness and innovation and investigating Phase 3 effects across different sectors and using different variables for the analysis and matching. Additionally, the impact of EU ETS on CO2 emissions is a scarcely researched topic and needs further studies to understand the impacts more thoroughly.

In conclusion, this thesis underscores the potential of environmental policies like the EU ETS to achieve regulatory goals without significantly impacting the economic performance of the participants. It continues to contribute to the small existing body of literature about EU ETS and almost non-existent work about Phase 3 by standing on the shoulders of previous research. As the EU and other regions continue to refine their approaches to carbon pricing and emissions trading, studies such as this will remain crucial in evaluating the effectiveness and economic implications of these policies.

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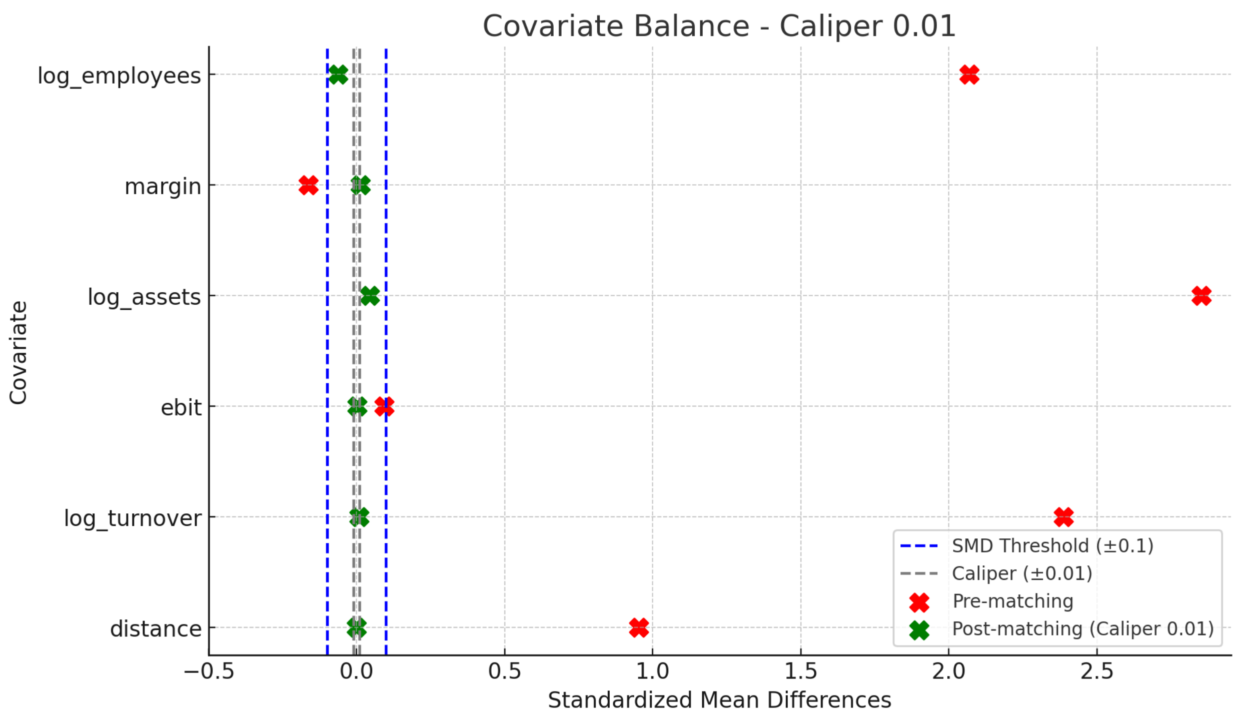
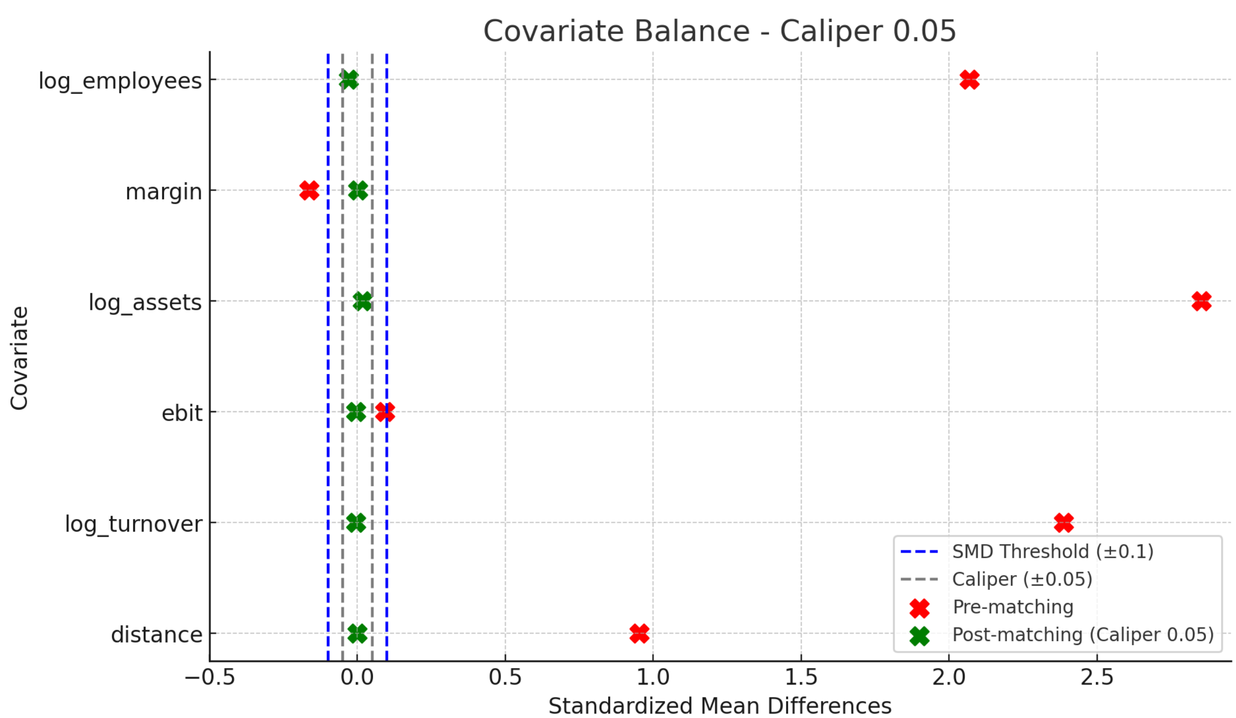
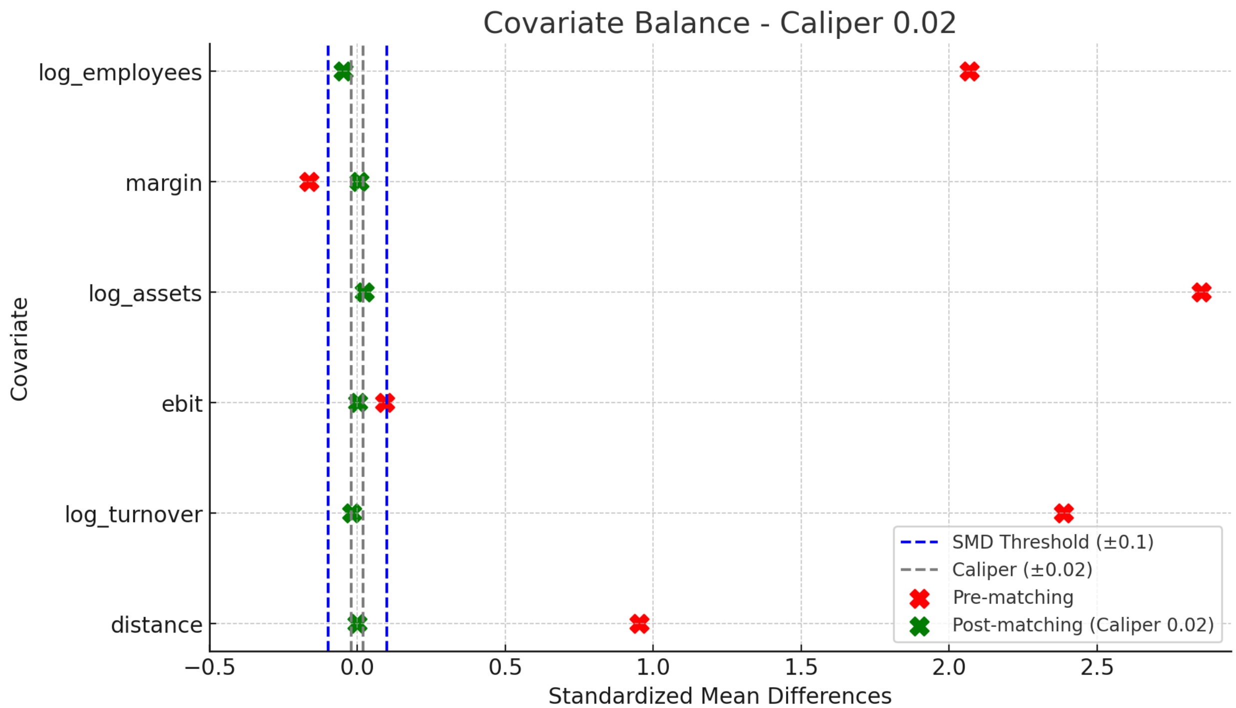
Google drive folder link for literature review

8. Appendices

Appendix A. Standardized Mean Differences with 0.01, 0.02, 0.05 Caliper.







Note: Graphs are created by the authors

Appendix B. Data Filtering Steps and Eliminated Observations.

Data filtering step	Sample size	Eliminated observations
Total nr. of accounts	**43 019**	27 854
Remove inactive accounts	15 165	13 791
Account opened in 2015-2020	1 374	383
Has BvD ID	991	390
Remove duplicate BvD ID-s	601	170
Remove firms with missing data (through BvD)	431	
Total	**431**	**42 588**

Note: Table is created by authors.

Appendix C. Number of Firms Joined By Year.

Year	# of firms joined	% of Total
2013	963	51,64%
2014	301	16,14%
2015	106	5,68%
2016	96	5,15%
2017	99	5,31%
2018	140	7,51%
2019	129	6,92%
2020	31	1,66%
[illegible]	[illegible]	

Note: Table is created by the authors

Appendix D. Propensity Score Matching Without and With a Caliper of 0.03.

Variable	Without caliper		With caliper 0.03	
	Coefficient	*p-value*	Coefficient	*p-value*
Log of turnover	0.10012	0.4356	0.10972	0.4
EBIT	13202,00	0.563	2506.6	0.299
Log of employee number	0.0638	0.509	0.0604	0.501
Log of total assets	0.14870	0.211	0.14124	0.210
Profit margin	0.17604	0.851	0.1237	0.911

Note: Table is created by the authors.

Appendix E. The Declaration of Using AI-based Tools.

In the context of this research, ChatGPT's application is specifically used towards identifying errors within R Studio code as well as correcting grammatical errors. We would like to point out that ChatGPT's role is not in the creation of textual content but rather in providing assistance in the refinement of existing material through paraphrasing.