Trading Behaviour of Regulated Companies in the EU ETS:

How do structural factors and institutional design affect strategic use and market efficiency?

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT in order to improve the language quality. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content.

Abstract

The European Union Emissions Trading System (EU ETS) constitutes the central market-based instrument of European climate policy. While cap-and-trade systems are theoretically cost-effective, real-world company behaviour is often influenced by transaction costs, specific company characteristics, and institutional constraints, leaving optimisation potentials untapped. The objective of this cumulative dissertation is to empirically investigate the mechanisms of actual trading behaviour and to analyse how structural and institutional factors shape the strategic use of the market. A profound understanding of these dynamics is essential for evaluating policy efficiency and for the further development of market design.

The empirical analysis is based on four peer-reviewed research papers. The data foundation consists of a company-level panel dataset that links transaction and compliance data from the European Union Transaction Log with structural and financial information from the ORBIS database. Methodologically, the analysis employs double-hurdle models, Poisson regressions, Heckman selection models, and Tobit models.

The first publication analyses market participation and trading intensity. Company size, the number of regulated installations, sector affiliation, and the net position prove to be key determinants. A central finding is the behavioural asymmetry between net buyers and net sellers: the former trade significantly more frequently and at higher volumes, suggesting a potential violation of the independence property of the Coase Theorem in practice.

The second publication investigates financial trading performance. The results indicate that profits from trading are closely linked to the net position, banking behaviour, timing of transactions, and the number of installations. Furthermore, the findings suggest that companies make efficient banking decisions by accounting for the opportunity costs of holding versus selling allowances.

The third publication sheds light on behavioural adjustments following the transition from free allocation to auctioning. The analysis reveals that companies facing higher carbon costs trade more frequently and diversify their trading partners more strongly, which aligns with theoretical expectations derived from search cost theory. However, the estimated effects are modest, suggesting that a higher share of auctioning does not generate prohibitive transaction costs.

The fourth publication analyses internal trading within National Ultimate Owners. Despite theoretical efficiency potentials, internal reallocation occurs only to a limited extent, suggesting that internal trading is driven more by corporate size and complexity than by internal optimisation potential.

Taken together, these contributions provide a comprehensive understanding of how institutional settings and cost incentives influence trading behaviour within the EU ETS. The results offer concrete implications for the future design of emissions trading systems.

This dissertation is based on research conducted at the Fraunhofer Institute for Systems and Innovation Research (ISI) and was supervised by Prof. Dr. Martin Wietschel at the Institute for Industrial Production (IIP) of the Karlsruhe Institute of Technology (KIT). The target degree is Dr. rer. pol.

Kurzfassung

Das Europäische Emissionshandelssystem (EU ETS) stellt das zentrale marktwirtschaftliche Instrument der europäischen Klimapolitik dar. Während Cap-and-Trade-Systeme theoretisch kosteneffizient sind, wird das tatsächliche Verhalten von Unternehmen in der Praxis häufig durch Transaktionskosten, spezifische Unternehmensmerkmale und institutionelle Restriktionen beeinflusst, wodurch Optimierungspotenziale ungenutzt bleiben. Ziel dieser kumulativen Dissertation ist es, die Mechanismen des tatsächlichen Handelsverhaltens empirisch zu untersuchen und zu analysieren, wie strukturelle und institutionelle Faktoren die strategische Nutzung des Marktes prägen. Ein fundiertes Verständnis dieser Dynamiken ist für die Bewertung der politischen Effizienz und die Weiterentwicklung des Marktdesigns unerlässlich.

Die empirische Analyse basiert auf vier begutachteten Forschungsarbeiten. Die Datengrundlage bildet ein Paneldatensatz auf Unternehmensebene, der Transaktions- und Compliance-Daten aus dem European Union Transaction Log mit strukturellen und finanziellen Informationen aus der ORBIS-Datenbank verknüpft. Methodisch kommen Double-Hurdle-Modelle, Poisson-Regressionen, Heckman-Selektionsmodelle und Tobit-Modelle zum Einsatz.

Die erste Veröffentlichung analysiert die Marktteilnahme und Handelsintensität. Unternehmensgröße, die Anzahl der regulierten Anlagen, die Branchenzugehörigkeit und die Netto-Position erweisen sich als zentrale Einflussfaktoren. Ein zentrales Ergebnis ist die Verhaltensasymmetrie zwischen Netto-Käufern und Netto-Verkäufern: Erstere handeln signifikant häufiger und mit höheren Volumina, was auf eine potenzielle Verletzung der Unabhängigkeitseigenschaft des Coase-Theorems in der Praxis hindeutet.

Die zweite Veröffentlichung untersucht den finanziellen Handelserfolg. Die Ergebnisse zeigen, dass Handelsgewinne eng mit der Netto-Position, dem Banking-Verhalten, dem Timing von Transaktionen und der Anzahl der Anlagen verknüpft sind. Darüber hinaus deuten die Befunde darauf hin, dass Unternehmen effiziente Banking-Entscheidungen treffen, indem sie die Opportunitätskosten des Haltens gegenüber dem Verkauf von Zertifikaten berücksichtigen.

Die dritte Veröffentlichung beleuchtet Verhaltensanpassungen infolge des Übergangs von der kostenlosen Zuteilung zur Auktionierung. Die Analyse zeigt, dass Unternehmen, die mit höheren CO_2-Kosten konfrontiert sind, häufiger handeln und ihre Handelspartner stärker diversifizieren, was theoretischen Erwartungen aus der Suchkostentheorie entspricht. Die geschätzten Effekte sind jedoch moderat, was darauf hindeutet, dass ein höherer Auktionsanteil keine prohibitiven Transaktionskosten verursacht.

Die vierte Veröffentlichung analysiert den internen Handel innerhalb von Unternehmensgruppen (National Ultimate Owners). Trotz theoretischer Effizienzpotenziale findet eine interne Umverteilung nur in begrenztem Umfang statt, was darauf hindeutet, dass interner Handel stärker von der Unternehmensgröße und -komplexität getrieben wird als vom internen Optimierungspotenzial.

Zusammengenommen bieten diese Beiträge ein umfassendes Verständnis darüber, wie institutionelle Rahmenbedingungen und Kostenanreize das Handelsverhalten im EU ETS beeinflussen. Die Ergebnisse liefern konkrete Implikationen für die zukünftige Ausgestaltung von Emissionshandelssystemen.

Diese Dissertation basiert auf Forschungsarbeiten am Fraunhofer-Institut für System- und Innovationsforschung (ISI) und wurde von Prof. Dr. Martin Wietschel am Institut für Industriebetriebslehre und Industrielle Produktion (IIP) des Karlsruher Instituts für Technologie (KIT) betreut. Der angestrebte akademische Grad ist Dr. rer. pol.

Part I

1. Introduction

1.1 Policy Background

Addressing climate change has become one of the most pressing global challenges of our time. The steady rise in global temperatures, driven predominantly by anthropogenic greenhouse gas (GHG) emissions, necessitates urgent and coordinated mitigation efforts. In response, the international community has taken significant steps to curb emissions and limit global warming (e.g. IPCC, 2023). At the global level, the United Nations Framework Convention on Climate Change (UNFCCC) provides the institutional framework for international climate negotiations, while the Intergovernmental Panel on Climate Change (IPCC) delivers the scientific basis for action. Landmark agreements under the UNFCCC – such as the Kyoto Protocol (United Nations, 1998) and the Paris Agreement (United Nations, 2016) – have established binding and non-binding commitments for countries to reduce emissions and limit global temperature rise to well below 2°C, aiming for 1.5°C above pre-industrial levels.

In line with these global developments, the European Union (EU) has implemented a broad set of climate and energy policies. The most prominent among these are the EU Emissions Trading System (EU ETS) (European Parliament and Council, 2003), launched in 2005, and its complementary instrument for non-ETS sectors, the Effort Sharing Decision/Regulation (ESR) (European Parliament and Council, 2009a). Further instruments include the Renewable Energy Directive (RED) (European Parliament and Council, 2009b), the Energy Efficiency Directive (EED) (European Parliament and Council, 2012), and the Regulation on Land Use, Land-Use Change and Forestry (LULUCF) (European Parliament and Council, 2018). Over time, the EU has strengthened and reformed its climate policy framework. The European Green Deal (European Commission, 2019), adopted in 2019, established a comprehensive roadmap towards a climate-neutral economy. This was followed by the "Fit for 55" (European Commission, 2021) legislative package and the European Climate Law (European Parliament and Council, 2021), which legally enshrines the EU's climate targets. Currently, the EU aims to reduce its net greenhouse gas emissions by at least 55% by 2030 compared to 1990 levels, representing a substantial increase in ambition relative to the previous target of a 40% reduction and marking a key milestone on the pathway to climate neutrality by 2050.

The EU ETS is the European Union's primary instrument for achieving cost-effective reductions in greenhouse gas emissions and represents a central pillar of EU climate policy, covering approximately 40% of total EU emissions. Since its launch in 2005, the system has evolved through successive trading periods – Period I (2005–2007), Period II (2008–2012), Period III (2013–2020), and Period IV (2021–2030) – to become a more robust and market-driven mechanism. As the world's first major international carbon market, the EU ETS has undergone continuous expansion in terms of sectoral and geographical coverage, regulatory sophistication, and environmental ambition.

Initially limited to stationary installations in the power and energy-intensive industrial sectors, the scope of the EU ETS was extended in 2012 to include intra-European aviation, and in 2024 to cover intra-European and – at 50% – extra-European maritime transport. Geographically, the system has expanded from its original coverage of the 25 EU Member States to include new Member States (Bulgaria, Romania, Croatia) and the countries of the European Economic Area (EEA), namely Iceland, Liechtenstein, and Norway. The United Kingdom exited the EU ETS following its withdrawal from the European Union. Moreover, since 2013, the EU ETS has regulated not only carbon dioxide (CO_2) but also nitrous oxide (N_2O) and perfluorocarbons (PFCs). Today, the system covers over 10,000 installations.

The EU ETS operates on a "cap-and-trade" principle: an annually declining cap sets the maximum allowable volume of emissions, and regulated entities must surrender one European Union Allowance (EUA) per tonne of CO_2-equivalent emitted. These allowances can be traded among regulated companies and other market participants, including financial intermediaries, thereby providing flexibility and enabling cost-efficient emissions reductions. Since 2008, banking of allowances – i.e. carrying over EUAs for use in future years – has been permitted without restriction. This was not the case during the first trading Period, when allowances could not be transferred to Period 2. As a result, a large surplus caused prices to collapse to nearly zero by the end of 2007.

EUAs are introduced into the market by the regulator through a combination of free allocation and auctions. The relative importance of these two mechanisms has shifted over time. During the first and second trading periods, the vast majority of allowances were allocated for free, primarily based on historical emissions. The third trading period brought substantial reforms, including the introduction of a Linear Reduction Factor (LRF), which annually reduces the cap by a fixed amount and thereby establishes a trajectory toward the EU ETS's emissions reduction target. Free allocation for electricity producers was abolished and granted only in exceptional cases. Allocation to industrial sectors became benchmark-based, with non–carbon leakage–exposed sectors facing a gradual phase-out of free allocation by 2030, while sectors at risk of carbon leakage continued to receive full free allocations. Importantly, the share of allowances auctioned increased significantly. Although the targeted auction share of 57% was not reached in Period 3, due to "backloading" measures aimed at addressing market oversupply, approximately 47% of allowances were auctioned during that period. These auctions are conducted via the common EU platform the European Energy Exchange (EEX) and generate substantial revenues, a portion of which is earmarked for climate-related investments. Since 2021, 100% of auction revenues must be used for climate and energy-related purposes; at the EU level, revenues feed into the Innovation and Modernisation Funds.

Despite the reforms introduced in 2013 (European Parliament and Council, 2009c), the EUA price fell below €3.50 in the same year due to persistent surplus and weak demand, remaining low for several years. This price depression led to allowance backloading between 2014 and 2016 and ultimately to the implementation of the Market Stability Reserve (MSR) (European Parliament and Council, 2015) in 2019. The MSR aims to stabilise the market by automatically adjusting auction volumes: when the market faces a surplus (measured by an upper threshold for the Total Number of Allowances in Circulation), a portion of allowances is withheld and placed into the reserve; conversely, if liquidity constraints emerge (measured by a lower threshold for the Total Number of Allowances in Circulation), allowances may be released from the MSR and reintroduced into the market. The announcement and implementation of the MSR contributed to a price recovery and a strengthening of the EUA price signal, although price volatility has continued in response to international crises (e.g. the COVID-19 pandemic, Russia's invasion of Ukraine).

As part of the European Green Deal, the "Fit-for-55" legislative package introduced far-reaching reforms to align the EU ETS with the EU's 2030 climate target of reducing GHG emissions by at least 55% compared to 1990 levels. This resulted in an adjustment of the specific reduction target under the EU ETS to 62% compared to 2005 levels. These reforms include a significant tightening of the cap and a strengthening of the MSR. In parallel, the Carbon Border Adjustment Mechanism (CBAM) (European Parliament and Council, 2023) will gradually replace free allocation in selected sectors. CBAM introduces a carbon price on imports that mirrors the cost of carbon under the EU ETS, further underscoring the central role of auctioning as the primary method of allowance allocation going forward.

1.2 Motivation

In theory, an emissions trading system leads to cost-effective GHG abatement. The interaction between total emissions, marginal abatement costs, and the stringency of the emissions cap jointly determines the allowance price. Companies with abatement costs below the price are incentivised to reduce emissions rather than purchase allowances, while companies with abatement costs above the price will prefer to purchase allowances or hold allocated allowances for compliance purposes. This market-based allocation facilitates emissions reductions where they are least costly, thereby promoting static efficiency, defined as the achievement of a given reduction target at the lowest total cost to society (Montgomery, 1972; Hahn and Stavins, 2011).

However, the extent to which this theoretical efficiency is realised in practice depends crucially on the actual trading behaviour of regulated companies. While the economic incentives are clearly defined in theory, companies may refrain from actively participating in allowance trading due to trading barriers. One of the most significant barriers in this context is transaction costs. These include search and information costs, market access fees for trading platforms, internal decision-making costs, and personnel costs associated with developing and implementing trading strategies. Therefore, the potential for efficiency gains through trading is constrained by the transaction costs that companies face (e.g. Stavins, 1995; Betz et al., 2010).

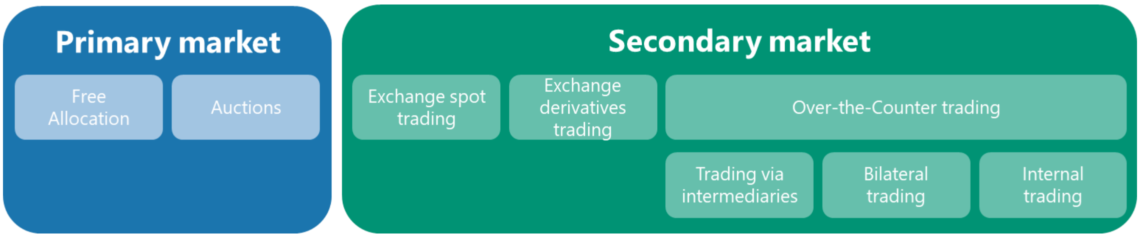
Company behaviour and transaction costs, in turn, are shaped by a range of institutional features and company-specific characteristics. Generous free allocation during the first two trading periods, based on historical emissions (commonly referred to as grandfathering), resulted in several inefficiencies, including not only windfall profits (e.g. Sijm et al., 2006; Cludius et al., 2020) but also entry barriers (e.g. Zaklan, 2013; Jaraitė-Kažukauskė and Kažukauskas, 2015; Cludius, 2018). In addition to these distortions, trading activity was dampened because companies with positive net positions, meaning their free allocation exceeded their verified emissions, had little incentive to purchase allowances, and selling excess allowances was often unattractive due to low prices that probably did not cover the associated transaction costs. These outcomes prompted calls for a higher share of auctioning to enforce participation and thereby improve market efficiency.

Auctioning offers several theoretical advantages over free allocation. It relies on market forces to allocate allowances to those companies with the highest willingness to pay, thereby reducing market distortions and enhancing transparency and political legitimacy (e.g. Schmalensee et al., 1998; Hepburn et al., 2006). Moreover, it levels the playing field between incumbents and new entrants, prevents windfall profits, and generates public revenues that can be used to finance climate investments or compensate distributional effects (e.g. Ehrhart et al., 2005; Benz et al., 2010). Nevertheless, auctioning increases compliance costs[1] and may affect the international competitiveness of companies, particularly in trade-exposed sectors.

The growing auction share since 2013 has compelled companies to engage more actively with the development and implementation of trading strategies. As the reform increased the share of companies with a shortage of free allowances, these entities are required to buy allowances, either through participation in primary auctions or through transactions on the secondary market. This, in turn, improves price discovery and contributes to a more efficient market. The secondary market offers a variety of trading options, including spot trading on exchanges, futures contracts, and over-the-counter (OTC) trading. OTC transactions are conducted bilaterally between companies or private individuals, such as EU ETS-regulated entities, financial intermediaries, or other private companies, and, in contrast to exchange-based transactions, allow for customised negotiations regarding price and volume (see Figure 1). In this context, the use of intermediaries has become a key strategic tool (DEHSt, 2014), enabling companies to hedge risk, manage compliance costs, and capitalise on price fluctuations. The significance of the secondary market has increased markedly over time: between the second and third trading periods, annual trading volumes rose by 27%, and the ratio of free allocation to traded volume increased from 1:8 to 1:23, indicating a growing awareness among companies of compliance costs and the financial optimisation of trading strategies.

[1] Compliance costs, as used here and in the following, refer to all costs associated with meeting EUA surrender obligations. They include, in particular, the EUA price multiplied by the number of allowances that must be purchased, potential abatement costs, and transaction costs such as search costs for trading partners, exchange participation fees, or commissions paid to intermediaries. A formal definition is provided in the conceptual model in Paper 3 (see Chapter 8.2).

Figure 1: Structure of Trading Channels within the EU ETS.



Source: Author's own illustration.

Beyond interactions on external markets, companies may also engage in internal trading, reallocating allowances between companies within the same corporate group. Since compliance obligations are defined at the installation level, corporate groups operating multiple installations across multiple subsidiaries can reduce transaction costs by reallocating allowances internally. Internal trading strategies may also include centralising trading operations within a dedicated trading unit or optimising allowance management across affiliated entities. If effectively implemented, such internal strategies can reduce external transaction costs and lower compliance costs. However, legal, organisational, and administrative constraints may limit companies' ability to fully exploit these opportunities.

The efficiency of the EU ETS hinges not only on its institutional design and market confidence that policymakers will strictly adhere to the targeted decarbonisation path (e.g. Perino and Willner, 2019), but also on the actual behaviour of the regulated companies. The willingness and capacity of companies to engage in emissions trading, the strategies they adopt, and the internal organisational decisions they make are all decisive for whether the theoretical promise of market-based regulation can be realised in practice.

The trading behaviour of companies under the EU ETS, and the role of transaction costs therein, has become the focus of an increasing number of empirical studies. These studies examine transaction costs (e.g. Jaraitė-Kažukauskė and Kažukauskas, 2015; Naegele, 2018; Baudry et al., 2021; Hintermann and Ludwig, 2023), trading participation (Zaklan, 2013), trading behaviour and patterns (Betz and Schmidt, 2016; Borghesi and Flori, 2018; Karpf et al., 2018; Zaklan, 2023), financial performance (Liu et al., 2017; Guo et al., 2020; Flori et al., 2024), and company valuation effects (Dewaelheyns et al., 2023). The evidence suggests that larger companies, those with a higher number of installations, and companies in the energy or carbon leakage-exposed sectors are more likely to participate in emissions trading and tend to do so more intensively.[2]

However, despite this literature, significant substantive and methodological research gaps remain. Substantively, questions extending beyond analysis of participation and trading volume have received limited attention. In particular, little is known about how the 2013 EU ETS reforms

[2] A comprehensive discussion of the state of research, including key findings pertaining to the individual research questions, is provided in Section 1.3, as well as in the introductory sections of the four papers in Part II, Chapters 6–9.

affected companies' trading behaviour or to what extent companies strategically exploit internal trading opportunities within corporate groups to minimise compliance costs.

From a methodological perspective, four main gaps remain. First, most analyses focus on a single trading period, typically the pilot period or, to some extent, the second period. Extending the temporal scope to include the third trading period enables an assessment of whether earlier findings persist as the market matures and participants gain experience. This broader coverage is essential given the evolving regulatory framework, including the authorization of inter-period allowance banking from the second period and the sharp increase in auctioning from 2013, which fundamentally altered allocation rules for the power sector and, via benchmarking, for industrial sectors.

Second, previous research has relied primarily on participation and total trading volume as indicators of behaviour. A broader set of measures, such as transaction frequency, the use of intermediaries, engagement in derivatives markets, the number of trading partners, and banking behaviour, provides a more comprehensive understanding of company strategies. Incorporating financial data from databases such as ORBIS facilitates a better proxy for financial capacity and managerial competencies underlying strategic sophistication.

Third, the level of analysis differs considerably across studies. Betz and Schmidt (2016) analyse installations; Jaraitė-Kažukauskė and Kažukauskas (2015), the national ultimate owner; and Cludius (2018), Hintermann and Ludwig (2023), Naegele (2018), and Zaklan (2013), the global ultimate owner. The company level, however, typically reflects the locus of strategic decision-making more accurately, while maintaining proximity to operational realities and avoiding frictions caused by coordination and information barriers at higher aggregation levels.

Finally, existing econometric approaches reveal methodological limitations arising from data constraints or insufficient temporal coverage. Only a few studies (e.g. Jaraitė-Kažukauskė and Kažukauskas, 2015) apply panel data methods such as a panel double-hurdle model, whereas most of the others, such as Liu et al. (2017), Guo et al. (2020), and Cludius (2018), rely on quantile or cross-sectional regressions. These designs do not exploit the advantages of panel data in capturing unobserved heterogeneity. Panel econometric models therefore offer a robust approach for identifying the structural and behavioural determinants of trading activity and outcomes in the EU ETS.[3]

This dissertation seeks to address these gaps. It investigates the drivers of participation, the determinants of trading intensity, and the extent to which trading strategies influence financial outcomes. Furthermore, it examines company responses to rising compliance costs due to declining free allocation and how companies minimise transaction costs through intra-group allowance transfers. The methodological gaps are addressed through a comprehensive, updated dataset and rigorous panel econometric techniques. By integrating these dimensions, the

[3] A detailed description of the specific research gaps addressed by each paper is provided in Chapter 1.3 and, in more extensive form, in the introductory sections of the individual publications (Chapters 6–9).

dissertation contributes to a more nuanced understanding of how trading strategies shape the performance of the EU ETS and how its regulatory design can be refined to enhance efficiency.

1.3 Research Questions

As outlined in Section 1.2, ETSs are intended to achieve environmental targets cost-effectively by equalising marginal abatement costs across regulated entities. However, this efficiency argument relies on the assumption of negligible transaction costs. In practice, transaction costs can significantly influence company behaviour and, therefore, the overall efficiency of the system (e.g. Stavins, 1995). These transaction costs can vary widely across companies, depending on their size, structure, sector, and institutional context. Betz et al. (2010) demonstrate that transaction costs are particularly relevant for smaller or less experienced companies, for whom the cost of market participation may outweigh the potential gains from trading. As a result, these companies may refrain from participating in trading activities altogether, despite theoretical monetary incentives to do so. In some cases, organisational constraints or a lack of strategic capacity further limit engagement with the market.

To reduce transaction costs, companies can adopt various trading strategies. One such approach involves the use of financial intermediaries, such as banks or brokers, who provide access to derivatives markets (e.g. futures and forwards) and participate in allowance auctions on behalf of their clients. Another important strategy is internal trading within corporate groups, which can reduce the need for external transactions and associated costs. Centralised trading units at the company or national ultimate owner (NUO) level may further lower administrative and information costs by coordinating trading decisions centrally.

The efficiency of the EU ETS thus depends not only on the regulatory framework itself, but also on how regulated companies respond, whether and how they participate, how actively they trade, which instruments and channels they use, and how they manage compliance across organisational structures.

Against this backdrop, this dissertation investigates the trading behaviour of companies regulated under the EU ETS. It explores the factors that encourage or hinder trading participation, the strategies companies adopt to reduce their compliance costs, and the implications of these strategies for the system's cost-efficiency.

The central research question is:

> *How do transaction costs, company characteristics, and institutional design shape the trading behaviour of regulated companies under the EU ETS?*

Answering this overarching question requires a deeper understanding of both structural drivers and strategic factors of trading behaviour in emissions markets. This includes:

- the determinants of the decision to participate in trading,
- how companies engage with intermediaries and derivatives markets,

- whether and how trading strategies lead to monetary trading profitability,
- how companies respond to changes in the regulatory framework,
- to what extent they utilise internal reallocation opportunities, and
- how these strategies evolve over time.

To obtain robust insights into these dimensions, this dissertation formulates a set of specific research questions that enable a systematic investigation of distinct yet interrelated aspects of company behaviour under the EU ETS. These questions are examined using multivariate econometric methods (see Section 2.3), applied to a unique company-level panel dataset that combines verified emissions, transactions, and allocation data from the European Union Transaction Log (EUTL) with financial and structural company information from the ORBIS database provided by Bureau van Dijk, and allowance price data from the European Energy Exchange (EEX) and the Intercontinental Exchange (ICE) (see Section 2.1).

1.3.1 Research Question 1

Participation in emissions trading is a fundamental requirement for the EU ETS to fulfil its efficiency objectives. Only when regulated companies with divergent abatement costs actively engage in the market can allowances be reallocated in a way that minimises aggregate compliance costs. However, participation and trading intensity vary substantially across companies. These variations can be attributed to transaction costs, which may act as a barrier to initiating trading and active engagement, especially for smaller or less experienced companies.

The academic literature highlights the role of transaction costs in shaping market participation (e.g. Williamson, 1989; Stavins, 1995). Empirical analyses in the EU ETS context confirm that such costs have influenced trading behaviour. Zaklan (2013) identifies structural determinants of participation during the pilot period. Jaraitė-Kažukauskė and Kažukauskas (2015) explicitly model transaction costs, demonstrating their deterrent effect, especially among small companies. Naegele (2018) finds substantial transaction costs by comparing EUA and offset credit prices. Hintermann and Ludwig (2023) find that cross-border trading raises transaction costs, while Cludius (2018) highlights barriers related to institutional settings and company characteristics, and Zaklan (2023) investigates the independence property of the Coase Theorem (Coase, 1960). Network-based analyses by Borghesi and Flori (2018) and Karpf et al. (2018), as well as cluster analyses by Betz and Schmidt (2016), further suggest that trading behaviour is influenced by company size, sector, number of installations, and net position (free allocation minus verified emissions).

This leads to the following research question:

How do the characteristics of individual companies and institutional features of the EU ETS influence companies' participation and intensity in emissions trading?

This question is examined in Paper 1 of the dissertation using the methodologies presented in Section 2 and contributes to the existing literature in four key respects:

- It covers a longer time period (2005–2014), including two years of Period 3, characterised by greater market maturity and regulatory reform, than most of the previous studies.
- It introduces behavioural indicators that reflect strategic trading beyond participation.
- It explores asymmetries in trading intensity between net buyers and net sellers, providing insights into the independence property of the Coase Theorem (Coase, 1960).
- It performs the analysis at the company level, which aligns more closely with actual decision-making structures than installation-level or NUO level data.

These contributions allow for a deeper understanding of the drivers of trading activity in the EU ETS and enable a more realistic assessment of the extent to which observed behaviour reflects the theoretical efficiency properties of the system.

1.3.2 Research Question 2

While participation in allowance trading, as analysed in Paper 1, is a necessary condition for the cost-efficiency of an emissions trading system, it remains unclear whether companies that engage more actively and make use of strategic instruments, such as financial intermediaries or futures contracts, are also more successful in terms of trading profitability than those that act passively and participate only for compliance purposes. If a more strategic engagement leads to higher trading profitability compared to a rather passive strategy, where the primary objective is simply to balance allowance holdings for compliance, this could strengthen companies' incentives to participate actively in the market. In turn, such behaviour may improve market liquidity and price discovery, thereby enhancing cost-efficiency at the system level.

This leads to the following research question:

How do the institutional framework, company characteristics, and trading strategies influence companies' profits from allowance trading under the EU ETS?

Despite its relevance, the determinants of trading success have received limited empirical attention. A small body of literature has investigated the role of company characteristics in explaining profits from trading. Cludius (2018) analyses trading outcomes during the first trading period, finding positive correlations between trading profits and net position, sector affiliation, and emission levels. Liu et al. (2017), as well as Guo et al. (2020), apply quantile regressions to the first two trading periods, linking trading success to net position, emission volumes, and abatement. However, these studies tend to focus on limited temporal scopes and do not look at trading strategies.

With the maturing of the EU ETS and the introduction of key regulatory changes, such as the expansion of auctioning in 2013 and the authorization of banking (from the second trading period onwards), the strategic environment of companies has fundamentally changed. As Hintermann et al. (2016) point out, banking has transformed companies' intertemporal decision-making. However, empirical studies linking strategic dimensions to trading performance remain rare.

The contribution of this study is fourfold:

- To the best of the author's knowledge, this is the first study to analyse trading performance across three trading periods of the EU ETS using panel data.
- It expands the analytical framework to incorporate strategic trading behaviour, thus providing a proxy for managerial competence.
- It explicitly accounts for selection bias, which may arise in this context because profits are only observed for companies that actually participate in trading, thereby improving empirical validity.
- It operates at the company level, providing more relevant insights into trading decisions than studies based on installations or Global Ultimate Owners.

Together, these contributions offer new insights into the interplay between the institutional framework, company characteristics, and trading strategies.

1.3.3 Research Question 3

The first two research questions take a structural perspective, examining barriers to allowance trading and factors driving trading profitability. In contrast, Research Question 3 focuses on a specific instrument, auctioning, under the EU ETS, which was intended to enhance allocative efficiency. It analyses how companies respond to the growing importance of auctioning as the main allocation method.

While auctioning is widely regarded as a more economically efficient and transparent approach (e.g. Schmalensee et al., 1998; Ehrhart et al., 2005; Hepburn et al., 2006; Benz et al., 2010), its impact on secondary market behaviour remains insufficiently explored. In particular, the shift from predominantly free allocation in the early periods of the EU ETS to a high auction share from 2013 onwards raises important questions about how companies adjust their strategies on the markets.

In theory, both allocation methods can achieve cost-effective emissions reductions. Under auctioning, market participants are expected to bid up to their marginal abatement costs, which, under competitive conditions, should lead to a market price equal to the marginal abatement cost of the system. Under free allocation, a similar outcome could be achieved through subsequent trading in the secondary market. Therefore, an increase in auctioning might, in principle, reduce the need for secondary transactions by incorporating cost signals directly into the primary market. At the same time, auctioning imposes direct financial costs on companies. Companies with a negative net position, i.e. emissions exceeding their free allocation, must acquire additional allowances through either auctions or secondary market trades.

Stigler's (1961) search theory posits that in imperfect markets, where identical goods are offered at different prices, buyers will continue to search for lower prices until the marginal cost of searching equals the expected price savings. The model further suggests that optimal search effort increases with the monetary value at stake, whether due to larger traded volumes or higher prices. In the context of the EU ETS, this implies that as the share of free allocation declines and auctioning becomes more prevalent, companies are likely to intensify their search for favourable trading opportunities in the secondary market. This behaviour implies higher transaction costs. Notably, such a response contrasts with the neoclassical assumption of frictionless markets, which would predict a decline in secondary market activity as auctioning becomes more dominant.

This leads to the following research question:

> *How do changes in companies' compliance costs, induced by increased auctioning under the EU ETS, affect their search efforts in the secondary market?*

To date, the empirical literature has provided only limited insights into this dimension of emissions trading. Existing studies on auctioning, such as Venmans (2016), suggest that a negative net position, typical in systems with a high share of auctioned allowances, strengthens incentives for abatement investments. Adamolekun (2024) finds that auctioning reduces price volatility, thereby facilitating low-carbon investment. However, the extent to which auctioning increases companies' search efforts and thereby raises transaction costs, potentially diminishing the theoretical efficiency gains of auctioning, has not yet been systematically investigated.

This study addresses this gap by examining whether changes in companies' net positions, driven by increasing auction shares, result in intensified search activity in secondary markets. Specifically, it investigates whether reduced free allocation prompts companies to trade more frequently and to engage with a broader range of trading partners. These two indicators serve as proxies for increased search effort and, by extension, for rising transaction costs.

This study makes several contributions:

- It focuses explicitly on behavioural responses to auctioning, a dimension that has not been the focus of previous empirical work.
- It analyses the regulatory and market transformations introduced after 2013, offering insights into a more mature period of the EU ETS.
- It measures financial incentives using the monetary value of the net position, rather than physical quantities, thus providing a more accurate reflection of companies' exposure to compliance costs.

By empirically addressing this question, the study contributes to a better understanding of a largely overlooked aspect of emissions trading design: the trading-related behavioural responses of companies facing rising compliance costs. The findings offer policy-relevant insights for the future design of auctioning rules and the implementation of instruments such as the CBAM.

1.3.4 Research Question 4

While Papers 1 and 3 examine the existence and reform-induced changes in transaction costs, Paper 4 investigates whether companies take advantage of a readily available option to reduce these costs. The decentralised structure of allowance allocation and compliance obligations under the EU ETS provides regulated companies with considerable scope for internal optimisation. NUOs controlling multiple regulated installations across different subsidiaries may reallocate allowances internally rather than relying exclusively on external market transactions. In the underlying dataset, 2,507 out of 6,737 companies (approximately 37% of the total) possess the capability to engage in such internal transfers, as they belong to an NUO that controls at least one additional regulated company. Furthermore, internal EUA trading can reduce transaction costs by avoiding external exchange fees and search costs, as well as by consolidating information within a centralised trading unit, thereby streamlining decision-making and enhancing coordination.

This leads to the following research question:

> *To what extent do companies exploit their potential for internal EUA trading, and which factors are associated with the use of this strategy under the EU ETS?*

Despite these potential efficiency gains, internal EUA transfers have received little attention in the empirical literature to date. Betz and Schmidt (2016) provide descriptive evidence indicating that companies do in practice centralise their trading activities by pooling allowances. Similarly, Nardone et al. (2025) find that trading among Italian companies occurs primarily between companies rather than installations, though their definition of internal trading excludes transfers between companies within the same NUO. Schultz (2024) shows that, towards the end of the compliance cycle, companies shift allowances from subsidiaries in jurisdictions with stricter accounting rules to those with more lenient standards, suggesting the presence of profit shifting.

This study makes several novel contributions:

- To the best of the author's knowledge, this is the first systematic analysis quantifying the determinants of internal trading practices within the EU ETS.
- It provides new insights into the extent to which companies make use of intra-organisational optimisation opportunities, thereby revealing the extent to which they succeed in avoiding transaction costs.

The findings of this analysis contribute to the broader discussion on the effectiveness of decentralised compliance structures.

1.4 Structure of the Thesis

This cumulative dissertation is structured as outlined in Figure 2. Part I (Sections 1–5) contains the framework chapters, while Part II (Sections 6–9) comprises four stand-alone research papers that form the core empirical contribution of the thesis. The papers are reproduced with unchanged content; only the formatting has been adapted to the layout of this dissertation. Full bibliographic information and DOIs for the original publications are provided below. Reuse of the published articles follows the applicable copyright and licensing terms of the respective publishers.

Abrell, Jan; Cludius, Johanna; Lehmann, Sascha; Schleich, Joachim; Betz, Regina. (2022). "Corporate Emissions-Trading Behaviour During the First Decade of the EU ETS." *Environmental & Resource Economics*, 83(1): 47–83. DOI 10.1007/s10640-021-00593-7.

Lehmann, Sascha; Schleich, Joachim; Pinkse, Jonatan. (2024). “Allocation or Skill? What Is Driving Corporate Trading Performance in the EU ETS?” *The Energy Journal*, 45(6): 203–221. DOI 10.1177/01956574241288994.

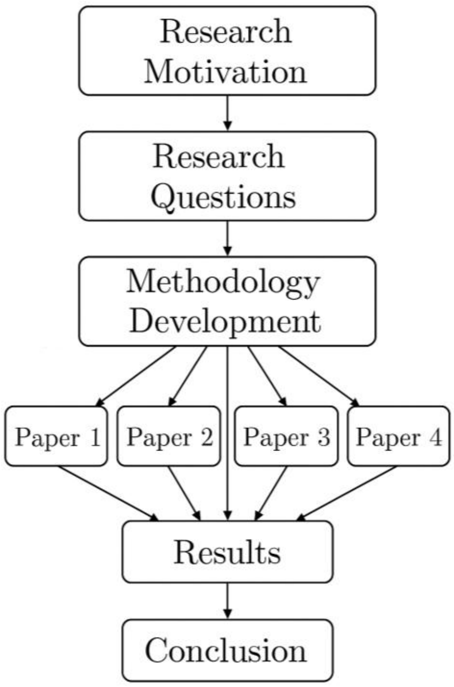
Lehmann, Sascha; Schleich, Joachim. (2025). “Does Increasing Auctioning in the EU ETS Increase Companies’ Search Efforts for Favourable Trading Options?” *Journal of Environmental Management*, 387: 125830. DOI 10.1016/j.jenvman.2025.125830.

Lehmann, Sascha; Schleich, Joachim. (2025). “Exploring Internal Trading in the EU Emissions Trading System: An Empirical Analysis.” *Energy Economics*, 152: 109035. DOI 10.1016/j.eneco.2025.109035.

Section 1 presents the background, motivation, and overarching objectives of the dissertation. Section 1.3 introduces the research questions, which are addressed in the four peer-reviewed papers.

Section 2 details the construction of the dataset, the selection of variables, and the econometric methods employed throughout the individual studies.

Figure 2: Structure of the Thesis.



Source: Author's own illustration.

Section 3 synthesises the findings of the four research papers in relation to the research questions introduced earlier.

Section 4 concludes the dissertation by summarising the main contributions, discussing implications for climate policy and the future design of emissions trading systems, and outlining avenues for further research.

Finally, Section 5 lists the references cited throughout the framework chapters.

1.5 Conceptual Integration of the four Research Papers

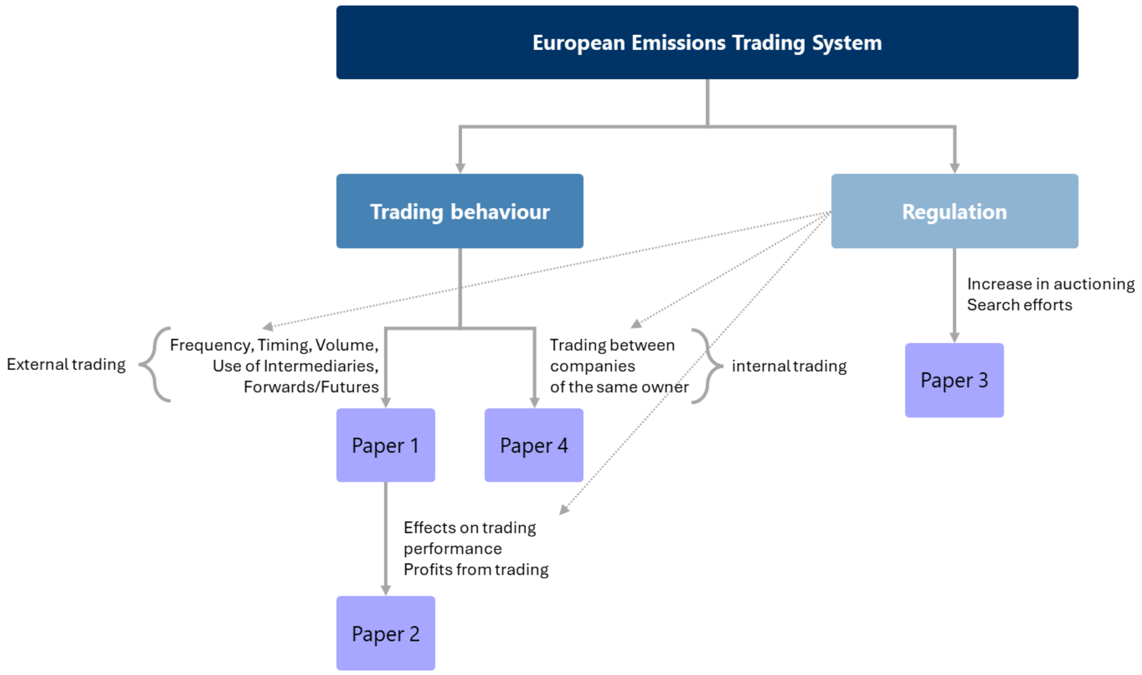
Figure 3 illustrates how the four research papers are conceptually interlinked within the overarching analytical framework of the dissertation. All analyses centre on the EU ETS and are guided by the central research question: "How do transaction costs, company characteristics, and institutional design shape the trading behaviour of regulated companies under the EU ETS?"

Papers 1, 2, and 4 primarily investigate company trading behaviour driven by structural factors and assess the extent to which such behaviour contributes to, or hinders, the cost-effectiveness of the system.

1. Paper 1 lays the empirical foundation by identifying structural and institutional factors influencing companies' participation and trading intensity.
2. Paper 2 explores whether market incentives, particularly trading profitability, encourage strategic engagement and broader use of the EU ETS.
3. Paper 4 extends the analysis to internal trading strategies, examining whether companies seek to reduce transaction costs through intra-group allowance transfers.

In contrast, Paper 3 takes a more regulatory perspective by focusing on the behavioural response to a key institutional change, namely the increase in auctioning, and whether this shift prompts greater search effort and trading activity in the secondary market, possibly affecting transaction costs. Importantly, the regulatory framework examined in Paper 3 also shapes the trading behaviour studied in Papers 1, 2, and 4, underlining the strong influence of policy design on company responses.

Figure 3: Conceptual Structure of the Dissertation and Interlinkages Between Research Papers.



Source: Author's own illustration.

2. Methods

2.1 Datasets, Data Preparation, and Levels of Analysis

The research questions developed in Section 1.3 of this dissertation require a dataset that was not readily available in an existing form. At the time of data collection in 2021, few comparable datasets had been constructed and applied in the literature, and none possessed the same level of integration between physical transaction records and corporate financial data, nor the same analytical potential. The construction of such a dataset therefore constitutes a central component and a distinctive feature of this dissertation.

The empirical analyses draw on a company-level panel dataset covering the period from 2005 to 2017.[4] This dataset was constructed by merging information from two primary sources. First, the European Union Transaction Log (EUTL) provides comprehensive data on verified emissions, free allocations, and all recorded transactions of EU emission allowances under the EU ETS. The EUTL is therefore indispensable for empirically analysing trading activity within the system. Second, the ORBIS database offers detailed company-level information, including financial indicators, industry classification, company size, and ownership structure.

The matching of these two data sources allows for the analysis of emissions trading behaviour at the level of regulated companies, rather than at the installation level. This shift aligns the analytical perspective with the organisational units where strategic decisions are typically made. In particular, the availability of ownership and group structure data in ORBIS makes it possible to aggregate EUTL information beyond the installation or account level and to define company-level variables relevant for the econometric analyses.

The analytical time frame initially covered the period from the launch of the EU ETS in 2005 to 2015 and served as the basis for Paper 1. A subsequent update extended the time frame to April 2017, providing the foundation for Papers 2 to 4. All data are aggregated by "trading year," defined as running from May of year t to April of year t+1. This definition ensures that all transactions associated with compliance for a given calendar year are captured within the same analytical period, as EUAs must be surrendered by the end of April in the following year.

This chapter describes the data collection, matching, and transformation processes used to construct the final dataset. It outlines how transaction-level information was systematically aggregated and how companies were identified and linked across datasets. It also presents the structure of the final dataset used in the multivariate econometric analyses.

[4] The transaction-level data under the EU ETS are published with a delay of at least three years (formerly five), typically between May and June of each year. Accordingly, the dataset used in this dissertation reflected the most recent data available at the time of its compilation in early 2021. Subsequent updates were not implemented due to the cost of accessing the ORBIS database and the substantial effort required for data processing.

2.1.1 The European Union Transaction Log (EUTL)

The EUTL (European Commission, 2024) constitutes the official registry infrastructure of the EU ETS. The EUTL has been operated by the European Commission since 2012, following the replacement of the former Community Independent Transaction Log (CITL) (European Commission, 2012). The CITL, which had been in place since the launch of the EU ETS in 2005, tracked and verified all allowance transactions between regulated entities and national registries to ensure compliance with EU rules. The transition to the EUTL was part of a broader effort to modernise the system and integrate it more effectively with international mechanisms, notably the International Transaction Log (ITL) (UNFCCC, 2024) maintained under the UNFCCC framework.

Since its establishment, the EUTL has served as the central IT infrastructure for monitoring all transactions within the EU ETS, including transfers between regulated companies, issuance of free allocations, surrender of allowances for compliance purposes, and the connection to the Swiss Emissions Trading System. Its comprehensive and standardised structure makes the EUTL the most authoritative source of information on trading behaviour under the EU ETS.

Within the EUTL, three distinct datasets are available, each providing different types of information relevant to analysing emissions trading behaviour:

- **Account Holder Dataset:** This dataset provides information on the identity and type of account holders, including company names, account numbers, and the country of registration.
- **Compliance Dataset:** This dataset contains annual installation-level information on verified emissions, free allocation, and surrendered allowances.
- **Transaction Dataset:** This dataset records all individual transactions of EU allowances between accounts, including information on transaction type, volume, date, and the identities of the transferring and receiving accounts.

At the time of constructing the dataset for this dissertation, the compliance data and the account holder dataset were published annually in May following the compliance cycle and made available as straightforward downloads via the website of the EUTL. In contrast, access to the transaction dataset was subject to a significant time lag: transactions were released with a delay of approximately three years and could only be downloaded in batches of 1,000 records. Given that the full dataset comprises over six million transactions, data extraction involved substantial effort and required the development of automated data retrieval scripts to overcome these restrictions.

In 2024, a new EUTL web interface was launched, significantly improving usability and data accessibility. However, the dataset used in this dissertation was compiled prior to this development and is therefore based on the earlier, more fragmented data retrieval process.

2.1.1.1 Account Holder Dataset

2.1.1.1.1 Account Types, Underlying Logic and Available Information

Trading in EUAs under the EU ETS is, in principle, not restricted to regulated companies. Non-compliance entities, such as financial intermediaries (which are often relevant for risk hedging strategies of compliance entities), as well as companies that treat EUAs as financial assets (e.g. banks or investment funds), and even private individuals, may participate in the market. To accommodate this diversity of actors and functions, the EUTL distinguishes between several account types, each serving specific regulatory and operational purposes:

- **Operator Holding Account (OHA):** Under the EU ETS, each regulated stationary installation is required to hold an OHA. Similarly, aircraft operators must maintain Aircraft Operator Accounts (AOAs). All administrative compliance-related transactions, such as the allocation of free allowances and the surrendering of EUAs for verified emissions, must be conducted through these accounts.
- **Person Holding Accounts (PHAs) and Trading Accounts (TAs):** In contrast, PHAs and TAs (the latter introduced in the third trading period) are available to non-compliance entities, private individuals, and also to regulated companies wishing to operate additional accounts for strategic trading purposes. While both PHAs and TAs allow for the holding and transfer of allowances, they differ in their technical functionality: most notably, TAs enable near real-time trading to accounts not on the trusted account list, whereas PHAs are subject to a security-related time delay of up to 26 hours for such transactions.
- **Administrative accounts:** These are maintained by national registries and EU institutions for purposes such as allocation, auctioning, and the cancellation of allowances.

The majority of PHAs and TAs are opened by non-compliance entities, such as financial intermediaries, but they are also used by compliance entities to manage trading and compliance activities in a more flexible or centralised manner (Betz and Schmidt, 2016; Cludius and Betz, 2020). In addition, some PHAs and TAs are held by non-governmental organisations or private individuals, although access for the latter has been significantly restricted due to tightened security regulations. Figure 4 and Figure 5 illustrate the type of information available for accounts listed in the EUTL. The account type is indicated, e.g. whether it is an OHA, PHA, or TA, as well as the country in which the account is registered. For OHAs, the associated installation is displayed via the installation ID. Additional information includes the name of the account holder and, crucially for the data matching process in this thesis, the company registration number. Moreover, contact information such as main addresses, postal code, city, and country is also recorded.

2.1.1.1.2 Matching of Former and Current Operator Holding Accounts

The migration of data from the CITL to the EUTL was accompanied by structural changes in the registry system, including the introduction of new account types. As part of this reform, each installation was required to be linked to a newly created OHA. However, since the EUTL reports only current registry information and does not document historical changes, it provides only the currently associated OHA for each installation, but not the one in place prior to the registry transition. Therefore, it was necessary to retrospectively identify and reconstruct the former OHAs based on available information.

To achieve this, a stepwise matching procedure was implemented:

- **Name matching**: First, account names were matched to installation names, and matches were accepted if they were unique.
- **Address matching**: Second, account addresses were matched to installation addresses, again accepting only unique matches.
- **Transaction-based matching**: In a third step, allocation information was used. Specifically, data on free allocation and surrendered allowances at the installation level were compared to corresponding transactions involving the same number of allowances and an administrative account from the respective national registry. This step also relied exclusively on unique matches and was applied first to allocation transactions, followed by surrender transactions.

Through this approach, 12,894 out of the 13,001 former OHAs were successfully matched to corresponding accounts in the post-2012 registry structure, resulting in a loss of 107 accounts from the dataset.

2.1.1.2 Compliance Data

The compliance dataset is provided at the installation level (see Figure 6) and contains detailed information on verified emissions, surrendered allowances, and the volume of free allocation received in each year. In addition, it includes a unique installation identifier, information on the installation's location (address), its main activity, the installation name, and the date of inclusion in the EU ETS.

2.1.1.3 Transaction Data

The EUTL records each transaction with detailed information (see Figure 7) on the transferring and acquiring accounts, their respective account types, the date and volume of the transaction, and the transaction type (e.g. free allocation, surrender, bilateral trade, auction). Importantly, the registry does not include transaction prices, nor does it capture futures or forward trading, except at the point of physical delivery. The final raw EUTL dataset used in this dissertation includes more than six million transactions, involving a traded volume of nearly 240 billion EUAs, recorded between 2005 and April 2017. It covers over 40,000 accounts and more than 17,000 installations. After excluding transactions in which both the buyer and the seller were non-compliance entities, the final dataset relevant for the analysis comprises approximately 200 billion allowances traded on the market.

Figure 4: General account information.

General Information							
Account Type	National Administrator	Related Installation/Aircraft Operator ID	Account Holder Name	Account Status	Account Opening Date	Account Closing Date	Company Registration No
Operator Holding Account	Austria	47	AGRANA Stärke GmbH	open	2005-06-16 00:00:00.0		FN 252477 s

Source: Screenshot from the former EUTL website.

Figure 5: Contact details.

Details on Contact Information						
Type	Name	Main Address Line	Secondary Address Line	Postal Code	City	Country
Account holder	AGRANA Stärke GmbH	Friedrich-Wilhelm-Raiffeisen-Platz 1		1020	Wien	Austria

Source: Screenshot from the former EUTL website.

Figure 6: Installation information.

Detailed EU ETS Phase Information - Compliance				
Installation/Aircraft Operator ID	Installation Name/Aircraft Operator Code*	Permit/Plan ID	Permit/Plan Date	Allowance Allocation
1	Baumit Baustoffe Bad Ischl	IKA119	2005-06-01	38416
2	Breitenfelder Edelstahl Mitterdorf	IES069	2005-11-23	13776

Total of Allowances Surrendered**	Total Verified Emissions**	Compliance Code on last 30 April	Account Status
278527	278527	A	open
123705	117319	A	open

Source: Screenshot from the former EUTL website.

Figure 7: Transaction data.

List of Transactions						
Transaction ID	Transaction Type	Transaction Date	Transaction Status	Transferring Registry	Transferring Account Type	Transferring Account Identifier
EU348866	10-2	2016-04-30 22:47:56.704	Completed	France	100	001DSD76353E Cent Therm Arjowiggins Pap Aa
EU348855	10-2	2016-04-30 15:09:14.719	Completed	France	100	SIDEFO

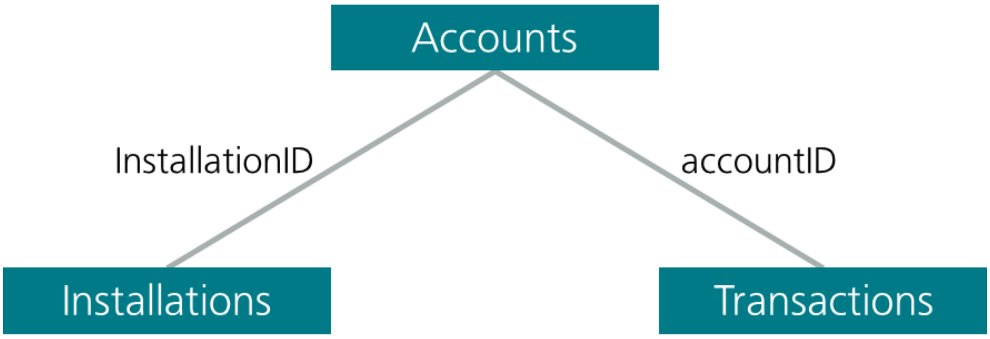
Transferring Account Holder	Acquiring Registry	Acquiring Account Type	Acquiring Account Identifier	Acquiring Account Holder	Nb of units
DALKIA	European Commission	100	EU Allowance deletion	European Commission	24254
SIDEFO	European Commission	100	EU Allowance deletion	European Commission	8794

Source: Screenshot from the former EUTL website.

2.1.1.4 Matching the Three EUTL Datasets

OHAs and installations are linked via a unique installation ID provided in the EUTL, which allows for a direct and reliable match between the compliance data and the account holder information. The matching of transactions to accounts was performed using the account IDs of the transferring and acquiring entities, as recorded in the transaction dataset (see Figure 8).

Figure 8: Relationship of data from the EUTL registry.



Source: Author's own illustration.

The matching of the three distinct datasets from the EUTL results in a transaction-level dataset that includes not only detailed information on the transactions themselves, but also data on the accounts involved and the associated installations.

2.1.2 The ORBIS Company Database

In addition to the EU ETS-related information obtained from the EUTL, this dissertation also utilises financial and structural company data from the ORBIS database, a commercial company-level dataset maintained by Bureau van Dijk (Bureau van Dijk, 2024). ORBIS provides information on the number of employees, total revenues, profits, industry classification (NACE), country of domicile, and corporate as well as ownership structure, including the national and global ultimate owner (NUO and GUO). This ownership information is essential for aggregating the EUTL data, which are originally available only at the account level, to higher organisational levels, such as the company or group level.

The matching of the EUTL and ORBIS datasets was primarily based on the company registration number, which is included in the EUTL account holder information (see Figure 4) and is also available in ORBIS. This unique identifier, in principle, allows for a reliable linkage of EU ETS data to company-level characteristics and ownership structures. However, in practice, direct matching is complicated by inconsistent formatting and reporting errors across the two databases.

To overcome these issues, a fuzzy matching approach was applied using the company registration number, account name, and account contact address. These variables served as input criteria for an automated batch search conducted within ORBIS. The search produced a list of potential matches accompanied by a similarity score. The final selection of the correct match was then conducted manually by evaluating the quality and consistency of the field-level matches across the returned candidates.

2.1.3 Data on EUA Prices: Spot and Futures, and Identification of Futures Trades

Price information on EUAs was collected from two main sources. Daily spot prices were obtained from the European Energy Exchange (EEX), while annual average futures prices were retrieved from the Intercontinental Exchange (ICE). These price data were matched to the transaction data based on the transaction date. Although the EUTL does not record whether a transaction results from a futures or forward contract, futures-based trades can be indirectly identified at the point of physical delivery, i.e. when the underlying allowances are transferred.

To identify transactions resulting from forwards and futures contracts, the approach of Cludius (2018) was followed, focusing on the activity of clearing accounts on typical delivery days. These dates marked the physical delivery of allowances stemming from forward and futures contracts, typically occurring at the end of November for forwards and in mid-to-late December for futures. For transactions on these identified delivery days, the average December one-year futures price of the corresponding year was used to approximate the transaction price for both futures and forwards.

The following delivery dates were identified:

Futures delivery days:

> 21–23 December 2005, 18–22 December 2006, 17–19 December 2007, 15–19 December 2008, 14–18 December 2009, 20–23 December 2010, 20–23 December 2011, 17–21 December 2012, 17–20 and 23 December 2013, 16–19 and 22–23 December 2014, 14–18 December 2015, 19–23 December 2016, and 13–15 and 18–22 December 2017.

Forwards delivery days:

> 30 November and 1 December 2005, 30 November and 1 December 2006, 30 November and 3 December 2007, 28 November and 1 December 2008, 30 November and 1 December 2009, 30 November and 1 December 2010, 30 November and 1 December 2011, 30 November and 3 December 2012, 29 November and 2 December 2013, 28 November and 1 December 2014, 30 November and 1 December 2015, 30 November and 1 December 2016, and 30 November and 1 December 2017.

2.1.4 Preparation of the Data

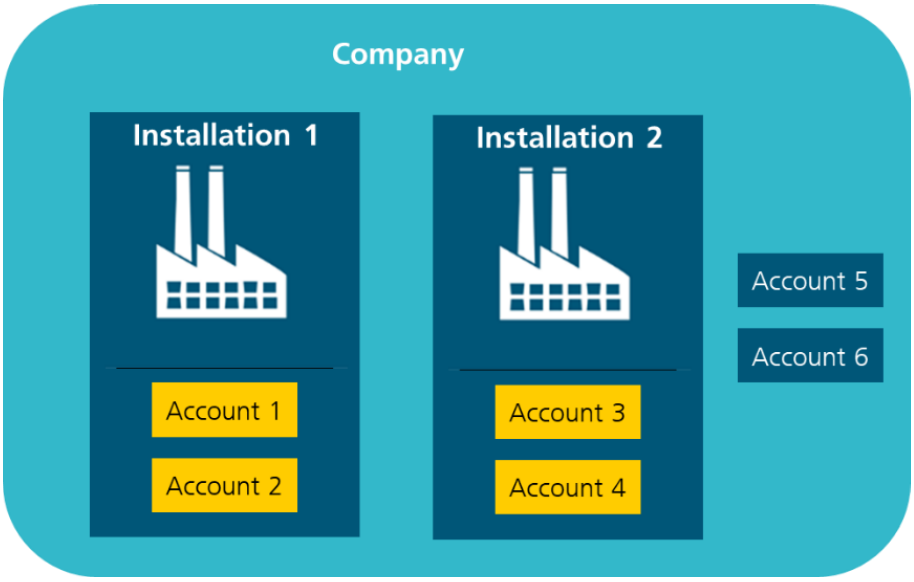
For the empirical analyses, only transactions involving OHAs, PHAs, and TAs were considered. All transactions involving public authorities, such as auctions, free allocation of allowances, or surrendering for compliance, were excluded. These transactions were disregarded because they are driven by regulatory obligations rather than strategic intent, and companies have limited or no discretion over their execution. As such, they are not relevant to the research questions addressed in this study. In addition, transactions between accounts associated with the same installation were excluded. These are assumed to reflect internal organisational transfers rather than strategic trading behaviour and are therefore not considered informative for the analysis.

The total transaction volume in the original database amounted to approximately 200 billion allowances. Around 65% of these transactions were either regulatory in nature or constituted intra-installation transfers. The remaining transaction volume, used for the empirical analysis, comprised approximately 70 billion allowances

In the next step, the transaction-level data were aggregated first to the account level and then, using the ORBIS data, to the company level. Based on this aggregation, a panel dataset was constructed at the level of individual companies by year. Since not all transactions could be linked to an account that was successfully matched to a company in ORBIS, the aggregation process resulted in a loss of approximately 10 billion allowances in traded volume. However, it is assumed that the exclusion of these unmatched transactions does not materially affect the results of the analysis, as matching failures appear unrelated to systematic company characteristics.

Following the aggregation, all non-compliance entities, primarily financial intermediaries, as well as airline operators (included in the system since 2012) were removed from the dataset, as they were not within the analytical scope of this study. Ultimately, a total of 15,014 companies remained in the final dataset.

Figure 9: Data structure and level of aggregation.



Source: Author's own illustration.

Figure 9 illustrates the final data structure. The lowest level of aggregation captures individual transactions. By summing all eligible transactions involving a specific account (i.e., excluding intra-installation transfers), data were aggregated to the account level (e.g. all transactions carried out by Account 1).

To aggregate data at the installation level, all accounts associated with a given installation were combined. For instance, in Figure 9, the total transaction volume of Installation 1 would include all transactions carried out by Account 1 and Account 2.

At the company level, transactions from all installations belonging to the same company were aggregated (Installation 1 and Installation 2). In addition, transactions from accounts not linked to any specific installation, such as PHAs or TAs, were also included in this aggregation. These accounts were assigned to the respective company via the company registration number and account holder name, as described in the matching procedure. These are represented by Accounts 5 and 6 in Figure 9.

2.1.5 Levels of Analysis

The matching between EUTL and ORBIS companies enables the construction of different levels of analysis based on the ownership structure provided in ORBIS (see Table 1). The lowest level of analysis, denoted as L0, corresponds to the account level, as directly observed in the EUTL.

The company level, denoted as L1, refers to the aggregation of all accounts and installations held by a single legal entity. A company may participate in allowance trading either through OHAs linked to its installations or through additional PHAs and TAs.

The ORBIS database also provides ownership information beyond the individual company. Level L2 captures the national ownership level, where several legally distinct companies, each potentially operating one or more installations, are held by the same national ultimate owner (NUO).

Finally, Level L3 refers to the global ownership level, which includes transnational corporate structures where companies in multiple countries participating in the EU ETS are owned by the same global ultimate owner (GUO).

Table 1: Possible Aggregation Levels According to Ownership Structure.

Ownership Level	Explanation
L0	Accounts as observed in the EUTL
L1	Company level
L2	National owner
L3	Global owner

The analysis in this dissertation is conducted at Level L1, implicitly assuming that companies act independently in their decisions regarding the transfer and trading of allowances. To the best of the author's knowledge, this study is among the first to perform a systematic analysis at the company level (L1). Existing literature has predominantly focused on the installation level (e.g. Betz and Schmidt, 2016), the NUO-level (e.g. Jaraitė-Kažukauskė and Kažukauskas, 2015), or the GUO-level, which is the most common aggregation level in prior studies.

2.1.6 Limitations and Data Loss

Some degree of data loss was unavoidable during the matching and aggregation processes. Approximately 10 billion allowances were associated with accounts that could not be linked to identifiable companies in the ORBIS database. In addition, for many matched companies, ORBIS did not provide sufficient financial information. As a result, some companies had to be excluded from parts of the regression analyses.

Beyond matching limitations, several restrictions arose due to data availability:

- The analysis of forwards and futures relied on typical delivery dates, as the EUTL does not explicitly indicate contract types.
- Reported prices reflect daily spot prices observed on exchanges rather than the actual transaction prices, which remain unobservable. This approximation may lead to measurement errors, particularly for OTC contracts concluded in advance at prices diverging from the spot rate at delivery.
- Information on banked allowances, i.e., allowances carried over from previous years, was difficult to construct consistently. Data inconsistencies occasionally resulted in implausible banking stocks, including negative banking stock values, which are not permissible under the EU ETS. These anomalies likely stem from ownership changes at the installation level without corresponding updates to the associated accounts, as well as from complications during the migration of registry data from the CITL to the EUTL. Therefore, observations with negative banking stocks were excluded from the analysis to ensure data validity.

Despite these limitations, the resulting dataset represents a sufficiently large and diverse sample of regulated companies, providing a robust foundation for the empirical analysis.

2.2 Variables used in the Empirical Analysis

To address the four research questions outlined in Section 1.3, a range of variables was developed from the dataset. Some of these serve as dependent variables, others as independent variables, and some appear in both roles, depending on the research question.

2.2.1 Dependent Variables

In total, seven dependent variables were employed across the four research questions. The selection of each variable was guided by the specific context of the corresponding research question. Three types of variables were used: (1) variables reflecting trading volume, (2) variables capturing the monetary value of traded volumes, and (3) variables indicating how frequently certain trading channels or partners were used.

Volume Variables:

- *Total Transactions* (Paper 1): Defined as the total volume of EUAs traded by a company in a given year.
- *Use of Forwards and Futures* (Paper 1): Defined as the volume of EUA trades classified as forward or futures contracts executed by a company in a given year.

Monetary Variables:

- *Profits* (Paper 2): Defined as the total value of EUA sales minus the total value of EUA acquisitions by a company in a given year. The value of each transaction was calculated by multiplying the quantity of allowances by the applicable market price, using spot prices for spot trades and futures prices for deliveries under forward or futures contracts.
- *Internal Trading Value* (Paper 4): Defined as the volume of EUA transactions con-ducted between companies belonging to the NUO, multiplied by the respective annual average spot price to obtain a monetary value.

Count Variables:

- *Transaction Frequency* (Paper 1 and Paper 3): Defined as the number of individual trades conducted by a company in a given year.
- *Use of Intermediaries* (Paper 1): Defined as the number of distinct financial intermediaries a company traded with in a given year. Intermediaries were identified based on specific NACE codes associated with the financial sector.
- *Number of Trading Partners* (Paper 3): Defined as the number of distinct counterparties a company traded with in a given year.

2.2.2 Covariates

The covariates defined and employed in this dissertation can be grouped into several categories. First, variables directly related to the allocation mechanisms, particularly free allocation, over which companies have only limited control. Second, variables reflecting strategic behaviour, such as the number of transactions, the use of intermediaries, or banking activities. Third, structural characteristics, including the number of installations or employees. Fourth, market-related factors, such as exposure to international competition, captured through carbon leakage status. Fifth, sector affiliation, and sixth, temporal and regional fixed effects.

Allocation and Position:

- *Net Position*: Difference between allocated EUAs and verified emissions in year t (in metric tons of CO_2eq).
- *Net Sellers*: Dummy variable equal to 1 if *net position* is > 0.
- *Net Position Value*: Net position multiplied by the annual average EUA price in year t.
- *Internal Trading Potential*: Absolute difference between a company's net position and that of its NUO group.

Strategic Behaviour:

- *Total Transactions*
- *Transaction Frequency*
- *Use of Intermediaries*
- *Use of Forwards and Futures*
- *Banking*: Allocation plus acquisitions minus verified emissions and transfers in year t (in metric tons of CO_2eq).
- *Banking Stock Value (t–1)*: Lagged banking stock including adjustments, multiplied by the EUA price in year t.
- *Late Buyers*: Number of EUA acquisitions made in January to April of the trading year.
- *Late Sellers*: Number of EUA transfers made in January to April of the trading year.

Structural Characteristics:

- *Employees*: Number of employees in the respective year.
- *Productivity*: Revenue per employee.
- *Installations*: Number of installations operated by the company.
- *Number of NUO Companies*: Total number of companies held by the NUO of a company.

Market Conditions:

- *Carbon Leakage*: Dummy variable equal to 1 if the company is part of a sector classified as at risk of carbon leakage under EU ETS rules.

Sector Classification:

- *Energy:* Dummy variable equal to 1 if the company is classified in the energy sector (NACE Rev. 2: 35.00–35.30).

Based on EUTL activity codes, distinguishing sectors:

- *Combustion*
- *Refining*
- *Steel*
- *Non-ferrous metals*
- *Lime and cement*
- *Glass*
- *Ceramics*
- *Mineral wool*
- *Gypsum and plasterboard*
- *Pulp and paper*
- *Chemicals*
- *Other industrial activities*

Time and Regional Controls:

- *Trading Periods*: Dummy variables for each EU ETS trading period (with Period I as the reference).

Region Dummies: Dummies for the following European regions to control for geographical heterogeneity (based on Jaraitė-Kažukauskė and Kažukauskas (2015)):

- *Region 1*: Austria (AT), Germany (DE), Liechtenstein (LI)
- *Region 2*: Belgium (BE), France (FR), Netherlands (NL)
- *Region 3*: Greece (GR), Cyprus (CY), Spain (ES), Italy (IT), Malta (MT), Portugal (PT)
- *Region 4*: Estonia (EE), Lithuania (LT), Latvia (LV), Poland (PL)
- *Region 5*: Czech Republic (CZ), Hungary (HU), Slovenia (SI), Slovakia (SK)
- *Region 6*: Denmark (DK), Finland (FI), Iceland (IS), Norway (NO), Sweden (SE)
- *Region 7*: United Kingdom (UK), Ireland (IE)
- *Region 8*: Bulgaria (BG), Croatia (HR), Romania (RO)

2.3 Econometric Methodologies

To empirically address the four research questions posed in this dissertation, four distinct econometric model types were applied, each selected to match the characteristics of the dependent variable and the specific analytical challenge of the respective study. These models (double-hurdle, Poisson, Heckman selection, and Tobit) are applied across Research Questions 1 through 4 based on the specific nature of the dependent variable in each paper.

All models are estimated using annual company-level panel data covering the period 2005 to 2017 (2005-2014 in Paper 1) and consistently employ the correlated random-effects (CRE) estimator proposed by Mundlak (1978) to account for time-invariant unobserved heterogeneity across companies. This modelling choice is particularly important because standard fixed-effects approaches are not suitable for these non-linear panel models and may suffer from the incidental-parameters problem, potentially leading to biased and inconsistent estimates when the time dimension is limited.

While all chosen models rely on parametric assumptions and thus impose structural restrictions on the data-generating process, their main strengths lie in their conceptual clarity, transparency, and direct interpretability regarding the investigated behavioural mechanisms. Their primary limitations result from sensitivity to distributional assumptions and potential model specification errors, which are addressed through extensive robustness checks and careful interpretation of the results. Detailed methodological discussions and model-specific justifications are provided in the respective papers.

2.3.1 Double Hurdle Models

Paper 1 investigates the determinants of trading participation and trading intensity among regulated companies in the EU ETS. Two of the four dependent variables, *total transactions* and *use of forwards and futures*, can take values ranging from zero to very large numbers and feature a substantial share of zero observations (approximately 44% and 90%, respectively). These zero values are interpreted as corner solutions that reflect deliberate company-level decisions not to participate in the emissions or derivatives markets.

To appropriately model this two-stage decision process, the paper applies double-hurdle models in the tradition of Cragg (1971), as adapted to the EU ETS context by Jaraitė-Kažukauskė and Kažukauskas (2015). This choice is methodologically justified, as the double-hurdle framework is specifically designed for situations where zero outcomes represent genuine economic decisions. In contrast, the Heckman selection model is intended for cases in which the outcome variable is unobserved for a non-random subset of observations, rather than being observed as zero.

The double-hurdle framework separates the outcome into two analytically distinct components:

- **Participation decision**: Whether a company engages in emissions trading at all, estimated using a Probit model.
- **Intensity decision**: Conditional on participation, the volume of emissions trading, estimated using a truncated regression model.

In the applied double-hurdle model, the first stage estimates the probability of participation using a binary Probit model, while the second stage estimates trading intensity using a truncated regression model. The advantage of this approach over standard censored Tobit models is its less restrictive distributional assumptions; specifically, participation and trading intensity are not assumed to be driven by the exact same process, which allows the coefficients of identical covariates to differ in sign or magnitude across the two stages. Furthermore, the model specification used allows for correlation between the error terms of the two stages. These features provide deeper insights into the distinct drivers of participation and trading intensity. However, it is acknowledged that the model still imposes distributional assumptions on the error terms (e.g. bivariate normal distribution for the error terms), which represents a primary limitation of the double-hurdle framework. For a detailed description and discussion of the methodological approach, see Chapter 6.2.3.

Formally, the participation equation is given by:

$$D_{it} = \begin{cases} 1 \; if \; D_{it}^* > 0 \\ 0 \; otherwise \end{cases} \tag{1}$$

$$D_{it}^* = x_{it}\boldsymbol{\beta} + z_i\boldsymbol{\gamma} + \alpha_{1,i} + \varepsilon_{1,it} \tag{2}$$

where D_{it} is an indicator variable capturing whether company i participates in an emissions trading activity at time t or not. D_{it}^* is a latent (unobserved) variable reflecting company i's net benefits derived from an emissions trading activity such as buying and selling EUAs. x_{it} is a vector of time-varying explanatory variables such as verified emissions. z_i is a vector of time-invariant explanatory variables such as sector affiliation. $\alpha_{1,i}$ denotes time-invariant company-specific unobservable factors such as company culture and $\varepsilon_{1,it}$ is an idiosyncratic error term with $\varepsilon_{1,it} \sim N(0,1)$.

The intensity decision is specified as:

$$Y_{it}^{*} = max\ (Y_{it}^{**}, 0) \tag{3}$$

$$Y_{it}^{**} = x_{it}\boldsymbol{\delta} + z_i\boldsymbol{\theta} + \alpha_{2,i} + \varepsilon_{2,it} \tag{4}$$

where Y_{it}^{**} indicates company i's desired level of the emissions trading activity at time t, $\alpha_{2,i}$ captures time-invariant company-specific unobservable factors, and $\varepsilon_{2,it}$ is an idiosyncratic error term with $\varepsilon_{2,it} \sim N(0, \sigma_{\varepsilon 2}^2)$.

Finally, the empirical specification of the double-hurdle model allows for non-zero correlation between the participation and intensity equations. The panel double-hurdle model is estimated using the *bootdhreg* command developed by Engel and Moffatt (2014) for Stata, which provides bootstrapped standard errors for robust inference.

2.3.2 Poisson Models

Poisson panel models allow analysis of count outcome variables, i.e., non-negative integers that reflect the frequency of discrete events. In the context of this dissertation, the following dependent variables fall into this category:

- *Use of intermediaries (Paper 1)*
- *Transaction frequency (Papers 1 and 3)*
- *Number of trading partners (Paper 3)*

For these right-skewed variables with a mode at zero, Poisson models offer clear advantages over linear or Tobit specifications. Linear models may predict negative values and misrepresent the distribution, while Tobit models treat zeros as censored rather than genuine outcomes. Poisson regression explicitly models count data, ensures non-negative predictions, and provides consistent estimates under the assumption of equidispersion. However, even when the equidispersion assumption is violated (overdispersion), the Poisson model is frequently preferred for inference on the conditional mean because it functions as a Quasi-Maximum Likelihood Estimator (QMLE). This means its estimates for the conditional mean remain consistent, provided the mean function is correctly specified and standard errors are robustly clustered. Its exponential mean function ensures strictly positive predicted values and accommodates the rapidly declining probability of higher count outcomes. For a detailed description and discussion of the methodological approach, see Chapter 6.2.3 and Chapter 8.3.3.

The probability of observing j transactions is modelled as:

$$\Pr(y_{it} = j | x_{it}, z_i, \alpha_{3,i}; \boldsymbol{\zeta}, \boldsymbol{\pi}) = \frac{[\exp(-\lambda_{it})](\lambda_{it})^{y_{it}}}{y_{it}!} \qquad \text{for } j=0,1,2,... \tag{5}$$

where $x_{it}$is a vector of time-varying explanatory variables such as free allocation or verified emissions, z_i is a vector of time-invariant explanatory variables such as carbon leakage or sector affiliation, α_i captures time-invariant company-specific unobservable factors such as company culture, and $\boldsymbol{\zeta}$ and $\boldsymbol{\pi}$ are vectors of parameters. Finally, λ_{it} denotes the conditional mean and the conditional variance of y_{it} and is modelled as:

$$\lambda_{it} = \exp\left(x_{it}\boldsymbol{\zeta} + z_i\boldsymbol{\pi} + \alpha_{3,i}\right) \tag{6}$$

Estimation is performed using the *xtpoisson* procedure in Stata, which implements maximum likelihood estimation. Standard errors are clustered at the company level to account for within-company correlation over time.

2.3.3 Heckman Selection Models

Paper 2 investigates the determinants of monetary trading success under the EU ETS. The methodological challenge arises from the fact that profits from trading are only observed for companies that actively participate in the market. For non-participating companies, representing approximately 44% of the observations, no profit data are available, not due to missingness at random but due to endogenous selection. Ignoring this non-random selection would result in biased and inconsistent estimates.

To address the issue of potential selection bias, a two-stage selection model adapted for panel data is employed. This framework is methodologically critical, as the outcome (profit) is unobservable for non-participants (incidental truncation), in contrast to the volume in Paper 1, which represents an observable corner solution. It jointly models (1) the company's decision to participate in trading and (2) the resulting trading profits, using full maximum likelihood estimation implemented via the *xtheckman* command in Stata 18. Compared with linear models, which often assume the outcome variable is observed for all units, or Tobit models, which handle censoring but may not explicitly model the selection process leading to zero outcomes, the Heckman selection model corrects for potential sample selection bias by explicitly modelling the participation process. While double-hurdle models, such as the one used in Paper 1, can also allow for dependence between the participation and outcome stages, the Heckman framework specifically models this through potential correlation between the error terms and panel-level random effects of both stages. This feature explicitly captures unobserved factors jointly influencing both participation and trading success, such as managerial ability or risk attitude, thereby aiming to improve the consistency and efficiency of the estimates. For a detailed description and discussion of the methodological approach, see Chapter 7.2.3.

Participation in trading is modelled as a latent decision process:

$$D_{it} = \begin{cases} 1 \; if \; D_{it}^{*} > 0 \\ 0 \; otherwise \end{cases} \tag{7}$$

$$D_{it}^{*} = v_{it}\delta + w_{i}\theta + \alpha_{1,i} + \varepsilon_{1,it} \tag{8}$$

where v_{it} denotes the time-varying covariates such as *net position,* w_i reflects time-invariant covariates, $\alpha_{1,i}$ captures time-invariant company-specific unobservable factors (i.e. the panel-level random effect for selection) such as company culture, and $\varepsilon_{1,it}$ stands for the idiosyncratic error in the participation equation.

Profits from trading, conditional on participation, are modelled as:

$$Y_{it} = x_{it}\beta + z_{i}\gamma + \alpha_{2,i} + \varepsilon_{2,it} \tag{9}$$

where Y_{it} reflects company i's level of profits from trading at time t, x_{it} denotes time-varying covariates (including the share of companies participating in emissions trading at the country level), z_i captures time-invariant covariates, $\alpha_{2,i}$ captures time-invariant company-specific unobservable factors (i.e. the panel-level random effect for the outcome), and $\varepsilon_{2,it}$ is the idiosyncratic error term in the outcome equation.

This estimation strategy provides a more robust treatment of selection bias compared to prior research in the EU ETS context (e.g. Cludius 2018; Liu et al. 2017; Guo et al. 2020), and yields new insights into the characteristics of companies that successfully profit from carbon trading.

2.3.4 Tobit Models

Paper 4 examines how companies use internal allowance trading as a strategy to reduce external transaction costs under the EU ETS. The empirical analysis focuses on companies that are organisationally capable of internal trading, specifically, those with at least one additional affiliated company under the same NUO.

The dependent variable is the monetary value of internal trading, observed annually at the company level. In 97% of all company-year observations, this value is zero, reflecting deliberate decisions not to engage in internal transactions. These zeros are interpreted as corner solutions, making standard linear models inappropriate for such outcomes, which are modelled as censoring at zero within the Tobit framework.

In principle, the structure of the outcome variable would be well suited to a double-hurdle model, which explicitly separates the participation and intensity decisions. The double-hurdle model represents the theoretically superior choice, as it better captures the complex decision structure. However, due to convergence issues in the estimation process, the double-hurdle specification could not be applied robustly in this context. Therefore, a Tobit model is employed as a methodologically tractable and widely used framework for modelling corner solutions. It allows for the application of a Correlated Random Effects estimator to control for unobserved heterogeneity, which is necessary for panel analysis. For a detailed description and discussion of the methodological approach, see Chapter 9.2.3.

The Tobit model is specified as follows:

$$\begin{aligned} y_{it}^* &= x_{it}\beta + z_i\gamma + \alpha_i + \varepsilon_{it} \\ y_{it} &= y_{it}^* \ if \ y_{it}^* \geq 0 \\ y_{it} &= 0 \ if \ y_{it}^* < 0 \end{aligned} \tag{10}$$

where y_{it}^* denotes company *i*'s latent (unobserved) level of *internal trading* at time t, y_{it} stands for company *i*'s observed level of *internal trading* at time t, x_{it} represents time-varying covariates such as *internal trading potential*, z_i reflects time-invariant covariates such as *number of NUO companies* or *energy*, α_i captures time-invariant, company-specific unobserved factors (i.e., the panel-level random effect), and ε_{it} is the idiosyncratic error term. Standard errors are clustered at the company level.

All continuous variables are log-transformed to mitigate the influence of outliers and enable elasticity-based interpretation of coefficients. In contrast, count and dummy variables (e.g. *number of installations*, *carbon leakage* status) remain in their original form. Estimation is conducted via maximum likelihood, and standard errors are clustered at the company level to account for within-entity correlation over time.

This approach allows for robust estimation of the structural drivers of internal trading and yields insights into the extent to which companies strategically reduce transaction costs by reallocating allowances within their corporate group.

The empirical analysis relies on two distinct identification strategies to establish causality for the key covariate, the *Internal Trading Potential (ITP)*.

General Identification: For the full sample including all installation types, identification relies on the assumption that *ITP* is exogenous conditional on the observed covariates. This assumption is plausible given that *ITP* is primarily determined by the allocation rules specified in the EU Emissions Trading Directive, which are externally imposed on companies and not determined by the companies themselves.

Quasi-Experimental Identification: For a subsample of companies operating combustion installations, the analysis exploits the allocation reform introduced in the third trading period (2013) as a quasi-experiment. Before 2013, combustion installations in both the energy and industry sectors were subject to identical allocation rules. From 2013 onwards, combustion installations in the energy sector (Treatment Group) effectively ceased receiving free allowances, while those in the industry sector (Control Group) continued to receive them. While this Quasi-Experimental Identification design significantly strengthens causal inference, the necessary restriction to a small subsample entails a risk of reduced statistical power, a key limitation that must be acknowledged.

To capture the causal effect of this policy change on the relationship between *ITP* and *internal trading*, the model is extended to include a triple interaction term:

$$y_{it}^{*} = \delta_1 Period\ 3_t + \delta_2(Period\ 3_t \times ITP_{it}) + \delta_3(Period\ 3_t \times energy) + \delta_4(energy_t \times ITP_{it}) + \delta_5(Period\ 3_t \times energy \times ITP_{it}) + \tilde{x}_{it}\tilde{\beta} + z_i\gamma + \alpha_i + \varepsilon_{it}. \qquad (10')$$

This setup mimics a Difference-in-Differences (DiD) framework with a continuous treatment effect. It tests the hypothesis that the removal of free allocation for the energy sector alters the effect of *ITP* on *internal trading* compared to the control group. In non-linear models like Tobit, the coefficient of the interaction term does not directly reflect the marginal effect of the interaction. Instead, the magnitude and significance of the interaction effect depend on the levels of all covariates. Therefore, standard t-tests on the interaction coefficient are insufficient. To rigorously interpret the results, the analysis focuses on the marginal effects of the interaction between the reform period, sector affiliation, and *ITP*.

2.4 Overview of Methods Applied

To improve clarity, Figure 10 provides an overview of all variables and estimation methods used, including their assignment to the four research questions (RQ1–RQ4). It summarises the methodologies introduced in Sections 2.2 to 2.3, by indicating preferred specifications (green) and robustness checks (yellow), as well as the estimation strategies applied for each dependent variable.

Figure 10: Overview of variables, estimation Methods, and their assignment to research questions.

Category	Variables	RQ1	RQ2	RQ3	RQ4
Dependent variables	*Total Transactions*	DH			
	Transaction Frequency	P		P	
	Use of Intermediaries	P			
	Use of Forwards and Futures	DH			
	Profits		H		
	Number of Trading Partners			P	
	Internal Trading Value				T
Covariates					
Allocation and Position	*Net Position*				
	Net sellers				
	Net Position Value				
	Internal Trading Potential				
Strategic Behaviour	*Total Transactions*				
	Transaction Frequency				
	Use of Intermediaries				
	Banking				
	Banking Stock Value				
	Late Buyers				
	Late Sellers				
Structural Characteristics	*Employees*				
	Productivity				
	Installations				
	Number of NUO Companies				
Market Conditions	*Carbon Leakage*				
Sector Classification	*Energy*				
	EUTL activity codes				
Time and Regional Controls	*Trading Periods*				
	Regions				

DH Double Hurdle
P Poisson
H Heckman Selection
T Tobit

Preferred specification
Robustness checks

Source: Author's own illustration.

3. Results

3.1 Research Question 1: *How do the characteristics of individual companies and institutional features of the EU ETS influence companies' participation and intensity in emissions trading?*

Paper 1 investigates how structural company characteristics and institutional features of the EU ETS shape the participation and trading intensity of regulated companies. The analysis draws on data from 2005 to 2014 and examines four key indicators of trading behaviour: total transaction volume, transaction frequency, use of intermediaries, and participation in the forwards and futures market.

The analysis is based on the dataset described in Section 2.1. The empirical strategy combines three modelling approaches: full-sample estimation, disaggregated models by trading period, and specifications with interaction terms that distinguish between net buyers and net sellers to test for the behavioural asymmetry that may challenge the independence property of the Coase Theorem (Coase, 1960). The estimations rely on double-hurdle models (see Section 2.3.1) for total transaction volume and derivatives use, and Poisson models (see Section 2.3.2) for transaction frequency and use of intermediaries.

The results (for detailed results and a discussion of the literature, see the results chapter in Paper 1, Section 6.3) show that participation and intensity in the EUA market are systematically linked to company-level characteristics. Companies with more unbalanced net positions are more likely to engage in trading and to do so more actively. Sector affiliation also matters: energy-sector companies and those classified as at risk of carbon leakage are consistently more active than their counterparts. Size effects are likewise important; companies with a larger number of employees or installations are more involved in allowance trading, though the magnitude of these effects varies by indicator and trading period. While productivity is generally positively correlated with trading intensity, its explanatory power is less consistent.

A disaggregated view across trading periods reveals distinct temporal patterns. Trading activity increased substantially in the second and third trading periods compared to the first. This increase is likely attributable to a combination of the post-2008 economic environment and institutional reforms introduced in 2013, including the shift to auctioning in the power sector. During the third period, intermediary use and derivatives trading became more prevalent, particularly among energy companies facing higher compliance costs.

Evidence on transaction costs is mixed. While the number of employees was a significant driver of trading in earlier periods, it lost significance in the third period, suggesting a possible reduction in size-related frictions. In contrast, the number of installations remains a consistent positive driver, indicating persistent search and information costs. This supports the view that emissions trading entails transaction costs, which are not fully mitigated over time.

A key contribution of the analysis lies in identifying a behavioural asymmetry between net buyers and net sellers. Companies in deficit positions are significantly more active in trading than those holding a surplus. This pattern may reflect bounded rationality, loss aversion, specific accounting rules, or institutional incentives that make compliance risks more salient than trading opportunities. The persistence of this asymmetry across trading periods challenges the validity of the independence property of the Coase Theorem (Coase, 1960), which assumes that, in the absence of transaction costs, the initial allocation of allowances should not affect market outcomes.

The findings are robust across alternative model specifications. They offer key implications for EU ETS design and governance. They support the shift towards full auctioning, showing that free allocation can lead to behavioural asymmetries and reduce allocative efficiency. Instruments like consignment auctions, where monetised allowances return revenue to holders, may internalise opportunity costs and promote participation. The analysis also identifies persistent transaction cost barriers for smaller companies and those with few installations. These could be mitigated through innovations such as a public electronic bulletin board to lower participation costs. For a detailed summary, see Section 6.4.

3.2 Research Question 2: *How do institutional framework, company characteristics and trading strategies influence companies' profits from allowance trading under the EU ETS?*

Paper 2 examines the determinants of company-level profits from emissions allowance trading under the EU ETS, drawing on data from 2005 to 2017 (see Section 2.1). The analysis investigates how the institutional context, structural characteristics, and trading strategies influence financial outcomes from trading. It introduces profits from trading as a performance metric and applies a panel Heckman selection model (see Section 2.3.3) to account for potential selection bias related to trading participation.

A central finding is the strong and positive relationship between a company's net position and trading profits. An increase in the net position is associated with higher profits from trading, underlining the central role of allocation. This finding is consistent with Paper 1 and confirms that allocation mechanisms significantly affect market behaviour and company performance.

Strategic trading behaviour also plays a crucial role. Banking of allowances, i.e., the decision to retain EUAs for future use or sale, is associated with lower profits from trading in the respective year. Furthermore, the similarity in the magnitude and the opposite sign of the net position and banking coefficients provides empirical evidence that companies account for the opportunity costs of holding allowances efficiently. This intertemporal optimisation reflects behaviour consistent with cost-effective emissions trading (Rubin, 1996), a dimension largely absent from previous empirical studies.

The timing of trading emerges as another relevant factor. In the first EU ETS period, purchasing EUAs during the true-up period, after the publication of verified emissions data, was associated with increased profitability, whereas selling during this period tended to reduce profits. These patterns suggest that market participants responded to information frictions and compliance deadlines, pointing to inefficiencies during the system's early years. Over time, however, these timing effects diminished, indicating growing market maturity and learning among participants. Nevertheless, the results are inconsistent with semi-strong market efficiency (Fama, 1970) during the system's early years.

In contrast, transaction frequency and use of intermediaries do not consistently correlate with profits. While more active trading and the use of brokers might imply better market access or strategic positioning. Trading volume, too, is not significantly associated to profits from trading, suggesting that trading magnitude alone does not guarantee success.

Among structural characteristics, only the number of installations shows a consistent and significant correlation with profits from trading. This indicates that multi-site companies may benefit from internal economies of scale, such as centralised compliance units or broader information flows, while other characteristics like sector affiliation, company size, and productivity do not exhibit significant explanatory power in this context. Thus, while trading volume itself does not drive profits, structural scale appears to be beneficial. Furthermore, the analysis finds no robust evidence that companies at risk of carbon leakage realise more profits from trading. This finding challenges the assumption that international competition drives more strategic behaviour, although it is important to note that the binary regulatory status used in the analysis may only imperfectly capture the actual intensity of competitive pressure.

Robustness checks confirm the stability of the main results across specifications. For detailed results, a discussion of the findings in the context of the literature, and robustness checks, see the results chapter in Paper 2, Section 7.3.

The findings offer several implications for emissions trading design. Efficient banking behaviour highlights the value of maintaining unrestricted banking to enhance cost-effective compliance. Regarding the timing of trading, the analysis shows that initial inefficiencies diminished over time, suggesting that market participants have successfully adapted their strategies through learning. Nevertheless, maintaining these strategic capabilities remains essential as EUA prices rise and compliance costs increase. Moreover, larger companies with more installations tend to profit more, suggesting returns to structural scale and the importance of operational trading capacity. To support smaller emitters, policymakers could promote collaborative solutions such as shared trading platforms. Overall, policy frameworks should combine market flexibility with targeted support to enable broader, strategic participation in emissions trading systems.

3.3 Research Question 3: *How do changes in companies' compliance costs, induced by increased auctioning under the EU ETS, affect their search efforts in the secondary market?*

Paper 3 investigates how changes in companies' compliance costs, specifically those resulting from the shift from free allocation to increased auctioning, affect search behaviour in the secondary market under the EU ETS. The analysis focuses on two proxies for search effort: the number of distinct trading partners and the frequency of transactions. It employs Poisson panel regression models (see Section 2.3.2), using a dataset covering the years 2005 to 2017 (see Section 2.1).

A central finding is that companies with more negative net positions, i.e., those with greater financial exposure to compliance obligations, engage more actively in the secondary market. Both the number of trading partners and transaction frequency increase with the monetary size of the net position. Although the absolute effect sizes are modest, the results are statistically robust and consistent with the theoretical search model developed in the paper, inspired by Stigler (1961), which predicts greater search effort when the monetary stakes are higher. These findings contribute to a better understanding of transaction costs in emissions trading and complement the insights of Paper 1.

In contrast, the banking stock, defined as the monetary value of previously banked allowances, shows no clear influence on search effort. A weak but significant association is found with the number of trading partners, but not with transaction frequency. Given the limitations of accurately tracking banked EUAs in the EUTL dataset, this result should be interpreted with caution. Indeed, alternative specifications using flow-based banking measures do not yield a statistically significant association, thereby corroborating the overall conclusion that banking has no clear influence on search effort.

Structural company characteristics also play an important role. In particular, the number of installations is positively and significantly associated with both proxies of search effort. This suggests that companies running more installations are better equipped to manage complex trading networks and to participate more efficiently in the market, potentially due to greater internal capacity, experience, or compliance infrastructure. These findings align with those presented in Paper 1. Other variables, such as carbon leakage status, do not significantly influence search behaviour. This challenges the assumption that international competitive pressure systematically leads to more sophisticated or intensive engagement in emissions markets.

Temporal patterns reveal a marked increase in search activity from the first to the second and third trading periods. Activity levels were highest in the second period. Consistent with interpretations in Paper 1, this peak likely reflects learning effects and regulatory reforms.

Robustness checks using alternative model specifications confirm the validity of the main findings. For detailed results, a discussion of the findings in the context of the literature, and robustness checks, see the results chapter in Paper 3, Section 8.4.

The findings have important implications for the design of emerging emissions trading systems in countries such as China, Türkiye, Vietnam, and Colombia. They suggest that increased auctioning does not significantly raise search-related transaction costs and may therefore facilitate more efficient market outcomes. This evidence supports the introduction of a substantial share of auctioning from the outset. In the EU context, these insights are timely in light of the gradual phase-out of free allocation under the CBAM. However, the allocative efficiency of auctioning depends on careful design. Thus, while auctioning can enhance efficiency, it should be implemented alongside supportive measures and broader market safeguards.

3.4 Research Question 4: *To what extent do companies exploit their potential for internal EUA trading, and which factors are associated with the use of this strategy under the EU ETS?*

Paper 4 investigates the extent to which companies regulated under the EU ETS exploit the potential for internal emissions allowance trading and identifies the factors associated with this strategy. Internal trading, defined as the reallocation of allowances between companies within the same National Ultimate Owner (NUO), is theoretically an effective means of reducing transaction costs by avoiding external market participation. The analysis combines descriptive statistics, to assess the prevalence of internal trading, with panel Tobit models (see Section 2.3.4), to identify its determinants using data from 2005 to 2017 (see Section 2.1). Crucially, the econometric strategy incorporates a standard Tobit approach and a quasi-experimental design based on a Difference-in-Differences logic to establish the causal effect of the internal trading potential.

The descriptive findings reveal that internal trading remains a relatively marginal phenomenon. Out of 2,507 companies in the final sample, only 260 (around 10.4%) conducted any internal transfers over the 13-year observation period. Even among companies with a positive internal trading potential (ITP), i.e. a theoretical potential to balance net positions internally, only 17% engaged in such trades in any given year. Interestingly, internal transactions also occur when ITP equals zero, suggesting that motives beyond balancing emissions positions, such as profit shifting or centralised compliance management, may be driving these transfers. A sectoral perspective shows that energy companies are more likely to make use of internal trading than industry companies. This pattern likely reflects greater experience with market-based instruments, more centralised organisational structures, and a higher degree of familiarity with trading processes within the energy sector (for a detailed descriptive statistical analysis, see Section 9.3.1).

The multivariate econometric analysis yields several additional insights (see Sections 9.3.2 and 9.3.3). Most notably, it does not support a statistically significant relationship between ITP and internal trading activity, and the estimated effect sizes are negligible. This finding, confirmed by both the general model and the quasi-experimental difference-in-differences approach, suggests that companies do not systematically utilise their internal reallocation potential to minimise external market participation. Potential explanations include internal administrative barriers, transfer pricing complexities, or profit shifting strategies that outweigh compliance cost minimisation.

However, the analysis of the full sample identifies a robust negative association between internal trading and banking. This supports the interpretation that companies treat these mechanisms as substitutes: while banking facilitates reallocation across time, internal trading facilitates reallocation across entities.

Structural and behavioural factors significantly influence trading decisions. Companies with a larger number of installations, those belonging to larger corporate groups, and those with higher transaction frequency are more likely to trade internally. These findings highlight the role of structural capacity and strategic learning. Conversely, companies at risk of carbon leakage are significantly less likely to engage in internal trading than those not at risk of carbon leakage, potentially due to stricter internal cash flow controls. Temporal patterns in the data indicate that internal trading increased over time, with significantly higher volumes recorded in the second and third trading periods compared to the first. This development likely reflects learning effects, as well as increased financial pressure following the reduction in free allocation starting in 2013 during the third period.

The quasi-experimental approach, applied to a subsample of combustion installations, exploits the change in allocation rules introduced in 2013. The analysis reveals no statistically significant divergence in marginal effects between the treatment group (energy sector) and the control group (industry sector) as ITP increases. Therefore, the removal of free allocation for the energy sector did not induce a differential utilisation of ITP compared to the control group. This finding corroborates the null result regarding ITP observed in the full sample analysis. Finally, estimates for other covariates remain consistent with the main model, with minor variations in significance levels attributable to reduced statistical power. Robustness checks using alternative specifications confirm the stability of the main results (see Section 9.3.4).

The findings challenge the premise that internal reallocation is inherently less costly than external trading, as substantial internal trading potentials remain untapped. This suggests that the current installation-based regulation creates administrative friction. Shifting the point of regulation to the company or NUO level could reduce transaction costs and streamline compliance, provided that transparency and legal certainty are maintained.

Nonetheless, the analysis is subject to limitations. Precise measurement of internal trading is constrained by the difficulty of identifying central trading entities not formally linked to an NUO in the available data. Moreover, internal or soft strategic drivers, such as profit shifting, transfer pricing, or specific corporate governance targets, remain unobservable.

4. Synthesis, Limitations, and Outlook

This dissertation investigates trading behaviour in the EU ETS by analysing the structural and strategic factors that influence companies' engagement in allowance markets. Drawing on a novel panel dataset that integrates verified emissions and transaction data from the European Union Transaction Log (EUTL) with company-level information from the ORBIS database, the analysis addresses four interrelated research questions through distinct empirical studies. The following section synthesises the main findings of these studies, highlighting their contributions to the academic understanding of emissions trading dynamics and their relevance for policy design. This is followed by a critical reflection on methodological and empirical limitations, as well as an outlook on potential directions for future research.

4.1 Summary of Main Findings and Contributions

4.1.1 Methodological Contributions

The empirical analysis relies on a novel company-level panel dataset constructed by merging data from the European Union Transaction Log (EUTL) and the ORBIS database. To the best of the author's knowledge, at the time of this dissertation's inception, this dataset offered a unique combination of scope and depth. First, it encompassed the entire geographical scope of the EU ETS from the system's launch through the early years of the third trading period (2005 to 2017). This timeframe is significantly longer than that of preceding studies and is crucial for capturing the market's evolution towards maturity. Specifically, it enables the assessment of behavioural responses to key regulatory shifts, such as the introduction of allowance banking in the second period and the increase in auctioning from 2013 onwards.

Second, the integration of financial and structural data from ORBIS represented a significant advancement in the literature. While prior studies have linked registry and financial data, the depth of this integration, covering a more extensive timeframe and enabling the construction of granular variables, allowed for a more comprehensive analysis. This data linkage enabled a shift in the level of analysis from the installation or ultimate owner level to the company level. This addresses a specific gap in prior research by targeting the organisational tier where strategic compliance decisions are typically formulated. Furthermore, by moving beyond simple participation and total volume metrics, the analysis incorporates transaction frequency, the use of intermediaries and derivatives, and banking behaviour to serve as a proxy for managerial competencies and strategic sophistication.

From an econometric perspective, this dissertation contributes to the literature by tailoring advanced panel estimators to the specific constraints of emissions trading data, such as censoring and selection bias. While previous studies often relied on cross-sectional or quantile regressions that neglect dynamic effects, the application of panel double-hurdle, Poisson, Heckman selection, and Tobit models allows for a more robust identification of structural and behavioural determinants. By consistently employing the correlated random-effects (CRE) estimator, the analysis effectively controls for time-invariant unobserved heterogeneity, a limitation prevalent in earlier work.

A distinct innovation lies in the identification strategy embedded in the quasi-experimental difference-in-differences (DiD) framework: This work is among the first to construct valid control groups from within the EU ETS population by exploiting the differential treatment of sectors in Period 3. This approach overcomes the limitations of previous studies regarding trading behaviour, which often lacked control groups, and the broader EU ETS literature that typically relied on comparisons with non-regulated companies.

4.1.2 Key Empirical Findings

The four peer-reviewed papers collectively contribute to a nuanced understanding of company responses to emissions trading, each examining a distinct yet interconnected aspect of trading behaviour: participation and intensity (RQ1), profitability (RQ2), search effort (RQ3), and internal trading (RQ4). Taken together, these questions form an integrated analytical framework that links market access, strategic behaviour, institutional change, and intra-organisational optimisation.

The first paper lays the empirical foundation by identifying key drivers of market participation and trading intensity. It reveals that companies' engagement in allowance trading is highly heterogeneous and largely determined by structural characteristics, especially company size, sector affiliation, and the number of regulated installations. A particularly salient finding is the behavioural asymmetry between net sellers and net buyers: companies with compliance deficits are significantly more likely to trade and to do so at higher volumes. This challenges the Coasean assumption (Coase, 1960) that initial allocation should not affect market outcomes and underscores the role of behavioural frictions in shaping emissions trading dynamics.

Building on these participation patterns, the second paper examines whether companies that engage more actively in emissions trading also profit more from it. It introduces trading profits as a performance metric and shows that profitability is strongly linked to companies' net positions, banking behaviour, and transaction timing. A particularly noteworthy finding is that companies appear to manage their banking decisions efficiently, factoring in the opportunity cost of market sales when deciding on banking. Regarding transaction timing, initial inefficiencies diminished over time, pointing to learning effects and growing market maturity. Furthermore, the analysis reveals a link between profits from trading and the number of installations operated by a company, indicating that companies with multiple sites might leverage structural advantages like centralised compliance management or broader information networks to achieve higher profits from emissions trading.

The third paper deepens the behavioural analysis by examining how companies respond to rising compliance costs triggered by the shift from free allocation to auctioning. The results show that companies with more negative net positions trade more frequently and diversify their counterparties, signalling intensified search efforts. As the estimated effects are modest in size, the findings suggest that the shift towards auctioning did not generate prohibitive transaction costs, thereby facilitating the broader policy move towards auction-based allocation.

The fourth paper adds an intra-organisational perspective by exploring whether companies exploit internal trading opportunities to reduce transaction costs. While such reallocation strategies are theoretically attractive, the empirical results show that internal trading remains the exception rather than the rule. Even among companies with significant internal trading potential, actual usage is limited. The analysis finds no clear correlation between internal trading potential and internal trading, but it does identify structural factors, such as the number of installations and the number of companies belonging to the same national ultimate owner, as enabling conditions. Conversely, companies at risk of carbon leakage are found to be significantly less likely to engage in internal trading. These findings suggest that companies do not systematically use internal trading as a cost-saving strategy, perhaps due to institutional or organisational barriers.

4.1.3 Synthesis of Cross-Cutting Patterns

Synthesising the findings across all four papers reveals four overarching patterns that advance the understanding of trading behaviour under the EU ETS.

First, structural characteristics, particularly company size, the number of regulated installations, and sector affiliation, consistently emerge as key determinants across all dimensions of trading behaviour, including participation, trading intensity, profitability, and internal trading. These findings suggest that larger companies and those operating multiple installations likely face lower transaction costs. In particular, the positive correlation between indicators of company size and market participation suggests the presence of substantial fixed costs associated with engaging in emissions trading, costs that smaller emitters may find difficult to absorb. The energy sector, which consistently exhibits more frequent and intensive trading activity, appears to benefit from sector-specific capabilities such as greater market experience or dedicated infrastructure.

Second, financial incentives, most notably the net position, play a dual role by shaping both the likelihood of participation and the intensity of trading activity. Companies with negative net positions tend to be more active, trade more frequently, and engage with a broader range of counterparties, indicating that financial pressure acts as a key behavioural driver. These patterns can be interpreted through the lens of loss aversion (Kahneman and Tversky, 1979), as companies search more actively for favourable trading opportunities when facing a negative net position than their counterparts with a surplus. The resulting behavioural asymmetry between net buyers and net sellers, empirically substantiated in Paper 1, challenges the Coase Theorem’s (Coase, 1960) prediction of allocation neutrality in the absence of transaction costs and suggests that the initial distribution of allowances continues to influence market behaviour through behavioural frictions and differing perceptions of opportunity costs.

Third, temporal dynamics emerge across all papers. Companies were generally more active in the second and third trading periods in terms of participation, search effort, and internal trading. This may partly reflect learning effects over time. For example, evidence from Paper 2 suggests that the timing of transactions, especially late-year trading, had a strong effect on profitability in the first trading period but became less relevant thereafter. These trends imply that companies gradually adapted to the logic and mechanics of emissions trading. At the same time, regulatory changes, most notably the shift to auctioning in Period 3, likely contributed to these behavioural adjustments, particularly with regard to participation and search intensity.

Fourth, across all four analyses, a high share of zero values in the indicators points to persistently low levels of participation, trading intensity, or internal trading. While this may seem surprising from a market efficiency perspective, it is understandable from a company point of view. During the observation period, EUA prices were low and free allocation levels were high, resulting in minimal compliance costs. This may have led companies to invest fewer resources in trading activities or to refrain from strategic engagement altogether. These patterns underscore that the EU ETS, at least until 2017, may have exerted insufficient financial pressure to incentivise widespread trading across the entire population of regulated entities. However, this situation has likely evolved in recent years. The sustained increase in EUA prices since 2018, combined with far-reaching regulatory reforms under the European Green Deal and the Fit-for-55 package, has considerably intensified the pressure on regulated companies. The tightening of the EU-wide greenhouse gas reduction target, the gradual phase-out of free allocation through the introduction of the CBAM, and the integration of low-carbon production routes into the EU ETS, thereby establishing a level playing field with conventional technologies, may have jointly prompted companies to place greater strategic emphasis on minimising compliance costs.

4.1.4 Policy and Managerial Implications

In terms of policy implications, the dissertation underscores the importance of considering behavioural heterogeneity and transaction costs in emissions trading design. Findings suggest that persistent transaction cost barriers, particularly for smaller companies and those with fewer installations, hinder market participation and efficiency. Policy interventions could focus on reducing these barriers, for instance by simplifying auction procedures or introducing easily accessible trading platforms, such as a public electronic bulletin board, to lower participation costs. The research lends support to the ongoing shift towards full auctioning, as generous free allocation was linked to inefficiencies and behavioural asymmetries between net buyers and sellers. Importantly, the increased financial pressure from auctioning does not appear to induce prohibitive search-related transaction costs, suggesting that the shift is manageable. For any remaining free allocation, mechanisms like consignment auctions, where monetised allowances return revenue to holders, may internalise opportunity costs and help recipients better recognise the opportunity costs of holding allowances, thereby encouraging more efficient market participation. Furthermore, the observation that companies generally employ banking efficiently highlights the value of maintaining flexibility for intertemporal allowance transfers to support cost-effective compliance. Lastly, the limited exploitation of internal trading potentials suggests that the current regulatory structure, specifically the installation-level point of compliance, might inhibit cost-saving intra-group optimisation. Therefore, re-evaluating this aspect could enhance overall system efficiency.

For companies, the findings yield several strategic implications. Trading profitability is closely associated not only with the initial allocation, reflected in the net position, but also with strategic capabilities, particularly the timing of transactions and the management of allowance banking. Although timing effects diminished after the early market periods, developing sophisticated trading capabilities remains essential as allowance prices rise, especially for companies with substantial compliance obligations. Conversely, for smaller entities, weighing the costs of building internal expertise against the benefits of outsourcing or passive strategies is crucial. Companies operating multiple installations appear to benefit from internal economies of scale, possibly achieved through centralised trading units or improved internal information flows. Conversely, companies facing significant transaction cost barriers may consider collaborative arrangements or information-sharing mechanisms to enhance market access and efficiency. Finally, the observed underutilisation of internal trading suggests that companies should re-examine organisational, legal, and administrative constraints that may hinder intra-group allowance reallocation, as optimising internal trading structures could further reduce compliance costs.

In sum, this dissertation provides an integrated empirical analysis of how companies interact with the EU ETS, respond to cost signals and institutional reforms, and how trading behaviour varies across heterogeneous company types.

4.2 Limitations and Critical Reflection

While this dissertation offers valuable empirical insights into company behaviour under the EU ETS, several limitations must be acknowledged to appropriately frame the scope and robustness of its findings. These limitations concern the availability and quality of data, the measurement of key variables, the interpretability of results, and the generalisability of the findings beyond the specific context of the EU ETS.

4.2.1 Data Limitations and Measurement Challenges

A central limitation lies in the nature of the underlying data. Although the EUTL provides uniquely detailed records on verified emissions and allowance transactions, it does not capture several important dimensions of corporate behaviour. Specifically, soft and strategic factors, such as trading intentions, internal decision-making processes, organisational culture, or the rationale behind individual transactions, remain unobservable. This restricts the explanatory power of the models and limits the capacity to account for behavioural heterogeneity among regulated companies. This limitation is typical of empirical research based on administrative or registry data.

Closely related is the challenge of measuring strategic trading behaviour. Proxies such as transaction frequency, the use of intermediaries, and banking behaviour are employed to approximate strategic intent, but these indicators remain indirect. Without qualitative insights or access to internal company-level data, it is not possible to determine with certainty whether observed patterns are the result of deliberate strategies or shaped by external constraints.

A further constraint arises from the lack of detailed information on over-the-counter (OTC) transactions. Specifically, the prices paid in bilaterally negotiated contracts are not reported in the EUTL. For example, when a company enters a forward agreement with a financial intermediary to deliver EUAs at a specified price and time, the transaction is only registered upon delivery and recorded at the market price prevailing on that date. As a result, such contracts, although functionally equivalent to forwards, appear in the dataset as spot trades, and the originally negotiated price remains unobservable. A similar limitation applies to exchange-traded derivatives: the EUTL does not indicate whether a transaction is part of a forward or futures contract. Accordingly, this study relied on typical EUA delivery dates and annual average futures prices to estimate contract values. While this approach smooths actual price variation and is therefore unlikely to produce false statistical significance, it may bias effect estimates toward zero and should be regarded as conservative.

Inconsistencies were also identified during the aggregation and verification of the EUTL data. In some cases, account-level balance sheets implied negative EUA holdings, a result incompatible with the EUTL's accounting framework. Such inconsistencies likely stem from errors during the historical migration of data from the CITL to the EUTL or from changes in installation ownership classifications. In addition, a small share of transactions may be misattributed or entirely missing. Where possible, such anomalies were identified and removed to improve data quality and ensure the reliability of the analysis.

Some data loss was also unavoidable during the data-matching process. Approximately 10 billion EUAs could not be linked to identifiable companies in the ORBIS database. Furthermore, ORBIS coverage is limited, particularly for small and medium-sized enterprises, and financial detail is often inconsistent. These gaps may bias the sample towards larger, more transparent companies and reduce representativeness. However, in most empirical models, specifications excluding financial ORBIS variables were also estimated to test for potential distortions. The results of these alternative models generally did not deviate substantially.

The classification of internal EUA trading also poses challenges. Although extensive efforts were made to identify trades between installations belonging to the same national ultimate owner, the classification may be incomplete. Some companies appear to have used dedicated trading subsidiaries to manage EUA flows, but these entities may not be formally linked to the relevant national ultimate owner in the ORBIS database. As a result, their transactions may be misclassified as external trades, potentially understating the extent of intra-group optimisation strategies.

4.2.2 Interpretation and Explanatory Power

Another important limitation concerns the interpretation of empirical results. With the exception of the quasi-experimental component of the analysis in Paper 4, which employs a difference-in-differences framework, the findings primarily represent robust statistical correlations rather than causal effects. For example, while the analysis shows that companies with more negative net positions tend to engage in more trading activity, it cannot be concluded that the net position itself is the causal factor. Unobserved variables, such as compliance strategies, internal governance arrangements, or risk preferences, may explain the observed behaviour.

Moreover, the analysis does not permit a direct quantification of transaction costs or benefits in monetary terms. This restricts the capacity to assess the findings in terms of actual efficiency gains or losses at the company or system level. Any assessment of cost-effectiveness from a welfare or macroeconomic perspective would require a broader modelling framework that accounts for marginal abatement costs, counterfactual compliance strategies, and general equilibrium effects, elements that lie beyond the scope of this dissertation.

4.2.3 Contextual Limitations and Generalisability

The generalisability of the findings also requires careful consideration. The EU ETS is the most mature and institutionalised cap-and-trade system globally, operating within a relatively stable regulatory framework and, since 2018, in a higher and more stable price environment. However, the data analysed in this dissertation cover only the period from 2005 to 2017, prior to the sharp and sustained price increases that began in 2018. Therefore, trading strategies observed in the analysis may differ from those developed under more stringent carbon price signals.

Moreover, the findings may not be readily transferable to emerging ETSs in regions such as China, South Korea, Latin America, or Southeast Asia. These systems differ significantly in terms of institutional structure, regulatory certainty, and corporate governance cultures. In such contexts, transaction costs may play a more prominent role due to lower market liquidity and higher administrative burdens. While the conceptual framework developed in this dissertation may offer valuable insights, the empirical results should not be applied without careful contextual adaptation.

4.2.4 Scope of Behavioural Analysis

Finally, the scope of the analysis is confined to trading behaviour. While trading represents a key compliance strategy under the EU ETS, it does not capture how companies invest in abatement or innovation in response to the policy. In particular, investments in transformative technologies require a sufficient degree of certainty and trust regarding future policy design. If such trust is lacking, even cost-efficient investments may be discouraged (e.g. Sitarz et al., 2024). A more complete understanding of corporate responses would require an integrated analysis of trading, abatement, and technology adoption. This would necessitate access to different types of data and a broader methodological approach, which remain avenues for future research.

In sum, while this dissertation provides robust empirical evidence on company trading behaviour under the EU ETS, its findings must be interpreted within a set of methodological, data-related, and contextual limitations. These constraints do not diminish the relevance of the results but instead define the analytical boundaries of the research and offer direction for future empirical work.

4.3 Outlook

Building on the findings and limitations of this dissertation, several promising avenues for future research emerge. A primary opportunity lies in updating the underlying dataset. Such an update would not only increase the number of observation years, particularly those following the significant EUA price increase in 2018, but also benefit from recent improvements in data accessibility and restructuring on the European Commission's website. These technical upgrades may have helped resolve some of the inconsistencies identified in the underlying version of the database, thereby increasing the reliability and completeness of the data for future empirical analyses.

Equally important is the integration of qualitative and behavioural insights. While registry data offer a robust quantitative basis for assessing trading activity, they provide limited information on the underlying motivations, organisational structures, or strategic considerations that inform company decisions. Combining registry-based analyses with qualitative methods, such as surveys, interviews, or in-depth case studies, could uncover the behavioural mechanisms behind trading patterns, including the role of internal governance, institutional knowledge, and company culture. This mixed-methods approach would allow for a more nuanced understanding of heterogeneity in corporate behaviour and provide richer inputs for the evaluation and refinement of policy instruments.

Another fruitful direction for future work involves extending the analytical focus beyond trading itself to examine the interaction between allowance trading, abatement activity, and innovation behaviour. While this dissertation has concentrated on trading as a compliance strategy, a more comprehensive analysis of emissions trading systems must also consider how trading decisions influence and are influenced by long-term investment, process innovations, and low-carbon technology adoption. This would require integrating additional data sources, such as technology-level indicators, company-level innovation metrics, or abatement cost estimates. Such an approach could significantly advance our understanding of the dynamic efficiency of the EU ETS.

A further area of development lies in the construction of monetary metrics that more directly link trading behaviour to economic outcomes. Estimating the transaction costs associated with various trading strategies or quantifying the profitability of trading activities under different market conditions would be particularly valuable. These efforts could be complemented by efforts to monetise internal optimisation practices, such as intra-group allowance reallocation. Ultimately, embedding such monetary assessments in a broader welfare or macroeconomic framework would enhance the ability to evaluate the efficiency gains or losses of trading strategies at the system level and could support policymakers in improving the future design of the EU ETS.

Future research should also address the question of transferability. As emissions trading systems continue to emerge in diverse institutional and regional contexts, such as China, South Korea, Latin America, or Southeast Asia, it becomes essential to test whether behavioural patterns observed under the EU ETS hold in other jurisdictions. However, applying the empirical frameworks developed in this dissertation is currently constrained by the fact that few other systems offer transparent transaction logs comparable to the EUTL. Overcoming these data availability hurdles would allow researchers to assess the role of contextual factors such as regulatory maturity, corporate governance traditions, and cultural attitudes toward risk and compliance. Comparative studies of this nature could inform the design of ETSs in emerging markets and contribute to the global diffusion of effective and context-sensitive trading system architectures.

Taken together, these directions offer a research agenda that can meaningfully advance the understanding of trading behaviour in emissions markets. By incorporating more recent data, enriching empirical methods with behavioural insights, exploring the interlinkages with abatement and innovation, developing monetary outcome metrics, and extending the analytical scope to other systems, future studies will be well-positioned to support the continued evolution of emissions trading as an effective, adaptive, and evidence-based climate policy instrument.

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Part II

6. Corporate Emissions-Trading Behaviour During the First Decade of the EU ETS

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Abstract:

This study analyses factors related to allowance-trading behaviour for the first ten years of the existence of the European Union Emissions Trading System (EU ETS). Our empirical analysis employs a dataset that combines information on trading activities for more than 6000 companies with company characteristics. Indicators of trading activity include the volume and the number of transactions as well as the usage of intermediaries and of derivatives markets. For 2005–2014 and for the individual trading periods, we find that trading behaviour is related to the size of a company, its net position (the difference between free allocations and verified emissions), its sector affiliation, productivity, and location. We also find evidence that trading-related transaction costs affect trading activity in the EU ETS in all trading periods. Our results further suggest that net buyers (companies whose verified emissions exceed free allocations in a given year) are more likely to participate in emissions trading and to trade at higher volumes than net sellers are. We explain this asymmetry in behaviour - which might lead to a violation of Coase's independence property - by potential asymmetries in the actual or perceived opportunity costs of holding allowances between net sellers and net buyers.

Keywords: Climate policy, emissions trading, EU ETS, transaction behaviour, transaction costs

6.1 Introduction

Since its inception in 2005, the European Union Emissions Trading System (EU ETS) has been one of the cornerstones of EU climate policy, set up to help the EU meet its climate targets in the covered sectors at the lowest cost. Regulating emissions by energy and energy-intensive industries and aircraft operators, a large number of companies with more than 11,000 installations formulate individual trading decisions and strategies vis-à-vis the EU carbon market. Over time, the EU ETS has grown as more countries and types of greenhouse gases (GHG) and activities are covered by the system. Starting with the first trading period as a pilot phase (2005–2007) and after a second trading period (2008–2012) dominated by the economic crisis and relatively low prices for EU allowances (EUAs), the EU ETS has further matured during the third trading period (2013–2020).

The EUA price has recently recovered, and has climbed above 50 Euro/tCO_2 in the Spring of 2021. Reasons for this price increase include changes in regulation, such as the introduction of the market stability reserve in 2019,[5] and the EU's raised ambitions on reducing greenhouse gas emissions to at least 55% below 1990 levels by 2030. This target is expected to set the EU on a path of becoming climate neutral by 2050. To this end, the emission target for the EU ETS will also have to become more ambitious. In addition, the EU is currently considering extending the scope of the EU ETS to include additional sectors such as maritime transport and possibly heating and transportation. It is therefore expected that the EU ETS will become even more instrumental to achieving future EU climate targets.

[5] The market stability reserve regulates the supply and demand of allowances depending on the number of allowances in circulation. It is expected to reduce the supply of allowances by at least 2,000 million EUAs by 2023 (e.g. Bocklet et al. 2019) and to affect the time profile of low-carbon investments (Perino and Willner 2019).

Emissions trading is considered an environmental policy instrument that achieves a given emissions target at minimum cost. Assuming that companies which are covered by an ETS bid for allowances at their marginal abatement costs, the price of emission allowances correctly signals scarcity in the allowance market (Montgomery 1972; Hahn and Stavins 2011). This efficiency result critically hinges on companies' willingness and ability to trade allowances. At least two factors might discourage companies from trading allowances, thereby reducing the efficiency of emissions trading. First, transaction costs discourage allowance trading and therefore increase total compliance costs (Stavins 1995). Second, companies may not correctly evaluate the opportunity cost of holding allowances. Consider a situation in which companies are allocated amounts that equal their emissions and thus that compliance is possible without further trading. The efficiency gains in emissions trading will be realized only if companies correctly evaluate the opportunity costs of holding allowances against the market price. By bidding marginal abatement costs into the market, companies could realize gains by reallocating allowances according to their costs. These two factors illustrate that understanding why and how companies trade allowances is critical for evaluating the performance of allowance markets and for improving the future design of emissions-trading systems.

In this paper, we ask how the characteristics of individual companies and institutional features of the emissions-trading system influence companies' trading behaviour. We empirically explore these factors in the context of the EU ETS for the years 2005 through 2014, i.e. the first ten years after the EU ETS came into force. To this end, we compile a large panel dataset of transactions in the EU ETS, allocations of allowances, and verified emissions from the EU transaction log (EUTL). We also include company characteristics from the ORBIS database. We relate companies' transactions to their characteristics, including size, number of installations, productivity, sector of operations, and net position (i.e. an allowance allocation minus verified emissions). To measure market participation, we construct several indicators, including the amount and number of transactions as well as the usage of intermediaries and derivatives markets. We then employ panel econometric methods to analyse the impact of companies' characteristics on market participation by companies. Because companies have gained experience and the administrative rules of the EU ETS have changed over time, we analyse trading behaviour jointly for all periods as well as separately for the first, second, and the first two years of the third trading period. Moreover, we separately estimate the impact of allowance positions, i.e. whether companies can be considered net sellers or buyers, on their trading behaviour.

We find that trading behaviour is related to a company's size, its net position, its sector affiliation, productivity, and location. Larger companies, those with higher (absolute) net positions, those operating in the energy or carbon leakage sectors (compared with non-carbon-leakage industries) and those with higher productivity are typically more likely to participate in the market and also to use the market more intensively. Considering differences across the three trading periods, we find that companies were generally more active in the second and third trading periods than in the first trading period. Finally, our results suggest that net buyers are more likely to participate in emissions trading and to trade higher volumes than net sellers. If the primary allocation of allowances impacts allowance positions, this asymmetry in trading behaviour possibly reflects a violation of the Coase (1960) independence property.

Several authors have analysed the transaction behaviour of companies regulated under the EU ETS. Zaklan (2013) analyses the determinants of participation in emissions trading in the pilot phase of the EU ETS. Likewise, Jaraitė-Kažukauskė and Kažukauskas (2015) analyse trading behaviour using an explicit notion of transaction costs. Exploring the gains and losses involved in allowances trading, Cludius (2018) also notes forgone trading opportunities, in particular for small companies. Exploiting price differences between EUAs and allowances from international offset markets (CERs, ERUs) in the second trading period of the EU ETS, Naegele (2018) also estimates substantial (fixed) transaction costs related to allowance trading under the EU ETS.

Hintermann and Ludwig (2019) find evidence of effects on transaction costs when trading allowances across country borders. Zaklan (2020) also concentrates on the second trading period and concludes that the method of primary allocation of allowances only weakly impacts abatement behaviour of electricity companies.[6] Relying on data for the first and second trading periods, Guo et al. (2020) find a positive correlation between profits from trading and abatement. Baudry et al. (2021) use a theoretical approach and data for the second trading period and find significant fixed and variable trading transaction costs. In addition to econometric approaches, network-based methods (Borghesi and Flori 2018; Karpf et al. 2018) and cluster analysis (Betz and Schmidt 2015) have also been used to study trading behaviour and trading patterns in the EU ETS.

Empirical evidence suggests that factors that explain whether a company trades EUAs in the market (i.e. decides to participate), also explain the level of participation (i.e. trade intensity). Larger companies, companies with more installations, and energy-sector companies are more likely to participate and more likely to trade intensively. Furthermore, a company's net position affects both participation and intensity decisions. Generally, a shortfall in allowances and the possibility of incurring a penalty seem to increase participation. Finally, company trading behaviour depends on ownership structure and the country or region in which a company is located.

Our analysis contributes to the existing literature in four major ways. First, existing studies analyse a single trading period, often the first and partly the second trading period.[7] We therefore add to the literature by extending that temporal scope to include parts of the third trading period

[6] Based on interviews with managers in the ceramics industry, however, Venmans (2016) concludes that companies which are short tend to abate more.

[7] In another context, however, Hintermann and Ludwig (2019) and Naegele (2018) use data through 2013 and 2012, respectively.

through the year 2014 and by analysing each period separately as well as jointly. Our study therefore provides insights into whether findings from the early phase of the EU ETS also hold in later years, when the market is more mature, and participants are more experienced. Furthermore, regulation of the EU ETS has changed over time. In particular, banking of EUAs into subsequent trading periods was allowed from the second trading periods onwards only. Thus, net sellers could decide to bank rather than sell excess allowances on the market before the end of the trading period. Moreover, the length of the trading periods has increased over time, providing companies with more flexibility to borrow allowances across years. In addition, from 2013 onwards, the share of auctioning increased substantially. Most notably, since 2013 companies in the power sector no longer receive EUAs for free (with some exceptions for generators located in Central and Eastern European countries). As a consequence, many companies were forced to rely on auctions and the market more intensively to be in compliance. Last but not least, the price of EUAs and hence the incentives for companies to use emissions trading efficiently varied over time. Despite the economic crisis, average EUA prices were higher in the second trading period than in the first trading period and at the beginning of the third period.

Second, previous analyses focus on participation and total trading volume as key indicators. In this analysis, we also consider the number of transactions, the use of market intermediaries such as brokers, banks and exchanges, and the use of forwards and futures markets. Thus, our set of indicators is more comprehensive and likely to capture not only search- and information-related transaction costs but also costs pertaining to managerial competencies. The EU ETS involves uncertainties about the fundamentals driving the market (including uncertainty about regulations). Employing brokers and other intermediaries, companies gain access to professional market information (after paying brokerage fees). Similarly, companies may employ intermediaries to manage their trading activities directly, broker trades with other system participants, use them as partners when entering into forwards or futures trading, or help them exploit opportunities to generate revenues, such as swapping cheaper international credits (CERs, ERUs) for more expensive EUAs (Cludius and Betz 2020). Financial products on the derivatives market enable companies to exploit price variations over time and manage market risks.

Third, our study emphasises asymmetric trading behaviour. We analyse how trading behaviour depends on companies' net positions, i.e. whether companies are net sellers or buyers. If companies' behaviour depends on their net positions, this is a strong indication of a failure of Coase's (1960) independence property, implying that the trading behaviour is independent of the method of primary allocation of allowances. We therefore add to the scarce empirical literature (Venmans, 2016; Zaklan 2020) on the independence of allowance allocation by analysing trading behaviour that varies with allowance positions.

Fourth, we employ a dataset which facilitates an analysis at the company level. Related studies have analysed transactions at either the level of individual installations (Betz and Schmidt 2015), the level of the national ultimate owner (Jaraitė-Kažukauskė and Kažukauskas 2015), or the level of the global ultimate owner (Cludius 2018; Hintermann and Ludwig 2019; Naegele 2018; Zaklan 2013).[8] We analyse transaction behaviour at the level closest to the point of regulation but not at the installation level. Operators of individual installations are unlikely to be responsible for making these decisions, as they might lack relevant expertise. Indeed, Betz and Schmidt (2015) observe that many companies pool EUAs for all their installations into one account. Because of language barriers, coordination and other types of transaction costs, the global ultimate owner is unlikely to be in charge of trading EUAs. We therefore believe that trading decisions are typically made at the level of the company or the national ultimate owner. For the purpose of this paper,

[8] For multi-national companies, the national ultimate owner is the subsidiary that owns all other subsidiaries in a given country. In contrast, the global ultimate owner is the global parent company that ultimately owns all subsidiaries (usually by controlling the national ultimate owners). We refer to a company as the legal organization that operates closest to the regulated entity, i.e. the installation.

we choose the company level because decisions at the company level also reflect decisions by the national ultimate owner, but not vice versa.

The remainder of our paper is organized as follows. In Section 6.2 we describe the methodology, including the dataset, the dependent and explanatory variables, and the econometric methods. Results are presented in Section 6.3. The final Section 6.4 summarizes the main findings and concludes.

6.2 Methodology

In this section, we first document how we assembled our data set. Then we report the dependent and explanatory variables used in the econometric analysis. Finally, we describe the econometric methods used.

6.2.1 Data

Our research is based on EUTL data, which can be downloaded free of charge from the European Commission's website, where the data on transactions are published with a three-year delay. The data used are organized into three datasets: (i) the main dataset containing all transactions completed in the EU ETS[9]; (ii) account data, which contain information pertaining to the accounts involved in transactions, such as account owners; and (iii) installation data, which provide information pertaining to free allocations and compliance per regulated installation. In addition, company information such as turnover, number of employees, and industry sector was taken from

[9] Trades of international offsets like certified emission reductions (CERs) and emission reduction units (ERUs) are included in the dataset as long as they take place within the EUTL registry. If an account registered within the EUTL acquires or transfers an offset certificate from a party not registered in the EUTL, the counterparty is usually not known. If both parties are registered in the EUTL, the transaction is treated like a normal transfer. For the period between 2008 and 2012 we are, in principle, able to identify the type of transferred units. Since 2013, this information is, however, no longer observable as offsets are converted into EUAs when imported into the system (banked offsets had to be converted as well).

the ORBIS database of the Bureau van Dijk. We matched the EUTL data to the ORBIS data using company registration numbers. In cases where a match with a registration number was not feasible, we matched the account names and addresses of the account holders to the ORBIS database.[10] For the sake of analysis, we aggregate transactions on an annual per-company basis. In doing so, we exclude administrative transactions such as primary allocations and surrenders of allowances. These transactions account for about 65 percent of the transaction volume, but they do not reflect trading activity. Following Cludius and Betz (2020), a (trading) year in our dataset is defined as running from May through April because the surrender of allowances for an observation year usually takes place in April of the following year. Our observation period thus uses observations between January 2005 and April 2015, which means that our analyses cover two full years of the third trading period.

We only include regulated stationary installations and respective companies in our econometric analysis. We thus exclude aircraft operators as well as all observations where both verified emissions and allocations were zero, thus ensuring that only EU ETS–regulated companies remain in the dataset and that plants that have ceased operations but are still listed in the EUTL were excluded. We further removed all transactions between accounts of the same installation because we consider these trades to take place for organizational purposes only. In comparison, we do not remove intra-company trades. Section 6.6 provides a more detailed description of how we compiled the data.[11]

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[10] This procedure extends work in previous studies (e.g. Jaraitė-Kažukauskė and Kažukauskas 2015; Hintermann and Ludwig 2019; Zaklan 2013) by using company registration numbers in addition to addresses and account names to match these datasets. This was possible after reporting of company registration numbers became mandatory in 2012.

[11] We do not correct the data for carousel VAT tax fraud, which was particularly relevant in the second trading period (e.g. Frunza et al. 2011). However, since we cannot clearly identify trades for tax fraud purposes in the data, we decided not to correct our data. Because our analysis includes accounts only of companies with at least one regulated installation and where information in the ORBIS database was available, most of the fraud-related transactions should be excluded. Fraud-related transactions were typically carried out via private accounts owned by shell companies which were not related to a company covered by the EU ETS.

6.2.2 Variables

6.2.2.1 Dependent variables

Our empirical analysis considers four indicators that reflect participation in emissions trading, as shown in Table 2.

We employ *total transactions* as measured by the volume of allowances transacted via purchases or sales per trading year. We also use *transaction frequency* as measured by the number of transactions a company carries out per year. A higher *transaction frequency* is assumed to reflect stronger participation in emissions trading. Further, we consider the *use of intermediaries* by a company to carry out its trades. To determine the number of intermediaries used, we identified those trading partners of a regulated entity that belong to the NACE financial services category. Finally, companies may use financial products that are available on the derivatives market to exploit price variations over time and manage market risks. We therefore consider the *use of forwards and futures* as reflecting a company's greater use of the EU ETS. Because only actual allowance transactions are registered in the EUTL, the volume of transactions that was carried out via forwards and futures contracts has to be estimated. We define the volume traded via forwards and futures as transactions that a company carried out on days when forwards or futures were typically delivered (see Cludius 2018). These days were determined by looking at trading activities in the so-called clearing accounts.[12]

[12] EUA futures are traded at regulated marketplaces (e.g. at the European Energy Exchange, Intercontinental Exchange). Participants must be registered, e.g. at the London Clearing House. The clearing accounts show heightened activity during a few days in December each year when futures are typically delivered. For our analysis, the following days showed significantly higher trade volumes (at least three times as high as on normal days) and are therefore selected to calculate the use of futures: 21-23/12 2005, 18-22/12 2006, 17-19/12 2007, 15-19/12 2008, 14-18/12 2009, 20-23/12 2010, 20-23/12 2011, 17-21/12 2012, 17-20/12 23/12 2013, 16-19/12 22-23/12 2014.
Forwards are traded bilaterally and not necessarily cleared. Delivery usually takes place during the last business day in November or the first business day in December. For our analysis, these days are: 30/11 01/12 2005, 30/11 01/12 2006, 30/11 03/12 2007, 28/11 01/12 2008, 30/11 01/12 2009, 30/11 01/12 2010, 30/11 01/12 2011, 30/11 03/12 2012, 29/11 02/12 2013, 28/11 01/12 2014.

6.2.2.2 Explanatory variables

Our choice of explanatory variables (see also Table 2; Table 4 in Section 6.7 reports the descriptive statistics) is guided by the existing literature and the availability of data. To account for companies' incentives to participate in the market we include the *net position*, which we define as the absolute value of the difference between the number of allowances allocated for free and verified emissions per year. Hence, *net position* takes nonnegative values and corresponds to a net deficit for buyers and a net surplus for sellers.[13]

Companies with a higher net surplus need to buy relatively fewer allowances or they can sell more allowances on the market to achieve compliance. Similarly, companies with larger net deficits must purchase more allowances (or further reduce emissions) to be in compliance. The existing literature finds companies' net surplus to be related to market participation and transaction volume (Cludius 2018, Jaraitė-Kažukauskė and Kažukauskas 2015, Martin et al. 2015, Naegele 2018, and Zaklan 2013). We therefore expect companies with higher net surpluses or with higher net deficits to use forwards and futures more intensively. As in Jaraitė-Kažukauskė and Kažukauskas (2015) and Zaklan (2013), our definitions of 'net surplus' and 'net deficit' do not account for EUAs which were banked from previous years or borrowed from subsequent years.

To capture the effects of sector affiliation, our set of explanatory variables includes two dummy variables. First, *carbon leakage* identifies companies belonging to a sector which is categorized as being at risk of carbon leakage under EU ETS rules.[14] Because they face import competition,

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[13] This definition follows the literature (e.g. Jaraitė-Kažukauskė and Kažukauskas, 2015; Zaklan et al. 2013) but abstracts from the fact that a company's verified emissions may depend on trading (versus abatement) activities and does not include banked allowances. As explained in Section 6.6, due to inconsistencies in the data, we did not include information from the EUTL pertaining to banked allowances. Accounting for banked allowances would increase the value of *net position*, because companies which are short (or long) in year t are likely to have been short (or long) in year t-1. Because borrowing, unlike banking, is not allowed across trading periods, accounting for banking would asymmetrically affect the net positions of net buyers and net sellers.

[14] The carbon-leakage list includes a large number of products from various industry sectors. In our case, these sectors include: refineries, iron and steel, metals, aluminium, cement and lime, glass and ceramics, pulp and paper, and chemicals as well as food, textiles, and machinery production.

these companies likely cannot fully pass on the additional CO_2 costs to their customers without losing market share (Cludius et al. 2020). Therefore, these companies are expected to have stronger incentives to use emissions trading to minimize compliance costs. Previous studies have not accounted for effects specific to companies operating in carbon-leakage sectors.

Second, *energy* denotes companies in the energy sector. These companies are often experienced traders of energy products. In particular, electricity generators typically sell electricity on spot and futures markets. Often, these products are traded at the same exchange as allowances (e.g. the European Energy Exchange—EEX). Hence, trading-related transaction costs should be lower and participation in emissions trading higher than for most non-energy companies. The findings for the sector dummies need to be interpreted by reference to the base category which comprises companies belonging to non-leakage industry sectors and organizations from sectors that operate combustion plants with more than 20 MW of nominal capacity (e.g. a university or large hospital operating a power plant). For the sake of brevity, we refer to this base category as the non-leakage industry sector.

Our explanatory variables also include *productivity* which is calculated as a company's revenues per employee. We expect that a company which enjoys higher per-capita revenues is also more likely to make greater use of emissions trading. To capture the effects of size on the use of emissions trading, our explanatory variables also include the number of *employees*. We also include the *number of installations*. Following Jaraitė-Kažukauskė and Kažukauskas (2015), we expect companies that operate more installations to be more active in emissions trading because they are believed to incur lower search and information costs.

Table 2: Description of dependent variables and covariates.

Variable	Description	Data base
Dependent variables		
Total transactions	Transaction volume of EUA in trading year t (in metric tons of CO_2eq.)	EUTL
Transaction frequency	Number of transactions in trading year t	EUTL
Use of intermediaries	Number of intermediaries used in trading year t	EUTL/ORBIS
Use of forwards and futures	Estimated transactions involving EUA via forwards and futures (in metric tons of CO_2eq.)	EUTL
Explanatory variables		
Net position	Allocation of EUA minus verified emissions in year t (absolute value in metric tons of CO_2eq.)	EUTL
Carbon leakage	Dummy =1, if company belongs to carbon leakage sector	ORBIS
Energy	Dummy = 1, if company belongs to energy sector according to NACE (rev2) classification (35.00 to 35.30)	ORBIS
Productivity	Calculated as revenues divided by number of employees in year t (in 100.000 Euro/employee)	ORBIS
Employees	Number of employees	ORBIS
Installations	Number of installations	EUTL
Period	Dummy for each trading period (base period is the first trading period)	EUTL
Region 1	Austria (AT), Germany (DE), Liechtenstein (LI)	EUTL
Region 2	Belgium (BE), France (FR), Netherlands (NL)	EUTL
Region 3	Greece (GR), Cyprus (CY), Spain (ES), Italy (IT), Malta (MT), Portugal (PT)	EUTL
Region 4	Estonia (EE), Lithuania (LT), Latvia (LV), Poland (PL)	EUTL
Region 5	Czech Republic (CZ), Hungary (HU), Slovenia (SI), Slovakia (SK)	EUTL
Region 6	Denmark (DK), Finland (FI), Iceland (IS), Norway (NO), Sweden (SE)	EUTL
Region 7	United Kingdom (UK), Ireland (IE)	EUTL
Region 8	Bulgaria (BG), Croatia (HR), Romania (RO)	EUTL

Further, to capture differences across trading periods we include a separate dummy for our trading periods (using the first trading period as the base period). Similarly, we control for region-specific effects by including a dummy variable for the regions. Region 1, which consists of the German-speaking countries (not including Switzerland and Luxembourg) is used as the base category. For the econometric estimations, we use the natural logarithms of *total transactions*, *use of forwards and futures, net position, productivity,* and *employees.*

6.2.3 Econometric Models

We employ panel econometric models to exploit the (unbalanced) panel structure of our data.[15] In particular, we run various types of econometric models to adequately reflect the nature of the dependent variables.

Double hurdle model

First, for *total transactions* and *use of forwards and futures*, our econometric models reflect the fact that, for a substantial portion of observations, the outcome is zero. More specifically, the share of zeros is about 44 percent for *total transactions* and 90 percent for the *use of forwards and futures* for the final samples in the multivariate analyses. These zeroes reflect company-level decisions to not participate in the market, for example, or to not trade in forwards and futures. In this case, running ordinary least squares models would result in biased parameter estimates. Following Jaraitė-Kažukauskė and Kažukauskas (2015), we therefore employ so-called "double-hurdle" panel models, which explicitly model the "participation decision" (first hurdle), i.e. whether companies decide to participate in the market at all, and the "intensity decision" (second hurdle), i.e. the extent to which companies use the market. Following the seminal work by Cragg (1971), the participation decision is essentially modelled as a Probit model and the intensity equation is modelled as a Tobit (corner solution) model. Double-hurdle models are preferable to standard Tobit models because the latter involve more restrictive distributional assumptions. For example, in Tobit models, the sign of the coefficient associated with a particular variable must be the same in both equations.

15 The panel is unbalanced because of exit and entry of companies and installations, and because countries joined the EU ETS at different points in time. In particular, the three non-EU members, Norway, Iceland, and Liechtenstein as well as Romania and Bulgaria joined the system in 2007 and Croatia in 2013.

Formally, we model the "participation decision" (first hurdle) in our "double hurdle" as

$$D_{it} = \begin{cases} 1 \; if \; D_{it}^{*} > 0 \\ 0 \;\; otherwise \end{cases} \tag{1}$$

$$D_{it}^{*} = x_{it}\boldsymbol{\beta} + z_i\boldsymbol{\gamma} + \alpha_{1,i} + \varepsilon_{1,it} \tag{2}$$

where D_{it} is an indicator variable capturing whether company i participates in an emissions trading activity at time t or not. D_{it}^{*} is a latent (unobserved) variable reflecting company i's net benefits derived from an emissions trading activity such as buying and selling EUAs. x_{it} is a vector of time-varying explanatory variables such as verified emissions. z_i is a vector of time-invariant explanatory variables such as sector affiliation. $\alpha_{1,i}$ denotes time-invariant company-specific unobservable factors such as company culture and $\varepsilon_{1,it}$ is an idiosyncratic error term with $\varepsilon_{1,it} \sim N(0,1)$.[16] Double-hurdle models are nonlinear models. Therefore, unlike with linear models, unobserved time-constant heterogeneity (e.g. company culture), which may be correlated with the covariates, cannot be managed by including company-specific fixed effects in the model and then employing a fixed-effects estimator. On the other hand, using a random effects estimator requires unobserved heterogeneity to be uncorrelated with the covariates. This assumption is likely to be restrictive in our context. We therefore employ the correlated random-effects estimator (CRE) developed by Mundlak (1978). To control for time-invariant unobserved heterogeneity, the CRE includes the company-specific means of the time-varying variables in the regression equations. Thus,

$$\alpha_{1,i} = \bar{x}_i\boldsymbol{\varphi} + \mu_i \tag{3}$$

[16] In this section, bold Greek letters denote parameter vectors.

where $\bar{x}_i$ is the mean of the x_{it} over time for company i, and $\mu_i \sim N(0, \sigma_\mu^2)$.[17] The (conditional) probability that a company passes the first hurdle, i.e. participates in an emissions trading activity, is then

$$\Pr\left(D_{it} = 1 \middle| x_{it}, z_i, \bar{x}_i, \mu_{i;} \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\varphi}\right) = \Phi(x_{it}\boldsymbol{\beta} + z_i\boldsymbol{\gamma} + \bar{x}_i\boldsymbol{\varphi} + \mu_i + \varepsilon_{1,it}) \tag{4}$$

where $\Phi(.)$ denotes the cumulative density function of the standard normal distribution.

We model the "intensity decision" (second hurdle) as

$$Y_{it}^{*} = max\,(Y_{it}^{**}, 0) \tag{5}$$

$$Y_{it}^{**} = x_{it}\boldsymbol{\delta} + z_i\boldsymbol{\theta} + \alpha_{2,i} + \varepsilon_{2,it} \tag{6}$$

where Y_{it}^{**} indicates company *i*'s desired level of the emissions trading activity at time t, $\alpha_{2,i}$ captures time-invariant company-specific unobservable factors, and $\varepsilon_{2,it}$ is an idiosyncratic error term with $\varepsilon_{2,it} \sim N(0, \sigma_{\varepsilon 2}^2)$. For the intensity decision, we model unobserved company-specific heterogeneity similar to equation (3). Combining both hurdles, the observed level of emissions trading activity of company *i* at time *t* is then

$$Y_{it} = D_{it}Y_{it}^{*} \tag{7}$$

Finally, our empirical specification of the double-hurdle model allows for non-zero correlation between the participation and intensity equations. We estimate the panel double-hurdle model using the *bootdhreg* command developed by Engel and Moffat (2014) for Stata, which provides bootstrapped standard errors.

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[17] The $\bar{x}_i$ are referred to as Mundlak terms. They pick up the "between variation" and may be interpreted as the long-run effects. In comparison, the time-varying variables pick up the "within variation" and may be interpreted as the short-run effects. Because we worry, that the effects of unobserved heterogeneity may be correlated with the explanatory variables, our presentation and interpretation of the results will focus on the time-varying effects.

Poisson model

To reflect the count nature of the dependent variables, *transaction frequency* and *use of intermediaries*, we estimate panel Poisson models. These models rely on equi-dispersion, i.e. the conditional mean is assumed to be equal to the conditional variance. Negative binomial models, for example, do not hinge on this assumption. Because they involve less restrictive distributional assumptions, however, we chose Poisson panel models as our preferred method for estimating the count data models.

Formally, the Poisson model assumes that the dependent variable (y_{it}), e.g. the number of transactions *j* carried out by company *i* during time *t*, follows a Poisson distribution. We specify the conditional probability of observing *j* as

$$\Pr\left(y_{it} = j | x_{it}, z_i, \alpha_{3,i}; \boldsymbol{\zeta}, \boldsymbol{\pi}\right) = \frac{[\exp(-\lambda_{it})](\lambda_{it})^{y_{it}}}{y_{it}!} \qquad \text{for } j=0,1,2,... \tag{8}$$

where λ_{it} denotes the conditional mean and the conditional variance of y_{it} and is modelled as

$$\lambda_{it} = \exp\left(x_{it}\boldsymbol{\zeta} + z_i\boldsymbol{\pi} + \alpha_{3,i}\right) \tag{9}$$

Similar to equations (2) and (6) in the double hurdle model, $\alpha_{3,i}$ captures time-invariant company-specific unobservable factors in the Poisson model. Likewise, we model unobserved company-specific heterogeneity as in equation (3). We estimate our CRE Poisson model via conditional maximum likelihood methods as implemented in Stata.

6.3 Results

We first present and discuss the results for the entire 2005–2014 period. We then summarize the findings of the analysis pertaining to the individual trading periods. Finally, we summarize the results obtained when distinguishing between net sellers and net buyers of allowances.

6.3.1 Results for the Full Period (2005–2014)

We present findings for our four indicators in Table 3. Robust standard errors are clustered at the company level and reported in parentheses below the parameter estimates. The final sample includes observations for 6,316 companies.

First, we note that the results for the Mundlak terms suggest that employing a pure random-effects estimator would lead to biased and inconsistent parameter estimates for all four models. In addition, for the two double-hurdle models, the coefficients associated with the Mills ratio are statistically significant, suggesting that imposing a zero covariance when estimating the participation and intensity equations would also result in biased and inconsistent parameter estimates. We turn now to the individual findings for the four indicators.

Total transactions

The first set of results reported in Table 3 represent the findings from estimating a double-hurdle model, where the first hurdle captures participation, i.e. whether a company buys or sells EUAs in a particular year or not. For those companies, the second hurdle captures the transaction intensity, i.e. the transaction volume. The results presented in Table 3 imply that a company that has a higher *net position*, is on the *carbon leakage* list, operates in the *energy sector* (as opposed to a non-carbon-leakage industries sector), enjoys higher *productivity*, has more *employees*, or operates more *installations* is more likely to participate in emissions trading and, conditional on participation, to also transact in larger volumes. Calculating the average marginal effects for the participation equation, we find that a one percent increase in the net position increases the probability of participating in emissions trading by on average 3.9 percentage points (see Section 6.8, Table 7). Similarly, operating in the *energy* sector (rather than in the non-carbon-leakage industries sector) increases the probability of participation by 6.3 percentage points. For the intensity equation, the coefficients presented in Table 3 reflect the marginal effects (or discrete probability effects for dummy variables) conditional on participation. Thus, a one percent increase in a company's net position increases the volume of transactions on average by about 0.37 percent (using the point estimate reported in Table 3 and keeping in mind that *total transactions* and *net position* are specified in natural logarithm). Belonging to the *energy* sector (as opposed to a non-carbon leakage industries sector) increases the total transaction volume by about 36 percent.

The probability of participating in emissions trading and transaction intensity were higher in the second and third trading periods than in the first trading period. In most regions, participation and intensity were typically lower than in the German-speaking base region. The probability of participating in emissions trading was higher than in the base region only in the Nordic countries.

Transaction frequency

The results for *transaction frequency* suggest that, on average, a company with a higher *net position* or which operates in a *carbon leakage* sector or the *energy* sector trades more frequently. Similarly, we find that larger companies (as measured by the number of *employees*) and companies with more *installations* trade more frequently. In comparison, we find no evidence that *productivity* is related to transaction frequency. Compared with its level in the first trading period, *transaction frequency* appears to have been higher in the second and third trading periods. The findings for the region dummies suggest that, compared with the German speaking countries, companies located in the Nordic countries trade more frequently while countries located in regions 4 and 7 trade less frequently.

For most explanatory variables, the size effects are rather substantial. For example, the point estimate associated with *energy* suggests that the mean *transaction frequency* associated with companies in the *energy* sector is about 40.5 percent (exp(0.340) = 1.405) higher than for companies operating in non-leakage industry sectors.

Use of intermediaries

A company with a higher *net position* or a company operating in a *carbon leakage* sector or in the *energy* sector uses more intermediaries. More productive companies and companies with more *installations* also use more intermediaries. In comparison, we find no evidence that the size of a company (as measured by employees) is related to the *use of intermediaries*. We further find that the *use of intermediaries* increased in the second and third trading periods compared with the first trading period. There is also substantial heterogeneity in the *use of intermediaries* across regions. Except for region 5, companies in most regions use fewer intermediaries than companies in the German-speaking region.

Again, the size effects are relevant. Operating in a *carbon leakage* sector, for example, is estimated to increase the average number of intermediaries used by about 22.5 percent (exp(0.203) = 1.225) compared with companies in non-carbon leakage industries sectors.

Table 3: Results for 2005–2014.

	Total transactions		Transaction frequency	Use of intermediaries	Use of forwards and futures	
	Participation	Intensity			Participation	Intensity
Net position	0.101***	0.373***	0.112***	0.108***	0.076***	0.520***
	(0.008)	(0.025)	(0.013)	(0.014)	(0.012)	(0.084)
Carbon leakage	0.103***	0.221***	0.135***	0.203***	0.101***	0.475***
	(0.021)	(0.044)	(0.036)	(0.062)	(0.040)	(0.156)
Energy	0.218***	0.361***	0.340***	0.193**	0.270***	1.717***
	(0.032)	(0.064)	(0.067)	(0.096)	(0.060)	(0.352)
Productivity	0.194***	0.135***	0.075	0.078*	0.030	0.313***
	(0.032)	(0.032)	(0.057)	(0.043)	(0.027)	(0.089)
Employees	0.110***	0.109***	0.132***	0.062	0.026	0.286***
	(0.028)	(0.030)	(0.048)	(0.050)	(0.031)	(0.112)
Installations	0.067***	0.051***	0.177***	0.023***	0.012***	0.040***
	(0.015)	(0.008)	(0.014)	(0.008)	(0.005)	(0.013)
Period 2	0.468***	0.839***	0.568***	1.069***	-0.034	3.146***

	(0.017)	(0.068)	(0.041)	(0.048)	(0.027)	(0.575)
Period 3	0.462***	0.535***	0.332***	0.839***	0.015	1.123***
	(0.021)	(0.066)	(0.055)	(0.055)	(0.029)	(0.195)
Region 2 (BE, FR, NL)	-0.216***	-0.191***	-0.017	-0.589***	-0.259***	-1.512***
	(0.038)	(0.072)	(0.160)	(0.208)	(0.046)	(0.356)
Region 3 (GR, IT, PT, ES, CY, MT)	0.019	-0.186***	0.047	-0.186*	-0.275***	-1.955***
	(0.032)	(0.047)	(0.068)	(0.104)	(0.045)	(0.356)
Region 4 (EE, LT, LV, PL)	-0.343***	-0.179**	-0.206***	-0.354***	-0.513***	-2.589***
	(0.040)	(0.083)	(0.076)	(0.109)	(0.067)	(0.607)
Region 5 (CZ, HU, SI, SK)	-0.040	-0.182***	-0.063	0.409***	-0.432***	-2.355***
	(0.036)	(0.072)	(0.066)	(0.089)	(0.056)	(0.515)
Region 6 (DK, FI, IS, NO, SE)	0.299***	-0.401***	0.239**	-0.844***	-0.076*	-0.842***
	(0.047)	(0.075)	(0.105)	(0.159)	(0.053)	(0.151)
Region 7 (UK, IE)	-0.044	-0.245***	-0.133*	-0.845***	-0.360***	-1.997***
	(0.048)	(0.077)	(0.077)	(0.129)	(0.055)	(0.495)
Region 8 (BG, HR, RO)	-0.098**	0.176***	-0.016	-0.100	-0.859***	-4.140***
	(0.053)	(0.099)	(0.092)	(0.129)	(0.100)	(1.021)
Mills ratio		0.831***				6.202***

		(0.229)				(1.381)
Mean net position	0.106***	0.573***	0.129***	0.124***	0.527***	1.042***
	(0.009)	(0.024)	(0.030)	(0.038)	(0.028)	(0.155)
Mean productivity	-0.212***	-0.022	0.024	-0.098*	0.171***	-0.031
	(0.033)	(0.039)	(0.058)	(0.055)	(0.034)	(0.093)
Mean employees	-0.134***	0.017	-0.0241	0.014	0.135***	0.182*
	(0.030)	(0.033)	(0.051)	(0.058)	(0.017)	(0.114)
Constant	-2.031	-0.748***	-3.164***	-4.856***	-3.753***	6.202***
	(0.064)	(0.416)	(0.096)	(0.162)	(0.095)	(1.381)
Log likelihood	-56332.57		-73885.28	-17160.12	-15624.39	
χ^2 (Prob> χ^2)	33701.99 (0.000)		6210.60 (0.000)	5873.94 (0.000)	3369.90 (0.000)	
Number of companies	6316		6316	6316	6316	
Number of observations	35056		35056	35056	35056	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Use of forwards and futures

Our findings for the *use of forwards and futures* imply that a company with a higher *net position* is more likely to participate in the derivatives market and, conditional on participation, to also trade forwards and futures in larger volumes. Calculating the average marginal effects, we find that an increase in the *net position* increases the probability of participating in the derivatives market by about 1.0 percentage points (see Section 6.8, Table 7). The results further suggest, for example, that for a company trading on the derivatives market, a one percent increase in the net position increases the volume of EUAs traded on the derivatives market by about 0.52 percent. Further, we find that operating in a *carbon leakage* sector or the *energy* sector increases a company's propensity to participate in the derivatives market and, conditional on participation, to trade in forwards and futures in higher volumes than companies operating in non-carbon-leakage industries sectors. For example, belonging to the *energy* sector increases the probability of participating in the derivatives market by about 2.2 percentage points. Both *productivity* and the number of *employees* appear to be positively related to the intensity of derivatives-market trading, but not with the decision to participate in this market. In comparison, companies with more *installations* are more likely to participate in the derivatives market and, conditional on participation, to trade at higher volumes of forwards and futures.

For the derivatives market, intensity of usage was stronger in the second and third trading periods than in the first trading period. Finally, participation and intensity were higher in the German-speaking region than in all other regions, ceteris paribus.

Discussion of results

In general, the estimation results for our explanatory variables for 2005–2014 are consistent across the four indicators that reflect companies' emissions-trading behaviour. More specifically, we find that the *net position* and operating in the *energy* sector increase emissions-trading activities in the EU ETS. In our double-hurdle models these variables are positively related with participation and, conditional on participation, with the volume of EUAs traded. These results are in line with the findings for the first trading period reported by Cludius (2018), Jaraitė-Kažukauskė and Kažukauskas (2015) and Zaklan (2013), who note the importance of net position and sector affiliation for companies' trading activities. As an extension to previous studies, our research explicitly accounts for the effects of operating in a *carbon leakage* sector on emissions-trading activities (as compared with companies operating in non-leakage industry sectors or the energy sector). We find operating in a carbon-leakage sector to be positively related to all indicators reflecting emissions-trading behaviour. Jaraitė-Kažukauskė and Kažukauskas (2015) include sectoral dummies for several ETS industry sectors and find that they are generally less likely to be active than energy companies. They do not, however, link their activity to the carbon-leakage status of a particular sector.

We also find that, in general, the number of *employees*, which we use as a proxy for the size of a company, is positively related to companies' emissions-trading activities (with the exception of the *use of intermediaries* and participation in the *use of forwards and futures*). Using the primary allocation to reflect company size, Jaraitė-Kažukauskė and Kažukauskas (2015) find for the first trading period that larger companies are more likely to participate in emissions trading. In addition, they find that company size (measured by fixed assets and total revenue) correlates positively with the intensity of inter-company trading of EUAs. For the second trading period, Baudry et al. (2021) find that larger companies (using the emissions volumes to proxy size) trade at higher volumes. Finally, Cludius and Betz (2020) conclude that larger companies (as measured by emissions volumes) are more likely to trade with a larger variety of intermediaries. Thus, our findings for size are generally in line with those reported in the existing literature, even though we employ a different proxy from those used in previous studies.

We further find that company *productivity* (i.e. revenues per employee) is typically positively related to our activity indicators (with the exception of *transaction frequency* and participation in *use of forwards and futures*). For the first trading period (and hence with a much smaller sample), Zaklan (2013) finds no evidence that a company's profitability (proxied as return on assets and as revenues compared with total assets) - which should be closely related to productivity - is associated with its trading activity.

We find the number of *installations* to be positively related to all four indicators of activity (including both participation and intensity of participation in *total transactions* as well as *use of forwards and futures*). These results speak directly to the findings by Jaraitė-Kažukauskė and Kažukauskas (2015), who conclude that trading-transaction costs existed in the introductory phase of the EU ETS. As evidence, they point to the positive relationship between intra-firm trading and the number of installations which are supposed to reflect search- and information-related costs. We find, similarly, that, for the entire study period of 2005–2014, the number of *installations* is positively related to market participation, the intensity of trading, and the *use of intermediaries*. Thus, following this line of argument, our findings for size and number of installations provide no evidence that trading-transaction costs have declined over time. Similarly, to findings reported by Jaraitė-Kažukauskė and Kažukauskas (2015), our results may suggest that transaction costs are characterized by economies of scale and - because they affect the intensity of transactions and forwards and futures - are composed of fixed and variable fractions.

The results for the region dummies indicate that a company's emissions-trading activities are related with its geographical location. For most regions, though, we found no clear patterns across the four indicators. The importance of the location of an installation or company for its trading behaviour has previously been noted in network analyses of the EU ETS (Borghesi and Flori 2018; Karpf et al. 2018). Likewise, Hintermann and Ludwig (2019) observe a "home bias" in companies' trading partner choices.

Finally, we observe that companies were generally more active in the second and third trading periods than in the first trading period. Transaction volume and trading frequency may have been particularly high in the second period as a result of the financial crisis. To increase liquidity, some companies sold their allowance allocations at the beginning of the trading year and later purchased the amount of allowances required for compliance just in time to meet the deadline (Cludius and Betz 2020). In the next section, we further explore differences between trading periods.

6.3.2 Results by Trading Period

To explore whether the effects of factors related to companies' emissions-trading activities have changed over time, we ran separate regressions for the three trading periods within the scope of the study. In this section, we briefly summarize our findings. We present the full estimation output in Section 6.9 (Table 8, Table 9, Table 10). Table 5 reports the descriptive statistics for the dependent and explanatory variables by trading period. In general, results for the individual trading periods are consistent with those presented for the entire 2005–2014 period of analysis in Table 3. This indicates that factors related to various emissions-trading activities remained stable over time. Yet, for some variables we observe differences across trading periods.

For companies participating in emissions trading we observe a stronger effect of *net position*, *carbon leakage* and *energy* on the intensity of *total transactions* in the second trading period than in the first and third trading periods. This finding may be explained by the higher average prices for EUAs in the second trading period compared with prices in the first trading period and compared with prices in 2013 and 2014.

For *transaction frequency,* we observe that the coefficient associated with *carbon leakage* is larger in the first trading period than in the second and third trading periods. This may be explained by the fact that carbon-leakage sectors such as cement and steel enjoyed particularly large surpluses of EUAs in the first trading period, which they eventually sold on the market, because banking of EUAs was not allowed between the first and the second trading periods. We further find *productivity* to be positively related to *transaction frequency* in the second trading period, while for the 2005–2014 period and for the first and third trading periods individually, this relationship is not statistically significant.

For *use of intermediaries*, the coefficient associated with *carbon leakage* is statistically significant for the second and third trading periods but not for the first trading period. Further, the effect of *energy* appears larger in the third trading period than in the first and second trading periods. We conjecture that this finding can be explained by the fact that since 2013 most companies in the power sector had to purchase virtually all the EUAs needed either at the auction or on the secondary market. To do so, they use market intermediaries more intensively. For example, EUTL data suggest that banks were the principal successful bidders at EUA auctions in 2013 and 2014.

For the *use of forwards and futures* we observe differences across periods mainly in the intensity equation. For example, findings reported in Table 10 suggest an increase in the coefficient associated with *net position* across trading periods. This finding might indicate that hedging becomes more relevant with tightening targets and the expectation of rising EUA prices. For *carbon leakage*, we find a statistically significant effect for the second trading period only, suggesting that the findings for 2005–2014 reported in Table 3 are driven predominantly by the activities taking place in this period. Most prominently, though, we observe a strong increase in the coefficient associated with *energy,* which again could be explained by the fact that in the third trading period the power sector no longer receives allowances for free but has to actively hedge its position on the secondary market.

We briefly turn to the variables that previous literature has assumed to capture transaction costs. For *employees*, we find some differences across trading periods. In particular, for *total transactions*, *transaction frequency*, and *use of intermediaries*, *employees* is statistically significant in in the first and second trading periods, but not in the third trading period. For *use of forwards and futures*, *employees* is found to be statistically significant for the participation decision in the first trading period only. In comparison, we find no strong evidence that the effects of the number of *installations* have weakened across trading periods. Thus, our findings provide mixed evidence that transaction costs have decreased over time.

6.3.3 Results for Total Transactions with Asymmetric Response for Net Sellers and Net Buyers

To explore whether the direction of the net position, i.e. whether a company's being "short" or "long" affects market participation and the intensity of transactions, we estimate a model which allows for an asymmetric response of net sellers and net buyers in the *total transactions* model. Net buyers (net sellers) are defined as companies where in a particular year the amount of free allocation is below (exceeds) verified emissions. Depending on its net position, a company may be classified as a net seller in one year and a net buyer in another year.

In theory, without market frictions, the opportunity costs of holding allowances should be the same for net buyers and net sellers. Thus, for a given net position, participation and trading intensity should not depend on whether companies are net sellers or net buyers. To explore this hypothesis for the data at hand, we include an interaction term to represent the relationship between net position and a dummy for net sellers as an additional explanatory variable. We present the results derived from estimating the double-hurdle model for *total transactions* for 2005–2014 in Section 6.10, Table 11 and the results for the individual trading periods in Table 12. Table 6 reports the descriptive statistics for the dependent and explanatory variables for net buyers and net sellers.

We first note that the findings for the other explanatory variables are virtually identical to those presented for 2005–2014 in Table 3 and for the individual trading periods in Table 8. In particular, though, we find that the coefficient associated with the interaction term is negative and statistically significant for the participation equation in all samples and for the intensity equation in all samples except for the third period sample. Thus, for a given net position, net buyers are more likely to participate in emissions trading and—conditional on participation—to trade at higher volumes than net sellers. This finding supports the view that the actual or perceived opportunity costs of holding allowances differ between net sellers and net buyers. This asymmetry possibly reflects a violation of Coase's (1960) independence property. Depending on the initial allocation of allowances, some companies might build long positions. Our results then imply that these companies trade less intensively, distorting the market result.

Perhaps, this asymmetry can be explained by citing net buyers' intentions to avoid noncompliance and penalties. In addition, building on Kahneman and Tversky (1979) and Kahneman et al. (1990), company decision makers may perceive their endowment of free allocation as a reference point. If they value losses against this references point stronger than gains of equal size, their willingness to pay for allowances is lower than their willingness to accept for selling allowances. As a consequence, opportunity costs differ between buyers and sellers. Moreover, accounting rules which require "short" companies to itemize the value of missing allowances in their accounting statements (Ellerman et al., 2010) may further contribute to this asymmetry.

In addition, we observe differences across trading periods, suggesting that this asymmetry in opportunity costs between net sellers and net buyers has declined over time. This finding might be explained by institutional changes such as longer trading periods providing companies with more flexibility to borrow allowances across years or the emergence of market intermediaries and derivatives markets. In addition, companies are likely to have learned through experience with the EU ETS over time, improving their capacity to assess the opportunity costs of holding allowances.[18]

6.3.4 Robustness Checks

To assess the robustness of the findings presented in Table 3 we carried out a series of additional analyses. These analyses allowed for alternative distributional assumptions and model specifications.

Distributional assumptions

Rather than employing CRE Poisson models to estimate the regression equations for *transaction frequency* and *use of intermediaries*, we also estimate those using CRE negative binomial models. Compared with the Poisson model, the conditional probability function of the negative binomial model includes an additional term reflecting unobserved heterogeneity, which is assumed to follow a gamma distribution. Thus, unlike standard Poisson models, negative binomial models do not assume equi-dispersion. For both the *transaction frequency* and *use of intermediaries* equations, the findings of the CRE negative binomial model are virtually identical to those reported in Table 3. We also estimated Poisson fixed-effects models. The findings for the time-varying variables are almost identical to those presented in Table 3.[19]

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[18] In general, the EU ETS allows banking of allowances across trading periods and years, but not borrowing across periods. For the first trading period, neither banking nor borrowing was possible across periods. Because allowances for the year t+1 are allocated before companies need to surrender allowances for emissions for year t, borrowing is de facto feasible also across years within the same trading period. Thus, the period pertaining to banking of allowances is longer than the period for borrowing.

[19] All findings that are not shown to save space are available from the authors upon request.

Model specification

First, following the literature (e.g. Zaklan 2013; Jaraitė-Kažukauskė and Kažukauskas 2015), we also distinguish between net buyers and net sellers by splitting the sample accordingly. In Table 13 and Table 14 in Section 6.11 we report the findings for net buyers and net sellers. At a very general level, the results we obtain for these samples are consistent with those for the full sample presented in Table 3. Thus, qualitatively, the factors related to companies' emissions-trading activities do not appear to differ between net buyers and net sellers. Noticeable differences pertaining to our explanatory variables exist, for example, for *carbon leakage*, where the coefficient in the participation equation for *total transactions* and for the *use of forwards and futures* is statistically different only for net sellers (and the full sample). Possibly, these null results for net buyers may reflect lower statistical power. In some instances, we also observe differences in the size effects. For example, the effects of *carbon leakage* are typically larger for net sellers than for net buyers. In comparison, the effects of *energy* are typically larger for net buyers than for net sellers. Finally, for *transaction frequency* and *use of intermediaries*, the effects of *net position* appear larger for net sellers than for net buyers, but we observe no differences for the other indicators.

Second, our results are very consistent with those reported in Table 3 if we use profit (before taxes) rather than revenues per employee. Because information on profits is often lacking in the ORBIS data base, employing profits rather than productivity involves a loss of almost 30% of observations. Our preferred specification therefore employs *productivity*. Third, because the dependent variables and revenues are contemporaneous, this may cause an endogeneity problem. More active use of emissions trading may increase revenues. We therefore estimated all models using lagged values for *productivity*. Because data on revenues and employees were available also for 2014, lagging *productivity* by one year did not cause any loss of observations. The results for these models are virtually identical to those reported in Table 3. Fourth, our preferred specification includes dummies for the three trading periods. To allow for a more fine-grained representation of temporal effects, we estimated the models using yearly dummies instead of trading-period dummies. The results for the explanatory variables are very similar to those shown in Table 3. Finally, to mitigate the effects of "outliers" at both ends of the distribution, we used ten categorical dummy variables reflecting the percentile of *net position*. For the Poisson models, the findings for the other explanatory variables are typically very similar to those displayed in Table 3. The double hurdle models, however, failed to achieve convergence.

6.4 Conclusions

The efficiency of any emissions-trading system relies on participants' ability and willingness to trade allowances. The ability to trade depends on transaction costs, while the willingness to trade depends, in particular, on a participant's evaluation of the opportunity costs of holding allowances. A better understanding of the factors related to a participant's decision whether and how to trade allowances helps explain the performance of an emissions-trading system and provides guidance for its design. In this paper, we analyse companies' allowances-trading behaviour for the first ten years of the EU ETS.

Our analyses extend previous studies for earlier periods of the EU ETS, yet we rely on a broader set of trading indicators. In addition to transaction volumes, we also consider *transaction frequency*, the *use of intermediaries*, and the *use of forwards and futures* markets. Our findings are similar for these four indicators. We find that trading behaviour is related to the size of a company, its net position (the difference between its free allocation and its verified emissions), its sector affiliation, productivity, and location. Larger companies, those with higher (absolute) *net positions*, companies operating in the *energy* and the *carbon leakage* sectors (compared with those in non-carbon leakage industries) and those with higher *productivity* are typically more likely to participate in the market and also to use the market more intensively.

Further, our findings suggest that trading-related transaction costs impact trading activity in the EU ETS. Our results are consistent with previous studies that find that transaction costs fall disproportionally on smaller companies and companies with fewer installations. Similarly, we conclude that transaction costs consist of fixed and variable components. However, we find ambiguous results whether the effects of transactions costs on companies' trading activities changed over time, depending on whether we use the number of employees or installations to capture transaction costs. Considering further differences across the three trading periods, we observe that companies were generally more active in the second and third trading periods than in the first trading period. Overall, the results pertaining to factors related to companies' trading activity are consistent across trading periods. The differences we found relate mostly to sector affiliation and net position and may be explained by changes in the price of allowances and in the evolution of the design of the EU ETS over time, in particular regarding the increasing share of auctions over time.

Last but not least, we explore differences in trading behaviour between net sellers and net buyers. Our results suggest that net buyers are more likely to participate in emissions trading and to trade at higher volumes than net sellers. This asymmetry in trading behaviour possibly reflects a violation of the Coase (1960) independence property. If market participants receive generous allowance budgets, they eventually build long positions. Our results imply that these companies trade less intensively, distorting the allowances market. We rationalize this asymmetric behaviour by citing differences in the actual or perceived opportunity costs of holding allowances between net sellers and net buyers. We further observe that this asymmetry decreases over time, possibly owing to institutional changes in the EU ETS (length of trading periods, emergence of intermediaries and derivatives markets) and learning effects on the side of companies.

To derive these findings we employ a dataset that combines information from various databases on trading activities and company characteristics. While this yields a rich set of information, some caveats remain. For example, for several accounts in the EUTL we could not match the name of the operator with the name of a company in the ORBIS database. Likewise, for many companies, the ORBIS database did not provide information indicating company characteristics. Our analysis pertaining to forwards and futures is based on information for typical delivery dates, which may result in a coarse approximation of actual transactions of forwards and futures as we cannot account for the transactions related to derivatives before they are delivered to the final buyer. In addition, data availability limitations prevented us from including information on banked allowances. Because of the rules on banking and borrowing in the EU ETS, including this information would affect the net positions of net buyers and net sellers asymmetrically. Similarly, accounting for transactions of allowances which are internal to companies may affect some of our results.

Our empirical findings have important policy implications. It is likely that the higher share of auctioning we observed from 2013 onwards has already increased companies' ability and willingness to actively participate in emissions trading and thus has likely increased efficiency. Transaction costs for small emitters and the asymmetry involved in assessing the opportunity costs of holding allowances between net buyers and net sellers remain issues to be resolved. Transaction costs for small emitters could be reduced by addressing barriers that prevent these companies from participating in the market, in particular in auctions. One example of how this could be done is the use of an electronic bulletin board as a trading institution that would be more accessible than an exchange for smaller companies (e.g. Cason and Gangadharan 1998).

For companies continuing to receive free allocations (e.g. because of concerns about carbon leakage), consignment auctions could be implemented. These revenue-neutral auctions require that free allocation be offered at auction, with the original holder receiving the financial value of allowances determined in the auction, while allowances themselves go to the highest bidder. Consignment auctions involve low administrative costs and enhance recognition of opportunity costs (Burtraw and McCormack 2017). A more radical approach involves replacing free allocation of allowances to carbon leakage sectors by a carbon border-adjustment mechanism, as currently discussed at EU level. This would further the transition of the EU ETS towards full auctioning and likely enhance price discovery and increase efficiency in the system.

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CRediT authorship contribution statement

- **Jan Abrell**: Conceptualization, Data curation, Writing – original draft, Writing – review & editing.
- **Johanna Cludius**: Conceptualization, Writing – original draft, Writing – review & editing.
- **Sascha Lehmann**: Data curation, Conceptualization, Methodology, Writing – original draft, Writing – review & editing.
- **Joachim Schleich**: Conceptualization, Methodology, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing.
- **Regina Betz**: Conceptualization, Supervision, Writing – review & editing.

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6.6 Appendix A: Construction of the Database

Compiling of the Data

The Union registry is an electronic database managed by the European Commission that records all allowance transactions carried out under the EU ETS, including the allocation and surrendering of allowances, but also all transactions taking place between market participants. The European Union Transaction Log (EUTL) monitors, records, and authorizes all transactions occurring in the Union registry. Via the EUTL, the European Commission publishes data on allowance transactions as well as details from the Union registry. This information is now available on a three-year delay. The data can be downloaded free of charge (https://ec.europa.eu/clima/ets/).

In the EUTL transactions take place between registered accounts. All liable installations covered by the EU ETS are required to open an Operator Holding Account (OHA) for stationary installations or Aircraft Operator Account (AOA) in the Union registry. In addition to these mandatory accounts, Person Holding Accounts (PHAs) and Trading Accounts (TAs) can be opened voluntarily in the Union registry for trading purposes.[20] Finally, a number of administrative accounts exist that belong either to the EU or to individual countries and are used for, amongst other procedures, the issuance, allocation, auctioning, or deletion of allowances.

On the account level, the EUTL includes information indicating the name of the account, the registry in which the account is registered, the related company registration number, and the associated account holder and installation. For account holders we know the name and address of the main account representative. For installations we know the type of activity and the address,

[20] TAs were introduced only in 2013 and allow, in contrast to PHAs, trading in real time, while PHAs are delayed by 26 hours (Art. 39.3 Registry Regulation No 389/2013). The majority of PHAs and TAs are opened by non-liable companies such as financial intermediaries as well as liable companies that use them to manage compliance and trading activities (Betz and Schmidt 2015; Cludius and Betz 2020). Some PHAs and TAs are held by non-governmental organizations or private individuals.

and compliance data, including annual allocations, verified emissions, and surrendered allowances.

The EUTL records transfers of allowances between two accounts, providing information about the accounts involved, transaction types, transaction dates, and the number of allowances. Trading in futures and forwards is recorded only at the expiration date when a derivative is delivered to a buyer. The EUTL does not reveal information on prices per EUA or total payments.

Until 2012, a decentralized system of national registries existed. These registries were aggregated and checked in the Community Independent Transaction Log (CITL). In 2012, information was migrated from the individual registries to a single EU-wide registry and the CITL was replaced by the EUTL. In this context, all installations received new OHAs, i.e. all banked allowances had to be transferred from the old accounts to the new accounts, requiring a high number of internal transfers.

In addition to EUTL data containing ETS-related information, we also use financial data on the liable companies from the ORBIS database operated by Bureau van Dijk. We use financial data on the number of employees, revenues, industry classification (NACE), the company registration number and the home country of a company. To match the EUTL and ORBIS datasets, we relied primarily on the company registration number, the account name, and addresses of account holders.

For the empirical analyses of transactions we consider only transactions involving OHAs, PHAs, or TAs. Thus, we do not consider transactions involving authorities such as the primary allocation or the surrendering of allowances. Because these EUA transactions are regulatory requirements rather than outcomes of deliberate decisions, they are not relevant in the context of this research.

After we matched the company information obtained from the ORBIS to the transaction-level dataset, we set up a panel dataset at the level of individual companies for our period of analysis.

Some trades were carried out by accounts that we were not able to link to an ORBIS company; these involved mainly PHAs and TAs. However, we did not exclude these trades completely from our analyses. For example, if two PHAs traded with each other but only the transferor had a link to ORBIS, that transfer would be included in the transfer volume for that company in our dataset. Because the buyer did not have a link to ORBIS, however, this transaction could not be included on the buyer side. We believe that omitting these transactions does not significantly affect the results of our analysis, because the relevant company-level transaction volumes, which are the subject of our analysis, are not affected by this adjustment. Eventually, data on allocations, verified emissions, and surrendered EUAs were aggregated at the company level.

In total, we have 40320 accounts in the initial list, of which 6466 could not be matched with ORBIS. The others were then aggregated to 15014 companies. For our multivariate analyses the dataset includes fewer companies because we only include EUTL activities (but not aircraft operators) where NACE codes were available. We also excluded all observations where both verified emissions and allocations were zero, thus ensuring that plants that have ceased operations but are still listed in the EUTL were excluded. This leaves us with 8767 companies. Of those, information on the number of employees, sales, and profits was available for 6964 companies. Finally, we eliminated all observations where allocation exceeded verified emissions by a factor of ten to limit the effects of errors in the EUTL on our results. This left us with 6611 companies. Because of collinearity in the data matrix the samples available for the econometric analyses are somewhat smaller and vary across analyses.

We also tried to track company banking of EUAs but found substantial inconsistencies in the data when adding up the banked allowances over time. For example, in the wake of a reorganization of the EUTL in 2012, in many cases banked allowances from the second trading period appeared to not have been adequately transferred to the third trading period.

Matching of former and current OHA

The reorganization of the EUTL in 2012 led to new account types such as aircraft operating holding accounts. Hence, each installation needed to be associated with a new OHA. However, the EUTL provides the current OHA related to an installation only, not the OHA that was in place before the regime switch. To infer the previous OHA we used the following procedure:[21]

(1) Matching the account name to the installation name and accepting matches if they are unique.

(2) Matching the account address to the installation address and accepting matches if they are unique.

(3) Matching on allocation information: In this stage, we use installation-level information on the amount of allowances allocated and surrendered and search for the corresponding transaction with the same amount of allowances and an administrative account of the respective registry involved. Again, only unique matches are accepted. We start with allocations followed by surrendering transfers.

This procedure allowed us to match more than 99 percent (i.e. 12894 of 13001) of the current OHAs to their OHAs before the regime switch.

Matching of EUTL accounts with companies in the ORBIS database

Since 2012 operators of accounts are obliged to report a VAT registration number within the EUTL. This can be either a national or European VAT number. Because the ORBIS database also uses these VAT numbers a direct matching of accounts between the two databases based on the VAT number should be possible. However, because of reporting errors and differences in the

[21] A more complete description of the processing of the EUTL data is available in Abrell (2021). The compiled data set is available for download under https://euets.info/background.

formatting a direct matching was not feasible. We therefore use fuzzy matching based on a VAT number, the name of the account associated with that number, and the address of the account contact. These variables are used in automatic ORBIS batch searching using the account data as criteria for the search in the ORBIS database. Batch searching returns a number of possible matches together with the matching score. We then select the final match by inspecting the quality of the matches of the single fields.

6.7 Appendix B: Descriptive Statistics

Table 4: Descriptive statistics for 2005-2014 (for largest sample used in Table 3).

	Mean	Std. Dev.		
		overall	between	within
Total transactions (in metric tons of CO_2eq.)	514990	7248713	5720526	4114349
Transaction frequency	3.37	13.2	10.716	6.604
Use of intermediaries	0.242	0.797	0.583	0.528
Use of forwards and futures (in metric tons of CO_2eq.)	62199	1525535	1398514	629350
Net position (in metric tons of CO_2eq.)	-10170	820983	599720	536386
Carbon leakage	0.419	0.493	0.494	0
Energy	0.231	0.421	0.408	0
Productivity (in 1000 Euro/employee)	13.7	142	230.1	51.9
Employees	1771	14109	10728	2351
Number of installations	2.16	3.41	2.96	0
Region 1 (AT, DE, LI)	0.167	0.373	0.376	0
Region 2 (BE, FR, NL)	0.13	0.336	0.347	0
Region 3 (GR, IT, PT, ES, CY, MT)	0.263	0.44	0.450	0
Region 4 (EE, LT, LV, PL)	0.105	0.307	0.308	0
Region 5 (CZ, HU, SI, SK)	0.124	0.329	0.307	0
Region 6 (DK, FI, IS, NO, SE)	0.090	0.286	0.263	0
Region 7 (UK, IE)	0.080	0.271	0.259	0
Region 8 (BG, HR, RO)	0.042	0.201	0.218	0
Number of companies/		6316		
Number of observations		35056		

Table 5: Descriptive statistics by trading period (for largest sample used in Table 8).

	2005-2007		2008-2012		2013-2014	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total transactions (in metric tons of CO_2eq.)	230904	2857846	605041	7940905	628648	8849416
Transaction frequency	2.18	8.9	4.02	15.7	3.24	10.9
Use of intermediaries	0.111	0.406	0.309	0.971	0.238	0.657
Use of forwards and futures (in metric tons of CO_2eq.)	17270	299727	77206	1520003	78425	2209160
Net position (in metric tons of CO_2eq.)	11425	411604	16137	640062	-94622	1355406
Carbon leakage	0.422	0.494	0.402	0.49	0.453	0.498
Energy	0.241	0.428	0.25	0.433	0.177	0.381
Productivity (in 1000 Euro/employee)	12.3	180	13.4	112	16.1	153
Employees	1913	14540	1748	13979	1664	13909
Number of installations	2.16	3.44	2.16	3.43	2.16	3.34
Region 1 (AT, DE, LI)	0.198	0.398	0.141	0.348	0.19	0.393
Region 2 (BE, FR, NL)	0.147	0.354	0.115	0.319	0.146	0.353
Region 3 (GR, IT, PT, ES, CY, MT)	0.2	0.4	0.277	0.447	0.301	0.459
Region 4 (EE, LT, LV, PL)	0.144	0.351	0.112	0.316	0.045	0.208
Region 5 (CZ, HU, SI, SK)	0.131	0.337	0.126	0.332	0.111	0.314
Region 6 (DK, FI, IS, NO, SE)	0.104	0.306	0.090	0.286	0.075	0.263
Region 7 (UK, IE)	0.063	0.244	0.091	0.287	0.073	0.26
Region 8 (BG, HR, RO)	0.013	0.115	0.049	0.217	0.059	0.235
Number of companies/	3643		4969		4306	
Number of observations	8939		18171		7946	

Table 6: Descriptive statistics for net-buyers and net-sellers for 2005-2014 (for largest sample used in Table 13 and Table 14).

	Net buyers		Net sellers	
	Mean	Std. Dev.	Mean	Std. Dev.
Total transactions (in metric tons of CO_2eq.)	956907	10167180	313478	5407431
Transaction frequency	4.12	15.0	3.03	12.3
Use of intermediaries	0.22	0.703	0.252	0.836
Use of forwards and futures (in metric tons of CO_2eq.)	115316	2106804	37977	1167371
Net position (in metric tons of CO_2eq.)	-173054	1380057	64105	308756
Carbon leakage	0.353	0.478	0.449	0.497
Energy	0.271	0.445	0.213	0.409
Productivity (in 1000 Euro/employee)	23.3	222	9.37	81.8
Employees	1881	16289	1721	12994
Number of installations	2.42	4.08	2.04	3.05
Region 1 (AT, DE, LI)	0.194	0.395	0.154	0.361
Region 2 (BE, FR, NL)	0.119	0.324	0.135	0.342
Region 3 (GR, IT, PT, ES, CY, MT)	0.273	0.446	0.258	0.437
Region 4 (EE, LT, LV, PL)	0.066	0.248	0.123	0.329
Region 5 (CZ, HU, SI, SK)	0.093	0.29	0.138	0.345
Region 6 (DK, FI, IS, NO, SE)	0.122	0.327	0.076	0.265
Region 7 (UK, IE)	0.087	0.282	0.076	0.266
Region 8 (BG, HR, RO)	0.0489	0.214	0.04	0.196
Number of companies/	4106		5478	
Number of observations	10979		24077	

6.8 Appendix C: Estimated average Marginal Effects for Participation Decision

Table 7: Estimated average marginal effects for participation decision for 2005-2014 - *Total transactions* and *use of forwards*.

	Total transactions	Use of forwards and futures
Net position	0.039***	0.009***
	(0.002)	(0.001)
Carbon leakage	0.013**	0.001
	(0.006)	(0.004)
Energy	0.063***	0.022***
	(0.008)	(0.005)
Productivity	0.033***	0.009**
	(0.006)	(0.004)
Employees	0.016**	0.009**
	(0.006)	(0.004)
Installations	0.024***	0.002***
	(0.001)	(0.000)
Period 2	0.167***	0.079***
	(0.006)	(0.004)
Period 3	0.165***	0.026***
	(0.007)	(0.005)
Region 2 (BE, FR, NL)	-0.073***	-0.039***
	(0.009)	(0.005)
Region 3 (GR, IT, PT, ES, CY, MT)	0.009	-0.047***
	(0.008)	(0.005)
Region 4 (EE, LT, LV, PL)	-0.125***	-0.074***

	(0.011)	(0.007)
Region 5 (CZ, HU, SI, SK)	-0.010	-0.055***
	(0.010)	(0.006)
Region 6 (DK, FI, IS, NO, SE)	0.115***	-0.018***
	(0.011)	(0.006)
Region 7 (UK, IE)	-0.018*	-0.064***
	(0.011)	(0.006)
Region 8 (BG, HR, RO)	-0.048***	-0.126***
	(0.014)	(0.011)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.9 Appendix D: Results by Trading Period

Table 8: Results by trading period - *Total transactions*.

	Total transactions 2005–2007		Total transactions 2008–2012		Total transactions 2013–2014	
	Participation	Intensity	Participation	Intensity	Participation	Intensity
Net position	0.124***	0.235***	0.114***	0.415***	0.029	0.134***
	(0.021)	(0.072)	(0.011)	(0.040)	(0.025)	(0.052)
Carbon leakage	0.150***	0.228**	0.097***	0.499***	0.102***	0.293***
	(0.038)	(0.112)	(0.03)	(0.060)	(0.032)	(0.085)
Energy	0.195***	0.461***	0.226***	0.807***	0.242***	0.437***
	(0.057)	(0.145)	(0.036)	(0.089)	(0.057)	(0.132)
Productivity	0.391***	0.443***	0.185***	0.399***	0.039	0.021
	(0.072)	(0.188)	(0.037)	(0.065)	(0.053)	(0.117)
Employees	0.340***	0.310**	0.076**	0.222***	0.017	0.372
	(0.079)	(0.184)	(0.040)	(0.039)	(0.079)	(0.406)
Installations	0.048***	0.059***	0.070***	0.071***	0.103***	0.091***
	(0.014)	(0.016)	(0.021)	(0.014)	(0.015)	(0.017)

Region 2 (BE, FR, NL)	-0.280***	0.236*	-0.271***	-0.702***	-0.040	-0.167*
	(0.055)	(0.167)	(0.055)	(0.109)	(0.052)	(0.129)
Region 3 (GR, IT, PT, ES, CY, MT)	-0.299***	0.344**	0.027	-0.395***	0.288***	-0.167*
	(0.043)	(0.174)	(0.045)	(0.064)	(0.047)	(0.105)
Region 4 (EE, LT, LV, PL)	-0.503***	0.166	-0.325***	-0.448***	-0.148**	-0.535***
	(0.061)	(0.253)	(0.056)	(0.123)	(0.084)	(0.17)
Region 5 (CZ, HU, SI, SK)	-0.148***	0.261**	0.000	-0.310***	-0.005	-0.377***
	(0.047)	(0.128)	(0.056)	(0.084)	(0.054)	(0.152)
Region 6 (DK, FI, IS, NO, SE)	0.360***	0.298**	0.356***	-0.474***	0.015	-0.469***
	(0.052)	(0.178)	(0.068)	(0.126)	(0.085)	(0.165)
Region 7 (UK, IE)	0.041	0.475***	-0.092*	-0.625***	0.036	-0.014
	(0.065)	(0.136)	(0.064)	(0.100)	(0.073)	(0.135)
Region 8 (BG, HR, RO)	-0.297***	-0.257	-0.216***	0.227*	0.248***	0.029
	(0.114)	(0.256)	(0.070)	(0.159)	(0.09)	(0.137)
Mills ratio		0.885		2.132***		0.885
		(0.715)		(0.507)		(0.715)
Mean net position	0.067***	0.633***	0.112***	0.570***	0.161***	0.774***
	(0.022)	(0.042)	(0.011)	(0.043)	(0.027)	(0.061)

Mean productivity	-0.367***	-0.293*	-0.248***	-0.253***	-0.015	0.120
	(0.076)	(0.190)	(0.040)	(0.083)	(0.056)	(0.11)
Mean employees	-0.327***	-0.156	-0.135***	-0.078*	-0.014	-0.237
	(0.080)	(0.178)	(0.044)	(0.048)	(0.082)	(0.411)
Constant	-2.010***	-0.612	-1.499***	-1.271**	-1.816***	-0.657
	(0.099)	(1.459)	(0.079)	(0.755)	(0.109)	(0.776)
Log likelihood	-12272.94		-29950.85		-14098.43	
χ^2 (Prob> χ^2)	5781.52 (0.000)		20738.16 (0.000)		6006.33 (0.000)	
Number of companies	3643		4969		4306	
Number of observations	8939		18171		7946	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Results by trading period - *Transaction frequency* and *use of intermediaries.*

	Transaction frequency 2005–2007	Transaction frequency 2008–2012	Transaction frequency 2013–2014	Use of intermediaries 2005–2007	Use of intermediaries 2008–2012	Use of intermediaries 2013–2014
Net position	0.099*	0.077***	0.042	0.105*	0.117***	0.0823**
	(0.052)	(0.015)	(0.027)	(0.057)	(0.021)	(0.040)
Carbon leakage	0.252***	0.127**	0.149***	0.072	0.215***	0.267***
	(0.068)	(0.051)	(0.049)	(0.115)	(0.080)	(0.086)
Energy	0.385***	0.364***	0.425***	0.270**	0.173*	0.459***
	(0.089)	(0.070)	(0.102)	(0.138)	(0.103)	(0.132)
Productivity	0.021	0.207***	0.087	0.376***	0.193***	0.175**
	(0.111)	(0.056)	(0.057)	(0.108)	(0.074)	(0.084)
Employees	0.222**	0.143**	-0.033	0.305**	0.108*	0.074
	(0.090)	(0.057)	(0.118)	(0.139)	(0.062)	(0.139)
Installations	0.149***	0.161***	0.170***	-0.000	0.028***	0.027***
	(0.013)	(0.013)	(0.014)	(0.011)	(0.010)	(0.010)
Region 2 (BE, FR, NL)	-0.278***	0.007	0.001	-0.414**	-0.601**	-0.681***

	(0.092)	(0.223)	(0.121)	(0.166)	(0.290)	(0.206)
Region 3 (GR, IT, PT, ES, CY, MT)	-0.334***	-0.017	0.176**	-0.158	-0.275**	-0.253**
	(0.074)	(0.084)	(0.068)	(0.151)	(0.130)	(0.105)
Region 4 (EE, LT, LV, PL)	-0.445***	-0.196**	-0.147	-0.299*	-0.518***	0.0276
	(0.112)	(0.086)	(0.108)	(0.178)	(0.121)	(0.152)
Region 5 (CZ, HU, SI, SK)	-0.076	-0.077	-0.162**	0.104	0.293***	0.738***
	(0.097)	(0.073)	(0.081)	(0.149)	(0.104)	(0.103)
Region 6 (DK, FI, IS, NO, SE)	0.456***	0.211*	0.090	-0.343	-1.042***	-0.592***
	(0.122)	(0.113)	(0.126)	(0.228)	(0.165)	(0.188)
Region 7 (UK, IE)	0.090	-0.267***	0.055	-0.253	-1.045***	-0.815***
	(0.132)	(0.073)	(0.147)	(0.203)	(0.152)	(0.224)
Region 8 (BG, HR, RO)	-0.423**	-0.108	0.138	-2.929***	-0.332**	0.470***
	(0.186)	(0.102)	(0.120)	(0.977)	(0.151)	(0.153)
Mean net position	0.179***	0.161***	0.262***	0.208***	0.135***	0.007
	(0.053)	(0.023)	(0.042)	(0.064)	(0.032)	(0.055)
Mean productivity	0.146	-0.145***	0.196	-0.384***	-0.238***	-0.149
	(0.122)	(0.049)	(0.209)	(0.127)	(0.073)	(0.096)
Mean employees	-0.114	-0.035	-0.018	-0.234*	-0.0361	0.0602

	(0.092)	(0.058)	(0.180)	(0.140)	(0.068)	(0.137)
Constant	-3.598***	-2.447***	-2.515***	-5.510***	-3.847***	-3.292***
	(0.143)	(0.138)	(0.128)	(0.278)	(0.226)	(0.192)
Log likelihood	-13683.75	-39521.30	-15384.61	-2773.90	-10173.36	-4269.09
χ^2 (Prob> χ^2)	1796.20 (0.000)	5972.98 (0.000)	3147.49 (0.000)	2749.99 (0.000)	2404.24 (0.000)	2018.47 (0.000)
Number of companies	3643	4969	4306	3643	4969	4306
Number of observations	8939	18171	7946	8939	18171	7946

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Results by trading period - *Use of forwards and futures*.

	Use of forwards and futures 2005–2007[22]		Use of forwards and futures 2008–2012		Use of forwards and futures 2013–2014	
	Participation	Intensity	Participation	Intensity	Participation	Intensity
Net position	0.093**	0.098	0.054***	0.293***	0.099**	0.872***
	(0.051)	(0.127)	(0.020)	(0.090)	(0.044)	(0.263)
Carbon leakage	0.171**	-0.147	0.159***	0.806***	0.019	-0.128
	(0.074)	(0.229)	(0.047)	(0.273)	(0.072)	(0.239)
Energy	0.356***	0.450*	0.286***	1.751***	0.391***	3.317***
	(0.091)	(0.290)	(0.063)	(0.490)	(0.098)	(0.844)
Productivity	0.193***	-0.062	0.000	0.125	-0.015	-0.592**
	(0.082)	(0.413)	(0.038)	(0.099)	(0.109)	(0.343)
Employees	0.328***	-0.197	-0.058	-0.081	-0.116	-0.440
	(0.095)	(0.638)	(0.046)	(0.152)	(0.110)	(0.787)
Installations	0.013**	-0.002	0.015***	0.051***	0.011*	0.063***

[22] Model converged assuming zero correlation between equations only.

	(0.007)	(0.016)	(0.005)	(0.020)	(0.008)	(0.020)
Region 2 (BE, FR, NL)	0.015	0.298**	-0.375***	-1.915***	-0.246***	-2.313***
	(0.099)	(0.221)	(0.058)	(0.635)	(0.083)	(0.538)
Region 3 (GR, IT, PT, ES, CY, MT)	-0.204**	0.465*	-0.335***	-2.002***	-0.262***	-3.377***
	(0.099)	(0.312)	(0.051)	(0.566)	(0.090)	(0.614)
Region 4 (EE, LT, LV, PL)	-0.156*	0.654***	-0.584***	-2.611***	-0.490***	-4.051***
	(0.102)	(0.269)	(0.074)	(0.965)	(0.135)	(1.099)
Region 5 (CZ, HU, SI, SK)	-0.347***	0.384*	-0.443***	-2.093***	-0.474***	-3.823***
	(0.099)	(0.288)	(0.064)	(0.737)	(0.105)	(0.954)
Region 6 (DK, FI, IS, NO, SE)	0.368***	0.009	-0.253***	-1.793***	-0.105	-0.959***
	(0.090)	(0.282)	(0.058)	(0.414)	(0.092)	(0.290)
Region 7 (UK, IE)	-0.131	0.751*	-0.458***	-2.390***	-0.267***	-2.111***
	(0.104)	(0.472)	(0.070)	(0.833)	(0.094)	(0.666)
Region 8 (BG, HR, RO)	-32.608***	-23.937***	-1.101***	-4.336***	-0.456***	-3.450***
	(12.506)	(6.976)	(0.128)	(1.814)	(0.141)	(0.924)
Mills ratio				5.522***		9.341***
				(1.986)		(2.534)
Mean net position	0.102**	0.367***	0.130***	0.977***	0.085**	0.903***

	(0.057)	(0.124)	(0.022)	(0.223)	(0.041)	(0.215)
Mean productivity	-0.132*	0.288	0.015	0.292***	-0.011	0.868***
	(0.082)	(0.444)	(0.040)	(0.113)	(0.114)	(0.358)
Mean employees	-0.266***	0.465	0.105**	0.607***	0.170*	1.151*
	(0.096)	(0.647)	(0.046)	(0.208)	(0.115)	(0.808)
Constant	-4.038***	3.060***	-3.000***	-13.791**	-3.395***	-28.266***
	(0.179)	(0.472)	(0.117)	(6.162)	(0.194)	(8.914)
Log likelihood	-2402.13		-10138.10		-2990.86	
χ^2 (Prob> χ^2)	1075.06 (0.000)		2485.04 (0.000)		505.02 (0.000)	
Number of companies	3643		4969		4306	
Number of observations	8939		18171		7946	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.10 Appendix E: Results for Total Transactions with Asymmetric Response for Net Sellers and Net Buyers

Table 11: Results for 2005–2014 - *Total transactions* with interaction between *net position* and *net sellers*.

	Total transactions	
	Participation	Intensity
Net position X net sellers	-0.036***	-0.027***
	(0.002)	(0.005)
Net position	0.160***	0.441***
	(0.009)	(0.026)
Carbon leakage	0.092***	0.273***
	(0.021)	(0.045)
Energy	0.173***	0.411***
	(0.033)	(0.063)
Productivity	0.040**	0.130***
	(0.024)	(0.032)
Employees	0.017	0.105***
	(0.021)	(0.030)
Installations	0.062***	0.058***
	(0.015)	(0.009)
Period 2	0.493***	1.062***
	(0.018)	(0.079)
Period 3	0.371***	0.658***
	(0.024)	(0.069)
Region 2 (BE, FR, NL)	-0.199***	-0.279***
	(0.037)	(0.072)
Region 3 (GR, IT, PT, ES, CY, MT)	0.014***	-0.193***
	(0.031)	(0.048)
Region 4 (EE, LT, LV, PL)	-0.341***	-0.335***
	(0.039)	(0.088)

Region 5 (CZ, HU, SI, SK)	-0.032	-0.197***
	(0.036)	(0.071)
Region 6 (DK, FI, IS, NO, SE)	0.291***	-0.274***
	(0.047)	(0.080)
Region 7 (UK, IE)	-0.057	-0.277***
	(0.046)	(0.077)
Region 8 (BG, HR, RO)	-0.135***	0.106
	(0.055)	(0.099)
Mills ratio		1.653***
		(0.261)
Mean net position	0.103***	0.631***
	(0.011)	(0.026)
Mean productivity	-0.082***	-0.043
	(0.026)	(0.039)
Mean employees	-0.050**	0.005
	(0.021)	(0.033)
Constant	-2.201***	-2.335***
	(0.074)	(0.261)
Log likelihood	-56154.31	
χ^2 (Prob> χ^2)	33774.66 (0.000)	
Number of companies	6316	
Number of observations	35056	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Results by trading period - *Total transactions* with interaction between *net position* and *net sellers*.

	Total transactions 2005–2007		Total transactions 2008–2012		Total transactions 2013–2014	
	Participation	Intensity	Participation	Intensity	Participation	Intensity
Net position X net sellers	-0.066***	-0.070***	-0.035***	-0.033*	-0.024***	-0.006
	(0.005)	(0.012)	(0.004)	(0.021)	(0.003)	(0.019)
Net position	0.183***	0.285***	0.150***	0.433***	0.051**	0.143*
	(0.024)	(0.057)	(0.012)	(0.128)	(0.026)	(0.089)
Carbon leakage	0.133***	0.223***	0.102***	0.498***	0.133***	0.302**
	(0.040)	(0.089)	(0.031)	(0.103)	(0.034)	(0.16)
Energy	0.201***	0.427***	0.202***	0.742***	0.223***	0.443**
	(0.058)	(0.123)	(0.043)	(0.150)	(0.063)	(0.224)
Productivity	0.359***	0.368***	0.169***	0.360***	0.033	0.027
	(0.069)	(0.144)	(0.037)	(0.134)	(0.052)	(0.134)
Employees	0.321***	0.254**	0.065*	0.201***	0.025	0.374
	(0.078)	(0.141)	(0.040)	(0.058)	(0.077)	(0.595)
Installations	0.044***	0.052***	0.066***	0.066***	0.105***	0.092***
	(0.014)	(0.011)	(0.026)	(0.024)	(0.016)	(0.031)
Region 2 (BE, FR, NL)	-0.230***	0.308***	-0.265***	-0.660*	-0.027	-0.164

	(0.054)	(0.119)	(0.059)	(0.471)	(0.058)	(0.347)
Region 3 (GR, IT, PT, ES, CY, MT)	-0.321***	0.288***	0.014***	-0.410	0.305***	-0.149***
	(0.043)	(0.128)	(0.056)	(0.230)	(0.059)	(0.12)
Region 4 (EE, LT, LV, PL)	-0.487***	0.214*	-0.333***	-0.416	-0.127*	-0.530*
	(0.058)	(0.166)	(0.065)	(0.529)	(0.088)	(0.379)
Region 5 (CZ, HU, SI, SK)	-0.139***	0.293***	0.004	-0.299	0.015	-0.372
	(0.050)	(0.113)	(0.055)	(0.246)	(0.064)	(0.332)
Region 6 (DK, FI, IS, NO, SE)	0.362***	0.277***	0.315***	-0.556***	0.079	-0.446***
	(0.051)	(0.113)	(0.077)	(0.127)	(0.093)	(0.183)
Region 7 (UK, IE)	-0.021	0.386***	-0.095*	-0.618**	0.039	-0.014
	(0.066)	(0.125)	(0.066)	(0.295)	(0.082)	(0.223)
Region 8 (BG, HR, RO)	-0.353***	-0.367**	-0.243***	0.232	0.264***	0.045
	(0.113)	(0.211)	(0.069)	(0.498)	(0.095)	(0.148)
Mills ratio		0.861**		1.938		1.779
		(.383)		(1.7)		(2.208)
Mean net position	0.093***	0.662***	0.119***	0.562	0.146***	0.773***
	(0.023)	(0.039)	(0.014)	(0.098)	(0.028)	(0.15)
Mean productivity	-0.365***	-0.254*	-0.251***	-0.226	-0.018	0.115
	(0.074)	(0.155)	(0.041)	(0.207)	(0.055)	(0.14)

Mean employees	-0.313***	-0.112	-0.126***	-0.053	-0.025	-0.238
	(0.079)	(0.140)	(0.043)	(0.099)	(.079)	(0.605)
Constant	-2.228***	-0.705	-1.585***	-0.985	-1.787***	-0.781
	(0.107)	(0.795)	(0.117)	(2.324)	(0.128)	(3.364)
Log likelihood	-12123.59		-29877.91		-14071.89	
χ^2 (Prob> χ^2)	5934.80 (0.000)		20781.87 (0.000)		6028.76 (0.000)	
Number of companies	3643		4969		4306	
Number of observations	8939		18171		7946	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.11 Appendix F: Results for Net Buyers and Net Sellers

Table 13: Results for *net buyers* 2005–2014.

	Total transactions		Transaction frequency	Use of intermediaries	Use of forwards and futures	
	Participation	Intensity			Participation	Intensity
Net position	0.138***	0.404***	0.044**	0.044***	0.075***	0.588***
	(0.012)	(0.040)	(0.018)	(0.015)	(0.024)	(0.112)
Carbon leakage	0.010	0.161***	0.090*	0.154*	0.050	0.173
	(0.034)	(0.064)	(0.048)	(0.092)	(0.064)	(0.183)
Energy	0.289***	0.579***	0.461***	0.365***	0.315 ***	2.401***
	(0.057)	(0.135)	(0.081)	(0.129)	(0.080)	(0.524)
Productivity	0.072*	0.167***	0.202***	0.116	0.027	0.080
	(0.045)	(0.062)	(0.074)	(0.135)	(0.062)	(0.235)
Employees	0.107***	0.260***	0.295***	0.285**	0.063	0.511**
	(0.037)	(0.078)	(0.089)	(0.131)	(0.053)	(0.225)
Installations	0.056***	0.051***	0.144***	0.017*	0.012**	0.040***
	(0.019)	(0.011)	(0.012)	(0.010)	(0.007)	(0.014)
Period 2	0.216***	0.722***	0.387***	0.551***	0.017	2.491***
	(0.036)	(0.086)	(0.093)	(0.103)	(0.072)	(0.387)

Period 3	0.143***	0.429***	0.333***	0.592***	0.021	1.254***
	(0.036)	(0.084)	(0.012)	(0.105)	(0.055)	(0.215)
Region 2 (BE, FR, NL)	-0.206***	-0.398***	-0.063	-0.614***	-0.337***	-2.353***
	(0.056)	(0.121)	(0.122)	(0.196)	(0.093)	(0.600)
Region 3 (GR, IT, PT, ES, CY, MT)	0.091**	-0.147**	0.023	-0.555***	-0.474***	-3.553***
	(0.053)	(0.076)	(0.060)	(0.116)	(0.071)	(0.674)
Region 4 (EE, LT, LV, PL)	-0.351***	-0.424***	-0.138	-0.227	-0.419***	-2.804***
	(0.069)	(0.146)	(0.099)	(0.158)	(0.118)	(0.620)
Region 5 (CZ, HU, SI, SK)	-0.046	-0.407***	-0.072	0.734***	-0.436***	-2.950***
	(0.062)	(0.094)	(0.078)	(0.111)	(0.110)	(0.608)
Region 6 (DK, FI, IS, NO, SE)	0.482***	-0.127	0.406***	-0.830***	-0.027	-0.576***
	(0.070)	(0.160)	(0.106)	(0.205)	(0.098)	(0.206)
Region 7 (UK, IE)	-0.044	-0.226**	-0.088	-0.769***	-0.316***	-1.959***
	(0.076)	(0.100)	(0.109)	(0.172)	(0.110)	(0.492)
Region 8 (BG, HR, RO)	0.037	0.157*	-0.049	0.215	-0.670***	-4.295***
	(0.084)	(0.119)	(0.104)	(0.159)	(0.147)	(1.077)
Mills ratio		2.145***				7.607***
		(0.556)				(1.687)
Mean net position	0.015	0.621***	0.150***	0.111***	0.317***	0.900***

	(0.013)	(0.028)	(0.027)	(0.033)	(0.059)	(0.128)
Mean productivity	-0.055	0.010	-0.011	0.025	0.124**	0.506**
	(0.048)	(0.060)	(0.078)	(0.139)	(0.056)	(0.260)
Mean employees	-0.096***	-0.050	-0.127	-0.140	0.088***	0.340*
	(0.038)	(0.072)	(0.090)	(0.133)	(0.028)	(0.226)
Constant	-1.377***	2.145***	-3.081***	-4.522***	-3.443***	7.607***
	(0.093)	(0.556)	(0.152)	(0.241)	(0.163)	(1.687)
Log likelihood	-18831.83		-22858.17	-5097.55	-4945.40	
χ^2 (Prob> χ^2)	16136.07 (0.000)		3398.16 (0.000)	2277.31 (0.000)	1499.46 (0.000)	
Number of companies	4106		4106	4106	4106	
Number of observations	10979		10979	10979	10979	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Results for *net sellers* 2005–2014.

	Total transactions		Transaction frequency	Use of intermediaries	Use of forwards and futures	
	Participation	Intensity			Participation	Intensity
Net position	0.151***	0.499***	0.141***	0.146***	0.071***	0.387***
	(0.012)	(0.029)	(0.015)	(0.019)	(.0160)	(0.110)
Carbon leakage	0.118***	0.318***	0.160***	0.192***	0.108**	0.412**
	(0.023)	(0.044)	(0.046)	(0.070)	(0.050)	(0.183)
Energy	0.129***	0.408***	0.319***	0.242**	0.254***	1.221***
	(0.042)	(0.050)	(0.076)	(0.107)	(0.064)	(0.415)
Productivity	0.030	0.146***	0.037	0.094**	0.032	0.434***
	(0.028)	(0.043)	(0.065)	(0.042)	(0.033)	(0.135)
Employees	-0.030	0.051*	0.062	0.006	0.000	0.196*
	(0.035)	(0.031)	(0.040)	(0.049)	(0.033)	(0.120)
Installations	0.062***	0.066***	0.173***	0.018*	0.011**	0.034**
	(0.013)	(0.010)	(0.015)	(0.010)	(0.005)	(0.020)
Period 2	0.570***	1.251***	0.641***	1.160***	-0.044	2.720***
	(0.024)	(0.097)	(0.046)	(0.054)	(0.036)	(0.906)
Period 3	0.492***	0.825***	0.418***	0.904***	0.021	0.007

	(0.033)	(0.099)	(0.064)	(0.073)	(0.032)	(0.262)
Region 2 (BE, FR, NL)	-0.229***	-0.293***	0.091	-0.463*	-0.223***	-1.001***
	(0.044)	(0.081)	(0.209)	(0.278)	(0.058)	(0.324)
Region 3 (GR, IT, PT, ES, CY, MT)	-0.055*	-0.236***	0.037	-0.094	-0.187***	-1.220***
	(0.038)	(0.046)	(0.086)	(0.124)	(0.055)	(0.283)
Region 4 (EE, LT, LV, PL)	-0.362***	-0.367***	-0.182**	-0.375***	-0.508***	-1.796**
	(0.054)	(0.093)	(0.088)	(0.125)	(0.066)	(0.795)
Region 5 (CZ, HU, SI, SK)	-0.048	-0.137***	-0.029	0.321***	-0.408***	-1.626***
	(0.043)	(0.062)	(0.079)	(0.108)	(0.066)	(0.659)
Region 6 (DK, FI, IS, NO, SE)	0.134***	-0.266***	0.098	-0.761***	-0.096	-0.788***
	(0.055)	(0.100)	(0.117)	(0.155)	(0.076)	(0.221)
Region 7 (UK, IE)	-0.093*	-0.347***	-0.142*	-0.936***	-0.388***	-1.706***
	(0.059)	(0.094)	(0.086)	(0.147)	(0.079)	(0.612)
Region 8 (BG, HR, RO)	-0.257***	0.042	-0.032	-0.227	-0.927***	-3.029**
	(0.062)	(0.105)	(0.114)	(0.165)	(0.107)	(1.467)
Mills ratio		1.842***				4.651***
		(0.265)				(1.894)
Mean net position	0.146***	0.634***	0.136***	0.122***	0.588***	1.023***
	(0.013)	(0.029)	(0.032)	(0.044)	(0.038)	(0.273)

Mean productivity	-0.101***	-0.087**	0.043	-0.147***	0.052	-0.157
	(0.028)	(0.048)	(0.066)	(0.056)	(0.058)	(0.143)
Mean employees	-0.023	0.004	0.042	0.065	0.169***	0.108
	(0.035)	(0.033)	(0.057)	(0.061)	(0.018)	(0.113)
Constant	-2.713***	1.842***	-3.548***	-5.188***	-3.978	4.651***
	(0.072)	(0.265)	(0.123)	(0.190)	(0.117)	(1.894)
Log likelihood	-37001.03		-48859.11	-12204.41	-10588.59	
χ^2 (Prob> χ^2)	17620.24 (0.000)		4850.62 (0.000)	4433.21 (0.000)	1836.55 (0.000)	
Number of companies	5478		5478	5478	5478	
Number of observations	24077		24077	24077	24077	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7. Allocation or Skill? What is Driving Corporate Trading Performance in the EU ETS?

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Abstract:

This study empirically analyses factors related to companies' profits from trading emission allowances in the European Union Emissions Trading System (EU ETS) for the period from 2005 to 2017 by combining information on trading activities with company characteristics of more than 6000 companies. The factors considered include net position (i.e. free allocation of allowances minus emissions), strategic skills (i.e. banking of allowances, timing of trading, transaction frequency, use of intermediaries), skill-related structural factors (i.e. number of installations, sector affiliation), market pressure, year and region effects. The results from estimating a Panel Heckman Selection Model suggest that companies' profits from buying and selling emission allowances are related to a company's net position, banking of allowances, timing of trading, and the number of installations. The findings further indicate that companies choose the number of banked allowances efficiently, i.e. they take into account the opportunity costs of selling these allowances on the market.

JEL Codes: Q48; Q54; Q58;

Keywords: Climate policy, emissions trading, EU ETS, banking, transaction behaviour, trading performance

7.1 Introduction

Since the start of the European Union's Emissions Trading System (EU ETS) in 2005, emissions trading has become a legitimate practice for companies to deal with climate change mitigation. The EU ETS has since grown in terms of the countries, greenhouse gases and activities covered by the system, and a considerable number of companies have become active participants on the market for carbon allowances.

After the first two trading periods (2005-2007 and 2008-2012), which were characterised by a high share of freely allocated European Union Allowances (EUAs), the European Commission introduced far-reaching reforms at the start of the third trading period (2013-2020). For example, most electricity generators no longer benefitted from free allocation of EUAs, and the allocation to companies in industrial sectors was based on benchmarks. Nevertheless, because the total number of available EUAs was still much larger than the demand, the EU ETS has experienced long periods with low prices for EUAs since 2005. More recently, regulations, such as the Market Stability Reserve (MSR), the EU Green Deal, and the 'Fit for 55' package[23] of the European Commission, have lowered the (expected) future supply of EUAs. Consequently, EUA prices have increased substantially, reaching a historic peak exceeding €100 per EUA in February 2023.

Emissions trading is a cost-efficient form of environmental regulation because it enables a given emissions target (i.e. the cap) to be achieved at minimum costs. The market price of emission allowances signals scarcity and incentivises companies to invest in emission abatement measures if their costs are below the price (e.g. Hahn & Stavins, 2011). Cost efficiency also requires that companies engage in the market in a way that maximises their profits from trading allowances. Conditional on abatement, companies can keep their compliance costs down by minimising the costs of purchasing allowances and maximising the revenues from selling allowances. A company's profits from emissions trading depend not only on the number of allowances it receives for free from the government via the primary allocation

[23] For example, the 'Fit for 55' package indicates that the EU ETS reduction target for 2030 will change from -43% to -61% compared to 2005.

mechanism, but also on its skills to develop and implement trading and abatement strategies. For example, profits from trading depend on whether a company trades allowances efficiently across years, i.e. banks and borrows allowances in an optimal way. Similarly, because the prices of EUAs vary over time, the timing of transactions can affect a company's trading performance.

In this paper, we empirically investigate factors related to companies' profits from trading EUAs for the period from 2005 to 2017, specifically considering the roles of free allocation and strategic skills.[24] To identify potential learning effects, we examined whether the role of these factors has changed over time. A better understanding of the factors underlying differences in companies' profits from emissions trading is important because it can provide insights for companies (into strategies) and for governments (into design) on how to improve emissions trading systems to achieve cost-efficient climate change mitigation.

Our time frame covers the first two trading periods and the first five years of the third trading period of the EU ETS. We employed transaction data from the European Union Transaction Log (EUTL) on all transactions within the EU ETS, which we compiled as a large panel dataset containing transactions, free allocation of EUAs, emissions, and the number of allowances banked per year. We matched this data with information on company characteristics taken from the ORBIS database. We used panel econometric methods to relate companies' profits from trading to their net position (i.e. the difference between the number of EUAs allocated for free and verified emissions in a given year), their trading strategies including banking of EUAs, timing of transactions, transaction frequency, and use of intermediaries), and company characteristics (e.g. number of installations, size, productivity, sector affiliation). Because trading performance is only observed for companies that participated in trading we used a Heckman procedure to account for potential selection bias.

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[24] We did not take companies' abatement measures into consideration in our empirical analysis. Because the prices for EU allowances were low during most of our observation period, monetary incentives to implement emissions abatement measures were also low. The empirical literature (e.g. Löfgren et al., 2014, Schaefer, 2019 and Klemetsen et al., 2020) typically finds no or only weak effects of the EU ETS on companies' emissions for this period. Therefore, our findings should not be tarnished by the fact that we did not consider companies' abatement measures in our analysis.

Our findings suggest that profits from trading emission allowances are higher for those companies that receive a larger number of free allowances, ceteris paribus. Likewise, the more allowances a company banks in a given year, the lower profits are in that year. Remarkably, we find that companies bank allowances efficiently. When they decide on the number of EUAs to bank, companies appear to correctly value the opportunity costs in terms of foregone revenues from selling the EUAs instead. Further, for the first two trading periods, companies that sell (buy) a relatively high share of allowances late in the trading year (February-April of next year) realise lower (higher) profits from trading than companies that spread their trading activities more evenly over the course of a trading year. Finally, our findings suggest that companies with a higher number of regulated installations achieve higher profits from trading.

Several empirical studies have econometrically examined the trading activities (i.e. market participation and/or volumes traded) of companies regulated by the EU ETS. Relying on data for the first trading period, Zaklan (2013) found that company participation in the EU ETS was related to company size, sector affiliation, ownership structure and the level of free allocation. Also for the first trading period, Jaraitė-Kažukauskė and Kažukauskas (2015) concluded that transaction costs such as search and information costs impeded trading because they found that smaller companies and companies with fewer installations were less likely to participate in the scheme and traded fewer allowances. Based on data from 2009-2017 for regulated electricity producers, Zaklan (2022) concludes that, because of transaction costs, Coase's independence property (i.e. a company's emissions do not depend on its allocation) may not hold for small companies. Using different measures to capture transaction costs, Baudry et al. (2021), Hintermann and Ludwig (2023), and Naegele (2018) all found trading costs to impede trading activities in the EU ETS. Baudry et al. (2021) and Naegele (2018) relied on data for the second trading period, while Hintermann and Ludwig (2023) used data for the period 2005-2013. For 2005 to 2014, Abrell et al. (2022) found companies' trading activities (i.e. trading volume, number of transactions, use of derivatives market, and use of financial intermediaries) to be related to their net position, company size, sector affiliation, productivity, location (i.e. country), and transaction costs. Employing network analysis, Borghesi and Flori (2018) and Karpf et al. (2018) analysed companies' trading behaviour and trading patterns in the EU ETS. Their results suggest that the location of an installation or company affects trading behaviour.

Hintermann et al. (2016) provide a review of the literature on prices and market behaviour for the second trading period. They conclude that the market has matured over time and that, in particular, the possibility of banking EUAs has led market actors to take into account future shortages. While they find evidence in the literature that EUA prices depend on fuel prices and the emission cap, they infer that the overall understanding of the EUA price is limited and that one cannot assert with confidence that prices accurately reflect abatement costs.

In a study, which is closest to our approach, Cludius (2018) related trading success in the first trading period - measured as the difference between allowances sold and bought between 2005 and 2007 - to allocation, sector affiliation, and emissions levels. She also included information on whether a company had a personal holding account (PHA) (in addition to an operator holding account), whether it traded via intermediaries, and the number of trades. Estimating cross-sectional selection models, she found that companies' profits from trading were positively related to their net position, energy sector affiliation, and their level of verified emissions.[25] If spot and average future prices were used to value transactions, trading performance was positively correlated with PHA and number of trades, but only the coefficient associated with the number of trades was statistically significant. The use of intermediaries was not found to be statistically significantly correlated with trading performance.[26] Liu et al. (2017) and Guo et al. (2020) employed quantile regressions to analyse corporate trading performance during the first two trading periods. According to Liu et al. (2017), trading success is positively correlated to a company's net position, emission levels and belonging to an industrial sector rather than to the energy sector. Guo et al. (2020) found that trading success is positively correlated with carbon abatements.

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25 Cludius (2018) estimates four models which differ in how transactions are valued. Her model 2b uses daily spot prices to value spot trading and average future prices to value forwards and futures, and it is the closest to our approach. Her other models employ the daily spot price, average yearly prices, or average prices for the trading period to value transactions.

26 Some of these findings do not hold, however, when alternative prices are used rather than the daily spot and average futures prices to value transactions.

In sum, only a few studies have explored the factors related to companies' trading performance and these typically focused on the role of the net position, the level of verified emissions and sector affiliation. Only Liu et al. (2017) included company-specific information in their analyses, while Cludius (2018) considered (some) variables reflecting corporate trading strategies, such as whether a company used intermediaries. No study has yet considered transactions during the third trading period to study trading success. Finally, despite using data from multiple years and periods, previous studies have not employed panel econometric estimators and have thus relied on potentially restrictive distributional assumptions.

Our analysis contributes to the existing literature in several ways. First, while previous studies analysing companies’ profits from trading in the EU ETS have considered allocation, verified emissions and company characteristics, we also consider factors related to strategic skills. In contrast to previous studies, our analysis includes the number of EUAs a company banks, which enables us to assess whether companies bank efficiently.[27] Second, in addition to transactions for the first and second trading periods, our data includes transactions from five full years of the third trading period and hence covers a longer time frame than previous studies. Because the market has matured over time, it is likely that companies have learned how to deal with this new instrument, and because regulation has changed over time, the results obtained from the early phase(s) of the EU ETS may not hold for later phases. For example, since the second trading period, banking of allowances across trading periods is permitted. In addition, the share of auctioning significantly increased in 2013. Third, we employ panel estimators, which account for potential selection bias. Existing studies analysing trading performance use cross-sectional models to account for selection (Cludius 2018) or cross-sectional quantile regression models (without selection) (Liu et al. 2017 and Guo et al. 2020). Fourth, we analyse trading performance at the company level, as do Abrell et al. (2022), but in a different context. Previous studies chose the level of the global ultimate owner (Cludius 2018; Hintermann and Ludwig 2023; Naegele 2018; Zaklan 2013) or the level of the

[27] Previous literature has investigated the effects of banking on the price of EUAs (e.g. Alberola and Chevallier, 2009; Schleich et al., 2006).

national owner (Jaraitė-Kažukauskė and Kažukauskas, 2015; Liu et al., 2017; Guo et al., 2020).[28] Therefore, our level of analysis is close to the point of regulation, but does not assume that trading decisions are made at the level of individual installations (e.g. Betz and Schmidt (2016)). Indeed, employing a cluster analysis, Betz and Schmidt (2016) found that some companies pool the allowances from all their installations in one account. Due to language barriers and coordination efforts, the global ultimate owner is unlikely to be the decision-maker concerned with executing the trading strategy. We believe that, in most cases, trading strategies are selected by the national owner or the individual company. As the trading strategies set by the national owner are likely to be reflected in the strategies at the company level, but not the other way around, we selected the company level for our analysis.

Our paper is organised as follows. In Section 7.2, we present the methodology including the data, the variables, and the econometric method. Section 7.3 presents and discusses the results, while Section 7.4 summarises the main findings and concludes.

7.2 Methodology

In this section, we describe the data, the variables used in the econometric analysis and the econometric methods.

7.2.1 Data

Our study relies on three different data sources: (i) The European Union Transaction Log (EUTL), which provides data on all transactions, account information such as ownership, and installations, including information on primary allocation and verified emissions; (ii) ORBIS from Bureau van Dijk, which contains data on companies such as turnover and the number of employees; and (iii) information on prices, which we collected from the European Energy Exchange (EEX) for spot prices and the Intercontinental Currency Exchange (ICE) for futures prices. Like Abrell et al. (2022), we matched

[28] Multinational companies usually have national ultimate owners in the countries in which they operate; these own the companies operating in the respective country. The global ultimate owner is the global parent company, which in the last consequence owns all the companies (usually via control of the national ultimate owners). We refer to a company as the legal organisation that is closest to the regulated entity, i.e. the installation.

EUTL and ORBIS data using company registration numbers. If this was not feasible, we used the addresses and names of the account holders. Price information was matched using transaction days. We valued all spot transactions at the respective daily price. To identify forwards and futures, we followed Cludius (2018) and Abrell et al. (2022) and considered activities of the clearing accounts on typical delivery days of forwards and futures.[29] For transactions on these days, we used the average one-year December future price of the respective year.

We then aggregated all the transaction data for each company on an annual level. In this step, we excluded administrative transactions, such as primary allocation and allowances surrendered. While these transactions account for almost two-thirds of all transactions in the EUTL, they do not reflect market transactions. All remaining transactions pertain to sales and purchases of EUAs. Because regulated companies may surrender allowances for emissions in year t until the end of April in year t+1, we follow Cludius and Betz (2020) and aggregate transaction for trading years (rather than the calendar years), which last from May in year t to April in year t+1. Our data set contains transactions up to April 2018, thus covering a total of five full years of the third trading period. To ensure that only regulated companies were included in our sample, we retained companies which owned at least one regulated stationary installation and excluded companies which received a primary allocation of zero allowances and had no verified emissions. We also excluded transactions conducted within the same installation, assuming that these transactions were due to organisational rather than trading-related motives. We did not exclude intra-company transactions, because they may have both strategic and organisational significance.[30] In Section 7.6, we provide a more detailed description of how we compiled the data.

7.2.2 Variables

In this section, we present the dependent variable and the covariates. Table 15 provides an overview.

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[29] For futures, these days are: 21–23/12 2005, 18–22/12 2006, 17–19/12 2007, 15–19/12 2008, 14–18/12 2009, 20–23/12 2010, 20–23/12 2011, 17–21/12 2012, 17–20/12 23/12 2013, 16–19/12 22–23/12 2014, 14–18/12 2015, 19-23/12 2016, 13-15/12 18-22/12 2017. For forwards, these days are: 30/11 01/12 2005, 30/11 01/12 2006, 30/11 03/12 2007, 28/11 01/12 2008, 30/11 01/12 2009, 30/11 01/12 2010, 30/11 01/12 2011, 30/11 03/12 2012, 29/11 02/12 2013, 28/11 01/12 2014, 30/11 01/12 2015, 30/11 01/12 2016, 30/11 01/12 2017.

[30] As we discuss in 3.6 (Robustness checks), our findings are robust to excluding intra-company transactions from the data.

7.2.2.1 Dependent variable

Profits from trading reflect the trading performance of regulated companies and are calculated as the difference between the value of all transfers and the value of all acquisitions made by a company. Maximising profits implies minimising costs of acquiring EUAs for companies with a negative net position (i.e. net buyers) and maximising revenues from selling EUAs for companies with a positive net position (i.e. net sellers). Thus, in general, *profits* may take on positive or negative values. As described in section 7.2.1, we calculated the value of transactions using spot and futures prices for EUAs.

7.2.2.2 Covariates

Our choice of covariates is driven by our research question, data availability and the existing literature. We grouped our set of covariates into allocation, skills, market pressure, and year and region effects.

Allocation

Net position is defined as the number of EUAs received for free minus verified emissions. The number of EUAs received for free is the outcome of the primary allocation and does not reflect trading skills. Because a higher net position allows companies to sell more allowances, ceteris paribus, we expected a positive correlation between trading performance and *net position*.[31]

Skills

We differentiated between two types of skills: strategic skills and skill-related structural factors. Four variables reflected strategic skills. First, we expected *banking* to have a negative effect on *profits*. The more allowances a company transfers into subsequent years, the fewer it can sell in a given trading year, and the lower the profits from trading will therefore be in that year. Controlling for *banking* is therefore essential but has not been done in previous studies analysing corporate trading activities or performance. We defined *banking* as the net position plus acquisitions minus sales for each trading year.[32] Second,

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[31] Whereas a company knows the number of allowances received for free before the start of the trading year, it may learn the exact level of verified emissions only at the end of March of the following year. Hence, for most of the trading year, a company typically does not know its exact net position.

[32] Our analysis did not account for borrowing. It is important to note that inter-period borrowing is not permitted in the EU ETS. While intra-period borrowing is possible, we cannot identify whether allowances issued in year t or year t+1 were utilized for compliance in year t. As a result, we are unable to incorporate intra-period borrowing into our analysis.

we included two variables that reflect the timing of buying and selling activities. *Late buyers* and *late sellers* were defined as the number of allowances traded in February, March, and April (i.e. during the so-called true-up period). *Late buyers* and *late sellers* were assumed to reflect the extent to which companies trade for compliance purposes, but the relation to *profits* is not clear and hinges on the EUA price during the true-up period relative to the remainder of a trading year. Late buyers (late sellers) benefit from low (high) prices during the true-up period. Third, *transaction frequency*, i.e. the number of transactions in trading year t, is supposed to reflect experience and learning effects. Assuming that frequent trading leads to learning effects (e.g. larger trading network, benefitting from price fluctuations), we anticipated this variable to be positively correlated with *profits*. Fourth, *use of intermediaries* measures the number of different intermediaries a company used in trading year t. We assumed that this variable reflects access to better information, thus leading to higher *profits*. Finally, *total transactions* stands for the total number of allowances traded in a year. Expecting that higher trading volumes would incur stronger learning effects, we hypothesised a positive correlation between *total transactions* and *profits*.

To investigate whether the effects of strategic skills on profits from trading changed over time, we included the interaction between the dummies representing the second and third trading period and the covariates reflecting the strategic skills (except banking).

Skill-related structural covariates include the *number of installations*, whether a company belongs to the *energy* sector, company *size*, and *productivity*. These variables are believed to reflect the extent to which companies have access to complementary assets and capabilities which enable them to trade EUAs more successfully. The *number of installations* captures the number of a company's installations governed by the EU ETS. Assuming that companies with a higher number of regulated installations more often have complementary assets such as specialised trading teams than companies with a lower number of installations, we expected the *number of installations* to be positively correlated with *profits*. *Energy* indicates whether a company belongs to the energy sector. These companies are more likely to be experienced in energy commodity trading and to have skills that complement trading EUAs. For example, electricity companies usually sell their electricity on spot and futures markets (e.g. on the EEX, where EUAs trading also takes place). We therefore expected energy companies to perform better than non-energy companies. Similarly, larger companies are more likely to have complementary assets and lower transaction costs per trade than smaller ones. We therefore hypothesised profits to be positively correlated with company size, measured by the number of *employees*. Finally, conjecturing that companies with more productive operations would also perform more successfully when it comes to buying and selling allowances, we anticipated profits to be positively associated with *productivity.* Like Abrell et al. (2022), we calculated *productivity* as the ratio of revenues to the number of employees.

To capture the effect of market pressure on trading performance, we included *carbon leakage*. Companies are assumed to face import competition from non-EU countries if they primarily produce products which appear on the carbon leakage list of the EU ETS regulations. Because these companies should have particularly strong incentives to keep compliance costs low, we anticipated a positive correlation between *carbon leakage* and *profits.*

Finally, we included dummies to control for effects which are specific to *trading periods* (i.e. 2005-2007, 2008-2012, and 2013-2020) and to regions. For regions, we used the same definition as Jaraitė-Kažukauskė and Kažukauskas (2015). In the empirical specification, we used the first trading period and Region 1 which consists of German-speaking countries, as the base categories.

Table 15: Description of dependent variable and covariates.[33]

Variable	Description	Time constant/varying	Data source
Dependent variable			
Profits	Difference between the value of all transfers and the value of all acquisitions in a trading year.	varying	EUTL, EEX, ICE
Covariates			
Allocation			
Net position	Allocation of EUA minus verified emissions in year t (absolute value in metric tons of CO_2eq.	varying	EUTL
Skills - strategic			
Banking	Allocation of EUA plus acquisitions minus verified emissions minus transfers in trading year (absolute value in metric tons of CO_2eq).	varying	EUTL
Late buyers	Absolute number of acquisitions in trading year.	varying	EUTL
Late sellers	Absolute number of transfers in trading year.	varying	EUTL
Transaction frequency	Number of transactions in trading year.	varying	EUTL
Use of intermediaries	Number of intermediaries used in trading year.	varying	EUTL
Total transactions	Transaction volume of EUA in trading year t (in metric tons of CO_2eq).	varying	EUTL
Skills – structural			
Installations	Number of installations in year t.	constant	EUTL
Energy	Dummy = 1, if company belongs to energy sector in year t according to NACE (rev2) classification (35.00 to 35.30).	constant	ORBIS
Employees	Number of employees in year t.	varying	ORBIS
Productivity	Calculated as revenues divided by number of employees in year t.	varying	ORBIS
Market pressure			
Carbon leakage	Dummy =1, if company affiliated with carbon leakage sector.	constant	EU ETS regulations

[33] To ensure that the coefficients are of approximately the same order of magnitude, we multiplied the initial values of the following variables as follows: *profits, net position, banking, late buyers*, and *late sellers* by 10^{-6}; *transaction frequency* and *carbon leakage* by 10^{-4}; *use of intermediaries*, and *installations* by 10^{-3}; *employees* and *productivity* by 10^{-8}; *total transactions* by 10^{-9}; and *energy* by 10^{-6}.

Variable	Description	Time constant/varying	Data source
Year and region effects			
Trading periods	Dummy for each trading period (base period is the first trading period)	constant	EUTL
Region 1	Austria (AT), Germany (DE), Liechtenstein (LI) (*base region*)	constant	EUTL
Region 2	Belgium (BE), France (FR), Netherlands (NL)	constant	EUTL
Region 3	Greece (GR), Cyprus (CY), Spain (ES), Italy (IT), Malta (MT), Portugal (PT)	constant	EUTL
Region 4	Estonia (EE), Lithuania (LT), Latvia (LV), Poland (PL)	constant	EUTL
Region 5	Czech Republic (CZ), Hungary (HU), Slovenia (SI), Slovakia (SK)	constant	EUTL
Region 6	Denmark (DK), Finland (FI), Iceland (IS), Norway (NO), Sweden (SE)	constant	EUTL
Region 7	United Kingdom (UK), Ireland (IE)	constant	EUTL
Region 8	Bulgaria (BG), Croatia (HR), Romania (RO)	constant	EUTL

7.2.3 Econometric Model

We employed a multivariate panel econometric analysis based on annual data at the level of individual companies.[34] However, profits from trading are only observed for companies that trade, i.e. participate in the market. In our final dataset, for example, we did not observe profits for about 44 percent of the observations, because companies decided not to buy or sell allowances. For these companies, data on profits are missing not at random but because they decided not to trade. We employed a Heckman-type selection estimator because unobserved factors may affect both participation (i.e. selection) and profits (i.e. outcome). We included the shares of companies participating in emissions trading at the country level as an additional covariate in the participation equation. We assumed that this share affects participation but not profits.

[34] Our panel data set is unbalanced because of the exit and entry of companies and installations over time, and because countries joined the EU ETS at different points in time. For example, the three non-EU member states Norway, Iceland, and Liechtenstein as well as the new member states Romania and Bulgaria joined the EU ETS in 2007, while Croatia joined in 2013.

We modelled participation as

$$D_{it} = \begin{cases} 1 \; if \; D_{it}^{*} > 0 \\ 0 \;\; otherwise \end{cases} \tag{1}$$

$$D_{it}^{*} = v_{it}\delta + w_i\theta + \alpha_{1,i} + \varepsilon_{1,it} \tag{2}$$

where v_{it} denotes the time-varying covariates such as *net position,* w_i reflects time-invariant covariates, $\alpha_{1,i}$ captures time-invariant company-specific unobservable factors (i.e. the panel-level random effect for selection) such as company culture, and $\varepsilon_{1,it}$ stands for the idiosyncratic error in the participation equation.

We modelled profits as

$$Y_{it} = x_{it}\beta + z_i\gamma + \alpha_{2,i} + \varepsilon_{2,it} \tag{3}$$

where Y_{it}reflects company *i*'s level of profits from trading at time *t*, x_{it} denotes time-varying covariates (including the share of companies participating in emissions trading at the country level)*,* z_i captures time-invariant covariates, $\alpha_{2,i}$ captures time-invariant company-specific unobservable factors (i.e. the panel-level random effect for the outcome), and $\varepsilon_{2,it}$ is the idiosyncratic error term in the participation equation. The random effects $\alpha_{1,i}$ and $\alpha_{2,i}$ are assumed to be bivariate normal. Similarly, the error terms $\varepsilon_{1,it}$ and $\varepsilon_{2,it}$ are assumed to have bivariate normal distribution and to be independent of the panel-level random effects $\alpha_{1,i}$ and $\alpha_{2,i}$. If either corr ($\varepsilon_{1,it}$, $\varepsilon_{2,it}$) or corr ($\alpha_{1,i}$,$\alpha_{2,i}$) are significant, selection is an issue. Because the Heckman panel model is nonlinear, unobserved time-constant heterogeneity (e.g. company culture), which may be correlated with the covariates, cannot be addressed by the fixed effects estimator in the same way as in the linear fixed effects model (where observed and unobserved time-constant effects are eliminated). We employed maximum likelihood methods to estimate the participation and profit equations, thereby accounting for the panel structure of the data. Specifically, we used the random effects estimator implemented via the *xtheckman* command in Stata 18, which relies on the joint distribution of the selection and outcome variables.[35]

Our methodology differs substantially from previous studies on corporate trading performance in the EU ETS, e.g. Cludius (2018), Liu et al. (2017) and Guo et al. (2020). Our findings are therefore not directly comparable to these studies.

7.3 Results and Discussion

We first present and discuss the results for the period 2005-2017 for our preferred specification and then the results obtained for a series of robustness checks. The results for the profits equation (2) are shown in Table 16 and for the participation equation (1) in Section 0, Table 18. First, we note that both the correlation of the error terms in the profit and participation equations and the correlation of the panel-level random effects are statistically significant (at $p< 0.01$), which supports the estimation of a selection model.

The results for the participation equation suggest that companies with a higher *net position*, with more *employees*, and with a higher number of regulated *installations* are more likely to participate in emissions trading, ceteris paribus. We note that our additional covariate in the selection equation, i.e. the shares of companies participating in emissions trading at the country level (*share active country*), is statistically significant and positive. In general, the results for the participation equation appear intuitive. Next, we turn to the results for the profit equation in Table 16.

7.3.1 Allocation

As expected, the higher a company's *net position*, the higher the *profits* from trading, ceteris paribus. This finding is consistent with the results of Cludius (2018) and Liu et al. (2017). The point estimate of

[35] Using a random effects estimator presumes that unobserved time-constant factors are not correlated with the covariates. This assumption may not hold in our context. In the robustness checks (section 7.3.6), we therefore present results from estimating a model that controls for time-invariant unobserved heterogeneity. The findings of this model are very similar to those of the random effects estimator reported in Table 16.

the coefficient associated with *net position* suggests that profits increase by €5.99 for an increase in the net position by one unit, i.e. receiving one additional EUA for free in the primary allocation or emitting one tonne less of $CO_{2eq.}$.[36,37]

Table 16: Results for profit equation of preferred model.

	Coefficient	SE
Allocation		
Net position	5.986***	(0.238)
Skills - strategic		
Banking	-5.724***	(0.323)
Late buyers	2.262**	(1.104)
Late buyers X P2	-1.838	(1.134)
Late buyers X P3	-2.469**	(1.101)
Late sellers	-2.841***	(1.103)
Late sellers X P2	2.423**	(1.131)
Late sellers X P3	2.972***	(1.098)
Transaction frequency	2.864	(3.891)
Transaction frequency X P2	-3.071	(3.684)
Transaction frequency X P3	-7.410**	(2.905)
Use of intermediaries	2.435	(6.924)
Use of intermediaries X P2	3.260	(7.081)
Use of intermediaries X P3	-2.590	(7.089)
Total transactions	3.347	(11.21)

36 For comparison, we observed a volume-weighted average price of €8.53 for all the transactions in our dataset.

37 To control for period-specific effects, such as the sharp drop in prices of EUAs at the end of the first trading period, we also ran a model which includes period interaction terms. As we report in the robustness check section, we failed to find any statistically significant differences for net position across the trading periods.

	Coefficient	SE
Skills - structural		
Number of installations	4.751***	(1.542)
Energy	683.9	(987.3)
Employees	13.82	(18.45)
Productivity	3.907	(10.05)
Market pressure		
Carbon leakage	73.68	(79.43)
Year and region effects		
Period 2	0.084***	(0.013)
Period 3	-0.031**	(0.014)
Region effects	yes	
Constant	-0.103***	(0.023)
corr ($\varepsilon_{1,it}$, $\varepsilon_{2,it}$)	0.274***	
corr ($\alpha_{1,i}$,$\alpha_{2,i}$)	0.778**	
χ^2 (29)	4430.37***	
Number of observations	37,695	
Number of companies	6,737	

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7.3.2 Strategic Skills

We found, as expected, a negative and statistically significant correlation between *banking* and *profits*. The results in Table 16 suggest that *banking* each additional EUA lowers *profits* by €5.72 on average. Interestingly, the coefficients associated with *banking* and *net surplus* are of about the same magnitude (but with opposite signs). This finding is therefore consistent with companies choosing the number of banked allowances efficiently, i.e. they adequately take into account the opportunity costs of banked allowances: rather than transferring allowances to the next period, they could have sold them on the market in this period.[38] To the best of our knowledge, this finding has not been previously derived using company-level data on transactions. Efficient banking (and borrowing) by companies, however, is a prerequisite for intertemporal profit maximisation by companies and for emissions trading systems to be economically efficient, i.e. to lead to minimal costs for meeting a given emissions target over time (see also Rubin, 1996).[39]

Our results for *late buyers (late sellers)* suggest a positive (negative) correlation with *profits* for the first trading period. On average, during the first trading period, profits were estimated to be €2.26 higher for each EUA purchased during the true-up period than for an average purchase of EUAs during the trading year, ceteris paribus. Vice versa, profits were estimated to be on average €2.84 lower for each EUA sold between February and April than for an average sale of EUAs during the trading year. Thus, in the first trading period, *late buyers* were better off and *late sellers* were worse off in terms of *profits* from trading than companies that spread their trading activities more evenly over the course of a trading year, ceteris paribus. This finding is inconsistent with the concept of an efficient market as defined by Fama (1970). This effect found for the timing of trading activities for the first trading period also holds for the second period, yet less pronounced, and - in terms of magnitude - essentially disappears for the third period.[40]

Our results for the first period can be explained by companies (erroneously) expecting the market to be short. Once it became known that the market was in fact long (i.e. once data on verified emissions in 2005 were published in late March of 2006) prices fell, leaving *late buyers* better off and *late sellers* worse off. Findings for later periods differ possibly because market participants have learned from their

38 This was confirmed by the results of a Wald test at p-value <0.01. Implicitly, we hereby assume that the (real) interest rate is zero which aligns well with the time frame considered.

39 In comparison, myopia on the part of companies, for example, would not be compatible with an efficient market outcome, but may help explain the observed EUA price path (e.g., Fuss et al., 2018; Quemin and Trotignon, 2019).

40 P-values of the corresponding Wald tests for period 2, i.e. for the sum of coefficients on *late buyers/late sellers* and period interaction terms) are 0.08 for *late buyers* and 0.02 for *late sellers*. For period 3, we find a negative correlation of *profits* with *late buyers* and a positive correlation with *late sellers* (p-values are 0.07 and 0.01), but the effect sizes are negligible.

experience in the first trading period. Also, because banking of allowances into future trading periods was permitted from the second period onwards (but not from the first period to the second period), companies with a surplus of allowances could bank them instead of being compelled to sell them on the market. This helped dampen price volatility, especially during the true-up period.

For *transaction frequency,* we found no evidence that companies trading more frequently in period 1 or period 2 realised higher *profits*. For period 3, we even found a negative correlation between *profits* and *transaction frequency* (p-value of Wald test for sum of coefficients on *transaction frequency* and interaction term = 0.04). Similar to our findings for the first two periods, Cludius (2018) did not find a statistically significant correlation between trading success and the number of trades in most of her models.

For *use of intermediaries*, we found no statistically significant correlation with *profits* for period 1 and period 3. For period 2, our results suggest, as anticipated, that using intermediaries was associated with higher *profits* (P-value of corresponding Wald test = 0.01). Similar to our findings for period 1 and period 2, Cludius (2018) also failed to find a significant correlation between trading success and the use of intermediaries. For period 1, Cantillon and Slechten (2023) conclude that significant market fragmentation hindered the aggregation of information concerning the overall supply and demand in the market. Hence, employing more intermediaries may not guarantee enhanced information quality. Further, the transactions carried out through intermediaries may be measured with error because we use the spot price on the transaction day rather than the price specified in the contract, which was not available to us.

Finally, the coefficient associated with *total transactions* displays the expected positive sign, but it is not statistically significant (p-value = 0.77).

7.3.3 Skill-related Structural Factors

The coefficient for the *number of installations* is, as expected, positive and statistically significant. This result supports our proposition that companies with more installations governed by the EU ETS also have more complementary assets that enable them to achieve higher profits from emissions trading than companies with fewer such installations.

As expected, we found a positive correlation of *profits* with *energy*, *employees* and *productivity*. However, the associated coefficients were not statistically significant at conventional levels. Therefore, we failed to find support for our proposition that energy companies find it easier to cope with the EU ETS market due to their experience with commodity exchange trading. Cludius (2018) did not find any positive correlation between affiliation to the electricity sector and trading performance in the model, which is closest to our approach, but did find a significant positive correlation in the other three models. We also found no-results for *productivity,* a finding that might be explained by the large amount of missing data.

7.3.4 Market Pressure

The coefficient associated with *carbon leakage* had the expected positive sign but failed to be statistically significant at conventional levels (p-value = 0.35). Thus, we found no support for our conjecture that companies facing higher competitive pressure have a higher incentive to optimise their trading performance than companies not facing such pressure. A possible explanation for our ‘no-result’ is that our proxy for leakage (i.e. a dummy which is set to 1 if the company is in a sector exposed to a significant risk of carbon leakage) may not adequately reflect the competitive pressure a company is facing from international trade. For example, we have identified companies as being at risk of carbon leakage if they belong to an industry sector where the majority of its products appear on the carbon leakage list used in EU regulations. Because these companies may, possibly as their main business, also produce products that are not on this list, they may erroneously be categorized as being at risk of carbon leakage in our data. An additional explanation for this 'null result' could be attributed to the relatively low prices for EUAs prevailing throughout most of the time frame considered in our analysis. Hence, the incentive to enhance trading performance due to competitive pressures from international markets remained comparatively low.

7.3.5 Year and Region Effects

In terms of trading *periods*, we observed that in the second trading *period* regulated companies were significantly more successful than in the first trading *period*, whereas they were significantly less successful in the third trading *period* than in the first trading *period*, ceteris paribus. The effect sizes, however, are small. The sum of the value of all trading transactions in a year add up to zero (the seller receives exactly the amount the buyer pays), i.e. companies that are not analysed in our dataset (e.g. financial intermediaries) form the counterpart position. In our case, this means that these participants, which our analysis did not include, traded less successfully in the second period than in the first and more successfully in the third period than in the first.

7.3.6 Robustness Checks

We examined the robustness of the results presented in Table 16 by employing a different estimation approach, modifying the specification of key variables, and considering the inclusion or exclusion of covariates.[41]

First, to account for the correlation between time-invariant unobserved factors and the covariates, we included the company-specific mean of the time-varying variables in our main model, akin to Mundlak (1978). Thus,

$$\alpha_{2,i} = \bar{x}_i \boldsymbol{\varphi} + \mu_i \tag{4}$$

where $\bar{x}_i$ is the mean of the x_{it} over time for company i, and μ_i is the idiosyncratic error term.[42] As Table 19 in Section 0 shows, the results of this model were almost identical to those reported in Table 16 for almost all covariates in terms of magnitude and significance level.

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41 We document the findings of most robustness checks in Section 0. Any results not shown for space-saving purposes are available upon request.

42 Essentially, the 'Mundlak terms' $\bar{x}_i$ pick up the “between variation” and may be interpreted as long-term effects. In comparison, the time-varying variables pick up the “within variation” and may be interpreted as short-term effects. Because our concern was that the effects of unobserved heterogeneity could be correlated with the explanatory variables, our presentation and interpretation of the results focused on the time-varying effects.

Next, previous literature investigating company trading behaviour in the EU ETS (e.g. Abrell et al., 2022; Liu et al. 2017) distinguishes between net buyers and net sellers to account for their different settings. Net buyers must acquire extra allowances to prevent incurring penalties on top of fulfilling their shortfall, ceteris paribus. In comparison, net sellers have the option to either sell or bank any surplus allowances. To allow for heterogeneity in the effects of our key covariates by net position, we also estimated a model which includes interaction terms for the variables reflecting strategic skills, using a dummy that reflects the net position of a company. We set this dummy variable net seller to 1 if the net position is positive. Table 20 shows the results of this model. We find that an increase in the *net position* by one tonne of CO_{2eq} is associated with higher profits for both net buyers and net sellers, but this increase is about €1.8 higher for net buyers than for net sellers, ceteris paribus. Similarly, an increase in *banking* by one tonne of CO_{2eq} is associated with lower profits for both net buyers and net sellers, but this decrease is about €1.9 lower for net buyers than for net sellers, ceteris paribus. The results for *net position* and *banking*, and *net positon X net sellers* and *banking X net sellers* suggest that both net seller and net buyer companies bank efficiently. Hence, our key finding derived for our preferred specification (see Table 16) also holds if we allow for heterogeneity by net position and banking. The results for *late buyers* (*late sellers*) imply a positive (negative) relationship with *profits* for *net buyers* during the first trading period. The coefficients associated with *late buyers X net sellers* (*late sellers X net sellers*) are of about the same magnitude as the coefficients associated with *late buyers* (*late sellers*), but of opposite signs. This finding is hardly surprising and suggests that *net buyers* (*net sellers*) benefitted (suffered) from buying (selling) allowances late in trading period 1. In other words, the findings for our preferred model for *late buyers* (*late sellers*) are essentially driven by *net buyers* (*net sellers*). Akin to our findings for our preferred model, the results for the triple interaction terms associated with *late buyers* and *late sellers* depicted in Table 20 suggest that any effects of late buying and selling vanish over time. For the remaining indicators reflecting strategic skills, skill-related structural factors, and market pressure, distinguishing between net buyers and net sellers does not appear to provide any additional insights compared to our preferred model. In our main specification, forwards/futures transactions and company-internal transactions[43] are included in the acquisitions and transfers considered. However, for forwards/futures transactions we cannot observe the actual price paid for the EUA because the contract and the transaction do not correspond to the same day. We use the average annual futures price as an approximation. As average prices cannot reflect price fluctuations, any profits from arbitrage would not be captured in the dataset. Therefore, our data may not fully capture the effects of using forwards/futures on profits from trading. Likewise, using the spot price to value intra-company trades (i.e. transactions between two installations of the same company) may prove inadequate, especially when companies consolidate their allowances in a single account (as discussed in Betz and Schmidt, 2016). As additional robustness checks, we therefore estimate a model where we exclude all forwards/futures from the transactions considered and a model where we exclude all internal trades. The results are depicted in Table 21 and Table 22 and are very similar to those obtained for our preferred specification. Hence, our results appear robust to excluding forwards/futures and internal acquisitions and transfers from the transactions considered in the analysis.

To examine whether the effects of strategic skills on *profits* changed across trading periods, our main specification included interaction terms between period dummies and *late buyers*, *late sellers*, *transaction frequency* and *use of intermediaries* (see Table 16). As an additional robustness test, we also analysed whether the effects of *net position, banking* and *total transactions* changed across trading periods. We found no evidence that the impact of *net position* and *total transactions* on *profits* changed across trading periods.[44] Unfortunately, models which included interaction terms between the period dummies and *banking* did not converge.

To capture the extent to which companies trade for compliance purposes, we considered all transactions during the true-up period to calculate *late buyers* and *late sellers.* It is possible, however, that some of those trades were driven by speculative motives. To control for speculative motives in our analysis, we estimated a model that incorporates an additional covariate capturing these motives. Specifically, we

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43 All transactions where the buying and selling accounts are associated with the same company.

44 For example, the p-value of the corresponding Wald test on the joint significance of the interaction terms for the second and third trading period is 0.72.

included the net volume share for the true-up period, i.e. the ratio between net acquisitions (= acquisitions-transfers) and total volume (= sum of acquisitions and transfers). A larger positive (negative) ratio is supposed to reflect a stronger speculative motive for net buyers (net sellers) during the true-up period. We find the coefficients associated with this indicator to be statistically significant and negative (positive) for the first (third) period at $p<0.1$. The size effect is rather small, however. Because all other findings are very similar to those obtained for our preferred specification, our results do not appear to be sensitive to potential speculative motives.

Finally, we estimated a model which included a company's emission intensity among the set of covariates. We defined emission intensity as verified *emissions per employee*. Emission intensity relates emissions to company size and is expected to be indicative of the financial pressure a company participating in the EU ETS experiences. We expected companies with a higher emission intensity to have stronger financial incentives to trade profitably. The coefficient associated with *emissions per employee* displayed the expected positive sign but failed to be statistically significant (p-value = 0.93). Possibly, and similar to our no-result for carbon leakage, this no-result for emission intensity may be attributed to the low EUA prices during most of the time frame considered in our analysis.

Overall, these additional robustness checks corroborate the findings obtained for our preferred specification. In particular, our finding that companies bank their allowances efficiently appears robust. Allowing for heterogeneity in the effects of strategic skills by the *net position* provides additional insights compared to our main specification for *late byers* and *late sellers* which resonate intuitively.

7.4 Conclusions

Cost-efficient emissions trading presumes that companies engage in the carbon market to maximise profits from emissions trading, minimise compliance costs and avoid fines for non-compliance. In this paper, we relied on a comprehensive dataset to empirically investigate factors related with companies' profits from trading emission allowances in the EU ETS for the period from 2005 to 2017. We considered the role of free allocation, strategic skills and skill-related structural factors.

Our results obtained from estimating a panel selection model suggest that profits from emissions trading are, as expected, to a large extent related to a company's net position: higher amounts of free allocation lead to higher profits from emissions trading, ceteris paribus. We also found evidence that profits from emissions trading are driven by strategic skills and some skill-related structural factors. With regard to strategic skills, our findings suggest that companies bank allowances efficiently: when they decide on the number of allowances to be transferred into future periods, companies adequately take into account the opportunity costs, i.e. the revenues they could have realised by selling these allowances on the market instead. This result also holds if we allow for the role of strategic factors on trading performance to differ between net sellers and net buyers. Further, we found that late buying (late selling) of allowances within a trading year was correlated positively (negatively) with profits from emissions trading in the first trading period. Distinguishing effects by net sellers and net buyers reveals that these findings for late buying (late selling) are essentially driven by *net buyers* (*net sellers*). In subsequent trading periods, such results could no longer be observed; this may reflect that companies had achieved learning effects. For skill-related structural factors, we found that companies with more installations achieve higher profits from trading, ceteris paribus.

Our findings have several implications for policymakers involved in the design of emissions trading schemes for companies engaged in emissions trading. On the one hand, the results imply that companies were able to use banking of EUAs efficiently, which highlights the importance for policymakers to allow for unrestricted banking of allowances in emissions trading systems to help companies meet emission targets at the lowest costs to society. On the other hand, the results concerning the timing of trading suggest that while some firms were able to time their trading activities well, others failed to profit from spreading their trades evenly over the year. Hence, it pays off for companies to invest in developing strategic trading skills because that way they can create a financial benefit. However, since quite a few companies still failed to realise that they could have used the EU ETS more cost-efficiently to comply with climate regulation, policymakers should make sure that participating companies are fully aware of the need to actively use the EU ETS' trading mechanism to lower their cost of compliance. Because the EUA price has increased over the past years, the EU ETS' regulatory burden has only grown, making it even more important for companies to use emissions trading in the most cost-efficient way. Further, the finding that having more regulated installations lead to higher profits from trading, ceteris paribus, suggest that there may be increasing returns to scale from trading in the EU ETS. In other words, to profit from emissions trading, scale matters which possibly reflects the conducive role of complementary assets in this context. If companies cannot achieve sufficient scale on their own, they could consider collaborating with other companies to aggregate their trading activities and share the costs of making structural investments for emissions trading such as specialised trading desks.

In conclusion, our findings were obtained for the period 2005-2017, which was characterised by relatively low prices for EUAs. Once data become available, future work could investigate the extent to which our findings also hold for periods with substantially higher prices, which mean stronger financial incentives for companies to buy and sell allowances efficiently and to enhance their strategic trading skills and structures.

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CRediT authorship contribution statement

- **Sascha Lehmann:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.
- **Joachim Schleich:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.
- **Jonatan Pinkse:** Conceptualization, Validation, Writing – review & editing.

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7.6 Appendix A.1: Compiling the Data

A.1.1 Data Sources and Preparation

The European Commission operates the electronic Database Union Registry. The database contains all transactions within the EU ETS, including free allocation, surrendered allowances and all transactions between market participants. The European Union Transaction Log (EUTL) records, checks and authorises these transactions. The Commission publishes all transactions and other details from the Union Registry under the EUTL. Data can be downloaded free of charge, but with a three-year delay in the case of transaction data.

The EUTL records all transactions made between registered accounts, although it is important to note that only registered accounts can trade allowances. Each regulated stationary installation must open at least one Operator Holding Account (OHA) and each airline must open at least one Aircraft Operator Account (AOA), through which the free allocation and surrender of allowances is transacted. In addition, companies, but also private individuals, can open Person Holding Accounts (PHA) and Trading Accounts (TA) in order to use them for trading. In addition, there are administrative accounts that are operated by the EU or the Member States and used, among other things, for free allocation, auctioning or the cancellation of allowances.

EUTL contains information about the account name, the registration (Member State), the company registration number as well as the assigned account holder and the assigned installation. The name and address of account holders are available. With regard to installations, the activity type, address, allocation, emissions, and the number of surrendered allowances are available.

The EUTL transaction information includes the accounts involved, the transaction type, the date and the quantity of allowances. Futures and forwards are recorded but not clearly identifiable and only on the actual delivery date and not when the contract was concluded. Prices are not shown by the EUTL.

With the 2012 reform, the Community Independent Transaction Log (CITL), which was a decentralised system until then, was migrated to the central EUTL operated by the Commission. During this process, all installations were given new OHAs (see A.1.2).

In addition to the EU ETS related EUTL data, we used company data from the ORBIS database of Bureau Van Dijk in our study. These include financial data on the number of employees, revenues, industry classification (NACE), the company registration number and the home country of a company. For information on matching the two data sets, see A.1.3.

For the spot price, we used price information from EEX and information on futures prices (one-year December futures) from ICE. Because we only know the delivery date for the futures, we priced them using the annual average price of the futures. The prices were matched with the transaction data using the date.

After we had matched all the databases, we set up a panel data set which is based on trans-actions. We aggregated this data such that the final data set included annual transactions per company. We removed all non-regulated companies (allocation and emissions is zero), because they are irrelevant to our research question, and also all transactions not matched with the ORBIS data. We did so, as only the ORBIS data allow the level of aggregation at company level and we needed the ORBIS information for our analyses. However, transactions from a company known in ORBIS to a company unknown in ORBIS are kept for the company known in ORBIS.

In our underlying dataset, we have 42007 accounts, of which we could not match 8142 to any company. The matched accounts are across 12319 companies. However, the number of companies included in the multivariate analyses is lower because we eliminated all aircraft operators and only included companies for which the NACE code (industry) is known. Furthermore, we eliminated all companies that have neither free allocation nor verified emissions, reducing the number of companies to about 9000. In our individual models, the number of companies was then usually slightly more than 6700. This is due to the fact that further companies were eliminated due to missing information on the number of employees and revenue and also due to collinearity.

We tried to include the stock of banked allowances per company, but found inconsistencies when adding them up. For example, during the restructuring in 2012, allowances were not always transferred in an appropriate and comprehensible way.

A.1.2 Matching of the New and Former OHAs

With the redesign of the European Union Transaction Log (EUTL) in 2012, new account types such as aircraft operating accounts were introduced. This also meant that all installations had to be linked to a new Operator Holding Account (OHA). However, the current data records of the EUTL only feature the current OHA and not the OHA from before the restructuring. We therefore had to match the previous OHAs with the respective installations. We handled this as follows:

- Compare account name and installation name and match if unambiguous.
- Compare account address and installation address and match if unambiguous.
- If 1 and 2 did not work, we used installation-level information on allocation and surrendered number of allowances and searched for the transaction and account be-hind it and the administrative account of the respective registration. Again, we only accepted unique matches. We first used allocations followed by surrendering transfers.

Using this methodology, we were able to match about 99% of the old OHAs to the new OHAs.

A.1.3 Matching the EUTL Data with Companies from the ORBIS Database

With the reform of accounts in 2012, all account holders were required to provide VAT registration numbers. This is either a national or a European number. The ORBIS database also contains the VAT number. Therefore, in theory, matching the two databases is possible without any major problems. However, data errors and format errors make matching difficult in practice. We therefore employed fuzzy matching based on VAT registration number, the name of the account linked to this number and the address of the account contact. The automatic ORBIS batch search uses these variables. Here, the account data served as criteria for the ORBIS data search. The batch search performed then provides several possible matches and a matching score for each option. The ultimate match was then done by checking the quality of the match in the individual fields.

7.7 Appendix A.2: Descriptive Statistics

Table 17: Descriptive statistics.

Dependent Variable	**Obs.**	**Mean**	**Min**	**Max**
Profits	91,064	-33,079	-12,088,990	4,979,894
Covariates				
Allocation				
Net position	68,632	-501	-10,415,690	7,608,230
Skills - strategic				
Banking	91,064	5,484	-10,430,520	7,608,230
Late buyers	91,064	25,359	0	52,146,820
Late buyers X P2	91,064	11,217	0	42,496,560
Late buyers X P3	91,064	13,008	0	52,146,820
Late sellers	91,064	19,978	0	52,346,160
Late sellers X P2	91,064	10,999	0	42,522,140
Late sellers X P3	91,064	7,576	0	52,346,160
Transaction frequency	91,064	11	0	60,030
Transaction frequency X P2	91,064	8	0	60,030
Transaction frequency X P3	91,064	2	0	9,894
Use of intermediaries	91,064	0.07	0.00	1.00
Use of intermediaries X P2	91,064	0.02	0.00	1.00
Use of intermediaries X P3	91,064	0.05	0.00	1.00
Total transactions	91,064	109,700	0	320,750,300
Skills - structural				
Number Installations	91,064	2.47	1.00	80.00
Energy	91,064	0.20	0.00	1.00
Employees	50,352	2,240	0	642,300
Productivity	46,299	2,090	-2,180	2,222,830
Market pressure				
Carbon leakage	82,135	0.37	0.00	1.00
Year and region effects				
Period 1	91,064	0.23	0.00	1.00

Period 2	91,064	0.39	0.00	1.00
Period 3	91,064	0.38	0.00	1.00
Region 1 (AU, DE, LI)	91,064	0.06	0.00	1.00
Region 2 (BE, FR, NL)	91,064	0.05	0.00	1.00
Region 3 (GR, IT, PT, ES, CY, MT)	91,064	0.14	0.00	1.00
Region 4 (EE, LT, LV, PL)	91,064	0.12	0.00	1.00
Region 5 (CZ, HU, SI, SK)	91,064	0.05	0.00	1.00
Region 6 (DK, FI, IS, NO, SE)	91,064	0.35	0.00	1.00
Region 7 (UK, IE)	91,064	0.03	0.00	1.00
Region 8 (BG, HR, RO)	91,064	0.14	0.00	1.00

7.8 Appendix A.3: Results for Participation Equation of Preferred Model

Table 18: Results for participation equation of preferred model.

	Coefficient	SE
Allocation		
Net position	-0.294***	(0.078)
Skills - structural		
Number of installations	132.4***	(12.17)
Energy	3676.	(3386.)
Employees	182.6**	(82.60)
Productivity	24.69	(56.46)
Market pressure		
Carbon leakage	366.7	(268.0)
Year and region effects		
Period 2	0.059**	(0.027)
Period 3	-0.177***	(0.036)
Region effects	yes	yes
Share active country	3.597***	(0.099)
Constant	-1.902***	(0.059)

Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

7.9 Appendix A.4: Results of Robustness Checks

Table 19: Results for profit equation of preferred model for Mundlak specification.

			Mundlak terms	
	Coefficient	SE	Coefficient	SE
Allocation				
Net position	5.840***	(0.257)	0.448*	(0.258)
Skills - strategic				
Banking	-5.604***	(0.345)	-0.419	(0.313)
Late buyers	2.209**	(1.106)	0.268	(0.414)
Late buyers X P2	-1.816	(1.135)	-0.192	(0.489)
Late buyers X P3	-2.407**	(1.110)	-0.226	(0.509)
Late sellers	-2.765**	(1.106)	-0.240	(0.254)
Late sellers X P2	2.349**	(1.133)	0.301	(0.323)
Late sellers X P3	2.906***	(1.106)	0.179	(0.384)
Transaction frequency	3.072	(3.887)	-0.716	(1.301)
Transaction frequency X P2	-3.127	(3.673)	0.076	(1.381)
Transaction frequency X P3	-7.552***	(2.905)	0.603	(1.274)
Use of intermediaries	6.265	(7.559)	-8.062	(8.395)
Use of intermediaries X P2	-3.446	(7.882)	16.96*	(9.965)
Use of intermediaries X P3	-6.394	(7.704)	8.377	(8.790)
Total transactions	3.081	(11.25)	-1.106	(11.83)
Skills - structural				
Number of Installations	4.916***	(1.543)		
Energy	654.0	(979.2)		
Employees	47.22	(79.17)	-33.52	(96.72)
Productivity	0.075	(12.78)	10.06	(14.73)
Market pressure				

Carbon leakage	72.05	(78.51)	
Year and region effects			
Period 2	0.072***	(0.014)	
Period 3	-0.036**	(0.016)	
Region effects	yes	yes	
Constant	-0.097***	(0.024)	
corr($\varepsilon_{1,it}$, $\varepsilon_{2,it}$)	0.276***		
corr ($\alpha_{1,i}$,$\alpha_{2,i}$)	0.945		
χ^2 (46)	4987.09***		
Number of observations	37,695		
Number of companies	6,737		

Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 20: Results for profit equation of model including interaction terms for net sellers.

	Coefficient	SE
Allocation		
Net position	6.493***	(0.154)
Net position X net sellers	-1.814***	(0.571)
Skills - strategic		
Banking	-6.406***	(0.168)
Banking X net sellers	1.876***	(0.667)
Late buyers	3.687***	(1.041)
Late buyers X net sellers	-3.636*	(1.937)
Late buyers X P2	-2.695**	(1.176)
Late buyers X net sellers X P2	2.606	(2.008)
Late buyers X P3	-3.779***	(1.049)
Late buyers X net sellers X P3	3.383*	(1.959)
Late sellers	-4.422***	(1.051)
Late sellers X net sellers	3.898**	(1.913)
Late sellers X P2	3.425***	(1.182)
Late sellers X net sellers X P2	-2.873	(1.978)
Late sellers X P3	4.506***	(1.051)
Late sellers X net sellers X P3	-3.675*	(1.926)
Transaction frequency	1.187	(8.059)
Transaction frequency X net sellers	1.436	(7.470)
Transaction frequency X P2	-1.219	(7.881)
Transaction frequency X net sellers X P2	-1.519	(7.448)
Transaction frequency X P3	-4.992	(7.080)
Transaction frequency X net sellers X P3	-4.036	(8.899)
Use of Intermediaries	8.652	(15.12)

Use of Intermediaries X net sellers	-6.298	(16.55)
Use of Intermediaries X P2	0.821	(15.34)
Use of Intermediaries X net sellers X P2	1.189	(17.10)
Use of Intermediaries X P3	-8.303	(15.25)
Use of Intermediaries X net sellers X P3	6.501	(16.47)
Total transactions	1.456	(11.79)
Skills - structural		
Number Installations	7.942***	(1.893)
Energy	1527	(1026)
Employees	18.09	(20.71)
Productivity	-3.511	(10.80)
Market pressure		
Carbon leakage	108.3	(82.61)
Year and region effects		
Period 2	-0.033	(0.020)
Period 2_s	0.201***	(0.016)
Period 3	0.007	(0.021)
Period 3_s	0.004	(0.016)
Region effects	yes	
Constant	-0.175***	(0.039)
corr($\varepsilon_{1,it}$, $\varepsilon_{2,it}$)	0.464***	
corr ($\alpha_{1,i}$,$\alpha_{2,i}$)	0.978***	
χ^2 (45)	5836.84***	
Number of observations	37,695	
Number of companies	6,737	

Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 21: Results for profit equation of model without forwards and future trades.

	Coefficient	SE
Allocation		
Net position	5.099***	(0.244)
Skills - strategic		
Banking	-4.842***	(0.298)
Late buyers	1.419	(1.079)
Late buyers X P2	-1.572	(1.099)
Late buyers X P3	-1.778*	(1.079)
Late sellers	-1.978*	(1.080)
Late sellers X P2	2.141*	(1.098)
Late sellers X P3	2.234**	(1.079)
Transaction frequency	1.924***	(4.321)
Transaction frequency X P2	-2.246	(4.039)
Transaction frequency X P3	-12.09**	(4.887)
Use of intermediaries	1.797	(6.588)
Use of intermediaries X P2	5.227	(6.923)
Use of intermediaries X P3	-2.075	(6.701)
Total transactions	2.858	(14.36)
Skills - structural		
Number of Installations	10.35***	(2.177)
Energy	1356.	(1141.)
Employees	3.034	(19.91)
Productivity	-2.550	(11.87)
Market pressure		
Carbon leakage	32.86	(92.15)
Year and region effects		

Period 2	0.113***	(0.014)
Period 3	-0.000	(0.016)
Region effects	yes	
Constant	-0.173***	(0.028)
corr($\varepsilon_{1,it}$, $\varepsilon_{2,it}$)	0.366***	
corr ($\alpha_{1,i}$,$\alpha_{2,i}$)	0.603***	
χ^2 (29)	2430.18***	
Number of observations	37,695	
Number of companies	6,737	

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 22: Results for profit equation of model without internal trades.

	Coefficient	SE
Allocation		
Net position	5.966***	(0.238)
Skills - strategic		
Banking	-5.705***	(0.322)
Late buyers	2.243**	(1.104)
Late buyers X P2	-1.743	(1.134)
Late buyers X P3	-2.452**	(1.101)
Late sellers	-2.820**	(1.103)
Late sellers X P2	2.326**	(1.132)
Late sellers X P3	2.955***	(1.099)
Transaction frequency	3.063	(3.886)
Transaction frequency X P2	-3.242	(3.681)
Transaction frequency X P3	-7.340**	(2.891)
Use of intermediaries	2.439	(6.916)
Use of intermediaries X P2	3.880	(7.099)
Use of intermediaries X P3	-2.860	(7.083)
Total transactions	2.472	(11.14)
Skills - structural		
Number of Installations	5.026***	(1.560)
Energy	691.5	(992.7)
Employees	13.37	(18.72)
Productivity	3.723	(10.05)
Market pressure		
Carbon leakage	88.86	(80.13)
Year and region effects		

Period 2	0.082***	(0.013)
Period 3	-0.030**	(0.014)
Region effects	yes	
Constant	-0.106***	(0.023)
corr($\varepsilon_{1,it}$, $\varepsilon_{2,it}$)	0.279***	
corr ($\alpha_{1,i}$,$\alpha_{2,i}$)	0.762***	
χ^2 (29)	4253.89***	
Number of observations	37,695	
Number of companies	6,737	

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

8. Does increasing auctioning in the EU ETS increase companies' search efforts for favourable trading options?

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Abstract:

The European Emissions Trading System was established in 2005 and regulates greenhouse gas emissions across energy, industry, and aviation sectors in EU Member States. Since 2013, the share of auctioned allowances has increased, and will further increase in the future. A higher share of auctioning is generally considered to improve efficiency of an emissions trading system. However, increased auctioning may increase search activity on the secondary market because it increases companies' financial incentives to find more favourable trading options, potentially undermining efficiency gains of auctioning compared to free allocation. Employing trading and company data from 2005 to 2017, this study empirically examines if increased auctioning affects companies' search for favourable secondary market trading options, specifically in terms of the number of trading partners and trading frequency. Results from estimating panel econometric models suggest that companies with a higher absolute net position value and higher banking stock value indeed intensify their secondary market search activities, ceteris paribus. Because the size effects appear to be rather small, however, any additional search costs are likely to be more than offset by the positive effects of a higher auction share compared to free allocation.

Keywords: Climate policy, emissions trading, EU ETS, search costs, transaction cost.

8.1 Introduction

Launched in 2005, the European Emissions Trading System (EU ETS) currently governs greenhouse gas emissions of about 10.000 installations in the energy and manufacturing industry in the European Union (EU), Iceland, Liechtenstein and Norway. Originally covering CO_2-emissions in 24 EU Member States, the system has increased over time in terms of regional scope (e.g. Bulgaria, Romania, Iceland, Liechtenstein and Norway joined in 2008, and Croatia in 2013), and greenhouse gas types (e.g. N_2O, PFC were added in 2013). In addition, the number of EU allowances (EUA) allocated each year was substantially reduced over time to be in line with tighter greenhouse gas emission targets at the EU level in the wake of the EU's Green Deal and 'fit-for-55' negotiations in 2021.[45]

Free allocation was the main allocation method in the early years of the EU ETS (e.g., Pauer, 2013). The share of allowances that could be auctioned off was capped at 5% in the first trading period and at 10% in the second trading period for each Member State. Most Member States, however auctioned off fewer EUAs than they could have. Since 2013, the majority of allowances have been auctioned off, with a target share of at least 57%. In particular, most electricity producers no longer receive allowances for free and allocation for installations in the manufacturing industry is generally based on product benchmarks. Furthermore, only installations in industries that are considered vulnerable to carbon leakage have since 2013 received full free allocation, whereas free allocation for installations from other industries has gradually been phased out and is scheduled to end in 2030. Based on our dataset, the actual

[45] We provide a more detailed description of the EU ETS in Section 8.7.

auctioning shares averaged approximately 0.1% for the first trading period, around 4% for the second trading period, and about 47% for the third trading period.[46]

More recent regulation on the carbon border adjustment mechanism (CBAM) implies that free allocation will be phased out for industries covered by the CBAM.[47] Hence, akin to energy companies, companies from manufacturing industries can no longer count on free allocation of EUAs but have to rely stronger on auctions and on the secondary market instead to secure the amount of EUAs required to be in compliance.

In the EU ETS, the secondary market is defined as all trading that is carried out by companies and does not involve free allocation, auctioning, and the surrender of allowances. The secondary market includes exchange trading (spot and future) and bilateral trading (over-the-counter) between regulated companies but also between financial intermediaries and regulated companies. Particularly for so-called over-the-counter (OTC) trades[48], the trading partners are free to negotiate prices bilaterally. The secondary market has expanded over time, as evidenced by a 27% increase in annual trading volume from the second to the third trading period in our dataset. Between 2011 and 2014[49], this growth was even more pronounced, with an increase of 45%. The ratio of free allocation to trading volume in the secondary market has also changed significantly between the second and third trading periods, increasing from a ratio of 1:8 to

[46] The target share for the third trading period was not achieved because of backloading, in particular. That is, about 900 million EUAs that were scheduled for auctioning during the period 2014–2016 were withheld to limit supply and stabilize the carbon price.

[47] Implemented gradually since October 2023, CBAM addresses concerns about carbon leakage und currently covers the production of electricity, cement, iron and steel, aluminum, fertilizers and hydrogen. CBAM levies an import duty on the greenhouse gas emissions associated with the production of these goods, aligning the costs for greenhouse gas emissions with those incurred under the EU ETS for products not manufactured within the EU.

[48] According to DEHSt (2014) the majority of traded EUAs on the secondary market are transferred via exchanges but the number of EU ETS-regulated companies participating at exchanges is far lower than the number of regulated companies trading OTC. This suggests that OTC trading plays an important role for regulated companies.

[49] The period from 2011 to 2014 is chosen because the trading volume in the secondary market for 2012 and 2013 may be distorted due to the transition of national registries to an EU registry. This transition led to the introduction of new trading accounts, requiring market participants to transfer their stock of EUAs to these accounts. This process could have influenced the observed trading activity during this timeframe.

approximately 1:23. This indicates a substantial growth in the significance of the secondary market.

Auctioning of allowances is often preferred to free allocation (e.g. Schmalensee et al., 1998; Hepburn et al., 2006; Benz et al., 2010; Venmans, 2016; Adamolekun, 2024). In contrast to free allocation, auctioning leverages the market mechanism during the primary allocation of allowances and is therefore less susceptible to lobbying. Unlike free allocation, auctioning treats incumbents and newcomers equally and does therefore not distort market entrance and avoids windfall profits.[50] Auctioning also generates revenues which may be used to address economic distortions elsewhere, to finance low-carbon innovation, and to alleviate potential regressive distributional effects of an ETS. Because companies must initially purchase allowances, auctioning increases their financial costs and may impede their competitiveness, especially against competitors from outside the EU. Hence, companies typically prefer free allocation to auctioning.

In theory, both allocation methods may achieve a given emission target at minimum costs (static efficiency). Because auction participants should bid according to their marginal abatement costs, the clearing price in a (double-sided) auction is expected to result in an equalization of the marginal abatement costs across companies. Under free allocation, subsequent buying and selling of EUAs on the secondary market leads to such an equalization. Therefore, an increase in auctioning means that some of the trades that would have taken place on the secondary market under free allocation no longer occur under higher auctioning shares. From this perspective, an increase in the auctioning share generally lowers the trading activity on the secondary market and may therefore lower the associated trading-related transaction costs (e.g.

[50] Free allocation meant that companies which were able to pass on the opportunity costs of EUAs to their customers enjoyed substantial windfall profits in the EU ETS, especially in the power and in several industry sectors (e.g. Sijm et al., 2006; Verde et al., 2019; Cludius et al., 2020; Dagoumas and Polemis, 2020).

search costs to find potential trading partners, entry costs for trading on platforms such as the European Energy Exchange)[51] but also the lobbying costs association with free allocation (e.g. Hepburn et al. 2006). Indeed, findings from various empirical studies suggest that transaction costs have prevented efficient trading in the EU ETS (e.g. Jaraitė-Kažukauskė and Kažukauskas, 2015; Baudry et al., 2021; Abrell et al., 2022; Hintermann and Ludwig, 2023). However, following an argument originally formalized by Stigler (1961), an increase in auctioning may result in higher activities on the secondary market. For example, for net buyers (i.e. companies which must acquire EUAs to cover their emissions), an increase in auctioning could reduce their net position and thereby increase the financial incentive to search for trading partners asking lower EUA prices. As a result, companies may not rely solely on auctions to meet their purchasing needs but may expand their search on other trading channels. This could lead to an increase in trading volume in the secondary market. In sum, the effects of auctioning on companies' activities on the secondary market may therefore generally be ambiguous.

In this paper, we analyse the effects of changes in companies' compliance costs resulting from an increase in auctioning in the EU ETS on their search efforts within the secondary market. Our findings are particularly relevant for policymakers assessing the costs and benefits of increased auctioning, especially in the aftermath of the CBAM phase-in.

Our empirical analysis comprises companies' trading activities between 2005 and 2017, i.e. for the first two trading periods of the EU ETS and the first five years of the third trading period. Relying primarily on data from the European Union Transaction Log (EUTL) and from the European Energy Exchange (EEX), we created a comprehensive dataset that includes information on transactions, account holders, free allocations, emissions and allowance prices.

[51] Unless the primary allocation happens to coincide with the cost-minimizing distribution of emissions across all installations.

We employed panel econometric methods to analyse the relations between companies' search efforts and a variable reflecting the effects of auctioning on companies' financial incentives. To capture the effects of auctioning we employ the value of a company's net position (i.e. free allocation minus verified emissions, multiplied by the EUA price). Hence our identification strategy exploits variation of the net position over time and across companies. We assume that as the auction share increases, the incentive to search for favourable trading options also increases. This approach does not directly measure the auction share, but rather captures the reduction in free allocation resulting from the changes in the auctioning shares in the EU ETS over time. To proxy companies' search efforts for more favourable prices, we consider two indicators: the number of trading partners and trading frequency. We assume that companies expanding their search efforts in the secondary market will engage with more trading partners and trade more frequently. For example, companies may find it advantageous to employ more trading partners (via bilateral trades, and exchange) because a single trading partner may not be able to sell (or buy) the desired quantity of EUAs at a given price. Likewise, exploiting differences in prices over time should increase trading frequency.

In line with the reasoning originally developed by Stigler (1961), our findings suggest that companies with a higher net position value in absolute terms engage in more search effort on the secondary market, ceteris paribus.

Our study adds to the existing literature in various ways. To the best of our knowledge, this is the first study which focuses on empirically analysing the effects of an increase in auctioning in the EU ETS on companies' search activities on the secondary market. Previous empirical analyses on trading behaviour in the EU ETS focuses on transaction costs (Jaraitė-Kažukauskė and Kažukauskas, 2015; Naegele, 2018; Baudry et al, 2021; Hintermann and Ludwig, 2023), trading participation (Zaklan, 2013), trading activity (Abrell et al., 2022), trading behaviour and trading patterns (Borghesi and Flori, 2018; Karpf et al., 2018; Zaklan, 2023), financial performance (Liu et al., 2017; Guo et al., 2020; Flori et al., 2024; Lehmann et al., 2024), and company value (Dewaelheyns et al., 2023). Previous literature on auctions under an ETS is mainly conceptual and focuses on design and efficiency, arguing that auctioning reduces market distortions, contributes to reflecting the true scarcity of allowances and to stabilizing allowance prices, improves transparency, and generates revenue that can be earmarked to finance mitigation measures (e.g., Benz et al., 2010; Ehrhart et al., 2005; Hepburn et al., 2006). Empirical studies, such as Venmans (2016), indicate that a negative net position - common in emissions trading systems with a high share of auctioned allowances - provides stronger incentives for abatement investments than a positive net position). Adamolekun (2024) shows that auctioning reduces price volatility, fostering investments in emissions reductions. Thus, our study addresses a research gap by empirically examining the relationship between auction share and companies' trading behaviour. In contrast to related previous studies (Abrell et al. 2022; Lehmann et al. 2024) our study employs monetary rather than physical values of net position, thus better reflecting the financial incentives driving corporate trading behaviour. Except for Lehmann et al. (2024), previous studies did not account for banking. Finally, previous analyses typically focus on the first two trading periods, whereas ours covers five years post 2013 reforms of the EU ETS.[52]

Our paper is structured as follows. In the second section we develop a simple analytical model to analyse the effects of auctioning in an ETS on companies' search efforts, and hence to motivate our empirical analysis. In the third section, we present the empirical methodology, including the data, the variables, and the econometric approach. In the fourth section we present

[52] We also note that our data comprises almost twice as many observations as Abrell et al. (2022) and Lehmann et al. (2024), which are – to our knowledge - the only other studies covering data up to 2017. Their reliance on ORBIS data, including company characteristics like employees and profitability, limits their sample. For our purposes, these characteristics seemed less crucial. As a robustness check (see section 8.4.2), we limit our analyses to companies included in the ORBIS data set.

and discuss the results of our main model specifications, and also present findings of various robustness checks. The final section summarizes and concludes.

8.2 Conceptual Model

In this section we develop a simple model which allows us to analytically derive the response by companies to an increase in auctioning on search efforts. Our model builds on Stigler (1961), adapted to incorporate features relevant to the analysis of emissions trading systems.

A price-taking company is assumed to choose the level of search effort x_s which minimizes total compliance cost

$$\overline{p} \cdot \gamma(x_s) \cdot [e(x_a) - \bar{E}] + TC(x_s) + C(e(x_a)) \quad (1)$$

where $\overline{p}$ is the price per EUA a buyer (seller) has to pay (obtains) without additional search effort, the factor $\gamma(x_s)$ captures the effect of search effort on $\overline{p}$, with $0 < \gamma(x_s) \leq 1$ and $\gamma'(x_s) < 0$ for buyers, and $\gamma(x_s) \geq 1$ and $\gamma'(x_s) > 0$ for sellers[53]. That is, additional search efforts lower (increase) the price for buyers (sellers). Company emissions are denoted by $e(x_a)$ and are assumed to decrease with higher abatement efforts x_a, i.e. $e'(x_a) < 0$. $\bar{E}$ reflects the number of EUAs received by a company for free via the primary allocation. Hence, $[e(x_a) - \bar{E}]$ denotes the net position of a company and $\overline{p} \cdot \gamma(x_s) \cdot [e(x_a) - \bar{E}]$ the net position value, $C(e(x_a))$ stands for a company's abatement costs, with $C'(e(x_a)) < 0$. Transaction costs are denoted by $TC(x_s)$, with $TC'(x_s) > 0$. Finally, we assume that marginal abatement costs and marginal transaction costs are increasing in effort, i.e. $C''(.) > 0$ and $TC''(.) > 0$. A company must decide how much of total available effort $\overline{x}$ to dedicate to search and to abatement, i.e. $\overline{x} = x_s + x_a$.

[53] For simplicity, our model is static and abstract, for example, from banking.

The first-order condition for the optimal level of x_s yields

$$\overline{p} \cdot \gamma'(x_s) \cdot [e(x_a) - \bar{E}] - \overline{p} \cdot \gamma(x_s) \cdot e'(x_a) + TC'(x_s) - C'(e(x_a)) \cdot e'(x_a) = 0 \quad (2)$$

Equation (2) implies that a company increases search efforts x_s until the marginal benefits equal the marginal costs. Marginal benefits are captured by the first set of terms in equation (2), i.e. the change in the value of the net position. For a net buyer (net seller), the marginal benefits reflect the decrease (increase) in expenses (revenues) associated with purchasing (selling) EUAs due to a decrease (increase) of the price. Marginal costs are composed of three sets of terms. For a net buyer (seller), the second set of terms in equation (2) reflects the additional expenses (revenues) associated with purchasing (selling) EUAs due to an increase (decrease) in emissions (because abatement effort increases). The third set of terms captures the marginal transaction costs, and the fourth set of terms the marginal abatement costs.[54]

We are particularly interested in how search effort changes in response to an increase in the auctioning share. We therefore take the total differential of (2) and obtain

$$\frac{dx_s}{d\bar{E}} = \frac{\overline{p} \cdot \gamma'(x_s)}{D} \quad (3)$$

Where the numerator of (3) captures the terms in the second-order condition. Because we consider a minimization problem, D>0. The sign of equation (3) is determined by the sign of $\gamma'(x_s)$. Thus, for net buyers (sellers), an increase in auctioning (i.e. a decrease in $\bar{E}$) results in an increase (decrease) in search effort. Intuitively, for net buyers (sellers) an increase in the auctioning share, ceteris paribus, means that they will purchase (sell) more (fewer) EUAs,

[54] Note that if γ is a constant and equal to 1, and transaction costs are always 0, equation (2) yields the familiar result $\overline{p} = -C'(e(x_a))$, i.e. companies exert abatement effort x_a until the marginal costs are equal to the price.

resulting in higher (lower) marginal benefits of search effort.[55] The specification of our empirical model will take this insight into account.

8.3 Empirical Methods

In this section, we present the data and variables used in our study and describe the econometric approach. Our empirical analyses focus on the effects of a change in the allocation of free allowances (e.g. via a change in the auctioning share) on companies' search efforts. Hence, compared to our conceptual model outlined in Section 8.2, we abstract from companies' compliance efforts. Further, because our data does not include direct measures of search efforts, we employ proxies.

8.3.1 Data

From the European Union Transaction Log (EUTL) we collected data on transactions of allowances, information on accounts and account owners (companies or private persons) and data of installations on primary allocation and verified emissions. Price data was gathered from the European Energy Exchange (EEX). We aggregated all the data on an annual basis for each individual company. For our purpose, considering the level of the individual company rather than the level of installation or at the global ultimate owner seems appropriate because trading decisions are likely to be made at the company level (e.g. Abrell et al., 2022). Administrative transactions such as primary allocation and allowances surrendered were excluded from the analysis as they do not reflect secondary market activities. These transactions account for almost two-thirds of all transactions in the EUTL. The remaining transactions in the dataset pertained exclusively to sales and purchases of European Union Allowances (EUAs). As suggested by Cludius and Betz (2020) we considered transactions during a trading year (May

[55] See Section 8.8 for further details on how equations (2) and (3) were derived.

in year t to April in year t+1) rather than a calendar year because regulated companies are permitted to surrender allowances for emissions until the end of April in year t+1. The dataset includes transactions up to April 2018 and thus covers five complete years of the third trading period. To ensure that our sample only includes regulated companies, we excluded companies that received no primary allocation of allowances and had no verified emissions. Moreover, transactions conducted within the same installation were dropped from the sample because we assume that these are a result of organizational rather than trading-related motives. In Section 8.9 we provide further details on how we compiled the data.

8.3.2 Variables

In this section, we present our dependent variables and our set of covariates. Table 23 provides an overview.

8.3.2.1 Dependent variables

Our empirical analysis includes two dependent variables, which we consider as proxies for search activity in the secondary market: the number of trading partners per company and year and the number of trades per company and year. The variable *trading partners* reflects the number of trading partners of a given company in a given year. It includes intermediaries, private persons, other regulated companies, and unregulated companies. If a company is making significant efforts to find trading opportunities, this should manifest in a higher number of trading partners. For example, companies that put more effort into searching for trading opportunities are more likely to connect with multiple partners rather than settling for the first available option. More intensive search efforts lead to a larger pool of potential counterparties, increasing the likelihood of finding better contract terms such as prices. As suggested by transaction cost theory (Williamson, 1989) and the literature on supply chain management (e.g., Sawik, 2014; Mehrjerdi and Shafiee, 2021), companies concerned about price volatility and risk may seek more trading partners to reduce dependence on any single entity. Following Abrell et al. (2022), we define *transaction frequency* as the number of trades a company carried out in a given year. Companies that frequently engage in trades likely put in greater effort to monitor market conditions, respond to regulatory changes and identify opportunities to take advantage of favourable price movements and manage risk.

8.3.2.2 Covariates

Our choice of covariates is driven by our research question, data availability and the existing literature. Our variables of interest are *net position value* and *banking stock value*. In addition, we include several control variables such as the number of regulated installations per company.

Net position value

The net position corresponds to the difference between the amount of free allocation and the number of verified emissions in a given year. As discussed earlier, we use net position as a proxy for auctioning. The higher the auctioning share, the lower the net position, ceteris paribus. In particular, the net position captures the effects of the reform of the ETS that lead to a substantial increase in auctioning and hence reduced free allocation from 2013 on. As suggested by our conceptual model, equation (3), an increase in the auctioning share results in higher (lower) marginal benefits of search effort for net buyers (sellers).

Empirical evidence suggests (e.g. Jaraitė-Kažukauskė and Kažukauskas, 2015), that the incentive for regulated companies to participate in the secondary market is related to the net position. In addition to the annual auction share, several other factors influence a company's free allocation amount. These include sector-, country-, and period-specific allocation rules, changes to the carbon leakage list, and the cross-sectoral correction factor (CSCF). In comparison, abatement efforts and a change in production affect the level of verified emissions. As financial incentives are important for our underlying research question, we multiply the net position by the average annual EUA price to obtain our variable of interest, *net position value*. *Net position value* reflects the cost pressure imposed on net buyers (companies with a negative net position) by the need to purchase EUAs and the opportunity cost of holding EUAs for net sellers (companies with a positive net position). For net buyers, a lower *net position value*, which corresponds to a higher negative value, results in higher compliance costs.[56] According to the analytical model developed in section 8.2, companies with higher compliance costs will spend more efforts on search than companies with lower compliance costs. In our context, these companies are expected to search (and find) for more *trading partners* and to display a higher *transaction frequency* on the secondary market than companies with lower compliance costs, ceteris paribus. Likewise, for net sellers, a higher *net position value* increases incentives to search favourable selling options. In our empirical analysis we therefore use the absolute value of a company's *net position value* and expect a positive correlation with our indicators of companies' search efforts.

Banking stock value

We first define the banking stock in year t as the banking stock in year t-1 plus free allocation plus acquisitions minus verified emissions minus transfers of a company in year t. To obtain the *banking stock value*, we multiplied the banking stock by the average EUA price of year t. We take into account, that banking was possible within the first trading period and from 2008 onwards. Allowances allocated during the first trading period were not valid in subsequent periods. *Banking stock value* reflects the value of all banked allowances of a company and is always positive because borrowing not permitted[57]. As a higher *banking stock value* leads to

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[56] The *net position value* also captures potential interactions of the EU ETS with other policy measures. At the company level, measures such as the industrial emission directive ensure the use of best available techniques, which may affect verified emissions. At the aggregate level, policies such as the renewable energy directive which promotes the use of renewable energies may lower the demand for EUAs, ultimately affecting their market price.

[57] The number of allowances held in an EU ETS account must always be greater than or equal to zero, because companies are not permitted to sell or surrender more allowances than they own across all their accounts.

lower compliance costs for a company in the following years, we include the *banking stock value* of the previous year (*banking stock value*$_{t-1}$) in our model and expect a negative correlation with our indicators of companies' search efforts.

Previous literature either did not consider banking at all due to data issues (e.g., Abrell et al., 2022) or included only companies' banking behaviour within a given year (e.g., Lehmann et al., 2024). We address data issues by reviewing - case-by-case - negative stock values at the account level. If another account of the same company could at least offset the same amount, it was considered plausible that the discrepancy resulted from internal accounting errors. If no such offset was plausible, the company was removed from the dataset. Therefore, all negative banking stock values at the company level were removed from the dataset, which should minimize inaccurate data entries.

Number of installations

Number of installations reflects the number of installations of a company that are regulated under the EU ETS. This variable provides a proxy for the size of the company. According to Jaraitė-Kažukauskė and Kažukauskas (2015) companies with a higher *number of installations* are more likely to participate in emissions trading, possibly because they have lower search and information costs than companies with fewer regulated installations. Abrell et al. (2022) also found that companies with a larger *number* of regulated *installations* are more likely to participate in the EU ETS and to trade more frequently. Using a different proxy for company size, Baudry et al. (2021) also found that larger companies trade more intensively on the secondary market. Furthermore, Cludius and Betz (2020) found that larger companies use a larger variety of intermediaries. Therefore, we expect a positive correlation between *number of installations* and our indicators of companies' search efforts.

Carbon leakage

We follow Abrell et al. (2022) and include a dummy variable indicating whether a company mainly produces products from the carbon leakage list.[58] Because these companies face intense competition from outside the EU, they are expected to have stronger incentives to minimize costs in general, which would also translate into stronger incentives to look for favourable EUA prices and to increase their search efforts.

Periods, regions and EU ETS activities

Akin to the studies in related contexts (e.g. Jaraitė-Kažukauskė and Kažukauskas 2015), we include dummies to control for effects which are specific to *trading periods* (i.e. 2005-2007, 2008-2012, and 2013-2020), such as changes in the regulatory framework, differences across *regions* such as economic, social and cultural factors, and EU ETS *activities* (see Table 23).

As base categories, we use trading *Period 1*, the German speaking region (*Region 1*), and the activity *Combustion* of fuels. The latter primarily refers to installations in the energy sector (e.g. electricity generation).

Literature in related contexts have found that period, regional, and sector aspects matter for companies' emission trading strategies. E.g. Abrell et al. (2022) found that participation and trading intensity of companies in the second and third period were higher than in the first period. Furthermore, network analyses of installation and company locations by Borghesi and Flori (2018) and Karpf et al. (2018) found that the location of an installation or a company is correlated with its trading behaviour. Hintermann and Ludwig (2023) also found a "home bias" meaning that companies trade more intensive with trading partners from the home region.

[58] The carbon-leakage list comprises of many products from various energy-intensive industry sectors such as iron and steel, metals, aluminum, refineries, cement and lime, glass and ceramics, and pulp and paper (European Commission 2014/746/EU).

Jaraitė-Kažukauskė and Kažukauskas (2015) and Abrell et al. (2022) found sector effects, indicating that companies from the energy sector are more likely to participate in the secondary market.

Table 23: Description of variables.

Variable	Description	Data source
Dependent variables		
Trading partners	Number of different trading partners in trading year.	EUTL
Transaction frequency	Number of transactions in trading year.	EUTL
Covariates		
Net position value	Absolute value of free allocation minus verified emissions in year t (in metric tons of CO_2eq) multiplied by the average EUA price in t.	EUTL
Banking stock value$_{t-1}$	*Banking stock* in t-2 plus *net position* in t-1 plus acquisitions minus transfers in t-1 (in metric tons of CO_2eq) multiplied by the average EUA price in t.	EUTL
Installations	Number of installations of a company in year t.	EUTL
Carbon leakage	Dummy =1, if company affiliated with carbon leakage sector.	EU ETS regulations
Trading periods	Dummy for each trading period (base period is the first trading period).	EUTL
Region 1	Austria (AT), Germany (DE), Liechtenstein (LI) (*base region*)	EUTL
Region 2	Belgium (BE), France (FR), Netherlands (NL)	EUTL
Region 3	Greece (GR), Cyprus (CY), Spain (ES), Italy (IT), Malta (MT), Portugal (PT)	EUTL
Region 4	Estonia (EE), Lithuania (LT), Latvia (LV), Poland (PL)	EUTL
Region 5	Czech Republic (CZ), Hungary (HU), Slovenia (SI), Slovakia (SK)	EUTL
Region 6	Denmark (DK), Finland (FI), Iceland (IS), Norway (NO), Sweden (SE)	EUTL
Region 7	United Kingdom (UK), Ireland (IE)	EUTL
Region 8	Bulgaria (BG), Croatia (HR), Romania (RO)	EUTL
Combustion	EUTL activities 1, 20	EUTL

Variable	Description	Data source
Refining	EUTL activities 2, 21	EUTL
Steel	EUTL activities 3, 4, 5, 22, 23, 24, 25	EUTL
Non-ferrous metals	EUTL activities 26, 27, 28	EUTL
Lime and cement	EUTL activities 6, 29, 30	EUTL
Glass	EUTL activities 7, 31	EUTL
Ceramics	EUTL activities 8, 32	EUTL
Mineral wool	EUTL activity 33	EUTL
Gypsum and plasterboard	EUTL activity 34	EUTL
Pulp and paper	EUTL activities 9, 35, 36	EUTL
Chemicals	EUTL activities 37, 38, 39, 40, 41, 42, 43, 44	EUTL
Other	EUTL activities 45, 46, 47, 99	EUTL

8.3.3 Econometric Model

We employed panel econometric methods to exploit the (unbalanced) panel structure of our data. To account for the count nature of the dependent variables (*trading partners, transaction frequency*), we estimated panel Poisson models. As a robustness check, we also estimated negative binomial models which do not presume equidispersion.[59]

Formally, the Poisson model assumes that the dependent variable (y_{it}), e.g. the number of trading partners *j* by company *i* during time *t*, follows a Poisson distribution. We specified the conditional probability of observing *j* as

$$\Pr(y_{it} = j | x_{it}, z_i\,, \alpha_i; \boldsymbol{\zeta}, \boldsymbol{\pi}) = \frac{[\exp(-\lambda_{it})](\lambda_{it})^{y_{it}}}{y_{it}!} \qquad \text{for } j=0,1,2,... \tag{4}$$

[59] Results of robustness checks are briefly discussed in section 8.4.2.

where x_{it} is a vector of time-varying explanatory variables such as free allocation or verified emissions, z_i is a vector of time-invariant explanatory variables such as carbon leakage or sector affiliation, α_i captures time-invariant company-specific unobservable factors such as company culture, and $\boldsymbol{\zeta}$ and $\boldsymbol{\pi}$ are vectors of parameters. Finally, λ_{it} denotes the conditional mean and the conditional variance of y_{it} and is modelled as

$$\lambda_{it} = \exp\left(x_{it}\boldsymbol{\zeta} + z_i\boldsymbol{\pi} + \alpha_i\right) \tag{5}$$

Because Poisson models are nonlinear models, employing fixed-effects estimators do not account for unobserved time-constant heterogeneity, unlike with linear models. We therefore employed the correlated random-effects estimator (CRE) established by Mundlak (1978). To account for time-invariant unobserved heterogeneity, the CRE incorporates the company-specific means of the time-varying variables (*Mean net position value* and *Mean banking stock value*) in the regression equation.[60] Thus,

$$\alpha_i = \bar{x}_i\boldsymbol{\varphi} + \mu_i \tag{6}$$

where $\bar{x}_i$ is the mean of the x_{it} over time for company i, $\boldsymbol{\varphi}$ is a vector of parameters, and $\mu_i \sim N(0, \sigma_\mu^2)$. We used the Stata procedure *xtpoisson* to estimate the Poisson models via maximum likelihood methods, with standard errors clustered at the company level.

60 In related contexts and using panel estimators, Jaraitė-Kažukauskė and Kažukauskas (2015) and Abrell et al. (2022) also use the CRE specification. The Mundlak terms, which capture the "between variation," can be viewed as long-run effects, whereas the time-varying variables, which capture the "within variation," can be viewed as short-run effects. Due to our concerns that the effects of unobserved heterogeneity may be correlated with the covariates, our interpretation and presentation of the findings will focus on the time-varying effects, similar to Jaraitė-Kažukauskė and Kažukauskas (2015) and Abrell et al. (2022).

8.4 Results and Discussion

In this section, we present and discuss the findings obtained from our preferred model followed by the findings obtained from a set of robustness checks. Our analysis is based on a final sample of 9.318 companies. Table 24 and Figure 11 show the outcomes for both indicators of companies' search efforts, i.e. *trading partners* and *transaction frequency*. We report the robust standard errors in parentheses below the parameter estimates. The results for the Mundlak terms indicate that using a random-effects estimator would result in biased and inconsistent parameter estimates for both models. Because the findings are quite similar for *trading partners* and *transaction frequency*, we combine the discussion for the covariates for both indicators of companies' search efforts to save space.

To facilitate the interpretation, Table 24 and Figure 11 show the results in terms of incidence rates. The incidence rate represents the factor by which the outcome variable changes in response to a one unit change in the covariate. Hence, a coefficient smaller than one indicates a negative relation, and a coefficient greater than one means a positive relation, ceteris paribus.

Table 24: Estimation results for preferred model.[61]

	Trading partners	Transaction frequency
Net position value	1.054***	1.194***
	(0.006)	(0.023)
Banking stock value$_{t-1}$	1.002***	1.001
	(0.001)	(0.004)
Number of installations	1.062***	1.114***
	(0.003)	(0.008)
Carbon leakage	1.011	1.026
	(0.009)	(0.045)

[61] Results for *net position value* and *banking stock value* in million euros.

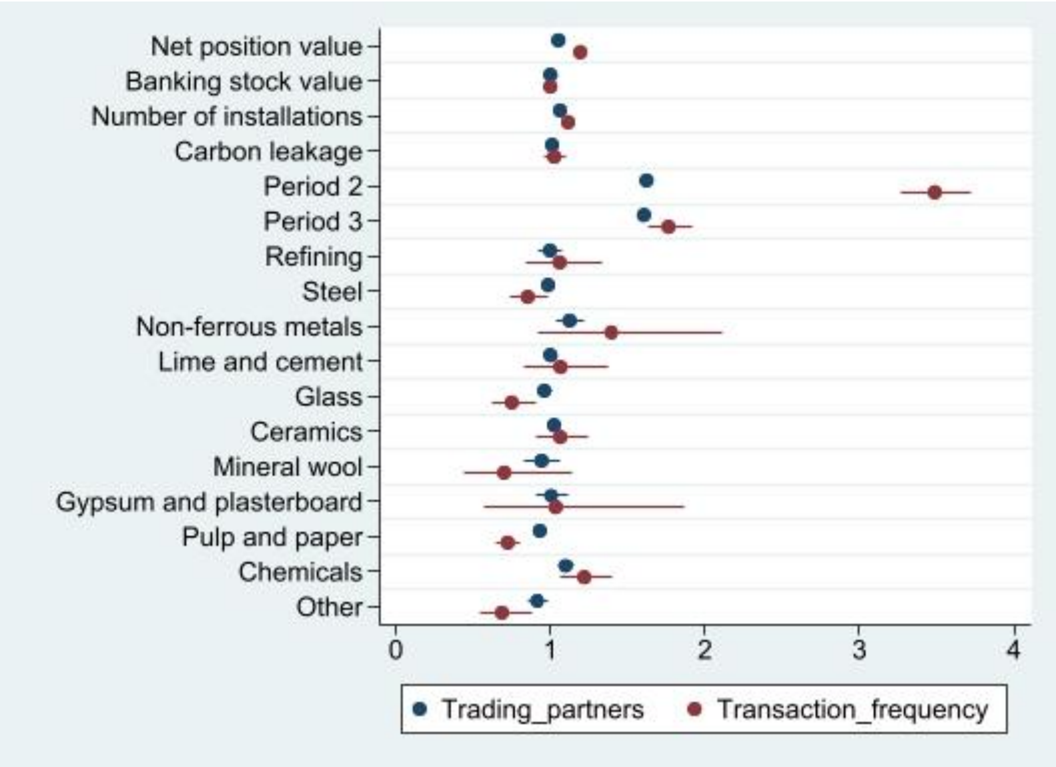
Period 2	1.624***	3.487***
	(0.014)	(0.138)
Period 3	1.603***	1.766***
	(0.019)	(0.085)
Region 2 (BE, FR, NL)	0.901***	1.037
	(0.025)	(0.224)
Region 3 (GR, IT, PT, ES, CY, MT)	0.828***	0.775***
	(0.018)	(0.072)
Region 4 (EE, LT, LV, PL)	1.029	0.839*
	(0.018)	(0.078)
Region 5 (CZ, HU, SI, SK)	0.997	0.994
	(0.022)	(0.143)
Region 6 (DK, FI, IS, NO, SE)	1.085***	0.869
	(0.017)	(0.075)
Region 7 (UK, IE)	1.132***	1.130
	(0.034)	(0.172)
Region 8 (BG, HR, RO)	0.949**	0.891
	(0.02)	(0.095)
Refining	0.997	1.056
	(0.048)	(0.151)
Steel	0.984	0.851*
	(0.024)	(0.072)
Non-ferrous metals	1.121**	1.393
	(0.053)	(0.352)
Lime and cement	1.003	1.067
	(0.020)	(0.164)
Glass	0.961	0.748**
	(0.027)	(0.088)
Ceramics	1.024*	1.065
	(0.014)	(0.100)

Mineral wool	0.940	0.703
	(0.073)	(0.207)
Gypsum and plasterboard	1.004	1.032
	(0.062)	(0.371)
Pulp and paper	0.930***	0.722***
	(0.017)	(0.045)
Chemicals	1.097***	1.220**
	(0.033)	(0.104)
Other	0.914**	0.685**
	(0.038)	(0.101)
Mean net position value	1.103***	1.585***
	(0.013)	(0.064)
Mean banking stock value	0.999	1.045***
	(0.001)	(0.017)
Constant	1.496***	1.234**
	(0.028)	(0.103)
Number of observations	68,606	68,606
Number of companies	9,318	9,318[62]

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[62] We removed 43 companies because they reported implausible figures on the number of trading partners and on transaction frequency.

Figure 11: Estimation results for preferred model (90% confidence intervals).[63]



Source: Stata illustration based on data described in Section 8.3.1.

8.4.1 Preferred Model

8.4.1.1 Net position value

Our analysis suggests a positive relation between search efforts, proxied by *trading partners* and *transaction frequency,* and auctioning, proxied by *net position value*. The results for the point estimate indicate that a company with a 1 million euros higher *net position value* in absolute terms (e.g. due to a change in free allocation, ceteris paribus) has on average 5.4 percent (1.054 - 1 = 0.054) more *trading partners* per year and on average a 19.4 percent (1.194 - 1 = 0.194) higher *transaction frequency*, ceteris paribus. That is, companies with a higher *net position value* (in absolute terms) engage in more search efforts in the secondary market, ceteris paribus. Considering the average number of 2.86 trading partners and the average number of 4.96 trades per company and year (Table 25), these figures translate into an increase in the mean

[63] For presentation purposes, region dummies, Mundlak terms, and the constant have been omitted from the figure.

number of trading partners by 0.15 and in the mean number of trades by 0.96. Thus, the findings for *net position value* are in line with the predictions derived from our analytical model, the effect sizes, however, appear to be rather small. Qualitatively, our results for *net position value* are also consistent with the findings by Zaklan (2013), Jaraitė-Kažukauskė and Kažukauskas (2015), Cludius (2018), Abrell et al. (2022), and Lehmann et al. (2024) in related contexts, albeit these studies used net position, i.e. physical values in tons of greenhouse gas emissions, rather than the *net position value*, i.e. monetary values.

8.4.1.2 Banking stock value

In contrast to our expectation, we found a positive correlation between *banking stock value*$_{t-1}$ and both indicators of companies' search efforts. However, the coefficients are small and close to 1 (implying small effect sizes) and only statistically significant at $p<0.1$ in the *trading partners* model.

8.4.1.3 Number of installations

Table 24 suggests that the *number of installations* is positively and statistically significantly related with *trading partners* and *transaction frequency*, ceteris paribus. These results are in line with the existing literature who found that larger companies trade more intensively (e.g. Jaraitė-Kažukauskė and Kažukauskas, 2015; Baudry et al., 2021; Abrell et al., 2022) or are more financially successful (Lehmann et al., 2024) on the secondary market than smaller companies. As argued by Jaraitė-Kažukauskė and Kažukauskas (2015) and Abrell et al. (2022), these results suggest that search costs may be lower for larger companies or that companies with more regulated installations have a larger network of potential trading partners due to their different sites, which could lead to lower search costs.

8.4.1.4 Carbon leakage

The results for companies at risk of *carbon leakage* suggest a positive relation with *trading partners* and *transaction frequency*, but the associated coefficients are not statistically significant at conventional levels.

8.4.1.5 Periods, regions, and EU ETS activities

The coefficients of the *period* dummies are positive and significant for both models, with the factor for the second trading *period* being higher than the factor for the third trading *period*[64]. These results are in line with the findings of Abrell et al. (2022), who also find stronger engagement of companies in emissions trading for the second and third trading *period* than for the first *period*.

Our results for the *region* dummies indicate that search efforts differ at least to some extent between *regions*. However, similar to Abrell et al. (2022), for example, our results do not indicate any clear patterns. Exceptions are companies from the regions Southern Europe (*Region 3*) and New Member States (*Region 8*). For these regions, the results suggest lower company activity on the secondary market than for the German-speaking base region. Finally, for the *activity*-related dummies, we found mixed results, with a trend towards negative relations with our indicators of companies' search efforts (except for the coefficients associated with chemicals activities, which are statistically significant and positive in both models). This indicates that companies from most industrial activities tend to use the secondary market less intensively than companies from the base activity, i.e. the combustion activity. These results thus support the findings by Jaraitė-Kažukauskė and Kažukauskas (2015) and Abrell et al. (2022), who conclude that the energy sector is more likely to participate in the EU ETS, ceteris paribus.

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[64] Supported by Wald tests.

8.4.2 Robustness Checks

To examine the robustness of our results shown in Table 24, we estimated several additional models.

First, we estimated a negative binomial model instead of a Poisson model. In contrast to the Poisson model, the negative binomial model does not rely on the assumption that the conditional mean is equal to the conditional variance. The results of this model appear in Section 0, Table 26. For most covariates the results are very similar in terms of size effects and significant levels as those shown for the Poisson model in Table 24. We further note that the p-values associated with the parameter estimates are typically lower for the negative binomial models than for the Poisson models.

Second, instead of using the stock of banked allowances to capture the effects of banking on companies' search efforts, we followed the approach of Lehmann et al. (2024) and considered the flow of banked allowances which we calculated as the net position plus acquisitions minus sales in a specific year. To get a monetary value, *banking position value*, we multiplied the flow of banked allowances by the average EUA price of that year[65]. Using the *banking position value* rather than the *banking stock value* may be preferable because the effects of potential data errors in the EUTL would affect all subsequent years when using the *banking stock value.* Such errors in the EUTL may occur in cases of account changes and changes in installation ownership if the transfer of banked allowances to new accounts has not been correctly recorded. When using instead the *banking position value* data errors pertaining to one year should not spill-over into subsequent years. We present the results for this robustness check in Table 27. The results of

[65] We note that unlike the *banking stock value*, *banking position value* may be negative if a company surrenders banked allowances.

this models in terms of magnitudes and significance levels of the estimated coefficients are very similar to those presented for our preferred model in Table 24.

To control for a possible omitted variable bias, we also estimated our models with additional company-specific information available from the ORBIS company database. To this end, we included a dummy for companies belonging to the energy sector based on NACE codes, similar to Abrell et al. (2022) and Lehmann et al. (2024), for example. In turn, the activity dummies no longer appear in this specification. In addition, we included the *number of employees* from the ORBIS data base as a proxy for company size. Because NACE codes and *number of employees* is only available for a subset of the original data base, the number of observations dropped from 68,606 to 40,746. We document the results for this specification in Table 28. They are generally very similar to those reported in Table 24 for our preferred models. In contrast to our preferred model though, the coefficient associated with *banking stock value* in the model for *trading partners* is no longer statistically significant at conventional levels of significance. The new variables *energy* and *number of employees* show a small positive relation with *trading partners* and *trading frequency*, but only the relation between *number of employees* and *trading partners* is statistically significant at conventional levels.

We further examined whether the effects of auction mechanisms differ by company characteristics such as sector affiliation, size, and productivity. To this end, we included interaction terms between *net position value* and dummy variables indicating whether a company (i) operates combustion or industrial installations based on EUTL activity codes, (ii) has more employees than the median company in the sample, (iii) operates more installations than the median company, and (iv) is more productive than the median company[66]. Hence, we estimated eight additional models. Only the interaction between *net position value* and

[66] We calculate productivity as the ratio between total revenues and the number of employees.

combustion in the transaction frequency model is positive and statistically significant. The interaction between *net position value* and the dummy representing companies in the upper half of the median split based on the number of installations is negative and statistically significant in both the trading partner and transaction frequency models. These findings suggest that companies in the combustion sector and companies operating fewer installations respond slightly more strongly to changes in their *net position value*. However, the associated effect sizes are rather small. The findings for the remaining covariates are consistent with those shown in Table 24.[67]

In sum, the findings of these robustness checks suggest that the results of our preferred model are robust to the alternative specifications considered.

8.5 Conclusions

In this paper we analyse if a change in the allocation rules in the EU ETS towards a higher share of auctioning affected regulated companies' search efforts on the secondary market for more favourable trading options. Based on an analytical model which is inspired by Stigler (1961), we expected companies to increase search efforts if the change in allocation rules leads to a greater shortage of EUAs (for net buyers) or to a greater surplus of EUAs (for net sellers). Our results from estimating panel econometric models on a comprehensive data set generally support these predictions for two indicators of search efforts on the secondary market, i.e. the number of *trading partners*, and *transaction frequency*. Thus, our results suggest that increasing auctioning in the EU ETS increases companies' search efforts for favourable trading options. While this may result in EUA prices more adequately signalling scarcity in the market, additional search efforts will also increase transaction costs for companies. Whereas a higher

[67] To save space, we did not include the results of these additional models in the paper. They are available from the corresponding author upon request.

share of auctioning essentially reflects a transfer of funds from companies to public treasuries, search costs directly affect economic efficiency. An increase in the auction share is economically efficient if the associated benefits exceed costs. The benefits include smaller market distortions, lower lobbying efforts (e.g. Hepburn et al. 2006), and transaction costs saved because there are fewer secondary market transactions required to achieve an efficient outcome. The costs include additional search costs. Whereas a cost-benefit analysis is beyond the scope of this study, our results provide some evidence that the effect of an increase in auctioning on search costs are likely to be small. For example, an increase in EUA acquisition costs by one million euros is estimated to result, on average, in 0.15 additional trading partners and 0.96 additional trades per company per year.

These insights are especially relevant for the design of emerging emissions trading systems, such as those being developed in China, Türkiye, Vietnam, and Colombia. They suggest that transaction costs related to finding advantageous trading opportunities are likely to remain low in a system with a high share of auctioning. Therefore, implementing a significant level of auctioning from the outset may contribute to more efficient outcomes. These findings are also relevant for EU policy making, notably in the context of phasing out free allocation in the context of recent regulation on the CBAM.

Policy makers should also consider that auctions must be carefully designed to achieve the intended positive effects, as highlighted by recent studies on China’s ETS (e.g., Tang et al., 2017; Wang et al., 2022; Yu et al., 2024). Additionally, research on China’s ETS has found that auctioning can hinder investments in green technologies (e.g., Yang et al., 2023), lead to less cost-efficient market outcomes compared to other allocation methods (e.g., Peng et al., 2022), and distort allowance prices (e.g., Ji et al., 2021).

The impact of increased auctioning on companies' efforts to seek advantageous trading opportunities, as examined in this study, is just one of many factors that should be considered when determining the appropriate share of auctioning in emissions trading systems.

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CRediT authorship contribution statement

- **Sascha Lehmann**: Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.
- **Joachim Schleich**: Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the language quality. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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8.7 Annex A.1: Policy Background: The EU Emissions Trading System and the Role of Auctions

The EU ETS is the EU's primary instrument for achieving cost-effective reductions in greenhouse gas emissions and a central pillar of the European Green Deal (European Commission, 2019), covering about 40% of total EU emissions. Since its launch in 2005, the ETS has evolved through successive trading phases to become a more robust, market-driven mechanism. The EU ETS applies to major emitting sectors such as power and heat generation, energy-intensive industries, and aviation within the European Economic Area (EEA).

The EU ETS is based on a "cap-and-trade" principle: a declining annual cap sets the maximum volume of emissions allowed, and regulated entities must surrender one allowance per tonne of CO_2-equivalent emitted. These allowances can be traded between regulated entities and other market participants like financial intermediaries, providing flexibility that leads to cost efficiency, as emissions are reduced where it is most cost-effective.

Starting with Period 3 (2013–2020), auctions have become economically relevant. More than half of all allowances are auctioned since then. By default, electricity generators no longer receive allowances for free, while companies in energy-intensive industries receive a diminishing share of allowances for free, based on performance benchmarks and exposure to carbon leakage.

Auctions are held on common EU platforms (e.g., EEX) and generate significant revenue, a portion of which is mandated for climate-related investments. Auctions allocate allowances transparently and efficiently, and provide a clear price signal to guide low-carbon investment decisions.

To address past issues of surplus allowances and ensure price stability within the EU ETS, the Market Stability Reserve (MSR) was introduced in 2019. The MSR adjusts the supply of allowances auctioned based on the total number of allowances in the market. When this number exceeds a certain threshold, a portion of allowances is withheld from auctions and placed into the MSR. If the market becomes too tight, allowances can be released. The MSR has proven effective in strengthening the carbon price signal and enhancing the resilience of the ETS.

As part of the European Green Deal, the Fit-for-55 package (European Commission, 2021) introduced far-reaching reforms to align the ETS with the EU's 2030 climate target of reducing GHG emissions by at least 55% compared to 1990 levels. These reforms include a significant tightening of the cap, a strengthening of the MSR, and an extension of the scope of the ETS. Notably, maritime transport has been included in the ETS from 2024 onwards, covering emissions from large vessels on intra-EU voyages and a share of extra-EU routes.

In parallel, the Carbon Border Adjustment Mechanism (CBAM) will gradually replace free allocation in specific sectors. The CBAM involves a carbon price on imports, mirroring the EU ETS carbon cost. This underscores the importance of auctioning as the primary allocation mechanism moving forward.

8.8 Annex A.2: Step-by-Step Derivation of the First-Order Condition (FOC) and Comparative Statics for the Conceptual Model developed in Section 8.2

This annex explains the steps involved in deriving the FOC for the company's optimization problem (equation 1) and the comparative static result that links search effort x_s to the allocation of free allowances $\bar{E}$.

A.2.1 Objective Function

A company chooses search effort x_s (and implicitly the abatement effort $x_a = \bar{x} - x_s$) to minimize total compliance costs:

$$\min \quad \overline{p} \cdot \gamma(x_s) \cdot [e(x_a) - \bar{E}] + TC(x_s) + C(e(x_a))$$

A2.2 Substitution of variables

Because total effort is fixed: $\bar{x} = x_s + x_a \Rightarrow x_a = \bar{x} - x_s$.

Hence, x_a can be expressed in terms of x_s.

A2.3 FOC

Differentiate the objective function with respect to x_s using the product and the chain rule:

Term 1: $\overline{p} \cdot \gamma(x_s) \cdot [e(\bar{x} - x_s) - \bar{E}]$

Applying the product and the chain rule, yields:

$\overline{p} \cdot \gamma'(x_s) \cdot [e(x_a) - \bar{E}] - \overline{p} \cdot \gamma(x_s) \cdot e'(x_a)$, with $x_a = \bar{x} - x_s$.

Term 2: Differentiating the second term with respect to x_s yields: $TC'(x_s)$

Term 3 Differentiating the second term with respect to x_s, applying the chain rule, yields: $C'(e(x_a)) \cdot e'(x_a)$.

Summing all terms yields the FOC, i.e. equation (2):

$$\overline{p} \cdot \gamma'(x_s) \cdot [e(x_a) - \bar{E}] - \overline{p} \cdot \gamma(x_s) \cdot e'(x_a) + TC'(x_s) - C'(e(x_a)) \cdot e'(x_a) = 0$$

A2.4 Extended interpretation of FOC

The FOC sets marginal benefit of search effort equal to the marginal costs. Suppose a company is a net buyer of EUAs, i.e., $e(x_a) - \bar{E} > 0$. The net benefits (first term) then reflect the decrease in costs of purchasing EUAs in response to an additional unit of search effort leading to a decrease in the purchase price of EUA. The three remaining terms reflect the marginal costs associated with a one unit increase in search effort. The second term reflects the additional costs of acquiring EUA because the increase in search effort implies a decrease in abatement effort and hence an increase in emissions. The third term reflects the increase in transaction costs resulting from an increase in search effort, and the third term to the change in abatement costs due to a decrease in abatement effort.

A.2.5 Comparative Statics: How does x_s change when $\bar{E}$ changes?

To assess this, totally differentiate the FOC with respect to $\bar{E}$ and x_s. Collecting terms, this yields

$$\{\overline{p} \cdot \gamma''(x_s) \cdot [e(x_a) - \bar{E}] - \overline{p} \cdot \gamma'(x_s) \cdot e'(x_a) \ + TC''(x_s) + C''(e(x_a)) \cdot [e'(x_a)]^2 \\ + C'(e(x_a)) \cdot e''(x_a)\} dx_s = \overline{p} \cdot \gamma'(x_s) d\bar{E}$$

The expression in {} corresponds to the second order condition and must be positive for a minimization problem. Denoting this expression as D, yields equation (3)

$$\frac{dx_s}{d\bar{E}} = \frac{\overline{p} \cdot \gamma'(x_s)}{D}.$$

8.9 Annex A.3: Compilation of the Data[68]

A.3.1 Data Sources and Preparation

The European Commission operates the electronic Database Union Registry. The database contains all transactions within the EU ETS, including free allocation, surrendered allowances and all transactions between market participants. The European Union Transaction Log (EUTL) records, checks and authorises these transactions. The Commission publishes all transactions and other details from the Union Registry under the EUTL. Data can be downloaded free of charge, but with a three-year delay in the case of transaction data.

[68] Section 8.9 partially relies on Lehman et al. (2024), with some sections quoted verbatim.

The EUTL records all transactions made between registered accounts, although it is important to note that only registered accounts can trade allowances. Each regulated stationary installation must open at least one Operator Holding Account (OHA) and each airline must open at least one Aircraft Operator Account (AOA), through which the free allocation and surrender of allowances is transacted. In addition, companies, but also private individuals, can open Person Holding Accounts (PHA) and Trading Accounts (TA) in order to use them for trading. In addition, there are administrative accounts that are operated by the EU or the Member States and used, among other things, for free allocation, auctioning or the cancellation of allowances.

EUTL contains information about the account name, the registration (Member State), the company registration number as well as the assigned account holder and the assigned installation. The name and address of account holders are available. With regard to installations, the activity type, address, allocation, emissions, and the number of surrendered allowances are available.

The EUTL transaction information includes the accounts involved, the transaction type, the date and the quantity of allowances. Futures and forwards are recorded but not clearly identifiable and only on the actual delivery date and not when the contract was concluded. Prices are not shown by the EUTL.

With the 2012 reform, the Community Independent Transaction Log (CITL), which was a decentralised system until then, was migrated to the central EUTL operated by the Commission. During this process, all installations were given new OHAs (see A.3.2).

In addition to the EU ETS related EUTL data, we used company data from the ORBIS database of Bureau Van Dijk in one of our robustness checks. These include financial data on the number of employees, revenues, industry classification (NACE), the company registration number and the home country of a company. For information on matching the two data sets, see A.3.3.

As prices, we use the unweighted average spot price from the EEX and match this to the EUTL data for the respective year.

After we had matched all the databases, we set up a panel data set which is based on transactions. We aggregated this data such that the final data set included annual transactions per company. We removed all non-regulated companies (allocation and emissions is zero), because they are irrelevant to our research question.

In our underlying dataset, we have 42007 accounts, of which we could not match 8142 to any company. The matched accounts are across 12319 companies. However, the number of companies included in the multivariate analyses is lower because we eliminated all aircraft operators and all companies that have neither free allocation nor verified emissions, reducing the number of companies to about 9352.

We tried to include the stock of banked allowances per company, but found inconsistencies when adding them up. For example, during the restructuring in 2012, allowances were not always transferred in an appropriate and comprehensible way.

A.3.2 Matching of the new and former OHAs

With the redesign of the European Union Transaction Log (EUTL) in 2012, new account types such as aircraft operating accounts were introduced. This also meant that all installations had to be linked to a new Operator Holding Account (OHA). However, the current data records of the EUTL only feature the current OHA and not the OHA from before the restructuring. We therefore had to match the previous OHAs with the respective installations. We handled this as follows:

(1) Compare account name and installation name and match if unambiguous.

(2) Compare account address and installation address and match if unambiguous.

(3) If 1 and 2 did not work, we used installation-level information on allocation and surrendered number of allowances and searched for the transaction and account behind it and the administrative account of the respective registration. Again, we only accepted unique matches. We first used allocations followed by surrendering transfers.

Using this methodology, we were able to match about 99% of the old OHAs to the new OHAs.

A.3.3 Matching the EUTL data with companies from the ORBIS database

With the reform of accounts in 2012, all account holders were required to provide VAT registration numbers. This is either a national or a European number. The ORBIS database also contains the VAT number. Therefore, in theory, matching the two databases is possible without any major problems. However, data errors and format errors make matching difficult in practice. We therefore employed fuzzy matching based on VAT registration number, the name of the account linked to this number and the address of the account contact. The automatic ORBIS batch search uses these variables. Here, the account data served as criteria for the ORBIS data search. The batch search performed then provides several possible matches and a matching score for each option. The ultimate match was then done by checking the quality of the match in the individual fields.

8.10 Annex A.4: Descriptive Statistics

Table 25: Descriptive statistics of final sample.

Variable	Obs.	Mean	Std. dev.	Min	Max
Dependent variables					
Trading partners	68,606	2.861	2.342	0	31
Transaction frequency	68,606	4.960	24.661	0	1832
Covariates					
Net position value	68,606	0.290	0.691	0	10.350
Banking stock value$_{t-1}$	68,606	0.561	4.953	0	369.471
Number of installations	68,606	2.805	3.224	1	74
Carbon leakage	68,606	0.345	0.475	0	1
Period 1	68,606	0.217	0.412	0	1
Period 2	68,606	0.388	0.487	0	1
Period 3	68,606	0.395	0.489	0	1
Region 1	68,606	0.070	0.255	0	1
Region 2	68,606	0.047	0.212	0	1
Region 3	68,606	0.131	0.337	0	1
Region 4	68,606	0.123	0.329	0	1
Region 5	68,606	0.050	0.218	0	1
Region 6	68,606	0.386	0.487	0	1
Region 7	68,606	0.035	0.185	0	1
Region 8	68,606	0.105	0.306	0	1
Combustion	68,606	0.637	0.481	0	1
Refining	68,606	0.012	0.109	0	1
Steel	68,606	0.033	0.179	0	1
Non-ferrous metals	68,606	0.007	0.081	0	1

Variable	Obs.	Mean	Std. dev.	Min	Max
Lime and cement	68,606	0.042	0.201	0	1
Glass	68,606	0.031	0.174	0	1
Ceramics	68,606	0.106	0.307	0	1
Mineral wool	68,606	0.002	0.047	0	1
Gypsum and plasterboard	68,606	0.001	0.036	0	1
Pulp and paper	68,606	0.061	0.239	0	1
Chemicals	68,606	0.018	0.133	0	1
Other	68,606	0.017	0.129	0	1

8.11 Annex A.5: Robustness Checks

Table 26: Estimation results for negative binomial model.

	Trading partners	Transaction frequency
Net position value	1.054***	1.210***
	(0.004)	(0.007)
Banking stock value$_{t-1}$	1.002***	1.000
	(0,000)	(0.001)
Number of installations	1.059***	1.050***
	(0.001)	(0.002)
Carbon leakage	1.011	1.055***
	(0.009)	(0.014)
Period 2	1.614***	1.827***
	(0.012)	(0.025)
Period 3	1.618***	1.777***
	(0.013)	(0.025)
Region 2 (BE, FR, NL)	0.902***	0.810***
	(0.021)	(0.029)
Region 3 (GR, IT, PT, ES, CY, MT)	0.824***	0.955*
	(0.014)	(0.025)
Region 4 (EE, LT, LV, PL)	1.041**	1.044*
	(0.018)	(0.027)
Region 5 (CZ, HU, SI, SK)	1.007	1.019
	(0.022)	(0.034)
Region 6 (DK, FI, IS, NO, SE)	1.096***	0.971
	(0.016)	(0.021)
Region 7 (UK, IE)	1.138***	1.171***
	(0.033)	(0.05)
Region 8 (BG, HR, RO)	0.944***	0.888***
	(0.017)	(0.024)

Refining	0.998	0.823***
	(0.040)	(0.046)
Steel	0.986	0.964
	(0.023)	(0.036)
Non-ferrous metals	1.117**	1.231***
	(0.054)	(0.096)
Lime and cement	1.005	0.966
	(0.022)	(0.031)
Glass	0.959	0.879***
	(0.025)	(0.034)
Ceramics	1.023	0.995
	(0.015)	(0.022)
Mineral wool	0.947	0.791
	(0.086)	(0.117)
Gypsum and plasterboard	1.015	0.801
	(0.106)	(0.148)
Pulp and paper	0.934***	1.020
	(0.017)	(0.029)
Chemicals	1.098***	1.249***
	(0.033)	(0.058)
Other	0.913**	0.980
	(0.035)	(0.055)
Mean net position value	1.101***	1.089***
	(0.010)	(0.015)
Mean banking stock value	0.999	0.998*
	(0.001)	(0.001)
Constant	27.424***	0.309***
	(2.532)	(0.007)
Number of observations	68,606	68,606
Number of companies	9,318	9,318

Table 27: Estimation results for alternative banking specification.

	Trading partners	Transaction frequency
Net position value	1.054***	1.197***
	(0.006)	(0.021)
Banking position value$_{t-1}$	1.002*	1.005*
	(0.001)	(0.003)
Number of installations	1.061***	1.108***
	(0.003)	(0.007)
Carbon leakage	1.011	1.019
	(0.009)	(0.042)
Period 2	1.624***	3.459***
	(0.014)	(0.135)
Period 3	1.605***	1.766***
	(0.020)	(0.082)
Region 2 (BE, FR, NL)	0.897***	0.847
	(0.025)	(0.152)
Region 3 (GR, IT, PT, ES, CY, MT)	0.826***	0.748***
	(0.018)	(0.067)
Region 4 (EE, LT, LV, PL)	1.029	0.832**
	(0.018)	(0.075)
Region 5 (CZ, HU, SI, SK)	0.999	0.984
	(0.022)	(0.138)
Region 6 (DK, FI, IS, NO, SE)	1.085***	0.858*
	(0.017)	(0.073)
Region 7 (UK, IE)	1.135***	1.137
	(0.034)	(0.168)
Region 8 (BG, HR, RO)	0.944***	0.825*
	(0.020)	(0.084)
Refining	0.997	0.999
	(0.047)	(0.129)

Steel	0.983	0.841**
	(0.023)	(0.063)
Non-ferrous metals	1.121**	1.406
	(0.053)	(0.347)
Lime and cement	1.002	1.051
	(0.020)	(0.168)
Glass	0.962	0.78**
	(0.027)	(0.091)
Ceramics	1.024*	1.065
	(0.014)	(0.097)
Mineral wool	0.941	0.766
	(0.073)	(0.231)
Gypsum and plasterboard	1.005	1.078
	(0.062)	(0.385)
Pulp and paper	0.931***	0.739***
	(0.017)	(0.043)
Chemicals	1.098***	1.261***
	(0.033)	(0.105)
Other	0.910**	0.694**
	(0.038)	(0.099)
Mean net position value	1.099***	1.493***
	(0.013)	(0.063)
Mean banking position value	1.004	1.123***
	(0.004)	(0.003)
Constant	1.498***	1.227**
	(0.028)	(0.101)
Number of observations	68,606	68,606
Number of companies	9,318	9,318

Table 28: Estimation results for restricted sample leveraging data from the ORBIS database.

	Trading partners	Transaction frequency
Net position value	1.045***	1.228***
	(0.007)	(0.021)
Banking stock value$_{-1}$	1.002	1.000
	(0.002)	(0.002)
Number of installations	1.059***	1.098***
	(0.003)	(0.009)
Energy	1.003	1.120
	(0.014)	(0.097)
Employees	1.000***	1.000
	(0.000)	(0.000)
Carbon leakage	1.010	1.043
	(0.012)	(0.057)
Period 2	1.679***	3.182***
	(0.020)	(0.160)
Period 3	1.631***	1.765***
	(0.025)	(0.097)
Region 2 (BE, FR, NL)	0.847***	0.793
	(0.028)	(0.122)
Region 3 (GR, IT, PT, ES, CY, MT)	0.795***	0.799**
	(0.020)	(0.087)
Region 4 (EE, LT, LV, PL)	1.021	0.811**
	(0.020)	(0.078)
Region 5 (CZ, HU, SI, SK)	0.993	1.015
	(0.024)	(0.170)
Region 6 (DK, FI, IS, NO, SE)	1.076***	0.892
	(0.019)	(0.087)
Region 7 (UK, IE)	1.041	0.849
	(0.035)	(0.103)

Region 8 (BG, HR, RO)	0.950*	0.994
	(0.025)	(0.119)
Mean net position value	1.109***	1.512***
	(0.015)	(0.064)
Mean banking stock value	1.001	1.057***
	(0.006)	(0.015)
Constant	1.497***	1.263**
	(0.032)	(0.128)
Number of observations	40,746	40,746
Number of companies	7,295	7,295

9. Exploring internal trading in the EU emissions trading system: An empirical analysis

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Abstract:

For more than two decades, the European Emissions Trading System (EU ETS), has regulated greenhouse gas emissions across various sectors, including energy, manufacturing, aviation, and maritime industries within the European Union (EU) and beyond. The trading of EU allowances (EUAs) allows emission targets to be met in a cost-efficient manner. This study examines internal trading, i.e., trading of allowances between companies belonging to the same National Ultimate Owner (NUO). Using data from the European Union Transaction Log, the ORBIS database, and the European Energy Exchange, we analyse company-specific internal trading patterns from 2005 to 2017. Supposing that internal trading results in lower transaction costs than external trading (e.g., through intermediaries and exchanges), our findings indicate the presence of barriers to internal trading: Only a small fraction of companies with internal trading opportunities engage in such activities, leaving most of the potential for internal trading untapped. According to the findings from panel-econometric analysis, the relation between internal trading and trading potential is not statistically significant, providing no evidence that companies prefer internal to external trading. They further suggest that internal trading is positively correlated with the number of companies belonging to the same NUO, the number of regulated installations, and with trading frequency, and negatively with allowance banking, for example. These findings remain robust across diverse alternative model specifications, sample compositions, and identification strategies, including quasi-experimental methods.

Keywords: Climate policy, emissions trading, EU ETS, internal trading, transaction cost, quasi-experiment.

JEL Classification: Q58, Q54, Q48, D22, C23

Abbreviation	Explanation
AOA	Aircraft Operator Account
CITL	Community Independent Transaction Log
CL	Carbon Leakage
CO_2eq	Carbon Dioxide Equivalent
CRE	Correlated Random Effects (Mundlak approach)
DiD	Difference-in-Differences
EC	European Commission
EEA	European Economic Area
EEX	European Energy Exchange
EU	European Union
EU ETS	European Union Emissions Trading System
EUA	European Union Allowance
EUTL	European Union Transaction Log
GHG	Greenhouse Gas
GUO	Global Ultimate Owner
ITP	Internal Trading Potential
MNE	Multinational Enterprise
NACE	Statistical Classification of Economic Activities in Europe
NUO	National Ultimate Owner
OHA	Operator Holding Account
ORBIS	Global Company Database by Bureau van Dijk

PHA	Person Holding Account
RECLAIM	Regional Clean Air Incentives Market
RGGI	Regional Greenhouse Gas Initiative
TA	Trading Account
UNFCCC	United Nations Framework Convention on Climate Change
VIF	Variance Inflation Factor

9.1 Introduction

Since 2005, the European Emissions Trading System (EU ETS) has regulated direct greenhouse gas (GHG) emissions from about 9000 companies operating approximately 17,500 installations across the energy, manufacturing, aviation, and maritime sectors within the European Union (EU), as well as in Iceland, Liechtenstein, and Norway. Over time, the number of EU allowances (EUAs) issued has significantly decreased, especially since 2013, in line with the EU's increasingly stringent GHG targets. Trading EUAs enables cost-efficient compliance with emission reduction targets. In the early phases of the EU ETS, most EUAs were allocated for free. However, since 2013, the majority have been auctioned, following a major reform of the system. Similarly, since the EU ETS regulates emissions at the installation level, companies operating several installations may transfer allowances between those installations (intra-company trading).[69]

Corporations with multiple companies operating installations may exploit internal trading opportunities by reallocating allowances from companies with a surplus to those with a shortage. Additionally, centralising emissions trading activities among companies under the same National Ultimate Owner (NUO) or Global Ultimate Owner (GUO) into a single or a few accounts can reduce administrative burdens and streamline trading operations.[70,71]

From a theoretical perspective, internal trading serves as an internal market within corporate groups. Drawing on transaction cost theory (e.g. Williamson, 1985) and arguments related to information

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69 Under the EU ETS, an installation is defined as a stationary technical unit that performs one or more regulated activities, including related processes that may affect emissions (European Union, 2003; European Commission, 2021; European Commission, n.d.). As a result, an installation typically covers an entire production process.

70 NUO/GUO denote the national/global ultimate owner of a company, defined as the entity that ultimately controls the company at the national/global level (Kalemli-Ozcan et al., n.d.). In our analysis, we apply a 50% ownership threshold to identify the NUO in the ORBIS database. In ORBIS, a NUO can itself be controlled by a GUO if the latter holds more than 50% of the NUO’s shares. Since our analysis is conducted at the NUO level, we do not further consider the GUO ownership structure.

71 The EU ETS includes several account types. The Operator Holding Account (OHA), is assigned to a specific installation and belongs to the company that owns that installation. Each OHA is tied to only one installation, though an installation may hold multiple OHAs. All administrative transactions with the regulatory authority must be processed through these accounts. Additionally, there are Person Holding Accounts (PHAs) and Trading Accounts (TAs), which can be voluntarily opened by regulated companies, intermediaries, or private individuals and are not linked to any specific regulated installation. PHAs and TAs are often used by companies or NUOs as central trading accounts.

asymmetry among market participants, companies under common ownership face lower costs when reallocating allowances internally than when conducting external trades. This is mainly because internal trading is expected to involve lower search costs such as finding trading partners, bargaining costs, and costs of accessing exchanges like the European Energy Exchange (EEX).[72] Internal trading also limits exposure to external price volatility. Transaction costs can impede market efficiency and increase emission reduction costs by discouraging companies from fully participating in EUA trading. (e.g., Betz et al., 2010; Jaraītė-Kažukauskė and Kažukauskas, 2015; Naegele, 2018; Cludius and Betz, 2020; Baudry et al., 2021; Abrell et al., 2022; Hintermann and Ludwig, 2023). Similarly, only a few companies - typically 15 to 26 bidders per auction (e.g., DEHSt 2025) - participate in EUA auctions conducted by the EEX, indicating significant transaction costs associated with external trading. Therefore, companies are expected to prioritise internal trading over external trading. Failure to do so may indicate barriers to internal trading, which could undermine the efficiency of the EU ETS.

In this study, we empirically analyse trading of EUAs between companies belonging to the same NUO. We assess the extent to which companies utilise such internal trading opportunities and examine related factors. To this end, we employ data for 2005 to 2017 from the European Union Transaction Log (EUTL), the ORBIS database, and the EEX, to construct a comprehensive dataset on transactions, account holders, free allocations, verified emissions, company characteristics, and allowance prices. In particular, combining the information provided in the EU EUTL with the ORBIS database allows us to identify trading between companies belonging to the same NUO. Our descriptive analysis indicates the extent to which companies utilise their potential for internal trading. Our multivariate panel econometric analyses explore the relationship between internal trading and factors identified in the literature as associated with companies' trading activities in the EU ETS. We thereby differentiate between two types of datasets and corresponding models: one based on all installations, and the other limited to combustion

[72] In theory, the sectoral composition of the NUO to which a company belongs may also affect internal trading. In particular, if the NUO is composed of vertically connected industries along the value chain, companies belonging to the same NUO are likely to trade more frequently, thereby lowering transaction costs and encouraging internal trading of EUAs. In practice, however, both final and intermediate goods are typically produced in the same installation or in different installations owned by the same company. Therefore, vertical production relationships generally do not result in inter-company trading of EUAs within the same NUO.

installations. The latter requires less restrictive assumptions to identify causal relationships. To this end, our identification strategy exploits institutional changes introduced from the third EU ETS trading period onward, which resulted in differential treatment of combustion installations across the energy and industry sectors.

Our descriptive results suggest that only a small fraction of companies with internal trading opportunities participate in such activities, leaving most of the potential for internal trading unexploited. Companies in the energy sector engage more strongly in internal trading than companies belonging to industry sectors. For both samples and corresponding models, our multivariate results suggest that internal trading is positively related with the number of companies belonging to the same NUO, trading frequency, and the number of installations per company, and negatively with allowance banking and with companies considered to be at risk of carbon leakage. In comparison, the relation between internal trading and trading potential is not statistically significant, providing no evidence that companies prefer internal to external trading. These results are robust across various model specifications, sample compositions, and identification strategies, including quasi-experimental methods.

To the best of our knowledge, ours is the first study to empirically analyse companies' internal trading behaviour within the EU ETS. It is closest to Nardone et al. (2025) who - focusing on companies in Italy - find that the vast majority of transactions occur between companies rather than between installations operated by the same company. Hence, their definition of 'internal trades' is very different from ours and does not consider trades between companies belonging to the same NUO. Other previous research on the EU ETS has examined transaction costs associated with trading in general (Jaraitė-Kažukauskė and Kažukauskas, 2015; Naegele, 2018; Baudry et al, 2021; Hintermann and Ludwig, 2023; Flori and Spelta, 2025), trading participation (Zaklan, 2013), various trading activities (Abrell et al., 2022), trading behaviour (Borghesi and Flori, 2018; Karpf et al., 2018; Zaklan, 2023, Lehmann and Schleich, 2025), financial performance (Liu et al., 2017; Cludius, 2018; Guo et al., 2020; Flori et al., 2024; Lehmann et al., 2024), and company value (Dewaelheyns et al., 2023), yet without distinguishing between internal and external trading. While most of these studies focus on the first (2005-2007) and second (2008-2012) trading periods, our analysis additionally encompasses five years following substantial reforms to the EU ETS in 2013.

We organise the remainder of this study as follows. In section 9.2, we outline the methodology, detailing the data, variables, and econometric methods employed. In Section 9.3, we present and discuss the descriptive results and the findings from our econometric analyses. In Section 9.4 we summarise the key findings and conclude.

9.2 Empirical methods

In this section, we present the data and variables and describe our econometric approach.

9.2.1 Data

Our dataset relies on the European Union Transaction Log (EUTL) and includes information on allowance transactions, account holders, and installation data related to verified emissions and the amount of free allocation of EUAs. We gathered data on company characteristics and ownership structures, including NUOs and GUOs, from the ORBIS database provided by Bureau van Dijk, using the company registration number to match both datasets. We obtained data on daily allowance prices from the EEX. Our dataset covers the period from 2005 to April 2018. Akin to Abrell et al. (2022) and Lehmann et al. (2024), we conduct our analysis at the company level, while the volume of internally traded allowances is calculated at the level of the NUO. We define internal transactions as transactions between accounts of the same NUO. The focus on the NUO is consistent with broader findings in the literature on multinational enterprise (MNE) strategy which shows that regional and national institutional frameworks, such as local trade integration, significantly shape MNEs' internal sourcing patterns and asset allocation, even within global corporations (e.g., Huang and Li, 2021). This supports the premise that internal trading yields the greatest transaction cost savings when conducted within national structures. Similarly, spatial distances, language barriers, and differing conditions across member states may reduce or eliminate the transaction cost advantages of internal trading compared to the open market. For example, Hintermann and Ludwig (2023) and Flori and Spelta (2025) observe that companies prefer to trade within national borders, attributing this preference to information and transaction costs. We therefore focus on transactions between accounts of the same NUO rather than the GUO.

Our dataset comprises only companies regulated under the EU ETS and includes transactions either between regulated companies or between regulated and non-regulated actors. Non-regulated actors such as banks and other market intermediaries are excluded. Furthermore, we excluded internal transactions between installations, as these are mainly organisational in nature rather than strategic. We restrict our analysis to companies with the capability to trade internally, specifically to companies belonging to a NUO with at least one other company. Additionally, our analysis excludes administrative transactions, such as the allocation of free EUAs or the surrender of allowances for compliance purposes. Following Cludius and Betz (2020), for example, a trading year ranges from May of year t to April of year t+1, given that companies are permitted to surrender allowances for compliance for year t until 30 April of year t+1. In Section 9.6, we provide more detailed information on data preparation.

Our empirical analyses employ two types of datasets. The first sample comprises of all companies in the dataset described above. The second sample includes only companies operating installations classified under the EU ETS activity 'combustion'.

9.2.2 Variables

9.2.2.1 Dependent variable

Table 29 provides an overview of all variables. We calculate *internal trading* as the internal trading volume of EUAs multiplied by the average annual EUA price. Internal trading is defined as the value of EUAs exchanged between companies within the same NUO during a given year. Using a monetary measure to capture companies trading behaviour should better reflect financial incentives than using physical measures (such as trading volume in tonnes) which have typically been used in studies analysing company trading behaviour in the EU ETS (e.g., Jaraitė-Kažukauskė and Kažukauskas, 2015; Cludius, 2018).[73]

9.2.2.2 Covariates

Our choice of covariates is driven by our research question, data availability, and the existing literature.

Internal trading potential

We define *internal trading potential (ITP)* as the absolute value of the difference between a company *i's* net position in year t (free allocation minus verified emissions) and the aggregate net position of its NUO, i.e., the sum of the net positions of all other companies belonging to the same NUO *J*:

$$ITP_{it} = \mid \sum_{j \in J, j \neq i} \left(allocation_{jt} - emissions_{jt} \right) - \left(allocation_{it} - emissions_{it} \right) \mid \text{, with } i \in J \qquad (1)$$

$ITP_i > 0$ indicates whether company *i* could transfer allowances to other companies within the same NUO to reduce their external purchase requirements, or whether companies within the same NUO could transfer allowances to company *i* to reduce the external purchase requirements of company *i*. ITP_i is large if company *i*'s net position and the aggregate net position of its NUO have opposite signs and are both quantitatively large.[74] ITP_i is small if company *i*'s net position and the aggregate net position of its NUO have the same sign and are of similar magnitudes. We use the value calculated for *ITP* when the net position of a company and its NUO have opposite signs. Otherwise, company *i* and the other companies of the same NUO (in aggregate) are either both long or both short in EUAs. In this case, there is no potential for internal trading and we set *ITP* to zero. Assuming companies prefer internal over external trading to save transaction costs, we expect a positive correlation between *ITP* and *internal trading*.

73 We exclude the top 2% of observations, as we assume that exceptionally high internal trading volumes are motivated by restructuring processes (e.g., transferring allowances to a new trading account) rather than strategic trading behaviour.

74 In the dataset underlying our analysis, during the first two trading periods, approximately 70% of all installations received more free allocations than needed to cover their verified emissions. For the third trading period, this share decreased to approximately 34%.

Banking

In the EU ETS, surplus allowances can be transferred into future years (banking). Only few studies on the EU ETS have considered banking. For example, Lehmann et al. (2024) find a negative correlation between banking and profits from allowance trading. Since allowances transferred into future years cannot be traded internally, we expect a negative relation between the amounts of allowances banked and *internal trading*.

Number of NUO companies

The variable *number of NUO companies* refers to the number of companies linked to the NUO of a company that operate regulated installations under the EU ETS, thus reflecting the number of potential internal trading partners within the same NUO. We assume that the incentives to strategically utilise internal trading increase with the number of regulated companies within a NUO, as we posit that a higher number of regulated companies also raises the likelihood of having entities within the NUO with different net positions. We therefore expect a positive correlation between the *number of NUO companies* and *internal trading*.

Transaction frequency

We define *transaction frequency* as the number of trades (both internal and external) conducted by a company. According to Lehmann et al. (2024) in a related context, *transaction frequency* reflects companies' skills such as learning and experience to employ emissions trading strategically to minimise the costs of participating in the EU ETS. We therefore expect a positive correlation between *transaction frequency* and *internal trading*.

Energy

Energy companies possess structural skills related to complementary assets and capabilities that facilitate their participation in external trading of EUAs (e.g., Lehmann et al, 2024). Their experience in trading energy commodities provides them with relevant expertise for EUA trading. For example, electricity providers often engage in spot and futures markets to sell their electricity on platforms like the EEX, which also facilitates EUA trading. Relatedly, research by Jaraitė-Kažukauskė and Kažukauskas (2015) and Abrell et al. (2022) indicates that energy companies are more actively engaged in external trading of EUAs than industrial companies. Consequently, transaction costs for external trading may be lower for energy companies, implying a negative relationship between *energy* and *internal trading*. Other factors, however, suggest a positive relationship. For example, complementary assets and capabilities enabling external trading of EUAs may also enable internal trading. Furthermore, energy companies may already have established specialised trading units. These units centrally manage not only electricity trading but also the trading of EUAs, thereby enhancing internal trading by consolidating allowances into central accounts. Consequently, we have no specific expectations regarding the direction or relationship between *energy* and *internal trading*.

Number of installations

The variable *number of installations* refers to the total number of a company's installations that are regulated under the EU ETS. According to Lehmann et al. (2024), the number of installations also reflects companies' structural skills enabling external trading of EUAs. Similarly, as argued by Jaraītė-Kažukauskė and Kažukauskas (2015), for example, a higher number of installations proxies for lower transaction costs associated with external trading, such as search and information costs. Indeed, companies operating a larger number of installations typically exhibit both a higher likelihood of participation in external trading and greater trading intensity (e.g., Jaraītė-Kažukauskė and Kažukauskas, 2015; Baudry et al., 2021; Abrell et al., 2022). They also tend to trade more profitably (Lehmann et al., 2024). Because skills enabling external trading may also enable internal trading, however, the relation between *number of installations* and *internal trading* appears ambiguous.

Carbon leakage

We include a dummy variable which indicates whether a company primarily produces goods listed on the *carbon leakage* list, similar to Abrell et al. (2022), Lehmann et al. (2024), and Nardone et al.

(2025).[75] These companies face greater competition from outside the EU and are unlikely to be able to fully transfer additional costs from emissions trading to their customers without losing their market position (e.g. Cludius et al., 2020). Therefore, they are expected to have stronger incentives to reduce their costs associated with emissions trading. Assuming that internal trading incurs lower transaction costs than external trading, these companies should have a greater incentive to trade internally, suggesting a positive correlation between *carbon leakage* and *internal trading*.

Periods and regions

Similarly to research in related contexts (e.g., Jaraitė-Kažukauskė and Kažukauskas, 2015), we include dummy variables to control for effects specific to different trading periods (i.e., 2005-2007, 2008-2012, and 2013-2020). For example, there may be positive learning effects related to emissions trading over time. Indeed, Abrell et al. (2022) observe companies to participate more actively and to trade more intensively in the second and third trading periods than in the first trading period. Likewise, we add dummies reflecting geographic *regions*, using the German-speaking region (*Region 1*) as the reference. The studies by Borghesi and Flori (2018) and Karpf et al. (2018) find that companies' trading behaviour in the EU ETS is related to their geographical location. According to Hintermann and Ludwig (2023) and Flori and Spelta (2025) companies tend to trade more intensively with partners from their home country, thus reflecting a 'home bias'.

[75] The carbon leakage list includes a wide range of products from various energy-intensive sectors, such as iron and steel, non-ferrous metals, aluminum, refineries, cement and lime, glass and ceramics, and pulp and paper (European Commission 2014/746/EU).

Table 29: Description of variables.

Variable	Description	Data source
Dependent variable		
Internal trading	Internal trading volume * EUA price.	EUTL
Covariates		
Internal trading potential	Net position NUO_J – net position (absolute value in metric tons of CO_2eq).	EUTL
Banking	Net position plus acquisitions minus transfers in a specific trading year (absolute value in metric tons of CO_2eq).	
Number of NUO companies	Number of companies owned by the NUO of a company.	ORBIS
Transaction frequency	Number trades conducted by a company in year t.	EUTL
Energy	Dummy = 1 if a company belongs to the energy sector.[76]	ORBIS
Number of Installations	Number of installations of a company.	EUTL
Carbon leakage	Dummy = 1 if a company primarily sells products listed on the carbon leakage list.	EU ETS regulation
Period 1	Dummy = 1 if observation pertains to first trading period (2005-2007) (*base period*).	EU ETS regulation
Period 2	Dummy = 1 if observation pertains to second trading period (2008-2012).	EU ETS regulation
Period 3	Dummy = 1 if observation pertains to third trading period (2013-2020).	EU ETS regulation
Region 1	Austria (AT), Germany (DE), Liechtenstein (LI) (*base region*).	EUTL
Region 2	Belgium (BE), France (FR), Netherlands (NL).	EUTL
Region 3	Greece (GR), Cyprus (CY), Spain (ES), Italy (IT), Malta (MT), Portugal (PT).	EUTL
Region 4	Estonia (EE), Lithuania (LT), Latvia (LV), Poland (PL).	EUTL
Region 5	Czech Republic (CZ), Hungary (HU), Slovenia (SI), Slovakia (SK).	EUTL
Region 6	Denmark (DK), Finland (FI), Iceland (IS), Norway (NO), Sweden (SE).	EUTL
Region 7	United Kingdom (UK), Ireland (IE).	EUTL
Region 8	Bulgaria (BG), Croatia (HR), Romania (RO).	EUTL

[76] NACE (rev2) classification (35.00 to 35.30).

9.2.3 Econometric Models and Identification

We conducted a multivariate panel econometric analysis using annual data at the individual company level.[77] Our analysis is restricted to companies with the capability to trade internally, specifically those with at least one other company within the same NUO. For a large share of our observations, *internal trading* is zero. These zeroes indicate company-level decisions to not trade internally. In this case, employing ordinary least squares models would lead to biased parameter estimates. Instead, we estimate a "corner solution" Tobit model

$$\begin{aligned} y_{it}^* &= x_{it}\beta + z_i\gamma + \alpha_i + \varepsilon_{it} \\ y_{it} &= y_{it}^* \;\; if \;\; y_{it}^* \geq 0 \quad , \\ y_{it} &= 0 \;\; if \;\; y_{it}^* < 0 \end{aligned} \tag{2}$$

where y_{it}^* denotes company i's latent (unobserved) level of *internal trading* at time t, y_{it} stands for company i's observed level of *internal trading* at time t, x_{it} represents time-varying covariates such as *internal trading potential*, z_i reflects time-invariant covariates such as *number of NUO companies* or *energy*, α_i captures time-invariant, company-specific unobserved factors (i.e., the panel-level random effect), and ε_{it} is the idiosyncratic error term. We cluster standard errors at the company level to account for potential heteroskedasticity and serial correlation within companies.

Tobit models are non-linear, meaning that, unlike linear models, unobserved time-constant heterogeneity (such as company culture), which may be correlated with the covariates, usually cannot be addressed by including company-specific fixed effects and using a fixed-effects estimator. Conversely, using a random effects estimator requires the unobserved heterogeneity to be uncorrelated with the covariates, a condition that is likely too restrictive in our context. Therefore, following studies such as Jaraitė-Kažukauskė and Kažukauskas (2015) and Abrell et al. (2022), we use the correlated random effects (CRE) estimator developed by Mundlak (1978). The CRE accounts for time-invariant

[77] Our panel dataset is unbalanced due to the entry and exit of companies and installations over time, as well as the entry and exit of countries. For example, non-EU countries such as Norway, Iceland, and Liechtenstein, along with new EU members Romania and Bulgaria, joined the EU ETS in 2007, while Croatia entered in 2013.

unobserved heterogeneity by including company-specific means of the time-varying variables in the regression equation. Hence,

$$\alpha_{1,i} = \bar{x}_i \varphi + \mu_i, \tag{3}$$

where $\bar{x}_i$ is the mean of the x_{it} over time for company i, and $\mu_i \sim N(0, \sigma_\mu^2)$.[78]

In our empirical specification, to mitigate the impact of outliers on the results, we use the log-transformed values of all variables except for *number of NUO companies, number of installations* and for all the dummy variables. The coefficients associated with the log-transformed covariates correspond to elasticities. The Tobit models were estimated using the xttobit procedure in Stata 17. Our empirical analysis comprises of two types of samples and models, relying on different identification strategies to establish causality for our key covariate *ITP* which is a continuous variable.

First, we estimate equations (2) and (3) for the sample including all installations. Our treatment variable is continuous and there is no clear "before" and "after" period. Hence, standard difference-in-difference (DiD) approaches are not applicable. Instead, our identification strategy assumes that *ITP* is exogenous conditional on observed covariates. That is, we assume that there are no omitted variables that are correlated with both *ITP* and *internal trading*. Assuming the treatment to be exogenous appears plausible given that *ITP* is primarily determined by allocation rules specified in the EU Emissions Trading Directive (European Parliament and Council, 2023), which are externally imposed on companies.

Second, we consider a subset of companies for which the change in allocation rules in the third trading period provides a quasi-experimental setting that facilitates causal inference. For the subsample that only uses combustion installations, causal identification exploits the allocation reform introduced in 2013. Thereby, we distinguish between companies operating combustion installations in the energy sector and companies operating combustion installations in the industry sectors. Prior to the reform, the

[78] The *xi* are known as Mundlak terms. They capture the "between variation" and can be interpreted as representing the long-run effects. In contrast, the time-varying variables capture the "within variation" and can be interpreted as reflecting the short-run effects. Because we are concerned, that the effects of unobserved heterogeneity may be correlated with the covariates, our analysis and interpretation of the results focusses on the time-varying effects.

same allocation rules applied to combustion installations in all sectors. Since 2013, combustion installations in the energy sector (‘treatment group’) have effectively received no free allowances, as they were deemed less exposed to international competition and capable of passing on most, if not all, of the opportunity costs associated with using EUAs (e.g. Sijm et al. 2006; Dagoumas and Polemis 2020). In contrast, combustion installations in the industry sectors (‘control group’) continued to receive allowances for free. Before 2013, both groups were subject to identical allocation rules. Since our primary interest lies in the relationship between *ITP* and *internal trading*, and in how this relationship may have changed as a result of the reform, we include all interaction terms combining the reform indicator (*Period 3*), the treatment indicator (*Energy*), and *ITP*. Hence, equation (2) becomes

$$y_{it}^{*} = \delta_1 Period\ 3_t + \delta_2(Period\ 3_t \times ITP_{it}) + \delta_3(Period\ 3_t \times energy) + \delta_4(energy_t \times ITP_{it}) + \delta_5(Period\ 3_t \times energy \times ITP_{it}) + \tilde{x}_{it}\tilde{\beta} + z_i\gamma + \alpha_i + \varepsilon_{it}. \quad (2')$$

This setup mimics a DiD framework with a continuous treatment effect. Reflecting our expectation that a larger *ITP* increases *internal trading*, the removal of free allocation of EUAs for the treatment group is expected to lower the effect of *ITP* on *internal trading* from 2013 onward compared to the control group. In a linear model, we would therefore expect a negative sign for δ_5. Because the Tobit model is non-linear, δ_5 does not capture this triple-interaction effect (e.g., Greene, 2010). Instead, we focus on the marginal effects of the interaction between *Period 3* (compared to the pre-treatment *Period 2*), *Energy* (compared to combustion installations in the non-energy sector) and *ITP*. Since in non-linear models, these marginal effects depend on the level of *ITP*, among others, it is not possible to perform a test on the general statistical significance of the triple-interaction terms. As suggested by Greene (2010), we instead employ a graphical analysis. For identification, we examine whether the parallel-trends assumption holds.

9.3 Results and Discussion

In this section, we present and discuss the findings of our descriptive analysis, followed by the results of our multivariate analysis, distinguishing between the models estimated for the sample including all installations, and for the sample including combustion installations only. We also present the findings from a series of robustness checks.

9.3.1 Results from the Descriptive Analysis

The analysis is based on a final sample of 2,507 companies, comprising a total of 15,947 observations. Among the companies with the opportunity for internal trading (defined as companies belonging to a NUO with at least two companies), only 260 (approximately 10.4%) trade internally.[79]

Regarding internal trading potential, 3,408 observations exhibit a positive *ITP*, corresponding to about 21,4% of all observations. About 17% of companies with *ITP*>0 in a given year, engage in internal trading (Table 30).

The share of energy companies trading internally tends to be higher than that of industry companies. We also observe that some companies trade internally even when *ITP* = 0, possibly because they pool EUAs in a central trading account – independent of whether they are short or long. Their share represents approximately 8.6% of companies with *ITP* = 0 in a given year. For each sector, it is lower than the share of companies with *ITP* > 0 that engage in internal trading. In sum, only 1.3% of companies with *ITP* > 0 fully exploiting their internal trading opportunities in a given year, meaning their trading volume matches or exceeds their internal trading potential. Overall, between 2005 and 2017, only about 1.6% of the internal trading potential was exploited.

We present an overview of the descriptive statistics for the dependent variables and the covariates in Table 32 in Section 9.7.

[79] To assess the sensitivity of these findings to different levels of aggregation, we also examined internal trading at the GUO level. Applying the same logic as before, we observe only 1 company more that trades internally than for our analysis based on the NUO level. This finding corroborates our decision to focus on the NUO level to analyse companies' internal trading behaviour.

Table 30: Share of companies trading internally by sector (2005 - 2017).

Sector	Companies trading internally in at least one year as a share of		Companies trading internally every year as a share of	
	ITP>0	all	*ITP*>0	all
Energy*	21.2%	12.6%	8.6%	7.3%
Refining	21.7%	13.5%	8.7%	5.4%
Iron and Steel	7.9%	5.6%	3.2%	2.2%
Nonferrous metals	0.0%	0.0%	0.0%	0.0%
Lime/Cement	16.4%	11.8%	1.5%	2.2%
Glass	22.2%	15.2%	8.9%	7.6%
Ceramics	10.3%	6.0%	3.7%	2.0%
Mineral Wool	0.0%	0.0%	0.0%	0.0%
Gypsum/Plasterboard	0.0%	0.0%	0.0%	0.0%
Pulp/Paper	8.5%	5.2%	4.9%	3.0%
Chemicals	12.2%	8.5%	7.3%	8.5%
Total	17.0%	10.4%	6.7%	5.5%

* The energy sector is defined based on the NACE (rev2) classification (35.00 to 35.30) rather than on the ETS activity 'combustion of fuels.' The latter category would include those industrial sectors that are not attributable to any other ETS activity. See also Section 9.2.2. Aggregation of ETS activity at industry sector level is based on Gores et al. (2021).

9.3.2 Results from the Multivariate Analysis for the Sample including all Installations

In this section we present and discuss the results of our preferred model specification. We focus on the estimated average marginal effects (and average discrete effects for dummy variables), as they offer an intuitive interpretation of the relationship between the dependent variable and the covariates.[80] In addition to the expected marginal effects on average *internal trading*, Table 31 presents the extensive margin, i.e., the change in the proportion of companies engaging in internal trading, and the intensive margin, i.e., the change in the mean of internal trading among companies that already trade internally. Distinguishing between the extensive and intensive margin allows us to disentangle two mechanisms:

80 In Table 33, we present the estimates of the coefficients for the latent level of internal trading, as described in Equation (2).

the extent to which a covariate relates to barriers to participation in internal trading (extensive margin) and the extent to which it relates to the intensity of internal trading for companies that already trade internally (intensive margin).

We note that one of the three Mundlak terms in Table 33 is statistically significant, indicating that a random-effects estimator would yield biased and inconsistent parameter estimates. The estimated intra-class correlation coefficient (rho) equates to 0.73, suggesting that most of the variance of *internal trading* is explained by differences between companies rather than within companies, thereby confirming the relevance of the panel structure. Moreover, variance inflation factors (mean VIF = 2.1, all individual VIFs below 5) indicate that multicollinearity is not a concern in our specification.

Table 31: Estimated average marginal effects on internal trading (sample including all installations).[†]

	Extensive margin [change in Prob(*internal trading* > 0)]	Intensive margin [change in E(*internal trading* | *internal trading* >)]	Change in average *internal trading*
Internal trading potential	-0.000	-0.010	-0.003
	(0.000)	(0.009)	(0.002)
Banking	-0.001***	-0.053***	-0.014**
	(0.000)	(0.020)	(0.005)
Number of NUO companies	0.001***	0.047***	0.012***
	(0.000)	(0.007)	(0.002)
Transaction frequency	0.006***	0.299***	0.077***
	(0.001)	(0.042)	(0.012)
Energy	0.002	0.080	0.021
	(0.005)	(0.230)	(0.059)
Number of installations	0.001*	0.025*	0.007*
	(0.000)	(0.014)	(0.004)
Carbon leakage	-0.016***	-0.776***	-0.200***
	(0.005)	(0.269)	(0.072)
Period 2	0.005*	0.262*	0.067*

	(0.003)	(0.136)	(0.035)
Period 3	0.008***	0.379***	0.098***
	(0.002)	(0.117)	(0.031)
Region 2 (BE, FR, NL)	-0.021	-1.032	-0.265
	(0.013)	(0.654)	(0.170)
Region 3 (GR, IT, PT, ES, CY, MT)	-0.034***	-1.656***	-0.426***
	(0.008)	(0.388)	(0.108)
Region 4 (EE, LT, LV, PL)	-0.015*	-0.716*	-0.184*
	(0.008)	(0.373)	(0.098)
Region 5 (CZ, HU, SI, SK)	-0.009	-0.435	-0.112
	(0.010)	(0.506)	(0.131)
Region 6 (DK, FI, IS, NO, SE)	-0.025***	-1.235***	-0.317***
	(0.006)	(0.297)	(0.082)
Region 7 (UK, IE)	-0.035***	-1.726***	-0.444***
	(0.011)	(0.545)	(0.147)
Region 8 (BG, HR, RO)	-0.039***	-1.920***	-0.494***
	(0.009)	(0.450)	(0.126)
Number of observations		15,947	
Number of companies		2,507	

†Robust standard errors appear in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

9.3.2.1 Internal trading potential

Table 31 does not provide convincing evidence of a statistical correlation between *ITP* and *internal trading* ($p = 0.30$). Also, the effect size on average *internal trading*, and the extensive and intensive margins are small. Therefore, our findings provide no support that companies with a higher *ITP* engage more in *internal trading*. This means that we do not find evidence that companies of the same NUO offset net positions internally to minimise external trading. Instead, these findings are consistent with the notion that there are barriers to internal trading. One possible explanation is that internal transactions may involve significant transaction costs - particularly if internal trading strategies are not centrally coordinated at the NUO level. For example, internal trading may involve negotiations between companies (e.g. over the price and traded volumes of EUAs) which may be more complex than trading at market prices on external platforms. Other barriers to internal trading may be due to differences in corporate taxes across locations. In this case, NUOs may shift EUAs (and hence accounting profits) to companies located in locations with the most favourable tax legislation. Indeed, Schultz (2024) finds that towards the end of a calendar year, allowances are transferred from subsidiaries in strict accounting jurisdictions to those in more lenient ones, suggesting arbitrage. Likewise, unless the NUO requires companies to trade internally, they may be reluctant to do so because internal trading affects companies' performance measures. For example, companies may prefer to purchase EUAs on the external market rather than increase the cash flow of an affiliated company within the same NUO through internal trading, as this could compromise their relative position within the same corporate group or holding.

9.3.2.2 Banking

Our results suggest a negative correlation between *banking* and *internal trading*. A 1% increase in *banking* corresponds to a decrease in average *internal trading* of about 0.01%. The extensive margin implies that a 1% increase in *banking* corresponds to a decrease in the probability of a company trading internally by about 0.1 percentage points. As suggested by the intensive margin, companies already trading internally decrease *internal trading* by 0.05% in response to a 1% increase in *banking*. These findings support our expectation that internal trading decreases as companies choose to bank more allowances.

9.3.2.3 Number of NUO companies

Our results indicate a statistically significant positive correlation between the number of NUO-affiliated companies and *internal trading*. An additional company within the same NUO corresponds to an increase in the probability that a company trades internally by approximately 0.1 percentage points and raises *internal trading* by 4.7% among companies already trading internally. The corresponding change in the average internal trading value amounts to 1.2%. As expected, a company's internal trading value increases with the number of companies belonging to the same NUO. The extensive margin, however, is small, suggesting that the *number of NUO companies* may play a minor role in a company's decision to engage in internal trading.

9.3.2.4 Transaction frequency

The coefficient associated with *transaction frequency* is positive and statistically significant. A 1% increase in *transaction frequency* is associated with a 0.6 percentage point higher likelihood that a company will trade internally, an increase in *internal trading* by 0.3% for companies that trade internally, and an increase in the average internal trading value by 0.08%. Thus, similar to Abrell et al. (2022) and Lehmann et al. (2024) in a related context, this finding supports the view that higher strategic skills (here: through learning and experience) are conducive to internal trading.

9.3.2.5 Energy

The coefficient associated with *energy* is not statistically significant, possibly due to opposing mechanisms. While energy companies tend to be more experienced in related trading activities than industry companies, suggesting a positive relation between *energy* and *internal trading*, they also often have centralised trading units managing EUAs, indicating a negative relationship. Our null result for *energy* is consistent with the findings of Nardone et al. (2025), who find no evidence that trading between installations operated by the same company is more prevalent among energy companies than industrial companies.

9.3.2.6 Number of installations

We find a statistically significant positive correlation between the *number of installations* and *internal trading*. An additional installation regulated under the EU ETS corresponds to an increase in the probability that a company trades internally by about 0.1 percentage points and increases the internal trading value by 2.5% among companies already trading internally. This amounts to a change in the average *internal trading* of 0.7%. This finding supports the view that a larger number of installations reflect higher structural skills enabling internal trading of EUAs. It is consistent with previous studies focusing on external trading (e.g. Jaraitė-Kažukauskė and Kažukauskas, 2015; Baudry et al., 2021; Abrell et al., 2022; Lehmann et al., 2024) and on intra-company trading (Nardone et al., 2025).

9.3.2.7 Carbon leakage

We find a statistically significant negative correlation between *carbon leakage* status and *internal trading*. Companies at risk of carbon leakage are 1.6 percentage points less likely to engage in internal trading than others. Among those that do, their internal trading volume is 78% lower and their average trading value is about 20% lower. These results contradict our initial expectation. When interpreting our no result for *ITP*, we speculate that companies may be reluctant to trade internally because internal trading affects their cash flows and hence their relative position within a NUO. This barrier to internal trading may be particularly pronounced for companies at risk of carbon leakage. We further note that our findings for carbon leakage are consistent with the existing literature. In particular, Nardone et al. (2025) find a significant negative relation between companies considered at risk of carbon leakage and their participation in trading between installations of the same company.

9.3.2.8 Periods and regions

We find that the average internal trading value was higher in period 2 and period 3 than in period 1, ceteris paribus. This finding appears to be mostly driven by companies who already traded internally rather than by more companies starting to trade internally over time. In general, these findings suggest that companies may have learned to better utilise their internal trading options over time, similar to the findings by Nardone et al. (2025) and Abrell et al. (2022) in related contexts.

Finally, our results for the regional dummies indicate that, in *regions 3, 5, 6,* and *8*, the share of companies trading internally, the share of internal trading of companies already trading internally, and the average internal trading value was lower than in the German-speaking region. These findings align with Abrell et al. (2022) regarding various companies' emissions trading activities.

9.3.3 Results from the Multivariate analysis for the Sample including Combustion Installations only

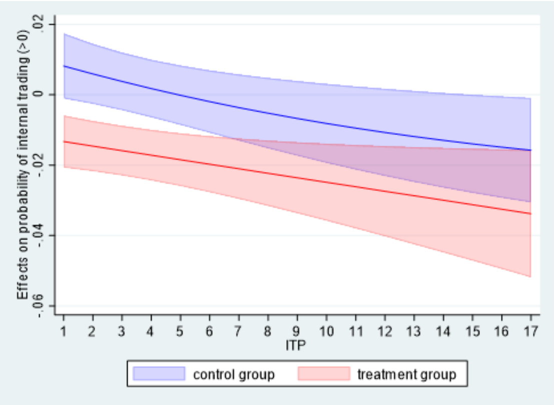
First, we note that limiting the sample to operators of combustion installations reduces the sample size from 15,947 to 9,294 observations. We then assess the validity of the parallel-trends assumption, which is crucial for identifying the causal effect of *ITP* on *internal trading*. First, a visual comparison of the means of *internal trading* for treatment and control groups across period 1 and period 2 suggests that the parallel trends assumption holds (Figure 13). Second, we conduct a placebo test which treats period 2 instead of period 3 as the treatment period using period 1 as the base period. Neither *Period 2* nor any of the associated interaction terms turns out to be statistically significant (see Table 34). Third, we perform a placebo test that considers period 2 as the post-treatment period while excluding *Period 3*. Again, this specification yields no statistically significant pseudo-effects for *Period 2* or any of the associated interaction terms (see Table 35). Taken together, these diagnostic tests support the validity of our identification strategy.

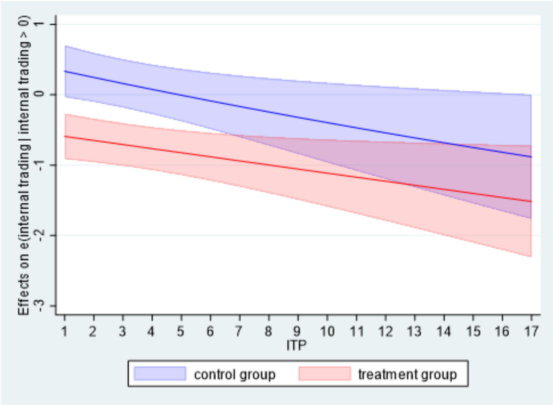
Turning to the results, we find that one of the Mundlak terms is statistically significant (see Table 36) implying that a random-effects estimator would be biased and inconsistent, similar to our findings for the sample including all installations. The estimated intra-class correlation coefficient (rho = 0.73) confirms the relevance of the panel structure, as most of the variance in the dependent variable is explained between rather than within companies. Finally, variance inflation factors (mean VIF = 2.3, all individual VIFs below 5) suggest that multicollinearity is not a concern.

Subsequently, we analyse the marginal effects of the triple interaction term (*Energy*×*Period3*×*ITP*) for the extensive and intensive margin. This allows us to assess how the relationship between *ITP* and *internal trading* changes due to the treatment in period 3, for *energy* companies and the control group. In particular, we are interested in whether the difference between the marginal effects for the treatment and control group changes as *ITP* increases. We estimate and display the marginal effects at integer values of *ITP* ranging from 1 to 17, corresponding to the range of *ITP* (see Table 38).

Figure 12 illustrates the results for the extensive margin (left panel) and intensive margin (right panel) showing the effect of the policy reform on *internal trading* by level of *ITP* for combustion installations in the energy sector (treatment group) and the industry sectors (control group). For both the control and treatment groups, the marginal effects appear to become more negative for higher values of *ITP*, suggesting that companies with higher *ITP* generally reacted more strongly to the reform in period 3. In particular though, Figure 12 provides no indication that the difference between the marginal effects for the treatment and control group changes as *ITP* increases, neither for the extensive margin, nor for the intensive margin. This finding supports the null result regarding the effects of *ITP* on *internal trading*, as observed in the sample relying on data for all installations and using an alternative methodology in Section 9.3.2.

Figure 12: Marginal effects of the policy reform on internal trading by sector and ITP (analysis including combustion installations only).





Left panel shows extensive margin, right panel shows intensive margin. Shaded areas correspond to 90% CI.

Finally, we note that the results for the remaining covariates are broadly consistent with those reported in Section 9.3.2 (see Table 37). Coefficients which are statistically significant exhibit the same signs as in the analysis for the sample including all installations. In the sample including combustion installations only, coefficients that are no longer statistically significant, i.e. *banking*, the *number of installations*, and *Region 4*, retain the same sign as reported in Section 9.3.2. The differences in statistical significance are likely due to the lower statistical power in the sample including combustion installations only.

9.3.4 Robustness Checks

To assess the robustness of the findings presented in Table 31, we conducted a series of supplementary analyses allowing for alternative model specifications.

First, to mitigate potential omitted variable bias, we included two variables from the ORBIS database which previous studies find to be related with emissions trading activities. We include the number of *employees* to capture the size of a company. Previous studies (e.g., Jaraītė-Kažukauskė and Kažukauskas, 2015; Baudry et al., 2021; Abrell et al., 2022) find larger companies to be more actively involved in emissions trading. We further include *revenue per worker*, defined as revenue per employee. Abrell et al. (2022) find companies with higher revenue per worker to be more actively engaged in various emissions trading activities. Assuming that larger companies and companies with higher revenue per worker are better at exploiting internal trading opportunities, we expect a positive correlation between both variables and *internal trading*. Including *employees* and *revenue per worker*, however, leads to a substantial reduction in sample size due to missing values. The number of observations decreases from 15,947 to 9,444 and the number of companies from 2,507 to 2,037. Results of estimating this model appear in Table 39. Accordingly, the marginal effects associated with *employees* and *revenue per worker* are small, and not statistically significant at conventional levels. The findings for most other variables are similar to those reported in Table 31. However, the coefficients for *banking* and *number of installations* are no longer statistically significant at conventional levels, most likely due to the lower statistical power.

Second, we estimated a model that includes only companies with *ITP>0* in the respective year, rather than all companies. This restriction reduces the number of observations to 3,408 and the number of companies to 1,364 companies. The results presented in Table 40 are qualitatively very similar to those shown in Table 31, yet *number of installations* is no longer statistically significant, most likely due to the lower statistical power.

Third, to examine whether our findings are sensitive to the definition of outliers, we re-estimated our model after removing the top 5% of observations with the highest levels of internal trading, instead of removing the top 2%. The results which are presented in Table 41 are generally quite similar to those shown in Table 31.

Fourth, we examine whether results differ between net buyers and net sellers, which are defined as companies whose net position (free allocation minus verified emissions) is negative (net buyers) or positive (net sellers). For example, net buyers may opt for internal transactions if they anticipate securing lower prices from companies within the same NUO, compared to those offered by brokers or exchanges. Similarly, net sellers may favour external transactions if they anticipate obtaining higher prices on the market than through internal trades. To assess whether these disparities affect the relationship between internal trading and the covariates, we estimate the models separately for net buyers and net sellers using both the sample including all installations and the quasi-experimental sample including combustion installations only. We document the findings for the sample including all installations in Table 43 for net buyers and in Table 42 for net sellers. Figure 14 displays the key finding for the sample using combustion installations only for net sellers. Due to the generous allocation of allowances during the first two trading periods for industry sectors in particular (e.g. Ellerman and Buchner, 2008), there are too few net buyers among operators of combustion installations in these sectors in the pre-treatment period to reliably estimate the model for the quasi-experimental setting.[81]

In general, the outcomes of the split-sample estimations are consistent with those reported in Sections 9.3.2 and 9.3.3 for the full samples. Some minor differences are observed in the results for net buyers (in the sample using all installations), where statistical significance tends to be lower than in the full sample, likely due to reduced statistical power stemming from the smaller number of observations. Consistent with our findings in Section 9.3.3., our results for net sellers for the quasi-experimental set up show no indication that the difference between the marginal effects for the treatment and control groups changes as *ITP* increases, either for the extensive or for the intensive margin.

Finally, we attempted to estimate double hurdle models because they imply less restrictive assumptions than Tobit models. For example, in double hurdle models, the signs of the intensive and extensive margins of a particular covariate may differ. Unfortunately, none of the double hurdle models that we estimated converged for our data.

9.4 Conclusions

This study is the first to analyse internal trading of EU allowances, which is expected to incur lower transaction costs than external trading. It covers the first three trading periods and is based on a comprehensive dataset that integrates information from the EUTL and the ORBIS database which provides company characteristics and allows identifying transactions within the same NUO as internal trading.

The findings from our descriptive analysis suggest that most companies, including those with large potentials for internal trading, do not trade internally. Thus, substantial opportunities for internal trading

[81] We observe only 112 industry companies that were net buyers with a positive *ITP* before 2013, of which only six engaged in internal trading.

remain untapped, possibly resulting in inefficient levels of transactions and abatement costs within the EU ETS.

The findings from our multivariate analyses imply a null result for the relation between companies' internal trading and their potentials for internal trading. Possible explanations include barriers to internal trading such as transaction costs that exceed those of external trading, strategic priorities such as transferring allowances to companies located in regions with the most favourable tax conditions, and competition between companies within a NUO. The latter may also explain why we find a negative correlation between internal trading and companies at risk of carbon leakage. Put differently, the null result on internal trading potential undermines the premise that external trading is more costly to companies than internal trading.

Next, our finding that EUA banking is negatively related to internal trading supports the view that banking allowances reduces the amount available for internally balancing net positions. We further find that the number of companies within a given NUO are positively associated with internal trading volumes, reflecting that companies in larger NUOs have greater opportunities for internal trading. The small extensive margin, however, suggests that this plays a minor role in a company's decision to engage in internal trading only. We further find that companies that trade more frequently also engage in more internal trading, possibly due to learning effects that enable them to utilise all available options to minimise costs within the EU ETS. In addition, a higher number of installations correlates with increased internal trading, possibly because companies operating more installations possess better structural skills for trading EUAs. Furthermore, we find that internal trading volumes are higher in periods 2 and 3 than in period 1, likely reflecting that companies have become more adept at utilising their internal trading options over time. Finally, companies in German-speaking countries generally show higher internal trading volumes than those in non-German-speaking countries.

These findings generally align with the existing literature on related topics. They are also robust across diverse alternative model specifications, sample compositions, and identification strategies, including a quasi-experimental approach. Nevertheless, some caveats remain. For example, due to data limitations, our analysis did not account for factors which may affect companies' internal trading decisions, such as performance targets for companies within an NUO, and variations in corporate taxes across company locations. Further, in our study, internal trading may be measured with error. For instance, companies may trade through a trading company set up by their NUO. Yet, unless this trading company legally belongs to their NUO, those trades would not be considered internal trades. Additionally, certain trading behaviours - such as pooling the entire stock of EUAs within a single trading account - could hide the extent to which companies exploit their internal trading potential, particularly if such pooling is applied regardless of whether such a potential exists or not. Our analysis draws on secondary data to examine internal trading. Hence, the scope of analysis is shaped by the availability of data. To deepen the understanding of the factors enabling and impeding internal and external trading within the EU ETS, future research may collect primary data through company surveys and detailed case study interviews. Furthermore, future research could employ gravity analysis to jointly examine internal and external trading, thus building on Hintermann and Ludwig (2023) and Flori et al. (2025) in related contexts. Future studies could also examine internal trading in other greenhouse gas emissions trading systems, including the national systems in China, Korea, and the UK, and the regional systems in the US such as California's Cap-and-Trade Program and the Regional Greenhouse Gas Initiative (RGGI). Similar studies may be applied to trading schemes targeting other pollutants, including SO_x and NO_x under RECLAIM in the US.

Our analysis provides relevant insights for policymakers seeking to better understand trading behaviour and enhance the efficiency of emissions trading systems. A central design element in this context is the point of regulation. In the EU ETS, regulation at the installation level offers key advantages, such as legal certainty and precise monitoring and verification of emissions. However, this decentralised structure may impede intra- and inter-company trading, as it requires each installation to manage allowances independently, thereby increasing transaction costs and administrative complexity. Regulating emissions at the level of the NUO for example, could alleviate these inefficiencies by allowing companies to centralise allowance management and streamline compliance across multiple sites. This may also facilitate more strategic trading decisions and greater responsiveness to market signals. However, these benefits must be carefully weighed against potential costs, such as reduced transparency, weaker oversight, and legal ambiguities regarding compliance responsibility. Finally, our results suggest that internal trading faces barriers, implying that for many companies, external trading may be less costly than internal trading. Identifying and understanding these barriers is essential for designing policies that improve the economic efficiency of the EU ETS.

CRediT authorship contribution statement

- **Sascha Lehmann:** Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.
- **Joachim Schleich:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the language quality. After using this tool, the authors reviewed and edited the content as needed.

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9.6 Appendix A1 Compilation of the Data[82]

A.1.1 Data Sources and Preparation

The European Commission (EC) manages the Union Registry, a centralised electronic database that documents all transactions carried out within the EU ETS. This includes allocations granted free of charge, the surrendering of allowances, and transactions conducted between various market participants. These activities are monitored and authorised through the European Union Transaction Log (EUTL)[83], which is responsible for recording and verifying every transaction. With a delay of three years, this data is publicly available via the EUTL interface where it can be downloaded for free.

Only entities with registered accounts are permitted to engage in trading emissions allowances. Each stationary installation under the EU ETS is required to maintain at least one Operator Holding Account (OHA), while airlines must open at least one Aircraft Operator Account (AOA). These accounts are used for receiving free allocations and fulfilling surrender obligations. Beyond these, companies and even private individuals may open Person Holding Accounts (PHA) or Trading Accounts (TA) to facilitate participation in allowance trading. Additionally, administrative accounts are maintained by EU institutions and individual Member States for regulatory purposes such as the primary allocation and the cancellation of EUAs.

The EUTL provides various account-level details, including account names, Member State of registration, company registration identifiers, designated account holders, and associated installations. For installations, data is available on activity type, physical address, verified emissions, and the amount of allocated and surrendered EUAs. Transaction-level records capture information on both accounts involved in a transaction, transaction type, date, and volume of allowances transferred, but not on the transaction price. To incorporate market price information, we used the unweighted annual average of spot prices from the EEX and linked these values to the corresponding years in the EUTL dataset.

[82] The description for compiling the data is partly based word for word on the data description of a paper by Lehmann et al. (2024).
[83] https://union-registry-data.ec.europa.eu/report/welcome.

Prior to a major structural reform in 2012, transaction monitoring was carried out via the decentralised Community Independent Transaction Log (CITL). As part of the reform, the CITL was integrated into the centralised EUTL managed by the EC, with new OHAs being assigned to all installations during the transition (see A.1.2).

To aggregate account-level data to the level of a company, NUO, and GUO we link EUTL data with company-level information from the ORBIS database via corporate registration numbers. ORBIS data further includes the number of employees, total revenues, industry classifications according to NACE codes, and the country of the headquarter. We provide further details regarding the matching methodology between these data sources in A.1.3.

Following the data matching, we constructed a panel dataset at the transaction level, which we then aggregated to reflect annual transactions per company. Entities that did not report either verified emissions or receive free allocations were excluded from the analysis, as they are not relevant to our research question.

The resulting dataset comprises 42,007 accounts, of which 8,142 could not be matched to any identifiable company. The remaining accounts correspond to 12,319 companies. However, the subset of companies included in our analyses is significantly smaller, as we exclude aircraft operators and companies lacking both allocations and verified emissions, resulting in a sample of approximately 9,000 companies. Moreover, we restrict the sample to companies that are able to trade internally - that is, companies with at least one other company belonging to the same NUO. The final analytical sample consists of 2,507 companies.

A.1.2 Matching Historical and Current Operator Holding Accounts (OHAs)

As part of the 2012 restructuring of the EUTL, the system was expanded to include new account categories, such as Aircraft Operator Accounts. This reform also required all installations participating in the EU ETS to be assigned new OHAs. However, the current EUTL dataset contains only the updated OHAs, with no direct reference to their predecessors. Consequently, it was necessary to reconstruct the linkages between former OHAs and the corresponding installations.

To achieve this, a multi-step matching procedure was employed:

(1) Name-based Matching: The account and installation names were compared, and matches were accepted only in cases where the correspondence was unambiguous.

(2) Address-based Matching: Where name comparisons proved inconclusive, we relied on matching account and installation addresses, again requiring unique associations.

(3) Transaction-based Matching: If 1 and 2 did not work, we used installation-level information on allocation and surrendered number of allowances and searched for the transaction and account behind it and the administrative account of the respective registration. Again, we only accepted unique matches. We first used allocations followed by surrendering transfers.

By applying this methodology, we were able to successfully match approximately 99% of old OHAs to their respective new OHAs.

A.1.3 Linking EUTL Data to Companies in the ORBIS Database

Following the 2012 restructuring of account systems within the EU ETS, all account holders were mandated to provide VAT identification numbers, which could be either national or EU VAT numbers. Since the ORBIS database also includes VAT information, it is, in principle, possible to link EUTL accounts to companies listed in ORBIS. However, in practice, this process is hindered by data entry errors, inconsistent formatting, and occasional omissions. To overcome these issues, we implemented a fuzzy matching approach using a combination of variables: the VAT registration number, the account name associated with the number, and the contact address linked to the account. These variables served as the basis for an automated batch search within ORBIS. This procedure returned multiple potential matches along with a matching score for each option. Final matches were selected manually, assessing the consistency and plausibility of the values across the individual data fields.

9.7 Appendix A2 Additional Results

Table 32: Descriptive statistics of the dependent variable and all covariates (sample including all installations).

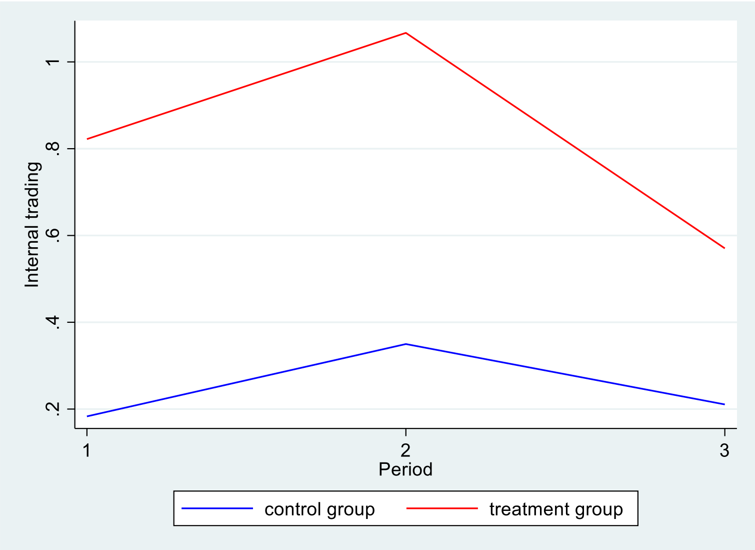
Variable	Obs.	Mean	Std. dev.	Min	Max
Dependent variable					
Internal trading	15,947	100,571	3,214,939	0	291,000,000
Covariates					
Internal trading potential	15,947	187,905	1,723,947	0	50,900,000
Banking	15,947	10,183	3,570,672	-414,000,000	213,000,000
Number of NUO companies	15,947	7.4	13.1	2	72
Transaction frequency	15,947	29	267	0	9,957
Energy	5,342			1	1
Number of Installations	14,057	3.9	6.4	1	80
Carbon leakage	5,260			1	1
Period 1	6,230			1	1
Period 2	3,612			1	1
Period 3	6,105			1	1
Region 1 (AT, DE, LI)	1,018			1	1
Region 2 (BE, FR, NL)	561			1	1
Region 3 (GR, CY, ES, IT, MT, PT)	2,825			1	1
Region 4 (EE, LT, LV, PL)	1,760			1	1
Region 5 (CZ, HU, SI, SK)	531			1	1
Region 6 (DK, FI, IS, NO, SE)	5,949			1	1
Region 7 (UK, IE)	584			1	1
Region 8 (BG, HR, RO)	2,141			1	1

Table 33: Estimated coefficients of the latent level of internal trading (sample including all installations).

	Coefficient (Standard errors in parentheses)
Internal trading potential	-0.092
	(0.087)
Banking	-0.493***
	(0.190)
Number of NUO companies	0.437***
	(0.066)
Transaction frequency	2.779***
	(0.390)
Energy	0.743
	(2.142)
Number of Installations	0.236*
	(0.128)
Carbon leakage	-7.216***
	(2.507)
Period 2	2.436*
	(1.265)
Period 3	3.527***
	(1.086)
Region 2	-9.591
	(6.085)
Region 3	-15.39***
	(3.617)
Region 4	-6.658*
	(3.470)
Region 5	-4.041
	(4.703)
Region 6	-11.470***
	(2.766)
Region 7	-16.040***

	(5.074)
Region 8	-17.850***
	(4.201)
Mean internal trading potential	0.423
	(0.287)
Mean banking	1.416
	(1.090)
Mean transaction frequency	0.793**
	(0.402)
Constant	-58.830***
	(5.365)
Observations	15,947
Companies	2,507

Figure 13: Means of internal trading for operators of combustion installations in energy and industry sectors across trading periods.



Source: Stata illustration based on data described in Section 9.2.1.

Table 34: Estimated coefficients of the latent level of internal trading; placebo test which treats period 2 instead of period 3 as the treatment period (analysis including combustion installations only).

	Coefficient (Standard errors in parentheses)
Period 2	1.772
	(2.047)
EnergyxPeriod 2	-1.643
	(2.622)
Period 2xITP	0.467
	(0.388)
EnergyxPeriod 2xITP	-0.319
	(0.501)
Energy	2.817
	(3.388)
EnergyxITP	0.646
	(0.43)
Internal trading potential	-0.380
	(0.334)
Banking	-0.086
	(0.288)
Number of NUO companies	0.510***
	(0.090)
Transaction frequency	2.638***
	(0.489)
Number of Installations	0.058
	(0.155)
Carbon leakage	-7.302**
	(3.403)
Region 2 (BE, FR, NL)	-6.377
	(7.453)
Region 3 (GR, IT, PT, ES, CY, MT)	-11.830***
	(4.327)
Region 4 (EE, LT, LV, PL)	-7.652*

	(4.540)
Region 5 (CZ, HU, SI, SK)	0.232
	(6.325)
Region 6 (DK, FI, IS, NO, SE)	-11.800***
	(3.467)
Region 7 (UK, IE)	-21.730***
	(8.427)
Region 8 (BG, HR, RO)	-22.630***
	(5.977)
Mean ITP	0.410
	(0.405)
Mean Banking	-1.571**
	(0.655)
Mean Transaction frequency	0.861
	(1.366)
Constant	-56.010***
	(7.126)
Observations	9,294
Companies	1,553

Table 35: Estimated coefficients of the latent level of internal trading; placebo test that considers period 2 as the post-treatment period while excluding Period 3 (analysis including combustion installations only).

	Coefficient (Standard errors in parentheses)
Period 2	1.833
	(2.267)
Period 3	5.409**
	(2.598)
EnergyxPeriod 2	-1.917
	(2.907)
EnergyxPeriod 3	-9.822***
	(3.444)
Period 2xITP	0.418
	(0.427)
Period 3xITP	-0.424
	(0.492)
Period 2xEnergyxITP	-0.325
	(0.550)
Period 3xEnergyxITP	-0.054
	(0.631)
Energy	3.082
	(3.385)
EnergyxITP	0.560
	(0.472)
Internal trading potential	-0.389
	(0.370)
Banking	-0.314
	(0.247)
Number of NUO companies	0.500***
	(0.078)
Transaction frequency	2.929***
	(0.472)
Number of Installations	0.177

	(0.145)
Carbon leakage	-9.172***
	(3.110)
Region 2 (BE, FR, NL)	-2.651
	(6.356)
Region 3 (GR, IT, PT, ES, CY, MT)	-13.730***
	(4.046)
Region 4 (EE, LT, LV, PL)	-5.872
	(3.968)
Region 5 (CZ, HU, SI, SK)	1.474
	(5.714)
Region 6 (DK, FI, IS, NO, SE)	-11.870***
	(3.193)
Region 7 (UK, IE)	-19.030***
	(6.961)
Region 8 (BG, HR, RO)	-24.420***
	(5.648)
Mean ITP	0.446
	(0.350)
Mean Banking	-1.295**
	(0.516)
Mean Transaction frequency	1.015
	(1.261)
Constant	-59.140***
	(6.244)
Observations	9,294
Companies	1,553

Table 36: Estimated coefficients of the latent level of internal trading (analysis including combustion installations only).

	Coefficient (Standard errors in parentheses)
Period 3 x Energy	-8.548***
	(2.823)
Period 3 x ITP	-0.746**
	(0.377)
Energy x ITP	0.298
	(0.239)
Period 3 x Energy x ITP	0.207
	(0.487)
ITP	-0.067
	(0.180)
Energy	1.813
	(2.784)
Period 3	3.661*
	(2.083)
Banking	-0.309
	(0.247)
Number of NUO companies	0.503***
	(0.078)
Transaction frequency	2.938***
	(0.474)
Number of installations	0.180
	(0.146)
Carbon leakage	-9.200***
	(3.128)
Period 1	-1.390
	(1.263)
Region 2 (BE, FR, NL)	-2.681
	(6.427)
Region 3 (GR, IT, PT, ES, CY, MT)	-13.80***

	(4.074)
Region 4 (EE, LT, LV, PL)	-5.973
	(4.007)
Region 5 (CZ, HU, SI, SK)	1.564
	(5.756)
Region 6 (DK, FI, IS, NO, SE)	-11.94***
	(3.221)
Region 7 (UK, IE)	-19.15***
	(7.006)
Region 8 (BG, HR, RO)	-24.750***
	(5.690)
Mean ITP	0.447
	(0.353)
Mean banking	-1.299**
	(0.518)
Mean transaction frequency	1.026
	(1.271)
Constant	-57.62***
	(6.138)
Observations	9,294
Companies	1,553

Table 37: Estimated average marginal effects on internal trading (analysis including combustion installations only).[84]

	Extensive margin [change in Prob(*internal trading* > 0)]	Intensive margin [change in E(*internal trading* | *internal trading* >)]
Internal trading potential	0.000	-0.018
	(0.000)	(0.013)
Banking	-0.001	-0.034
	(0.001)	(0.027)
Number of NUO companies	0.001***	0.056***
	(0.000)	(0.009)
Transaction frequency	0.008***	0.326***
	(0.001)	(0.053)
Energy	0.001	0.019
	(0.007)	(0.286)
Number of installations	0.000	0.020
	(0.000)	(0.016)
Carbon leakage	-0.024***	-1.022***
	(0.008)	(0.346)
Period 1	-0.004	-0.154
	(0.003)	(0.140)
Period 3	-0.006*	-0.161
	(0.003)	(0.148)
Region 2 (BE, FR, NL)	-0.007	-0.298
	(0.017)	(0.714)
Region 3 (GR, IT, PT, ES, CY, MT)	-0.015	-0.663
	(0.010)	(0.445)
Region 4 (EE, LT, LV, PL)	-0.036***	-1.533***
	(0.010)	(0.451)
Region 5 (CZ, HU, SI, SK)	0.004	0.174

[84] Marginal effects for interaction terms are shown in

.

	(0.015)	(0.639)
Region 6 (DK, FI, IS, NO, SE)	-0.031***	-1.327***
	(0.008)	(0.357)
Region 7 (UK, IE)	-0.049***	-2.127***
	(0.018)	(0.777)
Region 8 (BG, HR, RO)	-0.064***	-2.748***
	(0.015)	(0.627)
Region 8 (BG, HR, RO)	0.004	0.184
	(0.005)	(0.208)
Observations	9,294	
Companies	1,553	

Table 38: Estimated average marginal effects of the reform on the relationship between ITP and internal trading (analysis including combustion installations only).

	Extensive margin [change in Prob(*internal trading* > 0)]		Intensive margin [change in E(*internal trading* | *internal trading* >)]	
	Energy=0	*Energy=1*	*Energy=0*	*Energy=1*
ITP = 1	0.008	-0.013***	0.333	-0.592***
	(0.006)	(0.005)	(0.224)	(0.197)
ITP = 2	0.006	-0.015***	0.245	-0.650***
	(0.005)	(0.004)	(0.212)	(0.187)
ITP = 3	0.004	-0.016***	0.159	-0.708***
	(0.005)	(0.004)	(0.208)	(0.183)
ITP = 4	0.002	-0.017***	0.075	-0.766***
	(0.005)	(0.005)	(0.214)	(0.193)
ITP = 5	0.000	-0.018***	-0.007	-0.824***
	(0.005)	(0.005)	(0.226)	(0.193)
ITP = 6	-0.002	-0.020***	-0.088	-0.882***
	(0.005)	(0.005)	(0.244)	(0.206)
ITP = 7	-0.004	-0.021***	-0.168	-0.940***
	(0.006)	(0.005)	(0.266)	(0.223)
ITP = 8	-0.005	-0.022***	-0.245	-0.998***
	(0.006)	(0.006)	(0.290)	(0.243)
ITP = 9	-0.007	-0.024***	-0.322	-1.056***
	(0.006)	(0.006)	(0.317)	(0.266)
ITP = 10	-0.008	-0.025***	-0.397	-1.114***
	(0.007)	(0.007)	(0.344)	(0.290)
ITP = 11	-0.009	-0.026***	-0.470	-1.171***
	(0.007)	(0.007)	(0.372)	(0.315)
ITP = 12	-0.011	-0.027***	-0.542	-1.229***
	(0.008)	(0.008)	(0.400)	(0.342)
ITP = 13	-0.012	-0.029***	-0.613	-1.287***
	(0.008)	(0.008)	(0.428)	(0.369)
ITP = 14	-0.013	-0.030***	-0.682	-1.344***

	(0.008)	(0.009)	(0.456)	(0.397)
ITP = 15	-0.014*	-0.031***	-0.750	-1.402***
	(0.008)	(0.010)	(0.483)	(0.426)
ITP = 16	-0.015*	-0.033***	-0.817	-1.459***
	(0.009)	(0.010)	(0.511)	(0.454)
ITP = 17	-0.016*	-0.034***	-0.883	-1.517***
	(0.009)	(0.011)	(0.538)	(0.483)
Observations		9,294		
Companies		1,553		

9.8 Appendix A3 Robustness Checks

Table 39: Estimated marginal effects including number of employees and productivity (analysis including all installations).

	Extensive margin [change in Prob(*internal trading* > 0)]	Intensive margin [change in E(*internal trading* | *internal trading* >)]	Change in average *internal trading*
Internal trading potential	-0.000	-0.019	-0.005
	(0.00)	(0.012)	(0.003)
Banking	-0.001	-0.035	-0.009
	(0.001)	(0.027)	(0.007)
Number of NUO companies	0.001***	0.045***	0.012***
	(0.000)	(0.009)	(0.003)
Transaction frequency	0.007***	0.328***	0.086***
	(0.001)	(0.054)	(0.016)
Energy	0.007	0.340	0.089
	(0.006)	(0.294)	(0.078)
Number of Installations	0.000	0.018	0.005
	(0.000)	(0.015)	(0.004)
Carbon leakage	-0.011*	-0.547*	-0.143*
	(0.006)	(0.303)	(0.081)
Employees	0.001	0.053	0.014
	(0.003)	(0.139)	(0.037)
Productivity	0.001	0.024	0.006
	(0.002)	(0.107)	(0.028)
Period 2	0.008**	0.400**	0.105**
	(0.004)	(0.176)	(0.047)
Period 3	0.010***	0.480***	0.126***
	(0.003)	(0.147)	(0.040)
Region 2	-0.010	-0.483	-0.127
	(0.014)	(0.657)	(0.173)
Region 3	-0.029***	-1.400***	-0.367***
	(0.010)	(0.464)	(0.128)

Region 4	-0.011	-0.538	-0.141
	(0.009)	(0.431)	(0.114)
Region 5	-0.006	-0.302	-0.079
	(0.011)	(0.533)	(0.140)
Region 6	-0.026***	-1.228***	-0.322***
	(0.007)	(0.330)	(0.093)
Region 7	-0.039***	-1.870***	-0.491***
	(0.013)	(0.624)	(0.171)
Region 8	-0.048***	-2.331***	-0.611***
	(0.012)	(0.557)	(0.161)
Observations		9,444	
Companies		2,037	

Table 40: Estimated marginal effects including only observations with internal trading potential (analysis including all installations).

	Extensive margin [change in Prob(*internal trading* > 0)]	Intensive margin [change in E(*internal trading* | *internal trading* >)]	Change in average *internal trading*
Internal trading potential	-0.000	-0.012	-0.004
	(0.000)	(0.010)	(0.003)
Banking	-0.001**	-0.047**	-0.014**
	(0.001)	(0.022)	(0.007)
Number of NUO companies	0.001***	0.045***	0.013***
	(0.000)	(0.007)	(0.002)
Transaction frequency	0.008***	0.330***	0.099***
	(0.001)	(0.045)	(0.015)
Energy	0.001	0.056	0.017
	(0.006)	(0.246)	(0.074)
Number of Installations	0.000	0.020	0.006
	(0.000)	(0.015)	(0.005)
Carbon leakage	-0.019***	-0.797***	-0.240***
	(0.007)	(0.288)	(0.090)
Period 2	0.010***	0.409***	0.123***
	(0.004)	(0.151)	(0.046)
Period 3	0.012***	0.510***	0.153***
	(0.003)	(0.131)	(0.041)
Region 2	-0.027	-1.138	-0.342
	(0.018)	(0.746)	(0.227)
Region 3	-0.040***	-1.690***	-0.508***
	(0.010)	(0.405)	(0.131)
Region 4	-0.015	-0.650	-0.196
	(0.009)	(0.397)	(0.121)
Region 5	-0.005	-0.214	-0.064
	(0.013)	(0.546)	(0.165)
Region 6	-0.031***	-1.300***	-0.391***

	(0.007)	(0.312)	(0.101)
Region 7	-0.041***	-1.714***	-0.516***
	(0.013)	(0.566)	(0.177)
Region 8	-0.045***	-1.887***	-0.568***
	(0.011)	(0.476)	(0.153)
Observations		3,408	
Companies		1,364	

Table 41: Estimated marginal effects from Tobit model excluding 5% (instead of 2%) outliers in internal trading (analysis including all installations).

	Extensive margin [change in Prob(*internal trading* > 0)]	Intensive margin [change in E(*internal trading* | *internal trading* >)]	Change in average *internal trading*
Internal trading potential	0.000	-0.008	-0.002
	(0.000)	(0.010)	(0.002)
Banking	0.001**	0.052**	0.012**
	(0.000)	(0.022)	(0.005)
Number of NUO companies	0.001***	0.044***	0.010***
	(0.000)	(0.007)	(0.002)
Transaction frequency	0.001**	0.036**	0.008**
	(0.000)	(0.017)	(0.004)
Energy	-0.015***	-0.781***	-0.175***
	(0.005)	(0.276)	(0.064)
Number of Installations	0.007***	0.394***	0.088***
	(0.001)	(0.058)	(0.014)
Carbon leakage	0.007**	0.372**	0.083**
	(0.003)	(0.148)	(0.034)
Period 2	0.010***	0.521***	0.117***
	(0.002)	(0.130)	(0.031)
Period 3	-0.018	-0.953	-0.213
	(0.012)	(0.640)	(0.145)
Region 2	-0.029***	-1.551***	-0.348***
	(0.007)	(0.391)	(0.095)
Region 3	-0.014**	-0.749**	-0.168*
	(0.007)	(0.377)	(0.086)
Region 4	-0.009	-0.487	-0.109
	(0.009)	(0.511)	(0.115)
Region 5	-0.023***	-1.236***	-0.277***
	(0.005)	(0.298)	(0.072)
Region 6	-0.027***	-1.457***	-0.327***

	(0.010)	(0.535)	(0.124)
Region 7	-0.036***	-1.953***	-0.438***
	(0.009)	(0.472)	(0.115)
Region 8	0.000	-0.008	-0.002
	(0.000)	(0.010)	(0.002)
Observations		15,340	
Companies		2,505	

Table 42: Estimated marginal effects net sellers (analysis including all installations).

	Extensive margin [change in Prob(*internal trading* > 0)]	Intensive margin [change in E(*internal trading* | *internal trading* >)]	Change in average *internal trading*
Internal trading potential	0.000	-0.015	-0.003
	(0.000)	(0.013)	(0.003)
Banking	-0.001***	-0.078***	-0.018***
	(0.001)	(0.028)	(0.006)
Number of NUO companies	0.001***	0.039***	0.009***
	(0.000)	(0.007)	(0.002)
Transaction frequency	0.005***	0.261***	0.059***
	(0.001)	(0.049)	(0.012)
Energy	0.002	0.133	0.030
	(0.004)	(0.242)	(0.055)
Number of Installations	0.000*	0.025*	0.006*
	(0.000)	(0.015)	(0.003)
Carbon leakage	-0.014***	-0.758***	-0.171**
	(0.005)	(0.286)	(0.067)
Period 2	0.010***	0.541***	0.122***
	(0.004)	(0.202)	(0.047)
Period 3	0.012***	0.634***	0.143***
	(0.004)	(0.190)	(0.045)
Region 2	-0.015	-0.809	-0.182
	(0.012)	(0.646)	(0.147)
Region 3	-0.025***	-1.346***	-0.303***
	(0.007)	(0.394)	(0.094)
Region 4	-0.007	-0.406	-0.091
	(0.007)	(0.380)	(0.086)
Region 5	-0.003	-0.162	-0.036
	(0.009)	(0.513)	(0.116)
Region 6	-0.022***	-1.173***	-0.264***
	(0.006)	(0.307)	(0.075)

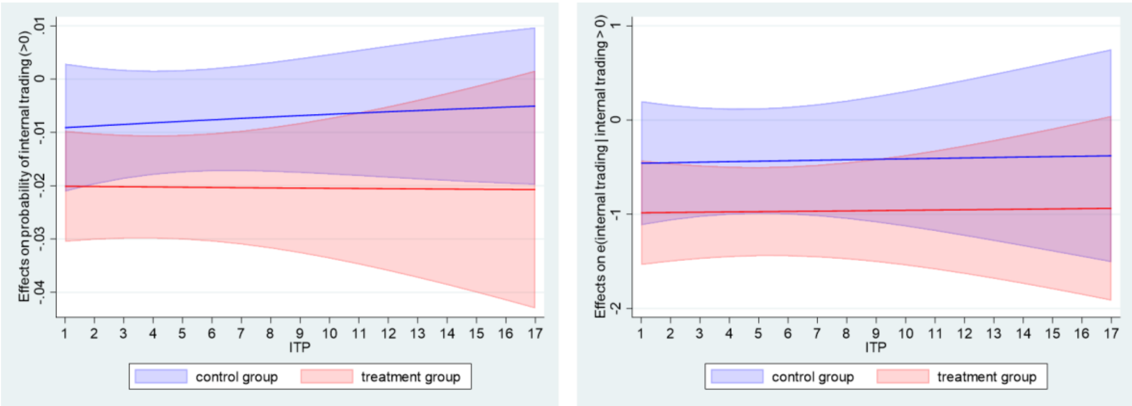
Region 7	-0.029***	-1.588***	-0.358***
	(0.011)	(0.574)	(0.135)
Region 8	-0.035***	-1.916***	-0.432***
	(0.009)	(0.496)	(0.121)
Observations		12,776	
Companies		300	

Table 43: Estimated marginal effects net buyers (analysis including all installations).

	Extensive margin [change in Prob(*internal trading* > 0)]	Intensive margin [change in E(*internal trading* | *internal trading* >)]	Change in average *internal trading*
Internal trading potential	0.000	-0.013	-0.005
	(0.001)	(0.020)	(0.007)
Banking	0.000	0.007	0.003
	(0.001)	(0.033)	(0.012)
Number of NUO companies	0.002***	0.062***	0.023***
	(0.000)	(0.011)	(0.005)
Transaction frequency	0.008***	0.250***	0.093***
	(0.003)	(0.080)	(0.031)
Energy	0.010	0.319	0.119
	(0.011)	(0.369)	(0.139)
Number of Installations	0.000	0.011	0.004
	(0.001)	(0.019)	(0.007)
Carbon leakage	-0.012	-0.381	-0.142
	(0.012)	(0.403)	(0.151)
Period 2	0.018*	0.570*	0.213*
	(0.010)	(0.326)	(0.123)
Period 3	0.023***	0.733***	0.274***
	(0.008)	(0.259)	(0.100)
Region 2	-0.031	-1.005	-0.375
	(0.040)	(1.282)	(0.481)
Region 3	-0.057***	-1.851***	-0.691***
	(0.019)	(0.623)	(0.248)
Region 4	-0.037**	-1.196**	-0.447*
	(0.018)	(0.596)	(0.229)
Region 5	-0.059*	-1.906*	-0.712*
	(0.032)	(1.057)	(0.403)
Region 6	-0.037***	-1.182***	-0.442**
	(0.013)	(0.446)	(0.175)

Region 7	-0.074***	-2.382***	-0.890**
	(0.027)	(0.898)	(0.351)
Region 8	-0.056***	-1.791***	-0.669***
	(0.019)	(0.645)	(0.253)
Observations		3,171	
Companies		146	

Figure 14: Marginal effects of the reform on the relationship between ITP and internal trading net sellers only (analysis including combustion installations only).



Left panel shows extensive margin, right panel shows intensive margin. Shaded areas correspond to 90% CI.

10. List of Publications

10.1 Peer-reviewed Publications

Abrell, Jan; Cludius, Johanna; Lehmann, Sascha; Schleich, Joachim; Betz, Regina. (2022). "Corporate Emissions-Trading Behaviour During the First Decade of the EU ETS." *Environmental & Resource Economics*, 83(1): 47–83. DOI 10.1007/s10640-021-00593-7.

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10.2 Further Publications

Aydemir, Ali, Warnke, Philine, Lehmann, Sascha und Arens, Marlene. (2024). "Dekarbonisierung der industriellen Produktion (DekarbInd) – Teilbericht 2: Erarbeitung von Eckpunkten für die Dekarbonisierung der Stahlindustrie." *Climate Change* 06/2024, Umweltbundesamt.https://www.umweltbundesamt.de/sites/default/files/medien/11850/publikationen/06_2024_cc_dekarblnd_tb2.pdf.

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Graichen, Verena; Förster, Hannah; Graichen, Jakob; Healy, Sean; Repenning, Julia; Schumacher, Katja; Duscha, Vicki; Friedrichsen, Nele; Lehmann, Sascha; Erdogmus, Gizem; Haug, Ines; Kim, Solbin; Zaklan, Aleksandar; Diekmann, Jochen. (2019). "Evaluierung und Weiterentwicklung des EU-Emissionshandels aus ökonomischer Perspektive für die Zeit nach 2020 (EU-ETS-7)." *Climate Change 29/2019*, Umweltbundesamt, Dessau-Roßlau.

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Wachsmuth, Jakob; Alexander-Haw, Abigail; Billerbeck, Anna; Breitschopf, Barbara; Brunzema, Iska; Berger, Carmen; Lehmann, Sascha; Panny, Julia; Rohde, Clemens; Zheng, Lin; Velten, Eike Karola; Duin, Laurens. (2023). “National Energy and Climate Plans: Evidence of Policy Impacts and Options for more Transparency.” *Climate Change* 38/2023. https://www.umweltbundesamt.de/publikationen/national-energy-climate-plans-evidence-of-policy.

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List of Abbreviations

Abbreviation	Full Term
AOA	Aircraft Operator Account
CBAM	Carbon Border Adjustment Mechanism
CITL	Community Independent Transaction Log
CO_2	Carbon Dioxide
CRE	Correlated Random Effects
DiD	Difference-in-Differences
EEA	European Economic Area
EED	Energy Efficiency Directive
EEX	European Energy Exchange
ESR	Effort Sharing Regulation
ETS	Emissions Trading System
EU ETS	European Union Emissions Trading System
EUA	European Union Allowance
EUTL	European Union Transaction Log
GHG	Greenhouse Gas
GUO	Global Ultimate Owner
ICE	Intercontinental Exchange
IPCC	Intergovernmental Panel on Climate Change
ITL	International Transaction Log
ITP	Internal Trading Potential
LRF	Linear Reduction Factor
LULUCF	Land Use, Land-Use Change and Forestry

Abbreviation	Full Term
MSR	Market Stability Reserve
NACE	Nomenclature statistique des activités économiques dans la Communauté européenne
NUO	National Ultimate Owner
N_2O	Nitrous Oxide
OHA	Operator Holding Account
OTC	Over-the-Counter
PFC	Perfluorocarbon
PHA	Person Holding Account
QMLE	Quasi-Maximum Likelihood Estimator
RED	Renewable Energy Directive
RQ	Research Question
TA	Trading Account
UNFCCC	United Nations Framework Convention on Climate Change