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07/08/2025

I am Gianluca Bidinot, a PhD candidate at the University of Reading, Henley Business School, ICMA Centre, with an expected completion date of September 25, 2026. My current research focuses on the impact of the EU Emissions Trading System (EU ETS) on the European steel sector, specifically investigating whether the policy has caused carbon leakage. I employ a combined micro-level approach using financial data from individual companies and plant-level emission estimates, alongside a macro-level analysis leveraging trade data to trace actual carbon flows linked to steel trade.

Looking ahead, I aim to extend this research framework to other high-emission sectors such as cement, pulp and paper, and aluminium, utilizing emissions and production estimates from Climate Trace. Additionally, I am interested in studying the effectiveness of renewable energy subsidies on the carbon intensity of electricity grids and their implications for achieving net-zero goals, including potential interactions with alternative energy sources like nuclear power.

I would be pleased to provide further information and can refer to my faculty advisors, Dr. Simone Varotto (s.varotto@henley.ac.uk) and Dr. Alfonso Dufour (a.dufour@henley.ac.uk), who can serve as references.

Thank you for your consideration.

Sincerely,
Gianluca Bidinot

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EDUCATION

PHD IN FINANCE — **ICMA Centre, Henley Business School, UK**
Climate Finance — **2023 - Present**
M.SC IN ECONOMICS AND FINANCE — **Università Ca' Foscari, VENICE, ITA**
Final grade 110 cum Laude — **2021-2023**

- Fully taught in English
- Main modules: Derivatives and Insurance, Stochastic Calculus for Finance, Financial Economics, Risk Measurement, International Financial Regulation, Behavioural Finance

B.SC IN ECONOMICS — **Università degli studi di Padova, PD, ITA**
Final grade 108 — **2018-2021**

- Major in Economics and Finance
- Minor in Political Economy

WORK EXPERIENCES

ICMA CENTRE — **Reading, UK**
Associate Lecturer — **2023 - Present**

- Modules taught: Credit Risk

BCC PORDENONESE E MONSILE — **Silea, Pramaggiore, Fiume Veneto, ITA**
Internship

- Update and revision of the mortgage collateral database — **June-August 2023**
- Post M&A integration process unit — **July-August 2017**
- Retail and commercial credit origination unit — **June-August 2016**

STUDIO COMMERCIALISTA LIUT — **Villotta di Chions, ITA**
Internship — **July-August 2021**

- Reconstruction of an over-indebted position for a Bankruptcy procedure
- General accounting procedures and Tax declarations

LANGUAGE KNOWLEDGE

- ITALIAN – C2 LEVEL (native speaker)
- ENGLISH – C1 LEVEL – IELTS Academic Band 8.0 07/2023

TECHNICAL SKILLS

- **Office package**: advanced knowledge
- **Python, R, Matlab:** intermediate knowledge
- **SQL:** intermediate knowledge

PERSONAL DEVELOPMENT AND SKILLS

During the last months of 2022 I had the opportunity to participate in the Bloomberg Trading Challenge where I acquainted myself with the Bloomberg interface and to make some practice at managing a portfolio.
I have always had an interest in volunteering which I have mainly expressed in mu participation in the Catholic Action of which I am an educator (since 2016). This experience has allowed me to learn how to relate with people of different backgrounds and ages and to actively collaborate in a group environment.

Hidden Emissions and Carbon Leakage in the EU Steel Sector

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Abstract

We are the first to study the potential direct and indirect carbon leakage effects of the EU Emissions Trading Scheme (ETS) in its newest phases on the EU steel industry, using independent plant-level emissions and production estimates. We employ a difference-in-differences framework, leveraging financial constraints as an identifying mechanism, to assess direct carbon leakage in steel plants operated by geographically diversified firms outside the EU27. We find no significant reallocation of production or emissions in those plants, indicating no evidence of direct carbon leakage.

To explore indirect carbon leakage, we analyse steel trade flows to and from the EU27 bloc. After constructing the carbon flows associated with steel trade, we find no significant increase in the share of imported "steel" CO_2 relative to the CO_2 resulting from domestic steel production. This result also holds when comparing imported and domestically produced raw steel.

Finally, to corroborate the previous results, we compare estimated emissions, verified emissions, and allocated emissions allowances (EUA) for the steel sector. We find that verified emissions are consistently lower than allocated allowances, implying that, on an aggregate level, the sector did not need to purchase additional permits. Moreover, verified emissions are lower than estimated emissions across the entire period analysed, which may suggest emissions underreporting.

Keywords: Carbon leakage, EU ETS, Financial constraints, Trade flows, Carbon flows

1. Introduction

The steel sector remains one of the largest contributors to industrial CO_2 emissions. Thus, it is important to investigate the effect that the EU Emissions Trading System (EU ETS)—the first and still the largest carbon market in operation globally— had and still has on the European steel industry. Specifically, we are interested in assessing whether the introduction of carbon pricing has led to carbon leakage, thereby undermining the primary objective of the program: emissions reduction. One of the main novelties of our analysis comes from the period analysed: 2015–2024, which covers most of Phases III and IV of the EU ETS, which up to now, have been left understudied.

We begin by analysing verified emissions and allowance data from the EU steel sector using the publicly available European Union Transaction Log (EUTL), which records all transactions under the EU ETS. We compare verified emissions and freely allocated emissions allowances at the national level. We find that in most of the EU member states, verified emissions are consistently below freely allocated allowances (the emissions permits), implying that the steel companies did not need to purchase additional allowances via auctions or secondary markets. This suggests the price signal intended by the EU ETS was not binding for the sector. A primary explanation is that the steel industry appears on all three of the carbon leakage risk lists compiled by the European Commission, entitling it to more generous free allocations aimed at mitigating carbon leakage risk, This phenomenon can at least partially be traced to a successful lobbying activity exercised by companies and sectors affected by the carbon policy, as suggested in the literature (e.g. Markussen and Svendsen (2005), and Böhringer and Rosendahl (2009)).

We then narrow our focus to steel plants with direct production capabilities, excluding rolling mills and specialized plants processing semi-finished goods. We compare their verified emissions and allocated allowances with independent emissions estimates from Climate TRACE. We observed that for a large number of plants, estimated emissions and verified emissions tend to diverge significantly, possibly suggesting problems in the reporting system or difficulties in the estimation tecnique. The majority of the inconsistencies are led by plant employing a combination of blast furnaces and basic oxygen furnaces (integrated steel mills that create steel starting directly from iron ore) which are the larger steel plants in the sample.

Given these findings, we would not expect to find any significant evidence

of carbon leakage, since verified emissions remain below freely allocated allowances—removing any possible incentive to reallocate production abroad due to compliance costs under the ETS.

We proceed to examine the two principal channels of carbon leakage: direct leakage, defined as a shift in production from EU-based plants to those owned outside the carbon-pricing regime; and what we define "indirect leakage", characterized by increased imports of carbon-intensive goods from countries not subject to equivalent regulation (also referred as “pollution-heavens” in the literature).

To assess potential direct leakage, we implement a plant-level microanalysis inspired by Bartram et al. (2022). We exploit the start of Phase IV (01/01/2021) as a quasi-natural experiment to examine whether geographically diversified firms shifted production to non-EU plants. We employ a difference-in-differences (DiD) approach at the plant level, including both plant and year fixed effects to control for time-invariant heterogeneity and common shocks that leverages financial constraints to uncover possible leakages. Firms are categorized as financially constrained or unconstrained using metrics adapted from Bartram et al. (2022), though we substitute some measures to account for unlisted firms. Our main regression specification indicates that, although emissions decrease post-2021 in EU plants of geographically diversified and financially constrained firms, we do not find a corresponding increase in emissions from their non-EU plants. This suggests no reallocation of production outside the EU in response to the policy. We conduct extensive robustness checks, including improvements to some controls applied in the reference paper of Bartram et al. (2022) (notably using proprietary estimated plant-level data on production and capacity given by Climate Trace), but across all specifications, we find no evidence supporting the reallocation hypothesis (i.e. direct carbon leakage.

For the indirect leakage analysis, we adopt a macro-oriented approach combining monthly steel trade data from Eurostat and Comext with monthly country-level emissions data to examine trends in both the volume of steel imports and the associated CO content. The analysis proceeds in two steps. First, we apply change-point detection algorithms to import and export data between EU countries and the rest of the world (2001–2024) to identify whether there are or not significant structural breaks and if they align with the introduction of different EU ETS phases. We find multiple statistically significant breakpoints in steel import from non-EU countries, some of which align closely with phase start dates.
Second, we examine how the ratio of imported steel and associated carbon flows

evolved relative to domestic steel production and emissions. Using monthly trade data and monthly steel carbon intensity estimates from 2015–2024, we construct carbon flow indicators that approximate the CO embedded in imported steel. While simple in concept, this approach represents a key methodological contribution of the paper, as it provides a close approximation of embodied carbon flows—enabled by granular emissions estimates at the steel-plant level and detailed production technology data. We find that the ratio of imported steel, direct (Scope 1), and total (Scope 1 + 2) steel-related emissions remain broadly stable throughout the sample period—with slight declines over the last part of the sample period. If indirect carbon leakage were occurring, we would expect these ratios to rise over time, reflecting and increase in the reliance of foreign more carbon-intensive imports to fill the insufficient domestic production (caused by the existence of a hypothetical positive carbon tax)

Our findings on both direct and indirect channels of leakage support our initial hypothesis: no significant carbon leakage has occurred in the European steel sector. The EU's anti-leakage provisions appear to have been effective. However, this success has come at a cost: generous free allocation has largely muted the intended price signal of the ETS, reducing incentives for firms to adopt cleaner production technologies and reduce their emissions footprint. Lastly, the stark divergence between some estimated emissions and verified emissions of large steel plants is a concern. Since the availability of independent third-party data has improved significantly in recent years an integration of the latter to complement official data could help improve the quality, the accountability and the positive outcomes of crucial policies such as the EU ETS.

2. BACKGROUND

2.1 Carbon policies and the EU ETS

Regulators have at their disposal two primary categories of policies to address carbon emissions: direct carbon pricing instruments, including Emissions Trading Schemes (ETSs), Carbon Taxes, and Carbon Crediting Mechanisms; and *indirect carbon pricing instruments*, such as fuel excise taxes, fossil fuel subsidies, and differentiated VAT rates. The former provides a clear price signal with the goal of reducing greenhouse gas (GHG) emissions, while the latter entails policies that alter product prices without direct proportionality to the associated emissions. As outlined in the World Bank's Carbon Pricing report *State and Trends of Carbon Pricing 2023* (2023), here are the general definitions of the main carbon policies:

1 **Emissions Trading Scheme (ETS)**: Implemented to curb the growth of pol-

lutant gas emissions from covered entities (firms), an ETS issues tradable emissions units (allowances) used to cover each firm's annual emissions. The ETS can take the form of a cap-and-trade system, where the maximum allowed emissions are determined by the number of allowances, or a rate-based system, where total emissions are not predefined, and each firm is assigned a performance benchmark to limit individual net emissions.

2 **Carbon Tax**: A direct taxation on emissions produced by firms or the emissions embedded in traded goods (e.g., EU CBAM)

3 **Carbon Crediting Mechanism**: This mechanism generates tradable certificates representing emissions reductions. Firms can obtain these certificates by participating in green projects committed to reducing or preventing new carbon emissions. Such projects may involve creating new forests, protecting existing forests from deforestation, or other green initiatives (see Financial Times article Bryan (2023*a*)).

2.2 EU ETS Overview

The EU Emissions Trading System (EU ETS)[1] was launched in **Phase I (2005–2007)** as a pilot to establish the infrastructure for monitoring, reporting, and verifying emissions, as well as creating a functioning market for trading emission allowances. Coverage initially included electric power plants and energy-intensive industries, based on installation size rather than emission thresholds. Caps and allowances were set at the national level using estimated emissions data, which resulted in over-allocation. Allowances could not be banked into the next phase, and prices collapsed to zero.

Phase II (2008–2012) marked the first full commitment period under the Kyoto Protocol, expanding coverage to additional sectors as defined in Directive 2003/87/EC. Banking of allowances between phases was permitted, and firms could use international credits via the *Clean Development Mechanism (CDM)* and *Joint Implementation (JI)*. The **European Union Transaction Log (EUTL)** was established to centralize registry operations, recording installation coverage, free allocations, allowance accounts, transfers, verified emissions, and reconciliations. Although caps were adjusted using verified emissions from Phase I, the 2008 financial crisis sharply reduced emissions, leading to a surplus of 1.7 billion

[1] All information sourced from the European Commission website *EU Emissions Trading System (EU ETS)* (2023).

EUAs[2] carried forward into Phase III.

Phase III (2013–2020) introduced a single EU-wide cap, replacing national caps, and significantly reduced the free allocation of allowances while increasing auctioning as the primary allocation method. Use of international credits was phased out to focus on domestic reductions. To address the surplus, the EU implemented: (i) a short-term *back-loading* measure, postponing the auctioning of 0.9 billion EUAs from 2014–2016 to 2019–2020; and (ii) the creation of the **Market Stability Reserve (MSR)** in 2019, a long-term mechanism to regulate allowance supply.

Phase IV (2021–2030) retains free allocation for the full phase, adds maritime transport to ETS coverage starting in 2024, and includes a scheduled directive review in 2026. The MSR operates under strict, rule-based criteria: back-loaded and unallocated allowances are transferred to the reserve; from 2023, stored allowances are capped at the volume auctioned in the previous year; and any excess is cancelled to maintain market stability.

Carbon Leakage Measures were introduced in Phase III to protect sectors at risk of relocating production to avoid carbon costs. Lists of such sectors at the NACE 4+ level were established through impact assessments and stakeholder consultations: 2013–2014 (164 sectors), 2015–2020 (175 sectors), and 2021–2030 (63 sectors). Free allocation for listed sectors is based on industry benchmarks and remains at 100% of calculated levels, while non-listed sectors face a progressive reduction in free allocations.

2.2.1 Literature on the ex-post evaluation

The literature on the ex-post valuation of the real effects of the EU Emission Trading System (ETS) predominantly focuses on the analysis of the program's first two phases. Contrary to initial concerns, the majority of studies, such as those by Arlinghaus (2015), Martin et al. (2015), and Venmans (2012), have found no significant negative impact on the competitiveness of the treated firms.

A particularly noteworthy study by Marin et al. (2018) tested the effect of the ETS program on several indicator for economic performance suchs as: employment,average wages,turnover,value added, markup, investment, labour productivity, total factor productivity and ROI. To carry out such study, they

[2] *Publication of the total number of allowances in circulation for the purposes of the Market Stability Reserve under the EU Emissions Trading System established by Directive 2003/87/EC* (2017)

constructed a counterfactual for treated firms, using a control group at the firm level as suggested by Calel and Dechezleprêtre (2016) and Jaraitė and Maria (2016). The authors concluded that the first two phases of the EU ETS had a positive impact on turnover, markup, investment intensity, and labor productivity for the treated firms. Various explanations for this phenomenon were proposed:

- **Pass-through of Additional Costs**: Treated firms appeared to pass through the additional costs to consumers, evidenced by an increase in markups.
- **Increased Labor Productivity**: A potential consequence of the rise in investment rate, though the robustness of this finding across the entire sample was not uniform.
- **Stimulated Innovation**: The policy may have stimulated low carbon related innovation among treated firms, contributing to increased competitiveness. Calel and Dechezleprêtre (2016) observed a circa 10% increase in low carbon-related patenting attributable to the EU ETS. although we need to remind that the positive effects of the increase in innovation should manifest itself on the medium-long term.

In an effort to measure carbon leakage,Naegele and Zaklan (2019) examined changes in trade flows, incorporating data from the European Transaction Log (EUTL) and the Global Trade Analysis Project (GTAP). Their findings indicated no significant evidence of carbon leakage, as there was no observable increase in embodied carbon imports or strong impacts on trade flows. The absence of statistically significant trade effects led the authors to infer that barriers preventing carbon leakage, such as the abundance of free allocated allowances in the first two phases of the EU ETS, fixed relocation costs, and other risk factors related to relocation, were greater than the emissions costs generated by the policy. This successful prevention of carbon leakage highlighted the effectiveness of the EU ETS in maintaining its intended environmental impact.

3. DATA

3.1 Emission Data

Steel production is a key indicator for estimating emissions (measured as kg CO2 per ton of steel), so having accurate and up-to-date data is vital for climate policy. However, competition in the global steel industry makes facility-level data hard to get. Usually, only country-level data is available, and it's often delayed by years, according to sources like E-PRTR, UNFCCC, and the US EPA. The methodology used by CLIMATE TRACE aims to tackle these issues by providing monthly

production and emissions estimates for individual steel plants, with just a one-month delay. It covers all plants listed in the Global Energy Monitor's Global Steel Plant Tracker (GEM, 2024). Instead of relying on rough capacity guesses, such as evenly splitting production or using average rates, this approach uses satellite data to spot activity changes in steel plants. By analyzing these patterns, it estimates production more accurately and quickly than traditional methods. Steel production releases direct emissions during the making of crude steel, and these vary depending on the production method: blast furnace-basic oxygen furnace (BF-BOF), direct reduced iron-electric arc furnace (DRI-EAF), or electric arc furnace (EAF). Since detailed emissions data for individual plants isn't publicly available, Climate trace used a "bottom-up" approach to estimate emissions. This involves two steps: first, calculating how much crude steel each plant produces (in tons), then multiplying that by an emissions factor (tons of CO2 per ton of steel) specific to the production method. We study each major production route—BF-BOF, DRI-EAF, and EAF—using a mix of satellite imagery, public reports, and academic studies.

For the estimation process, two methods were employed: For plants like BF-BOF, which operate at high temperatures (over 1,200°C) and release detectable heat from units such as coke plants, sinter plants, blast furnaces, slag pits, and basic oxygen furnaces, we rely on satellite imagery to measure activity and infer output. This approach, supported by studies like Zhou et al. (2018), Marchese et al. (2019), and Liangrocapart et al. (2020), works well when heat signals are clear. For plants where satellites do not pick up heat—like most EAF or DRI-EAF facilities—we use a simpler method: we calculate each plant's share of the total steel capacity of a country and apply that to the country's reported production for the time period. These plant-level estimates can then be added to match national statistics. For more details on the modeling, see M'Barek and Gray (2021).

3.1.1 Environmental Protection Agency Data

To establish a benchmark for our estimated emissions data, we utilized one of the most comprehensive global emissions datasets: the U.S. Environmental Protection Agency (EPA) repository. Under the Clean Air Act (CAA), originally enacted in 1963, the EPA began collecting mandatory reports on greenhouse gas (GHG) emissions—including carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, sulfur hexafluoride, and nitrogen trifluoride—through the Mandatory Greenhouse Gas Reporting Rule, finalized in September 2009. This regulation requires all facilities emitting 25,000 metric tons or more of CO_2-equivalent (CO_2e) annually to report their emissions. In addition to direct emitters, relevant suppliers of fossil fuels and industrial gases are also required to

report under this program.

In our analysis, we compared the estimated emissions of iron and steel plants in our dataset with those reported in the EPA's Facility Level Information on Greenhouse Gases Tool (FLIGHT). While the FLIGHT database contains emissions data from 2011 to 2023, we restricted our comparison to the 2015–2023 period to align with the timeframe covered by the Climate TRACE dataset.

3.1.2 Steel facility inventory dataset

The Global Energy Monitor (GEM) provides detailed data on steel plants through its Global Steel Plant Tracker (GSPT). This includes facility-level details like GPS coordinates, owner, production capacity, age, product type, and technology used. The dataset covers all plants with a capacity of at least 500,000 metric tons per year (0.5 Mt/a) that are currently operating, as well as those proposed or under construction since 2017, or retired or mothballed since 2020. By 2024, there were 1,163 unique facilities with a total capacity of 3.4 billion tons spread across 89 countries.
Although GEM provides geolocation for each plant, some coordinates are approximate. Therefore, to improve accuracy, the initial coordinates were improved using Google Maps API and OpenStreetMap, followed by a manual check for all locations.

3.1.3 Remote sensing

Satellite-based production estimates use multispectral imagery from two sources: the European Space Agency (ESA) Copernicus Sentinel mission and the U.S. Geological Survey (USGS) and NASA Landsat program. The Sentinel mission, with a 20-meter resolution and a 5-day revisit using two satellites (Sentinel-2A and 2B), provides images dating back to 2015 for 2A and 2017 for 2B (ESA, 2024). The Landsat program, with a 30-meter resolution and an 8-day revisit using two satellites (Landsat-8 and 9), offers images from 2013 for Landsat-8 and 2021 for Landsat-9 (NASA and USGS, 2024a, 2024b). All images were processed using Google Earth Engine . To detect heat from steel plants, surface reflectance data were analyzed. For the estimation between 2015 and 2020, Climate trace employed the Normalised Heat Index (NHI) which was calculated using the difference between two shortwave infrared (SWIR) bands for each satellite:

- Sentinel-2A/B: $NHI = (B12 - B11)/(B12 + B11)$
- Landsat-8/9: $NHI = (B7 - B6)/(B7 + B6)$

From 2021 onwards, this was updated to the tri-spectral Thermal Anomaly Index (TAI), which uses two SWIR bands and a near-infrared (NIR) band to better spot high-temperature activity (based on Yongxue et al., 2021):

- Sentinel-2A/B: $TAI = (B12 - B11)/B8a$
- Landsat-8/9: $TAI = (B7 - B6)/B5$

Here, B refers to specific wavelength bands each satellite measures. These ratios help identify heat from industrial processes while reducing interference from other reflections. To combine Sentinel and Landsat data into one consistent dataset, pixel values were adjusted using NASA's band pass methods (NASA, 2018). This boosts the frequency of usable images for tracking changes over time. We exclude images with less than 80% coverage of a facility or more than 20% cloud cover.

3.1.4 Production data

National steel production data for the Climate Trace model comes mainly from the World Steel Association, collected monthly.Data covers all countries and provinces starting from January 2015. In a few countries—like Albania, Morocco, and North Korea—only yearly data was available, so monthly estimate figures were evenly split from the annual totals. In 12 countries, production data existed but no matching plants were listed in the GEM database, likely because it only includes facilities with capacities above 0.5 Mt/a.

3.1.5 Emissions factor data

To convert steel production into emissions, from 2015 to 2020 emissions factors (tons of CO2 per ton of steel) that varied by production method and country were used. These came from Global Efficiency Intelligence (GEI, 2022) for 17 countries: Brazil, Canada, China, France, Germany, India, Italy, Japan, Mexico, Poland, Russia, South Korea, Spain, Turkey, Ukraine, the United States, and Vietnam. For other countries, a median emissions factor was applied for each production process to avoid skewing results with extreme values. Power-related emissions (e.g., from electricity use) were excluded, as they're tracked separately in the Climate TRACE Electricity sector. From 2021 onward, Climate Trace shifted to using global average emissions factors and electricity use data from the Mission Possible Partnership's Steel Transition Strategy (MPP, 2024), simplifying the approach across all production routes.

3.1.6 Production and Emission estimates

For BF-BOF plants, which operate at high temperatures (over 1,200°C) and release heat from units like blast furnaces (BFs), coke ovens, sinter plants, pellet plants, and basic oxygen furnaces (BOFs), satellite imagery was employed to detect hotspots. These heat sources were tracked by their intensity over time using the Thermal Anomaly Index (TAI) or Normalised Heat Index (NHI) from satellite data. Then, for each plan a time-series of hotspot signals was extracted and normalized to be subsequently matched to monthly country-level production data from the World Steel Association. An optimization process was then used to find a relationship—or weight—between the hotspot strength and production, ensuring estimates were not exceeding a plant's maximum capacity. This method covers 345 BF-BOF plants and 2,301 sub-assets across 40 countries.

For plants not tracked by satellites (e.g., EAF facilities with less detectable heat), we use a simpler method. We calculate each plant's share of a country's total steel capacity and multiply it by the country's remaining production (after subtracting satellite-based estimates). For example, in a country with two plants—A (capacity C_A) and B (capacity C_B)—and total production P for a month, their estimates are:

- $P_A = (C_A/(C_A + C_B))P$
- $P_B = (C_B/(C_A + C_B))P$

For BF-BOF plants not monitored by satellites, an average utilization rate was applied from similar facilities in the same country or region, based on satellite data. For EAF plants instead, a regional average utilization rate from historical national production and capacity was used.

Facility level emissions estimates were then calculated by multiplying production estimates the for the relevant emissions factors.

3.2 Ownership Data

The Climate TRACE ownership dataset is built through a two-stage process: (1) compiling asset-level ownership data for individual steel plants, and (2) mapping these to ultimate parent companies. Steel plants are defined as facilities producing ≥ 0.5 Mt/year of crude steel, with core data sourced from the Global Steel Plant Tracker (GSPT) maintained by Global Energy Monitor (GEM). Ownership is expressed as "percent financial interest" and extracted from GEM's *owner* field, defaulting to *parent* if missing. Plants are aggregated into a consolidated dataset,

then processed by an algorithm linking each owner to its ultimate parent through corporate networks, including subsidiaries and joint ventures. Emissions are assigned proportionally to ownership shares, following WorldSteel's attribution rules (>50% = 100%, 30–50% = pro-rated, <30% = excluded).

Three external datasets—Wikidata, OpenCorporates, and the Global Legal Entity Identifier Foundation (GLEIF)—are used to map and verify ownership. Names are standardized in OpenRefine through string-matching and removal of sector-specific or legal suffixes. Unresolved or high-impact cases are resolved manually using corporate disclosures and industry sources. Validation against WorldSteel's 2021 data for the top 114 producers yielded 81% coverage, with gaps mainly due to missing GEM plant data rather than mapping errors.

Following mapping, the dataset was merged with ORBIS ownership records to attach financial data. This required extensive manual corrections for naming inconsistencies and misidentified corporate structures. Chinese firms were systematically excluded due to both structural mismatches and, most importantly, the near-absence of financial data in ORBIS.

3.3 Financial constraints Data

Following the approach of Bartram et al. (2022), we decided to construct a composite financial constraint index to evaluate whether the degree of financial constrainedness influenced the emissions-related decisions of firms subjected to the EU Emissions Trading System (EU ETS). Given that the analysis encompassed an expanded sample of both listed and non-listed firms linked to steel plants via our augmented ownership mapping, the financial constraint indexes we reference to required adaptation to accommodate this heterogeneity. Consequently, a tailored combination of indexes was selected: the SA Index, the FCP Index (per Schauer et al. (2019)), the Size Index, the Payout Index, and the Credit Rating Index. This mix balances applicability across firm types, with the FCP Index specifically chosen for its robustness in assessing private firms' financial health, complementing the listed-firm focus of Bartram et al.'s original framework. Financial data were sourced from ORBIS for the timeframe 2010–2023, and from Bloomberg for the same timeframe (the rating of long and short term debt)

3.3.1 Hadlock and Pierce Index

Starting from a critique of the limitations of the Kaplan-Zingales (KZ) index, the Hadlock and Pierce (2010) employed ordered logit models to identify predictors

of constraint status, derived from managerial disclosures categorized into five levels. Their analysis reveals firm size and age as robust, exogenous indicators, contrasting with the inconsistent performance of KZ index components like cash holdings, which positively correlate with constraints contrary to prior assumptions. With a pseudo-R^2 of 0.133 in-sample, the SA index outperforms the KZ index (correlation near zero) and is partially aligned with the Whited-Wu index due to shared size effects. Its validity is corroborated by significant cash flow sensitivity of cash among constrained firms, per Almeida et al. (2004), offering a practical, theoretically sound alternative for financial constraints research which leverages on the notion that smaller, younger firms face greater capital access limitations. It is calculated as :

$$SA\ Index_{i,t} = -0.737 Size_{i,t} + 0.043 Size_{i,t}^2 - 0.040 Age_{i,t}$$

where **Size** is defined as the natural logarithm of total asset (total asset are capped at $4.5 billion) and **Age** is years since incorporation (capped at 37).

3.3.2 FCP Index

In their study Schauer et al. (2019) introduce the FCP index, a novel measure of financial constraints tailored to enhance the identification of constrained firms across both private and public domains. They derive this index by leveraging a unique dataset from the ifo Investment Survey, spanning 1989 to 2012, which captures managers' self-assessments of financial constraints among private German manufacturing firms. Recognizing the limitations of extant indices—such as the KZ, WW, SA, and ASCL measures—which exhibited significant misclassification rates (approximately 14–15%) when benchmarked against survey responses, the study employs logit regressions to systematically identify a parsimonious set of predictors. All the financial data are lagged by one period to mitigate endogeneity concerns. This specification achieves robust in-sample discriminatory power, with an area under the ROC curve (AUC) of 0.699, and outperforms prior measures in out-of-sample forecasts (AUC ranging from 0.686 to 0.765 for 2009–2012). The index's design reflects a deliberate focus on variables that capture both internal financial health and external financing frictions, offering a theoretically grounded and empirically validated tool for assessing financial constraints.

$$FCP_{i,t} = -0.123 F_Size_{i,t-1} - 0.024 Int_Cov_{i,t-1} - 4.404 ROA_{i,t-1} - 1.716 C_Hold_{i,t-1}$$

where we define **F_Size** as the natural logarithm of the total assets (the different name is to differentiate from the one employed in the SA index), **Int_Cov**

as the ratio between the EBIT and the interest expense,and **C_Hold** as the ratio between cash holding and total assets

3.3.3 Firm Size Index

Firm size, measured as the natural logarithm of total assets, is used because smaller firms typically face greater financing frictions. Small firms are often younger, less established, and less known to investors, making them more vulnerable to capital market imperfections. As noted in Almeida et al. (2004) and Gilchrist and Himmelberg (1995), smaller firms tend to lack the scale and reputation to secure external funds easily. Larger firms, by contrast, benefit from economies of scale, greater visibility, and established relationships with lenders and investors, reducing their reliance on internal cash reserves. The authors rank firms annually by asset size, assigning those in the bottom three deciles as constrained and the top three as unconstrained, expecting smaller firms to exhibit higher cash flow sensitivity of cash due to limited external financing options.

3.3.4 Payout Index

The payout ratio, calculated as total distributions (dividends plus stock repurchases) divided by profit after tax, proxies financial constraints because constrained firms tend to retain earnings rather than distribute them to shareholders. This follows Fazzari et al. (1988), who suggest that firms facing financing constraints prioritize internal funds for investment over payouts. Constrained firms, anticipating future funding needs and limited external access, conserve cash by keeping payout ratios low. Unconstrained firms, with readily available external capital, can afford higher payouts without jeopardizing investment opportunities. The study ranks firms annually, placing those in the bottom three deciles (low payouts) as constrained and the top three (high payouts) as unconstrained, hypothesizing that low-payout firms will save more cash from cash flows.

3.3.5 Credit Rating Index

Credit ratings, encompassing bond and commercial paper ratings, reflect the market's assessment of a firm's creditworthiness and access to debt markets. Firms without bond or commercial paper ratings—or those never rated during the sample period—are classified as constrained, as they likely face higher borrowing costs or are excluded from these markets altogether. This approach draws from Whited (1992), Kashyap et al. (1994), and Calomiris et al. (1995), who argue that unrated firms or those with lower credit quality struggle to raise external funds. Conversely, firms with rated debt (especially high ratings) are unconstrained, enjoying lower

financing costs and greater market confidence. The authors assign firms with no ratings and positive debt as constrained, expecting them to hoard cash due to restricted access, while rated firms show no systematic cash-saving behavior.

3.4 Trade flows Data

To investigate potential indirect carbon leakage through trade flows—a central objective of this analysis—trade data for the "Iron and Steel" category were sourced from Eurostat and the Comext database, covering monthly imports and exports for all European countries from 2000 to 2024. To align with Climate TRACE's output—lacking specific steel plant production lines—the analysis adopted the 2-digit level of the Combined Nomenclature (CN) classification (Chapter 72: Iron and Steel), encompassing a wider range of iron and steel products. This approach accepts the inclusion of goods not directly tied to the analyzed plants' output, such as semi-finished or alloyed steel, prioritizing the detection of trade-driven carbon leakage over precise production correspondence. These data, extracted at the 2-digit level detail transactions within the European Union and with non-EU countries. The extended timeframe, beginning in 2000, diverges from Climate Trace's emissions estimates (available from 2015 onward) to capture trade flow evolution preceding and following key EU carbon taxation milestones: the EU Emissions Trading System (EU ETS) inception in 2004, and subsequent phases in 2008 (Phase II), 2013 (Phase III) and 2021 (Phase IV).

3.5 European Union transaction log Data

The European Union Transaction Log (EUTL) is the central registry of the EU Emissions Trading System, recording all compliance-related transactions for regulated installations and aircraft operators. It contains detailed information on the verified annual greenhouse gas emissions of each installation, the number of freely allocated allowances, surrendered allowances, and any transfers between accounts. For this study, we extracted from the EUTL the verified emissions and freely allocated allowances for all steel plants in the EU 27, for the period 2005-2024.

4. Methodology

4.1 Financial Constraint Index

This section outlines the construction of the composite financial constraint index, first as developed by Bartram et al. (2022) and then as adapted in this study to suit a mixed sample of listed and non-listed firms across 2015–2023.

4.1.1 Rolling Window Methodology

Given the financial data coverage we had for our sample of listed and non-listed firms during the pre-sample period, we opted to diverge from Bartram et al. (2022)'s static construction of the composite financial constraint index, adopting instead a dynamic approach which exploits rolling windows to leverage the gradual improvement in data availability over time. This rolling window measure calculates the composite index for each year t within the main study period (2015–2023) by drawing on five years of prior data (t-5 to t1). For each annual iteration, we select firms with complete essential in-sample financial data (to allow the presence of the most common financial controls in each regressions), compute values for individual indices (SA, FCP, payout ratio, size ratio) annually within this sub-sample, assign percentile ranks to reflect each firm's relative position, average these ranks across the five-year window (except for the credit rating index, which follows the same separate method employed in Bartram et al. (2022)), classify firms as constrained or unconstrained per index, and aggregate these classifications into a composite index, which will designate the level of financial constraint for each firm i on year t that is classified constrained by at least three of the five indexes. This process is repeated sequentially for each year in the main period, ensuring the index adapts to evolving data quality. The shift to a dynamic framework addresses the uneven thoroughness of pre-sample data, which would have hampered a fixed-period approach, and capitalizes on the progressive enhancement of financial records, thereby providing a more robust and temporally sensitive measure of financial constraint which lifts the assumption of static financial constraints in order to get closer to the real world were the level fo financial constraint can change through time.

4.2 Difference-in-Differences

Drawing on the framework established by Bartram et al. (2022), we investigate the influence of the European Union Emissions Trading System (EU ETS) on emissions patterns within the European and global steel industry, focusing specifically on the introduction of its fourth phase in 2021, as our emissions and production data commence in 2015.

Firstly, we tested wether the steel plants owned by geographically diversified firms (firms that own at least one plant inside Europe and one in the rest of the world) adjusted their emissions in response to the introduction of phase IV of EU ETS. We employed the following specification for the regression:

$$\log(1+\text{Emissions}_{i,j,t}) = \alpha + \beta\,\text{EuPlant}_j \times \text{After}_t + \gamma' X_{i,t} + a_j + b_t + \varepsilon_{i,j,t} \quad (1)$$

where $\log(1+\text{Emissions}_{i,j,t})$ is the natural logarithm of the metric tonnes of CO_2 emitted by plant j of firm i in year t. $Euplant_j$ is a dummy variable equal to one if plant j is located in europe and 0 otherwise. $After_t$ is a dummy variable equal to one from 2021 onwards, and 0 otherwise. $X_{i,t}$ is a vector of firm-level financial control variables which in our study are Total debt (defined as the ratio between the sum of long and short term debt and total assets), ROA (calculated using the net income), and size (the natural logarithm of total assets). Lastly, a_j and b_t denote respectively plant fixed effects and year fixed effects. We estimate separately for constrained and unconstrained firms. Standard errors are adjusted for clustering at firm and country level.

Next, we focused on studying possible production spillovers to plants located outside europe. In order to do so, we decide to compare the plants located outside europe and owned by geographically diversified firms with the plants located outside europe and owned by geographically non-diversified firms. To test this hypothesis we employed the following regressions specification:

$$\begin{aligned}\log(1+\text{Emissions}_{i,j,t}) = \alpha &+ \beta_1\,\text{DivFirm}_{i,t} + \beta_2\,\text{DivFirm}_{i,t} \times \text{After}_t \\ &+ \gamma' X_{i,t} + a_j + b_t + \varepsilon_{i,j,t}\end{aligned} \quad (2)$$

Sadly, $DivFirm_{i,t}$ is subsumed by fixed effects, but we included it to be as close as possible with the setup of Bartram et al. (2022). As we can see we moved from a plant level specification in (1) to a firm-level setup of (2) as $DivFirmi,t$ is defined at the firm level. We estimate separately for constrained and unconstrained firms. Standard errors are adjusted for clustering at firm and country level.

Then in order to compare both group (constrained and unconstrained firms) at the same time we employed two triple-difference specifications as was done in Bartram et al. (2022). We wrote the specification of the two pooled regressions as follows:

$$\begin{aligned}\log(1+\text{Emissions}_{i,j,t}) = \alpha &+ \beta_1 \text{Constrained}_i + \beta_2 \text{After}_t \times \text{Constrained}_i \\ &+ \beta_3 \text{EuPlant}_j \times \text{Constrained}_i + \beta_4 \text{EuPlant}_j \times \text{After}_t \\ &+ \beta_5 \text{EuPlant}_j \times \text{After}_t \times \text{Constrained}_i \\ &+ \gamma' X_{i,t} + a_j + b_t + \varepsilon_{i,j,t}\end{aligned} \quad (3)$$

$$\begin{aligned}\log(1+\text{Emissions}_{i,j,t}) = \alpha &+ \beta_1 \text{Constrained}_i + \beta_2 \text{DivFirm}_{i,t} + \beta_3 \text{After}_t \times \text{Constrained}_i \\ &+ \beta_4 \text{DivFirm}_{i,t} \times \text{Constrained}_i + \beta_5 \text{DivFirm}_{i,t} \times \text{After}_t \\ &+ \beta_6 \text{DivFirm}_{i,t} \times \text{After}_t \times \text{Constrained}_i \\ &+ \gamma' X_{i,t} + a_j + b_t + \varepsilon_{i,j,t}\end{aligned} \tag{4}$$

In addition to these two analyses which were employed in Bartram et al. (2022) we decide to add a third case which use the same specification of (2) and (4) but aims at assessing the emissions patterns of european steel plants comparing the ones owned by geographically diversified firms and geographically non-diversified firms.

4.3 Change Point

Our change point detection framework builds on the Sequential Binary Segmentation Cross-Entropy (SBS-CE) method originally proposed in **??**. In that context, the authors develop a model-based segmentation approach in which time series are divided into intervals with locally constant MIDAS-ARDL model parameters. Change points correspond to statistically significant structural changes in the underlying model parameters, and are identified by minimizing a penalized likelihood-based cost function using a modified BIC (mBIC) criterion.

$$\text{mBIC} : P \approx \frac{3}{2} N \log(T) + \frac{1}{2} \sum_{i=1}^{N+1} \log(\tau_i - \tau_{i-1}) \tag{5}$$

To tailor this approach to our monthly trade flow data, we replace the MIDAS-ARDL specification with a standard ARIMA(p, d, q) model (specifically in our case a ARIMA (1,1,1)) which better accommodates the frequency and the type of our data. Change points are detected by applying the SBS-CE optimization scheme with the Cross-Entropy method over rolling and expanding windows. We decided to apply this specific method for its capability of being used by discrete search method and in appropriateness in change detection on time series.

We adapt the multiple change point detection framework introduced in Sojoudi et al. (2025), which integrates Sequential Binary Segmentation via Cross Entropy (SBS-CE) with MIDAS-ARDL regressions, to our context using an ARIMA(p, d, q) model. The original framework consists of four core stages:

1 **Segmentation via SBS-CE**: Candidate change points are first identified by applying the SBS-CE algorithm to rolling windows along the time se-

ries. This stochastic search procedure select a set of candidate break dates, $\tilde{N} = \tau_1' \ldots, \tau_{\tilde{N}}$, based on deviations in model parameters across windows.

2 **Clustering of Change Points**: Since rolling windows may overlap and detect the same structural break multiple times, the candidate change points are clustered to consolidate repeated detections. This reduces the set from $\tilde{N}$ to N distinct change point candidates corresponding to meaningful structural shifts.

3 **FIFO Hypothesis Testing**: To validate the significance of each clustered change point, a First-In-First-Out (FIFO) hypothesis testing procedure is applied. Each candidate inside a cluster is tested sequentially using a local likelihood ratio test within a window centered around the proposed break date. The test, starting with the first candidate of the first cluster, perform the hypothesis test until a suitable candidate is found, when this happen, the algorithm will select it as the significant change point for the specific cluster and then will proceed to analyse the next cluster until all are covered.

4 **Final Parameter Estimation**: Once the change points localization is finalized, the final model parameters are estimated by maximising a log likelihood function composed by the sum of all the singular log likelihood function corresponding to the segments created by the change points.

5. RESULTS

5.1 Verified emission and Allocated allowances

The first step in this paper necessarily begins with an examination of the fundamental features of the policy under analysis. Accordingly, our initial task was to study the relationship between the verified emissions of European steel plants covered by the ETS and the number of allocated allowances these plants received over the entire duration of the carbon pricing scheme. The overarching objective of the EU ETS program has been to curb industrial carbon emissions in the most polluting sectors of the European Union through a carbon price signal intended to incentivize firms to replace outdated, high-emission production methods with cleaner technologies, and to stimulate technological innovation. For such a policy to be effective, two key conditions had to be satisfied:

1 the price signal must be positive and sufficiently strong to spur innovation and technological change; and

2 there must be mechanisms to counteract carbon leakage.

Without the latter, firms producing tradable goods could reallocate part of their production capacity outside the ETS jurisdiction—where no carbon price applies—and subsequently import the goods back into the EU market, effectively undermining the policy's intended effect.

In this section, we focus on studying the first condition: the presence of a positive price signal. For this to occur, the number of freely allocated allowances to plants must be lower than their verified emissions, thereby forcing firms to purchase additional allowances on the primary auctions or secondary market to cover the gap. To examine this, we analyzed verified emissions and allocated allowances for all steel plants in each EU27 country using publicly available data fromt the EUTL, the ETS database. In our analysis, we distinguish between plants directly producing steel (plants present in the Climate Trace database) and plants processing semi-finished steel products (e.g., rolling mills and specialized facilities), which are categorized under "code 24" in the EUTL classification for all the steel-related plants.

Table 1: Comparison of average coverage ratio for steel producing plants and code 24 plants. Period 2005-2024

EU27 Country	**Steel Producing Plants (%)**	**Code 24 Plants (%)**
AUT	92.0	91.7
BEL	179.9	178.0
BGR	107.5	110.2
CZE	146.0	144.6
DEU	115.3	114.4
ESP	142.4	143.5
FIN	103.3	104.6
FRA	112.7	114.8
HUN	2474.5	236.3
ITA	146.0	143.5
LUX	105.4	105.9
NLD	171.1	170.5
POL	156.9	166.6
PRT	142.3	142.3
ROU	153.4	153.1
SVK	91.0	91.2
SVN	91.4	87.5
SWE	166.7	159.9
EU27	124.0	123.9

Our findings reveal that, over the entire duration of the ETS, the European steel sector has consistently received more free allowances than its verified emissions, effectively shielding it from the carbon price signal the policy was designed to impose. This can be largely explained by the fact that the steel industry has been included in all three European Commission lists of sectors deemed at risk of carbon leakage, thereby benefiting from preferential allocation. Even when restricting the sample to Phase III and Phase IV (2013–2024)—periods that introduced direct auctioning and a stated reduction in free allocation—most EU countries still received more allowances than their steel plants emitted.

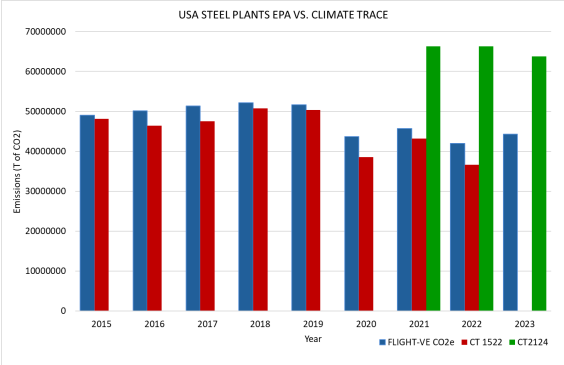
Table 2: Comparison of average coverage ratio for steel producing plants and code 24 plants. Period 2013-2024

EU27 Country	**Steel Producing Plants (%)**	**Code 24 Plants (%)**
AUT	73.3	73.5
BEL	161.8	162.4
BGR	105.1	105.9
CZE	155.3	154.1
DEU	105.6	104.8
ESP	125.7	126.4
FIN	91.2	91.2
FRA	111.1	111.4
HUN	4033.2	301.5
ITA	158.0	154.3
LUX	81.2	81.2
NLD	167.5	166.6
POL	168.6	184.2
PRT	112.2	112.2
ROU	123.3	123.6
SVK	73.5	73.5
SVN	87.9	82.4
SWE	131.4	126.9
EU27	114.8	114.7

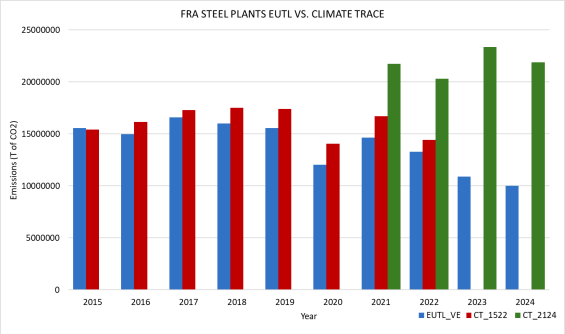
From this clear initial result, we formalize our research hypothesis: given that the industry has been consistently over-allocated allowances relative to verified emissions, we expect to find no significant evidence of carbon leakage—whether in its direct or indirect form—arising from the introduction of the EU ETS in the next section of the paper.

5.1.1 Verified emission vs. Estimated emissions

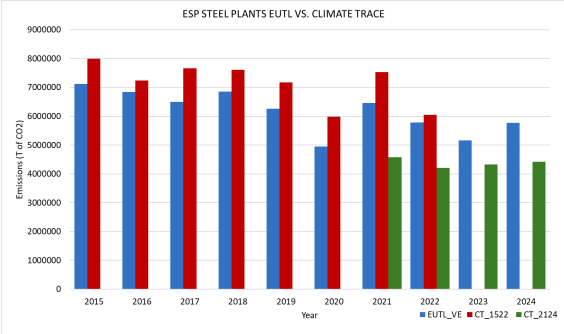
For the comparison between verified emissions reported in the EUTL database and the estimates generated by Climate Trace, we manually matched individual plants. In some cases, this required selecting plants from the EUTL database with activity codes different from "24," which is normally associated with steel production. This was necessary, for example, in Germany, where large integrated steel mills were split into several facilities—such as the main steel mill, the boiler sections, and the coking plant—rather than being reported as a single unit in the EUTL databse, as was the case in other countries. Consequently, we present only a subset of countries for which we consider the matching criteria to be more satisfactorily met at the current time of our research. For completeness, we also include the comparison for the United States, which, despite not having an ETS program implemented nationwide, still collect high-quality greenhouse gas emissions data for the majority of its industrial plants through the Environmental Protection Agency (EPA) under the Clean Air Act.



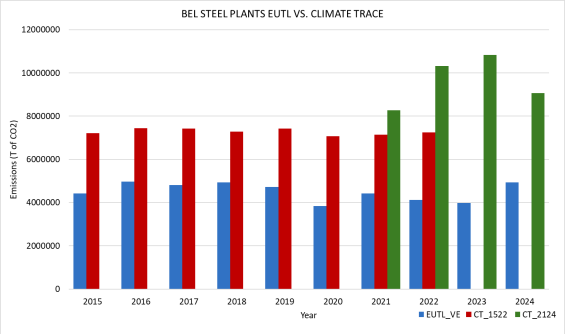
(a) USA



(b) FRA



(c) ESP



(d) BEL

Figure 1: Verified emission vs. Estimated Emissions

5.2 Direct Carbon Leakage study

5.2.1 Reallocation of emissions and potential spillovers

In this section, we report the results of our main set of regressions, which focus on $log(1 + \text{Emissions})$. The results are divided among three tables: 3 studies the behavior of plants owned by geographically diversified firms as they adapt to the introduction of the latest phase of the ETS program; in 4, we explore potential spillover effects by comparing plants owned by geographically diversified firms outside the EU with plants outside the scope of the ETS policy; lastly, 5 narrows the analysis to EU plants only, comparing those owned by geographically diversified firms to those owned by firms operating exclusively within the EU.

The panels are structured to first present the unconditional results, shown in columns 1 and 2, which do not condition on financial constraints. Columns 3–6 present results for subsamples created through the financial constraint dummy. Column 7 reports the full pooled regression, representing the final triple-difference specification, which combines constrained and unconstrained firms altogether.

In Table 3 we estimate Eq.(1) (1-6) and Eq.(3) (7) on the sample made by plants owned by geographically diversified firms reports emissions responses in EU27 plants owned by geographically diversified firms. The key variables, `euplant_after` for the first equation and `euplant_FC_after` for last, capture the post-2021 change in emissions in these plants.
Across specifications, `euplant_after` is consistently negative in regressions on financially constrained subsamples, suggesting a reduction in emissions post-2021 among EU plants of constrained, diversified firms. This effect is statistically significant at the 10% level in columns 3 and 5 (coefficients –0.5311 and –0.6023, respectively), broadly consistent with Bartram et al. (2022)'s findings, though at lower significance. In the pooled regression (Column 7), the triple interaction `euplant_FC_after` is negative and significant at the 5% level (–0.8378), indicating that constrained firms reduced emissions more sharply in EU27 plants after 2021. The interaction `euplant_FC` is positive and significant (0.6113, $p < 0.01$), suggesting higher baseline emissions in these plants. `FC_after` is also positive (0.6562, $p < 0.1$), while `FC_dummy` is negative and highly significant (–0.4431, $p < 0.001$), possibly reflecting a correlation between financial constraints and smaller firms with lower emissions.

Table 3: EU27 vs. non-EU27 plants (geographically diversified firms)

Dependent Variable:	log(1+emissions_quantity)						
			Financial constraint subsamples				
			Const.	Unconst.	Const.	Unconst.	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
euplant_after	-0.3263	-0.2116	-0.5311*	-0.2059	-0.6023*	0.1135	0.1068
	(0.2258)	(0.1303)	(0.2521)	(0.1394)	(0.3088)	(0.2039)	(0.2131)
euplant_FC_after							-0.8378**
							(0.3419)
euplant_FC							0.6113***
							(0.2008)
FC_after							0.6562*
							(0.3299)
FC_dummy							-0.4431****
							(0.1079)
Total_debt		-0.5927	-0.3129	1.010	-0.2362	-0.0688	-0.8983
		(0.7824)	(1.042)	(0.9391)	(1.178)	(0.5977)	(0.6302)
size		1.375**	0.6185	1.021**	0.4034	1.417***	1.376**
		(0.6034)	(0.5668)	(0.3405)	(0.5804)	(0.3447)	(0.6022)
ROA		0.0084	0.0198***	0.0024	0.0246**	0.0063	0.0097
		(0.0091)	(0.0062)	(0.0030)	(0.0113)	(0.0070)	(0.0078)
Fixed-effects							
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	No	No	Yes	Yes	Yes
Fit statistics							
R^2	0.73979	0.74776	0.87315	0.78265	0.87444	0.78665	0.75089
Observations	936	936	401	535	401	535	936

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

In Table 4 we explore potential spillovers to non-EU27 plants (`euplant = 0`) by comparing diversified and undiversified firms through the estimation of Eq. (2) and Eq.(4). The coefficient on `div_after` , which captures post-2021 changes in emissions for diversified firms, is statistically insignificant across all specifications, with mixed signs across constrained and unconstrained subsamples. These results provide no evidence of emissions reallocation to non-EU27 plants. In the pooled regression (Column 7), the triple interaction `div_FC_after` is positive but insignificant (0.6119), again offering no support for the reallocation hypothesis. The interaction `div_FC` is negative and significant at the 10% level (–0.3990), indicating that non-EU27 plants of constrained diversified firms had lower baseline emissions

pre-2021.

Table 4: Spillovers to non-EU27 plants (diversified vs. undiversified firms)

Dependent Variable:	log(1+emissions_quantity)						
			Financial constraint subsamples				
			Const.	Unconst.	Const.	Unconst.	Pooled
	(1)	(2)	(3)	(5)	(4)	(6)	(7)
Variables							
div_after	0.0442	0.0889	0.2627	-0.1319	0.2659	-0.2402	-0.1414
	(0.2208)	(0.1853)	(0.3052)	(0.1928)	(0.3758)	(0.1763)	(0.2065)
div_FC_after							0.6119
							(0.3672)
div_FC							-0.3990*
							(0.2148)
FC_after							-0.1296
							(0.1383)
FC_dummy							-0.0071
							(0.1054)
Total_debt		1.067**	0.6227*	0.8922*	0.6108	1.062**	1.064**
		(0.4262)	(0.3423)	(0.4695)	(0.4260)	(0.3953)	(0.4212)
size		0.4607****	0.4160**	0.3435**	0.4163**	0.2851**	0.4472****
		(0.1202)	(0.1931)	(0.1491)	(0.2039)	(0.1258)	(0.1162)
ROA		0.0028	0.0121***	0.0098*	0.0099	0.0050	0.0033
		(0.0068)	(0.0043)	(0.0055)	(0.0069)	(0.0081)	(0.0074)
Fixed-effects							
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	No	No	Yes	Yes	Yes
Fit statistics							
R^2	0.71601	0.72059	0.80771	0.75236	0.80915	0.75394	0.72161
Observations	2,239	2,239	956	1,283	956	1,283	2,239

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

In Table 5 we extend the analysis to all EU27 plants, testing whether geographically diversified firms adjusted emissions differently than undiversified firms after 2021. The coefficient on `div_after` is generally insignificant (e.g., –0.0512 in Column 3), and this holds across both constrained and unconstrained subsamples. In the pooled regression (Column 7), `div_FC` is positive and significant (0.0676, $p < 0.05$), suggesting higher baseline emissions in constrained, diversified EU27 plants. However, the triple interaction terms involving `div_FC_after` remain insignificant, indicating no meaningful differential response post-policy. While this panel provides suggestive insights on the behaviour of firms with different asset location distribution, we find limited evidence of significant treatment effects.

Table 5: Intra EU27 behaviour (diversified vs. undiversified firms)

Dependent Variable:	log(1+emissions_quantity)						
			Financial constraint subsamples				
			Const.	Unconst.	Const.	Unconst.	Pooled
	(1)	(2)	(3)	(5)	(4)	(6)	(7)
Variables							
div_after	0.0824	0.0524	-0.0512	0.1011	-0.0311	0.2536	0.2350
	(0.0991)	(0.0992)	(0.0948)	(0.1112)	(0.1209)	(0.1645)	(0.1830)
div_FC_after							-0.2677
							(0.2178)
div_FC							0.0676**
							(0.0302)
FC_after							0.0442
							(0.1210)
FC_dummy							-0.0270
							(0.0241)
Total_debt		0.2950	0.9933**	-0.8217	0.7832	-1.306	0.2141
		(0.3029)	(0.3566)	(0.6835)	(0.4657)	(0.8773)	(0.3137)
size		-0.1664	-0.3291**	-0.5794****	-0.2506	-0.2943	-0.1838
		(0.1685)	(0.1281)	(0.1305)	(0.1769)	(0.2374)	(0.1577)
ROA		-0.0016	0.0023	0.0040	0.0006	-0.0030	-0.0018
		(0.0018)	(0.0036)	(0.0041)	(0.0039)	(0.0064)	(0.0024)
Fixed-effects							
source_id	Yes	Yes	Yes	Yes	Yes	Yes	Yes
years	Yes	Yes	No	No	Yes	Yes	Yes
Fit statistics							
R^2	0.96890	0.96912	0.97063	0.99059	0.97276	0.99294	0.96945
Observations	770	770	497	273	497	273	770

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Overall, the results presented in the latter three tables support the initial hypothesis developed from comparing the number of allocated allowances for European steel plants and their verified emissions, which suggested that the large volume of emissions permits allocated to the sector muted the price signal of the ETS program. Consistent with this, we find no evidence of spillover effects following the introduction of the fourth phase of the ETS. Interestingly, we find that plants belonging to financially constrained firms reduced their emissions after 2021, which could potentially be explained by their greater exposure to market pressure, which intensified following the COVID pandemic.

Alternative specification for the financial constraints This section replicates the robustness controls that in Bartram et al. (2022) were aimed at controlling for alternative specifications of financial constraint measures. The results reported accounts for the composite financial constraint index, alongside the five individual measures from which the composite index is constructed: the SA index, FCP index, payout ratio, size ratio, and credit rating index (CRI). The composite index, denoted `FC_dummy`, classifies a firm as financially constrained (value of 1) if it meets the constraint threshold in at least three of these five indices. Results are presented in Tables 6, 7, and 8, covering diversified firms within EU27 and non-EU27 regions, non-EU27 plants of diversified versus undiversified firms, and intra-EU27 comparisons, respectively. By comparing the composite measure against individual indices, this section evaluates the robustness of emissions responses, shedding light on methodological influences and sample composition effects.

Table 6 examines emissions responses among geographically diversified firms (those with plants in both EU27 and non-EU27 regions), comparing the composite financial constraint index with its constituent individual measures. The composite index yields significant findings: the triple interaction `euplant_Const_after` is negative and significant (-0.8378, $p < 0.05$), indicating a substantial emissions reduction in EU27 plants of constrained firms post-2021, while `euplant_Const` is positive and highly significant (0.6113, $p < 0.01$), reflecting higher baseline emissions. Additionally, `FC_after` (0.6562, $p < 0.1$) and `FC_dummy` (-0.4431, $p < 0.001$) suggest constraint-related dynamics, with `size` consistently significant (e.g., 1.376, $p < 0.05$). However, these results prove non-robust across alternative specifications. The SA index shows a significant `FC_after` (0.4659, $p < 0.1$) but no significant triple interaction (-0.1861, $p > 0.1$), while the FCP index yields a marginally significant `FC_dummy` (-0.6337, $p < 0.1$). The payout ratio, size ratio, and CRI indices produce no significant coefficients for key interaction terms, with only

the size ratio showing a notable baseline effect (euplant_Const, 0.1632, $p < 0.001$). This lack of consistency may stem from methodological differences—such as the dynamic rolling window versus Bartram et al. (2022)'s static approach—or the inclusion of private firms, which may exhibit distinct behaviors compared to listed firms when employing only one individual index as a financial constraint proxy. Alternatively, data gaps addressed through aggregation in the composite index could dilute individual measure effects, undermining robustness.

Table 6: Financial constraint: alternative specification PANEL A

Dependent Variable:	log(1+emissions_quantity)					
		Alternative Constraint Measures				
	Composite (1)	SA (2)	FCP (3)	Payout (4)	Size (5)	CRI (6)
Variables						
euplant_after	0.1068	-0.0169	0.0668	-0.0849	-0.1848	-0.2253
	(0.2131)	(0.0821)	(0.1177)	(0.3703)	(0.1554)	(0.1683)
euplant_Const_after	-0.8378**	-0.1861	-0.4588	-0.2776	0.0958	0.3182
	(0.3419)	(0.1735)	(0.3438)	(0.4246)	(0.1925)	(0.1829)
euplant_Const	0.6113***	-0.0726	0.5480	0.1627	0.1632****	
	(0.2008)	(0.1851)	(0.4167)	(0.2010)	(0.0397)	
FC_after	0.6562*	0.4659*	0.8065	0.1049	-0.4741	-0.5051**
	(0.3299)	(0.2402)	(0.4898)	(0.4201)	(0.3425)	(0.1838)
FC_dummy	-0.4431****	-0.4779**	-0.6337*	0.0071	0.4316	-1.185****
	(0.1079)	(0.2031)	(0.3576)	(0.1231)	(0.4873)	(0.0932)
Total_debt	-0.8983	-0.2039	-0.5734	-0.6236	-0.3269	-0.6640
	(0.6302)	(0.6363)	(0.9014)	(0.5603)	(0.6475)	(0.7139)
size	1.376**	1.503**	1.433*	1.367*	1.532**	1.341**
	(0.6022)	(0.5881)	(0.7537)	(0.6699)	(0.6289)	(0.5420)
ROA	0.0097	0.0067	0.0089	0.0093	0.0073	0.0068
	(0.0078)	(0.0091)	(0.0112)	(0.0107)	(0.0109)	(0.0087)
Fixed-effects						
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.75089	0.74853	0.75235	0.74805	0.74848	0.74895
Observations	936	936	936	936	936	936

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Table 7 shifts focus to non-EU27 plants, comparing diversified and undiversified firms to explore emissions responses under alternative constraint specifications. The composite index generates largely insignificant coefficients, with the exception of a marginally significant baseline interaction `div_Const` (-0.3990, $p < 0.1$) and robust control effects (`Total_debt`, 1.064, $p < 0.05$; `size`, 0.4472, $p < 0.001$). In contrast, individual indices reveal varied patterns. The FCP index stands out, producing significant coefficients across multiple terms: `div_after` (-0.4788, $p < 0.05$), `div_Const_after` (0.9056, $p < 0.05$), `div_Const` (-0.7959, $p < 0.1$), and `Const_after` (-0.3310, $p < 0.05$), suggesting a coherent emissions response among constrained diversified firms' non-EU27 plants. The CRI index also shows significance, with `div_Const_after` (-0.7286, $p < 0.05$) and `div_Const` (-0.9229, $p < 0.01$), though of opposite sign to FCP, potentially balancing the composite's insignificance. The SA, payout, and size indices, however, align more closely with the composite's lack of significance, with no notable interaction effects (e.g., SA's `div_after`, -0.2688, $p > 0.1$). This divergence highlights that the composite's muted results may result from offsetting effects between FCP and CRI, compounded by the dynamic construction and mixed firm sample, differing from Bartram et al. (2022)'s listed-only context, where such patterns might be more pronounced.

Table 7: Financial constraint: alternative specification PANEL B

Dependent Variable:	log(1+emissions_quantity)					
		Alternative Constraint Measures				
	Composite	SA	FCP	Payout	Size	CRI
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
div_after	-0.1414	-0.2688	-0.4788**	0.0310	0.0550	0.2214
	(0.2065)	(0.3070)	(0.1768)	(0.4291)	(0.1968)	(0.1642)
div_Const_after	0.6119	0.3079	0.9056**	0.0839	-0.1932	-0.7286**
	(0.3767)	(0.4452)	(0.3890)	(0.4138)	(0.3996)	(0.3044)
div_Const	-0.3990*	-0.2552	-0.7959*	0.0308	0.0677	-0.9229***
	(0.2148)	(0.1703)	(0.4242)	(0.2089)	(0.3303)	(0.3187)
Const_after	-0.1296	0.2504	-0.3310**	0.0564	-0.1607	0.1245
	(0.1383)	(0.3065)	(0.1572)	(0.2862)	(0.3148)	(0.2222)
Const_dummy	-0.0071	-0.0936	0.1643*	-0.0446	0.0213	-0.3713
	(0.1054)	(0.1904)	(0.0876)	(0.1377)	(0.3601)	(0.3730)
Total_debt	1.064**	1.119**	1.033**	1.038**	1.084**	0.9660**
	(0.4212)	(0.4479)	(0.4338)	(0.4181)	(0.4522)	(0.4293)
size	0.4472****	0.4657****	0.4097***	0.4589****	0.4625****	0.4177***
	(0.1162)	(0.1234)	(0.1262)	(0.1271)	(0.1257)	(0.1395)
ROA	0.0033	0.0021	0.0028	0.0027	0.0026	0.0029
	(0.0074)	(0.0066)	(0.0072)	(0.0064)	(0.0068)	(0.0062)
Fixed-effects						
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.72161	0.72116	0.72290	0.72066	0.72080	0.72177
Observations	2,239	2,239	2,239	2,239	2,239	2,239

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Table 8 examines intra-EU27 emissions responses, comparing diversified and undiversified firms across constraint specifications. The composite index yields a significant baseline `div_Const` (0.0676, $p < 0.05$), indicating higher pre-treatment emissions in constrained diversified firms' EU27 plants, but other interaction terms like `div_Const_after` (-0.2677, $p > 0.1$) are insignificant. The payout ratio index deviates markedly, showing significant coefficients for `div_Const_after` (-0.7380, $p < 0.01$), `div_Const` (0.5045, $p < 0.001$), and `FC_after` (0.7191, $p < 0.001$), suggesting a robust emissions response among constrained diversified firms,

contrasting with the composite's muted outcome. The SA index shows a significant `FC_after` (0.2410, $p < 0.05$), while the CRI index indicates a negative `FC_after` (-0.4207, $p < 0.1$), but neither replicates the payout's breadth of significance. The FCP and size indices align with the composite's insignificance, with no notable effects (e.g., FCP's `div_after`, 0.0286, $p > 0.1$). %Control variables like `ROA` show sporadic significance (e.g., -0.0031, $p < 0.05$ for size), but Overall, the composite's results appear mediated by the averaging of diverse individual index effects. This pattern mirrors Panel B, where opposing significant coefficients (e.g., payout vs. others) may cancel out, reflecting the influence of the rolling window, private firm inclusion, and data aggregation, which diverge from Bartram et al. (2022)'s static, listed-firm framework.

Table 8: Financial constraint: alternative specification PANEL C

Dependent Variable:	log(1+emissions_quantity)					
		Alternative Constraint Measures				
	Composite	SA	FCP	Payout	Size	CRI
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
div_after	0.2350	-0.0041	0.0286	0.1420	-0.0453	-0.2537
	(0.1830)	(0.0470)	(0.1134)	(0.1332)	(0.1277)	(0.2112)
div_Const_after	-0.2677	0.0134	0.0056	-0.7380***	0.0379	0.1577
	(0.2178)	(0.0990)	(0.1376)	(0.1815)	(0.1099)	(0.2360)
div_Const	0.0676**	-0.0777	-0.1804*	0.5045****		
	(0.0302)	(0.1296)	(0.0969)	(0.1109)		
FC_after	0.0442	0.2410**	0.1046	0.7191****	-0.3059**	-0.4207*
	(0.1210)	(0.1077)	(0.0996)	(0.1546)	(0.1118)	(0.2034)
FC_dummy	-0.0270	0.1005	0.0423	-0.4819***	-0.0743	
	(0.0241)	(0.0623)	(0.0941)	(0.1246)	(0.0888)	
Total_debt	0.2141	0.1366	0.2917	0.3496	0.0638	0.1596
	(0.3137)	(0.3447)	(0.2794)	(0.2525)	(0.3185)	(0.3114)
size	-0.1838	-0.1113	-0.1204	-0.1142	-0.1009	-0.1350
	(0.1577)	(0.1200)	(0.1530)	(0.1447)	(0.0990)	(0.1470)
ROA	-0.0018	-0.0023	-0.0015	0.0002	-0.0031**	-0.0021
	(0.0024)	(0.0015)	(0.0016)	(0.0018)	(0.0014)	(0.0027)
Fixed-effects						
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.96945	0.97015	0.96946	0.97089	0.97054	0.97013
Observations	770	770	770	770	770	770

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

5.3 Economic mechanisms and Robustness controlls

5.3.1 Financial Constraint and Excess Capacity

This section replicates and extends the analysis of excess capacity runned by Bartram et al. (2022), aiming to assess whether steel plants with differing levels of

excess capacity exhibit distinct emissions responses to the regulatory treatment implemented in 2021. The investigation focuses on whether high excess capacity facilitates emissions reallocations compared to low excess capacity, particularly under varying financial constraints and firm diversification statuses. To this end, excess capacity is quantified through annual ratios of unused capacity to total production capacity, with plants assigned to `High` or `Low` categories based on their percentile rankings relative to the median each year—plants above the median are designated `High = 1` (and `Low = 0`), and those below are `Low = 1` (and `High = 0`). This methodology mirrors the construction of financial constraint variables, enabling a consistent comparative framework.

Table 9 examines emissions patterns among plants owned by geographically diversified firms—those with steel facilities in both EU27 and non-EU27 regions by high and low excess capacity. The analysis reveals distinct responses contingent on capacity levels and financial constraints. In the low excess capacity subsample (Column 2), EU27 plants of unconstrained firms exhibit a significant post-2021 emissions increase, with the coefficient on `euplant_after` at 0.3960 ($p < 0.05$), suggesting that these plants may leverage available capacity to boost production. Conversely, the interaction term `euplant_FC_after` is negative and significant (-0.2069, $p < 0.05$), indicating that EU27 plants owned by constrained firms reduced emissions, potentially due to limited financial flexibility under regulatory pressure. In the high excess capacity subsample (Column 1), the coefficient on `euplant_after` is negative but insignificant (-0.8938, $p > 0.1$), while `euplant_FC` is positive and significant at the 10% level (0.6506, $p < 0.1$), reflecting higher baseline emissions among constrained firms' plants. These results suggest that constrained firms curtailed emissions across their EU27 plants, with the effect most pronounced in low-capacity settings, possibly due to capacity constraints amplifying treatment effects.

Table 9: Emission reallocations to plants with excess capacity PANEL A

Dependent Variable:	log(1+emissions_quantity)	
	Excess capacity at target European and non-European plant	
	High	Low
	(1)	(2)
Variables		
euplant_after	-0.8938	0.3960**
	(0.6612)	(0.1788)
euplant_FC_after	-0.6389	-0.2069**
	(0.7507)	(0.0931)
euplant_FC	0.6506*	0.0697**
	(0.3343)	(0.0306)
FC_after	0.3481	0.1132
	(0.6716)	(0.1020)
FC_dummy	-0.4787**	0.0386
	(0.1776)	(0.0253)
Total_debt	-4.389	0.0515
	(3.143)	(0.2828)
size	3.041	0.0620
	(1.772)	(0.3021)
ROA	0.0332**	-0.0022
	(0.0149)	(0.0051)
Fixed-effects		
Plant FE	Yes	Yes
Years FE	Yes	Yes
Fit statistics		
R^2	0.85431	0.97991
Observations	439	495

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Turning to non-EU27 plants, Table 10 compares emissions responses between plants owned by diversified and undiversified firms, testing for carbon leakage—where emissions might shift from EU27 to non-EU27 regions—across high and low excess capacity levels. The coefficients on `div_after`, which captures post-2021 emissions changes in non-EU27 plants of diversified firms, are statistically insignificant in both subsamples (0.3972, $p > 0.1$ for high; -0.0572, $p > 0.1$ for

low), with no consistent directional pattern. Interaction terms involving financial constraints, such as `div_FC_after`, similarly lack significance (e.g., 0.0123, $p > 0.1$ for high), providing no evidence of emissions reallocation. For carbon leakage to be substantiated, one would anticipate increased emissions in non-EU27 plants of diversified firms, particularly those with high excess capacity capable of absorbing shifted production. The absence of such effects suggests that treatment-induced emissions changes in the EU27 did not precipitate detectable spillovers to non-EU27 regions, irrespective of capacity levels.

Table 10: Emission reallocations to plants with excess capacity PANEL B

Dependent Variable:	log(1+emissions_quantity)	
	Excess capacity at target non-European plant	
	High	Low
	(1)	(2)
Variables		
div_after	0.3972	-0.0572
	(0.6898)	(0.1368)
div_FC_after	0.0123	0.0468
	(0.7087)	(0.2096)
div_FC	-0.4232	-0.0789
	(0.3984)	(0.0913)
FC_after	-0.0190	0.0919
	(0.4668)	(0.1524)
FC_dummy	-0.0850	0.0928
	(0.2046)	(0.1003)
Total_debt	0.9039*	0.2604
	(0.4966)	(0.2162)
size	0.4822**	0.2130
	(0.2369)	(0.1315)
ROA	0.0055	-0.0025
	(0.0135)	(0.0031)
Fixed-effects		
Plant FE	Yes	Yes
Years	Yes	Yes
Fit statistics		
R^2	0.77286	0.97771
Observations	1,116	1,114

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Table 11 extends the analysis to all EU27 plants, comparing emissions responses between those owned by diversified and undiversified firms across high and low excess capacity subsamples, an exploration beyond Bartram et al.'s scope aimed at clarifying diversification's intra-regional role. The coefficients on `div_after`, assessing post-2021 differences, are insignificant in both subsamples (-0.0448, $p > 0.1$ for high; 0.2115, $p > 0.1$ for low), indicating no substantial differential response attributable to diversification. However, in the low excess capacity subsample (Column 2), the interaction `div_FC` is positive and significant at the 5% level (0.1790, $p < 0.05$), suggesting that pre-treatment emissions were higher in EU27 plants of constrained diversified firms. The paucity of significant post-treatment coefficients suggests that diversification does not markedly influence emissions adjustments within EU27 plants, with excess capacity playing a limited role. This finding underscores that financial constraints may shape baseline emissions more than post-2021 responses within the treated region.

Table 11: Emission reallocations to plants with excess capacity PANEL C

Dependent Variable:	log(1+emissions_quantity)	
	Excess capacity at target European plant	
	High	Low
	(1)	(2)
Variables		
div_after	-0.0448	0.2115
	(0.2249)	(0.1482)
div_FC_after	-0.1367	-0.1147
	(0.2496)	(0.1523)
div_FC	-0.1447	0.1790**
	(0.1174)	(0.0705)
FC_after	-0.0900	-0.0071
	(0.1801)	(0.0819)
FC_dummy	-0.0074	-0.0704
	(0.0420)	(0.0481)
Total_debt	-0.1462	0.1838
	(0.4176)	(0.3179)
size	0.1081	-0.4897**
	(0.1024)	(0.1812)
ROA	-0.0025	-0.0010
	(0.0020)	(0.0021)
Fixed-effects		
Plant FE	Yes	Yes
Years	Yes	Yes
Fit statistics		
R^2	0.96175	0.98932
Observations	381	388

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Collectively, these results diverge from Bartram et al. (2022)'s conclusions, where treatment-induced increases in variable production costs were interpreted as one of the main sourced of the triggered emissions leakage. Here, no clear evidence of leakage emerges across the analyses, despite examining excess capacity as a potential conduit for reallocation. This discrepancy may reflect the steel industry's cost structure, where fixed costs predominate over variable ones. Even if the 2021 treatment altered variable costs, the prevalence of fixed costs could have diminished incentives for emissions reallocation, counteracting the leakage effect posited by Bartram et al. (2022) The significant emissions reductions observed in constrained EU27 plants with low excess capacity, alongside the lack of increases in non-EU27 plants, suggest that financial constraints and capacity limitations may reinforce localized compliance rather than facilitate cross-regional shifts. These insights highlight the industry-specific dynamics mediating treatment effects, inviting further investigation into how cost structures and capacity interplay with regulatory interventions to shape emissions outcomes.

5.3.2 Carbon Efficiency and Production Shifting

This section replicates the analysis of Bartram et al. (2022)'s Table 6, aiming to discern whether changes in steel plant emissions stem from enhanced carbon efficiency—producing equivalent steel output with greener technologies—or from production shifting across plants. The investigation focus on a Triple Difference-in-Differences (DiD) framework, examining emissions, steel production, carbon intensity, and excess capacity as dependent variables, with results detailed in Tables 12, 13, and 14. These panels focus on geographically diversified firms within EU27 and non-EU27 regions, non-EU27 plants of diversified versus undiversified firms, and intra-EU27 comparisons, respectively. The natural logarithms of emissions quantity, steel production, and excess capacity, alongside direct carbon intensity (emissions per unit of steel), serve as key metrics, with standard errors clustered at firm and country levels to ensure robust inference. This multi-variable approach elucidates whether emissions reductions reflect technological improvements or spatial reallocations, offering insights into the interplay of financial constraints and geographic diversification in shaping post-2021 emissions patterns.

Table 12 explores emissions dynamics among geographically diversified firms—those owning steel plants in both EU27 and non-EU27 regions—across the aforementioned four dependent variables: emissions, steel production, carbon intensity, and excess capacity. The triple interaction term `euplant_FC_after` reveals a significant emissions reduction in EU27 plants of constrained firms

post-2021 (-0.8378, $p < 0.05$), paralleled by a notable decrease in steel production (-0.5372, $p < 0.1$) and carbon intensity (-0.3873, $p < 0.05$). These findings suggest that the observed emissions decline is a composite effect of reduced output and improved carbon efficiency, potentially driven by the progressive decommissioning of older, less environmentally efficient plants or the adoption of technologies such as exhaust filtration systems, consistent with industry trends toward capital stock renewal. The baseline interaction `euplant_FC` is positive and highly significant across emissions (0.6113, $p < 0.01$), steel production (0.6094, $p < 0.01$), and carbon intensity (0.1343, $p < 0.001$), indicating higher pre-treatment levels among constrained firms' EU27 plants. Meanwhile, `FC_after` shows positive effects on emissions (0.6562, $p < 0.1$), production (0.4996, $p < 0.1$), and intensity (0.1989, $p < 0.05$), while `FC_dummy` is strongly negative for emissions (-0.4431, $p < 0.001$) and production (-0.5114, $p < 0.01$), hinting at a size-mediated constraint effect. Excess capacity decreases significantly post-treatment (-0.6284, $p < 0.1$), but the lack of significance in `euplant_FC_after` for this metric (0.6787, $p > 0.1$) suggests no substantial capacity shift, reinforcing the primacy of efficiency gains and output reduction in driving emissions changes.

Table 12: Carbon efficiency vs. production shifting PANEL A

Dependent Variables:	log(1+emissions_quantity)	log(1+steel_production)	carbon_intensity	log(1+excess_capacity)
Model:	(1)	(2)	(3)	(4)
Variables				
euplant_after	0.1068	-0.2905*	0.4027*	-0.6284*
	(0.2131)	(0.1630)	(0.2115)	(0.3466)
euplant_FC_after	-0.8378**	-0.5372*	-0.3873**	0.6787
	(0.3419)	(0.2656)	(0.1601)	(0.4113)
euplant_FC	0.6113***	0.6094***	0.1343****	-0.1212
	(0.2008)	(0.2076)	(0.0263)	(0.0834)
FC_after	0.6562*	0.4996*	0.1989**	-0.5833
	(0.3299)	(0.2592)	(0.0784)	(0.3828)
FC_dummy	-0.4431****	-0.5114***	-0.0203	0.0697
	(0.1079)	(0.1436)	(0.0167)	(0.0654)
Total_debt	-0.8983	-0.9695	-0.0296	-1.207
	(0.6302)	(0.6322)	(0.3088)	(0.9914)
size	1.376**	1.348**	0.1177	-0.0996
	(0.6022)	(0.5539)	(0.2285)	(0.2319)
ROA	0.0097	0.0054*	0.0069	-0.0101
	(0.0078)	(0.0030)	(0.0058)	(0.0076)
Fixed-effects				
Plant FE	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	Yes	Yes
Fit statistics				
R^2	0.75089	0.55719	0.86876	0.66676
Observations	936	936	936	936

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Table 13 shifts focus to non-EU27 plants (`euplant = 0`), comparing diversified and undiversified firms to probe for production shifting and carbon efficiency changes outside Europe. The coefficients on `div_after` across all dependent variables—emissions (-0.1414, $p > 0.1$), steel production (-0.0751, $p > 0.1$), carbon intensity (-0.1059, $p > 0.1$), and excess capacity (0.2774, $p > 0.1$)—are statistically insignificant, indicating no significant post-2021 changes attributable to diversification. The triple interaction `div_FC_after` is significant only for steel production (0.5701, $p < 0.05$), suggesting that non-EU27 plants of constrained diversified firms increased output relative to those of constrained undiversified firms, yet this does not translate into significant emissions or intensity shifts (0.6119, $p > 0.1$ and 0.2017, $p > 0.1$, respectively). The absence of significant effects on carbon intensity and excess capacity (e.g., -0.6106, $p > 0.1$ for the latter) underscores a technological stationarity and lack of capacity adjustments, with no evidence of abnormal production transfer from EU27 plants, which would manifest as a significant negative change in excess capacity. The baseline `div_FC` term is negative for emissions (-0.3990, $p < 0.1$), hinting at lower pre-treatment levels.

Table 13: Carbon efficiency vs. production shifting PANEL B

Dependent Variables:	log(1+emissions_quantity)	log(1+steel_production)	carbon_intensity	log(1+excess_capacity)
Model:	(1)	(2)	(3)	(4)
Variables				
div_after	-0.1414	-0.0751	-0.1059	0.2774
	(0.2065)	(0.1505)	(0.1459)	(0.2113)
div_FC_after	0.6119	0.5701**	0.2017	-0.6106
	(0.3672)	(0.2766)	(0.1256)	(0.4914)
div_FC	-0.3990*	-0.4544	-0.0059	-0.0952
	(0.2148)	(0.2834)	(0.0297)	(0.1291)
FC_after	-0.1296	-0.2738**	0.0010	-0.0172
	(0.1383)	(0.1332)	(0.0702)	(0.1056)
FC_dummy	-0.0071	0.0040	-0.0219	0.1440
	(0.1054)	(0.1071)	(0.0483)	(0.1259)
Total_debt	1.064**	0.9417**	0.0903	-0.5041*
	(0.4212)	(0.4324)	(0.1120)	(0.2948)
size	0.4472****	0.2699*	0.1080**	-0.1748
	(0.1162)	(0.1459)	(0.0509)	(0.1534)
ROA	0.0033	0.0039	0.0002	0.0018
	(0.0074)	(0.0072)	(0.0012)	(0.0056)
Fixed-effects				
Plant FE	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	Yes	Yes
Fit statistics				
R^2	0.72161	0.58162	0.87866	0.61008
Observations	2,239	2,239	2,239	2,239

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Table 14 examines intra-EU27 behavior (`euplant = 1`), comparing diversified and undiversified firms to assess differential responses in emissions, production, intensity, and capacity. The coefficient on `div_after` is insignificant across all variables—emissions (0.2350, $p > 0.1$), steel production (0.0475, $p > 0.1$), carbon intensity (0.2244, $p > 0.1$), and excess capacity (-0.2028, $p > 0.1$)—suggesting that diversification does not markedly alter post-2021 outcomes within EU27 plants. However, the baseline interaction `div_FC` is positive and significant for emissions (0.0676, $p < 0.05$) and carbon intensity (0.1247, $p < 0.01$), indicating that EU27 plants of constrained diversified firms exhibited higher emissions and carbon intensity pre-treatment compared to their undiversified counterparts. The triple interaction `div_FC_after` lacks significance across all metrics (e.g., -0.2677, $p > 0.1$ for emissions; -0.2055, $p > 0.1$ for intensity), implying no differential post-treatment shift. The high R^2 values (e.g., 0.97072 for production) reflecting robust fixed effects rather than treatment-driven changes. These results suggest that within the EU27, carbon efficiency and production adjustments are not significantly influenced by diversification, with constrained diversified firms maintaining higher baseline intensity without notable post-2021 adaptation.

Table 14: Carbon efficiency vs. production shifting PANEL C

Dependent Variables:	log(1+emissions_quantity)	log(1+steel_production)	carbon_intensity	log(1+excess_capacity)
Model:	(1)	(2)	(3)	(4)
Variables				
div_after	0.2350	0.0475	0.2244	-0.2028
	(0.1830)	(0.0914)	(0.1894)	(0.2119)
div_FC_after	-0.2677	-0.1078	-0.2055	0.2377
	(0.2178)	(0.0973)	(0.1886)	(0.1569)
div_FC	0.0676**	0.0081	0.1247***	-0.0373
	(0.0302)	(0.0276)	(0.0330)	(0.0550)
FC_after	0.0442	0.0454	-0.0027	-0.1449
	(0.1210)	(0.0808)	(0.0902)	(0.1702)
FC_dummy	-0.0270	-0.0109	-0.0414	0.0503
	(0.0241)	(0.0221)	(0.0302)	(0.0515)
Total_debt	0.2141	0.0597	0.0606	-0.1217
	(0.3137)	(0.1949)	(0.2772)	(0.2983)
size	-0.1838	0.1122	-0.2465	-0.1205
	(0.1577)	(0.0678)	(0.1544)	(0.1488)
ROA	-0.0018	-0.0006	-0.0019	0.0003
	(0.0024)	(0.0017)	(0.0025)	(0.0028)
Fixed-effects				
Plant FE	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	Yes	Yes
Fit statistics				
R^2	0.96945	0.97072	0.92510	0.83660
Observations	770	770	770	770

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

5.3.3 Do Emissions Chase Growth Opportunities ?

This section explores whether variations in country-level GDP growth rate influence steel plant emissions patterns, extending the analysis from Bartram et al. (2022), who utilized U.S. state-level GDP data. Here, global country GDP data, expressed in 2015 USD terms and sourced from the World Bank, replace state-level metrics to assess growth opportunities' impact on emissions behavior across diverse regions. The GDP growth rate is calculated as the natural logarithm of the ratio of GDP at time t to GDP at time t1, converted to a percentage—a standard approach for capturing exponential trends. This variable, denoted `gdp_growthrate`, is incorporated as a standalone factor and interacted with key variables of interest (e.g., `euplant`, `div`, `FC`, `after`) to examine its mediating effects on emissions. Results are presented in Tables 15, 16, and 17, covering diversified firms in EU27 and non-EU27 regions, non-EU27 plants of diversified versus undiversified firms, and intra-EU27 comparisons, respectively. By augmenting the baseline specification with GDP interactions, this analysis probes whether emissions "chase" growth opportunities or reflect other dynamics, such as regulatory pressures or financial constraints.

Table 15 investigates emissions responses among geographically diversified firms—those with plants in both EU27 and non-EU27 regions—incorporating GDP growth rate interactions to assess their explanatory power. The initial specifications (Columns 1–3) progressively introduce GDP terms, revealing significant effects as interactions are added. In Column 2, `euplant_gdp` is positive and significant (0.0514, $p < 0.05$), while `euplant_after_gdp` is negative and highly significant (-0.1026, $p < 0.01$), suggesting that higher GDP growth correlates with increased baseline emissions in EU27 plants, mitigated post-2021. Column 3 introduces financial constraints, with `euplant_FC_gdp` (0.1290, $p < 0.01$) and `euplant_FC_after_gdp` (-0.2188, $p < 0.05$) indicating that constrained firms' EU27 plants exhibit amplified emissions sensitivity to GDP growth, reduced after 2021. The pooled regression (Column 6) enhances these insights, showing significant triple interactions—`euplant_FC` (0.4454, $p < 0.05$), `euplant_FC_after` (-0.2707, $p < 0.05$), `euplant_FC_gdp` (0.0899, $p < 0.1$), and the quadruple interaction `euplant_FC_after_gdp` (-0.1952, $p < 0.1$). Additionally, `FC_gdp` (-0.0868, $p < 0.05$) and `FC_after_gdp` (0.1790, $p < 0.05$) highlight a negative baseline correlation between GDP growth and emissions for constrained firms, reversed post-treatment. Compared to the baseline (3), GDP inclusion alters the significance landscape, with `euplant_after` losing prominence (-0.1405, $p > 0.1$). This suggests a negative relationship between GDP growth and emissions in EU27 plants, stronger among constrained firms, consistent with advanced economies' trends where growth often decouples from emissions due to efficiency or regulatory factors.

Table 15: Controlling for growth opportunities PANEL A

Dependent Variable:	log(1+emissions_quantity)					
				Financial constraint subsamples		
				Const.	Unconst.	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
euplant_after				-0.4123	-0.1859	-0.1405
				(0.5314)	(0.3123)	(0.3125)
euplant_gdp		0.0514**	0.0068	0.1284	0.0179	0.0112
		(0.0176)	(0.0197)	(0.0937)	(0.0171)	(0.0164)
euplant_after_gdp		-0.1026***	0.0069	-0.1835**	0.0460	0.0407
		(0.0276)	(0.0432)	(0.0728)	(0.0430)	(0.0483)
euplant_FC						0.4454**
						(0.1767)
euplant_FC_after						-0.2707**
						(0.1157)
euplant_FC_gdp			0.1290***			0.0899*
			(0.0362)			(0.0469)
euplant_FC_after_gdp			-0.2188**			-0.1952*
			(0.0988)			(0.1051)
FC_dummy						-0.2804**
						(0.1016)
FC_after						0.1581
						(0.1673)
FC_gdp		-0.0569**	-0.1144****			-0.0868**
		(0.0252)	(0.0183)			(0.0314)
after_gdp		-0.0342	-0.0675	0.1952*	-0.0549***	-0.0767
		(0.0490)	(0.0498)	(0.0999)	(0.0163)	(0.0602)
FC_after_gdp		0.1116	0.1910**			0.1790**
		(0.0665)	(0.0701)			(0.0785)
Total_debt	-0.5836	-0.6579	-0.9610	-0.0018	-0.1401	-1.015
	(0.7962)	(0.8811)	(0.7603)	(1.138)	(0.7599)	(0.7389)
size	1.425**	1.428*	1.379*	0.3247	1.538****	1.354*
	(0.6234)	(0.6939)	(0.6924)	(0.5211)	(0.2698)	(0.6842)
ROA	0.0084	0.0074	0.0084	0.0306**	-0.0008	0.0091
	(0.0083)	(0.0087)	(0.0110)	(0.0138)	(0.0042)	(0.0092)
gdp_growthrate	-0.0178	-0.0157	0.0012	-0.1764	-0.0272	-0.0078
	(0.0138)	(0.0401)	(0.0374)	(0.1118)	(0.0282)	(0.0351)
Fixed-effects						
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.74757	0.75052	0.75233	0.88222	0.78768	0.75350
Observations	936	936	936	401	535	936

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Table 16 examines non-EU27 plants, comparing diversified and undiversified firms to determine if GDP growth drives emissions shifts outside Europe. Across specifications, most coefficients of interest are insignificant, contrasting with Panel A's richness. In Column 2, `div_gdp` (-0.0305, $p > 0.1$) and `div_after_gdp` (0.0313, $p > 0.1$) lack significance, indicating no direct GDP-emissions link for diversified firms' non-EU27 plants. Column 3 introduces constraint interactions, with `div_FC_gdp` (-0.1243, $p < 0.001$) and `div_FC_after_gdp` (0.1830, $p < 0.05$) significant, suggesting that constrained diversified firms reduce emissions as GDP grows, an effect moderated post-2021. The pooled regression (Column 6) retains `div_FC_gdp` significance (-0.1009, $p < 0.01$), but `div_FC_after_gdp` (0.1509, $p > 0.1$) and other terms (e.g., `div_after`, 0.0793, $p > 0.1$) fade, indicating limited post-treatment impact. GDP growth's role here is confined to constrained diversified firms' baseline emissions, not supporting a broad "chasing" of growth opportunities hypothesis. This sparsity contrasts with Panel A, suggesting non-EU27 plants' emissions are less tied to local economic growth, possibly due to weaker regulatory pressures or production stability.

Table 16: Controlling for growth opportunities PANEL B

Dependent Variable:	log(1+emissions_quantity)					
				Financial constraint subsamples		
				Const.	Unconst.	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
div_FC						-0.2073
						(0.1920)
div_after				0.3002	0.0158	0.0793
				(0.3487)	(0.2498)	(0.3728)
div_gdp		-0.0305	0.0059	-0.1185	0.0026	0.0041
		(0.0251)	(0.0303)	(0.0901)	(0.0282)	(0.0298)
div_after_gdp		0.0313	-0.0398	0.1156	-0.0582*	-0.0590
		(0.0316)	(0.0414)	(0.1000)	(0.0338)	(0.0565)
div_FC_after						0.3103
						(0.2228)
div_FC_gdp			-0.1243****			-0.1009***
			(0.0241)			(0.0296)
div_FC_after_gdp			0.1830**			0.1509
			(0.0882)			(0.1123)
FC_dummy						-0.0255
						(0.1068)
FC_after						-0.2009
						(0.1305)
FC_gdp		-0.0207	0.0111			0.0107
		(0.0259)	(0.0227)			(0.0229)
after_gdp		0.0041	0.0202	0.0633	0.0205	0.0156
		(0.0375)	(0.0344)	(0.0511)	(0.0318)	(0.0312)
FC_after_gdp		0.0263	-0.0187			0.0109
		(0.0393)	(0.0421)			(0.0425)
Total_debt	1.070**	1.059**	1.062**	0.6660	1.062**	1.061**
	(0.4315)	(0.4106)	(0.4220)	(0.4793)	(0.3930)	(0.4147)
size	0.4583****	0.4616****	0.4478****	0.4319**	0.2930**	0.4475****
	(0.1202)	(0.1192)	(0.1144)	(0.2087)	(0.1159)	(0.1155)
ROA	0.0032	0.0037	0.0035	0.0125*	0.0044	0.0035
	(0.0072)	(0.0071)	(0.0082)	(0.0073)	(0.0087)	(0.0076)
gdp_growthrate	-0.0070	-0.0023	-0.0143	-0.0315	-0.0180	-0.0155
	(0.0123)	(0.0190)	(0.0165)	(0.0234)	(0.0182)	(0.0170)
Fixed-effects						
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.72058	0.72111	0.72223	0.81315	0.75428	0.72276
Observations	2,239	2,239	2,239	956	1,283	2,239

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

Table 17 focuses on intra-EU27 plants, comparing diversified and undiversified firms to assess GDP growth's influence within the treated region. The results are notably sparse, with most interaction terms insignificant. In Column 2, `after_gdp` is negative and highly significant (-0.0706, $p < 0.01$), a pattern persisting across specifications (e.g., -0.0919, $p < 0.01$ in Column 6), indicating that post-2021 emissions in EU27 plants decrease as GDP growth rises, irrespective of diversification or constraint status. Column 3 adds `div_after_gdp` (0.0457, $p < 0.1$), suggesting a slight positive moderation for diversified firms, but this fades in the pooled regression (0.0474, $p > 0.1$). Constraint-related terms like `div_FC_gdp` (0.0065, $p > 0.1$) and `div_FC_after_gdp` (-0.0467, $p > 0.1$) lack significance, as do `div_after` (0.0048, $p > 0.1$) and `div_FC_after` (-0.0963, $p > 0.1$). The dominance of `after_gdp` suggests that within EU27, unconstrained firms' emissions decline with GDP growth post-2021, potentially reflecting regulatory compliance or efficiency gains, but diversification and constraints play minimal roles, differing from Panel A's nuanced interactions and Panel B's selective significance.

Table 17: Controlling for growth opportunities PANEL C

Dependent Variable:	log(1+emissions_quantity)					
				Financial constraint subsamples		
				Const.	Unconst.	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
div_after				-0.1193	0.0286	0.0048
				(0.1653)	(0.2027)	(0.2376)
div_gdp		0.0031	-0.0016	0.0054	-0.0009	-0.0012
		(0.0045)	(0.0033)	(0.0048)	(0.0029)	(0.0033)
div_after_gdp		0.0050	0.0457*	0.0101	0.0453	0.0474
		(0.0129)	(0.0248)	(0.0155)	(0.0366)	(0.0409)
div_FC						0.0440
						(0.0367)
div_FC_after						-0.0963
						(0.2849)
div_FC_gdp			0.0082			0.0065
			(0.0058)			(0.0051)
div_FC_after_gdp			-0.0592			-0.0467
			(0.0382)			(0.0474)
FC_dummy						-0.0127
						(0.0218)
FC_after						0.0143
						(0.1737)
FC_gdp		0.0018	-0.0027			-0.0026
		(0.0028)	(0.0061)			(0.0063)
after_gdp		-0.0706***	-0.0872***	-0.0709**	-0.0908***	-0.0919***
		(0.0210)	(0.0254)	(0.0284)	(0.0266)	(0.0249)
FC_after_gdp		-0.0102	0.0139			0.0130
		(0.0133)	(0.0189)			(0.0243)
Total_debt	0.3528	0.2005	0.2023	0.6754	-1.177	0.1924
	(0.2379)	(0.3046)	(0.2874)	(0.4799)	(0.7863)	(0.3135)
size	-0.1594	-0.1147	-0.1374	-0.2178	-0.2173	-0.1462
	(0.1421)	(0.1281)	(0.1083)	(0.1487)	(0.2097)	(0.1207)
ROA	-0.0020	-0.0031*	-0.0026	-0.0012	-0.0037	-0.0028
	(0.0016)	(0.0018)	(0.0015)	(0.0037)	(0.0047)	(0.0023)
gdp_growthrate	-0.0243**	-0.0012	0.0017	0.0031	0.0031	0.0018
	(0.0092)	(0.0095)	(0.0117)	(0.0148)	(0.0109)	(0.0115)
Fixed-effects						
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.96958	0.97047	0.97071	0.97374	0.99369	0.97076
Observations	770	770	770	497	273	770

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

5.3.4 Firm-level outcomes

This section adapts Table 9 from Bartram et al. (2022) to examine firm-level emissions and operational efficiency (ROA) post-2021 treatment, omitting Tobin's Q due to a mix of listed and non-listed firms, with results in Table 18. For diversified firms (Column 1), constrained firms show an insignificant emissions drop (`FC_after`, -0.1807, $p > 0.1$), while the placebo sample of non-diversified firms (Column 2) shows no significant increase (0.0282, $p > 0.1$), with `size` notably driving emissions in the latter (0.8540, $p < 0.001$). Operational efficiency in diversified firms (Column 3) remains unaffected by treatment (`FC_after`, -1.397, $p > 0.1$), though high leverage significantly reduces ROA (-19.53, $p < 0.001$). These findings suggest the treatment minimally impacts firm-level emissions or profitability, with leverage, not regulatory shifts, shaping operational outcomes.

Table 18: Firm-level outcomes

Dependent Variable:	log(1+firm_emissions_quantity)		Operational Efficiency
		Placebo sample	ROA
Model:	(1)	(2)	(3)
Variables			
FC_after	-0.1807	0.0282	-1.397
	(0.4615)	(0.1355)	(3.195)
Total_debt	0.9778	0.6890	-19.53****
	(1.309)	(0.4145)	(3.099)
size	0.1535	0.8540****	4.598
	(0.6777)	(0.1958)	(4.134)
ROA	0.0171	-0.0132	
	(0.0169)	(0.0080)	
TA_turnover			3.467
			(2.741)
Fixed-effects			
Firm FE	Yes	Yes	Yes
Years FE	Yes	Yes	Yes
Fit statistics			
R^2	0.95297	0.82226	0.63293
Observations	153	894	153

Clustered (Firm level & Country level) standard-errors in parentheses
*Signif. Codes: ****: 0.001, ***: 0.01, **: 0.05, *: 0.1*

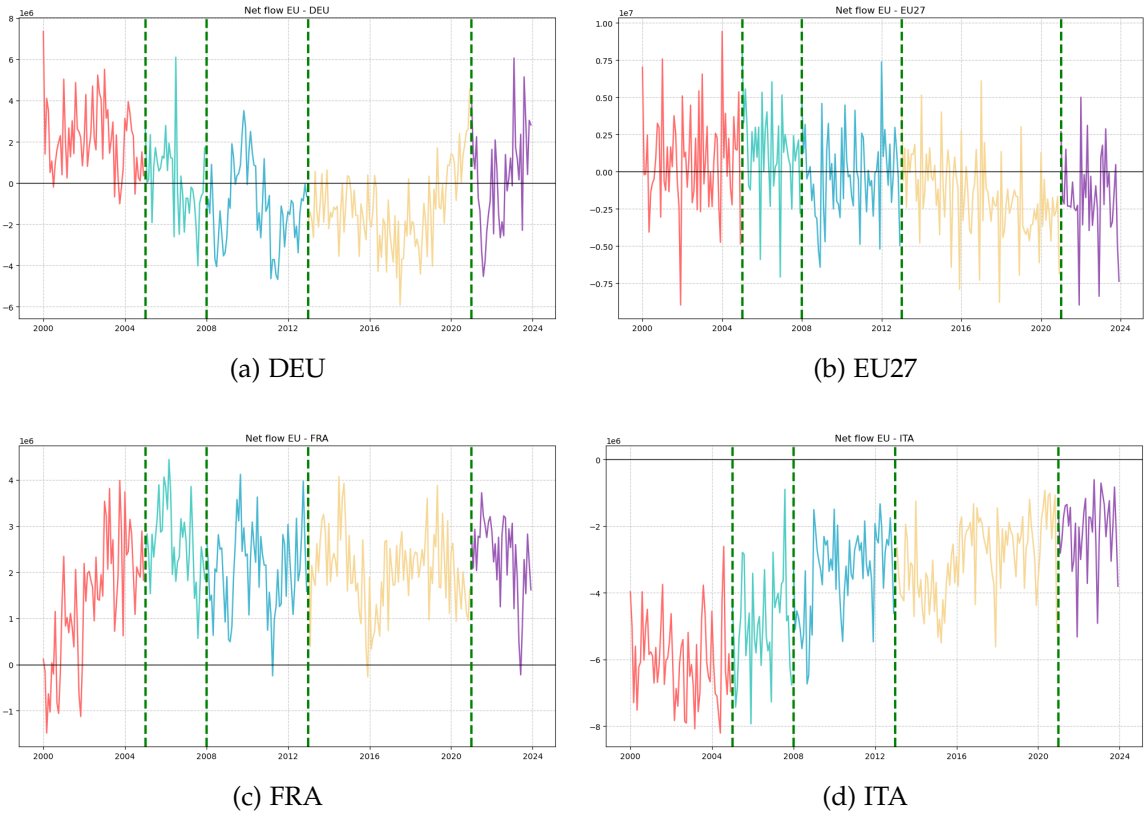
5.4 Indirect Carbon Leakage study

5.4.1 Change-point detection

In this section, we analyze the first set of available trade data, which consist of the Eurostat records on imports and exports, disaggregated into two categories: trade with other EU countries and with the rest of the world; for each EU member state from January 2000 to December 2024. To provide a clearer picture of the data under investigation, we begin by plotting the intra-EU net steel flow (see Table2), calculated as exports to the rest of the EU minus imports from the rest of the EU. A positive value indicates that the country is a net exporter within the Union, while a negative value denotes a net importer. Similarly, we construct the

net steel flow with the rest of the world (see Table3) using the same approach. To enhance interpretability, we divide the time series into the pre-ETS period and the four subsequent phases of the EU carbon pricing scheme and adding separate colour coding.

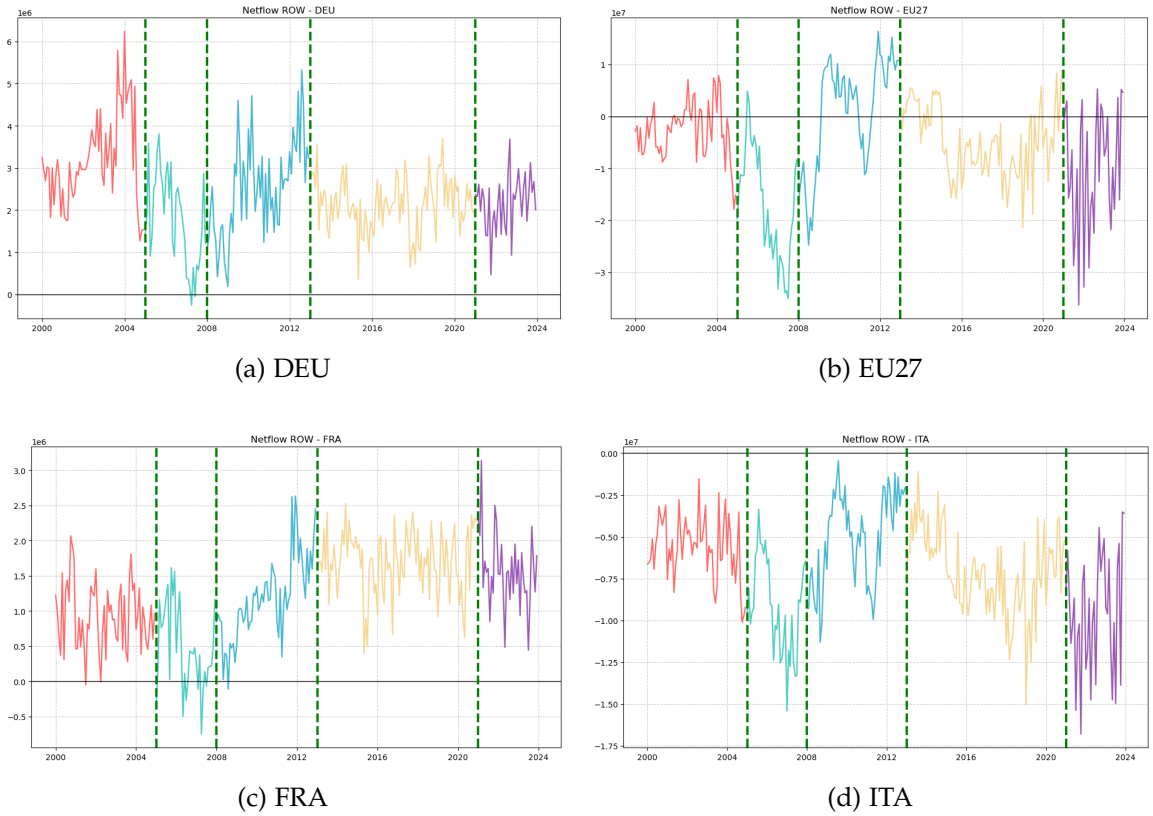
Even from a visual inspection, certain national series (here we have provide a selection of countries, nominally: Germany, Italy, France, and the aggregated EU27 bloc) exhibit apparent structural breaks in their trade flows. This observation motivates a closer investigation of trade between EU countries and non-EU partners, as any indirect carbon leakage resulting from the implementation of the EU ETS should primarily manifest in altered trade patterns with trade partners from the rest of the world.



(a) DEU (b) EU27

(c) FRA (d) ITA

Figure 2: Net steel flow intra EU



(a) DEU (b) EU27

(c) FRA (d) ITA

Figure 3: Net steel flow with ROW

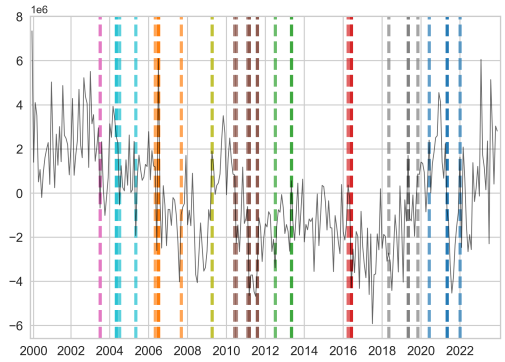
To analys the above mentioned trade series we apply a change-point detection technique known as Sequential Binary Segmentation with Cross Entropy (SBS-CE), as developed in Sojoudi et al. (2025), to identify potential structural shifts in the trade patterns of EU countries. This particular method was chosen over more basic alternatives such as standard binary segmentation or other conventional change-point algorithms, due to them requiring prior preprocessing—such as deseasonalization—to filter out noise and seasonal fluctuations. In contrast, the SBS-CE algorithm performs robustly even on raw trade series, demonstrating strong resistance to both seasonal patterns and idiosyncratic noise.

For completeness, we present the results of this procedure across both trade dimensions. Figure 4 reports the outcome of the change-point analysis on the intra-EU net steel flows, while Figure 6 displays the corresponding results for net steel flows between EU countries and the rest of the world (ROW). In each case, the left-hand side panels display all potential breakpoint candidates following the clustering stage (each cluster shown in a distinct color), whereas the right-hand panels highlight the final set of statistically significant breakpoints (in

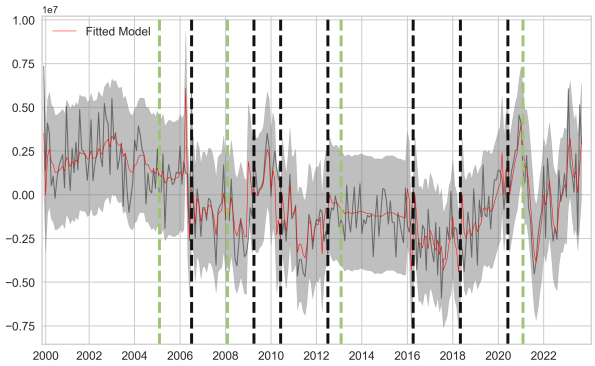
black), alongside vertical lines indicating the official start dates of each of the four EU ETS phases.

We adopt a 1% significance level throughout to ensure that only substantial and statistically robust breakpoints are retained. Several identified structural breaks align closely with the introduction of one or more ETS phases. Minor time discrepancies—where breaks occur slightly before or after the official start dates—are not unexpected. The phased implementation of the EU ETS is typically discussed and announced well in advance, allowing market participants to anticipate regulatory shifts and adjust production or logistics decisions accordingly. Moreover, physical adjustments to trade flows—such as reconfiguring shipping routes or sourcing alternatives—often require lead time, further justifying slight lead or lag deviations in detected breakpoints relative to the formal regulatory calendar, depending on the economic decisions and strategies of market participants.

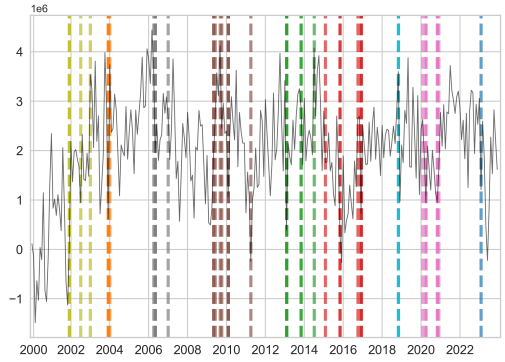
While the presence of multiple breakpoints in the steel trade series is evident, and some align closely with the rollout of ETS phases, steel remains a globally integrated market influenced by numerous competing forces. These can include global demand cycles, supply disruptions, or trade policy changes, each capable of counteracting or amplifying carbon pricing effects. As such, while we document statistically significant structural changes in trade flows during the lifetime of the ETS program, this alone is not sufficient to confirm the presence of indirect carbon leakage. To further investigate this hypothesis, we turn to more granular trade data to construct steel and carbon flow indicators, as discussed in the next section.



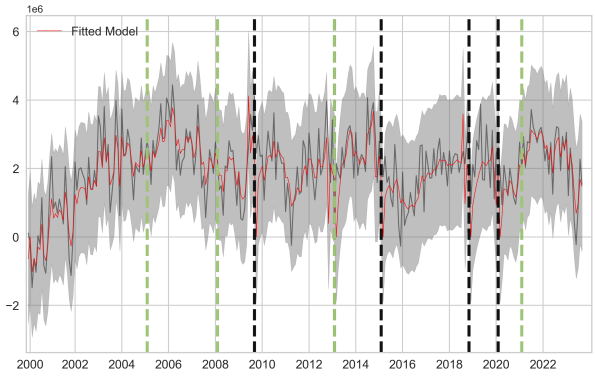
(a) DEU pre-clustering



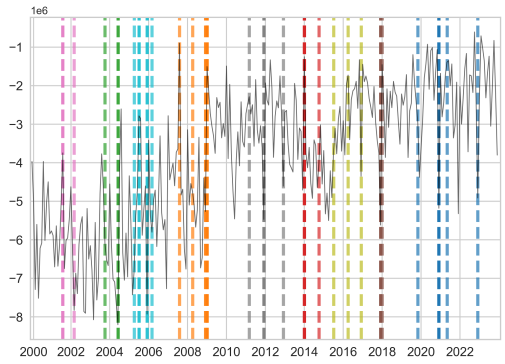
(b) DEU post-clustering



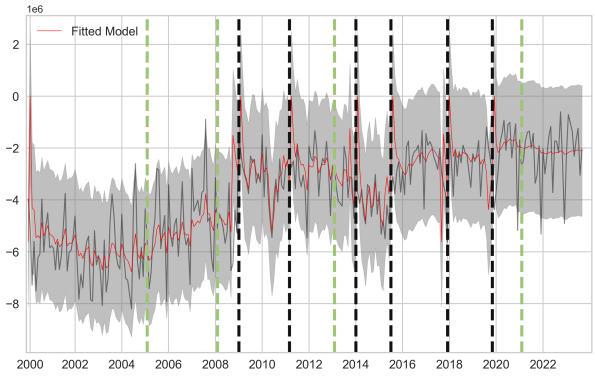
(c) FRA pre-clustering



(d) FRA post-clustering

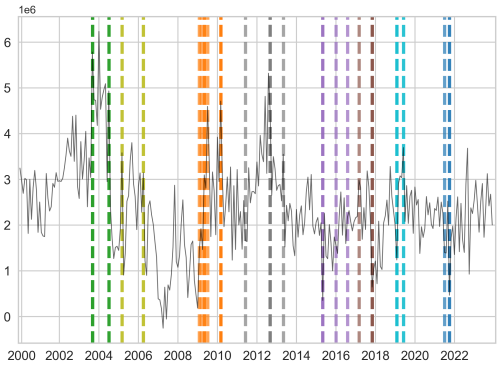


(e) ITA pre-clustering

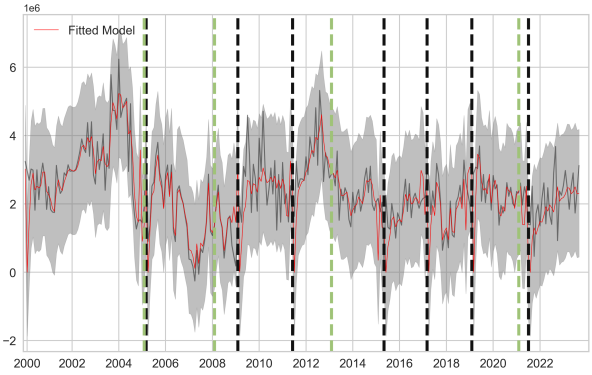


(f) ITA post-clustering

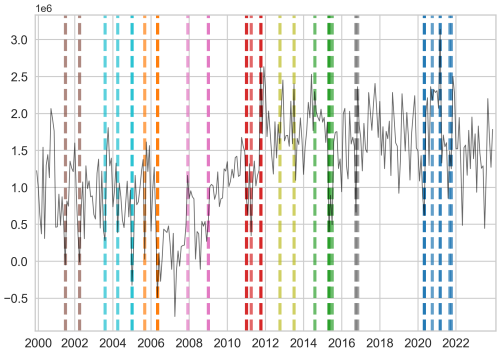
Figure 4: Intra EU steel trade analysis



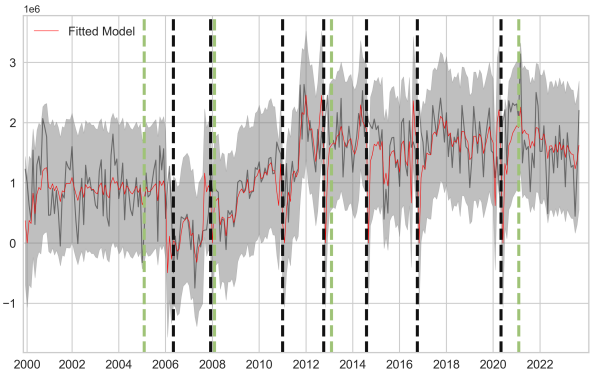
(a) DEU pre-clustering



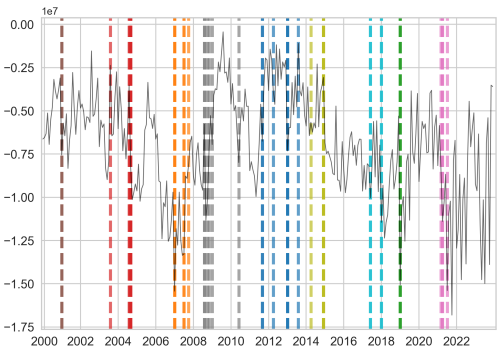
(b) DEU post-clustering



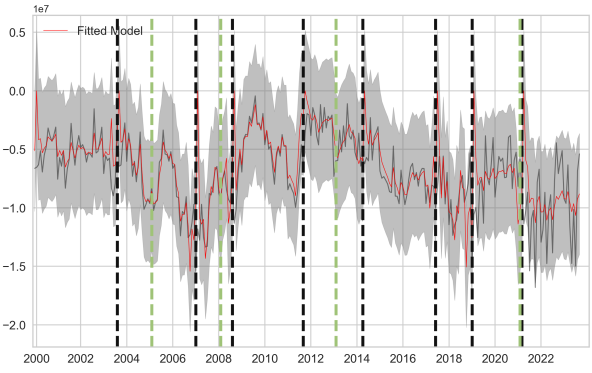
(c) FRA pre-clustering



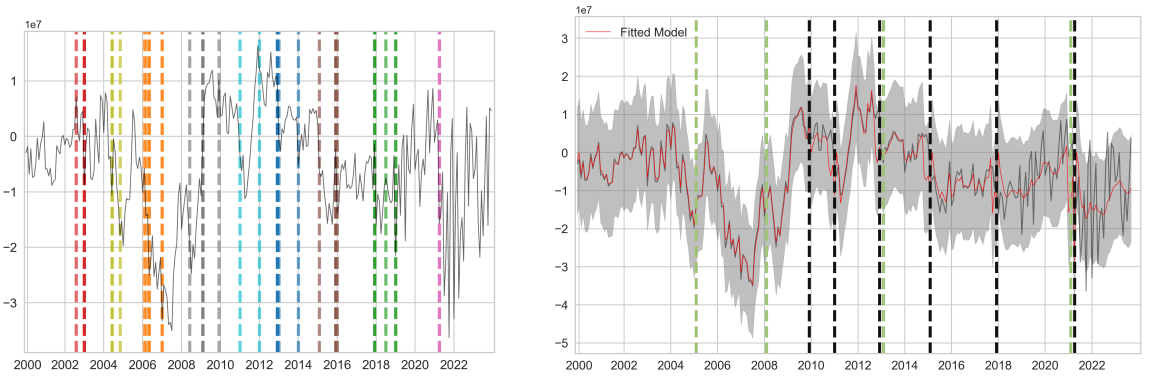
(d) FRA post-clustering



(e) ITA pre-clustering



(f) ITA post-clustering



(a) EU27 pre-clustering

(b) EU27 post-clustering

Figure 6: ROW-EU steel trade analysis

5.4.2 Carbon flows

To construct reliable indicators of carbon and steel flows, we relied on the more granular trade data available from the Comext database. This dataset provides monthly import and export records for each EU27 member state, disaggregated by trade partner. Thanks to this level of detail, we are able to track the exact monthly volumes of iron and steel traded between each EU country and every other country in the world.

Given our focus on testing for indirect carbon leakage, we concentrate on the import component of the steel supply chain—specifically, imports originating from countries outside the EU27 bloc. To ensure the relevance and traceability of our carbon intensity estimates, we restrict our analysis to imports from countries that actively produce steel (i.e., those with operational steel plants). Excluding imports from non-steel-producing countries does not affect our results materially, as trade volumes from such countries are negligible in comparison to total EU imports.

We construct monthly import volumes of steel and iron for the EU27 bloc over the period 2015–2024, consistent with the time frame for which we have emissions estimates and carbon intensity data. To combine trade volumes with carbon intensity measures, we estimate each country's median carbon intensity by dividing its total steel sector emissions by its total steel production. We then assume that all steel imported from a given producing country was manufactured domestically in that same country. While this assumption is clearly strong, we are unaware of any international trade dataset that provides origin-of-production information at this level of detail, and thus consider this a reasonable and

necessary approximation for our analysis.

With these assumptions in place, we generate monthly carbon flows by multiplying trade volumes by estimated carbon intensities. In addition to direct carbon flows—reflecting only scope 1 emissions from the steel production process—we also construct total carbon flows that include scope 2 emissions related to electricity consumption in steelmaking.

The key output of this exercise is represented by the red lines in the following figures, which show the ratio of imported steel or "imported steel CO_2" to total EU steel and "steel CO_2" supply. These ratios—our primary outcome variables—remain essentially flat over the sample period, with only minor fluctuations and even signs of a slight decline in recent years. This stability provides no support for the indirect carbon leakage hypothesis. Were such leakage occurring, we would expect to observe rising ratios over time, indicating an increasing reliance on more carbon-intensive, imported steel to substitute for domestically produced steel constrained by the EU ETS. Instead, our findings suggest no such substitution is taking place.

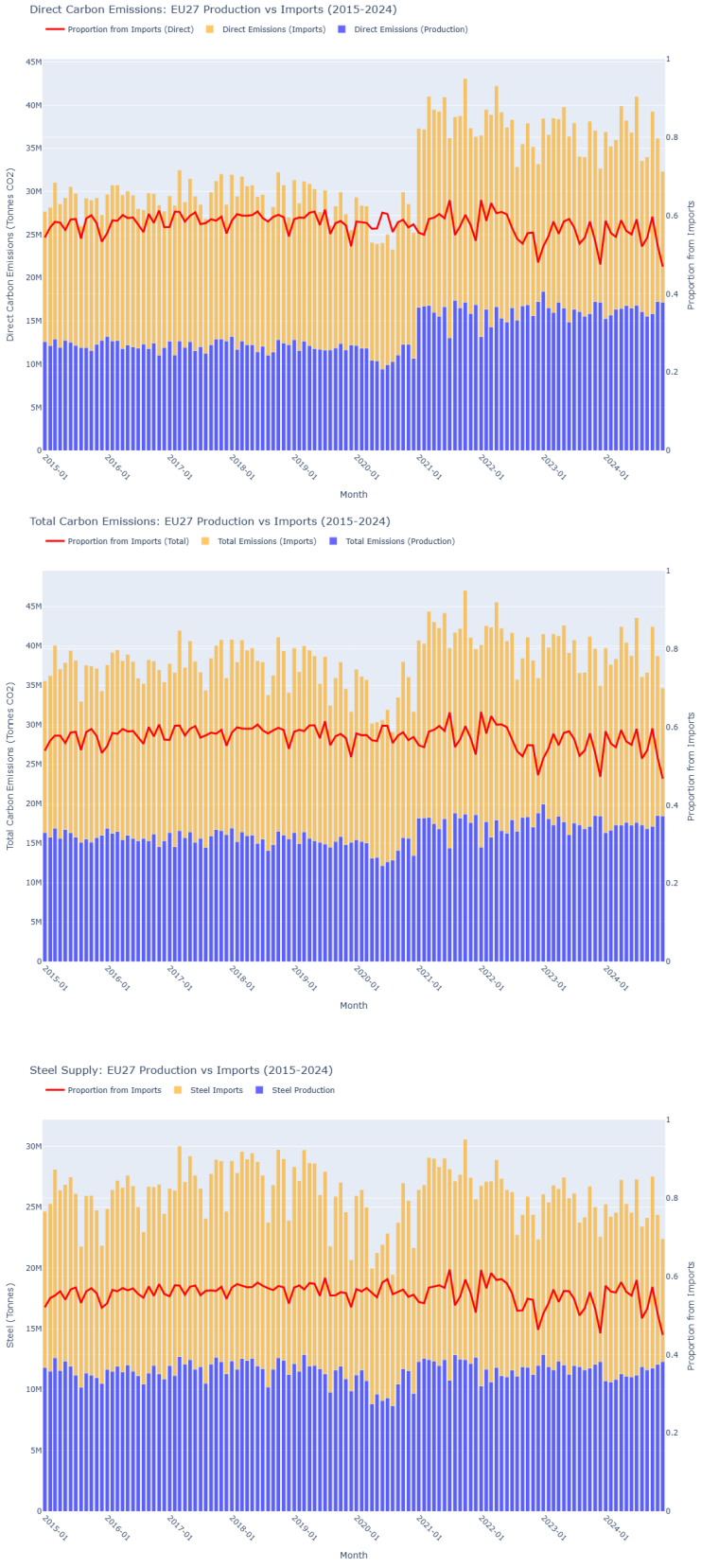


Figure 7: Final carbon flows and steel flows

6. Conclusions

Our analysis highlights that the prevalence of freely allocated allowances far exceeds verified emissions for most firms, effectively insulating them from the carbon tax and limiting incentives for emission reduction. We test for carbon leakage by examining whether emissions and production shift to plants owned by geographically diversified firms outside the EU and find no evidence of such reallocation, thereby ruling out direct carbon leakage. Moreover, by tracking the ratio of imported "steel CO_2" to total "steel CO_2" supply alongside the ratio of imported steel over the total steel supply present in the EU market, we document a stable pattern over the period, providing no support for the indirect carbon leakage hypothesis.These findings indicate that the EU ETS, as currently designed with its anti-carbon leakage measures, has not induced firms to relocate emissions or production outside the regulatory boundary, nor has it led to an increase in imported carbon-intensive steel products.

The novelty of our study lies in the integration of independent asset-level estimates with firm financial data and granular trade flows data, allowing a more comprehensive understanding of how climate policy affects firm behavior and market outcomes. This holistic granted by the mix of micro and macro-level approaches reveals that while the policy aims to reduce emissions, the extensive use of free allowances may blunt its effectiveness and shield firms from carbon costs without triggering leakage.

Our results contribute to the literature on the real effects of climate policy by demonstrating the importance of allowance allocation and firm structure in shaping firms' responses. From a policy perspective, these findings underscore the need for recalibrating allocation mechanisms and enhancing coordination across jurisdictions to prevent unintended distortions and ensure the environmental effectiveness of the EU ETS, which are culminating in the introduction of the Carbon Border Adjustment Mechanism (CBAM), to finaly solve the leakage risk. Ultimately, our study provides a foundation for policymakers seeking to design more robust climate regulations that minimize leakage risks and promote genuine emission reductions within the steel sector.

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