1 Introduction

Carbon pricing has rapidly expanded globally, with over 70 jurisdictions adopting carbon taxes or emissions trading systems that cover approximately 23% of global emissions (World Bank, 2024). As carbon prices have reached historic levels (surpassing €100 per tonne in the EU Emissions Trading System (ETS)concerns about the impact on competitiveness in energy-intensive and trade-exposed (EITE) sectors have grown. These concerns have led to the introduction of the EU's Carbon Border Adjustment Mechanism (CBAM), which will impose carbon costs on imports of iron, steel, and other carbon-intensive products starting in 2026.

Empirical evidence regarding the trade effects of carbon pricing is still limited and inconclusive. Systematic reviews indicate that the average impacts are modest (Venmans et al., 2020; OECD, 2023). However, recent studies focused on specific sectors suggest that carbon pricing may lead to a decrease in exports of carbon-intensive products (Rubínová et al., 2024; OECD, 2024). Despite this, existing literature has not thoroughly examined trade outcomes beyond 2022 or analysed product-level variations within energy-intensive and trade-exposed (EITE) sectors.

This paper fills this gap by examining the impact of carbon pricing on iron and steel exports from 2022 to 2024, a period when carbon prices reached unprecedented levels. Using UN Comtrade trade data merged with World Bank carbon pricing information, I estimate the elasticity of steel exports with respect to carbon prices, allowing effects to differ between raw steel (HS 72) and processed steel articles (HS 73).

2 Data

2.1 Trade data

I obtain bilateral trade data from UN Comtrade (WITS) at the HS 6-digit level for 2022–2024, focusing on HS chapters 72 (iron and steel) and 73 (steel articles) due to their carbon intensity. For each exporter–importer–product–year observation, the data include export values (thousands of current USD) and quantities. I construct a panel of major steel exporters, removing observations with missing identifiers, zero/negative values, or implausible unit values following standard procedures (Feenstra et al., 2004).

2.2 Carbon Pricing Instruments Data

Carbon pricing data come from the World Bank's Compliance Price dataset (1990–2025), covering carbon taxes and emissions trading systems (ETS). I extract country-year variables including regime type, average prices (All_Price_Mean, ETS_Price_Mean, Tax_Price_Mean), and the number of active schemes. Analysis focuses on compliance instruments (mandatory price signals) for 2022–2024, excluding voluntary offsets[1].

2.3 Merging Data

I merge datasets by exporter ISO3 code and year, creating an exporter–product–year panel with 200 observations across 36 countries.

[1] I exclude voluntary offset or credit mechanisms from the main analysis because participation in these is discretionary, and the resulting price signals are not directly linked to production decisions (Baranzini et al., 2017)

3 Explanatory Data Analysis

Figure 1 maps average carbon pricing levels across countries in 2024. European countries demonstrate the highest carbon pricing levels in 2024, with prices exceeding \$75/tCO2e, while North American and Oceanic regions maintain moderate pricing levels between \$25-50/tCO2e. This geographic variation highlights the heterogeneity in the implementation of carbon pricing policies across developed economies.

Figure 2 reveals that both HS72 and HS73 face similar trade-weighted carbon price exposure (\$44.7 vs \$40.9/tCO_2e) and comparable export volumes (~\$950B each), suggesting that any differential effects captured by the interaction term δ in Equation 1 reflect differences in carbon intensity or production structure rather than baseline exposure. The similar magnitudes justify pooling both product categories in a single regression framework with product fixed effects.

Figure 3 plots the unconditional relationship between prices and log export values. The negative slope for both product categories in the raw data (without controlling for country characteristics) disappears once country fixed effects are added (Table 2, Column 2), suggesting that the cross-sectional correlation is driven by time-variant country differences rather than within-country variation in carbon prices. This highlights the importance of controlling for unobserved heterogeneity.

Figure 4 shows that trade-weighted carbon price exposure peaked in 2023 for both product categories before declining through 2024, tracking the volatility in the EU ETS prices during this period. The parallel movement across HS72 and HS73 suggests common exposure to the same carbon pricing regimes, though the short time series (3 years) limits the within-country variation available for fixed effects estimation in Table 2.

Table 1 reports summary statistics for key trade outcomes and carbon pricing variables, separately for countries with both an ETS and a carbon tax and for countries with ETS-only regimes. Countries with both ETS and carbon tax instruments have lower average carbon prices (€61.2 vs €70.3) but substantially smaller export values (€5.8B vs €12.0B). This may reflect different industrial structures rather than policy effects. The large standard deviations in export values indicate substantial heterogeneity across countries, motivating the use of country fixed effects in the regression analysis.

Table 1: Summary statistics of key variables

	Both		ETS only	
	Mean	**SD**	**Mean**	**SD**
Export value (USD 1,000)	5774178	6218878.89	11963363.6	21695003.2
Log export value	14.9932109	1.15663732	14.5642095	2.47734006
Average carbon price	61.2128593	25.2102183	70.3188797	26.843778
ETS price	73.7019278	NA	70.3188797	NA
Tax price	48.6428167	NA	NA	NA
Number of ETS schemes	1.54	1.90914863	1.68	1.92212004
Number of Carbon taxes	1.24	1.0162319	0	0
N	100		100	

Fig 1 : Average carbon pricing levels across countries in 2024.

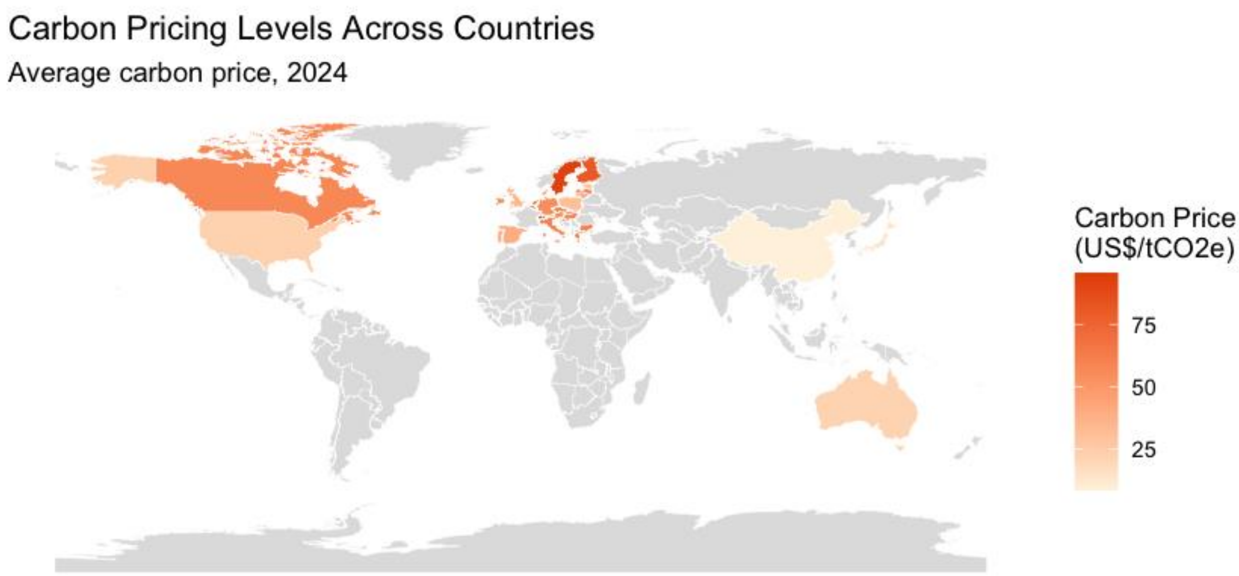


Fig 2: Comparison of trade-weighted carbon price exposure and total export volumes.

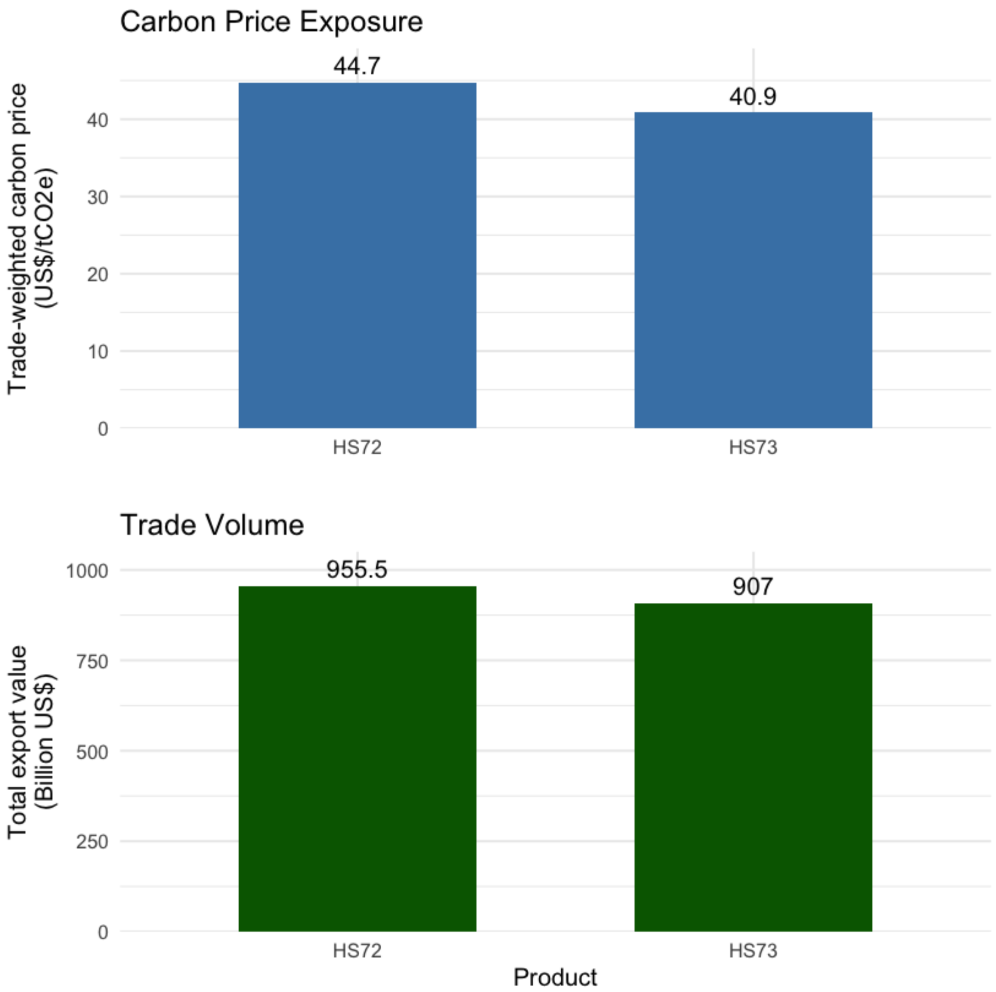


Fig 3: Unconditional Relationship Between Carbon Prices and Steel Exports

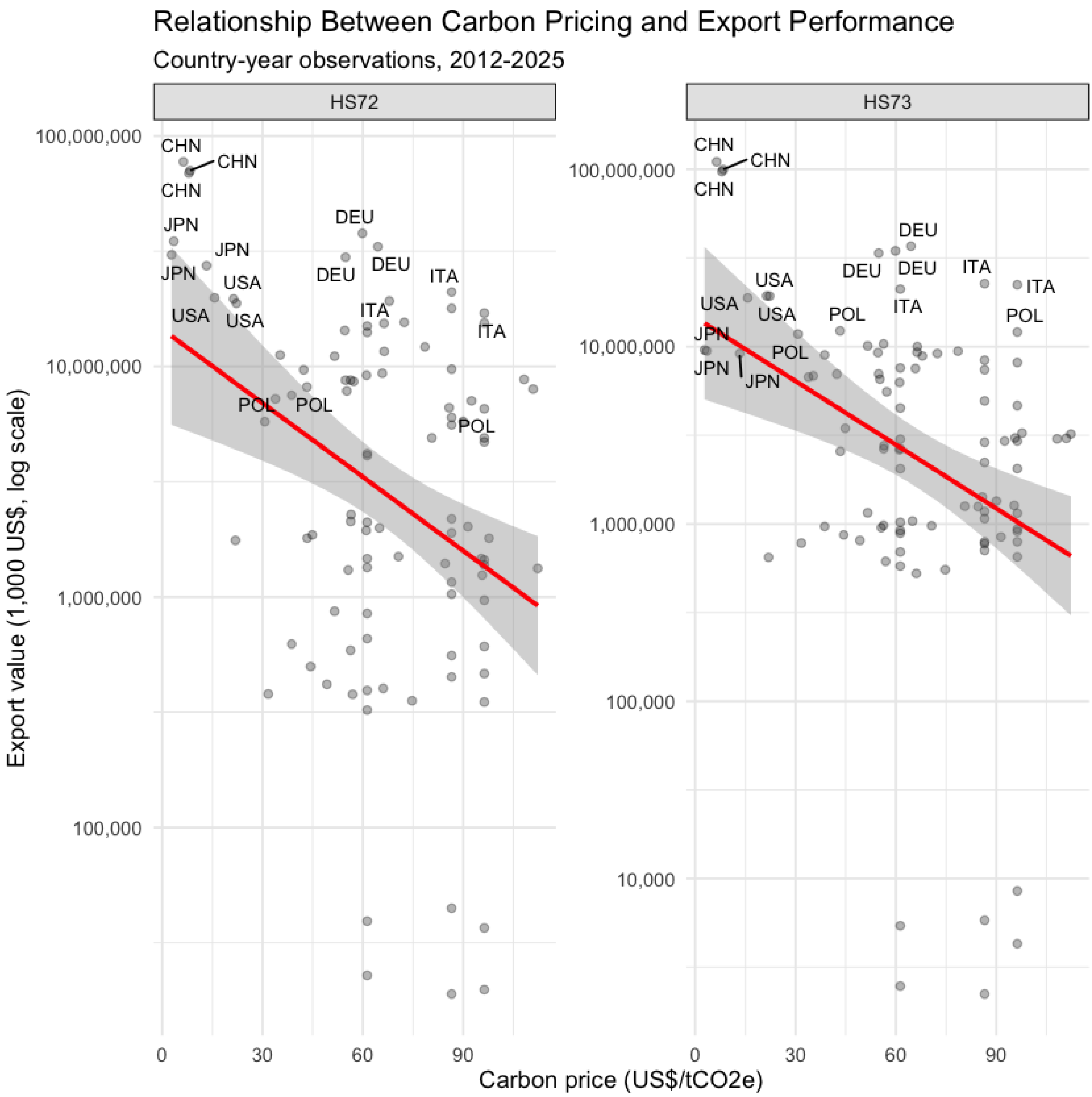
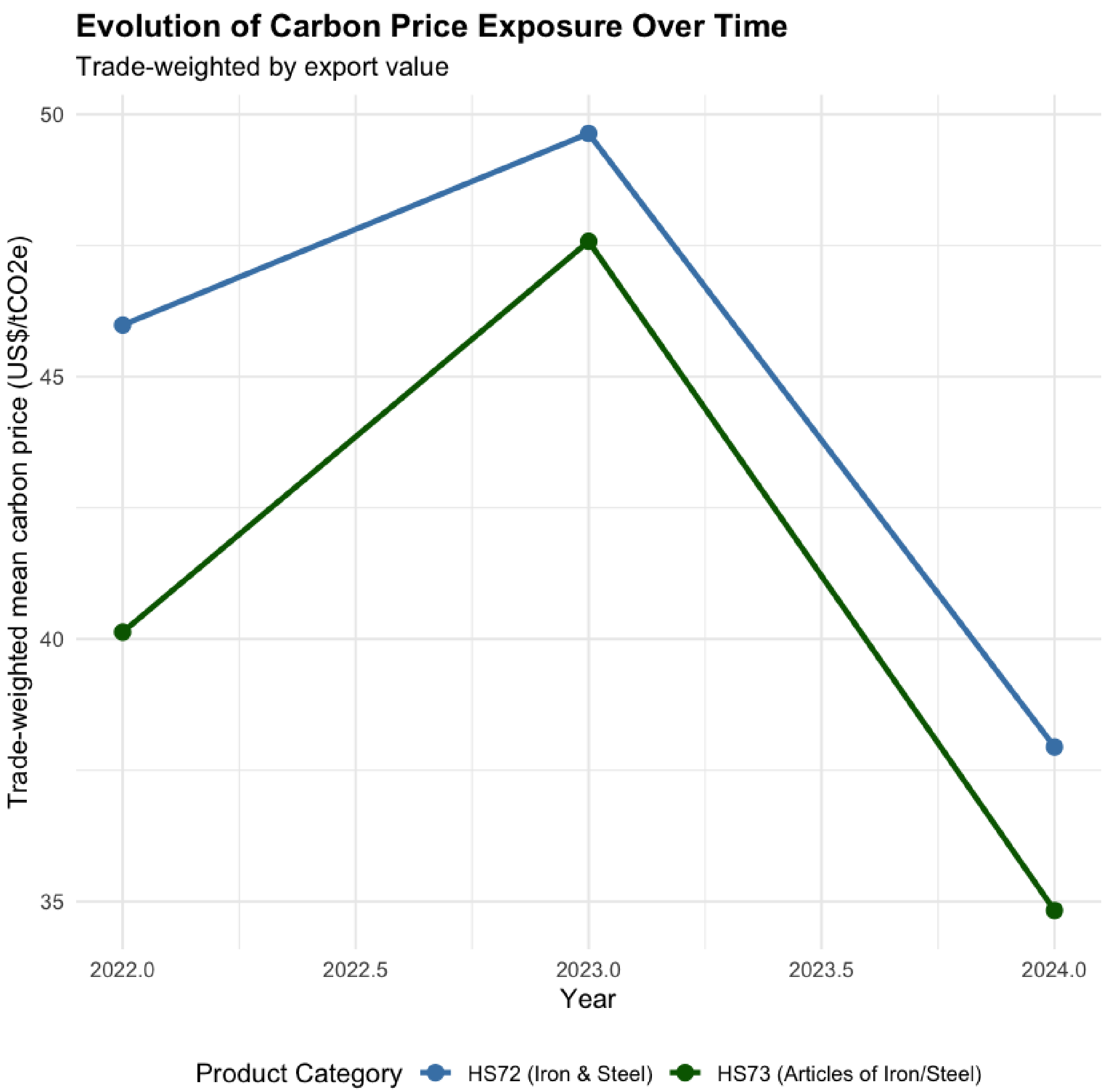


Fig 4: evolution of trade-weighted carbon price exposure for HS72 and HS73 over the period 2022–2024.



4 Methodology

To quantify the relationship between carbon pricing and export performance in energy-intensive steel sectors, I estimate the following baseline linear regression model[2]:

$$y_{ipt} = \alpha + \beta \cdot CP_{it} + \theta \cdot HS73_p + \delta \cdot (CP_{it} \times HS73_p) + \mu_i + \tau_t + \varepsilon_{ipt} \quad (1)$$

where y_{ipt} denotes the natural logarithm of export value (in thousands of US dollars) for product $p \in$ {HS72, HS73} from exporter country i in year t. CP_{it} is the average compliance carbon price (in USD per tonne of CO_2) in exporter country i and year t[3]. HS73_p is an indicator variable equal to one for products in HS chapter 73 and zero for HS 72[4]. μ_i and denote exporter and year fixed effects, respectively, which control for time-invariant country τ_t characteristics and common global shocks affecting steel trade. ε_{ipt} is an idiosyncratic error term. Standard errors are clustered at the exporter level throughout to account for arbitrary serial correlation and heteroskedasticity within countries over time.

The coefficient β identifies the effect of carbon pricing on steel exports under the assumption that, conditional on country and year fixed effects, variation in carbon prices is orthogonal to unobserved determinants of export performance. This assumption may be violated if governments adjust carbon prices in response to competitiveness concerns, an endogeneity issue I cannot address with the current data. Future work should employ instrumental variables (e.g., political shocks, EU-wide ETS price changes) to establish causality.

The three-year panel limits the within-country variation exploited by the fixed effects estimator. With country fixed effects, identification is obtained solely from changes in carbon prices within each country between 2022 and 2024. The limited time variation may reduce statistical power to detect effects, particularly given that carbon prices in many countries remained relatively stable during this period.

5 Results

Table 2 reports estimates from four nested specifications that progressively add controls and interactions. Column (1) presents a pooled OLS regression without fixed effects, estimating the unconditional correlation between carbon prices and export values. Column (2) adds exporter fixed effects (μ_i), which absorb time-invariant country characteristics[5]. Column (3) further includes year fixed effects (τ_t), controlling for common global shocks[6]. Column (4), the main specification, allows the carbon price effect to differ between raw steel (HS72) and steel articles (HS73) by including the interaction term $CP_{it} \times HS73_p$, while retaining both exporter and year fixed effects.

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[2] Baseline regression model inspired by regression models with product level bi-lateral trade flows(Teusch et al.,2024)

[3] As measured by the World Bank's Carbon Pricing Dashboard.

[4] allowing the coefficient δ to capture the differential effect of carbon pricing on finished steel products relative to raw steel.

[5] Time invariant characteristics such as technological capabilities, resource endowments, and trade infrastructure

[6] Common global shocks such as commodity price movements, exchange rate fluctuations, or pandemic-related disruptions that affect all exporters symmetrically (Anderson and van Wincoop(2003), Santos Silva and Tenreyro(2006).

The coefficient of interest, β, measures the percentage change in exports associated with a one dollar increase in the carbon price, holding product type and fixed effects constant. In the interaction specification (Column 4), β it captures the effect for HS72 products, while providing the effect for HS73 products[7]

It represents a progression of specifications to assess the robustness of the estimated relationship. The large negative coefficient in Column 1 (-0.026***) reflects cross-sectional differences: countries with higher carbon prices tend to have lower steel exports. However, this correlation may be spurious, driven by omitted variables such as technological capabilities or resource endowments. Columns 2-4 add fixed effects to control for these confounders. The dramatic change in coefficient magnitude and significance between Columns 1 and 2 reveals substantial omitted variable bias in the pooled specification. Once country characteristics are controlled (Columns 2-4), the estimated effects become small and statistically insignificant, suggesting either: (a) no detectable short-run effect of carbon pricing on steel exports, or (b) insufficient statistical power due to limited within-country variation over the 3-year period.

Table 2: Regression Results: Carbon Pricing and Export Performance in Iron and Steel

	(1) POOLED	(2) + COUNTRY FE	(3) + YEAR FE	(4) PRODUCT INTERACTION
CARBON PRICE	-0.026***	0.002**	0.000	0.002
	(0.004)	(0.001)	(0.001)	(0.003)
HS73 (DUMMY)				0.007
				(0.302)
CARBON PRICE × HS73				-0.003
				(0.005)
CONSTANT	16.494***			
	(0.290)			
OBSERVATIONS	200	200	200	200
R^2	0.126	0.959	0.960	0.963
ADJ. R^2	0.121	0.951	0.951	0.954

Standard errors clustered by exporter. *** p<0.01, ** p<0.05, * p<0.1.

[7] A negative estimate of β would be consistent with carbon pricing reducing the competitiveness of domestic steel producers in export markets (the "competitiveness channel"), while the sign and magnitude of δ reveal whether this effect differs across product complexity.

6 Discussion and Conclusion

This paper examines the relationship between carbon pricing and steel export competitiveness using a short panel of 36 countries from 2022-2024. The analysis yields three main findings:

First, there is a strong negative cross-sectional correlation between carbon prices and steel exports (Column 1). However, this relationship disappears once country fixed effects are introduced, indicating that the cross-sectional pattern reflects time-invariant country characteristics rather than carbon pricing effects.

Second, within-country changes in carbon prices over 2022-2024 show small and statistically insignificant effects on steel exports for both raw (HS72) and processed (HS73) steel products (Column 4: $\beta = 0.002$, $\delta = -0.003$, both $p > 0.10$). The null result may reflect: (i) genuinely small, short-run effects, (ii) insufficient statistical power from limited time variation, or (iii) policy offsets such as free allowance allocations in the EU ETS that buffer competitiveness impacts.

Third, the high R^2 in specifications with country fixed effects (>0.95) confirms that most variation in steel exports is explained by time-invariant country characteristics and common time shocks, leaving limited residual variation for carbon price effects to explain.

These findings carry important implications for carbon leakage debates. The absence of detectable short-run export effects, despite historically high carbon prices, may suggest either: (a) existing mechanisms (free allowances, efficiency improvements) effectively mitigate competitiveness concerns in the short run, or (b) longer time horizons are needed to observe meaningful responses. The EU's CBAM, scheduled for 2026, implicitly assumes that carbon pricing creates competitiveness risks warranting border adjustments. This analysis provides a pre-CBAM baseline for evaluating whether these concerns materialise in steel trade patterns.

Limitations and Future Research

The analysis faces several limitations. First, the 3-year panel severely constrains statistical power, as fixed effects estimation relies on within-country variation that is minimal over such a short period. Second, carbon prices may be endogenous to trade outcomes if governments adjust policy stringency in response to competitiveness pressures. Third, the analysis cannot distinguish between production shifting (carbon leakage) and efficiency improvements (reductions in emissions intensity).

Future research should prioritise: (1) extending the time series to capture longer-run adjustments, (2) exploiting quasi-experimental variation in carbon pricing through policy shocks, (3) analysing bilateral trade flows to directly test for carbon leakage to jurisdictions without carbon pricing, and (4) incorporating firm-level data to examine heterogeneous responses across the steel value chain. As carbon pricing expands globally and prices continue to rise, understanding these competitiveness-environment trade-offs will become increasingly critical for effective policy design.

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