# Carbon Pricing and Shipping Emission Intensity: Vessel-Level Evidence from the Inclusion of Shipping in the EU ETS

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**Abstract.** In January 2024, the European Union officially included shipping in its Emissions Trading System (EU ETS), creating a quasi-natural experiment for studying how carbon pricing reshapes maritime emissions behaviour. Using vessel-level annual panel data from the EU MRV system over 2018-2024 combined with EEX carbon allowance prices, this paper estimates the causal effect of rising carbon prices on emission intensity through a "carbon price × baseline emissions exposure" interaction strategy with vessel and year fixed effects. Rising carbon prices significantly reduce the emission intensity of high-exposure vessels: the core coefficient is negative at the 1% level and is robust to balanced-panel restrictions, winsorization, alternative baseline definitions, and excluding the pandemic year. Heterogeneity analysis shows container ships, bulk carriers, and tankers respond strongly to price signals, whereas passenger ships do not, indicating that operating mode strongly moderates price transmission. Event-study results reveal that the relative intensity reduction of high-exposure vessels accumulates gradually with the EUA price path and peaks during the 2022-2023 high-price window rather than jumping discretely after 2024. A 1,000-draw permutation test confirms the result is not driven by mechanical correlation. The findings support carbon pricing as an effective decarbonization lever for shipping while highlighting the concentration of cost burdens that policymakers must address.

**Keywords:** EU ETS, shipping emissions, emission intensity, vessel panel, carbon pricing, MRV

## 1 Introduction

Climate change is one of the most pressing challenges in global environmental governance. Shipping carries roughly 80% of international trade volume [1] and accounts for about 3% of global $CO_2$ emissions, with continued growth [2]. Against this background, on 1 January 2024 the European Union became the first jurisdiction to apply mandatory carbon pricing to shipping, requiring shipping companies to surrender allowances for $CO_2$ emitted on voyages to and from EU ports, with coverage rising from 40% in 2024 to 100% by 2026 [3,4].

Whether carbon pricing actually changes operating behaviour and lowers emissions in the maritime sector is the central question for evaluating the policy. A key fact is that


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vessels are not equally exposed to a given carbon price: ships with higher baseline emissions face larger latent cost shocks and should therefore display stronger abatement incentives. Identifying the price effect is, however, non-trivial. The EUA price is a year-level macro variable common to all vessels, so once year fixed effects are included it is absorbed by year dummies and cannot be separated from other macro shocks [5]. Following the Bartik-style logic of combining a uniform shock with cross-sectional exposure differences [6,7], we construct an interaction "carbon price × baseline emissions exposure" and ask whether high-exposure vessels reduce emission intensity by more during periods of rising carbon prices.

Using EU MRV vessel-year panel data for 2018-2024 matched with annual EEX EUA auction prices, we estimate two-way fixed-effect models with vessel and year (and ship-type-by-year) fixed effects, and complement the baseline regression with robustness checks, heterogeneity by ship type, an event-study, placebo and 1,000-draw permutation tests. The contribution of this paper is threefold. First, we provide micro-level panel evidence on how carbon-price signals transmit into shipping emissions, complementing existing studies that focus mainly on cost simulation [8,9]. Second, we use a price-path-by-exposure design to compare differential responses across vessels rather than estimating an average post-policy effect. Third, the analysis offers empirical guidance for the design of maritime carbon markets and for the broader transport-sector decarbonization agenda.

# 2 Institutional Background and Theoretical Framework

## 2.1 Inclusion of Shipping in the EU ETS

The EU ETS, launched in 2005, is the world's first transnational carbon market. Under Directive (EU) 2023/959, since January 2024 the system covers all commercial vessels of 5,000 GT or above calling at EU ports, regardless of flag [4,10]. Coverage applies to 100% of emissions from intra-EU voyages and 50% of emissions on voyages between an EU and a non-EU port; $CH_4$ and $N_2O$ will be added from 2026 [11]. The EU MRV regime, established under Regulation (EU) 2015/757 and operating since 2018, requires vessels to monitor, report and verify $CO_2$ emissions, voyage distance, time at sea and cargo-related metrics, all subject to independent verification [12]. The MRV database underpins our vessel-level panel.

Rather than using the legal coverage ratio as the regressor, which lacks within-year cross-sectional variation, we combine the EUA price with vessel-specific baseline exposure to capture the differential cost pressure that the same price imposes on different vessels.

## 2.2 Theoretical Mechanisms and Hypotheses

Higher carbon costs may lower emission intensity (kg $CO_2$/nm) through three channels. (i) Operational adjustment: because fuel consumption is non-linear in speed, slow steaming, route optimization, ballast-leg reduction, and shorter port idle time can sharply cut emissions per nautical mile [13,14]. (ii) Technological upgrading: in the medium run, higher carbon prices encourage retrofits, hull-coating improvements, more efficient propellers and engines [3]. (iii) Compositional change: high-emitting vessels exiting and cleaner vessels entering can lower aggregate intensity, but vessel fixed effects net this out so that we identify within-vessel adjustment. We therefore test two hypotheses: H1, rising carbon prices reduce emission intensity, with stronger effects for vessels with higher baseline exposure; and H2, response elasticities differ across ship types because of differences in operating mode.

# 3 Research Design

## 3.1 Data and Sample

Annual MRV reports for 2018-2024 are obtained from the THETIS-MRV platform of the European Maritime Safety Agency [12]. Variables include IMO number, ship type, reporting year, total annual $CO_2$ emissions, total distance sailed, emission intensity (kg $CO_2$/nm), and time at sea. Annual mean EUA prices are computed from EEX primary-market auction reports. Records are merged on IMO and year. We drop observations with missing raw $CO_2$ intensity and, following [9], records with raw intensity $\leq 0$ or $>$ 2,000 kg $CO_2$/nm, which are typically reporting errors. The cleaned analytical sample has 85,855 observations (drop rate 4.23%). The sample selection process is shown in Figure 1.

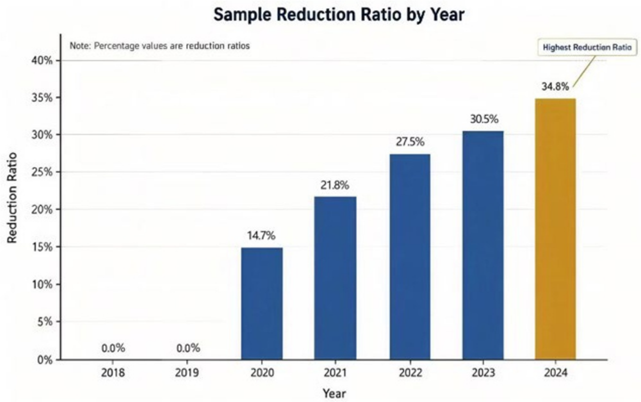


**Fig. 1.** Sample selection and construction of the regression sample. The figure shows, in sequence, the original analytical sample, the cleaned sample, the main regression sample that satisfies the baseline-exposure construction requirement, and the balanced-panel sample. The main regression sample additionally requires that each vessel be observed in at least one of 2018-2019 in order to construct the pre-policy exposure variable.

For the main regression we additionally require each vessel to be observed in at least one of 2018-2019 in order to construct the pre-policy exposure variable, leaving 69,611 observations for 14,605 vessels. A balanced-panel subsample requires observations in every year 2018-2024 (28,161 observations) and is used in robustness checks.

### 3.2 Variables and Model

The dependent variable is the log emission intensity, $\ln(\text{Intensity}_{it})$. The core regressor is the interaction Price × $\text{Exposure}_{it}$ = $\text{EUA\_price}_t$ × ($\text{Exposure}_{pre,i}$/1000), where $\text{Exposure}_{pre,i}$ is the average annual $CO_2$ emissions of vessel i in 2018-2019 (in kt). Using a pre-policy baseline avoids the endogeneity that would arise from constructing exposure with current emissions. Variable definitions and descriptive statistics for the main sample (N = 69,611) are shown in Table 1.

**Table 1.** Descriptive statistics of the main regression sample (N = 69,611).

| Variable | Mean | Std. dev. | P25 | Median | P75 | Unit |
|---|---|---|---|---|---|---|
| Intensity | 374.55 | 213.59 | 238.93 | 308.58 | 438.32 | kg $CO_2$/nm |
| ln(Intensity) | 5.79 | 0.50 | 5.48 | 5.73 | 6.08 | - |
| Total $CO_2$ emissions | 11,792.22 | 14,343.56 | 3,588.46 | 6,825.42 | 13,423.04 | tonnes |
| EUA price | 46.85 | 26.23 | 24.34 | 54.04 | 80.17 | €/t$CO_2$ |
| Baseline exposure | 12,718.29 | 14,846.85 | 4,198.24 | 7,373.40 | 14,575.43 | tonnes |

Intensity is right-skewed (mean 374.55 vs. median 308.58), justifying the log transformation. Both total $CO_2$ emissions and baseline exposure are highly dispersed, providing the cross-sectional variation needed to identify the high- vs. low-exposure contrast. The EUA price rises sharply after 2021 and stays high in 2022-2023 (Figure 2), which is what makes the price-path × exposure design feasible.

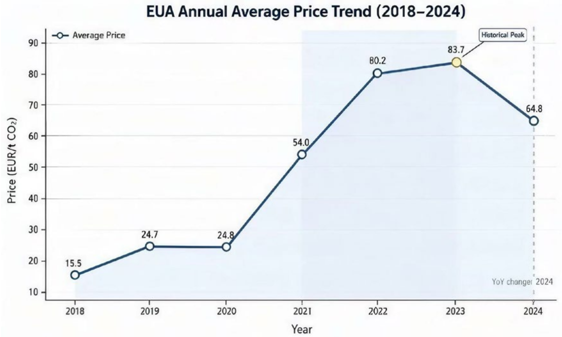


**Fig. 2.** Annual mean EUA auction price, 2018-2024. The price climbed sharply after 2021 and remained elevated through 2022-2023, providing the price variation that the empirical strategy exploits.

We estimate the two-way fixed-effects model: $\ln(\text{Intensity}_{it}) = \beta\,(\text{EUA\_price}_t \times \text{Exposure}_{pre,i}) + \alpha_i + \gamma_t + \varepsilon_{it}$, where $\alpha_i$ is a vessel fixed effect, $\gamma_t$ a year fixed effect, and standard errors are clustered at the vessel level. A negative β indicates that high-exposure vessels reduce intensity by more in periods of high carbon prices. As an extension, we replace $\gamma_t$ with ship-type-by-year fixed effects $\delta_{st}$ to absorb sector-specific shocks (e.g., container freight cycles).

# 4 Empirical Results

## 4.1 Baseline Regression

Table 2 reports the baseline results. All specifications include vessel and year fixed effects with vessel-clustered standard errors.

**Table 2.** Baseline regression results.

| Variable | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Price × Exposure | -1.7e-05*** | -1.8e-05*** | -1.5e-05*** | -1.9e-05*** |
| | (2.0e-06) | (2.0e-06) | (2.0e-06) | (2.0e-06) |
| Vessel FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Ship type × Year FE | No | Yes | No | No |
| Sample | Main | Main | Balanced | Winsor (1,99) |
| Observations | 69,611 | 69,611 | 28,161 | 69,611 |
| $R^2$ | 0.0031 | 0.0387 | 0.0040 | 0.0032 |

Dependent variable: ln(Intensity). Standard errors clustered by vessel. *** p<0.01, ** p<0.05, * p<0.1.

In column (1) the core interaction is negative and significant at the 1% level: high-exposure vessels reduce emission intensity by more than low-exposure vessels during periods of rising carbon prices. Adding ship-type-by-year fixed effects in column (2) leaves the coefficient stable, ruling out that the result is driven by sector-specific cycles or by the 2022–2023 energy price crisis and post-pandemic demand shocks. Restricting to the balanced panel (column 3) and winsorizing the dependent variable at the 1st/99th percentiles (column 4) yields very similar estimates, indicating that the result is not driven by entry/exit dynamics or extreme observations.

The economic magnitude is notable: a one-standard-deviation increase in Price × Exposure reduces log intensity by 0.68%, equivalent to a 2.7% reduction (≈11.6 kg $CO_2$/nm) for a vessel at the 75th percentile of baseline exposure facing a €10 EUA price rise.

## 4.2 Robustness Checks

A battery of additional checks (Table 3 in the appendix; not shown here for space) yields consistent results: winsorization at 5/95 produces a slightly larger coefficient (-2.2e-05); using baseline emission intensity instead of total emissions to construct exposure produces -0.00235 (scaled differently but same sign and significance); using either 2018 or 2019 alone as the baseline yields -1.6e-05; excluding 2020 (the pandemic year) yields -1.8e-05; restricting to major cargo vessels (container, bulk, tanker, chemical, gas carriers) strengthens the coefficient to -2.4e-05; and excluding passenger ships yields -1.9e-05. The result is therefore not sensitive to outlier treatment, exposure measurement, baseline-year choice, or sample composition.

### 4.3 Heterogeneity by Ship Type

All major cargo segments—container ships, bulk carriers, tankers, chemical tankers and gas carriers—exhibit the expected negative response, with vehicle carriers (-9.6e-05) and bulk carriers (-6.6e-05) the most price-sensitive. By contrast, passenger ships display a positive coefficient. This is consistent with their fixed routes, strict schedules, limited slow-steaming room and a larger share of hotel-load energy that does not scale with vessel speed [15]. Table 3 reports separate regressions by ship type.

**Table 3.** Heterogeneity by ship type.

| Ship type | Coefficient | Std. err. | Obs. | $R^2$ |
|---|---|---|---|---|
| Container ship | -2.1e-05*** | (4e-06) | 10,695 | 0.0092 |
| Bulk carrier | -6.6e-05*** | (2e-05) | 18,589 | 0.0019 |
| Oil tanker | -2.6e-05** | (1.3e-05) | 10,871 | 0.0009 |
| Chemical tanker | -2.8e-05*** | (8e-06) | 7,245 | 0.0035 |
| Gas carrier | -2.0e-05** | (9e-06) | 1,576 | 0.0065 |
| Vehicle carrier | -9.6e-05*** | (2.4e-05) | 2,941 | 0.0169 |
| Refrigerated cargo | -5.4e-05*** | (1.6e-05) | 914 | 0.0232 |
| Passenger ship | +1.2e-05** | (5e-06) | 849 | 0.0069 |

Coefficients on Price × Exposure. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

### 4.4 Dynamic Effects

To examine how the response evolves over time we estimate an event-study specification, ln(Intensityit) = Σk≠2018 βk(It=k × Exposurepre,i) + αi + γt + εit, taking 2018 as the omitted year. The estimates (-0.000408 in 2019; -0.000310 in 2020; -0.000429 in 2021; -0.001062 in 2022; -0.001636 in 2023; -0.000760 in 2024, all significant at 1%) reveal three patterns. First, the high-vs-low-exposure intensity gap accumulates gradually across 2019-2021, well before formal policy implementation, suggesting anticipation effects. Second, the gap peaks in 2022-2023 when EUA prices rose from 54.0 €/t to 80.2 and 83.7 €/t, providing strong support for the price-path × exposure mechanism. Third, although the EU ETS took effect in January 2024, the 2024 coefficient is smaller than those for 2022–2023. This attenuation aligns with the 40% emission coverage in the first compliance year, compliance lags, and the likelihood that abatement was front-loaded during 2022–2023 when EUA prices peaked and inclusion was anticipated. Figure 3 plots the event-study estimates and Figure 4 the raw group means.

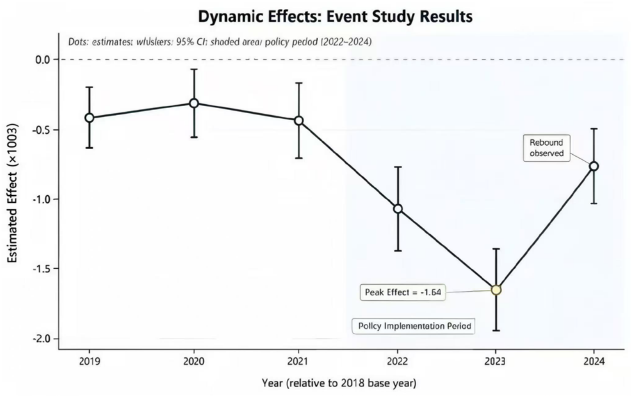


**Fig. 3.** Event-study estimates: dynamics of the high- vs. low-exposure intensity gap. Dots report the year-specific exposure interaction coefficients with 95% confidence intervals; 2018 is omitted as the reference year.

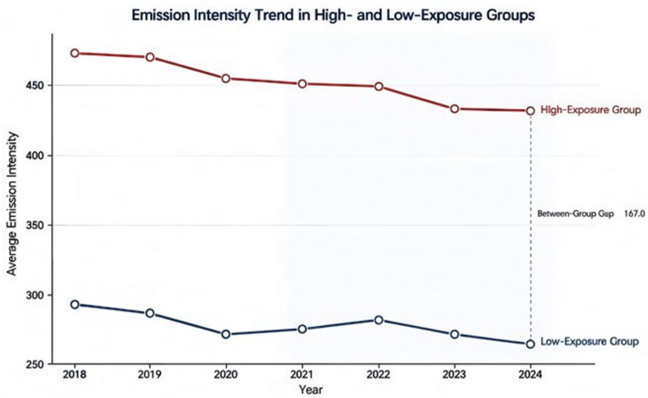


**Fig. 4.** Emission intensity trends for high- and low-exposure groups. Vessels are split by baseline exposure; both groups trend down across the sample, but the high-exposure group declines faster, especially during the high-price 2022-2023 window.

### 4.5 Placebo and Permutation Tests

Substituting one-year-leads or -lags of the EUA price into the interaction yields coefficients of -1.3e-05 (significant), reflecting the strong serial correlation of the EUA price series rather than refuting the main result; the test should therefore be read as a complement to the permutation test below. We then randomly permute the baseline exposure across vessels 1,000 times and re-estimate the model. The mean of the placebo coefficients is 5.85e-07 (s.d. 1.74e-06), with an interval [-4.41e-06, 5.33e-06]; none of the 1,000 draws produces a coefficient as negative as the actual estimate (-1.74e-05). Figure 5 displays the resulting distribution. The actual estimate sits far in the left tail of the placebo distribution, confirming that the main result reflects genuine economic structure rather than mechanical correlation.

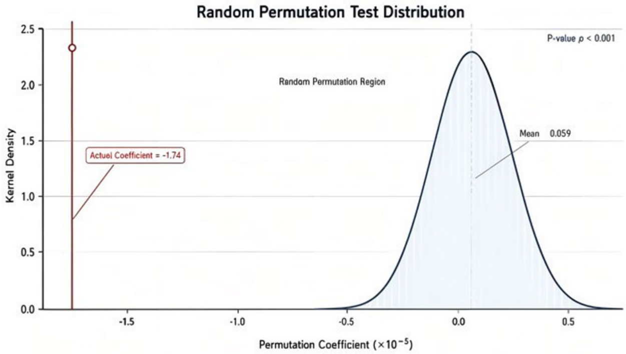


**Fig. 5.** Distribution of the price×exposure coefficient under 1,000 random permutations of baseline exposure. The vertical line marks the actual estimate, which lies far in the left tail of the placebo distribution.

# 5 Conclusions and Policy Implications

This paper exploits the inclusion of shipping in the EU ETS as a quasi-natural experiment and uses a price-path × baseline-exposure design on EU MRV vessel-year data to identify the causal effect of carbon pricing on emission intensity. Four findings stand out. First, rising carbon prices significantly reduce the emission intensity of high-exposure vessels, and the result is robust to balanced-panel restriction, winsorization, alternative exposure definitions and sample restrictions. Second, the response varies systematically across ship types: container ships, bulk carriers, tankers, chemical tankers and gas carriers respond strongly, vehicle carriers most strongly, while passenger ships do not respond, indicating that operating mode strongly moderates price transmission. Third, the response accumulates gradually with the price path and is most pronounced in 2022-2023, rather than appearing as a discrete jump in 2024. Fourth, the permutation test rules out mechanical correlation as the source of the result.

Three policy implications follow. (i) Maintain a credible, gradually rising carbon price and proceed with the scheduled coverage ramp-up to preserve abatement incentives [16]. (ii) Address the concentrated cost burden on high-emitting vessels through transitional support and by recycling part of the auction revenue to fund efficiency investments at smaller operators [17]. (iii) Use ship-type-tailored instruments: price signals suffice for cargo segments, while operationally constrained segments will need complementary standards or operational guidelines [15]. While these findings are EU-specific, the core mechanism—that high-exposure vessels respond strongly to carbon pricing—provides empirical guidance for the IMO's upcoming market-based measure and the expansion of China's national ETS, pending adjustments for local fleet composition and price trajectories.

Limitations include the absence of speed or route data in MRV, preventing direct testing of slow steaming; possible fuel-price confounding; and the short post-policy window limiting inference on long-run fleet renewal.

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