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The Carbon Market Paradox: When Emissions Do Not Determine Trading Actions

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Abstract: This study examined how carbon pricing and compliance costs affect corporate trading behaviour in carbon markets. It addressed a gap in understanding how market-oriented climate policies shape corporate conduct at the micro level. The study used a two-stage quantitative methodology and analysed 5,000 firm-level records from four sectors (cement, energy, manufacturing, steel) and multiple fuel types. Multiple linear regression identified determinants of carbon prices and compliance costs. Logistic regression assessed whether these factors could predict firms' trading decisions—whether to purchase or sell allowances. Sensitivity and scenario analyses tested model robustness under theoretical conditions: high emissions, policy tightening, demand shock, and price escalation. Results showed very weak links between operational variables and market outcomes. The carbon price regression had an R^2 of 0.0019, and the compliance cost regression had an R^2 of 0.0007, indicating that firm-level factors explain less than 0.2% of price variation. This is not a statistical failure—it's the key finding and the novel contribution of this study: treating near-zero explanatory power as substantive evidence that carbon pricing and trading are driven mainly by external policy frameworks, regulatory uncertainty, and strategic anticipation—not current emissions or compliance costs. The logistic regression's accuracy was 0.50 and ROC-AUC 0.48, consistent with random classification, further supporting the conclusion. The results show that effective carbon markets need more than price signals. Clear regulatory rules, stable allowance mechanisms, and supportive institutional infrastructure are crucial for aligning firm incentives with real emission-reduction objectives.

Keywords: Carbon Trading Behaviour; Carbon Pricing Determinants; Firm-Level Emission Strategies; Policy Uncertainty; Strategic Compliance Decisions

1. Introduction

The worsening climate crisis has made carbon emissions one of the most urgent environmental challenges today. Governments have introduced market-based mechanisms, especially carbon trading, to put a price on greenhouse gas emissions and drive reductions. The principle is simple: if companies have to pay for emissions, they will try to reduce their footprint by improving efficiency or by buying permits in compliance markets. But it is unclear whether these systems translate carbon pricing and compliance costs into actual corporate decisions.

This study asks: how do carbon pricing and compliance costs influence firms' trading behaviour and strategic responses in carbon markets? It covers both compliance and voluntary markets, focusing on how price signals and regulatory costs shape decisions about emission-reduction investment, production adjustments, and carbon credit trading. Since the Kyoto Protocol, carbon markets have expanded. China has created the largest trading system, and the EU continues to reform its Emissions Trading System (ETS). For policymakers and firms, understanding how

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these markets actually work—rather than how they should work—remains an important and open question.

The existing literature offers competing views. Proponents argue that carbon trading generates effective market signals. These signals direct capital toward low-cost emission reductions and green technology investments [1]. Empirical work finds that well-designed carbon pricing can yield both environmental and economic co-benefits [2]. Critics, however, see persistent market failures: price volatility, permit over-allocation, and questions about the additionality and quality of offsets [3]. Variation in outcomes across regions and industries raises further concerns about equity and effectiveness [4].

There is extra uncertainty in developing economies. New carbon markets face challenges with liquidity, transparency, and long-term price stability. Most research examines aggregate market or policy-level effects. Few studies analyse how specific firms, faced with carbon compliance, make decisions.

This study addresses that gap through three principal hypotheses. First, higher carbon prices encourage investment in emission-reduction technologies when abatement costs fall below the carbon price. Second, firms adjust production and supply chains to reduce carbon-intensive activities. Third, firms shift financial strategies—actively trading carbon credits and managing carbon risk—as a function of market conditions. The study further posits that the direction and magnitude of these effects depend on carbon price levels, market volatility, regulatory design, and firm-specific characteristics, including sector, size, and technological capacity.

The analytical framework integrates a systematic literature review with quantitative modelling of corporate decision-making under carbon constraints. Three components structure the approach: a cross-market synthesis of how carbon pricing affects corporate behaviour; a theoretical investigation linking compliance costs to strategic choices via cost internalisation, investment under uncertainty, and market-based environmental regulation; and an analysis of how market design features—including allocation methods, price floors and ceilings, offset provisions, and penalty structures—condition the relationship between carbon pricing and firm conduct.

The study aims to show that carbon pricing has real, but nonlinear, effects on corporate strategy. Elevated carbon prices should correlate with increased investment in emission reductions and greater participation in credit markets, though threshold effects are likely. High compliance cost uncertainty is expected to delay investment, consistent with real-options theory [5]. Energy-intensive industries should show stronger price sensitivity. Importantly, these findings are also expected to reveal the inadequacy of price signals alone and highlight the complementary institutional infrastructure needed to make markets work. These insights are intended to inform policy design that maximises environmental effectiveness while remaining economically viable and compatible with low-carbon technological transitions.

2. Literature Review

The academic literature offers substantial evidence that carbon trading mechanisms can reshape corporate behaviour through market-driven incentives. Proponents argue that cap-and-trade systems give firms the flexibility to choose the most cost-effective emission-reduction pathway—whether through operational improvements or permit purchases—thereby achieving environmental targets at lower aggregate cost [1]. This efficiency argument is reinforced by research showing that stable carbon prices and predictable compliance obligations incentivise investment in clean technology research and development, potentially accelerating the structural shift toward a low-carbon economy [1,6].

Beyond emission reduction, carbon trading creates new revenue opportunities. Firms that reduce emissions below their allocation can profit from permit sales, while growing demand for low-carbon technology and carbon management expertise supports new market segments and employment in clean technology and environmental services [7]. Wang et al. [8] demonstrate that carbon trading mechanisms facilitate green technology innovation in manufacturing by generating distinct price signals that reward investment in emission reduction. Evidence from established markets supports this view. The EU ETS, in operation since 2005, has shown that emission reductions and economic competitiveness need not be in conflict [9]. China's phased rollout of regional pilots leading to a national trading system represents arguably the most ambitious application of market mechanisms to climate governance at scale [10].

Yet carbon trading is not without serious criticism. Market failures—particularly permit over-allocation—can suppress carbon prices to levels that undermine long-run investment incentives [11,12]. Regulatory uncertainty and shifting policy environments make compliance costs difficult to predict, which in turn discourages sustained investment in low-carbon technologies and can stifle innovation [13]. Environmental integrity concerns are equally significant. Inferior carbon credits, especially in voluntary offset markets, allow firms to claim compliance without delivering real emission reductions—what critics describe as greenwashing [14]. Where projects lack additionality (meaning reductions would have occurred regardless of carbon finance), the credits they generate represent accounting gains rather than genuine atmospheric benefits.

Other structural problems compound these concerns. Emissions leakage—where regulated firms shift carbon-intensive activities to unregulated jurisdictions—undermines the aggregate effectiveness of any trading scheme [15]. Permanence concerns around carbon sequestration further complicate offset integrity. Equity dimensions also demand attention. Carbon trading systems can impose disproportionate burdens on developing-country host communities when offset projects are developed under lower environmental and social standards, raising concerns about displacement and the commodification of pollution rights [16, 17]. Firms that rely on controversial offsets face increasing reputational risks as environmental scrutiny from investors, regulators, and consumers intensifies [18].

Collectively, these critiques underscore that the effectiveness of carbon markets depends critically on robust regulatory design, transparent governance, and continuous monitoring. Without frameworks that protect environmental integrity, maintain price stability, and ensure equitable outcomes, market incentives may not align with broader social and climate goals. This has direct implications for how researchers interpret empirical results—including the findings presented in this study.

3. Methods

This study employed a two-stage quantitative methodology to analyse corporate conduct in carbon trading markets. The study sought to elucidate the determinants of carbon pricing and compliance costs, and to assess the extent to which these factors shape firms' trading behaviours. A systematic four-stage workflow was followed to ensure methodological precision and cross-method validation.

The first stage defined the research questions around the causes of carbon prices, compliance costs, and trading actions. The second stage involved obtaining and preparing operational, emissions, and economic data from a structured carbon-trading dataset. The dataset comprises 5,000 firm-level records from companies across four industries (cement, energy, manufacturing, and steel) using various fuel types. Data were cleaned, normalised, and categorical variables were encoded using one-hot encoding to prepare them for regression analysis.

The third stage applied two quantitative methods. Multiple linear regression was used as the primary method to assess how key variables affect carbon prices and compliance costs, yielding coefficients, R^2 values, and RMSE. Logistic regression was then applied to assess whether the same factors can also predict firms' binary trading decisions—specifically, whether to buy or sell carbon allowances—using accuracy, recall, and ROC-AUC. The fourth stage validated and interpreted findings across both models. The dual-method design strengthens the analysis by verifying whether the price and cost relationships identified in the first model carry through to observable market actions. Integrating both regression methods allows the study to examine not only economic determinants but also behavioural responses, offering a more complete picture of market functioning and policy responsiveness. This approach aligns with established multi-method designs in empirical market research [19,20].

3.1. Multiple Linear Regression

Multiple linear regression served as the initial analytical method, examining the influence of operational and emission-related variables on carbon pricing and compliance costs. This approach quantifies linear relationships between dependent and independent variables, and clarifies how fluctuations in energy demand, emissions produced, and emission allowances affect financial outcomes [19]. Two models were specified:

Model 1: YCompliance_Cost_USD = β0 + β1(Energy_Demand) + β2(Emission_Produced) + β3(Emission_Allowance) + β4(Fuel_Type) + β5(Industry_Type) + ε

Model 2: YCarbon_Price_USD_per_t = β0 + β1(Energy_Demand) + β2(Emission_Produced) + β3(Emission_Allowance) + β4(Fuel_Type) + β5(Industry_Type) + ε

The two models independently capture the determinants of carbon price per ton of CO_2 and compliance cost in

USD, isolating the financial consequences of emission performance and operational characteristics. This approach is consistent with established practices in energy market research [21], where multiple regression is commonly used to evaluate economic and environmental interdependencies. Both models provide a systematic framework for examining how firm-level operational and emissions metrics translate into financial outcomes in carbon trading markets.

3.2. Logistic Regression

Logistic regression was the second analytical method, examining whether the combined effects of operational, emissions, and economic factors can predict a firm's trading decision—specifically, whether to buy or sell carbon allowances. This method is appropriate for modelling binary behavioural outcomes and explains how firms respond to cost and market signals [19]. The model is specified as:

Model 3: logit(P(Buy)) = α0 + α1(Energy_Demand) + α2(Emission_Produced) + α3(Emission_Allowance) + α4(Fuel_Type) + α5(Industry_Type) + α6(Carbon_Price) + α7(Compliance_Cost)

This model extends the prior regression findings by incorporating Carbon Price and Compliance Cost—derived from Model 1 and Model 2—into the behavioural analysis. Including these financial variables tests whether economic outcomes actually influence strategic market behaviour [22]. Logistic regression enables the study to assess how a firm's operational profile and financial position jointly affect the probability that it will buy or sell allowances, thereby validating whether the economic relationships identified in the first stage carry over into actual trading actions.

3.3. Sensitivity and Scenario Analysis

Sensitivity analysis was conducted to assess how changes in key independent variables affect model outputs and stability. Emission_Produced_tCO2, Energy_Demand_MWh, and Carbon_Price_USD_per_t were selected as the variables most likely to influence carbon pricing, compliance costs, and trading behaviour. Baseline values were set at variable means or medians to represent typical market conditions. Four hypothetical scenarios were then constructed: a High-Emission Scenario (+20% emissions), a Policy Tightening Scenario (+10% carbon price), a Demand Shock Scenario (+15% energy demand), and a Price Surge Scenario. The Price Surge Scenario is operationalised through the Optimization_Scenario variable—a binary flag in the dataset identifying firm-observations under simulated market stress conditions characterised by simultaneous increases in carbon price and energy demand, intended to represent extreme policy tightening or supply disruptions.

Both regression and classification models were re-evaluated under each scenario to capture changes in predicted Carbon_Price_USD_per_t, Compliance_Cost_USD, and the probability of Target_Trade_Action. The ±20% perturbation range was chosen to represent plausible short-run variability in market conditions without departing from the dataset's observed distribution. Sensitivity metrics were expressed as elasticity values, indicating how much outcomes change in response to given input changes. The magnitude of variation across scenarios was used to assess the significance of those changes. Consistent results across scenarios indicate model stability, while substantial deviations highlight areas of uncertainty and potential behavioural volatility in carbon trading dynamics [23].

4. Results and Discussion

4.1. Descriptive Analysis

The three-stage analytical framework described in the Methods section—multiple linear regression, logistic regression, and sensitivity analysis—now yields the following results. This section begins with descriptive statistics that characterise the dataset across industries, fuel types, energy demand, and emissions, before moving to the regression and classification findings that constitute the core of the study. **Table 1** reports the mean values of key variables by industry type. Sectors with higher average energy demand and emissions also incur higher compliance costs, indicating that energy-intensive industries bear a disproportionate burden under carbon pricing mechanisms.

Table 1. Summary Statistics by Industry Type.

Industry Type	Energy Demand MWh (Mean)	Emission Produced tCO_2 (Mean)	Emission Allowance tCO_2 (Mean)	Carbon Price USD (Mean)	Compliance Cost USD (Mean)
Cement	1,755.14	960.61	963.43	27.60	12,390.57
Energy	1,756.39	969.44	967.51	27.50	12,522.15
Manufacturing	1,725.54	953.91	949.90	27.36	12,461.91
Steel	1,748.88	955.55	952.64	27.69	12,545.05

Table 2 summarises the relationship between fuel type, emission intensity, and trading behaviour. The mean value of the trading action variable approximates the proportion of firms more likely to purchase credits (Target_Trade_Action = 1).

Table 2. Fuel Type and Trading Behaviour.

Fuel Type	Observations	Target Trade Action (Ave)	Emission Produced tCO_2 (Ave)	Carbon Price USD (Ave)
Coal	1,227	0.50	967.86	27.39
Mixed Fuel	1,244	0.48	947.73	27.56
Natural Gas	1,281	0.50	974.94	27.58
Renewable	1,248	0.54	948.39	27.60

Table 3 provides overall descriptive statistics summarising central tendencies and variability across all quantitative variables. These results characterise the dataset's structure and provide the reference frame for interpreting regression and sensitivity results.

Table 3. Overall Descriptive Statistics.

Statistic	Energy Demand MWh	Emission Produced tCO_2	Emission Allowance tCO_2	Carbon Price USD	Compliance Cost USD
Count	5,000	5,000	5,000	5,000	5,000
Mean	1,746.21	959.81	958.25	27.53	12,480.17
Std. Dev.	714.78	478.43	492.69	4.32	4,336.62
Min	500.65	153.42	0.00	20.00	5,005.04
25th Pct.	1,141.88	574.82	573.50	23.85	8,706.11
Median	1,733.03	887.85	890.98	27.52	12,451.02
75th Pct.	2,356.26	1,271.68	1,283.91	31.28	16,166.65
Max	2,999.51	2,343.70	2,537.70	35.00	19,998.20

Three observations stand out. First, industry-level variation in energy demand is substantial, and sectors with the highest average demand—cement and energy—also carry the highest compliance costs, confirming their heightened exposure to carbon pricing policy. Second, fuel type correlates with emission intensity and trading tendency: firms using fossil fuels produce more emissions and show a slightly higher average propensity to purchase credits, consistent with structural reliance on external allowance markets. Notably, **Table 2** reveals a counterintuitive pattern: firms using renewable fuels exhibit the highest average propensity to buy allowances (0.54) compared to coal or natural gas users (approximately 0.50). This finding is plausible under several explanations. Renewable-fuel firms may participate strategically in carbon markets as hedging instruments or to accumulate green certificates that confer compliance flexibility. Alternatively, they may be positioning ahead of anticipated regulatory tightening, purchasing allowances before prices rise. This pattern warrants further investigation in future research, as it suggests that fuel type alone is insufficient to predict trading direction. Third, carbon prices in the dataset cluster in the USD 25–30 per tonne range, while compliance cost variability across firms reflects genuinely different levels of emissions exposure. The descriptive statistics enable immediate comparisons across fuel types and industries, providing a starting point for the regression and sensitivity analyses that follow.

4.2. Regression Results

The regression models revealed a striking, theoretically significant result: observable firm-level variables explain almost none of the variation in either carbon prices or compliance costs. As shown in **Table 4**, Model 1 produced an R^2 of 0.0007 for compliance cost and an RMSE of USD 4,334. Model 2 produced an R^2 of 0.0019 for carbon price and an RMSE of USD 4.31 per tonne. In practical terms, operational factors such as energy demand, emissions, fuel type, and industry classification account for less than 0.2% of variation in either outcome variable.

This is not a modelling failure—it is the central finding. The near-zero explanatory power of firm-level operational variables confirms the 'Paradox' hypothesis: carbon pricing in this dataset is driven by forces outside the firm. This is consistent with the broader literature, which shows that external policy factors—regulatory frameworks, allowance scarcity, and speculative behaviour—are the primary determinants of carbon price formation rather than the technical abatement cost signals that efficient market theory would predict [24,25].

Table 4. Regression Coefficients: Carbon Price and Compliance Cost.

Variables	Compliance Cost Coefficient (Model 1)	Carbon Price Coefficient (Model 2)
Fuel_Type_Mixed Fuel	−100.4923	0.1795
Fuel_Type_Natural Gas	−111.8769	0.1968
Fuel_Type_Renewable	−39.7119	0.2201
Industry_Type_Energy	131.9411	−0.0989
Industry_Type_Manufacturing	77.8128	−0.2445
Industry_Type_Steel	155.2022	0.0934
Energy_Demand_MWh	0.2048	−0.0000839
Emission_Produced_tCO_2	−0.1947	−0.0000648
Emission_Allowance_tCO_2	−0.0131	0.0004
R^2	0.0007	0.0019
RMSE	4,334 USD	4.31 USD/t

Model 2 explains approximately 0.2% of the variation in carbon prices, reaffirming that observable firm-level operational metrics have a negligible influence on market price formation. This is consistent with prior research attributing carbon price dynamics to external policy signals and speculative behaviour rather than to firm-level abatement activity [26].

4.3. Logistic Regression Results: Trading Decisions

The logistic regression model yielded an accuracy of 0.50, a precision (Buy) of 0.51, a recall (Buy) of 0.60, and an ROC-AUC of 0.48. These results indicate that the model performs at essentially random-chance levels: it cannot reliably predict whether a firm will buy or sell carbon credits based solely on observable quantitative data. This finding is consistent with the literature, which shows that corporate trading strategies are frequently shaped by expectations, regulatory anticipation, and internal sustainability objectives rather than by immediate market signals [27].

Model 3 confirms that neither emissions, fuel type, nor industry sector explains compliance-driven trading decisions in any meaningful sense. The full set of estimated logistic coefficients is reported in **Table 5**. The near-zero coefficients across all features, including Carbon Price and Compliance Cost, suggest that costs may depend instead on strategic compliance management or anticipatory policy positioning (e.g., the Optimization_Scenario variable). The classification model's random-chance performance indicates that the decision to buy or sell credits is driven by non-observable strategic, policy, or expectation-based factors rather than by the quantitative metrics captured in this dataset.

Table 5. Logistic Regression Coefficients: Trade Classification.

Feature	Logistic Coefficient
Fuel_Type_Mixed Fuel	−0.0003
Fuel_Type_Natural Gas	−0.0003
Fuel_Type_Renewable	0.0007
Industry_Type_Energy	0.0007
Industry_Type_Manufacturing	0.0003
Industry_Type_Steel	−0.0002
Energy_Demand_MWh	0.0000767
Emission_Produced_tCO_2	−0.0005
Emission_Allowance_tCO_2	0.0004
Carbon_Price_USD_per_t	0.0033
Compliance_Cost_USD	−0.00000610
Accuracy	0.50
Precision (Buy)	0.51
Recall (Buy)	0.60
ROC-AUC	0.48

Figure 1 displays the ROC curve for the classification model. Receiver Operating Characteristic (ROC) and Confusion Matrix analyses were used to assess predictive performance. The AUC measures a model's ability to distinguish between classes; a value of 0.48 is effectively at the chance level, confirming the model's inability to discriminate between buyers and sellers.

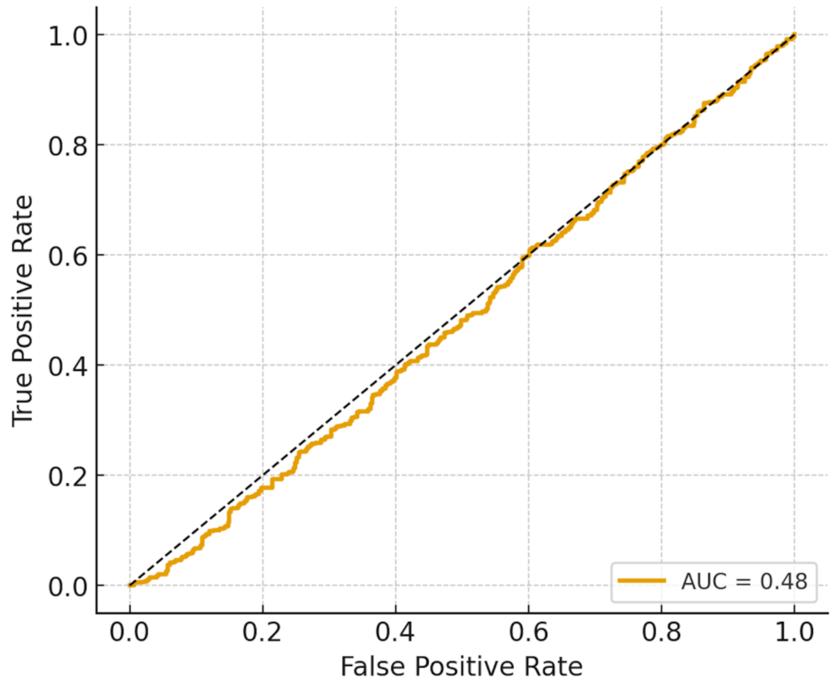

Figure 1. The ROC curve.

Figure 1 confirms that the model cannot discriminate between firms that buy and those that sell allowances, as the curve closely follows the diagonal reference line.

The confusion matrix (**Table 6**) shows 198 true negatives (sell decisions correctly classified) and 302 true positives (buy decisions correctly classified), alongside 296 false positives and 204 false negatives. The balanced distribution of errors indicates that the model has no meaningful directional bias—it simply cannot extract a predictive signal from the available features. These results reinforce the conclusion that corporate trading decisions are predominantly shaped by strategic and policy considerations rather than observable emission or cost data.

Table 6. Confusion Matrix: Logistic Regression Predictions vs. Actual Trading Actions.

	Predicted: Sell (0)	**Predicted: Buy (1)**
Actual: Sell (0)	198 (True Negative)	296 (False Positive)
Actual: Buy (1)	204 (False Negative)	302 (True Positive)

Taken together, the dual-method results demonstrate that neither operational nor emissions data effectively predict carbon market behaviour. Carbon pricing, compliance costs, and trading decisions appear to be governed by strategic foresight and regulatory anticipation rather than by the firm-level metrics commonly captured in quantitative datasets [28].

4.4. Sensitivity and Scenario Analysis

4.4.1. Carbon Price Model

Figure 2 presents sensitivity results for the carbon price model across three principal drivers—emissions produced, energy demand, and carbon price—under baseline, −20%, and +20% scenarios. The results are unambiguous: the regression model shows negligible sensitivity to any individual operational variable. No plant-level metric—including energy demand or emission volume—had a meaningful effect on the predicted carbon price per tonne. This is consistent with the very low R^2 of 0.002 from the base regression and confirms that carbon price formation is driven by policy architecture and market dynamics—regulatory frameworks, allowance scarcity, and speculative activity—rather than by firm-level operating conditions [25].

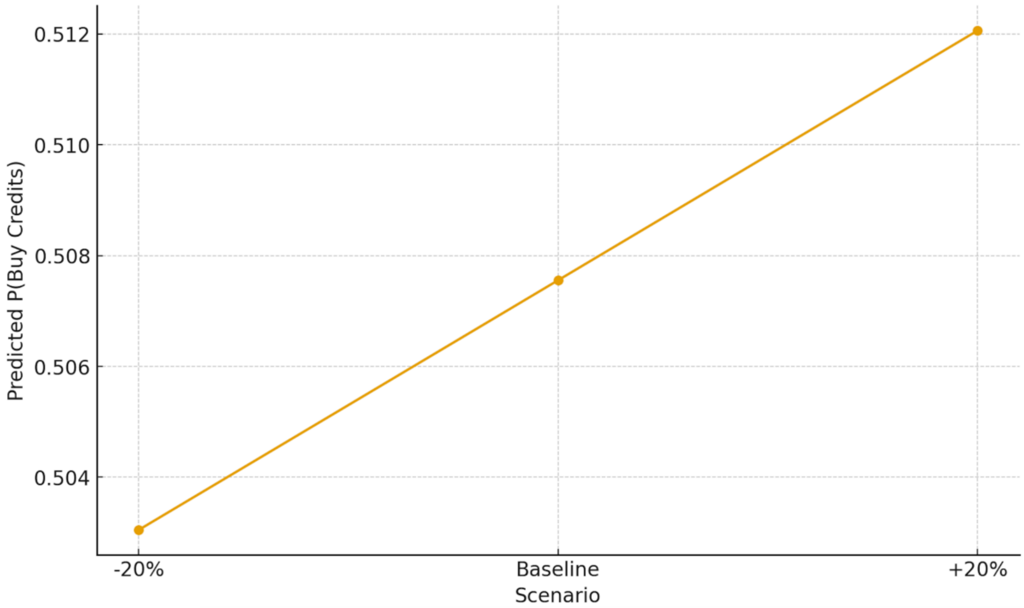

Figure 2. Carbon Price Model Sensitivity across ±20% Scenarios.

4.4.2. Trade Decision Model (Buy vs. Sell)

Figure 3 presents the predicted probability of credit purchase (Target_Trade_Action = 1) across −20%, baseline, and +20% scenarios for each of the three key variables. All three variables showed minimal sensitivity. A ±20% change in Emission_Produced_tCO$_2$ shifted the predicted buy probability from approximately 0.53 to 0.49. A ±20% change in Energy_Demand_MWh produced a shift of only a few tenths of a percentage point (roughly 0.50 to 0.514). Carbon_Price_USD_per_t had a similarly limited effect, with the model response moving from approximately 0.504 to 0.512 across the full range.

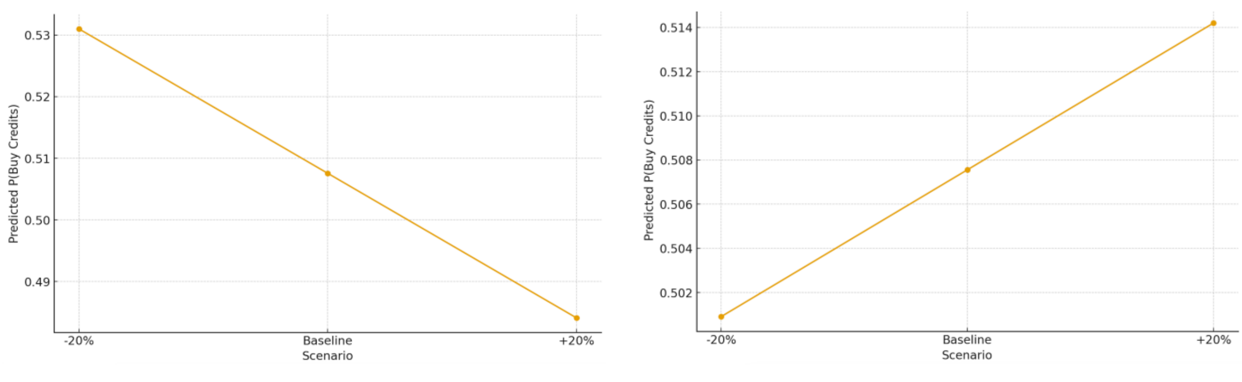

Figure 3. Sensitivity of Trade Decision Model—Energy Demand and Emission Produced tCO$_2$ across Scenarios.

Across all tested shocks, the model's predicted buy probability remained close to 0.5—consistent with its ROC-AUC of 0.48 and effectively indistinguishable from chance. These results confirm that companies' trading decisions are not primarily responsive to short-run operational or cost changes. Instead, decision-making reflects broader strategic factors: anticipated regulatory shifts, internal compliance priorities, and risk management frameworks [28].

The combined scenario results offer a clear and coherent picture. Carbon price predictions remain stable despite substantial operational perturbations, reinforcing that price formation is policy-driven rather than firm-driven [28]. Credit purchase probabilities likewise show minimal variation, indicating that compliance strategies are anchored in long-run financial planning and regulatory anticipation rather than direct emissions management.

The broader implications are significant. Recent data show that carbon pricing instruments now cover approximately 24% of global emissions, according to the World Bank. Yet, as this study confirms, pricing formation remains largely independent of individual firm characteristics. This aligns with OECD findings that fuel excise taxes declined following the energy crisis while emissions trading expanded, suggesting that external macroeconomic and policy factors systematically overshadow firm-level price signals [29]. The logistic model's random-chance performance further supports the IMF's observation that firms' responses to carbon regulations involve rising input costs alongside growing turnover—a pattern reflecting strategic adaptation rather than simple cost avoidance [30]. These empirical regularities point to a deeper issue in carbon market design: the mismatch between the economic theory underpinning cap-and-trade and the institutional reality in which firms actually operate. Standard models assume that firms respond rationally to marginal abatement cost signals, trading allowances until the permit price equals their internal cost of cutting emissions. The present findings challenge that assumption at the firm level. When neither emissions volumes, energy intensity, nor fuel type predicts prices or trading behaviour, the market is not functioning as a clean price-discovery mechanism. Instead, it is operating as a policy institution where expectations, regulatory timing, and strategic positioning matter far more than current operational data. This interpretation is consistent with the behavioural finance literature, which documents that asset prices in thin or informationally opaque markets can decouple from underlying fundamentals for extended periods. Carbon markets share several features with such markets: relatively few active participants in many national schemes, politically sensitive price floors, and periodic policy interventions that create discontinuities. The result is that firm-level data—even high-quality operational data—may carry very little information about where prices will go or what trading actions will be optimal. For firms navigating this environment, the implication is practical. Compliance strategy should be treated as a form of regulatory risk management rather than a simple cost minimisation exercise. Firms that invest in regulatory intelligence—monitoring policy signals, engaging with standard-setting processes, and building scenario-planning capacity—are likely to outperform those that simply react to current prices. This conclusion parallels findings in the environmental management literature, where proactive firms that engage early with sustainability regulations consistently achieve better financial outcomes than reactive counterparts.

The study's low explanatory power also raises productive questions about variable selection. Colmer et al. [31] show that firms change production technologies when the present value of switching exceeds switching costs, implying that technological readiness and capital investment capacity are important conditioning variables—both of which are not captured here. The dataset also lacks proxies for policy stringency, regulatory anticipation indicators, and strategic positioning variables needed to fully explain compliance behaviour.

The failure to predict trading behaviour likely reflects deeper measurement challenges as well. Threshold effects and nonlinear dynamics are plausible: larger emission reductions at the firm level are associated with greater trading profits [30], suggesting that linear models simply cannot capture the strategic architecture of carbon market participation. The inverted U-relationship between trading volume and enterprise development [32] further implies that timing and market maturity are absent from the current analysis.

This study, therefore, unintentionally makes a constructive point: plant-level compliance decisions are embedded in a strategic ecosystem that quantitative operational metrics alone cannot explain. The low predictive power is not a shortcoming of the research design—it is evidence that successful carbon market participants employ forward-looking strategies that go well beyond short-run cost responses. Policymakers should take this seriously: effective carbon pricing requires not only well-calibrated price levels, but also the institutional infrastructure to close information gaps, build strategic capacity, and support technological transitions.

5. Conclusion

This study examined the influence of carbon pricing and compliance costs on firms' trading behaviour, using a two-stage quantitative methodology integrating multiple linear and logistic regression analyses. The examination of 5,000 firm-level records spanning four industries and multiple fuel types produced results that fundamentally challenge conventional assumptions about the efficiency of carbon markets.

The multiple linear regression models yielded R^2 values of 0.0019 for carbon price determination and 0.0007 for compliance cost prediction. Observable firm-level operational variables—including energy demand, emissions produced, emission allowances, fuel type, and industry classification—account for less than 0.2% of variation in either outcome. The logistic regression model produced an accuracy of 0.50 and an ROC-AUC of 0.48, confirming that firms' strategic buy-or-sell decisions cannot be reliably predicted from operational and emission data alone. Sensitivity and scenario analyses corroborated these conclusions: carbon price predictions remained essentially stable across ±20% perturbations in key variables, and the probability of credit purchase shifted only marginally.

Taken together, these empirical findings contest the neoclassical assumption of efficient carbon markets in which prices directly reflect marginal abatement costs. The tenuous relationship between operational variables and market outcomes suggests that exogenous factors—regulatory design, government policy announcements, allowance allocation mechanisms, and speculative behaviour—are the primary drivers of carbon price formation. The failure to predict trading decisions from observable data further implies that corporate buy-sell strategies are grounded in long-run strategic planning rather than short-run reactions to current market conditions. This decoupling between firm-level operations and market outcomes is itself a policy-relevant finding: it suggests that price signals, however well-calibrated, cannot substitute for the institutional depth required to make carbon markets function as genuine instruments of emissions reduction.

For policymakers, this means price signals alone are insufficient. Complementary measures are needed: stable, transparent regulatory frameworks; reliable policy communication; price stability mechanisms; and institutional support for technological transitions. For firms active in carbon markets, the findings highlight the importance of strategic capacity that goes beyond emissions management—specifically, the ability to anticipate regulatory developments, conduct scenario analysis, and manage carbon risk as a distinct organisational function. Markets that fail to deliver clean price signals will not correct themselves through firm behaviour alone; institutional design must fill that gap. Without it, the gap between policy intent and market outcome will persist.

Limitation

This study has several important limitations that readers should consider when interpreting the findings. First, and most critically, the analysis is based on a structured synthetic dataset generated to simulate firm-level carbon-trading conditions across four industrial sectors. While synthetic data allow controlled investigation of structural relationships, they do not capture the full complexity of real carbon markets, including EU ETS, RGGI, or China's national ETS. Policy conclusions drawn here should therefore be treated as directional rather than definitive, and replication on real-world market data is a necessary next step to validate these findings. Second, the near-zero R^2 values (0.0019 and 0.0007) are most parsimoniously explained by omitted variable bias rather than by market paradox alone. The models exclude variables known to drive carbon price dynamics—regulatory announcements, allowance auction outcomes, macroeconomic conditions, and strategic compliance proxies. Applying omitted variable diagnostics such as the Ramsey RESET test in future work would help distinguish genuine price exogeneity from model underspecification. Third, the logistic regression's ROC-AUC of 0.48 falls marginally below 0.50, which means the model performs slightly worse than random chance. While this is statistically indistinguishable from a coin flip given the balanced class distribution, it suggests that the model has no directional predictive capacity whatsoever. Reporting F1-score and calibration curves in future extensions would provide a more complete picture of classifier behaviour. Fourth, the cross-sectional design limits analysis of temporal dynamics and learning effects. Future research should draw on mixed-methods approaches combining quantitative analysis with qualitative firm-level interviews, text mining of policy documents, and longitudinal designs that track firms across full compliance periods. Comparative studies across different carbon trading systems would further strengthen the generalisability of these findings.

Author Contributions

Conceptualization, E.S. and M.R.Y.; methodology, E.S.; software, E.S. and A.J.K.A.-a.; validation, M.R.Y., H. and A.J.K.A.-a.; formal analysis, E.S.; investigation, E.S. and H.; resources, M.R.Y.; data curation, A.J.K.A.-a.; writing—original draft preparation, E.S.; writing—review and editing, M.R.Y. and H.; visualization, A.J.K.A.-a.; supervision,

E.S.; project administration, E.S. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable. This study did not involve human participants or animals; the analysis relied solely on a structured synthetic dataset constructed for methodological demonstration.

Informed Consent Statement

Not applicable. This study did not involve human participants.

Data Availability Statement

The dataset used in this study is a structured, synthetic dataset generated to replicate firm-level carbon-trading conditions across four industrial sectors. As discussed in the Limitations section, synthetic data are used to ensure controlled analytical conditions; readers should consider this when extending conclusions to real-world markets. Data are available upon reasonable request to the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

This manuscript used AI-assisted tools for language refinement and technical proofreading purposes. Claude (Anthropic) was employed solely to improve grammatical accuracy, sentence structure, and academic tone. All research design, data collection, statistical analysis, theoretical frameworks, and substantive conclusions represent the original intellectual work of the author. This declaration aligns with emerging best practices in academic publishing regarding transparency in AI-assisted writing. All empirical analyses were conducted in R and Python. In Python, linearmodels and statsmodels were used for panel data modelling, while pandas and numpy were used for data processing. Visualisation was produced using ggplot2 in R and matplotlib in Python.

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