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Carbon Emissions and Corporate Performance in an Emerging Market: Evidence from Thailand

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Abstract

This paper examines the financial relevance of corporate greenhouse gas (GHG) emissions for Thai listed firms during 2022–2024, a critical period of intensified transition risks and disclosure mandates. Using firm-reported total GHG emissions matched to firm financials, we first document that emissions are highly concentrated: a small set of issuers accounts for a disproportionate share of aggregate emissions, implying that financed-emissions exposure can be reduced efficiently through targeted engagement and reallocation toward the largest contributors. We then estimate pooled panel regressions with year and sector fixed effects and firm-clustered standard errors, relating profitability (ROA, ROE) and valuation (Tobin's $\boldsymbol{Q}$) to log emissions, firm size, and controls, while allowing the emissions association to vary with market capitalization via a centered interaction. Across outcomes, higher emissions are associated with weaker firm performance and lower valuation; in the baseline specification, the coefficient on **log(GHG)** is negative and statistically significant for ROA, ROE, and Tobin's $\boldsymbol{Q}$. Results are similar when emissions are lagged by one year, and economic-magnitude calculations indicate that a 10% increase in emissions corresponds to modest declines in accounting profitability but a more noticeable reduction in Tobin's $\boldsymbol{Q}$, consistent with markets pricing expected transition costs before they fully materialize in contemporaneous earnings. At the same time, causality-oriented diagnostics show that past performance predicts subsequent emissions and that future emissions predict current outcomes, highlighting that the estimates should be interpreted as conditional correlations rather than causal effects. Overall, the evidence suggests that emissions measures carry information relevant to valuation and risk assessment in the Thai equity market and provides

practical guidance for investor stewardship and financed-emissions management in a setting where emissions are concentrated among a small number of firms.

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1 Introduction

Climate change has become a first-order issue for corporate finance and asset pricing. As climate policy tightens and the cost of emitting greenhouse gases (GHG) is increasingly internalized through regulation, taxes, supply-chain requirements, and investor stewardship, firms with higher emissions face transition risks that can affect both expected cash flows and discount rates. The macroeconomic imperative to reduce emissions is well established in the climate science and policy literature Intergovernmental Panel on Climate Change (IPCC) (2022), and the energy transition is reshaping industry economics and competitive dynamics International Energy Agency (IEA) (2023). For financial economists, the central question is how carbon exposure maps into firm value, profitability, and risk premia.

From a sustainable-finance perspective, the central question is how carbon exposure should be measured and mapped into financial outcomes so that investors can manage transition risk while credibly reducing financed emissions. In practice, portfolio decarbonisation is implemented through a mix of exclusion and divestment screens, portfolio tilts, and stewardship/engagement with high emitters; fossil-fuel divestment, in particular, requires concrete implementation rules (e.g., defining the exclusion universe, rebalancing mechanics, and tracking error constraints) that can materially affect portfolio risk, return, and the magnitude of carbon reduction Marupanthorn (2024), Marupanthorn et al. (2024), Marupanthorn et al. (2024). These design choices make firm-level emissions data economically consequential because they determine which firms are classified as "high-carbon," how capital is reallocated, and how quickly portfolio footprints can fall. Understanding whether and how emissions are associated with firm profitability, valuation, and risk is therefore essential not only for risk pricing, but also for evaluating the feasibility and trade-offs of investor decarbonisation strategies.

A finance-based view emphasizes two channels through which emissions can matter. First, the *cash-flow channel*: higher emissions can imply higher expected compliance costs (e.g., carbon taxes or cap-and-trade), greater future abatement CAPEX/OPEX, litigation and regulatory risk, and potential demand or supply-chain penalties, reducing expected cash flows. Second, the *discount-rate channel*: carbon-intensive firms may face higher required returns due to transition risk, tail risk, and changes in investor clientele, raising the cost of capital and depressing valuations even if near-term profits remain strong. These channels motivate empirical tests linking emissions not only to accounting profitability but also to market valuation, where discount-rate effects are expected to be most visible.

Consistent with these mechanisms, a growing literature documents that carbon exposure is financially material. Early evidence links broader environmental performance to market value Konar and Cohen (2001). More direct evidence shows that

higher carbon emissions are associated with lower firm values and that disclosure can mitigate valuation discounts, consistent with emissions affecting investor expectations and uncertainty about future liabilities Matsumura et al. (2014); Saka and Oshika (2014). In regulated settings, emissions can become particularly salient because they proxy for compliance costs and policy exposure; for example, reported emissions are valuation-relevant under the EU Emissions Trading Scheme Clarkson et al. (2015). Complementary cross-country evidence also finds a negative association between emissions and firm value, and suggests the relation is stronger where regulatory stringency and carbon-policy credibility are higher Choi and Luo (2021).

Climate finance research further argues that carbon exposure can be priced through risk premia and downside risk. In the cross-section of stock returns, firms with higher emissions can earn higher realized returns, consistent with markets demanding compensation for carbon exposure and/or with demand effects from screening and constrained investing Bolton and Kacperczyk (2021). Options-based evidence shows that carbon-intensive firms exhibit higher downside tail-risk premia, especially when climate attention increases, implying that carbon exposure is linked to priced crash risk and higher costs of downside protection Ilhan et al. (2021). Climate-related information shocks also matter for portfolio risk management: climate news is reflected in asset prices and can be hedged using targeted portfolios Engle et al. (2020). At the institutional level, survey-based evidence indicates that investors perceive climate risks—and especially transition risks—as relevant for investment decisions and risk management Krueger et al. (2020). These findings collectively support the view that emissions can affect firm value through discount-rate channels in addition to cash-flow effects.

A related corporate finance literature highlights that environmental externalities and carbon intensity can influence financing conditions. Environmental concerns are linked to a higher cost of capital Chava (2014), and carbon intensity has been associated with a higher cost of equity capital Trinks et al. (2022), which is consistent with lenders and equity investors requiring compensation for climate-related risks or responding to clientele and mandate constraints. From an operating perspective, studies also examine the performance implications of emissions reductions and environmental investment. For example, emissions and environmental R&D are linked to firm performance in ways consistent with trade-offs between abatement investment and efficiency gains Lee et al. (2015), while evidence suggests that emissions reductions can be associated with improved financial performance, consistent with operational efficiencies and lower risk premia as firms transition Lewandowski (2017); Ibishova et al. (2024). A meta-analysis synthesizes this broader literature and finds that better corporate carbon performance is, on average, positively associated with financial performance, while emphasizing that estimates are heterogeneous and sensitive to measurement choices (e.g., absolute emissions versus intensity; scope coverage; verification) and institutional context Busch and Lewandowski (2018).

A broad meta-analysis by Horváthová (2010) shows that the sign and strength of the environmental–financial performance nexus vary systematically with empirical design and institutional context. Using firm-level data, Iwata and Okada (2011)

report that greenhouse-gas reductions are associated with stronger market-based performance for Japanese manufacturers, with heterogeneity across "clean" and "dirty" industries. Lioui and Sharma (2012) find that environmental CSR is on average negatively related to ROA and Tobin's Q, but can create value indirectly through innovation (R&D). Focusing specifically on carbon outcomes, Misani and Pogutz (2015) document non-linear valuation effects of carbon emissions and show that environmental management processes can moderate the emissions–valuation link in carbon-intensive sectors. More recently, Trinks et al. (2020) develop a production-theory measure of *carbon efficiency* and find that carbon-efficient firms exhibit higher profitability and lower systematic risk in an international sample. These findings motivate testing whether similar patterns hold in a Southeast Asian emerging market where disclosure regimes, policy pressure, and investor composition differ; our Thailand evidence contributes to this gap by combining sectoral concentration mapping with firm-level panel regressions using directly reported emissions.

Evidence from emerging markets remains comparatively limited even though these markets can be both carbon intensive and policy sensitive. Empirical relationships are often context-dependent because carbon pricing regimes, disclosure mandates, investor clientele, and industry composition differ across countries. Studies outside advanced markets document mixed but often economically meaningful associations between emissions and corporate outcomes, including profitability and valuation effects that vary across sectors and institutional settings Ganda (2018); Rokhmawati et al. (2017); He et al. (2016); Nichita et al. (2021). This heterogeneity makes country-specific evidence important for both academic understanding and practical investment decisions, particularly when investors allocate capital across markets with different transition pathways and policy credibility.

Two additional stylized facts motivate focusing on heterogeneity across firms within a market. First, emissions are highly concentrated: a relatively small set of large producers and entities accounts for a substantial share of aggregate industrial emissions Griffin (2017a); InfluenceMap (2024). Second, emissions and firm size are closely linked. Larger firms operate at greater scale and tend to report higher absolute emissions, and they may face stronger scrutiny and disclosure expectations; consistent with this, disclosure studies show that size and stakeholder pressure are associated with greater climate-related disclosure Stanny and Ely (2008); Stanny (2013); Choi et al. (2013). In addition, global evidence emphasizes that emissions are tightly related to firm scale (e.g., sales) and become available to investors with reporting lags, which has implications for empirical design and for how markets incorporate emissions information Zhang (2025). Together, these insights suggest that the emissions–performance relationship may be stronger (or at least more detectable) among large, visible firms and in sectors where emissions are economically material.

We provide evidence for Thailand, a major emerging market in Southeast Asia where listed firms span carbon-intensive activities (e.g., energy, industrials, materials, and transportation-related businesses) as well as large service sectors. We assemble firm-level GHG emissions data for Thai listed companies and address two questions: (i) how reported emissions are distributed across sectors and firms, and (ii) whether higher emissions are associated with weaker firm performance and lower valuation

after controlling for standard firm characteristics. Our empirical design relates firm-level GHG emissions to accounting- and market-based outcomes commonly used in corporate finance: return on assets (ROA), return on equity (ROE), and Tobin's Q. We estimate panel regressions with standard controls (including firm size, leverage, and growth) and fixed effects where appropriate, and we examine whether firm size moderates the emissions–performance relationship.

H1 Firms with higher GHG emissions exhibit weaker financial performance, measured by lower ROA, lower ROE, and lower Tobin's Q, after controlling for firm characteristics.
H2 Firm size moderates the relationship between emissions and financial performance; the association between GHG emissions and ROA/ROE/Tobin's Q differs systematically between smaller and larger firms.

Our results are consistent with an economically meaningful emissions penalty in Thai listed firms. Higher GHG emissions are associated with lower profitability (ROA and ROE) and lower market valuation (Tobin's Q) across years and specifications. Interaction tests further suggest that firm size shapes the marginal association between emissions and performance, consistent with differential capacity to manage transition exposure and/or differences in how markets price carbon risk for large, visible firms. Sectoral analysis indicates that emissions are unevenly distributed across sectors and frequently concentrated among a small set of high emitters, highlighting the importance of firm-level granularity when measuring carbon exposure.

This study contributes to the climate-finance and emerging-markets literatures in three ways. First, it provides finance-oriented evidence on the emissions–performance relationship in Thailand using both accounting- and market-based measures, connecting transition exposure to profitability and valuation. Second, it documents sectoral emissions distribution and concentration, informing portfolio construction, engagement strategies, and transition-risk assessment. Third, it links the empirical patterns to finance mechanisms—cash-flow and discount-rate channels—through which emissions may affect firm outcomes, and highlights the role of firm size as a key dimension of heterogeneity.

The paper proceeds as follows. We first describe the data sources, emissions measurement, and sample construction, and we document how emissions are distributed across sectors and concentrated among a small set of issuers. We then present the empirical framework that relates firm outcomes (ROA, ROE, and Tobin's Q) to emissions, firm size, and controls, including an interaction that allows the emissions association to vary with market capitalization. Next, we report pooled panel results with year and sector fixed effects and firm-clustered inference, and we complement these estimates with a lagged-emissions robustness check to reduce concerns about contemporaneous simultaneity. We also translate key coefficients into economically interpretable magnitudes (e.g., the implied effect of a 10% increase in emissions). Finally, we discuss implications for sustainable finance and investor stewardship in Thailand and conclude.

2 Data Description

The framework of this research focuses on publicly listed companies in Thailand's stock market that have published sustainability reports, including disclosures of greenhouse gas (GHG) emissions. Specifically, the dataset comprises 122 firms out of 923 listed companies for each of the years 2022, 2023, and 2024. The study period spans from 2022 to 2024, coinciding with the timeframe during which the Stock Exchange of Thailand (SET) began mandating the disclosure of sustainability-related data. The selected firms are those with complete GHG emissions records and all relevant independent variables required for the analysis, as will be discussed in the following sections.

GHG emissions (`GHG`) are measured as *total reported* greenhouse gas emissions in tonnes of CO_2-equivalent (tCO_2e), as compiled by Refinitiv Workspace from firms' sustainability disclosures to the Stock Exchange of Thailand (SET). The dataset reports a single total emissions figure, so the analysis does not disaggregate Scope 1/2/3 emissions.

To reconcile the market-wide concentration analysis with the regression sample, we distinguish between (i) the broader set of emitters used to map emissions concentration across sectors, and (ii) the balanced panel used for estimating emissions–performance regressions. Across the Stock Exchange of Thailand (SET), our reference universe consists of 923 listed firms over 2022–2024, which we use only to provide context on market coverage. From this universe, we identify 176 firms that report total greenhouse gas (GHG) emissions and can be mapped to a GICS sector; this sample is used for the emissions concentration analysis and sectoral mapping. Finally, our regression analysis relies on a balanced panel of 122 firms with complete emissions and financial variables for all years from 2022 to 2024, which is used to estimate the relationships between emissions and firm outcomes (ROA, ROE, and Tobin's Q). Market capitalisation and accounting variables are measured in Thai baht (THB) as reported by Refinitiv; emissions are in tCO_2e.

To construct the variables used in this research, the following firm-level indicators were retrieved: Total Assets, Total Liabilities, Year-over-Year (YoY) Change in Total Assets, Market capitalisation, Revenue from Business Activities, Net Income after Tax, and GICS Sector classification. All data were obtained from the Refinitiv Workspace database. These indicators form the basis for computing the financial metrics summarized in Table 1.

The dependent variables chosen in this study `RoE`, `RoA`, and `Tobin's Q` represent comprehensive and theoretically grounded measures of a firm's financial performance. `RoE` (Return on Equity) reflects the firm's ability to generate profits from shareholders' equity and is widely used as an indicator of profitability and financial efficiency from the investors' perspective. `RoA` (Return on Assets) provides a broader measure of performance by evaluating how effectively a company utilizes its total asset base to generate net income, independent of its financing structure. Meanwhile, `Tobin's Q`, defined as the ratio of the firm's market value (inclusive of market capitalisation and liabilities) to its asset replacement cost, serves as a forward-looking valuation metric that captures market expectations and investment potential. Collectively, these three variables offer a balanced view of internal financial outcomes and external market

Table 1 Summary of Constructed Financial Variables

Variable	Label	Definition / Formula	Model Role
`RoE`	Return on Equity	$\frac{\text{Net Income after Tax}}{\text{Total Assets} - \text{Total Liabilities}}$	Dependent
`RoA`	Return on Assets	$\frac{\text{Net Income after Tax}}{\text{Total Assets}}$	Dependent
`Tobin's Q`	Tobin's Q Ratio	$\frac{\text{Market capitalisation} + \text{Total Liabilities}}{\text{Total Assets}}$	Dependent
`MktCap`	Market capitalisation	Total company market capitalisation	Independent
`PF`	Operating efficiency (Revenue/Assets)	$\frac{\text{Total Revenue from Business Activities}}{\text{Total Assets}}$	Independent
`IF`	Investment Factor	$\frac{\text{Total Assets, YoY \% Change}}{100}$	Independent
`GHG`	Greenhouse Gases Emission (tCO2e)	-	Independent

valuation, making them well-suited for empirical investigation into the determinants of corporate financial performance.

Table 2 presents the descriptive statistics for the variables *Emission*, *Market capitalisation (MktCap)*, *Operating efficiency (PF)*, *Investment Factor (IF)* over the years 2022 to 2024. The results demonstrate consistency in sample size (122 firms) across all three years, allowing for reliable intertemporal comparisons. Emissions display a rising trend, with the mean increasing from approximately 3.68 million in 2022 to 4.33 million in 2024, accompanied by increasing standard deviations, indicating growing variation in carbon output among firms. Market capitalisation remains relatively stable, with mean values consistently around THB 66 billion, though high standard deviations reflect a wide dispersion likely due to firm size heterogeneity. PF and IF are stable across years, with PF slightly declining in 2024 and IF remaining near zero throughout, implying consistent profitability and investment behaviour. The leverage ratio also remains stable, averaging between 2.61 and 2.65, with consistent spread across years. The observed medians across variables suggest relatively stable central tendencies, while the broad range between minimum and maximum values, particularly in emissions and market capitalisation, indicates right-skewed distributions influenced by large outliers. These consistent statistical profiles over time reflect a stable firm composition and align with prior findings in the literature (e.g., Ganda, 2017),

Table 2 Descriptive statistics: emissions (tCO_2e), market capitalisation (THB), operating efficiency (PF), and investment (IF)

Year	**Statistic**	Emission (tCO_2e)	MktCap (THB)	PF	IF
2022	Mean	3,680,482.000	66,097,050,000	0.650	0.004
	Std	15,175,910.000	141,183,400,000	0.595	0.091
	Min	7.000	116,041,900	0.025	-0.351
	50%	80,842.240	18,841,360,000	0.494	-0.005
	Max	146,626,700	892,593,600,000	3.075	0.332
2023	Mean	4,201,507.000	66,301,130,000	0.660	0.007
	Std	17,553,900.000	141,396,500,000	0.648	0.088
	Min	8.000	146,312,300	0.027	-0.306
	50%	83,273.110	18,905,520,000	0.487	0.005
	Max	177,056,800	885,452,900,000	3.513	0.247
2024	Mean	4,332,260.000	66,461,780,000	0.635	0.005
	Std	17,542,960.000	141,450,500,000	0.606	0.098
	Min	10.500	116,041,900	0.024	-0.218
	50%	92,569.000	18,408,750,000	0.467	0.002
	Max	176,507,700	878,312,100,000	3.728	0.437

supporting further panel-based econometric analysis linking environmental disclosure to financial performance.

Table 3 Descriptive Statistics (Part 2): RoE to Tobin's Q

Year	**Statistic**	RoE	RoA	Tobin's Q
2022	Mean	0.099	0.049	1.212
	Std	0.099	0.056	0.822
	Min	-0.242	-0.118	0.264
	50%	0.090	0.041	0.932
	Max	0.368	0.277	5.550
2023	Mean	0.091	0.046	1.185
	Std	0.089	0.053	0.758
	Min	-0.157	-0.083	0.478
	50%	0.092	0.035	0.919
	Max	0.462	0.242	4.665
2024	Mean	0.076	0.040	1.168
	Std	0.104	0.060	0.731
	Min	-0.274	-0.140	0.288
	50%	0.081	0.032	0.930
	Max	0.360	0.240	4.467

3 Sectoral GHG Emissions and Concentration

Before estimating firm-level regressions, we first examine how GHG emissions are distributed across sectors and within sectors. This step is essential because emissions data are typically heavy-tailed and can be dominated by a small number of "super-emitters." If the cross-sectional distribution is highly skewed, then OLS estimates may be disproportionately influenced by a few extreme observations, and the interpretation of an average emissions–performance relationship becomes unclear (i.e., whether it reflects a broad market pattern or only the behaviour of outliers). Sectoral concentration analysis therefore serves two purposes: it (i) provides economic context for transition-risk exposure in the market and (ii) motivates the regression design (log transformations and interaction terms) by documenting the degree of skewness and the role of large emitters.

A large body of climate and energy research shows that emissions are highly heterogeneous across sectors, with power generation, heavy industry, transport and buildings together accounting for the bulk of global greenhouse gas (GHG) output, while services and many light manufacturing activities contribute comparatively little Intergovernmental Panel on Climate Change (IPCC) (2022); International Energy Agency (IEA) (2023); Marupanthorn et al. (2024). Because technologies, abatement costs and policy instruments differ markedly across sectors, both transition pathways and financial risks are often analysed on a sectoral basis rather than at the aggregate level Bataille et al. (2018); Battiston et al. (2017). For investors and regulators, understanding how emissions are distributed across sectors and within sectors is therefore a natural starting point for designing targeted engagement, stress tests and decarbonisation strategies.

A robust finding in the climate literature is that anthropogenic GHG emissions are highly unevenly distributed: a relatively small set of producers or assets accounts for a disproportionate share of the total. At the global level, Heede Heede (2014) traces around two-thirds of cumulative industrial CO_2 and methane emissions since the mid-nineteenth century to just 90 fossil-fuel and cement companies, the so-called "carbon majors". Building on this work, subsequent Carbon Majors reports show that a few dozen large fossil-fuel producers continue to dominate industrial emissions, underscoring the importance of firm- or group-level concentration for both climate policy and investor engagement Griffin (2017b). A similar heavy-tailed pattern emerges at the facility level: studies of methane leakage from oil and gas systems find that a small minority of plants or pieces of equipment—often labelled "super-emitters"— are responsible for a large fraction of observed emissions, rather than emissions being spread evenly across all sources Brandt et al. (2014). Overall, this evidence points to the presence of large outliers in the emissions distribution and implies that targeted interventions on a limited number of entities can deliver outsized climate benefits.

In listed equity markets, these concentration patterns translate into a small group of very carbon-intensive firms driving the bulk of portfolio or index-level financed emissions, while the majority of firms contribute relatively little on a standalone basis. For investors and regulators, identifying such corporate "super-emitters" is therefore crucial for designing effective engagement, transition planning and stress testing. In this

section, we document the degree of emissions concentration among Thai listed companies over 2022–2024, both at the market and sector level. Specifically, we identify, for each GICS sector, the single largest three-year emitter and quantify its share of sectoral emissions, thereby providing a sectoral map of Thai "super-emitters" and highlighting where emissions are structural (spread across many firms) versus dominated by one or two outliers.[1]

The empirical analysis covers listed companies in Thailand over the period 2022–2024. In total, there are 176 companies distributed across 11 GICS sectors: Industrials (23), Consumer Staples (22), Materials (21), Consumer Discretionary (20), Financials (20), Real Estate (20), Utilities (15), Communication Services (11), Energy (9), Information Technology (8), and Health Care (7).

The concentration results use all firms with reported GHG disclosures that can be mapped to GICS sectors (176 firms). The regression analysis that follows requires complete emissions and financial variables and therefore uses a balanced subset of 122 firms (366 firm-year observations).

Aggregating over all firms and years, total GHG emissions amount to approximately 1.56×10^9 units.[2] For each sector, we compute the *average annual* GHG volume over 2022–2024, based on yearly sector sums.

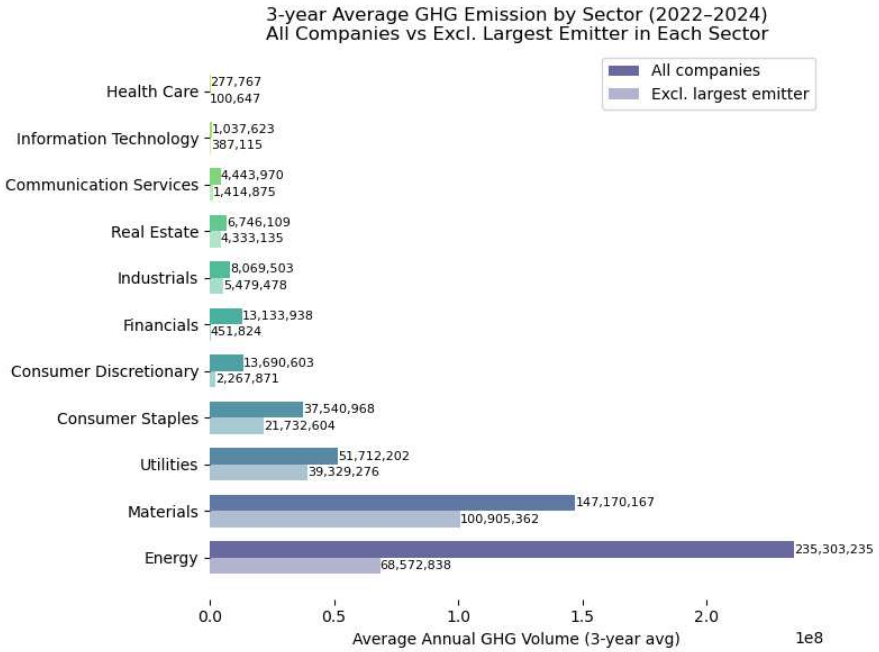


Fig. 1 Three-year average annual GHG emissions by sector (2022–2024), reported both including all companies (dark bars) and excluding the single largest three-year emitter in each sector (light bars).

[1] To avoid singling out specific issuers, company names/tickers are replaced with anonymised identifiers (e.g., `Firm-E1`).

[2] Units are the same as those used in the underlying GHG accounting.

For every sector, the company with the highest cumulative GHG emissions over 2022–2024 is then identified. Table 4 summarises these firms (anonymised), their three-year emission totals, their share of sector emissions, and the number of companies in each sector.

Table 4 Largest three-year GHG emitters by sector (2022–2024) (anonymised).

Sector	Top emitter (anonymised)	3-year GHG	Sector share	# firms
Communication Services	Firm-CS1	9,087,286	68.2%	11
Consumer Discretionary	Firm-CD1	34,268,196	83.4%	20
Consumer Staples	Firm-CS2	47,425,092	42.1%	22
Energy	Firm-E1	500,191,193	70.9%	9
Financials	Firm-F1	38,046,344	96.6%	20
Health Care	Firm-HC1	531,361	63.8%	7
Industrials	Firm-I1	7,770,076	32.1%	23
Information Technology	Firm-IT1	1,951,524	62.7%	8
Materials	Firm-M1	138,794,415	31.4%	21
Real Estate	Firm-RE1	7,238,921	35.8%	20
Utilities	Firm-U1	37,148,780	23.9%	15

Across all sectors, these 11 firms represent only about 6% of the company universe (11 out of 176), yet they account for roughly 5.3×10^8 units of GHG, i.e. about 53% of total emissions. The emission profile of the market is therefore highly concentrated.

Figure 1 displays a horizontal bar chart with sectors on the vertical axis and average annual GHG emissions on the horizontal axis. For each sector there are two bars. The darker bar shows the average annual GHG emissions when all companies in the sector are included. The lighter bar shows the average annual GHG emissions after removing the single largest three-year emitter in that sector, as listed in Table 4. The numerical labels at the ends of the bars report the corresponding average annual emission volumes.

The relative length of the dark and light bars provides a visual measure of how dominant the largest emitter is within each sector. In sectors where the light bar is close to the dark bar, emissions are spread across many firms. In sectors where the light bar is much shorter or almost disappears, most of the sector footprint is attributable to a single company.

The chart shows that Energy has the highest overall emissions, followed by Materials, Utilities and Consumer Staples. However, once the largest emitter in each sector is removed, the ranking changes: Materials and Utilities remain important, whereas the Energy sector bar shrinks substantially because `Firm-E1` is responsible for about 71% of Energy emissions. Financials and Consumer Discretionary exhibit the most extreme concentration. In Financials, `Firm-F1` alone accounts for approximately 96.6% of sector emissions; the light bar in Figure 1 is almost negligible compared with the dark bar. In Consumer Discretionary, `Firm-CD1` contributes about 83.4% of sector emissions and the residual sector footprint becomes relatively small once this firm is excluded. Communication Services, Health Care and Information Technology also

show high concentration, with the largest firm in each sector contributing around 60–70% of emissions.

By contrast, Materials, Utilities, Consumer Staples, Industrials and Real Estate remain substantial even after the largest emitter is removed. In these sectors the top firm contributes between roughly 24% and 42% of emissions, so a large fraction of the footprint is generated by the remaining companies. The light bars in Figure 1 therefore remain relatively long for these sectors, indicating a more even distribution of emissions.

Overall, the evidence from Figure 1 and Table 4 points to marked concentration of GHG emissions in a small set of corporate "super-emitters." The 11 anonymised top emitters together drive more than half of total listed emissions while representing only a small fraction of the investable universe. In sectors with extremely high concentration, such as Financials, Consumer Discretionary, Energy and Communication Services, engagement with a single company can materially change the sector-level footprint. In more diffuse sectors, such as Materials, Utilities, Industrials, Consumer Staples and Real Estate, emissions are more structural and require broader, sector-wide decarbonisation strategies rather than focusing on a single firm. Importantly for the regression analysis that follows, these patterns imply that (i) log transforms are appropriate, (ii) results should be interpreted with attention to outliers, and (iii) heterogeneity by firm size and sector is economically meaningful when assessing the emissions–performance nexus.

4 Effect of the GHG Emission on Firm Performance

4.1 Correlation and Covariance Analysis

This section presents preliminary diagnostic analysis to assess the relationships among key variables before conducting multivariate regression. Specifically, we examine the pairwise Pearson correlations between GHG emissions and firm-level financial indicators to explore potential linear associations.

Table 6 presents the lower-triangular Pearson correlation matrices for 2022-2024, offering preliminary insight into the bivariate relationships between GHG emissions and financial indicators. In contrast, emissions show modest but persistent negative correlations with ROA, ROE, and Tobin's Q, suggesting potential value and profitability penalties for carbon-intensive firms.

An examination of the correlation matrices in Table 6 reveals a high degree of consistency in the direction (sign) of correlations across the three years (2022-2024). The positive correlation between GHG emissions and market capitalisation remains strong and statistically significant throughout, underscoring the persistent scale effect whereby larger firms tend to emit more due to greater operational output. In contrast, GHG emissions exhibit modest but consistently negative correlations with ROA, ROE, and Tobin's Q, suggesting that carbon-intensive firms may be associated with lower profitability and market valuation. This sign stability across years provides preliminary evidence that the relationships under investigation are not merely sample-specific

or period-sensitive. It also reinforces the conceptual expectations set forth in Hypothesis H1 to 3 and supports the use of multivariate regression analysis to formally test whether these associations hold after controlling for firm-specific characteristics.

To verify the homogeneity of the covariance structure among the firm-level study variables, we formally test the following hypothesis:

$$H_0 : \mathbf{\Sigma}_{2022} = \mathbf{\Sigma}_{2023} = \mathbf{\Sigma}_{2024} \quad \text{vs.} \quad H_A : \exists\, i \neq j \text{ such that } \mathbf{\Sigma}_i \neq \mathbf{\Sigma}_j,$$

where $\mathbf{\Sigma}_t$ denotes the population covariance matrix of financial and GHG-related variables in year t. Box's M test is employed to assess whether these covariance matrices differ significantly across the three periods (2022-2024). The test yields a chi-square statistic of 98.08 with 90 degrees of freedom and a p-value of 0.263. Since the p-value exceeds the conventional threshold of 0.05, we fail to reject the null hypothesis of equality in covariance matrices.

4.2 Model Specifications

This study relates firm–level financial performance to carbon emissions and key firm characteristics using a system of regression equations. For each firm i and year t, three separate models are estimated with Return on Assets (ROA), Return on Equity (ROE) and Tobin's Q as dependent variables. The specifications are

$$\begin{aligned}\texttt{ROA}_{it} &= \alpha_0 + \alpha_1 \log(\text{MktCap}_{it}) + \alpha_2 \log(\text{GHG}_{it}) + \alpha_3 \texttt{PF}_{it} + \alpha_4 \texttt{IF}_{it} \\ &\quad + \alpha_5 \big(\log(\text{MktCap}_{it}) + \log(\text{GHG}_{it}) \big) + \varepsilon_{1it}, \end{aligned} \tag{1}$$

$$\begin{aligned}\texttt{ROE}_{it} &= \beta_0 + \beta_1 \log(\text{MktCap}_{it}) + \beta_2 \log(\text{GHG}_{it}) + \beta_3 \texttt{PF}_{it} + \beta_4 \texttt{IF}_{it} \\ &\quad + \beta_5 \big(\log(\text{MktCap}_{it}) + \log(\text{GHG}_{it}) \big) + \varepsilon_{2it}, \end{aligned} \tag{2}$$

$$\begin{aligned}\texttt{TobinQ}_{it} &= \gamma_0 + \gamma_1 \log(\text{MktCap}_{it}) + \gamma_2 \log(\text{GHG}_{it}) + \gamma_3 \texttt{PF}_{it} + \gamma_4 \texttt{IF}_{it} \\ &\quad + \gamma_5 \big(\log(\text{MktCap}_{it}) + \log(\text{GHG}_{it}) \big) + \varepsilon_{3it}. \end{aligned} \tag{3}$$

In all three equations, firm size is measured by the natural logarithm of market capitalisation, $\log(\text{MktCap}_{it})$, and carbon emissions are captured by the natural logarithm of total greenhouse gas emissions, $\log(\text{GHG}_{it})$. $\texttt{PF}_{it}$ is an operating-efficiency proxy constructed from operating revenues relative to the asset base, while $\texttt{IF}_{it}$ is an investment factor that proxies the intensity of capital expenditure.

The key non–linear component of the specification is the interaction term $\log(\text{MktCap}_{it}) \times \log(\text{GHG}_{it})$. This term allows the marginal association between emissions and financial performance to vary with firm size. A statistically significant interaction coefficient (α_5, β_5 or γ_5) indicates that the effect of changes in emissions on ROA, ROE or Tobin's Q is different for larger firms than for smaller ones, even after controlling for profitability and investment intensity. The remaining regressors enter the models in a linear fashion and capture average partial effects of firm fundamentals and real activity on each performance measure.

The error terms ε_{1it}, ε_{2it} and ε_{3it} represent unobserved influences on financial performance that are not captured by the explanatory variables. The indices i and t

denote, respectively, firms and years, reflecting the panel structure of the data. The parameter vectors $\{\alpha_j\}_{j=0}^{5}$, $\{\beta_j\}_{j=0}^{5}$ and $\{\gamma_j\}_{j=0}^{5}$ are estimated separately for each dependent variable and summarise how firm size, emissions and financial characteristics co–move with ROA, ROE and Tobin's Q over the sample period. Under the usual regression assumptions of linearity, absence of perfect multicollinearity and exogeneity of the regressors, these coefficients can be interpreted as conditional marginal effects, and the fitted equations can be used to generate counterfactual scenarios in which firm–level emissions are shocked while holding other characteristics fixed.

5 Causality, Endogeneity, and Economic Magnitude

This study documents the relationship between corporate greenhouse gas (GHG) emissions and firm outcomes for Thai listed firms over 2022–2024. Throughout, we interpret the baseline estimates as *conditional correlations* rather than causal effects. This conservative interpretation follows standard guidance in empirical corporate finance and applied econometrics: when key regressors (here, emissions) may be jointly determined with outcomes, regression coefficients generally require additional identifying variation (e.g., quasi-experiments or valid instruments) to be interpreted causally (Roberts and Whited 2013; Angrist and Pischke 2009; Wooldridge 2010).

The regression coefficients capture differences in average performance (ROA, ROE, Tobin's Q) across firms with different emissions levels, conditional on the included controls and fixed effects. Because emissions, financial performance, and firm characteristics may be jointly determined, the estimates should not be interpreted as the causal impact of emissions on performance without additional identification assumptions (Roberts and Whited 2013).

Several endogeneity concerns are especially relevant in the emissions–performance setting (Roberts and Whited 2013; Wooldridge 2010). Firstly, financially stronger firms may have greater capacity to invest in energy efficiency, process upgrades, abatement capital expenditures, and monitoring/reporting systems that reduce (or change the measurement of) emissions. Conversely, firms experiencing financial distress may delay abatement investments or shift production toward more carbon-intensive processes. In both cases, contemporaneous emissions and performance can move together because performance affects emissions choices, not only because emissions affect performance.

Secondly, unobserved firm attributes—production technology, managerial quality, governance, product mix, export orientation, or exposure to multinational supply-chain requirements—can affect both emissions and financial outcomes. If these factors are correlated with emissions and are not fully captured by observed controls and fixed effects, the estimated emissions coefficients can reflect confounding rather than an emissions-related mechanism.

Finally, corporate emissions are typically self-reported (often with heterogeneous boundaries and assurance), and reporting itself may be endogenous to firm characteristics and stakeholder pressure. Classical measurement error in emissions attenuates coefficients, while non-classical measurement error or selective disclosure can bias estimates in either direction (Wooldridge 2010).

5.1 Empirical Implementation and Diagnostic Checks

Consistent with the implemented analysis procedure, we address these concerns using (i) fixed effects to absorb common shocks and time-invariant sector differences, (ii) conservative inference via firm-clustered standard errors, and (iii) a lagged-emissions specification to reduce contemporaneous simultaneity.

For each outcome $Y_{it} \in \{\text{ROA}, \text{ROE}, \text{Tobin's } Q\}$, we estimate a pooled panel model with year and sector fixed effects:

$$Y_{it} = \alpha + \beta_1 \log(\text{GHG}_{it}) + \beta_2 \log(\text{MktCap}_{it}) + \mathbf{X}'_{it}\boldsymbol{\gamma} + \beta_3 \Big(\widetilde{\log(\text{GHG}_{it})} + \widetilde{\log(\text{MktCap}_{it})} \Big) + \tau_t + \eta_s + \varepsilon_{it}, \tag{4}$$

where τ_t and η_s denote year and sector fixed effects, respectively, and $\mathbf{X}_{it}$ includes the controls used in the empirical implementation (PF and IF). Fixed effects are a standard way to absorb unobserved heterogeneity that is common within groups (years or sectors) and could otherwise confound the relationship of interest (Wooldridge 2010). The interaction term is constructed as the product of centered logs, i.e., $\widetilde{\log(\text{GHG}_{it})} = \log(\text{GHG}_{it}) - \overline{\log(\text{GHG})}$ and analogously for $\widetilde{\log(\text{MktCap}_{it})}$, so that β_1 can be interpreted as the marginal association between emissions and the outcome at average firm size.

Inference and clustering. In panel settings, ignoring within-firm error correlation can materially understate standard errors. We therefore use heteroskedasticity-robust standard errors clustered at the firm level (by instrument/ticker), which remains valid under arbitrary serial correlation and heteroskedasticity within a firm over time (Arellano 1987; Petersen 2009; Cameron and Miller 2015).

Lagged emissions. To reduce contemporaneous simultaneity, we re-estimate the model using lagged emissions:

$$Y_{it} = \alpha + \beta_1 \log(\text{GHG}_{i,t-1}) + \beta_2 \log(\text{MktCap}_{it}) + \mathbf{X}'_{it}\boldsymbol{\gamma} + \beta_3 \Big(\widetilde{\log(\text{GHG}_{i,t-1})} + \widetilde{\log(\text{MktCap}_{it})} \Big) + \tau_t + \eta_s + \varepsilon_{it}. \tag{5}$$

Lagging emissions is widely used as a robustness check in settings where outcomes and firm policies may respond contemporaneously to each other; it mitigates same-period feedback but does not eliminate endogeneity from time-varying omitted variables (Wooldridge 2010).

Causality-oriented "falsification" diagnostics. While the analysis remains descriptive, two additional diagnostics (implemented in this paper where the panel structure permits) are informative about directionality and confounding.

First, a placebo-style *lead test* replaces emissions with future emissions while holding the specification fixed:

$$Y_{it} = \alpha + \phi \log(\text{GHG}_{i,t+1}) + \beta_2 \log(\text{MktCap}_{it}) + \mathbf{X}'_{it}\boldsymbol{\gamma} + \beta_3 \Big(\widetilde{\log(\text{GHG}_{i,t+1})} + \widetilde{\log(\text{MktCap}_{it})} \Big) + \tau_t + \eta_s + \varepsilon_{it}. \tag{6}$$

Lead tests are commonly used as falsification checks in panel/event-study designs: under a causal story where emissions affect performance contemporaneously or with

lags, future emissions should not systematically predict current outcomes once controls and fixed effects are included; significant lead effects instead suggest persistent unobservables or stable differences in firm "type" (Autor 2003; Angrist and Pischke 2009).

Second, a *reverse-prediction* diagnostic assesses whether past performance predicts subsequent emissions:

$$\log(\text{GHG}_{it}) = \kappa + \delta\, Y_{i,t-1} + \lambda \log(\text{MktCap}_{it}) + \mathbf{X}_{it}'\boldsymbol{\theta} + \tau_t + \eta_s + u_{it}. \tag{7}$$

This regression is closely related in spirit to Granger-style predictive tests, where lagged values of one variable are used to assess whether it helps forecast another (Granger 1969). With longer panels, one can implement formal panel Granger-causality tests that pool information across firms while allowing heterogeneity (Dumitrescu and Hurlin 2012).

What would be required for a causal interpretation? Stronger identification would typically require plausibly exogenous variation in emissions (or in the marginal cost of emitting), such as policy discontinuities, energy-price shocks, or externally valid instruments. In panel corporate-finance applications, common approaches include (i) richer fixed-effects structures (e.g., firm fixed effects when sufficient within-firm variation exists), (ii) instrumental variables/2SLS with standard diagnostics for instrument relevance and validity (e.g., first-stage strength and overidentification tests), and (iii) dynamic-panel GMM estimators when outcomes are persistent and regressors are endogenous (Angrist and Pischke 2009; Wooldridge 2010; Arellano and Bond 1991; Blundell and Bond 1998; Roodman 2009; Staiger and Stock 1997; Stock and Yogo 2005; Hansen 1982).

5.2 Economic Magnitude and Materiality

To assess materiality, we translate the estimated coefficients into economically meaningful changes. Because emissions enter in logs, the coefficient on log(GHG) is a *semi-elasticity*: it approximates the change in Y associated with a 1% change in emissions, holding other regressors fixed (Wooldridge 2010). In particular, a 10% increase in emissions corresponds to $\Delta \log(\text{GHG}) = \ln(1.10) \approx 0.0953$.

With the centered-log interaction, the marginal association between emissions and the outcome depends on firm size:

$$\frac{\partial Y}{\partial \log(\text{GHG})} = \beta_1 + \beta_3 \log(\widetilde{\text{MktCap}}). \tag{8}$$

Accordingly, the implied change in the outcome from a 10% increase in emissions is:

$$\Delta Y \approx \ln(1.10) \times \left(\beta_1 + \beta_3 \log(\widetilde{\text{MktCap}})\right). \tag{9}$$

Following the implemented procedure, we evaluate $\log(\widetilde{\text{MktCap}})$ at representative firm sizes (the 25th, 50th, and 75th percentiles of log(MktCap), centered by the sample

mean) and report the implied ΔY for ROA, ROE, and Tobin's Q in the Numerical Results section (Table 14).

6 Numerical Results

6.1 Preliminary Diagnostics and Bivariate Relationships

Table 5 Box's M Test for Equality of Covariance Matrices (2022–2024)

Statistic	Value	Interpretation
χ^2 Statistic	37.31	Test statistic value
Degrees of Freedom	72	Based on $p(p+1)/2(k-1)$
p-value	0.999	Not statistically significant at 0.05 level

The result of Box's M test indicates that the covariance matrices of firm-level financial and environmental variables from 2022 to 2024 are statistically indistinguishable ($p = 0.999$). This suggests that the variance and interdependence structures—capturing how indicators such as GHG emissions, profitability, market valuation, and the study variables co-vary—have remained stable over the study period.

The homogeneity of covariance matrices lends credibility to the underlying panel data model. It implies that the joint distribution of financial and environmental variables has not undergone significant structural shifts, despite potential macroeconomic or policy changes during this time. This statistical stability justifies the assumption that relationships estimated in the regression models are not driven by temporal volatility or regime change, but rather reflect consistent cross-sectional patterns. As a result, the observed associations between GHG emissions and financial outcomes—such as ROA, ROE, and Tobin's Q—can be interpreted with greater confidence as stable features of firm behaviour, rather than artifacts of evolving risk structures or time-varying multicollinearity.

Table 6 reports lower-triangular correlation matrices for the main variables in each year (2022–2024).

While these correlations are informative, they do not account for confounding variables or causal direction. Therefore, we treat them as descriptive and do not rely on correlation analysis for formal hypothesis testing. Instead, we rely on multivariate regression coefficients, which provide a more rigorous framework by controlling for firm characteristics such as size, investment, and leverage. This approach enables us to isolate the marginal effect of GHG emissions on firm performance, thus offering a more robust test of Hypotheses H1–H2.

Across all three years, emissions are positively correlated with market capitalisation, indicating that larger firms tend to report higher absolute emissions. Correlations between emissions and performance measures are comparatively small in magnitude, while ROA and ROE are strongly correlated as expected. Overall, the bivariate patterns provide useful context but the multivariate regressions below remain the primary basis for hypothesis evaluation.

Table 6 Lower Triangular Correlation Matrices (2022-2024) with 0.05 Significance

2022							
Variable	Emission	MktCap	PF	IF	RoE	RoA	Tobin's Q
Emission	1.000 *						
MktCap	0.530 *	1.000 *					
PF	0.097	-0.105	1.000*				
IF	-0.188 *	0.146	0.009	1.000*			
RoE	-0.066	0.054	0.314*	0.243*	1.000*		
RoA	-0.088	-0.067	0.337*	0.194*	0.872*	1.000*	
Tobin's Q	-0.095	0.236 *	0.148	0.303*	0.466*	0.513*	1.000 *
2023							
Variable	Emission	MktCap	PF	IF	RoE	RoA	Tobin's Q
Emission	1.000 *						
MktCap	0.556 *	1.000 *					
PF	0.049	-0.112	1.000*				
IF	-0.067	0.008	0.074	1.000*			
RoE	-0.086	0.152	0.077	0.290*	1.000*		
RoA	-0.088	-0.001	0.202*	0.329*	0.873*	1.000*	
Tobin's Q	-0.092	0.209 *	0.145	0.163	0.507*	0.595*	1.000 *
2024							
Variable	Emission	MktCap	PF	IF	RoE	RoA	Tobin's Q
Emission	1.000 *						
MktCap	0.549 *	1.000 *					
PF	0.117	-0.091	1.000*				
IF	-0.170	-0.044	-0.030	1.000*			
RoE	-0.141	0.215 *	0.114	0.349*	1.000*		
RoA	-0.130	0.062	0.236*	0.311*	0.874*	1.000*	
Tobin's Q	-0.094	0.210 *	0.175	0.233*	0.520*	0.590*	1.000 *

Note: Asterisk (*) denotes statistical significance at the 0.05 level. Only the lower triangle is shown due to matrix symmetry.

6.2 Baseline Regression Results

Tables 7–9 report the main regressions estimated separately for each year. Each specification relates firm performance (ROA, ROE, and Tobin's Q) to log(GHG), log(MktCap), profitability, investment, and the interaction log(GHG)+log(MktCap).

The year-by-year regression results in Tables 7–9 exhibit a remarkably stable pattern in both the signs and magnitudes of the key coefficients. Across all three years and all three specifications (ROA, ROE and Tobin's Q), the coefficient on log greenhouse gas emissions (GHG) is negative and statistically significant at conventional levels. For ROA, the GHG coefficient ranges from -0.010 in 2022 to -0.004 in 2023 and -0.008 in 2024; for ROE, it moves from -0.017 to -0.009 and back to -0.018; and for Tobin's Q it gradually declines in absolute value from -0.176 (2022) to -0.116 (2023)

Table 7 Regression Results with GHG–Market Cap Interaction 2022

ROA							
Metric	Constant	GHG	Market Cap	Profitability	Investment	GHG × MktCap	R^2
Coef.	-0.218	-0.010	0.012	0.039	0.097	0.002	0.284
t-stat	-3.550	-5.738	5.440	5.163	1.960	2.518	
p-value	0.001*	0.000*	0.000*	0.000*	0.052	0.013*	
ROE							
Metric	Constant	GHG	Market Cap	Profitability	Investment	GHG × MktCap	R^2
Coef.	-0.477	-0.017	0.022	0.069	0.204	0.006	0.341
t-stat	-4.767	-6.134	6.341	5.692	2.524	4.064	
p-value	0.000*	0.000*	0.000*	0.000*	0.013*	0.000*	
Tobin's Q							
Metric	Constant	GHG	Market Cap	Profitability	Investment	GHG × MktCap	R^2
Coef.	-4.457	-0.176	0.232	0.387	2.237	0.056	0.354
t-stat	-4.909	-7.029	7.225	3.493	3.042	4.549	
p-value	0.000*	0.000*	0.000*	0.001*	0.003*	0.000*	

Note: Coefficient estimates are obtained using Ordinary Least Squares (OLS) on log-transformed GHG and market capitalisation. The t-statistics and p-values are reported below each coefficient. Asterisks (*) denote statistical significance at the 5% level ($p < 0.05$).

Table 8 Regression Results with GHG–Market Cap Interaction 2023

ROA							
Metric	Constant	GHG	Market Cap	Profitability	Investment	GHG × MktCap	R^2
Coef.	-0.075	-0.004	0.005	0.022	0.217	0.001	0.202
t-stat	-1.220	-2.458	2.318	3.103	4.716	1.126	
p-value	0.224	0.015*	0.022*	0.002*	0.000*	0.262	
ROE							
Metric	Constant	GHG	Market Cap	Profitability	Investment	GHG × MktCap	R^2
Coef.	-0.221	-0.009	0.012	0.022	0.319	0.003	0.176
t-stat	-2.150	-3.044	3.226	1.886	4.156	2.369	
p-value	0.033*	0.003*	0.002*	0.061	0.000*	0.019*	
Tobin's Q							
Metric	Constant	GHG	Market Cap	Profitability	Investment	GHG × MktCap	R^2
Coef.	-3.274	-0.116	0.165	0.318	0.743	0.048	0.223
t-stat	-4.268	-5.391	5.918	3.635	1.298	4.757	
p-value	0.000*	0.000*	0.000*	0.000*	0.196	0.000*	

Note: Coefficient estimates are obtained using Ordinary Least Squares (OLS) on log-transformed GHG and market capitalisation. The t-statistics and p-values are reported below each coefficient. Asterisks (*) denote statistical significance at the 5% level ($p < 0.05$).

Table 9 Regression Results with GHG–Market Cap Interaction 2024

ROA							
Metric	Constant	GHG	Market Cap	Profitability	Investment	GHG × MktCap	R^2
Coef.	-0.183	-0.008	0.010	0.030	0.136	0.002	0.204
t-stat	-2.926	-4.354	4.255	4.177	2.908	2.270	
p-value	0.004*	0.000*	0.000*	0.000*	0.004*	0.025*	
ROE							
Metric	Constant	GHG	Market Cap	Profitability	Investment	GHG × MktCap	R^2
Coef.	-0.484	-0.018	0.023	0.039	0.206	0.006	0.205
t-stat	-4.069	-5.173	5.328	2.838	2.304	3.431	
p-value	0.000*	0.000*	0.000*	0.005*	0.023*	0.001*	
Tobin's Q							
Metric	Constant	GHG	Market Cap	Profitability	Investment	GHG × MktCap	R^2
Coef.	-2.696	-0.097	0.140	0.293	1.253	0.043	0.229
t-stat	-3.875	-4.883	5.522	3.638	2.401	4.564	
p-value	0.000*	0.000*	0.000*	0.000*	0.018*	0.000*	

Note: Coefficient estimates are obtained using Ordinary Least Squares (OLS) on log-transformed GHG and market capitalisation. The t-statistics and p-values are reported below each coefficient. Asterisks (*) denote statistical significance at the 5% level ($p < 0.05$).

and -0.097 (2024). Although the absolute effects in 2023 are somewhat smaller, the direction of impact is unchanged: conditional on firm size, profitability and investment, higher log emissions are consistently associated with lower accounting profitability and lower market valuation. Financially, this supports the view that more carbon-intensive firms face higher operating and transition risks that depress returns and are priced as a discount by equity investors.

The coefficients on log market capitalisation are uniformly positive and highly significant across all years and outcome variables. For example, the market capitalisation coefficient on ROE is 0.022, 0.012 and 0.023 in 2022, 2023 and 2024, respectively, while for Tobin's Q it declines modestly from 0.232 to 0.165 and 0.140. This persistent size premium indicates that larger firms tend to exhibit stronger profitability and higher valuation multiples, even after controlling for emissions and other firm characteristics. Such a pattern is consistent with scale economies, better diversification and stronger access to capital markets. The profitability factor also enters with a positive and, in most cases, statistically significant coefficient in all six accounting models and all three valuation models, confirming that firms with stronger operating performance and higher margins deliver better ROA, ROE and Tobin's Q. The investment factor remains positive in every specification. Its effect is especially pronounced in the Tobin's Q regressions, where the coefficient lies between 0.743 and 2.237, reflecting that the market tends to reward firms that invest more aggressively, as such investment signals growth opportunities and future cash-flow potential.

A key feature of the specification is the interaction term between log GHG and log market capitalisation, which captures how the emissions-performance relationship

varies with firm size. This interaction term is positive in every year and for every performance measure, and it is statistically significant in almost all cases. For ROE, the interaction coefficient is 0.006, 0.003 and 0.006 in 2022, 2023 and 2024; for Tobin's Q it remains in a relatively narrow band between 0.043 and 0.056. Taken together with the negative main effect of GHG, these estimates indicate that the association between emissions and firm outcomes varies systematically with firm size. We quantify the implied marginal effects at different market-cap percentiles in Table 14.

Collectively, the three yearly tables point to a coherent and robust financial narrative. The signs of the main coefficients are stable over time: GHG remains negatively related to all performance measures, market capitalisation and profitability are consistently positively related, and the GHG-size interaction is always positive. The numerical values of these coefficients show only moderate variation from 2022 to 2024, with 2023 generally characterised by somewhat smaller absolute effects and slightly lower R^2 values, but without any reversals of sign. The R^2 statistics, which range from about 0.18 to 0.35, indicate that the models explain a meaningful fraction of cross-sectional variation in performance, in line with typical firm-level regressions. Overall, the evidence suggests that, throughout the sample period, carbon intensity is systematically associated with weaker profitability and lower valuation, that larger firms enjoy a persistent performance advantage, and that firm size materially moderates the way in which the market prices carbon risk.

The numerical results in Tables 7–9 provide direct evidence on both hypotheses. For **H1**, the coefficient on $\log(\texttt{GHG})$ is negative and statistically significant in *every* specification across 2022–2024 for ROA, ROE, and Tobin's Q (e.g., ROA: -0.010, -0.004, -0.008; ROE: -0.017, -0.009, -0.018; Tobin's Q: -0.176, -0.116, -0.097, all with $p < 0.05$). This consistent sign pattern supports H1: conditional on firm size, profitability and investment, higher emissions are associated with lower accounting profitability and lower market valuation. For **H2**, the interaction term $\log(\texttt{GHG})+\log(\texttt{MktCap})$ is positive in all years and is statistically significant in almost all models (e.g., ROE: 0.006, 0.003, 0.006; Tobin's Q: 0.056, 0.048, 0.043). Combined with the negative main effect of emissions, this indicates that the emissions–performance relationship is heterogeneous with respect to firm size, consistent with the moderation component of H2. emissions-related penalty, while larger firms appear better able to attenuate the performance and valuation impact of higher emissions. Overall, the regression evidence therefore supports H1 and provides evidence consistent with the moderation component of H2.

6.3 Robustness Checks

This part reports robustness results for the two panel specifications introduced in the preceding section. Table 10 presents estimates from the contemporaneous pooled panel model in Eq. (4), while Table 11 reports the corresponding estimates from the lagged-emissions specification in Eq. (5). Both models are estimated by OLS including year and sector fixed effects, and statistical inference is based on heteroskedasticity-robust standard errors clustered at the firm level (instrument/ticker), allowing for arbitrary within-firm serial correlation over time.

Table 10 Pooled panel regressions from Eq. (4)

	ROA	ROE	Tobin's Q
$\log(\text{GHG}_{it})$	-0.0091***	-0.0130***	-0.1317***
	(0.0024)	(0.0037)	(0.0361)
R^2	0.372	0.268	0.348

Notes: Estimates are from Eq. (4). OLS with year and sector fixed effects; robust standard errors clustered at the firm level (instrument/ticker). Additional regressors included but omitted for brevity: $\log(\text{MktCap}_{it})$, PF, IF, and the centered interaction term $\log(\widetilde{\text{GHG}}_{it}) + \log(\widetilde{\text{MktCap}}_{it})$. *Significance:* Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10 shows that the coefficient on contemporaneous emissions, $\log(\text{GHG}_{it})$, is negative and statistically significant for all three outcomes. In economic terms, conditional on year effects, sector effects, and the included controls, higher-emitting firms exhibit lower accounting profitability (ROA and ROE) and lower market valuation (Tobin's Q). The reported R^2 values indicate that the combination of covariates and fixed effects explains a meaningful fraction of cross-sectional and time-series variation in firm outcomes in this setting.

Table 11 Lagged emissions robustness check from Eq. (5)

	ROA	ROE	Tobin's Q
$\log(\text{GHG}_{i,t-1})$	-0.0097***	-0.0125***	-0.1228***
	(0.0029)	(0.0046)	(0.0371)
R^2	0.388	0.295	0.361

Notes: Estimates are from Eq. (5). OLS with year and sector fixed effects; robust standard errors clustered at the firm level (instrument/ticker). Additional regressors included but omitted for brevity: $\log(\text{MktCap}_{it})$, PF, IF, and the centered interaction term $\log(\widetilde{\text{GHG}}_{i,t-1}) + \log(\widetilde{\text{MktCap}}_{it})$. *Significance:* Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11 reports results from the lagged-emissions specification in Eq. (5). The estimated association between emissions and subsequent firm outcomes remains negative and statistically significant across ROA, ROE, and Tobin's Q, with magnitudes close to those obtained using contemporaneous emissions in Table 10. This pattern is consistent with the view that the baseline relationship is not driven solely by contemporaneous feedback from performance to emissions. The reduced sample size reflects the requirement of consecutive firm-year observations for constructing $\log(\text{GHG}_{i,t-1})$, yet model fit remains comparable.

Overall, the results provide internally consistent evidence that higher emissions are associated with weaker profitability and lower valuation for Thai listed firms over 2022–2024. The stability of the estimates when using lagged emissions, combined with year and sector fixed effects and firm-clustered inference, strengthens the credibility of the empirical patterns documented in this study. At the same time, these estimates should be interpreted as conditional correlations: lagging emissions reduces concerns about contemporaneous simultaneity, but it does not fully rule out bias

from time-varying unobservables (e.g., technology upgrades, governance changes, or shifts in exposure to carbon-related regulation). Accordingly, the robustness results motivate future work employing stronger identification strategies—such as externally valid instruments, longer panels enabling firm fixed effects and dynamic specifications, or quasi-experimental variation from policy shocks—to more sharply isolate causal mechanisms.

6.4 Causality-Oriented Diagnostics: Reverse Prediction and Lead Tests

This part reports two diagnostics designed to probe the direction of influence between emissions and firm outcomes. These exercises do not deliver causal identification on their own; rather, they provide evidence on whether the documented emissions–performance associations are plausibly driven by reverse causality (performance affecting emissions) and/or by persistent unobserved factors that jointly shape emissions and outcomes.

Table 12 Reverse-prediction diagnostic: lagged performance predicting emissions (Year and Sector FE; firm-clustered SE)

	ROA_{t-1}	ROE_{t-1}	Tobin's Q_{t-1}
$Y_{i,t-1}$	-11.3942***	-4.1893**	-0.4690**
	(3.9813)	(1.7665)	(0.2103)
N	287	287	287
R^2	0.587	0.570	0.574

Notes: Dependent variable is $\log(\text{GHG}_{it})$. OLS with firm-clustered robust standard errors. Year and sector fixed effects included. Additional regressors included but omitted for brevity: $\log(\text{MktCap}_{it})$, PF, and IF.
Significance: Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13 Lead test: $\log(\text{GHG})_{t+1}$ predicting current outcomes (Year and Sector FE; firm-clustered SE)

	ROA	ROE	Tobin's Q
$\log(\text{GHG}_{i,t+1})$	-0.0083***	-0.0129***	-0.1331***
	(0.0029)	(0.0048)	(0.0397)
N	287	287	287
R^2	0.356	0.261	0.349

Notes: OLS with firm-clustered robust standard errors. Year and sector fixed effects included. Additional regressors included but omitted for brevity: $\log(\text{MktCap}_{it})$, PF, IF, and the centered interaction term constructed using $\log(\text{GHG}_{i,t+1})$.
Significance: Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12 estimates a reverse-prediction specification in which the dependent variable is firm-level emissions, $\log(\text{GHG}_{it})$, and the key regressor is lagged firm performance, $Y_{i,t-1}$, considered one outcome at a time (ROA, ROE, and Tobin's Q). All regressions include year and sector fixed effects and use firm-clustered robust standard errors; additional controls (log market capitalization, PF, and IF) are included but omitted from the table for compactness.

Across all three columns, lagged performance is negatively and statistically significantly related to subsequent emissions. The coefficients are economically large in magnitude for accounting measures: the estimate on ROA_{t-1} is -11.3942 ($p < 0.01$) and the estimate on ROE_{t-1} is -4.1893 ($p < 0.05$). For Tobin's Q, the coefficient is -0.4690 ($p < 0.05$). Interpreted literally, these estimates imply that better-performing firms in period $t-1$ tend to report lower emissions in period t, conditional on sector, year, and observed firm controls.

This pattern is consistent with a reverse-causality mechanism highlighted in the endogeneity discussion: financially stronger firms may have greater capacity to invest in emissions abatement, cleaner production processes, energy efficiency, and monitoring/reporting infrastructure, which can reduce emissions (or improve measurement and disclosure). The results also align with a broader "capability" interpretation in which profitability and valuation facilitate managerial attention and capital allocation toward operational improvements that affect emissions.

However, the reverse-prediction evidence should be interpreted cautiously. A negative relationship between $Y_{i,t-1}$ and $\log(\text{GHG}_{it})$ can also arise from persistent unobservables or time-varying shocks that affect both performance and emissions (e.g., technology upgrades, shifts in product mix, export-market requirements, or governance improvements). In other words, Table 12 indicates that reverse causality is empirically plausible in this setting, reinforcing the need for conservative language in interpreting the baseline emissions–performance coefficients. The relatively high R^2 values (0.570–0.587) suggest that the combination of fixed effects and covariates explains a substantial share of variation in emissions, but they do not, by themselves, validate a causal interpretation.

Table 13 reports a placebo-style lead test that replaces contemporaneous emissions with future emissions, $\log(\text{GHG}_{i,t+1})$, in the outcome regressions. Under a causal interpretation where emissions affect firm outcomes contemporaneously or with lags, future emissions should not systematically predict current performance once controls and fixed effects are included. In contrast, if emissions and performance are jointly driven by persistent firm characteristics (or if reporting/selection processes are stable over time), then future emissions may still correlate with current outcomes.

The lead coefficients are negative and highly statistically significant for all outcomes: -0.0083 for ROA, -0.0129 for ROE, and -0.1331 for Tobin's Q (all $p < 0.01$). Notably, the magnitudes are close to those obtained in the contemporaneous and lagged-emissions specifications. This finding implies that firms that will have higher emissions in $t+1$ already exhibit lower profitability and valuation in period t, even after conditioning on year and sector effects and observable controls.

The interpretation of this placebo result is important. Rather than supporting a causal claim, statistically strong lead effects typically suggest that the emissions

measure is capturing relatively persistent firm attributes (e.g., technology, operating model, management quality, product mix) or stable differences in stakeholder scrutiny and disclosure practices that are correlated with both emissions and performance. In such circumstances, emissions may act as a proxy for underlying "firm type" or structural characteristics that evolve slowly, causing both current and future emissions to correlate with current outcomes. Accordingly, the lead test strengthens the case for treating the baseline estimates as conditional correlations and highlights the value of stronger identification strategies (e.g., quasi-experimental shocks, externally valid instruments, or longer panels enabling richer within-firm designs).

The results provide two complementary insights. First, the reverse-prediction results indicate that better past performance is associated with lower subsequent emissions, consistent with the presence of feedback from outcomes to emissions management and disclosure. Second, the lead test shows that future emissions predict current outcomes with similar magnitudes, which is consistent with persistent confounding or stable firm characteristics jointly determining emissions and performance. Therefore, while the main regressions document robust and economically interpretable associations between emissions and firm outcomes, these diagnostics reinforce a conservative interpretation: without additional exogenous variation, the estimated coefficients should not be read as causal effects of emissions on profitability or valuation.

6.5 Economic Magnitude and Practical Significance

Table 14 Economic magnitude: implied effect of a 10% increase in emissions

Outcome	Firm size (by market cap)	Marginal effect	Implied ΔY (10%)
RoA	Small (p25)	-0.0071	-0.0007
RoA	Median (p50)	-0.0093	-0.0009
RoA	Large (p75)	-0.0110	-0.0010
RoE	Small (p25)	-0.0100	-0.0010
RoE	Median (p50)	-0.0133	-0.0013
RoE	Large (p75)	-0.0160	-0.0015
Tobin's Q	Small (p25)	-0.1300	-0.0124
Tobin's Q	Median (p50)	-0.1319	-0.0126
Tobin's Q	Large (p75)	-0.1334	-0.0127

Notes: The marginal effect is computed as $\partial Y/\partial \log(\text{GHG}) = \beta_{\text{GHG}} + \beta_{\text{int}} \cdot \widetilde{\log(\text{MktCap})}$, evaluated at the 25th/50th/75th percentiles of log(MktCap). The implied change for a 10% increase in emissions is $\Delta Y \approx \ln(1.10) \times \partial Y/\partial \log(\text{GHG})$.

Table 14 translates the regression estimates into economically interpretable magnitudes using $\Delta Y \approx \ln(1.10) \times \partial Y/\partial \log(\text{GHG})$, where $\ln(1.10) \approx 0.0953$. For accounting performance, the implied effects are small but uniformly negative: a 10% increase in emissions corresponds to a decline in ROA of approximately 0.0007–0.0010 and a decline in ROE of approximately 0.0010–0.0015.[3] While modest on a per-10%

[3]If ROA/ROE are expressed in decimal units, these correspond to approximately 0.07–0.10 and 0.10–0.15 percentage points, respectively.

basis, these effects may be economically meaningful when comparing firms with large emissions differentials (e.g., across the tails of the emissions distribution) or when considering cumulative changes over multiple years.

For market valuation, the implied magnitude is larger: a 10% increase in emissions is associated with a decrease in Tobin's Q of approximately 0.0124–0.0127. Because Tobin's Q is a valuation ratio, changes of this size can be material at scale, particularly for large-cap firms where small ratio movements correspond to sizable differences in market value. The stronger sensitivity of valuation relative to contemporaneous profitability is consistent with the interpretation that investors may price expected future transition costs and regulatory tightening before these costs are fully reflected in current accounting outcomes.

Table 14 also illustrates how the implied marginal effect varies across firm size through the interaction structure. For ROA and ROE, the marginal effect becomes more negative as market capitalization increases (e.g., ROA shifts from -0.0071 for small firms to -0.0110 for large firms; ROE from -0.0100 to -0.0160). This pattern suggests that, conditional on sector and year, higher emissions are more strongly associated with weaker accounting performance among larger firms, potentially reflecting greater scrutiny from capital markets and stakeholders as well as higher expected transition-related liabilities.

In contrast, the marginal effects for Tobin's Q are very similar across the size distribution (approximately -0.130 to -0.133), indicating that the valuation association is broadly present across firm sizes in these calculations.

Overall, the magnitude analysis indicates that the emissions–performance relationship documented in this study is economically small in contemporaneous profitability terms but more pronounced in market valuation. Taken together with the negative and statistically significant regression estimates, the evidence is consistent with a channel in which higher-emitting firms face valuation discounts—potentially reflecting priced expectations of transition risk—even when the near-term impact on accounting profitability appears limited.

7 Conclusions

This study links firm-reported GHG emissions to accounting performance and market valuation for Thai listed firms over 2022–2024. Two broad conclusions emerge. First, emissions in the Thai market are highly concentrated across a small number of issuers and sectors. This concentration matters for both policy and practice: from a portfolio perspective, financed-emissions exposure is driven by a limited set of firms, implying that engagement and transition planning that prioritise the largest emitters can deliver outsized reductions in financed emissions and potentially in climate-related portfolio risk. From a regulatory perspective, concentration implies that improvements in measurement, reporting, and mitigation among a small group of high-emitting firms can meaningfully affect aggregate outcomes.

Second, in firm-level regressions with year and sector fixed effects and firm-clustered inference, higher emissions are consistently associated with weaker outcomes.

Emissions are negatively related to ROA and ROE, and the association is economically more pronounced for Tobin's Q, suggesting that valuation channels may reflect forward-looking transition costs, regulatory exposure, and investor scrutiny more strongly than contemporaneous profitability. The lagged-emissions specification yields qualitatively similar results, reducing concerns that the baseline associations are driven purely by same-year feedback between performance and emissions. Moreover, the interaction-based magnitude calculations indicate that profitability sensitivity to emissions is more negative for larger firms, consistent with the idea that larger issuers face stronger market discipline, disclosure pressure, and stakeholder attention.

At the same time, the paper's causality-oriented diagnostics underscore the limits of causal interpretation in a short panel. Past firm performance predicts subsequent emissions, consistent with a reverse-causality channel (e.g., financially stronger firms having greater capacity to invest in abatement and reporting quality) and/or with time-varying omitted factors that jointly affect emissions and outcomes. In addition, future emissions predict current outcomes with comparable magnitudes, a pattern that is difficult to reconcile with a simple contemporaneous causal story and instead points to persistent firm characteristics, stable business models, or unobserved heterogeneity that co-moves with both emissions and performance. Taken together, these diagnostics reinforce that the primary contribution of this study is to document robust conditional correlations and economically interpretable magnitudes, rather than to establish causal effects.

The results support policies that improve the credibility, comparability, and decision-usefulness of emissions information. Given the high concentration of emissions among a small set of firms, policymakers can achieve meaningful gains by strengthening disclosure requirements and assurance expectations for large emitters and emissions-intensive sectors, including clearer definitions of boundaries, improved consistency across scopes, and more comparable intensity metrics and transition-plan disclosures. Complementary policies that lower the cost of abatement and measurement—such as support for energy-efficiency upgrades, clean-technology adoption, and MRV (measurement, reporting, and verification) infrastructure—can reduce frictions that limit both real emissions reductions and reporting quality. Finally, as Thailand advances climate-policy instruments (including carbon-pricing and sectoral standards), predictable implementation paths and transparent guidance can reduce uncertainty and improve the pricing of transition risk in capital markets.

For investors, the negative association between emissions and Tobin's Q indicates that carbon exposure and transition risk are relevant for valuation in the Thai equity market during the sample period. Investors may benefit from integrating emissions measures (levels and intensities), emissions trajectories, and disclosure quality into valuation and risk frameworks, while recognising that emissions can proxy for broader business-model and governance characteristics. Because emissions are concentrated, stewardship and engagement efforts can be prioritised efficiently: focusing on high-emitting issuers, requesting credible transition plans and capital-expenditure alignment, and monitoring progress in emissions trajectories and reporting assurance.

Given the evidence of feedback and persistent confounding, the most defensible interpretation is that emissions operate as a risk and firm-characteristics signal rather than a standalone causal determinant of performance.

Future research can strengthen identification by extending the time horizon, incorporating scope-specific emissions and verification indicators, and exploiting plausibly exogenous variation (e.g., policy discontinuities, energy-price shocks, or externally valid instruments) to more cleanly separate causal channels from selection and omitted-variable bias.

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Declarations

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Pasin Marupanthorn: Writing – original draft, Investigation, Validation, Resources, Formal Analysis, Data curation, Quantitative Modeling and Conceptualization.

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