The Dual Impact of Carbon Emissions and Financial Performance

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Abstract

This thesis examines the relationship between carbon emissions and financial performance in Asian markets, employing Panel Vector Autoregression (PVAR) and pooled Ordinary Least Squares (OLS) regression. The study utilizes a comprehensive dataset covering firm-level data from 2007 to 2022, allowing for a robust analysis of the complex relationships between environmental and financial factors. The findings provide weak evidence for a carbon premium, suggesting that investors may demand higher returns from firms with high carbon emissions to compensate for environmental risks. Additionally, the results indicate that emission-intensive firms may face financial risks, as higher emission intensity is associated with increased leverage. However, other financial metrics, such as Return on Assets (ROA) and Market-to-Book Ratio, show inconsistent relationships with carbon emissions. These results highlight the challenges of reducing emissions and their limited influence on financial outcomes in emerging markets where regulatory pressures and market dynamics differ significantly from those in advanced economies. The study underscores the importance of tailored regulatory frameworks and strategic investments in sustainability, offering insights for policymakers and firms trying to find the golden path between environmental and financial goals.

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Resumo

Esta tese examina a relação entre as emissões de carbono e o desempenho financeiro nos mercados asiáticos, empregando a regressão Panel Vetor Autoregression (PVAR) e a regressão Ordinary Least Squares (OLS) agrupada. O estudo utiliza um conjunto de dados abrangente que cobre dados ao nível das empresas de 2007 a 2022, permitindo uma análise robusta das relações complexas entre factores ambientais e financeiros. Os resultados fornecem evidências fracas de um prémio de carbono, sugerindo que os investidores podem exigir retornos mais altos de empresas com altas emissões de carbono para compensar os riscos ambientais. Além disso, os resultados indicam que as empresas com emissões intensivas podem enfrentar riscos financeiros, uma vez que uma maior intensidade de emissões está associada a uma maior alavancagem. No entanto, outras métricas financeiras, como a rendibilidade dos activos (ROA) e o rácio mercado-valor contabilístico, apresentam relações inconsistentes com as emissões de carbono. Estes resultados realçam os desafios da redução das emissões e a sua influência limitada nos resultados financeiros nos mercados emergentes, onde as pressões regulamentares e a dinâmica do mercado diferem significativamente das das economias avançadas. O estudo sublinha a importância de enquadramentos regulamentares adaptados e de investimentos estratégicos em sustentabilidade, oferecendo perspectivas aos decisores políticos e às empresas que tentam encontrar o caminho de ouro entre os objectivos ambientais e financeiros.

Título: O Duplo Impacto das Emissões de Carbono e do Desempenho Financeiro

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Palavras-chave: Emissões de Carbono, Desempenho Financeiro, Mercados Asiáticos, Autoregressão Vetorial em Painel (PVAR), Regressão por Mínimos Quadrados Ordinários (OLS), Hipótese do Prémio de Carbono, Intensidade de Emissão

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1. Introduction

The issue of climate change is one of the most pressing issues in the global world, therefore, companies face intense pressure to minimize their impact. In particular, carbon emissions are a critical concern as they are responsible for the greenhouse effect. Firms, especially those in high-energy industries, play a pivotal role in this context. Their ability to generate profit while minimizing ecological costs is crucial for sustainable development. This is especially relevant given the rapid industrialization of Asian economies, which has significantly increased emissions.

There is a significant body of earlier literature on the relationship between corporate performance and corporate environmental reports. For instance, Clarkson et al. (2011) analyse the "feed-forward" mechanism between environmental sensitivity and business performance, discovering that firms with better environmental records tend to outperform their peers. Similarly, Hart and Ahuja (1996) provide evidence that reductions in emissions can be achieved with cost benefits and improved operations in the future. These are important findings as firms seek to align their activities with the emerging global policy on sustainable development.

However, the dynamics in specific Asian markets might differ considerably from those in the Western economies due to the nature of the industrial structure, legal systems, and the level of economic growth. China, India, and Southeast Asia have experienced rapid industrialization in the last two decades and have become important players in the global economy through manufacturing and investment. Their transformation positions them as promising markets for future economic development. According to Zhang et al. (2020), Asia has witnessed a significant increase in carbon emissions, so it becomes critical to understand how firms can adapt to the goal of sustainability. The pressure and compulsion for controlling the carbon emission is also different in the Asian Economies which along with the regulatory and social requirements of sustainability also makes the sustainability picture complex in Asia.

The core of this thesis aims to examine the relationship between carbon emissions and some of the most important financial factors at the firm level in Asia. In a more precise way, the research will examine the patterns in changes in carbon emissions and carbon emission intensity with respect to various market-based and accounting-based financial measures such as Stock Returns, Returns on Assets, and Market-to-Book ratios. Additionally, it will explore how changes in these environmental variables affect financial performance. Using a sample of Asian firms, this research aims to contribute to the still limited literature on sustainability in emerging markets. There is scarce literature on how Asian economies affect environmental decisions, despite their growing importance in global economic and environmental trends. Filling this gap is crucial for assessing the role of the region in these critical issues.

The relationships between carbon emissions and financial indicators in this thesis are primarily examined using Panel Vector Autoregression (PVAR) models. PVAR models allow for dynamic feedback to be identified and estimated between different variables, but they don't need a strict causal relationship to work. Here, the use of financial variables and carbon emissions are best captured as endogenous, in that each of them can affect the other at different time horizons.

In addition to the PVAR model, this thesis also employs a pooled Ordinary Least Squares (OLS) regression. This method estimates the overall relationship between financial performance and carbon emissions across all firms, assuming the relationship is homogeneous for every firm. While the PVAR model captures the dynamic interactions and feedback effects over time, the pooled OLS regression offers a more straightforward analysis of the overall trends and correlations in the data. This analysis also discusses the different trends between sectors regarding carbon emissions, providing insights into sector-specific dynamics.

By employing both the PVAR model and the pooled OLS regression, the thesis seeks to answer key questions such as: How does variation in the financial performance indicators affect carbon emissions? Conversely, how do carbon emissions affect firm performance? Data about the Asian firms has been collected for a 15-year period (2007-2022). To accommodate these interdependencies, the PVAR model employs lags of the variables, allowing the analysis to determine both short-term and long-term impacts of financial and environmental actions. The pooled OLS regression complements this by providing insights into the overall patterns and relationships in the dataset.

2. Literature review

The relationship between CO2 emissions and financial performance has attracted significant research attention as companies face increasing pressures from regulatory bodies, investors, and consumers to adopt sustainable practices. Research in developed countries generally shows emissions' negative impact on financial performance due to strict environmental regulations and greater investor demand for environmentally friendly practices. On the other hand, due to less pressure of regularities in emerging markets, the outcome varies and the relationship between emissions and financial results is not that strong. Horváthová (2010), in her meta-analysis, notes that differences in empirical methods, such as regression techniques, panel data analysis, and structural equation modeling, significantly influence results, with more sophisticated econometric techniques often yielding weaker or nuanced relationships.

2.1 Advanced Economies

In advanced economies, firms with high carbon emissions face greater risks due to strict environmental regulations and more sensitive markets. As a result, a carbon premium often emerges, where investors demand higher expected returns to compensate for the increased risk associated with high emissions. This premium is therefore associated with carbon risk as perceived by investors and not with the positive effect of emissions on the operational financial performance of a firm.

Matsumura et al. (2014) use Heckman's two-step approach to correct self-selection bias while working on S&P 500 firms between 2006 and 2008. Their results indicate that carbon emissions are negatively associated with firm value, which proves that investors discourage companies from emissions. However, emission transparency has a positive effect on valuation showing that the market favours companies that are responsible for their emissions.

Konar and Cohen (2001) also examined S&P 500 firms and used a regression analysis to test the relationship between environmental performance and financial outcomes, as firms with fewer emissions report higher financial performance. The study, which analyses data from 321 firms in 1989, notes that companies with proactive environmental strategies gain investment, as markets embrace sustainability.

In a study conducted by Hassel et al. (2005), the nature of the relationship between environmental performance and investment in developed markets was analysed using a panel data analysis. The data they used consisted of 71 firms listed on the stock exchange in Sweden from 1998-2000. Their results support the suggestion that companies with good environmental practices are likely to have higher profitability and market value thus underlining the efficiency of sustainability in developed countries.

Examining 174 of the largest companies by market cap within the Dow Jones Global Index, Busch and Hoffmann (2011) undertook an OLS regression analysis specifically to assess the effect of carbon management on financial performance. They discovered that companies managing their emissions can improve financial returns, particularly in markets with strict carbon regulations and where investors place a high value on sustainability.

Bolton and Kacperczyk (2021), in <Do Investors Care About Carbon Risk?=, used panel regression models for the period 2005-2017, on 3421 US companies, to examine carbon risk's effect on firm valuation. They found that investors demand higher expected returns for high-emission firms, a reflection of the carbon premium that arises in response to the risks associated with high emissions, especially in sectors with environmental regulations. Their findings highlight that in advanced markets, investors actively price in carbon risk, demanding additional returns for bearing the increased risk caused by emissions.

Overall, these studies imply that in the developed world, CO_2 emissions carry a financial cost that is priced into the risk profile, leading to a carbon premium. The methods applied like Heckman procedures, panel data analysis, and Ordinary Least Squares regression show that the financial costs of emissions are gradually emerging in the contexts of both the fully regulated sector and the competitive market.

2.2 Emerging Economies

In contrast, studies in emerging economies, including China, India, South Africa, and Southern Europe, reveal a more complex and often weaker relationship between carbon emissions and financial performance. In these regions, the regulatory and investor pressures seem to be low, thereby enabling the firms to achieve more economic growth at the expense of the environment with less or even the absence of a carbon premium.

Robaina and Madaleno (2019) used PVAR and FGLS regressions in their analysis of firms from 17 Portuguese sectors from 2008 through 2016 to understand how emissions reductions relate to financial performance. Their findings suggest that emissions management is often perceived as a cost in these firms, with weaker financial gains from environmental performance. The study's PVAR approach highlights the minimal effect of emissions on financial performance, particularly in emerging markets where environmental regulations are more flexible.

Li et al. (2017) applied a two-stage least squares regression on 1179 observations of Chinese energy-intensive listed companies in 2012-2014. The study notes that a positive relationship between environmental responsibility and financial performance exists, however, mainly under strict regulatory conditions. They provide their findings that in emerging nations where the authorities lack regulatory force, carbon emissions are unlikely to affect financial returns negatively.

Ganda and Samson (2018), in their study on 63 South African firms for the 2015 fiscal year, also used multiple regression analyses. The study concluded that as emissions increase, firms' profitability decreases. However, they also pointed out that these costs could be mitigated through operational efficiencies and made it clear that in some emerging markets, the economic benefits from growth through operations might overcome the cost of emissions in some cases.

Qureshi and Akbar (2017) studied a group of Chinese firms listed on Shanghai and Shenzhen stock exchanges from 200932016, comprising 1988 firm-year observations. Their research provided a quantitative method by performing regression analyses to compare the ESG factors in emerging markets and positively affirming the correlation with financial performance. Nevertheless, the paper finds that the emissions-performance link depends on sector characteristics, underlining industry-specific and market factors.

Delmas et al. (2015) used longitudinal data for 1095 U.S. corporations from 2004 to 2008. They employed qualitative and quantitative methodologies on the dispersed effect of national regulation on the relation between emissions and financial performance. They argued that countries with less stringent regulations have fewer negative coefficients between emissions and financial performance. This study provided evidence for the idea that the strength of regulations influences this relationship, thus I placed it in this section of the literature review.

Another study by García-Sánchez and Prado-Lorenzo (2012) regarding emissions in emerging markets, using panel data techniques, also proved to be inconclusive and showed that some firms' emission levels had no practical correlation with their financial performance. Thus, this research supports the notion that the intensity of the regulations is a significant determinant of environmental stewardship in returns on investment.

Sarumpaet (2005) examined the relationship between environmental performance and financial performance among Indonesian companies using data from 87 firms. The study employed a regression analysis and found that environmental performance was not significantly associated with financial performance, measured by Return on Assets (ROA). The author highlights the importance of environmental management systems and the potential for international standards to drive environmental improvements in emerging markets.

These studies show that in the case of emerging markets, the link between carbon emissions and financial performance can be weaker or mixed and depends on the estimators used. For instance, employing GMM, 2SLS or PVAR methods usually provide more reliable and contextually appropriate results relating to regulatory compliance, industry environment and economic factors.

2.3 Conclusion

Carbon emission and financial performance is an area of considerable research, and the literature is quite pronounced in its differentiation between developed and developing countries. In advanced markets, CO2 emissions generally exhibit a negative relationship with financial performance due to strict policies and high investor expectations, as demonstrated by numerous studies using rigorous econometric models. Conversely, in emerging markets, the relationship between CO2 emissions and financial performance can be positive, negative, or even ambivalent, depending on regulatory standards, economic factors, and industry conditions. Horváthová (2010) agrees with the fact that methodological differences could be the reason for divergent results, which include numerous investigations employing more sound econometric methods showing a much weaker or even inverse U-shaped relationship between emissions and financial performance. This variation provides important context for the present study, which finds weak evidence for a carbon premium, indicating that, in line with emerging market findings, emissions may have a limited impact on financial performance where regulatory pressures are lower.

3. Data

3.1 Data preparation

This section outlines the data preparation process for the study, ensuring the dataset is suitable for PVAR and a panel regression analysis. The dataset is sourced entirely from Refinitiv Eikon, a leading provider of financial data. It covers Asian firm-level data from 2007 to 2022 and includes key financial and environmental variables.

The data preparation involved several key steps. Initially, the datasets from Refinitiv Eikon were merged into one aggregated panel dataset. Following this, the data was cleaned to remove any duplicates or invalid entries. The next step involved filtering the dataset to retain only those observations that had corresponding CO2 emission data by date and firm. To address the influence of outliers, a winsorizing approach was employed. This method replaces extreme values with their respective percentile thresholds, ensuring that values below the 1st and above the 99th percentile are set to these boundaries (Sullivan et al., 2021). Winsorizing maintains the integrity of the data distribution while reducing the disproportionate impact of outliers. This process was applied consistently across all variables. Additionally, further filtering was applied to keep only those companies with at least five consecutive CO2 observations, and any observations not part of these consecutive groups were removed. These steps were crucial to ensure a minimum of three observations per group after the eventual differencing of the variables and considering the necessary added lags for the PVAR models. Finally, we are left with 702 firms and 7370 firm-year observations, showing more than 10 consecutive observations on average per firm.

3.2 Variables

In this study my variable selection was mainly based on the literature mentioned above, trying to make sure that I control for every variable that can potentially have a significant relationship with carbon emission, which is the main variable of interest. Below is a summary of the variables included in the dataset:

Carbon Emission (CO2 Equivalents Emission Total)

This is the primary environmental variable in the study, measured in metric tons of CO2 equivalents (tCO2e). The metric aggregates various greenhouse gases, such as methane (CH4) and nitrous oxide (N2O), by converting their emissions into the equivalent amount of carbon dioxide based on their global warming potential (GWP). This standardized measurement allows for consistent comparison across firms and industries. The data is reported annually and reflects

Scope 1 (direct operations) and, in some cases, Scope 2 (purchased electricity) emissions. Values range from 1,126 tCO2e to 84,133,900 tCO2e, with a mean of 3,615,780 tCO2e, demonstrating considerable variability across firms. Larger firms and those in energy-intensive sectors like manufacturing tend to report higher emissions.

Carbon Emission Intensity

This variable, calculated as total carbon emissions divided by the logarithm of total assets, captures carbon emissions relative to Firm Size. The normalized metric enables cross-firm comparisons by accounting for operational scale. The mean value of 175,776 with a standard deviation of 441419 indicates substantial diversity.

Log Returns (Logarithm of Total Return Index)

This variable measures stock returns, adjusted for stock splits and dividends, with a logarithmic transformation to stabilize variance. Companies show varying performance with returns ranging from significant gains to losses. Using the log scale helps to compare financial performance changes more effectively across firms, regardless of their size or market capitalization.

M/B Ratio

The Market-to-Book Ratio measures the ratio between the market value of a firm and its book value of equity and has a mean of 1.19 and a standard deviation of 1.20. This reversed ratio (M/B) is more appropriate for the study, since it reflects market growth expectations compared to emissions and financial performance. High ratios, for example, are often observed in the technology industry while low ratios are common in the utilities or manufacturing industries.

Leverage Ratio

Calculated as total liabilities divided by total assets, the Leverage Ratio ranges from 0 to 0.79, with a mean of 0.24. Higher leverage values are often observed in capital-intensive sectors like energy or real estate, indicating reliance on debt to finance operations. Such firms may have problems of sustainability and financial limitations to the implementation of such measures.

Net Income

This variable reflects firms' overall profitability, with values ranging from significant losses (-332 million USD) to substantial gains (4.95 billion USD), and a median of 13.44 million USD. The wide range also shows the financial variation of firms in the dataset, which are from different industries and at different stages of development. Big firms or those in mature industries have less volatility in their profitability than small firms or those in young or competitive industries.

Quick Ratio

A measure of liquidity, the Quick Ratio is calculated as the ratio of a firm's most liquid assets (cash, marketable securities, and receivables) to its current liabilities. It ranges from 0.16 to 6.64, with a mean of 1.23, indicating that most of the firms in the dataset are in a position to comfortably meet their short-term liabilities. Firms with higher liquidity may have greater capacity to allocate resources toward sustainability initiatives.

Log of Total Assets (Size)

Logged Total Assets, a proxy for Firm Size, range from 12.89 to 26.39, with a mean of 19.75. Large firms tend to have higher carbon emissions, however, they are also more efficient and hence have lower emission intensity. This variable captures the extent of operational diversity of firms in the dataset.

Return on Assets (ROA)

ROA measures how effectively a firm uses its assets to generate earnings, with values in this dataset ranging from -15.69% to 32.11% and a mean of 5.24%. Variability in ROA reflects differences in profitability across firms and industries. Higher ROA is often associated with better utilization of assets in order to generate earnings.

Sector Dummies (FTSE Industry Sectors)

Industry-specific dummies are included in the dataset to control for sectoral effects on emissions and financial performance. These dummies account for industry-specific operational and environmental characteristics which makes the analysis more robust. The dataset contains a diverse array of industries, as classified by the FTSE Industry Classification Benchmark (ICB), including:

- *Basic Materials (11): Mining, chemicals, construction materials, and forest products, typically associated with high emissions due to resource extraction and processing. This sector is used as the reference category in this study.*

- *Industrials (13): Manufacturing, construction, aerospace, and general industrials.*

- *Consumer Goods (17): Automobiles, food producers, personal goods, and household products.*

- *Health Care (23): Pharmaceuticals and biotechnology.*
- *Consumer Services (24): Retail, media, and travel services.*
- *Telecommunications (27): Fixed-line and mobile communication services.*
- *Utilities (33): Water, gas, and electric utilities.*
- *Financials (34): Banking, insurance, and investment services.*
- *Technology (35): Software, IT services, and electronics.*
- *Real Estate (37): REITs and real estate services.*
- *Aerospace & Defense (45): Aircraft and defense systems.*
- *Oil & Gas (5): Exploration, extraction, refining, and distribution of oil and natural gas.*
- *Support Services (53): Business support and outsourcing.*
- *Industrial Goods & Services (55): Conglomerates and transportation.*
- *Energy (57): Companies involved in the production and distribution of energy, including both renewable and non-renewable sources.*
- *Media (65): Broadcasting and publishing.*
- *Travel & Leisure (67): Hotels, restaurants, and airlines.*
- *Food & Beverage (75): Food production and beverage manufacturing.*
- *Personal Goods (86): Apparel and luxury goods.*
- *Household Products (87): Home appliances and related products.*
- *Technology Hardware & Equipment (95): Electronics and devices.*

Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max	Median	Observations
Carbon Emission (tCO2e)	3615780	9200485	1126	84133900	477296	7370
Carbon Emission Intensity	175776	441419	68	4906616	24197	7370
Log Returns	6.82	1.66	1.86	11.75	6.73	7370
M/B Ratio	1.19	1.2	0.05	12.41	0.8	7370
Leverage Ratio	0.24	0.16	0	0.79	0.23	7370
Net Income (million USD)	125.71	451.94	-332.47	4957.72	13.44	7370
Quick Ratio	1.23	0.86	0.16	6.64	1	7370
Size	19.75	2.38	12.89	26.39	19.98	7370
ROA (%)	5.24	5.31	-15.69	32.11	4.39	7370

Table 1: Descriptive statistics

The use of diverse variables and sectoral classifications gives a detailed framework for evaluating emissions and financial outcomes. The combination of normalized metrics such as emission intensity, along with sector dummies ensures that the analysis is balanced and not skewed towards firm-specific and industry effects.

4. Methodology

This section outlines the methodology used to investigate the relationships between carbon emissions and financial performance using two modelling approaches: the Panel Vector Autoregressive (PVAR) model and the pooled Ordinary Least Squares (OLS) regression. These approaches allow us to capture both dynamic and static relationships between emissions and financial variables.

The PVAR model is a multivariate time series model that analyses the dynamic interactions between variables in a time series context. This makes it suitable for studying the changes in the environmental and financial performance indicators and their interdependence. Unlike static models, which focus on contemporaneous relationships, PVAR models incorporate time-lagged relationships between variables, enabling a more comprehensive understanding of both immediate and cumulative effects (Canova and Ciccarelli, 2013). A key advantage of the PVAR model is that it treats all variables as endogenous, allowing it to capture two-way relationships and feedback loops (Nwafor et al., 2016). This is especially useful in the analysis of the environmental-financial interface since it does not assume which variable is purely dependent or independent, thus solving problems of endogeneity such as reverse causality. The PVAR model is designed to provide a snapshot of the temporal structure and feedback mechanisms of the system by estimating the effects of past values of each variable on current values.

The general equation of the PVAR model is as follows:

$$Y_{it} = A_1 Y_{it-1} + A_2 Y_{it-2} + \cdots + A_p Y_{it-p} + \mu_i + \varepsilon_{it} \quad (1)$$

In this equation Y_{it} represents the vector of endogenous variables for firm (i) at time (t). The matrices A_1, A_2, … , A_p are the coefficient matrices that capture the relationships between the variables and their lags. The term μ_i denotes the vector of constants specific to each firm, and ε_{it} is the vector of error terms (Canova and Ciccarelli, 2013). Key features of the PVAR model include dynamic interdependencies, temporal effects, and cross-sectional heterogeneity (Canova and Ciccarelli, 2013). The stability of the PVAR model was verified using an eigenvalue stability test. Stability ensures that shocks to the system do not cause explosive growth in variables over time but instead dissipate, affirming that identified relationships remain consistent over time without leading to instability in the data (Abrigo and Love, 2016).

To determine the appropriate number of lags for the PVAR models, the Akaike Information Criterion (AIC), Bayes-Schwarz Criterion (BIC), and Hannan-Quinn Criterion (HQC) were used. These information criteria are used to compare different statistical models and select the one that best balances goodness of fit and model complexity. Furthermore, to achieve stationarity first-differencing was applied to the variables. Testing for stationarity is crucial for time-series data. A process is strictly stationary if the joint distribution of any segments of the time series remains unchanged when shifted in time by a constant amount. This means that the statistical properties, such as mean, variance, and higher-order moments, are invariant over time (Kirchgässner et al., 2012). However, this strict condition is rarely met in practice, therefore, the literature often uses a more relaxed definition, where only the mean and variance need to be constant over time, and the autocovariance function depends solely on the lag. This is known as weak stationarity, and it is sufficient for the valid use of time series models. For the purposes of this thesis, I will use the term 'stationarity' to refer to it. Stationarity was tested using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Phillips-Perron (PP) tests. These tests complement each other because the KPSS test's null hypothesis is that the process is stationary, while the PP test's null hypothesis is that the process contains a unit root. This dual approach helps eliminate type I and II errors (Kirchgässner et al., 2012).

To complement the PVAR analysis, a panel regression model was employed to assess direct, static relationships between emissions metrics and financial variables. Unlike the PVAR model, which captures dynamic interactions, the panel regression focuses on contemporaneous associations, helping to understand immediate relationships across firms and sectors. The panel regression model aims to optimize the residuals by minimizing the squared differences between the observed and predicted values, thereby providing the best linear unbiased estimates of the relationships between the variables (Wooldridge, 2010).

The general equation of the firm fixed effect pooled OLS regression model is structured as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_k X_{k,it} + \omega_i + \varepsilon_{it} \tag{2}$$

In this equation, Y_{it} represents the dependent variable for firm (i) at time (t). The $X_{1,it}$, $X_{2,it}$, …, $X_{k,it}$ are the independent variables that capture the relationships between the variables, including any dummy variables. The term ω_i denotes the firm fixed effects, and ε_{it} is the error term. Firm fixed effects were used in the panel regressions to control for unobserved heterogeneity across firms. This approach helps to account for time-invariant characteristics of the firms that could influence both the dependent and independent variables, ensuring that the estimated relationships are not biased by these unobserved factors (Wooldridge, 2010).

Several diagnostic tests were conducted to ensure the robustness of the models. Multicollinearity was assessed using the Variance Inflation Factor (VIF), with high VIF values indicating potential multicollinearity issues. To address heteroskedasticity, which is common in time series data due to varying residual variances, robust standard errors were employed. This adjustment helps to account for differences in variance and provides more reliable standard error estimates. The normality of residuals was considered, although the Central Limit Theorem suggests that with a sufficiently large sample size, the distribution of residuals will approximate normality (Verbeek, 2008). Autocorrelation, where a variable is correlated with its past values, can lead to inefficient estimators, and was addressed by differencing the variables in the panel regressions to also ensure comparability with the PVAR model.

In the primary analysis, total CO2 emissions were used as the dependent variable to test the association with different financial performance measures. In addition to this primary analysis, a supplementary analysis was conducted using both the PVAR and panel regression models with carbon emission intensity as the dependent variable. This supplementary analysis aims to provide insights into emissions efficiency across firms by examining emissions relative to output. The PVAR model for carbon emission intensity follows the same structure as the primary PVAR model, capturing dynamic interdependencies among variables over time. Similarly, the panel regression model for carbon emission intensity assesses direct, static relationships between emission intensity and financial variables, also incorporating dummy variables to account for industry-specific effects.

According to Horváthová (2010), the methodological decisions can significantly influence the results in the environmental-financial research. Models such as PVAR take into account feedback effects that vary with time, which enables the interaction between variables to develop over time, while static models provide a straightforward, time-invariant perspective of the data. Therefore, this study will use both dynamic and static analyses in order to gain a broad view of the emissions-financial performance nexus while capitalizing on the strengths of each approach.

5. Results

This section presents the findings from two complementary analyses. One focuses on total carbon emissions and the other on carbon emission intensity. Both analyses used the same financial variables, including the M/B Ratio, Log Returns, Leverage Ratio, Quick Ratio, Net Income, ROA, and sector dummies. However, while the total CO2 emissions model included the log of Total Assets, the emission intensity model did not, as emission intensity itself captures emissions relative to Firm Size or output.

5.1 Main Analysis: Total CO2 Emissions

The primary analysis examines total CO2 emissions and their association with financial performance indicators, using both a PVAR model and a pooled OLS regression. This two-fold approach captures both dynamic and contemporaneous relationships.

5.1.1 PVAR Model Results for CO2 Emissions

The stability of the PVAR model was confirmed using the eigenvalue stability test. All eigenvalues were found to lie within the unit circle, indicating that the model is stable. The Akaike Information Criterion (AIC), Bayes-Schwarz Criterion (BIC), and Hannan-Quinn Criterion (HQC) suggested an optimal lag length of 3, 1, and 3 respectively for the model. Given these results and the yearly nature of the data, a lag of more than one year was considered excessive. Therefore, a single lag was used for both PVAR models to avoid weakening the model. First-differencing was applied to the variables, and after differencing, all variables were found to be stationary according to both KPSS and PP tests at the 1% significance level. This confirms that the mean and variance are constant over time and the autocovariance function depends only on the lag (Kirchgässner et al., 2012).

Interpreting the coefficients in models where both the dependent and independent variables are differenced can be challenging, however, the direction of these relationships remains crucial. In these models, the focus is not on the magnitude of the coefficients, but rather on understanding whether the relationship is positive or negative. This provides valuable insights into how changes in one variable are associated with changes in another. The PVAR model results show only a few significant effects, which means that there is a weak direct link between CO2 emissions and financial results.

Log Returns show a marginally significant positive relationship with CO2 emissions ($p = 0.068$). This suggests a potential carbon premium, where firms with higher emissions may provide higher stock returns to compensate for risks associated with environmental liabilities.

This result aligns with Bolton and Kacperczyk (2021), who documented similar findings in developed markets. However, the borderline significance suggests this relationship might not be robust in emerging markets, highlighting the need for further investigation.

The autoregressive term for CO2 emissions shows a highly significant positive coefficient. This result indicates that there is a high level of serial correlation in the CO2 emissions, implying that current emissions are strongly influenced by past emissions. Such a finding is consistent with the expected persistence in emissions even after taking a first difference of the data. This phenomenon is often observed in environmental data, as firms' emission levels change gradually over time due to ongoing processes and operational constraints. For instance, Alkhathlan and Javid (2013) illustrate that emissions are often tied to established production technologies and capital investments, which can take years to transition toward more sustainable systems. Similarly, Martin et al. (2012) highlight how regulatory, financial, and technological barriers can slow the adoption of emission-reducing innovations, contributing to the persistence of emissions.

Variable	**Coefficient (s.e.)**
Carbon Emission	0.9121 (0.1777) ***
Log Returns	0.0312 (0.0171) *
M/B Ratio	-0.0011 (0.1107)
Leverage Ratio	0.0410 (0.0531)
Net Income	0.0233 (0.1126)
Quick Ratio	-0.0084 (0.0387)
Size	0.0011 (0.0097)
ROA	-0.0135 (0.235)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2: Effect of lagged Carbon Emission

Variable	Coefficient (s.e.)
Lag1_Log Returns	0.0276 (0.0487)
Lag1_M/B Ratio	0.0053 (0.0121)
Lag1_Leverage Ratio	0.0129 (0.0281)
Lag1_Net Income	0.0023 (0.0115)
Lag1_Quick Ratio	0.0053 (0.0110)
Lag1_Size	0.0079 (0.1219)
Lag1_ROA	0.0032 (0.0088)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3: Effect of lagged financial metrics on Carbon Emission

5.1.1.1 Implications

The presence of the autoregressive term for CO2 emissions implies that emission reductions will likely require sustained interventions and regulatory oversight, as firms show a tendency of being slow to change their environmental footprints. On the other hand, the observed link with stock returns provides only weak support to the carbon premium hypothesis, and it is not sufficient to confirm it.

All other variables in the model, such as Firm Size, Market-to-Book Ratio, Leverage Ratio, ROA, Net Income, and Quick Ratio, show highly insignificant p-values, suggesting these factors have limited explanatory power for variations in CO2 emissions in this dataset. Additionally, the lag of the financial variables does not seem to influence carbon emissions either.

5.1.2 Panel Regression Results for CO2 Emissions

Multicollinearity was evaluated through the Variance Inflation Factor (VIF). All VIF values were under 2, suggesting that multicollinearity is not an issue in the model. The residuals were found to be heteroskedastic, therefore robust standard errors were employed. This method solves the issue of varying residual variances, providing more reliable standard error estimates. The residuals were also tested for normality using the Jarque-Bera test, which indicated that the residuals were not normally distributed. However, given the large sample size, the Central Limit Theorem (CLT) suggests that the distribution of residuals will approximate normality, mitigating concerns about non-normality (Verbeek, 2008). Despite differencing the variables, the Breusch-Godfrey/Wooldridge test for serial correlation indicated the presence of autocorrelation in the idiosyncratic errors. This suggests that autocorrelation remains an issue. While this can affect the efficiency of the estimators, robust standard errors help mitigate some of the impact. However, it is important to acknowledge this limitation in the interpretation of the results.

Similarly to the PVAR model, it is difficult to interpret the coefficients of the pooled OLS model due to differencing, and the focus is rather on the direction and significance of the relationships. The pooled OLS results indicate that certain financial metrics and industry sectors have significant impacts on carbon emissions.

The negative association between the M/B Ratio and CO_2 emissions ($p = 0.069$) suggests that firms with higher market valuations relative to book value tend to emit less CO_2. This finding may be attributed to reputational and investor pressure since sustainable environmental practices can enhance firm value by attracting investors with a conscience. Friede et al. (2015) for instance show that pressures such as these lead to a positive relationship between environmental performance and financial metrics such as valuation ratios.

Firm Size, measured by the log of total assets, has a strong positive relationship with CO_2 emissions ($p < 0.001$). Larger firms generally operate on a greater scale, with broader operations and higher resource demands, leading to increased emissions. Sectors such as manufacturing, logistics, or resource extraction often contain the largest firms, inherently contributing to higher emissions due to the nature of their industries (Dahlmann et al., 2019). However, larger firms may also have greater capacity to invest in emissions-reduction technologies, which adds complexity to the relationship.

The positive relationship between stock returns and CO_2 emissions ($p = 0.092$) may reflect reverse causality, since the PVAR results showed that the lag of CO_2 emissions positively impacts stock returns, rather than the other way around. Despite this, it is also possible that high-performing firms may expand their operations, resulting in increased emissions. This bidirectional relationship aligns with findings from Zhang et al. (2022), who identify feedback loops between financial performance and environmental impacts, particularly in emission-intensive sectors where operational growth often means increased emissions as well.

The results indicate that increases in leverage are associated with increases in CO_2 emissions ($p < 0.001$). This could reflect the reliance of emission-intensive industries on debt to fund capital-intensive operations or meet regulatory compliance costs. O’Brien and David (2014) highlight that financial constraints tied to high leverage can hinder investments in emissions-reduction measures, potentially exacerbating firms' carbon footprints.

The weak negative association between the Quick Ratio and CO2 emissions ($p = 0.074$) suggests that more liquid firms are better positioned to reduce emissions. Liquidity enables firms to allocate resources toward sustainability initiatives, such as energy efficiency improvements or cleaner production methods. This finding is in line with Hart and Ahuja (1996), who document that resource availability plays a critical role in driving environmental performance improvements.

A positive relationship between ROA and CO2 emissions ($p = 0.003$) implies that a firm being profitable does not necessarily mean it is also environmentally friendly. This may reflect sectoral dynamics where high-emission industries, such as energy or heavy manufacturing, generate higher returns due to strong Asian market demand or operational efficiencies that do not prioritize emissions reductions.

Net Income does not appear to have a significant impact on CO2 emissions ($p = 0.603$). This suggests that overall profitability may not have a direct or consistent relationship with emissions, possibly due to differences in company strategies and regulatory conditions.

The model includes several FTSE industry dummies to capture sectoral variations. The results for the sector dummies are interpreted relative to the 'Basic Materials' sector, which serves as the reference category. Significant findings include the following sectors.

Consumer Goods: The sector is associated with significantly lower emissions compared to the baseline ($p < 0.01$). This may be surprising for some, as consumer goods production can be energy intensive. A possible explanation is that firms in this sector may benefit from improvements in production efficiency and supply chain optimization. The shift toward sustainable packaging and resource-efficient manufacturing processes likely contributes to these findings (Lacy et al., 2020; Wei et al., 2020).

Health Care: This sector also has lower emissions relative to the baseline ($p < 0.01$), characterized by operations that are less resource-intensive than those in heavy manufacturing or energy sectors. Initiatives aimed at reducing energy use in pharmaceutical production and hospital operations may help explain these results (International Finance Corporation, 2021).).

Consumer Services: Showing a strong negative relationship with emissions ($p < 0.001$), this sector primarily consists of service-oriented industries that typically have lower emissions.

Digitalization and minimal reliance on heavy manufacturing processes likely contribute to this result (IEA, 2021).

Industrial Goods & Services: Surprisingly, also displaying a negative association with emissions ($p < 0.01$), however, this is probably caused by the services component of this sector which is typically characterized by low emissions. According to Frei et al. (2020), emissions vary depending on the specific nature of industrial operations.

Aerospace & Defence: The strong positive relationship ($p < 0.001$) is understandable, as manufacturing aircraft and defence systems often involves energy-intensive processes such as metalworking, machining, and fuel testing, which drive emissions (Rao & Holt, 2005).

Oil & Gas: Interestingly, this sector reveals a significant negative correlation with emissions ($p < 0.001$). This could suggest a sample bias in the analysis, where many companies included are transitioning to renewable energy or implementing cleaner production technologies like carbon capture and storage (CCS) (IEA, 2021). Furthermore, regulatory pressures may drive emission reductions in this sector, which has traditionally been linked to high emissions.

Real Estate: Marginally lower emissions in the real estate sector are consistent with current trends towards energy efficiency and sustainable construction methods. Green building certifications like LEED and BREEAM have encouraged lower operational emissions (World Green Building Council, 2021).

Utilities: The utilities sector also shows marginally lower emissions compared to the baseline. This may be due to increased investments in renewable energy sources such as wind and solar, leading to a decreased reliance on coal and natural gas (Frei et al., 2020).

Carbon Emission Regression Results (Robust s.e.)

Variables	**Coefficients**
M/B Ratio	-0.027*
	(0.015)
Size	0.187***
	(0.041)
Log Returns	0.053*
	(0.031)
Leverage Ratio	0.115***
	(0.026)
Quick Ratio	-0.027*
	(0.015)
Net Income	0.012
	(0.022)
ROA	0.030***
	(0.010)
Industrials	-0.001
	(0.010)
Consumer Goods	-0.207***
	(0.079)
Health Care	-0.217***
	(0.077)
Consumer Services	-0.371***
	(0.080)
Telecommunications	-0.185**
	(0.083)
Utilities	-0.152*
	(0.092)
Real Estate	-0.026*
	(0.016)
Aerospace & Defense	0.058***
	(0.018)
Oil & Gas	-0.137***
	(0.026)
Industrial Goods & Services	-0.226***
	(0.078)
Energy	0.382
	(0.316)

Media	-0.001
	(0.003)
Food & Beverage	0.033
	(0.156)
Personal Goods	0.338
	(0.315)
Technology Hardware & Equipment	-0.062
	(0.039)
Dependent variable:	Carbon Emission
Weak Instruments	13.786^{***}(df = 4; 742)
Sargan	87.66^{***}(df = 3)
Wald Test	46.942^{***}(df = 12; 745)
Observations	7,369
R^2	0.051
Adjusted R^2	-0.052
F Statistic	16.307^{***} (df = 22; 6645)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: Carbon Emission regression results with differenced fixed effects model (robust s.e.)

The dynamic PVAR model shows that CO2 emissions might positively influence stock returns, supporting the hypothesis of a carbon premium. However, in the case of static panel regression the goal is to find the determinants of CO2 emissions, including Firm Size, liquidity, and profitability. The methodological difference presents challenges when trying to assert causality.

In the pooled OLS, for instance, the positive correlation between emissions and Firm Size likely reflects that bigger firms operate on a larger scale and hence emissions will be bigger as well. However, reverse causality can be present as well, as firms in high-emission industries might grow larger due to their resource-heavy production processes. A similar interpretation can be made for the correlation of the Quick Ratio with emissions. Firms with greater liquidity may be more inclined to invest in sustainable practices, as noted by Hart and Ahuja (1996). On the other hand, companies that successfully reduce emissions might improve their liquidity by avoiding regulatory penalties or attracting investors who are eco-conscious.

The relationship between CO2 emissions and leverage further exemplifies these challenges. High leverage could signal that the firms are making investments in emissions-intensive capital projects, such as manufacturing plants. Conversely, firms under financial stress might also ignore environment friendliness and increase their carbon footprint. These bidirectional connections highlight the importance of using methodologies that can tackle endogeneity problems, such as PVAR.

5.2 Supplementary Analysis: Carbon Emission Intensity

The supplementary analysis on carbon emission intensity focuses on emissions per unit of output, which provides information on emissions efficiency across firms.

5.2.1 PVAR Model Results for Emission Intensity

The diagnostic tests used for the PVAR model, and their results were similar to the main analysis. The stability of the model was also verified with all the eigenvalues being less than 1. The optimal lag length was found to be one year, while first-differencing ensured that all variables were stationary according to both the KPSS and the PP tests at 1% significance level.

The PVAR model for carbon emission intensity also only identifies one significant relationship related to it.

Emission Intensity and Leverage Ratio: Carbon emission intensity shows a positive effect on the Leverage Ratio at a 6% significance level ($p = 0.051$). This implies that firms with high emission intensity may depend on debt financing more than firms with low emission intensity. Leverage Ratio can be viewed as a negative sign for financial stability since debt use increases financial risk. High emission intensity of firms may lead to borrowing to finance operations or expansion, and this shows industry-specific emissions patterns that could impact financial health (Ganda and Samson, 2018). This indicates a potential negative influence of carbon emission intensity on financial performance.

Unsurprisingly, emission intensity is also persistent over time, similar to total CO_2 emissions. This reflects the structural and operational challenges firms face in reducing environmental metrics, alongside the long-term nature of sustainability investments (Alkhathlan and Javid, 2013; Martin et al., 2012).

Variable	Coefficient (Std Error)
Carbon Emission Intensity	0.8088 (0.2268) ***
Log Returns	0.0260 (0.0164)
M/B Ratio	-0.0467 (0.0659)
Leverage Ratio	0.0716 (0.0367) *
Net Income	-0.0364 (0.0592)
Quick Ratio	-0.0135 (0.0320)
ROA	-0.1412 (0.1077)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5: Effect of lagged Carbon Emission Intensity

Variable	Coefficient (Std Error)
Lag1_Log Returns	-0.0113 (0.0625)
Lag1_M/B Ratio	-0.0036 (0.0164)
Lag1_Leverage Ratio	0.0195 (0.0331)
Lag1_Net Income	-0.0034 (0.0104)
Lag1_Quick Ratio	0.0012 (0.0118)
Lag1_ROA	0.0087 (0.0099)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6: Effect of lagged financial metrics on Carbon Emission Intensity

5.2.2 Panel Regression Results for Emission Intensity

The diagnostic tests used in this section and their results were also identical to the main analysis. There was no issue of multicollinearity since all the VIF values were below 2. The residuals were heteroskedastic, therefore, robust standard errors were used. The Jarque-Bera test rejected the null hypothesis of normality of residuals, but this is not a concern here due to the large sample size and Central Limit Theorem. Despite differencing the variables, the Breusch-Godfrey/Wooldridge test indicated the presence of autocorrelation in the idiosyncratic errors, which remains a limitation.

The panel regression results for carbon emission intensity reveal multiple significant relationships.

M/B Ratio: The results reveal a strong negative correlation ($p < 0.001$) which indicates that firms with higher valuation control emissions more efficiently. This could be the result of reputational issues or pressure from investors to adopt environmentally friendly practices.

Log Returns: A positive correlation with emission intensity ($p < 0.01$) shows that firms with higher emission intensity may generate higher returns, as suggested by the carbon premium hypothesis. Again, we are assuming that this is a case of reverse causality, and it is actually carbon emissions which affect the stock returns.

Leverage Ratio: The positive coefficient with emission intensity ($p < 0.001$) indicates that debt reliance results in emission-intensive operations. However, the PVAR model shows that this relationship can be endogenous, where emission intensity increases leverage rather than the other way round. This could suggest that emission intensive firms have difficulties in financing their operations or in adopting cleaner technologies.

Quick Ratio: This variable shows a marginally significant negative association with emission intensity ($p = 0.072$), implying that firms with better liquidity may have more resources to allocate to emission reduction or efficiency improvement.

ROA: Similarly to the main analysis, the positive relationship ($p = 0.022$) between ROA and emission intensity shows that high profitability does not imply low emission per output. The same hypothesis can be made here, that certain industries are profitable and emission-intensive by nature.

The FTSE sector dummies reveal distinct sectoral variations in emission intensity. The results for the sector dummies are interpreted relative to the 'Basic Materials' sector, which serves as the reference category. Significant findings include the following sectors.

Consumer Goods: The sector shows a significant negative relationship with emission intensity ($p < 0.001$). This could reflect improvements in production efficiency, energy management, and sustainable practices that reduce emissions per unit of output. For example, consumer goods companies are increasingly adopting energy-efficient technologies and sustainable sourcing, which help lower emissions intensity. (Lacy et al., 2020).

Food & Beverage: Although the Food & Beverage sector did not show a significant positive relationship with emission intensity in this model or in the main analysis, it is widely recognized as emission-intensive due to agricultural and livestock processes, high energy consumption, and processing demands. Variability in emission intensity within the sector could reflect differing levels of sustainability practices among firms (Poore and Nemecek, 2018; Springmann et al., 2018).

Telecommunications and Utilities: Both sectors exhibit significant negative associations with emission intensity ($p < 0.001$). The telecommunications sector's service-based nature naturally limits its emissions per unit, while utilities are reducing emission intensity by investing in renewable energy sources and cleaner technologies (IEA, 2021). For example, energy providers increasingly source from wind and solar, reducing carbon output per megawatt-hour of energy produced (Frei et al., 2020).

Oil & Gas: The strong negative association with emission intensity ($p < 0.001$) may be due to sectoral measures to control emissions through technology enhancement, compliance with emission standards, and transition to cleaner energy such as natural gas and renewable energy. This trend corresponds with the industry reports that point to the sector's interest in emission reduction by means of cleaner production and carbon capture (IEA, 2021; TCFD, 2017).

Personal Goods and Technology Hardware & Equipment: Among the subsectors, technology hardware firms have the strongest negative correlation with emission intensity ($p < 0.001$) perhaps due to the sector's emphasis on the development of sustainable practices and energy efficiency. These sectors are known to source energy for their operations and ensure that they minimize the carbon footprint within their value chains, in line with their carbon neutrality goals (Green Electronics Council, 2020).

Carbon Emission Intensity Regression Results (Robust s.e.)

Variables	Coefficients
M/B Ratio	-0.050***
	(0.014)
Log Returns	0.080***
	(0.031)
Leverage Ratio	0.126***
	(0.027)
Quick Ratio	-0.029*
	(0.016)
Net Income	0.031
	(0.021)
ROA	0.026**
	(0.011)
Industrials	-0.017*
	(0.009)
Consumer Goods	-0.304***
	(0.046)
Health Care	-0.186***
	(0.045)
Consumer Services	-0.436***
	(0.052)
Telecommunications	-0.308***
	(0.049)
Utilities	-0.291***
	(0.059)
Real Estate	-0.077***
	(0.014)
Aerospace & Defense	0.012
	(0.014)
Oil & Gas	-0.224***
	(0.029)
Industrial Goods & Services	-0.288***
	(0.048)
Energy	0.381
	(0.349)
Media	0.008**
	(0.003)

Food & Beverage	0.002
	(0.222)
Personal Goods	0.408
	(0.348)
Technology Hardware & Equipment	-0.123***
	(0.037)
Dependent variable:	Carbon Emission Intensity
Weak Instruments	13.786***(df = 4; 742)
Sargan	87.66***(df = 3)
Wald Test	46.942***(df = 12; 745)
Observations	7,369
R^2	0.028
Adjusted R^2	-0.077
F Statistic	9.280*** (df = 21; 6646)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7: Carbon Emission Intensity regression results with differenced fixed effects model (robust s.e.)

In summary, both Carbon Emission and Carbon Emission Intensity show complex relationships with financial performance. The significant and positive effect of emission intensity on leverage suggests that firms with high emission intensity may be under financial pressure since they use more debt to finance their activities. Furthermore, sectoral patterns show that emissions issues vary by industry due to energy requirements for production and distribution. Such industry-specific results provide support to the earlier findings that the impact of emissions on financial performance is contingent on industry characteristics, financial management and market sentiments. Some studies have indicated that industries that involve high manufacturing and distribution processes are the most emitting due to issues with packaging, transportation, and sourcing of raw materials (Wei et al., 2020; Poore and Nemecek, 2018).

These results, combined with the carbon premium identified in the baseline PVAR model, suggest that although higher emissions may be associated with higher market returns, potentially due to investor compensation for environmental risks, such gains may be accompanied by higher leverage, which is financially risky. The results thus imply that there are industry-specific factors and methodological factors that have important influences on the relationship between emissions and financial performance. This conclusion is in line with the existing literature that has suggested that the financial cost of emissions is a function of sector and regulation.

6. Conclusion

This thesis analyses the relationship between carbon emissions and financial performance in Asian markets, using econometric methodologies such as PVAR and pooled OLS regression. By focusing on a region with unique regulatory, economic, and industrial characteristics., this study contributes to the growing literature on sustainability in emerging markets.

The findings provide weak evidence for the presence of a carbon premium in Asian markets. Although a marginally significant positive relationship between stock returns and carbon emissions was observed, these results are not robust enough to confidently support the hypothesis that investors demand higher returns from high-emission firms to compensate for environmental risks. This is in contrast with findings in advanced economies, such as those by Bolton and Kacperczyk (2021), who identified a stronger and more stable carbon premium under higher regulatory pressure and greater investor awareness.

The results also provide weak evidence that carbon emissions negatively affect accounting-based financial metrics. In the supplementary PVAR model for the analysis of Carbon Emission Intensity, a positive effect on the Leverage Ratio was observed, suggesting that emission-intensive firms may use more debt financing. This is potentially due to the fact that high emissions may be financially costly to these firms, and they may struggle to meet the dual challenge of sustainability and operations. However, other financial variables, such as ROA and Market-to-Book Ratio, show inconsistent or insignificant relationships with carbon emissions, which indicates that emissions are not yet a definitive factor in determining financial performance of firms.

These findings are consistent with Horváthová's (2010) meta-analysis, which points out that differences in the empirical methods used, including regression techniques, panel data analysis, and structural equation modelling, affect results. This study also shows that when more refined econometric methods such as the PVAR model are applied, the relationships are weaker and less clear. This underlines the significance of the methodological choice in the correct identification of the dependencies between carbon emissions and financial performance.

Additionally, the persistence of carbon emissions over time highlights the structural and operational challenges firms face in reducing their environmental footprint. This stagnation indicates that large reductions are only possible with continued efforts through policy changes, technology advancement or change in market perceptions. It is evident that sectoral dynamics and firm specific factors are likely to have a greater impact than emissions on the financial performance especially in emerging markets.

6.1 External Validity

The external validity of these findings is constrained by the fact that the study is conducted in Asian markets, which have unique regulatory systems, economic environment, and investors. Even though the comparison based on carbon emission intensity is possible, one should be careful when applying the results obtained to other regions with more strict environmental regulation, such as Europe or North America where the financial consequences of emissions are often significantly higher.

Furthermore, sector-specific dynamics play a critical role in the emissions-financial performance relationship. Industries with high emission intensities, such as manufacturing or energy, may show different patterns compared to service-oriented or technology sectors. Extending this research to other areas or industries may offer additional understanding of the generalization of the observed trends. For instance, investigating how regulatory environments and investor behaviour vary across regions would increase the external validity of the findings.

6.2 Research Limitations

This study has several limitations that must be acknowledged. First, the sample includes firms in Asia for the period of 2007 to 2022, which might not reflect the current global policies or recent technological changes that affect the emissions-financial performance nexus. Future studies could incorporate more recent data to reflect emerging trends in sustainability and carbon management.

Second, despite the fact that the econometric methodologies used in the study are capable of estimating both dynamic and static associations, the results are still sensitive to variable choice and model specification. In particular, the pooled OLS regression is prone to reverse causality, as it does not provide evidence whether changes in financial variables drive emissions or vice versa. Additionally, the aggregated firm-level emissions data used in this study does not include the supply chain emissions and indirect environmental impacts, which could give a more comprehensive picture of the firms' environmental responsibility.

Finally, the analysis of sectoral differences in carbon emissions and financial performance was incomplete. While industry dummies were included, a more detailed sector-specific analysis could reveal stronger relationships or patterns within certain industries. Future studies should overcome these limitations by using more refined emissions data and including more regions. Another interesting project opportunity is to investigate the impact of sustainability initiatives and technological innovations in reducing emissions and their financial implications.

Despite these limitations, this study provides a foundational understanding of the complex dynamics between carbon emissions and financial performance in Asian markets, highlighting the challenges and opportunities in aligning sustainability with financial performance. The findings showcase the necessity of the combined adoption of the regulatory reforms and sustainability initiatives to achieve environmental and economic objectives. As the global focus on sustainability continuously grows, future research and policymaking can build upon these insights to encourage sustainable development and responsible financial practices.

Bibliography

Alkhathlan, K., & Javid, M. (2013). Carbon emissions and economic growth in Saudi Arabia: An aggregate and disaggregate analysis. *Energy Policy, 62*, 1525-1532.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics, 142*(2), 517-549.

Busch, T., & Hoffmann, V. H. (2011). How hot is your bottom line? Linking carbon and financial performance. *Business & Society, 50*(2), 233-265.

Canova, F., & Ciccarelli, M. (2013). Panel vector autoregressive models: A survey. *Advances in Econometrics, 32*, 205-246.

Clarkson, P. M., Li, Y., Richardson, G. D., & Vasvari, F. P. (2011). Does it really pay to be green? Determinants and consequences of proactive environmental strategies. *Journal of Accounting and Public Policy, 30*(2), 122-144.

Dahlmann, F., Branicki, L., & Brammer, S. (2019). Managing carbon aspirations: The influence of corporate climate change targets on environmental performance. *Journal of Business Ethics, 158*(1), 1-24.

Delmas, M. A., Nairn-Birch, N., & Lim, J. (2015). Dynamics of environmental and financial performance: The case of greenhouse gas emissions. *Organization & Environment, 28*(4), 374-393.

Frei, R., Jack, L., & Burchell, J. (2020). Carbon management practices and the UK logistics sector: A case for voluntary engagement? *Journal of Cleaner Production, 256*, 120-130.

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment, 5*(4), 210-233.

Ganda, F., & Samson, A. (2018). The impact of carbon emissions on corporate financial performance: Evidence from the South African firms. *Sustainability, 10*(7), 2398.

García-Sánchez, I. M., & Prado-Lorenzo, J. M. (2012). Greenhouse gas emission practices and financial performance. *International Journal of Climate Change Strategies and Management, 4*(3), 260-276.

Hart, S. L., & Ahuja, G. (1996). Does it pay to be green? An empirical examination of the relationship between emission reduction and firm performance. *Business Strategy and the Environment, 5*(1), 30-37.

Hassel, L., Nilsson, H., & Nyquist, S. (2005). The value relevance of environmental performance. *European Accounting Review, 14*(1), 41-61.

Horváthová, E. (2010). Does environmental performance affect financial performance? A meta-analysis. *Ecological Economics, 70*(1), 52-59.

International Energy Agency (IEA). (2021). *World Energy Outlook 2021*. Paris: IEA.

International Finance Corporation. (2021). *Climate Investment Opportunities in Emerging Markets*. Washington, DC: IFC.

Kirchgässner, G., Wolters, J., & Hassler, U. (2012). *Introduction to Modern Time Series Analysis*. Springer Science & Business Media.

Konar, S., & Cohen, M. A. (2001). Does the market value environmental performance? *Review of Economics and Statistics, 83*(2), 281-289.

Lacy, P., Long, J., & Spindler, W. (2020). *The Circular Economy Handbook: Realizing the Circular Advantage*. Palgrave Macmillan.

Li, D., Huang, M., Ren, S., Chen, X., & Ning, L. (2017). Environmental legitimacy, green innovation, and corporate carbon disclosure: Evidence from CDP China 100. *Journal of Business Ethics, 150*(4), 1089-1104.

Martin, R., Muûls, M., & Wagner, U. J. (2012). Carbon markets, carbon prices and innovation: Evidence from interviews with managers. *Journal of Environmental Economics and Management, 64*(2), 290-306.

Matsumura, E. M., Prakash, R., & Vera-Muñoz, S. C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *The Accounting Review, 89*(2), 695-724.

Nwafor, M., Ogujiuba, K., & Asogwa, R. (2016). Panel vector autoregressive (PVAR) analysis of fiscal policy and private investment in Nigeria. *Journal of Economics and Sustainable Development, 7*(13), 1-12.

O'Brien, J. P., & David, P. (2014). Firm growth and type of debt: The paradox of discretion. *Journal of Business Research, 67*(11), 2371-2378.

Poore, J., & Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. *Science, 360*(6392), 987-992.

Qureshi, M. A., & Akbar, M. (2017). Do investors care about carbon risk? Evidence from the stock performance of Chinese firms. *Journal of Cleaner Production, 142*, 3175-3184.

Rao, P., & Holt, D. (2005). Do green supply chains lead to competitiveness and economic performance? *International Journal of Operations & Production Management, 25*(9), 898-916.

Robaina, M., & Madaleno, M. (2019). The impact of carbon emissions on financial performance: Evidence from Portuguese firms. *Sustainability, 11*(3), 847.

Sarumpaet, S. (2005). The relationship between environmental performance and financial performance of Indonesian companies. *Journal of Cleaner Production, 13*(1), 57-70.

Springmann, M., Clark, M., Mason-D'Croz, D., Wiebe, K., Bodirsky, B. L., Lassaletta, L., ... & Tilman, D. (2018). Options for keeping the food system within environmental limits. *Nature, 562*(7728), 519-525.

Sullivan, G. M., & Feinn, R. (2021). Using effect size4or why the P value is not enough. *Journal of Graduate Medical Education, 4*(3), 279-282.

Task Force on Climate-related Financial Disclosures (TCFD). (2017). *Recommendations of the Task Force on Climate-related Financial Disclosures*. Basel: Financial Stability Board.

Verbeek, M. (2008). *A Guide to Modern Econometrics*. John Wiley & Sons.

Wei, W., Zhang, Z., & Wang, X. (2020). The impact of carbon emissions on financial performance: Evidence from the Chinese manufacturing industry. *Journal of Cleaner Production, 256*, 120-130.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Zhang, D., Rong, Z., & Ji, Q. (2020). Green innovation and firm performance: Evidence from listed companies in China. *Technological Forecasting and Social Change, 158*, 120-132.

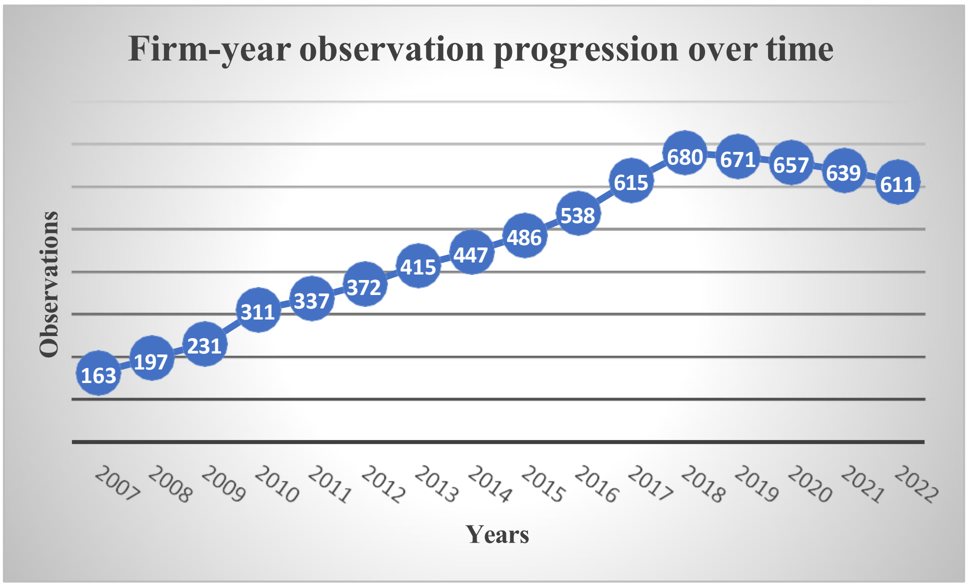
Appendix

Appendix 1: Data sources

Variable	Use	Source	Definition
CO2 Equivalents Emission Total	Variable of Interest	Refinitiv	The total amount of greenhouse gases emitted, expressed as the equivalent amount of carbon dioxide, which allows for comparison of emissions from various gases based on their global warming potential
Carbon Emission Intensity	Variable of Interest	Refinitiv	Created by dividing CO2 Equivalents Emission Total by Size (log Total Assets)
Log Returns	Independent variable	Refinitiv	Created by applying a logarithmic transformation to the Total Return Index variable (RI)
M/B Ratio	Independent variable	Refinitiv	Created by dividing Market Capitalization by Total Assets
Leverage Ratio	Independent variable	Refinitiv	Created by dividing Total Debt by Total Assets
Net Income	Independent variable	Refinitiv	The total profit of a company after all expenses, taxes, and costs have been subtracted from total revenue
Quick Ratio	Independent variable	Refinitiv	A measure of a company's short-term liquidity, calculated as (Current Assets - Inventory) / Current Liabilities
Size	Independent variable	Refinitiv	Created by applying a logarithmic transformation to the Total Assets variable, which serves as a proxy for firm size
ROA	Independent variable	Refinitiv	Return on Assets, calculated as Net Income divided by Total Assets

FTSE Sector Dummies	Control Variable	Refinitiv	Dummy variables representing different sectors as classified by the FTSE indices

Appendix 2: Number of observations in each period



Appendix 3: Number of unique firms in each country

Country	Number of Firms
Japan	252
China	135
India	72
Taiwan	58
South Korea	47
Hong Kong	36
Malaysia	29
Thailand	23
Singapore	21
Indonesia	17
Philippines	12