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Unveiling the Impacts of Corporate Environmental, Social, and Governance Disclosure

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Abstract: Amidst heightened scrutiny of corporate environmental, social, and governance (ESG) practices, this study employs threshold techniques combined with artificial neural networks to examine the impact of ESG disclosure on companies, emphasizing its pivotal role in promoting sustainability. Analyzing data from Taiwan's 20 industries from 2012 to 2022, it finds that while ESG engagement positively influences financial performance, it also underscores the vital connection between corporate practices and sustainable development. This analysis explores the relationship between carbon emissions, operating expenses, and financial performance in the overall sample and a threshold sample based on a threshold variable. In the overall sample, carbon emissions significantly increase operating expenses, accompanied by other influential variables. Introducing a threshold value of firm size alters the dynamics, showing a positive and more pronounced impact in the threshold sample. The examination of financial performance metrics reveals significant positive associations with carbon emissions, particularly when the threshold is not met or exceeded. Intriguingly, subgroup analysis indicates a negative association between carbon emissions and financial performance within the larger-size subgroup, in stark contrast to a more pronounced positive relationship observed in the smaller-size subgroup. Furthermore, the developed ANN model exhibits robust learning capabilities, underscoring its efficacy in capturing complex patterns within the data. It suggests its potential as a reliable tool for accurately predicting carbon emissions across diverse scenarios, facilitating informed decision-making and policy formulation to mitigate environmental impact.

Keywords: ESG; sustainability; Taiwan; financial performance; costs

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1. Introduction

Integrating environmental, social, and governance (ESG) disclosure into business practices is vital for fostering sustainable development. This integration necessitates a multifaceted approach that begins with strong leadership commitment and developing a comprehensive ESG strategy. Companies must conduct materiality assessments to identify key ESG factors relevant to their operations and stakeholders, followed by robust data collection mechanisms to track performance. Adherence to standardized reporting frameworks ensures transparency and comparability of disclosures, while integrated reporting provides stakeholders with a holistic view of the company's sustainability performance. Engagement with stakeholders facilitates dialogue and feedback, fostering accountability and trust. Continuous improvement, incorporating ESG into risk management, capacity building, collaboration, and incentivizing ESG performance further reinforce the integration of sustainability principles into the organization's DNA. Through these concerted efforts, businesses can mitigate risks and capitalize on opportunities, contributing positively to society and the environment while enhancing their long-term resilience and competitiveness [1,2].

Organizations have increasingly prioritized sustainability, with efforts ranging from internal initiatives to broader societal contributions, including addressing the Sustainable

Development Goals (SDGs). Despite these endeavors, SDG integration into organizational systems has been limited [3]. Incentives and drivers can be of internal or external nature. Several theories exist to explain engagements in corporate sustainability. The natural resource-based view focuses on gaining a competitive advantage and maximizing the firm, such that bounded instrumentality is present. The managing view might be either the win-win perspective or the trade-off perspective. ESG disclosure has become a pivotal aspect of corporate reporting, with companies striving to provide a comprehensive picture of their responsible practices. The United Nations assertion in the 2004 report "Who Cares Wins" underlines the importance of ESG actions and scores in determining a company's longevity and financial performance. Given the significance of ESG in the corporate landscape, this study focuses on unveiling the impacts of ESG disclosure on the Taiwanese industries. Among them, the electronics sector, a crucial pillar of Taiwan's economy, is deeply intertwined with ESG issues due to its substantial resource usage, complex supply chains, and large workforce. By scrutinizing relationships between carbon emissions, ESG disclosure, sustainability report verification, and financial performance and costs, this research aims to provide valuable insights into ESG disclosure across 20 industries.

Koller et al. (2019) [4] associate ESG with five critical aspects related to cash flow, highlighting its impact on revenue growth, cost reduction, regulatory compliance, employee productivity, and investment optimization. Effective ESG implementation can address operational costs, impacting profits by up to 60%. Environmental, social, and governance (ESG) considerations have become integral to assessing a company's sustainability and responsible business practices. Within the ESG framework, the environmental aspect focuses on a company's impact on the planet, particularly concerning carbon emissions. Companies are evaluated based on their commitment to measuring, disclosing, and reducing their carbon footprint, encompassing direct and indirect emissions from their operations and supply chains. As regulatory bodies and reporting standards evolve, there is a growing emphasis on standardized ESG reporting, providing investors with more precise insights into a company's sustainability efforts, including its initiatives to address carbon emissions.

Three are the extensive use of standalone disclosure or CSR performance from rating services to identify CSR disclosure determinants [5]. These inconsistencies suggest that the impact of ESG on firms' costs is context-dependent and influenced by factors such as regulatory frameworks, corporate governance, and firm finance. This study employs threshold regression analysis to examine the relationships, considering the clustering of observations based on 20 industries and time. Then, ANNs are applied to construct a model predicting a firm's carbon emission amount. By examining the Taiwanese context, this study aims to contribute valuable insights into the dynamics of ESG disclosure and its impact on firm performance and expenses in a region where corporate practices are evolving.

This study investigates the intricate relationship between carbon emissions, operating expenses, and financial performance across 20 industries in Taiwan. To focus on specific sectors, the research aims to provide actionable insights for enhancing environmental, social, and governance (ESG) practices, particularly regarding carbon emissions disclosure. Understanding this relationship is crucial for developing effective sustainability strategies and improving corporate decision-making processes. The initial findings reveal a positive association between carbon emissions and operating expenses, with notable variations based on firm size. Moreover, this study identifies significant thresholds related to firm size, underscoring the importance of considering this factor in sustainability efforts. Additionally, this research explores the potential of artificial neural networks (ANNs) for predicting carbon emissions, offering a promising approach to inform targeted sustainability initiatives and foster a more sustainable future.

In all samples, it is found that carbon emissions significantly increase operating expenses, alongside other influential variables. Introducing a threshold of a firm's total assets alters the dynamics of carbon emissions and operating expenses, with a positive but less pronounced impact on the threshold sample. Further examination of financial performance metrics (ROA and ROE) reveals significant positive associations with carbon emissions, primarily when the particular threshold is not met. Primarily, a negative association is observed in the larger-size subgroup, contrasting with a more pronounced positive relationship in the smaller-size subgroup. The threshold test identifies a significant threshold value for total assets, indicating a structural break in the relationship. These findings offer practical insights for decision-makers, refining the understanding of the interplay between carbon emissions, operating expenses, and financial performance. They also highlight the importance of integrating ESG considerations into business operations to advance sustainability objectives and address global challenges effectively while concurrently driving up costs.

The remainder of the paper is organized to delve into the prior literature, underlying models, and empirical analyses. It explores the models, data collection procedures, and variable measurements, leading to a discussion of the results. Practical implications are presented, and this study concludes with a summary of findings and avenues for future research.

2. Literature Review

Sustainable investing (SI) has emerged as a significant area of interest within both financial and academic spheres, drawing upon historical precedents and contemporary motivations. Contemporary investors continue to be motivated by altruistic concerns, as evidenced by studies highlighting their desire to align financial activities with ethical values [6]. Brest et al. (2018) [7] provide a conceptual framework for understanding the impact of SI, laying the groundwork for assessing its effectiveness in driving positive social and environmental outcomes. Talan and Sharma (2019) [8] emphasize the centrality of the ESG approach in sustainable investment, which is reflected in various terms, such as socially responsible, ethical, and impact investment.

The literature on implementing and disclosing environmental, social, and governance (ESG) practices presents a nuanced understanding of their impact on firm performance across different contexts. Adams et al. [9,10] argue that ESG implementation, particularly in developed countries such as Europe, necessitates adopting the concept of Double Materiality, wherein firms must disclose how socio-environmental issues affect their value and financial risks. However, is a prevailing tendency in developing countries, as highlighted by Alshehhi et al. [11] and Rahman et al. [12], is the limited integration of conventional materiality concepts. This hesitancy towards ESG adoption is further substantiated by [12–14], who suggest that firms often fear increased operating costs and uncertain impacts on financial performance, resulting in inconclusive empirical evidence regarding the relationship between ESG and firm performance (FP). The discourse also acknowledges the bi-directional relationship between ESG and FP, as noted by Waddock and Graves [15] and Zahid et al. [16], requiring control for endogeneity. Furthermore, studies have highlighted the significance of governance within ESG dimensions, with mixed findings regarding its impact on accounting versus market performance [17–19]. Moreover, Alareeni, and Hamdan [20] highlight the friction in existing literature, with some studies showing a positive association between corporate sustainability and FP, while others show no or negative association. The literature also underscores the need for further investigation into the multidimensional impacts of ESG on FP, covering both accounting and market performance, particularly in developing countries where practices may vary. Despite the inconsistent empirical evidence, there is a growing recognition that ESG disclosures can enhance a firm's competitive advantage [21,22] and may even influence investor decisions [23,24]. A recent study by Chen et al. [25] reinforces the positive impact of ESG practices on financial performance.

The literature on ESG factors and their relationship with costs presents a complex landscape, with diverse findings. Bialkowski and Starks [26] highlight the substantial growth in investment associated with ESG goals over the past two decades. However, this growth needs to be met with skepticism regarding the impact on portfolio efficiency and performance. While some studies, such as [27–30], document higher risk-adjusted returns for firms with negative ESG characteristics, others, such as [31,32], find that high-ESG firms outperform. Moreover, Kim and Yoon [33] and Brandon et al. [34] reveal that despite commitments to responsible investing, many fund managers need to significantly improve ESG performance, suggesting a disconnect between intentions and outcomes. Anti-ESG regulations, as shown by Garrett and Ivanov [35], can have significant social costs, indicating potential conflicts between regulatory measures and market demands. Additionally, Ceccarelli et al. [36] illustrate that while funds labeled as 'low-carbon' attract significant inflows, they may sacrifice diversification benefits, pointing to potential trade-offs in ESG investing. Berg et al. [37] provide insights into the predictive power of ESG measures on returns, suggesting a nuanced relationship between ESG factors and financial outcomes.

While there is a growing consensus on the importance of ESG practices, their impact on firm performance and cost remains complex and context-dependent. This research untangles these complexities, particularly in Taiwan. Only then can the strategies to maximize the positive impacts of ESG disclosure for firms across various contexts be tailored. Through this endeavor, this study contributes to advancing sustainability efforts and promoting responsible corporate practices in Taiwan and beyond.

3. The Threshold Model

The threshold regression (TR) model, characterized by its discrete nature, elucidates a straightforward nonlinear regression type. It incorporates piecewise linear specifications and regime switching, triggered when an observed variable surpasses undisclosed thresholds. TR specifications have gained popularity due to their simplicity in interpretation and capacity to generate intriguing nonlinearities and dynamic patterns. This research undertakes the estimation of TR models, accommodating both known and unknown thresholds.

Let us start with a standard multiple linear regression model with observations and potential thresholds that define different regimes. These regimes help to analyze how the relationship between variables changes depending on certain conditions. Although using an index t represents observations, the model does not require time series data.

Within each regime, there is a specific linear regression equation:

$$y_{it} = X'_{it}\beta + Z'_{it}\partial_j + \varepsilon_t \tag{1}$$

The regressors are split into X and Z groups, and the coefficients of X variables stay the same across all regimes. The coefficients of Z variables change depending on the specific regime.

Assume the presence of a threshold variable h_t along with strictly ascending threshold values ($\tau_1 < \tau_2 < \cdots < \tau_m$). A particular regime exists if and only if:

$$\tau_j \leq h_t < \tau_{j+1} \tag{2}$$

where $\tau_0 = -\infty$ and $\tau_{n+1} = \infty$. The regime j is identified if the threshold value falls within a specific range, defined by its corresponding thresholds. Then, a single threshold with two regimes is defined as follows:

$$\begin{array}{ll} y_{it} = X'_{it}\beta + Z'_{it}\partial_1 + \varepsilon_t & \text{if} -\infty < h_t < \tau_1 \\ y_{it} = X'_{it}\beta + Z'_{it}\partial_2 + \varepsilon_t & \text{if } \tau_1 \leq h_t < \infty \end{array} \tag{3}$$

By employing an indicator function that assumes the value 1 when the expression is true and 0 otherwise, the individual regime specifications are unified into a single equation:

$$y_{it} = X'_{it}\beta + \sum_{j=0}^{n} 1_j(h_t, \tau) + Z'_{it}\partial_j + \varepsilon_t \tag{4}$$

Once the threshold variable and the regression specification in Equation (4) are determined, the objective is to identify the coefficients and the threshold values.

The estimation process, denoted, is widely recognized in the literature on breakpoint testing and regression (Hansen, 2000 [38]; Perron, 2006 [39]). By rearranging the observation index to ensure the threshold variable is non-decreasing, it becomes apparent that the estimation of threshold and breakpoint models is fundamentally equivalent, as highlighted by Bai and Perron in 2003 [40]. In essence, threshold regressions can be conceptualized as breakpoint least squares regressions, with the data reorganized based on the threshold variable.

4. The Data and Empirical Results

4.1. Data

This study used a sample comprising 861 companies from 20 industries listed on the Taiwan Stock Exchange. The study period spans from 2012 to 2022, encompassing eleven years. After excluding data with non-available values, 6273 observations are used for analysis. The data utilized in this study are sourced from the TEJ (Taiwan Economic Journal) database, renowned for its comprehensive coverage of financial data about Taiwanese companies. Additionally, this study integrates data from the Market Observation Post System (MOPS), a real-time market surveillance tool employed by both the Taiwan Stock Exchange Inc. (TWSE) and Taipei Exchange (TPEx). MOPS plays a crucial role in monitoring trading activities, ensuring fair markets, and detecting irregularities or potential market manipulation, thus contributing to maintaining market integrity.

Table 1 offers an overview of the variables employed in this research. The variables utilized in this research encompass a diverse set of financial, operational, environmental, and governance metrics.

Table 1. Variable description.

Variable	Descriptions
SIZ	Natural logarithm of the total assets.
TAA	The ratio of the sum of goodwill and intangible assets to total assets.
ARV	Accounts receivable and notes/total assets—ratio of accounts receivable and notes to total assets.
IBT	The ratio of profit before tax to paid-in capital.
OEP	The ratio of operating expenses to net operating income.
PBT	The ratio of profit before tax to net operating income.
ROA	Return on assets adjusted for comprehensive income.
ROE	Return on equity adjusted for comprehensive income.
DER	Debt ratio—ratio of debt to equity.
CAE	The ratio of carbon emissions to net operating income.
MSZ	Natural logarithm of the number of managers.
REB	The ratio of directors' and supervisors' remuneration to profit before tax.
BDP	Percentage of shares held by directors and supervisors.
MNP	Percentage of shares held by managers.
COP	Group corporate shareholding percentage—percentage of shares held by the group corporate.
INB	Natural logarithm of the number of independent directors and supervisors.

The natural logarithm of total assets (SIZ) is employed, possibly for distributional adjustments. At the same time, the TAA variable reflects the ratio of goodwill and intangible assets to total assets, offering insights into the composition of a firm's assets. ARV gauges the proportion of assets in accounts receivable and notes, while the IBT assesses profitability relative to paid-in capital. The OEP and PBT ratios explore operating expenses and pre-tax profit vis à vis net operating income, respectively, offering efficiency metrics. Comprehensive income adjustments in ROA and ROE provide nuanced perspectives on asset and equity utilization. The DER explores financial leverage through the debt-to-equity ratio. CAE brings environmental considerations, measuring carbon emissions against net operating income. Workforce size is transformed logarithmically with MSZ. Governance-related variables include REB, reflecting directors' and supervisors' remuneration as a profit percentage before tax; BDP and MNP, indicating shareholding percentages for directors, supervisors, and managers; and COP, representing the group corporate shareholding percentage. Lastly, the logarithm of the number of independent directors and supervisors (INB) provides a transformed count in governance analysis. These variables offer a comprehensive framework for understanding and evaluating various aspects of organizational performance and behavior.

The Variance inflation factor (VIF) assesses multicollinearity in a regression model. VIF values less than five generally indicate the absence of a significant multicollinearity issue. In this range, the independence of the variables is reasonably assured. For VIF values between 5 and 10, caution is warranted, as it suggests potential multicollinearity. The VIF matrix in Table 2 comprehensively assesses multicollinearity among the variables in a regression model.

Table 2. Variance inflation factor matrix.

	CAE	**PBT**	**SIZ**	**TAA**	**ARV**	**IBT**	**DER**	**MSZ**	**REB**	**BDP**	**MNP**	**INB**
CAE	1	1.008	1.513	1.512	1.512	1.514	1.514	1.513	1.514	1.514	1.514	1.513
PBT	1.010	1	1.515	1.515	1.517	1.515	1.518	1.517	1.517	1.518	1.517	1.517
SIZ	2.070	2.068	1	2.070	2.034	1.996	1.652	1.693	2.059	2.020	1.990	2.030
TAA	1.019	1.019	1.020	1	1.016	1.020	1.020	1.018	1.021	1.020	1.020	1.019
ARV	1.072	1.074	1.054	1.069	1	1.057	1.048	1.074	1.074	1.069	1.065	1.070
IBT	1.069	1.067	1.030	1.069	1.052	1	1.036	1.069	1.069	1.068	1.067	1.066
DER	1.534	1.535	1.224	1.534	1.498	1.488	1	1.515	1.535	1.534	1.535	1.535
MSZ	1.471	1.473	1.204	1.468	1.473	1.472	1.454	1	1.471	1.473	1.460	1.471
REB	1.017	1.016	1.010	1.016	1.016	1.017	1.017	1.015	1	1.014	1.017	1.014
BDP	1.048	1.048	1.022	1.047	1.043	1.046	1.047	1.048	1.045	1	1.048	1.047
MNP	1.072	1.073	1.030	1.072	1.064	1.070	1.073	1.063	1.073	1.073	1	1.072
INB	1.056	1.057	1.036	1.055	1.053	1.054	1.057	1.056	1.054	1.056	1.057	1
OEP	1.514	1.518	2.072	1.021	1.074	1.069	1.535	1.473	1.017	1.048	1.073	1.057
ROA	1.514	1.518	2.072	1.021	1.074	1.069	1.535	1.473	1.017	1.048	1.073	1.057
ROE	1.514	1.518	2.072	1.021	1.074	1.069	1.535	1.473	1.017	1.048	1.073	1.057

Generally, most VIF values are close to 1, suggesting no significant multicollinearity issue exists for most pairs of variables, which are particularly evident for variables CAE, PBT, TAA, ARV, IBT, MSZ, REB, BDP, MNP, INB, OEP, ROA, and ROE. Some variables exhibit moderate VIF values (between 1 and 2), indicating a potential, but not severe, multicollinearity issue. Notably, variables SIZ and DER have VIF values around 2, suggesting a moderate correlation with other variables in the model. The VIF matrix indicates that the multicollinearity among the variables in the regression model is generally manageable, with most variables showing low VIF values.

Table 3 presents a comprehensive set of descriptive statistics for the variables under scrutiny in the research, offering insights into their central tendencies, variabilities, and distributional characteristics. Notably, the mean and median values provide measures of central tendency, shedding light on the average and middle values, respectively. The distribution of carbon emissions (CAE) appears positively skewed, with a mean of 0.009 and a median of 0.001, indicating that the majority of observations have relatively low carbon emissions.

The natural logarithm of total assets (SIZ) exhibits a distribution that appears relatively normal, given the proximity of its mean (16.459) and median (16.179). The profit before tax (IBT) displays substantial variability, evident in its wide range (from −1098.830 to 4189.340) and a high standard deviation of 109.655. The Debt Ratio (DER) and Directors and Supervisors' Shareholding Percentage (BDP) both show positively skewed distributions, indicating a concentration of values towards lower ratios or percentages. Additionally, as their wide ranges and standard deviations suggest, variables such as Return on Assets (ROA) and Return on Equity (ROE) demonstrate notable variability. These descriptive statistics provide a foundational understanding of the dataset's characteristics, aiding in identifying potential outliers and guiding further analyses in the research.

Table 3. Descriptive statistics.

	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
CAE	0.009	0.001	5.047	0.000	0.096	6273
SIZ	16.459	16.179	23.214	11.501	1.823	6273
TAA	0.018	0.002	0.939	0.000	0.060	6273
ARV	0.136	0.115	0.900	0.000	0.111	6273
IBT	49.256	26.420	4189.340	−1098.830	109.655	6273
DER	45.231	44.440	98.020	0.610	20.136	6273
MSZ	2.193	2.079	5.429	0.000	0.763	6273
REB	1.249	0.980	238.810	−33.510	3.317	6273
BDP	23.124	18.760	96.460	0.000	17.186	6273
MNP	0.821	0.230	23.930	0.000	1.657	6273
INB	1.002	1.099	1.792	0.000	0.301	6273
PBT	−0.046	0.090	13.656	−177.807	3.676	6273
OEP	0.347	0.138	183.930	−1.338	3.992	6273
ROA	5.186	4.510	79.160	−98.230	8.302	6273
ROE	9.261	9.120	137.360	−114.450	14.481	6273

4.2. Empirical Results

The firm's size is selected as the threshold value because it plays a pivotal role in determining the scale and scope of a firm's operations, significantly influencing its carbon emissions. Using firm size as the threshold value, it can capture how firms transition from smaller-scale operations, where emissions may be relatively lower, to larger-scale operations, where emissions are likely to increase significantly. This approach allows the identification and analysis of the impact of firm size on carbon emissions, providing evidence of the relationship between firm characteristics and environmental performance.

The threshold model (5) is applied to examine the impact of carbon emissions (CAE) on operating expenses (OEP) as well as Return on Assets (ROA) and Return on Equity (ROE).

$$y_{it} = \sum_{j=0}^{n} 1_j(\mathrm{SIZ}, \Phi) + Z'_{it}\partial_j + \varepsilon_t \tag{5}$$

where y represents OEP, ROA, and ROE separately; Z includes TAA, ARV, IBT, PBT, DER, CAE, MSZ, REB, BDP, MNP, COP, and INB; SIZ is the threshold variable; Φ is the threshold value detected.

The significant threshold suggests a nonlinear relationship in the data when the specified threshold is crossed. In this study, the threshold test is employed to assess the impact of the variable SIZ (total assets), with the chosen threshold providing a critical point for analysis. The identified threshold value suggests that the impact of total assets on the dependent variable is different below and above this threshold. Companies with total assets below this threshold may exhibit a different relationship with the dependent variable than those with total assets above this threshold.

Table 4 presents the results of an analysis of the effect of carbon emissions (CAE) on operating expenses (OEP) across two different samples: the All sample and the Threshold sample, distinguished by the threshold variable SIZ (Φ), with values either less than 14.75202 or greater than or equal to 14.75202.

In all samples, the coefficient for CAE is 7.811, with significance at the 1% level, indicating a highly significant positive effect on operating expenses. This result suggests that an increase in carbon emissions is associated with a substantial increase in operating expenses. Other variables, such as PBT, ARV, IBT, MSZ, and DER also significantly affect operating expenses. Other variables in the analysis also exhibit noteworthy relationships with operating expenses. PBT (profit before tax), SIZ (size), ARV (asset revaluation), MSZ (market size), and IBT (income before tax) all demonstrate statistically significant impacts on operating expenses across different threshold values.

Table 4. The effect of carbon emissions (CAE) on operating expenses (OEP).

Variable	All Samples		Threshold Sample			
			SIZ < 14.75202		14.75202 ≤ SIZ	
C	−1.679		49.888		−11.914	
CAE	7.811	***	14.117	***	−0.633	
PBT	−0.911	***	−0.684	***	−0.992	***
SIZ	−0.010		−0.017		0.009	
TAA	0.534	**	8.729	***	−0.047	
ARV	−0.478	***	−0.946	**	−0.725	***
IBT	0.001	***	0.001	**	0.000	***
DER	0.000		0.002		−0.001	
MSZ	0.095	***	0.388	***	0.049	**
REB	0.003		0.037	*	0.002	
BDP	−0.001		0.003		−0.001	
MNP	0.015	*	0.004		0.006	
INB	0.004		0.128		−0.006	
Year control	Yes		Yes		Yes	
R-squared	0.921		0.936			
Adjusted R-squared	0.920		0.936			
F-statistic	5585.45	***	3401.585	***		
Threshold Test						
Threshold variable: SIZ					Total assets (Thousand)	
Threshold value (Φ)	14.75202	***			2,551,071	
Significant at the 0.01 level. (Bai-Perron critical values.)						

Note: Each row in the table represents the coefficients for various independent variables, and their respective statistical significance is denoted by asterisks, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

The adjusted R-squared values indicate the goodness of fit for the models, with the entire sample model having an adjusted R-squared of 0.920 and the threshold sample model having a higher adjusted R-squared of 0.936. The F-statistics, which test the overall significance of the models, are highly significant for both the entire sample and the threshold sample, reinforcing the reliability of the results. In the threshold sample, where the SIZ is greater than or equal to 14.75202, the relationship between CAE and OEP changes. The coefficient for CAE becomes 14.117 with three asterisks, implying a significant positive effect, but the magnitude of the effect has decreased compared to all samples. This result suggests that the impact of carbon emissions on operating expenses is still positive but less pronounced when the threshold is crossed. The other independent variables show varying significance and coefficient changes between the two samples.

The threshold level is 6,480,618 for total assets (thousand). This value serves as a reference point, and its significance becomes apparent when interpreting the effect of carbon emissions (CAE) on Return on Assets (ROA), as demonstrated in the earlier analysis of Table 5. The threshold value (Φ) of 15.68432 is marked with a 1% level, indicating high statistical significance. This result suggests that the chosen threshold value is crucial in distinguishing between different data segments or identifying a critical point where the relationship between variables undergoes a significant change.

The impact of carbon emissions (CAE) on Return on Assets (ROA) in both the overall sample and a subset defined by a threshold Φ. In the overall sample, the coefficient for CAE is 7.803 with a 1% level, indicating a highly significant positive relationship with ROA. This result suggests that an increase in carbon emissions is associated with a higher Return on Assets for the entire sample. When examining the threshold sample, which includes cases where SIZ is lower than 15.68432, the coefficient for CAE is 19.326, also marked with a 1% level, indicating a highly significant positive association with ROA.

Table 5. The effect of carbon emissions (CAE) on ROA.

Variable	All Sample		Threshold Sample			
			SIZ < 15.68432		15.68432 ≤ SIZ	
C	−269.030	***	−445.188	***	−112.256	
CAE	7.803	***	19.326	***	−3.988	
PBT	0.451	***	0.861	***	0.114	***
SIZ	0.376	***	2.222	***	−0.109	
TAA	−5.173	***	−11.600	***	−2.433	*
ARV	6.471	***	11.962	***	2.330	***
IBT	0.035	***	0.040	***	0.032	***
DER	−0.117	***	−0.145	***	−0.102	***
MSZ	0.562	***	0.331		0.509	***
REB	0.121	***	1.093	***	0.020	
BDP	0.035	***	0.061	***	0.023	***
MNP	0.205	***	0.216	***	0.191	**
INB	0.196		−0.572		1.073	***
Year control	Yes		Yes		Yes	
R-squared	0.362		0.420			
Adjusted R-squared	0.361		0.418			
F-statistic	273.4961	***	167.563		***	
Threshold Test						
Threshold variable: SIZ					Total assets (thousand)	
Threshold value (Φ)	15.68432	***			6,480,618	
Significant at the 0.01 level. (Bai-Perron critical values.)						

Note: Each row in the table represents the coefficients for various independent variables, and their respective statistical significance is denoted by asterisks, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Other control variables in the model also exhibit statistically significant coefficients. For instance, PBT, TAA, ARV, IBT, and DER all show positive and statistically significant relationships with ROA in the overall and threshold samples. On the other hand, size (SIZ), Total Asset Turnover (TAA), and Earnings Before Interest and Tax (EBIT) exhibit negative coefficients, indicating a negative impact on ROA.

Table 6 presents the impact of carbon emissions (CAE) on Return on Equity (ROE) across two subgroups: the entire sample and a threshold sample based on the Φ value. The variables included in the analysis are denoted as C, CAE, PBT, SIZ, TAA, ARV, IBT, DER, MSZ, REB, BDP, MNP, INB, and various control variables, with the presence of a year control in both subsets. The threshold test suggests a significant change in the relationship between the total assets variable and the dependent variable (ROA) at 14.77198. The statistical significance at the 0.01 level implies a high degree of confidence in the identified threshold, reinforcing its relevance in the model.

The CAE variable has a positive coefficient of 11.891, implying that an increase in carbon emissions is associated with an increase in ROE. Other variables, such as PBT, SIZ, TAA, ARV, IBT, DER, MSZ, REB, BDP, MNP, and INB, also exhibit significant coefficients, each contributing to the overall explanatory power of the model.

In the threshold sample where SIZ is lower than 14.77198, the coefficient CAE is 28.446. The positive sign for CAE implies a positive relationship with ROE in this subgroup. The magnitude of the coefficients for CAE is higher in the threshold sample than the entire sample, indicating a potentially more robust effect of these variables on ROE in firms with smaller sizes. Additionally, control variables such as PBT, SIZ, TAA, ARV, IBT, DER, MSZ, REB, BDP, MNP, and INB also display significant coefficients in the threshold sample, contributing to the overall explanatory power of the model. Year controls in both subsets ensure the analysis accounts for potential time-related variations.

Table 6. The effect of carbon emissions (CAE) on ROE.

Variable	**All Sample**		**Threshold Sample**			
			SIZ < 14.77198		**14.77198 ≤ SIZ**	
C	−463.995	***	−1198.513	***	−124.161	
CAE	11.891	***	28.446	***	−0.448	
PBT	0.633	***	1.193	***	0.316	***
SIZ	0.816	***	7.767	***	−0.064	
TAA	−5.987	**	−18.323	**	−2.417	
ARV	15.338	***	33.305	***	9.968	***
IBT	0.059	***	0.035	***	0.068	***
DER	−0.087	***	−0.266	***	−0.041	***
MSZ	1.028	***	1.462	*	0.738	***
REB	0.235	***	2.540	***	0.127	***
BDP	0.063	***	0.205	***	0.043	***
MNP	0.319	***	0.714	***	0.158	
INB	1.104	*	−1.032		2.278	***
Year control	Yes		Yes		Yes	
R-squared	0.291			0.347		
Adjusted R-squared	0.290			0.344		
F-statistic	197.900	***	122.91		***	
Threshold Test						
Threshold variable: SIZ					Total assets (thousand)	
Threshold value(Φ)	14.77198		***		2,602,513	
Significant at the 0.01 level. (Bai-Perron critical values.)						

Note: Each row in the table represents the coefficients for various independent variables, and their respective statistical significance is denoted by asterisks, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

The analysis conducted on the relationship between carbon emissions (CAE) and operating expenses (OEP) and financial performance across two distinct samples, the All sample and the Threshold sample, provides evidence for the nuanced nature of this association. In all samples where the threshold variable is not considered, the results indicate a highly significant positive effect of carbon emissions on operating expenses, suggesting that an increase in carbon emissions is associated with a substantial rise in operating expenses. Several other variables, including PBT, ARV, IBT, MSZ, and DER, also exhibit significant impacts on operating expenses, emphasizing the multifaceted nature of the relationship.

Intriguingly, when introducing the threshold variable and distinguishing between cases where it is less than 14.75202 and those greater than or equal to 14.75202, the dynamics of the CAE-OEP relationship undergo a shift. In the threshold sample, the coefficient for CAE remains positive but increases to 14.117 for smaller companies, indicating a more pronounced impact on operating expenses than the entire sample. High carbon emissions significantly increase smaller companies' operating expenses; higher carbon emissions often correlate with greater energy consumption. Small businesses typically have limited resources to invest in energy-efficient technologies or renewable energy sources, making them more vulnerable to rising energy costs associated with carbon-intensive operations. High carbon emissions contribute to environmental degradation and pose financial risks that can disproportionately burden smaller companies.

Moving beyond OEP, the analysis examines the impact of CAE on Return on Assets (ROA) and Return on Equity (ROE) across both overall and threshold samples. The results reveal that the positive relationship between CAE and ROA is significant in both samples, with the magnitude of the effect even more pronounced when the threshold is not met or exceeded. The control variables, such as profit before tax (PBT), total assets (TAA), asset recovery value (ARV), income before tax (IBT), and debt-to-equity ratio (DER) also exhibit consistent positive associations with ROA in both sample categories. Similarly, in the context of ROE, the analysis uncovers a negative association between carbon emissions and ROE in the larger firms ($\Phi \geq 14.77198$) subgroups, emphasizing a detrimental effect on ROE. However, in the smaller firms ($\Phi < 14.77198$) group, the positive relationship between CAE and ROE becomes more pronounced, underlining the threshold's significance in influencing the impact's direction and strength. High carbon emissions, alongside high ROA and ROE for smaller companies, can be attributed to limited resources for investing in greener technologies, prevalent carbon-intensive activities in sectors like manufacturing or transportation, and lower stakeholder scrutiny regarding emissions reduction. While this may boost short-term profitability, it poses long-term risks, including regulatory non-compliance, reputational damage, and environmental sustainability concerns.

The threshold test results indicate a statistically significant threshold value for total assets (SIZ), suggesting a structural break in the relationship under consideration. Researchers and practitioners can use this information to refine their understanding of the dynamics between total assets and the dependent variable in the given context, potentially informing decision-making.

4.3. Artificial Neural Networks (ANNs) for Predicting Carbon Emissions

Artificial neural networks (ANNs) represent a powerful paradigm, inspired by the structure and function of the human brain. These computational models consist of interconnected nodes, or "neurons", organized into layers that process and transform input data into meaningful output. Through learning from testing data, ANNs can autonomously discern complex patterns and relationships, making them invaluable tools in various fields, such as machine learning, pattern recognition, and predictive analytics. Binh (2024) [41] conducted a study on the construction of an artificial neural network (ANN) to analyze the determinants influencing firms' decisions to engage in corporate social responsibility (CSR) and found the ANN to be superior to the traditional logit model. By accurately forecasting emissions, ANN can inform decision-making processes to reduce environmental impact and promote sustainability.

Threshold detection for carbon emissions involves identifying critical points at which the relationship between carbon emissions and other variables undergoes significant changes or shifts in behavior. Table 7 presents the results of threshold detection for carbon emissions (CAE), specifically focusing on the threshold test with two different values of Ξ (1 and 2). The F-statistic for the threshold test, with Ξ is equal to 1, is reported as 207.514 at a significance level of 1%, indicating high statistical significance. This result suggests a significant threshold effect in the CAE relationship when Ξ equals 1. The large F-statistic implies a structural change or breakpoint in the relationship between CAE and the dependent variable(s) at this threshold value.

Table 7. Thresholds detection for carbon emissions (CAE).

Threshold Test	$\Xi = 1$	$\Xi = 2$
F-statistic	207.514 ***	2.101
Threshold value	[0.00882597]	[.]

Note: The maximum threshold applied for each detection is 5. The critical values are from Bai-Perron (2003). Threshold values of two dependent variables are all significant at the 1% (***) level.

Conversely, when Ξ is set to 2, the F-statistic is reported as 2.101, which is not statistically significant. This result suggests that the model does not detect a significant threshold effect at $\Xi = 2$. The comparison between the two F-statistics underscores the importance of identifying the appropriate threshold value to capture structural changes in the relationship between CAE and the dependent variable(s). The reported threshold values corresponding to the significant threshold test are [0.00882597]. These values signify the specific points at which a structural change occurs in the relationship under consideration.

The mentioned threshold value is employed for classifying carbon emissions (CAE) into two groups: 1 for instances with values equal to or exceeding the higher threshold (0.00882597) and 0 for those falling below the threshold. This binary classification approach simplifies the prediction task, allowing the model to categorize CAE outcomes into distinct groups based on the designated threshold. The threshold value serves as a critical reference point, delineating between different levels or scenarios of CAE. This classification scheme enhances interpretability and practical utility, enabling decision-makers to identify and address instances where carbon emissions exceed a specified threshold level, facilitating targeted interventions or strategies by the classification outcome.

Table 8 and Figure 1 present a comprehensive breakdown of carbon emissions (CAE) across diverse industries, classified into two distinct groups: CEA = 0 and CEA = 1.

Table 8. Classification of carbon emissions by industry.

Industry No. (IND)	Industry Name	CEA = 0	CEA = 1	Total Obs.
11	Cement	22	62	84
12	Food	190	17	207
13	Petrochemicals	95	89	184
14	Textiles	108	70	178
15	Mechanical Equipment	259	17	276
16	Electric Wires	35		35
17	Chemicals	559	100	659
18	Glass/Ceramics	13	10	23
19	Paper Making	5	34	39
20	Steel	157	72	229
21	Rubber/Tires	36	20	56
22	Automobiles	80	1	81
23	Electronics	2672	307	2979
25	Construction	241	8	249
26	Transportation	65	73	138
27	Tourism	109	23	132
28	Finance	325		325
29	Department Stores	82	3	85
30	Securities	68	1	69
99	Other	212	33	245
Total obs.:		5333	940	6273

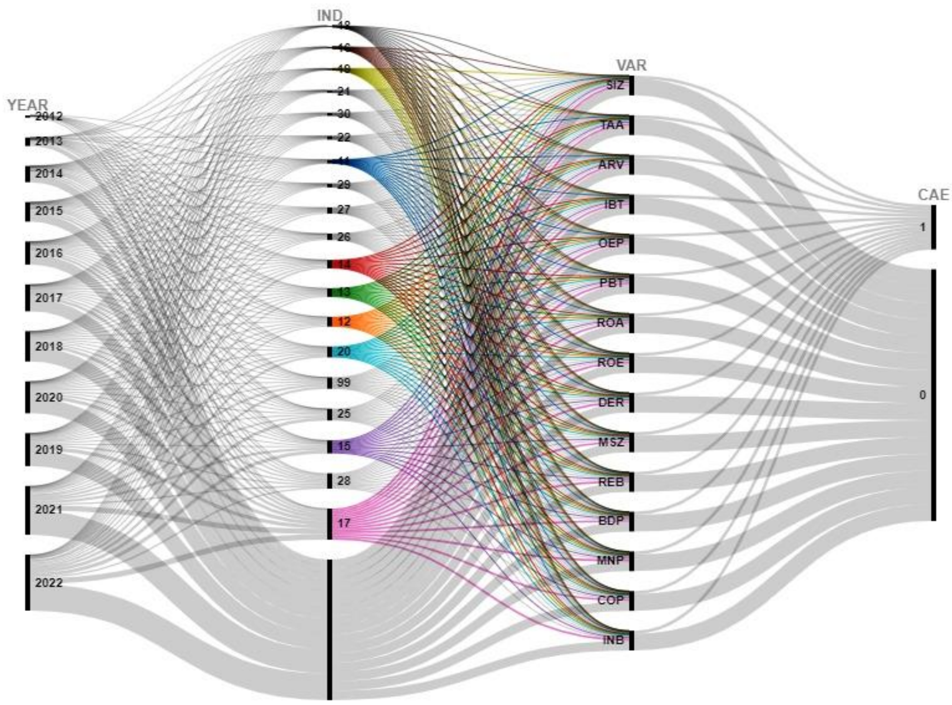

Figure 1. Data classification by year, industry, variables, and carbon emissions.

The observation counts within each category offer valuable insights into the prevalence of emissions exceeding the threshold across different industries. Notably, industries such as electronics, chemicals, and mechanical equipment exhibit considerable counts under CEA = 1, indicating a significant proportion of emissions surpassing the specified threshold within these sectors. Conversely, industries with higher counts under CEA = 0 suggest a lower prevalence of emissions surpassing the threshold.

Figure 2 presents the architecture of an artificial neural network (ANN) designed to predict carbon emissions (CAE).

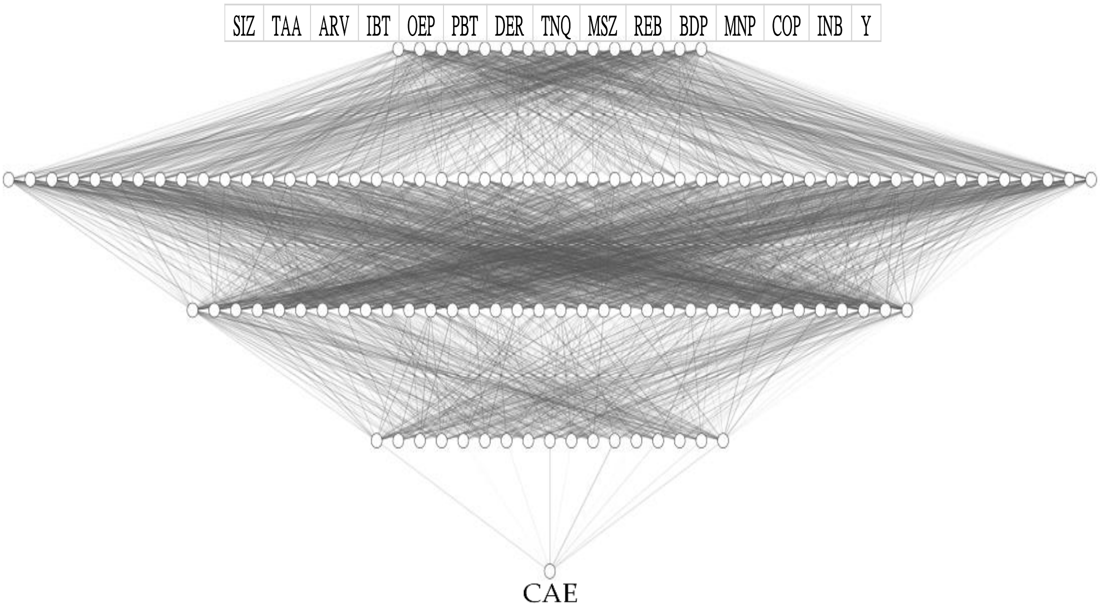

Figure 2. Artificial neural network (ANN) architecture for CAE prediction.

The network comprises stacked layers, each housing multiple neurons. The input layer, with 15 neurons, is likely tasked with receiving a set of diverse input features, such as SIZ, TAA, ARV, IBT, OEP, PBT, DER, TNQ, MSZ, REB, BDP, MNP, COP, INB, and year control Y. Subsequent layers include 51, 34, and 17 neurons, indicating a progression towards more abstract feature extraction and refinement. The final layer consists of a single output neuron, representing a binary CAE prediction (0 or 1). The architecture suggests the network's capacity to discern intricate patterns within the input data, facilitating accurate predictions of binary CAE outcomes based on the provided features.

Figure 3 shows a line graph of the accuracy of a machine-learning model over time. The x-axis is labeled "Epoch," and the y-axis is labeled "Accuracy." The graph has two lines: a blue line labeled "Train" and an orange line labeled "Validation." Both lines start at around 0.8 accuracy and increase over time.

The artificial neural network (ANN) architecture for predicting carbon emissions (CAE) demonstrates robust learning capabilities. The training accuracy curve reaching approximately 0.96 suggests that the model effectively learns from the training dataset, showcasing a high level of accuracy in predicting CAE outcomes during the training phase. Similarly, the validation accuracy curve, peaking at around 0.89, indicates that the model generalizes well to unseen data, demonstrating its ability to make accurate predictions on new and independent datasets. The observed leveling off of both training and validation accuracy lines implies that the model achieves a stable and reliable level of accuracy, avoiding overfitting the training data.

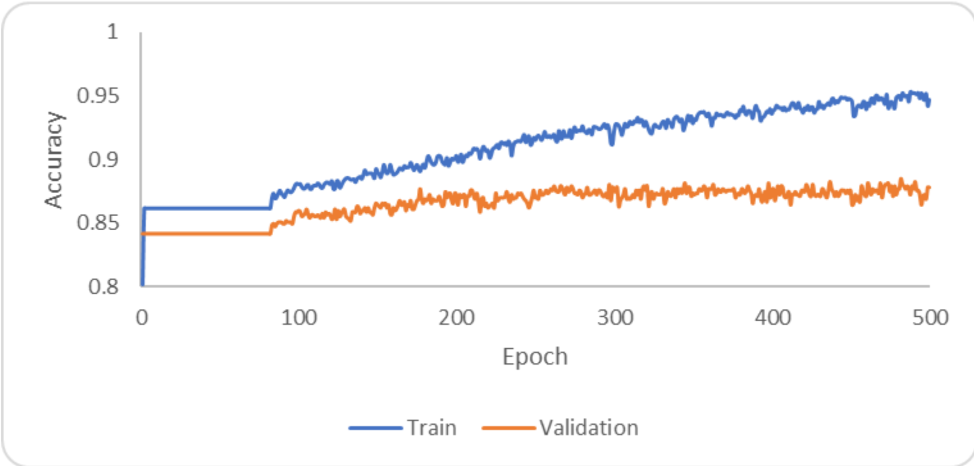

Figure 3. Artificial neural network (ANN) tracking CAE accuracy over time.

Applying the artificial neural network (ANN) architecture for predicting carbon emissions (CAE) offers several advantages in addressing the environmental data's complex and dynamic nature. Firstly, ANNs excel in capturing nonlinear relationships and patterns within data, making them well-suited for modeling the intricate interactions that influence carbon emissions. Additionally, ANNs can handle large and diverse datasets efficiently, enabling the integration of various input variables to improve prediction accuracy. Furthermore, ANNs can adapt and learn from data, allowing continuous refinement and optimization of emission prediction models over time. By harnessing the power of ANNs, stakeholders can develop robust and reliable tools for forecasting carbon emissions, facilitating informed decision-making, and developing effective mitigation strategies to combat climate change.

The results from the threshold method unveil a statistically significant threshold value for total assets, indicating a structural break in the relationship under examination. This finding holds substantial implications for researchers and practitioners, offering valuable insights into the nuanced dynamics between total assets and the dependent variable within the specific context analyzed. By acknowledging and understanding this threshold, stakeholders can refine their strategies and decision-making processes accordingly.

By widening the lens to include a broader debate on results obtained from other countries, it becomes evident that similarities and differences exist in the impact of ESG practices on firm performance and cost. While there is a growing consensus on the importance of ESG practices globally, their effects remain complex and contingent upon various contextual factors. Therefore, this research contributes to untangling these complexities, particularly within the context of Taiwan. By elucidating the intricate interplay between ESG practices, firm performance, and cost, this study offers valuable insights that can inform tailored strategies to maximize the positive impacts of ESG disclosure for firms across diverse contexts. Further research and cross-country comparisons will be essential to deepen our understanding and generalize the findings to a broader international context.

5. Conclusions

This analysis brings to light the significant positive impact of carbon emissions on operating expenses and emphasizes the importance of considering threshold effects in predicting carbon emissions. Further exploration of financial performance metrics, such as Return on Assets (ROA) and Return on Equity (ROE), adds depth to this study, revealing varied associations based on threshold values and highlighting the interconnectedness of environmental impact and financial outcomes. The identified threshold values, particularly in the context of total assets, serve as pivotal reference points for categorizing carbon emissions outcomes into distinct groups. Additionally, the developed artificial neural network (ANN) for predicting carbon emissions demonstrates robust learning capabilities, underscoring its proficiency in capturing complex patterns within the data and its potential for accurately predicting carbon emissions across diverse scenarios.

These comprehensive findings underscore the intricate interplay between carbon emissions and financial performance indicators, providing insights into the importance of considering threshold effects for a nuanced understanding of the relationships within the analyzed variables. The identified threshold values are crucial in delineating distinct data segments and capturing critical points where relationships undergo significant changes. Such insights contribute to a more robust interpretation of the impact of carbon emissions on financial performance, offering valuable implications for strategic decision-making and sustainability efforts across various organizational contexts.

The findings also shed light on the challenges faced by smaller companies in mitigating carbon emissions, as limited resources often hinder investment in greener technologies or renewable energy sources. This vulnerability to rising energy costs associated with carbon-intensive operations poses environmental and financial risks, disproportionately affecting smaller companies.

Moreover, the results reveal a significant threshold value for total assets, indicating a structural break in the relationship under examination. This finding holds substantial implications for researchers and practitioners, offering valuable insights into the nuanced dynamics between total assets and the dependent variable within the specific context analyzed. Acknowledging and understanding this threshold empowers stakeholders to refine their strategies and decision-making processes accordingly.

The connection between corporate environmental, social, and governance (ESG) disclosure and sustainability is multifaceted and mutually reinforcing. By fostering transparency, accountability, risk management, stakeholder engagement, access to capital, innovation, and competitive advantage, ESG disclosure contributes to sustainability. It underscores the importance of sustainable business practices in achieving long-term value creation for all stakeholders.

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