A Causal AI Approach to Identifying the Financial Determinants of ESG Ratings

Chi-Chen Wu[1], Kuei-Kuei Lai[2], Tsung-Nan Chou [3], Jian-Fa Li[4*]

[1]*Department of Finance, Chaoyang University of Technology*, Taichung , Taiwan, cherry73271128@gmail.com

[2] *Department of Business Administration, Chaoyang University of Technology*, Taichung , Taiwan, laikk.tw@gmail.com

[3]*Department of Finance, Chaoyang University of Technology*, Taichung , Taiwan, tnchou@cyut.edu.tw

[4*]*Correspoding Author*, *Department of Finance, Chaoyang University of Technology*, Taichung , Taiwan, jfli@cyut.edu.tw

***Abstract*- Sustainable development has become a priority for firms and investors, with environmental, social, and governance (ESG) ratings now widely used to assess non-financial performance and sustainability risk. Using Causal Artificial Intelligence (Causal AI) through the DoWhy framework, this study identifies financial variables that causally influence ESG ratings for listed and over-the-counter firms in Taiwan. Earnings per share (EPS) and pre-tax net income per share emerge as the primary causal drivers of overall ESG ratings and the environmental dimension. The social dimension is causally influenced by return on operating assets, quick ratio, and debt ratio, while the governance dimension is driven by return on operating assets and net asset value per share. These relationships remain robust across multiple refutation tests, demonstrating the effectiveness of Causal AI in providing causal—rather than correlational—evidence on the financial determinants of ESG performance.**

Keywords-ESG, Causal AI; DoWhy; Causal inference; Financial determinants

1. INTRODUCTION

Environmental, social, and governance (ESG) responsibility has become a core criterion in evaluating corporate behavior. Since the United Nations' *Who Cares Wins* (2005) report emphasized integrating ESG considerations into capital markets, ESG ratings have shifted from peripheral disclosure tools to central measures of sustainability, risk exposure, and long-term value. They now influence investment screening, credit evaluations, stewardship practices, and regulatory oversight, shaping firms' access to capital and legitimacy among stakeholders.

ESG ratings consolidate information about firms' environmental practices, social responsibility, and governance quality. Firms with higher ESG ratings are perceived as more resilient to regulatory, reputational, and operational risks and may benefit from lower capital costs and competitive advantages. Accordingly, managers face growing pressure to align financial decisions and strategies with ESG objectives.

Despite their importance, the mechanisms determining ESG ratings remain insufficiently examined. Prior research has primarily focused on how ESG affects financial outcomes, with fewer studies exploring the reverse question: which financial characteristics causally influence ESG ratings? This gap is particularly relevant in emerging markets such as Taiwan, where ESG disclosures are increasing and institutional investors are integrating ESG into decision-making. Understanding whether profitability, leverage, liquidity, or asset structure causally drive ESG ratings is critical for companies formulating ESG strategies and for policymakers designing effective incentives.

Traditional empirical approaches, such as regression and panel models, rely on strong assumptions and are vulnerable to omitted variable bias and reverse causality. Machine learning models, while useful for prediction, rarely provide interpretable causal explanations. Consequently, much existing evidence remains correlational.

Causal Artificial Intelligence (Causal AI), grounded in structural causal models and counterfactual reasoning, offers a more rigorous solution (Pearl, 2009). The DoWhy framework enables explicit causal modeling, identification of valid estimands, estimation using suitable methods, and refutation through robustness checks (Sharma & Kiciman, 2020). This approach supports claims about causal effects rather than mere associations. Against this backdrop, this study investigates the financial determinants of ESG ratings for listed and over-the-counter firms in Taiwan using Causal AI. Specifically, we aim to:

a. Develop a causal model linking key financial metrics—such as earnings per share (EPS), pre-tax net income per share, return on operating assets, liquidity, leverage, and net asset value per share—to overall ESG ratings and their sub-dimensions.

b. Apply the DoWhy framework to identify, estimate, and refute causal effects, distinguishing true causal relationships from spurious correlations.

The study contributes by: a. identifying financial indicators that exert a credible causal influence on ESG ratings; b. demonstrating the value of Causal AI in ESG research through a transparent and reproducible workflow; and c. enriching ESG literature in emerging markets, particularly Taiwan. Overall, the findings advance understanding of how financial performance shapes perceived sustainability and how causal inference can guide corporate and policy decisions.

2. LITERATURE REVIEW

2.1 ESG Ratings and Financial Performance

ESG ratings have become a core tool for assessing corporate sustainability, risk exposure, and long-term value, complementing traditional financial metrics in investment and regulatory decisions (United Nations, 2005). Empirical evidence shows that firms with stronger ESG performance often benefit from lower risk, reduced financing costs, and higher firm value (Giese et al., 2019; 2021), suggesting that ESG ratings signal managerial quality and strategic resilience rather than mere ethical intent. However, ESG evaluation remains complex: measurement inconsistency and rating heterogeneity persist (Kotsantonis & Serafeim, 2019). Recent findings also link robust ESG practices and disclosure quality to improved accounting performance (Li et al., 2024), indicating that ESG is increasingly integrated into value creation.

Financial flexibility plays an important role. Firms with stronger cash flows and lower leverage are more capable of investing in sustainability initiatives, while financially constrained firms face trade-offs that limit ESG engagement (Stoiljković et al., 2024). Research further shows a bidirectional relationship between ESG and financial outcomes—ESG affects firm value and managerial behavior, and financial performance can reinforce ESG improvement (Liu, 2020; Velte, 2019; Wedajo et al., 2024; Kumar, 2025).

Despite growing evidence, key gaps remain. Prior work largely examines whether ESG improves financial outcomes, rather than whether specific financial characteristics causally determine ESG ratings. Moreover, most empirical studies rely on regression-based methods that only partially address endogeneity and reverse causality, and very few employ explicit causal identification—particularly in emerging markets such as Taiwan.

To address these gaps, this study applies Causal AI to identify the causal effects of firm-level financial variables—profitability, leverage, liquidity, and net asset value per share-on ESG ratings.

2.2 Causal AI in ESG and Financial Analysis

Machine learning is increasingly used in finance and ESG analytics to forecast prices, assess risk, and predict ESG scores, but these models prioritize predictive accuracy and rely on correlations. They cannot answer whether changing a financial variable would alter ESG outcomes-a critical limitation for investors, regulators, and managers seeking causal and policy-relevant insights.

Causal Artificial Intelligence (Causal AI), based on structural causal models (Pearl, 2009), overcomes this limitation by explicitly representing assumptions through directed acyclic graphs (DAGs) and enabling counterfactual inference. This is particularly valuable in ESG–finance research, where financial performance, disclosure quality, and sustainability practices interact through feedback and simultaneity.

Recent tools-such as Tetrad, *pcalg*, *bnlearn*, and Python libraries including DoWhy (Sharma & Kiciman, 2020), EconML, CausalML, causal-learn, and Salesforce’s CausalAI (Arpit et al., 2023)—provide end-to-end workflows for causal modeling and robustness testing. DoWhy is notable for its structured sequence of model → identify → estimate → refute, which makes causal assumptions explicit and testable. Despite growing awareness, most ESG studies still rely on regressions or prediction-focused machine learning, producing correlational findings that do not establish whether financial characteristics *cause* differences in ESG ratings. Consequently, managerial and policy conclusions may be misleading.

To address this gap, this study applies Causal AI via DoWhy to firms in Taiwan. By defining a causal graph, identifying valid estimands, estimating effects, and performing refutation tests, we (i) isolate true financial determinants of ESG ratings, (ii) examine causal effects across ESG sub-dimensions, and (iii) demonstrate a transparent, replicable causal workflow for ESG analysis.

3. RESERCH METHDOLOGY

This study investigates the causal impact of firm financial characteristics on ESG ratings, including environmental (E), social (S), and governance (G) sub-dimensions. Financial variables capture profitability, growth, and solvency, and are derived from audited financial statements. Profitability measures include ROA, ROE, EPS, pre-tax and sustainable EPS, ROOA, and operating and gross profit margins, reflecting efficiency, shareholder value creation, and capacity to fund ESG initiatives. Growth is measured by revenue and net profit growth, while solvency and capital structure are captured by current and quick ratios, interest coverage, debt ratio, and net asset value per share, reflecting liquidity, leverage, and financial strength. These variables constitute the treatment set in the causal framework, enabling identification of financial indicators that robustly influence overall and dimension-specific ESG ratings.

3.2 DoWhy Framework for Causal Inference

Traditional regression-based and machine learning models primarily identify associations and predictive patterns, offering limited guidance on whether changes in financial variables would *cause* changes in ESG ratings. To obtain causally interpretable evidence, this study adopts a Causal AI approach implemented via the DoWhy framework (Sharma & Kiciman, 2020), which structures the analysis into four steps: modeling, identification, estimation, and refutation. This design enhances transparency, robustness, and policy relevance.

a. Modeling: Causal Graph Construction

We specify directed acyclic graphs (DAGs) to represent hypothesized causal links among financial variables and ESG outcomes, including overall ESG scores, E, S, G sub-dimensions, and relevant controls (firm size, industry, time effects). DAG structures are cross-validated using three causal discovery algorithms: PC (constraint-based; Spirtes et al., 2000), GES (score-based; Chickering, 2002), and LiNGAM (linear non-Gaussian; Shimizu et al., 2006). Concordant patterns inform the final DAG for DoWhy analysis.

b. Identification uses the back-door criterion to control for confounders and, where appropriate, the front-door criterion via mediators, formalizing estimands such as the average causal effect of EPS on ESG outcomes.

c. Estimation employs linear regression with controls and alternative specifications (e.g., fixed effects, re-weighting) to quantify how marginal changes in financial variables affect ESG and its E, S, G dimensions.

d. Refutation tests robustness using DoWhy procedures: (a) Data Subset Refuter (random subsamples), (b) Random Common Cause Refuter (simulated confounders), and (c) Placebo Treatment Refuter (randomized treatment/outcome). Across all procedures, consistent results support the conclusion that selected financial indicators are genuine causal determinants of ESG performance, providing credible, dimension-specific insights grounded in rigorous causal inference.

4. EMPIRICAL RESULTS AND DISCUSSION

This study uses publicly available data from the Taiwan Economic Journal (TEJ), focusing on ESG ratings and key financial indicators (e.g., ROE, ROA, debt ratio) for listed and OTC firms in 2023. The year 2023 is selected because Taiwan's ESG reporting standards had become fully established, ensuring comprehensive and comparable disclosure. Earlier years (2020–2022) were affected by COVID-19–related operational and financial distortions, which could obscure underlying ESG–financial relationships. Limiting the analysis to 2023 therefore provides a clearer and more reliable assessment of the causal links between financial characteristics and ESG performance.

4.1.1 PC Model Analysis

The PC algorithm, a constraint-based causal discovery method, was applied to identify potential causal relationships between ESG (composite score X0), its environmental (E), social (S), and governance (G) dimensions, and key financial variables. The resulting causal matrix (Fig. 1) highlights statistically significant links (black cells) between ESG metrics and financial indicators.

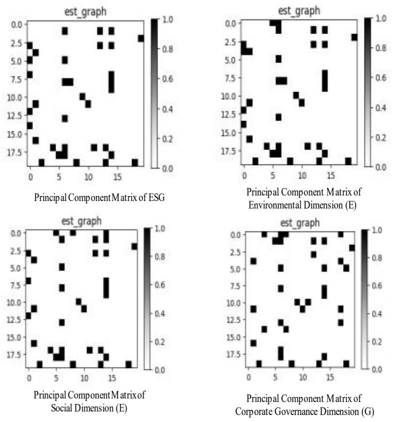

Figure 1. Principal Component (PC) Matrix Diagram of ESG and Its Dimensions (E, S, and G)

The ESG score (X0) is causally linked to revenue (X3), ROE (X5), current ratio (X7), pre-tax EPS (X12), and debt ratio (X14). Environmental (E) and social (S) dimensions show distinct financial influences, while governance (G) is unaffected, highlighting the role of non-financial factors. Results suggest ESG dimensions respond differently to financial drivers, calling for tailored management strategies.

4.1.2 GES Model Analysis

The GES algorithm, a score-based structural learning approach, iteratively adjusts edges to optimize causal network fit. As shown in Figure 2, the ESG composite score and its dimensions exhibit robust causal relationships with several financial variables, particularly ROE (X5) and pre-tax EPS (X12). For the environmental dimension (E),

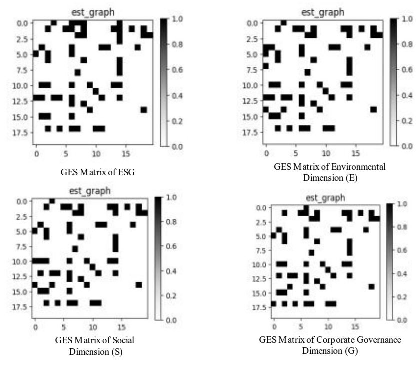

Figure 2 GES Matrix of ESG and Its Components (E, S, and G)

significant predictors include EPS (X4), ROE (X5), current ratio (X7), pre-tax EPS (X12), and debt ratio (X14); for the social dimension (S), ROE (X5), book value per share

(X10), and debt ratio (X14) emerge as key determinants; for corporate governance (G), ROE (X5) and persistent EPS (X17) are influential. These findings reinforce the importance of profitability and earnings capacity as central drivers of ESG outcomes, while highlighting those different dimensions are sensitive to distinct financial factors.

4.1.3 LiNGAM Model Analysis

The LiNGAM model assumes linear non-Gaussian distributions to infer causal relationships. Fig. 3 demonstrates that the ESG composite score and social and governance dimensions (S, G) show no significant causal links with financial

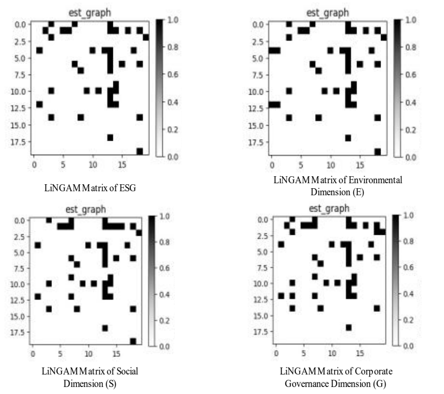

Figure 3 LiNGAM Matrix of ESG and Its Components (E, S, and G)

variables under this model. In contrast, the environmental dimension (E) is significantly influenced by EPS (X4) and pre-tax EPS (X12), indicating that profitability selectively drives environmental sustainability outcomes.

4.1.4 Integrative Insights

Integration of PC, GES, and LiNGAM results provides a robust perspective on ESG–financial relationships. Profitability and earnings capacity consistently emerge as key determinants, particularly for environmental and social dimensions, which are sensitive to both operational performance and liquidity. Corporate governance, however, appears largely shaped by non-financial factors. These findings underscore the need for firms to align financial strategies with sustainable governance practices to improve overall ESG performance.

4.2 Directed Acyclic Graph (DAG) Analyses

DAGs visualize direct causal effects, where arrows indicate causality and coefficients quantify effect magnitude.

4.2.1 ESG Composite Score

Fig. 4 illustrates positive causal relationships between the ESG composite score (X0) and multiple financial variables. ROE (X5) and return on operating assets (X6) reflect capital and asset utilization efficiency, enabling effective investment in ESG initiatives. Net asset value per share (X10) signals financial stability, supporting long-term ESG planning and reducing the risk of interrupted sustainability investments.

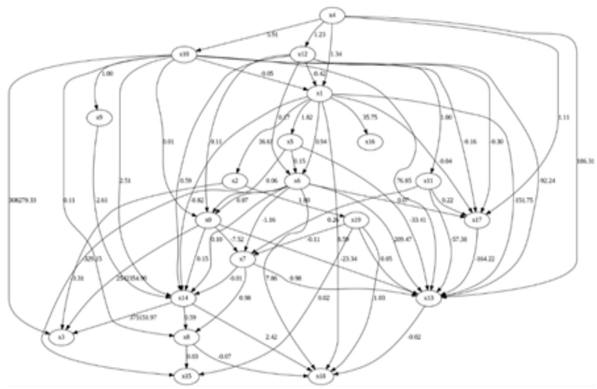

Figure 4. Directed Acyclic Graph (DAG) of ESG

Pre-tax EPS (X12) exerts a notable causal effect (coefficient = 0.11), indicating that profitability allows firms to implement sustainability initiatives, including carbon management, human rights programs, and enhanced governance transparency.

4.2.2 Environmental Dimension (E)

Fig. 5 shows the environmental dimension score is positively influenced by EPS (X4), ROE (X5), return on operating assets (X6), net asset value per share (X10), and pre-tax EPS (X12), with X12 having the strongest effect (coefficient = 1.1). Net asset value per share (X11)

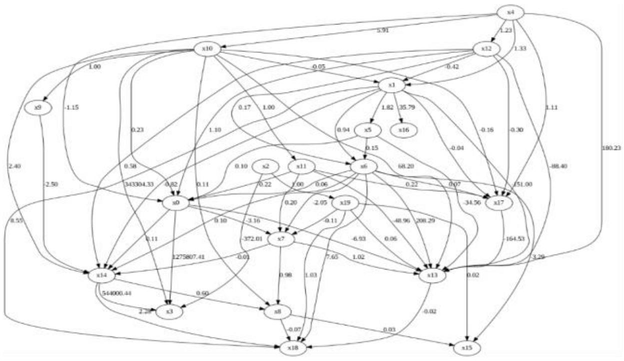

Figure 5. Directed Acyclic Graph (DAG) of the Environmental Dimension Score (E)

negatively affects environmental performance (coefficient = -0.22), suggesting that certain capital allocations may constrain investments in environmental initiatives. These results indicate that profitability, asset efficiency, and capital allocation decisions are critical for improving environmental sustainability performance.

4.2.3 Social Dimension (S)

Fig. 6 illustrates positive causal effects of return on operating assets (X5), quick ratio (X8), and debt ratio (X14) on social scores, each with a coefficient of 1.0.

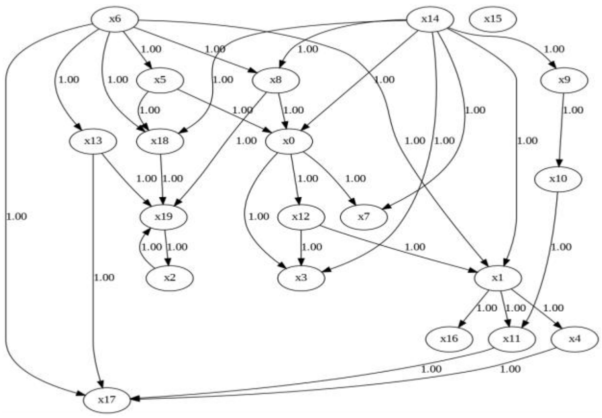

Figure 6 Directed Acyclic Graph (DAG) of the Social Dimension Score (E)

Operational efficiency, short-term liquidity, and a balanced leverage structure support the firm’s capacity to engage in stakeholder-focused social initiatives, including employee welfare, community engagement, and transparent reporting.

4.2.4 Corporate Governance Dimension (G)

Figure 7 shows that corporate governance scores are positively influenced by return

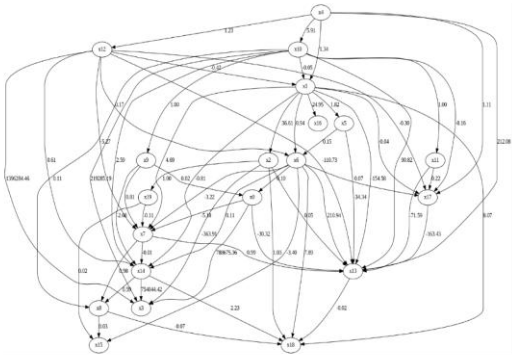

Figure 7 Directed Acyclic Graph (DAG) of the Corporate Governance Dimension Score (E)

on operating assets (X6) and book value per share (X9), with X6 exerting the strongest effect (0.1). These results suggest that effective asset utilization and a solid capital structure enhance governance performance, improve shareholder confidence, and facilitate regulatory compliance.

4.3 Identification of Causal Effects

Causal effects were estimated using both back-door and front-door criteria. The back-door criterion controls for confounders, while the front-door criterion incorporates mediating variables to capture indirect pathways.

Back-door analysis confirms that ROA, EPS, ROE, return on operating assets, net asset value per share (A), and pre-tax net income per share significantly influence ESG performance. ROA affects ESG after controlling for X10 and X12; ROE remains significant after controlling for ROA; return on operating assets retains significance after adjusting for ROA, ROE, and X12. EPS demonstrates a direct causal effect independent of confounders.

Front-door analysis identifies mediators-including gross profit margin, ROA, ROE, net asset value per share, and EPS-through which EPS indirectly impacts ESG scores, indicating that corporate financial structure and profitability jointly shape ESG performance.

Notably, short-term liquidity and leverage indicators (e.g., current ratio, quick ratio, debt ratio) do not exhibit significant causal effects, suggesting that long-term profitability and operational efficiency are more influential in determining ESG outcomes.

4.4 Estimation and Robustness

Linear regression and three robustness tests-Data Subset Refuter, Random Common Cause, and Placebo Treatment-were employed to validate causal estimates.

4.4.1 ESG Composite Score

As shown in Table 1, EPS (0.34) and pre-tax net income (0.29) positively influence ESG ratings, whereas ROA (-0.19) negatively affects ESG, implying a trade-off between profit efficiency and sustainability investment. All robustness tests confirm stable and reliable estimates (p-values > 0.9).

Table 1 Estimation and Refutation Test of ESG

Financial Variable	casual effect	subset	subset p-value	random	random p-value	placebo	placebo p-value
ROA	-0.19	0.19	0.9	0.19	0.94	0.002	0.9
Earnings per Share (EPS)	0.34	0.34	0.64	0.34	0.96	0.0003	0.98
ROE	0.094	0.1	0.74	0.094	0.98	0.0004	0.94
Return on Operating Assets	0.056	0.063	0.42	0.056	1	0.0008	0.92
book value per share (A)	0.038	0.04	0.88	0.038	1	0.0047	0.96
pre-tax net income per share	0.29	0.29	0.8	0.29	0.94	0.005	0.94

Note: *p*-value closer to 1 indicates higher explanatory power and greater predictive reliability.

4.4.2 Environmental Dimension

Table 2 shows that both earnings per share (EPS) and pre-tax net income have a strong positive impact on environmental performance, with coefficients of 0.46 and 1.105, respectively. This suggests that firms with higher profitability are better able to invest in environmentally sustainable practices, possibly because they have more financial resources to allocate toward green initiatives or can afford to implement stricter environmental standards. In contrast, return on assets (ROA) has a small negative effect (-0.018), indicating that efficiency in using assets does not strongly translate into better environmental outcomes. Robustness checks across different model specifications and control variables support these findings, reinforcing the conclusion that overall profitability, rather than operational efficiency, is a key driver of environmental sustainability in firms.

Table 2 Estimation and Refutation Test of the Environmental Dimension Score (E)

Financial Variable	casual effect	subset	subset p-value	random	random p-value	placebo	placebo p-value
ROA	-0.018	-0.02	1	-0.018	0.96	0.9	0.018
Earnings per Share (EPS)	0.46	0.47	0.62	0.46	0.98	-0.003	0.96
ROE	0.21	0.21	0.82	0.21	0.86	0.0064	0.72
Return on Operating Assets	0.013	0.016	0.7	0.013	0.98	0.0015	0.91
book value per share (A)	0.05	0.06	0.78	0.05	0.9	0.0034	0.64
pre-tax net income per share	1.105	1.023	0.76	1.105	0.9	0.003	0.86

Note: *p*-value closer to 1 indicates higher explanatory power and greater predictive reliability.

4.4.3 Social Dimension

ROA (0.3), book value per share B (0.34), and book value per share A (0.5) positively affect social scores in Table 3. Robustness tests confirm statistical significance and absence of spurious effects.

Table 3 Estimation and Refutation Test of the Social Dimension Score (S)

Financial Variable	casual effect	subset	subset p-value	random	random p-value	placebo	placebo p-value
ROA	0.3	0.31	0.86	0.3	0.76	-0.0015	0.3
book value per share (B)	0.34	0.035	0.96	0.034	0.86	-0.0033	0.64
book value per share (A)	0.5	0.52	0.88	0.5	0.86	-0.0035	0.6

Note: *p*-value closer to 1 indicates higher explanatory power and greater predictive reliability.

4.4.4 Corporate Governance Dimension

Table 4 shows that profitability measures positively influence corporate governance scores. EPS (0.28), ROE (0.101), and return on operating assets (0.096) are all associated with stronger governance, likely reflecting the greater resources and controls available to profitable firms. In contrast, book value per share has a minor negative effect, possibly due to capital allocation complexities in more capital-intensive firms. Robustness checks confirm the reliability of these results, highlighting profitability as a key driver of governance quality.

Table 4 Estimation and Refutation Test of the Corporate Governance Dimension Score (G)

Financial Variable	casual effect	subset	subset p-value	random	random p-value	placebo	placebo p-value
ROA	0.0009	0.0012	0.98	0.0009	0.94	0.0034	0.96
Earnings per Share (EPS)	0.28	0.28	0.54	0.28	0.84	0.0013	0.94
ROE	0.101	0.11	1	0.101	0.9	0.0028	0.88
operating return on assets	0.096	0.096	0.58	0.096	0.86	-0.003	0.74
book value per share (A)	-0.08	-0.067	1	-0.08	0.88	0.00035	0.96
pre-tax net income per share	0.024	0.026	0.76	0.024	0.9	-0.0007	0.96

Note: *p*-value closer to 1 indicates higher explanatory power and greater predictive reliability.

4.5 Implications and Contributions

This study provides causal evidence on ESG–financial linkages among Taiwanese listed and OTC firms using PC, GES, and LiNGAM models with DAG-based identification. Profitability indicators—EPS, pre-tax net income, ROE, and return on operating assets—consistently drive ESG outcomes, while liquidity and leverage are less influential. Environmental performance responds mainly to profitability, social performance to operational efficiency and leverage, and governance to asset utilization and capital structure. The findings demonstrate the heterogeneous financial determinants of ESG dimensions and the value of causal AI, offering actionable guidance for firms, investors, and policymakers and supporting ESG frameworks that emphasize long-term financial sustainability.

5. CONCLUSION

This study applies Causal AI via DoWhy, supported by PC, GES, and LiNGAM algorithms, to identify financial variables that causally shape ESG ratings for listed and OTC firms in Taiwan. The results provide dimension-specific insights with both theoretical and practical relevance.

Profitability and earnings capacity are the strongest causal determinants. EPS and pre-tax net income per share positively affect overall ESG ratings, particularly the environmental dimension, indicating that stable earnings enable firms to invest in sustainability initiatives and comply with regulatory standards. ROOA positively influences social and governance dimensions, reflecting the role of efficient asset management in supporting stakeholder engagement, internal controls, and governance quality. NAVPS strengthens governance outcomes, while liquidity and leverage measures exhibit weak or inconsistent effects, acting as contextual factors rather than primary drivers.

The study makes three contributions. First, it reverses the traditional ESG–finance lens by showing how financial characteristics drive ESG ratings, highlighting that ratings encode firms' financial resilience. Second, it demonstrates the value of Causal AI in ESG research: combining discovery algorithms with the DoWhy workflow (*model, identify, estimate, refute*) enhances interpretability, robustness, and counterfactual understanding. Third, by examining Taiwanese firms under a mature ESG regime, it provides evidence from an emerging yet sophisticated market, showing that ESG ratings are grounded in observable financial fundamentals rather than symbolic compliance.

For managers, investors, and policymakers, the findings emphasize that ESG performance depends on sustainable earnings, efficient asset use, and financial solidity, not merely liquidity or low leverage. Causal AI thus offers actionable guidance for corporate strategy, investment decisions, and policy design, while establishing a methodological benchmark for future research on the financial foundations of sustainable enterprise.

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