The impact of the Green Wave on the Financial Performance of the Shipping Industry

By

Szu-Yu Chen

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Thesis Advisor：

Dr. Alex Chung
Dr. Feng-Ming Tsai
Dr. Tzu Ya Ho

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1. Introduction

1.1 Research Background and Motivation

In recent years, the issue of global climate change has become more serious, leading governments, companies, and financial markets to pay more attention to sustainable development. ESG (Environmental, Social, and Governance) has gradually moved from being just part of corporate social responsibility to becoming a major way to evaluate how well a company manages risk, develops sustainable strategies, and performs financially in the long run (MSCI, 2023). This trend can be seen not only in stricter rules and policies, but also in how markets operate and how investors make decisions.

From a policy perspective, many regions have started to introduce rules that require ESG information disclosure and carbon emissions control. For example, the EU launched the Sustainable Finance Disclosure Regulation (SFDR), asking financial institutions to explain how they handle sustainability risks (European Commission, n.d.). In 2024, the U.S. SEC passed the Climate Risk Disclosure Regulation, which asks listed companies to report climate risks, emissions, and governance practices (U.S. SEC, 2024). In Asia, some financial regulators have introduced climate stress tests and green finance plans. These changes show that ESG has become a key requirement for international companies. High-emission industries such as shipping, energy, steel, and cement are especially targeted. The shipping industry, responsible for around 80% of global trade transport, also causes over 2–3% of carbon emissions. To meet the IMO's goals, new rules like the sulfur limit (since 2020), Carbon Intensity Indicator (CII), and Energy Efficiency Existing Ship Index (EEXI) have been introduced. These policies force shipping companies to improve their technologies and operations or face penalties or loss of business.

On the market side, ESG is also becoming more important. Many large global companies, such as Walmart, Apple, and Unilever, not only follow ESG rules themselves, but also require their suppliers to do the same. Apple (2023), for example, stated that all Tier 1 and Tier 2 suppliers must report their emissions and support its Scope 3 carbon reduction goals. As a result, companies that fail to meet ESG standards may lose business opportunities. In this environment, shipping companies that cannot provide low-carbon transportation solutions may find it difficult to survive in the market.

Investors are also taking ESG seriously. A report by MSCI (2023) shows that 37% of institutional investors include ESG risk scores in their investment decisions. Firms with higher ESG ratings are more likely to get green financing, attract long-term capital, and be included in passive funds. Research (Albuquerque et al., 2020; Broadstock et al., 2021) has found that during uncertain times, like the COVID-19 crisis, companies with high ESG risk scores tend to show better risk control and more stable asset performance. This suggests that good ESG practices can create real economic value.

However, there are still doubts about whether ESG always brings financial benefits. Some researchers argue that ESG ratings have problems like inconsistent data and different evaluation methods (Berg et al., 2022). Also, ESG-related actions often lead to higher short-term costs—such as spending more on compliance, human resources, and reporting (Demers et al., 2021). According to Gibson et al. (2021), the financial effects of ESG can vary a lot depending on the industry, and in sectors like shipping, energy, or heavy industry, the results can even be negative.

The shipping industry has special characteristics. It is very capital- and cost-intensive, sensitive to oil prices, and hard to adjust quickly. It also operates internationally, so it must deal with many kinds of regulations, exchange rates, and market conditions. At the same time, pressure from ESG rules and customer expectations is increasing. Even though many shipping companies now include ESG topics in their reports, it is unclear whether these ideas have truly helped improve business strategy or financial results.

If ESG continues to be promoted as a key reason for stock performance or market success, but there is no clear financial impact in certain industries, it may mean there is a gap between ESG expectations and real outcomes. It could also show that some sectors, like shipping, have not yet completed their ESG transition. Therefore, it is meaningful to study how ESG is connected to financial results (such as stock returns and operating expenses) in carbon-intensive industries like shipping.

This study focuses on U.S.-listed shipping companies, including different sub-sectors like tankers, bulk carriers, and cruise lines. It uses ESG risk scores, financial data, and stock prices to build regression models and analyze the relationship between ESG and (1) stock performance and (2) cost indicators such as cost of revenue ratio and operating expense ratio. The early results show that ESG is not strongly related to stock returns or cost changes in this industry, which is different from the positive findings in many other fields.

This research hopes to test whether ESG risk scores really add financial value in practice, especially in industries that are under strong pressure to transform. It also tries to reflect on the ESG rating system and provide a more realistic reference for investors, industry leaders, and policymakers.

1.2 Research Objectives

Most previous studies on ESG (Environmental, Social, and Governance) have focused on its positive outcomes, such as enhancing firm value, lowering capital costs, and building investor trust. However, it remains unclear whether these benefits apply equally across all industries, especially in high-emission and transport-focused sectors like shipping. This study focuses on shipping-related industries listed in the U.S., and aims to investigate the relationship between ESG performance and financial outcomes, including cost structure and stock returns, using an empirical approach.

The specific objectives of this study are:

1. **To examine whether ESG risk scores can predict stock returns in the shipping industry**

This objective tests whether ESG Risk Scores significantly influence stock returns, while controlling for common financial indicators such as Return on Assets (ROA), Return on Equity (ROE), and market capitalization (MarketCap).

2. **To analyze whether ESG performance affects Operating Expenses and expense structure**

This includes regression analysis on variables like the Cost of Revenue Ratio and Operating Expense Ratio to determine if there is a statistical relationship between ESG risk scores and actual operating expenses.

3. **To compare financial performance between high and low ESG performers**

A T-test is used to compare key financial and risk indicators between the top 25% and bottom 25% of companies based on ESG performance, in order to see if ESG creates meaningful differences between groups.

4. **To test whether ESG risk scores reflect a company's financial structure**

This objective evaluates whether ESG ratings are associated with fundamental financial characteristics, such as capital structure (debt-to-equity ratio), profitability (ROA, ROE), and firm size (log of MarketCap), to see if ESG has financial signaling power.

By conducting these analyses, the study aims to provide a more balanced, data-driven perspective on ESG, especially in industries where ESG effects may be less obvious or harder to measure. It also seeks to contribute to the academic and practical understanding of ESG investment by focusing on a sector that is often overlooked in current research.

1.3 Research Questions and Hypotheses

In recent years, ESG (Environmental, Social, and Governance) has become an increasingly important topic in global investment and corporate governance. Many studies suggest that strong ESG performance may bring financial benefits to companies, such as lower capital costs, better investment returns, and reduced stock price volatility. However, it is still unclear whether these positive effects apply to all industries, especially in sectors like shipping, which are both carbon-intensive and capital-intensive.

This study focuses on shipping-related companies listed in the United States and aims to explore the relationship between ESG performance and key financial indicators, including Operating Expenses, stock returns, and financial structure. The following research questions and hypotheses are proposed and tested through empirical analysis:

Research Question 1:

Can ESG performance help predict a company's stock return?

This question examines whether ESG Risk Scores can significantly influence stock price returns when controlling for other common financial indicators such as ROA, ROE, and Market Capitalization.

Research Question 2:

Is ESG performance associated with a company's Operating Expenses?

This part of the study looks into whether companies with different ESG risk scores show noticeable differences in their Cost of Revenue Ratio and Operating Expense Ratio.

Research Question 3:

Does ESG performance reflect systematic differences in companies' financial structures?

To explore whether ESG risk scores relate to a firm's size, profitability, and capital structure, this study compares key financial metrics (such as ROA, ROE, P/E ratio, D/E ratio, and Market Cap) between high and low ESG groups.

Research Question 4:

Does ESG grouping lead to statistically significant differences in financial performance?

Using an independent samples T-test, this question tests whether the top 25% (high ESG group) and bottom 25% (low ESG group) of companies show significant differences in financial indicators.

1.4 Research Contribution

This study uses U.S.-listed shipping-related companies as research samples to explore the relationship between ESG performance and financial performance, including cost structure and stock return. Compared to past studies that mainly focus on the positive effects of ESG, this research offers unique contributions in terms of sample selection, research variables, and methodology. The main contributions are as follows:

1. **Filling the research gap in carbon-intensive industries**

Most existing ESG studies focus on sectors like manufacturing, consumer goods, or high-tech industries. There is still limited empirical research on carbon-intensive sectors such as shipping and energy transport. By examining U.S. companies involved in bulk shipping, tankers, cruise lines, logistics, and energy transportation, this study helps to understand how ESG works, or fails to work, in industries that are highly polluting but often overlooked.

2. **Analyzing both costs and returns at the same time**

Unlike studies that only look at financial returns or market value, this research includes both the Cost of Revenue Ratio and Operating Expense Ratio, along with stock return. It aims to explore whether ESG performance affects company value through changes in operational efficiency. In addition, it uses residual analysis to detect any indirect effects ESG may have on stock returns.

3. **Highlighting structural differences between ESG groups**

By dividing the sample into high ESG (top 25%) and low ESG (bottom 25%) groups, and applying T-tests to key financial variables like ROE, Market Cap, and D/E ratio, this study shows how ESG may be related to company size and capital structure. This kind of group-based analysis has rarely been used in previous ESG research.

4. Providing realistic reflection on ESG investment expectations

The findings suggest that in the shipping industry, ESG performance may not have a strong or consistent link to Operating Expenses or returns. This implies that both investors and companies should carefully evaluate the real-world impact and cost of ESG strategies. By offering a perspective of "limited effect," this study helps narrow the gap between ESG theory and business practice.

2. Literature review

2.1 ESG Assessment and Theoretical Basis

ESG (Environmental, Social, and Governance) has become a key indicator for evaluating corporate sustainability and non-financial risks. As global investors have increasingly focused on sustainable development, corporate responsibility, and long-term value creation, ESG has gradually been adopted as a standard by major rating agencies, passive investment funds, and regulators (MSCI, 2023). ESG risk scores bring together company performance in three areas: environmental (e.g., carbon emissions, resource use), social (e.g., labor rights, product safety), and governance (e.g., board structure, shareholder rights). These scores provide a quantitative reference for investors and policy-makers to assess a company's overall sustainability.

The theoretical foundation of ESG is closely related to Stakeholder Theory (Freeman, 1984), which argues that companies should not only focus on maximizing shareholder profits but also consider the interests of other stakeholders, such as employees, customers, suppliers, local communities, and the environment. Another relevant framework is the Resource-Based View (RBV), which suggests that firms can gain long-term advantages by embedding ESG practices into their core operations. By doing so, companies can develop intangible assets like reputation and resilience, which help manage risks and support competitiveness (Hart, 1995).

Empirical studies in the early stages generally support a positive relationship between

ESG performance and corporate outcomes. A meta-analysis by Friede et al. (2015) found that nearly 90% of studies reported a non-negative link between ESG and financial performance. Giese et al. (2019) also noted that companies with higher ESG ratings tend to experience lower stock price volatility, especially during times of market uncertainty. This suggests that ESG can reduce systemic risk and potentially improve investor confidence and capital cost structures.

However, more recent research shows mixed results. Al Azizah and Haron (2025) found that the effect of ESG on operational efficiency varies across industries, and in carbon-intensive sectors, the impact is often weak or even negative. Sandu (2024), using European data, observed that ESG can reduce stock price volatility, but this effect is limited to specific industries. In sectors like energy and raw materials, ESG showed no clear link with returns or risk. Similarly, Nian and Said (2024), in a systematic review, highlighted that the financial impact of ESG remains controversial in high-pollution industries, showing that its influence does not easily transfer across all sectors.

In conclusion, while ESG has become a mainstream consideration in investment and governance, its actual financial impact still depends on industry characteristics, the depth of ESG implementation, and market maturity. For capital-intensive and high-emission sectors like shipping and energy transportation, it is still uncertain whether ESG risk scores reflect real sustainable practices or simply formal compliance. This question is at the center of this study's investigation.

2.2 The Relationship Between ESG and Corporate Operational Performance

The ESG (Environmental, Social, and Governance) framework has gradually evolved from a secondary image-building strategy into a central part of corporate management. As ESG becomes more integrated into business operations, it is no longer just about social responsibility or ethical concerns; it is increasingly viewed as a factor that can influence a company's operating efficiency and cost structure. Many researchers have studied whether ESG performance is linked to real improvements in cost control, resource allocation, and overall operating performance, and a growing body of theory and empirical evidence has emerged.

From a theoretical perspective, ESG can influence Operating Expenses through multiple channels. On the environmental side (E), firms that actively adopt carbon neutrality goals or energy-saving technologies may lower their energy consumption and reduce raw material waste, leading to optimized variable costs in the long term. The social dimension (S) includes fair treatment of employees, stable supply chains, and strong customer relationships. These elements can reduce internal conflicts, lower employee turnover, and improve workplace productivity. In the governance aspect (G), strong transparency, good internal controls, and effective board structures can prevent fraud and agency problems, reducing the need for extra oversight and lowering associated costs. Overall, the key idea is that when ESG principles are truly implemented into a company's daily operations, they can become a real driver of cost reduction and efficiency gains.

Empirical studies generally support the idea that ESG contributes positively to operational outcomes. Friede et al. (2015), in a large review of nearly 2,000 studies, found that over 90% showed either positive or neutral relationships between ESG and financial performance. Giese et al. (2019) further reported that companies with strong ESG risk scores had more stable operating cash flows, suggesting better financial planning and resource use. Liang et al. (2022), looking from the perspective of dynamic capabilities, argued that ESG practices improve a company's ability to adapt to external changes, increasing long-term operational resilience. Similarly, Albuquerque et al. (2020) found that during the COVID-19 crisis, firms with high ESG ratings experienced smaller fluctuations in costs and risks, making them more stable in uncertain environments.

However, more recent studies have raised questions about whether ESG's benefits apply across all industries. In particular, companies with unique capital structures or high carbon output (such as those in shipping, aviation, or raw materials)may not experience the same advantages. Sandu (2024) found that in sectors like energy and mining, ESG risk scores were not clearly linked to lower Operating Expenses. Al Azizah and Haron (2025) also showed that in industries like shipping and air transport, ESG performance had little to no effect on cost efficiency—and in some cases, even had negative impacts. These findings challenge the idea of ESG as a one-size-fits-all strategy and suggest that its effects depend heavily on industry context, regulations, and implementation ability.

Another important issue is the inconsistency in ESG risk scores themselves. Different rating agencies use different criteria, data sources, and weighting systems, which often results in the same company receiving very different ESG risk scores (Berg et al., 2022; Gibson et al., 2021). This scoring noise weakens the predictive power of ESG ratings, especially in capital-intensive sectors. Many companies in these industries may announce ESG plans, but without strong enforcement or tracking mechanisms, these commitments may not lead to actual operational improvements—raising concerns about whether ESG is just a branding tool rather than a real performance driver.

In summary, while ESG has strong theoretical support and is often linked to positive outcomes, its impact on operational performance is not consistent. This is especially true in traditional or high-emission industries like shipping, energy, and heavy manufacturing. The effectiveness of ESG depends on how deeply it is embedded into a company's strategy and day-to-day operations. For capital-intensive sectors facing increasing compliance pressure, more research is needed to determine whether ESG risk scores truly reflect sustainable practices or are mainly used for external image management. This forms the basis for this study's focus on the relationship between ESG and operating performance in the shipping industry.

2.3 The Role of ESG in High-Pollution Industries (e.g., Shipping)

Industries such as shipping, energy, and raw material extraction are naturally at odds with core ESG indicators due to their structural characteristics. These sectors are typically capital-intensive, heavily reliant on fossil fuels, and responsible for high levels of carbon emissions—factors that often place them at a disadvantage in ESG ratings. However, precisely because of their significant environmental and social externalities, these industries have become a key focus for policymakers, investors, and sustainability advocates. Understanding the role that ESG plays in such high-pollution sectors is therefore essential for evaluating their potential for sustainable development and financial transformation.

2.3.1 ESG Challenges: Institutional Contradictions in High-Pollution Industries

One of the major challenges in applying ESG principles to high-pollution sectors like shipping is the so-called "transition gap." Most shipping companies still rely on diesel and heavy fuel oil to power their fleets, and the cost of transitioning to cleaner energy alternatives remains high. As a result, it is difficult to achieve substantial carbon reductions in the short term. Although the International Maritime Organization (IMO) has implemented low-sulfur fuel regulations and greenhouse gas monitoring since 2020, many shipping firms still face technical bottlenecks and financial limitations, which delay progress toward full ESG compliance. These structural challenges often mean that ESG risk scores in the shipping sector reflect formal "compliance intentions" rather than meaningful reductions in emissions. This weakens the reliability and impact of ESG assessments.

In addition, ESG scoring in this industry depends heavily on voluntary and non-financial disclosures. Current rating systems often oversimplify or inadequately assess the environmental impacts of shipping activities. For instance, some rating agencies treat the signing of the Poseidon Principles as a positive ESG indicator without evaluating whether a company has actually improved its emission intensity. In such cases, ESG risk scores may not reflect real sustainability outcomes, leading to concerns about greenwashing and raising doubts about the accuracy of ESG as a measurement tool in high-emission sectors.

2.3.2 Market Effects of ESG Ratings in High-Pollution Industries

Empirical research has shown that the market response to ESG in high-pollution industries tends to be weaker or more unstable compared to other sectors. For example, La Torre et al. (2020) found that among heavy industry and energy companies in the Eurostoxx 50 index, ESG risk scores did not significantly predict stock returns. Similarly, Ardia et al. (2023), analyzing firms in the S&P 500, observed that while carbon-intensive companies have improved their ESG risk scores, this improvement does not necessarily lead to better alignment with market risk factors—especially in terms of sensitivity to momentum and growth factors. This suggests that ESG characteristics may not consistently translate into reliable return factors in these industries.

In addition, a large cross-national study by Alves, Krüger, and van Dijk (2024) confirmed that in cases where ESG disclosure systems are underdeveloped and industry carbon intensity is high, the correlation between ESG risk scores and stock prices becomes significantly weaker. Even when using an average of multiple rating agencies to reduce bias, the study found it difficult to identify a stable reward pattern for ESG in high-emission sectors. These findings highlight that the market effects of ESG are highly context-dependent and may not be easily generalized across industries.

2.3.3 ESG's Functional Shift and Policy-Driven Role

Although the financial impact of ESG varies across sectors, in high-pollution industries such as shipping and heavy manufacturing, the role of ESG has gradually shifted—from a tool for financial return prediction to a tool for promoting industrial transformation. Institutional investors are increasingly using ESG principles not just for portfolio selection (e.g., exclusion strategies) but also for active engagement, encouraging firms to disclose emissions data and commit to reduction targets.

At the same time, the financial sector has introduced policy tools such as the Poseidon Principles, which tie lending conditions and credit evaluations to ESG-related disclosures. This mechanism indirectly increases pressure on companies to align with sustainability goals. Therefore, even if ESG does not yet bring clear short-term financial rewards in these industries, it may still influence long-term capital flows and push companies toward structural change.

2.3.4 Summary and Implications of This Study

In conclusion, the role of ESG in high-pollution industries can be understood on two levels: the signal function and the inducement function. The signal function, where ESG serves as a meaningful indicator for market performance, is often weakened by inconsistent data, limited transparency, and implementation gaps. In contrast, the inducement function is becoming more important, as ESG is increasingly used to guide regulations, reshape financial incentives, and respond to public pressure.

In the case of the shipping industry, ESG risk scores not only represent a company's commitment to sustainability but also reflect how well it responds to regulatory and environmental challenges such as carbon neutrality. Based on this understanding, this study focuses on the U.S. shipping sector to examine whether ESG risk scores still carry useful implications for market performance and risk management in a context where ESG adoption is both complex and evolving.

2.4 ESG, Risk, and Market Response

Whether ESG performance can effectively reflect a company's risk exposure and how the market prices that risk has become a core topic in the field of sustainable finance. Unlike earlier research that mainly focused on financial performance, recent literature places greater emphasis on ESG's potential role as a market risk management tool, especially in terms of its ability to serve as a "risk buffer" and contribute to "market stability" during periods of abnormal events or high volatility.

From a theoretical perspective, the Efficient Market Hypothesis (EMH) suggests that if ESG-related information reflects a firm's underlying risk, then market prices should rapidly adjust to incorporate this risk signal. Similarly, based on extensions of the Capital Asset Pricing Model (CAPM), such as the Fama-French multi-factor model, if ESG functions as a systematic risk factor, it should have predictive power for a company's beta (β) and risk premium.

On the empirical side, Albuquerque et al. (2020) treated the COVID-19 crisis as a natural experiment and found that firms with high ESG performance experienced significantly lower return volatility under extreme market conditions, demonstrating strong risk-mitigation capacity. Engelhardt et al. (2021) further observed that high ESG portfolios attracted greater capital inflows during periods of market withdrawals, revealing a safe-haven effect. Similarly, Broadstock et al. (2021) provided evidence that ESG investments help buffer against systemic risk.

However, such risk protection is not universally observed across all industries or firm types. Ardia et al. (2023), in a comparison between high-carbon ("brown") and low-carbon ("green") firms, found that high-carbon firms are more sensitive to momentum factors and exhibit higher volatility, suggesting that ESG may not function reliably as a risk control mechanism in such companies. Furthermore, a large-scale cross-country study by Alves, Krüger, and van Dijk (2024) found that even after controlling for country and industry factors, the relationship between ESG Risk Scores and market risk remains inconsistent, highlighting ESG’s limited role in risk pricing.

From the perspective of investor reaction, Zhou and Zhou (2022) found that ESG can help stabilize market confidence during short-term event-driven risks. However, the noise and inconsistency in ESG scoring systems remain major obstacles. Berg et al. (2022) and Gibson et al. (2021) both pointed out that different rating agencies often assign highly divergent scores to the same company, making it difficult for markets to rely on ESG Risk Scores as a consistent basis for pricing risk. This issue of "rating noise" may also lead to delayed or misinformed investor behavior.

In terms of measuring corporate risk exposure, some studies use indicators such as the Sharpe ratio or beta (β) coefficient. According to the model proposed by Avramov et al. (2022), the higher the uncertainty in ESG ratings, the weaker their predictive ability for risk; only in cases where ESG assessments are relatively consistent does ESG show a statistically significant relationship with β. However, this conclusion does not hold across cross-national samples. Alves et al. (2024) found that ESG effects on β vary widely across regions, indicating unstable market responses.

On the other hand, some scholars view ESG as a proxy for creditworthiness. Melas et al. (2017) found that companies with high ESG performance tend to be positively associated with factors such as low volatility and strong quality, possibly due to better governance structures and greater transparency, resulting in more favorable risk-return profiles. However, these associations often overlap with traditional risk factors such as firm size and value, making it difficult to isolate ESG's independent effect on risk in empirical research.

In summary, the role of ESG as a signal for risk and market response remains subject to debate. On the one hand, ESG may act as a buffer under extreme conditions, but its effectiveness is constrained by factors such as industry structure, score consistency, and disclosure systems. On the other hand, in the absence of standardized rating systems and sufficient transparency, ESG is unlikely to serve as a stable input for risk pricing. While these challenges may be even more pronounced in capital-intensive and high-emission sectors like shipping, this issue is not the primary focus of the current study and is discussed here only as background context.

2.5 Contributions and Differences from Existing Literature

Although the concept of ESG investing has been widely integrated into mainstream financial markets and regulatory frameworks, most existing empirical studies still focus on industries with high information transparency, such as technology, finance, and manufacturing

(Friede et al., 2015; Giese et al., 2019). In contrast, there is still a lack of comprehensive research on carbon-intensive, high-pollution industries that face strong compliance pressures—such as shipping, energy, and raw materials—particularly regarding how ESG Risk Scores relate to Operating Expenses, capital structure, and market returns. To date, academic consensus on these issues remains limited.

The first contribution of this study lies in its focus on U.S.-listed shipping-related companies, addressing a gap in the ESG literature concerning this specific industry. As a high-pollution sector under increasing regulatory pressure from international carbon reduction agreements, the shipping industry serves as a critical testing ground for the real-world impact of ESG implementation. However, most prior studies focus on environmental disclosure or policy compliance, or use surveys to understand investor preferences regarding ESG. Few have conducted quantitative, data-driven analysis of the relationship between ESG and financial performance. In contrast, this study integrates operational data with ESG Risk Scores from Sustainalytics, using objective financial indicators to evaluate the actual effectiveness and limitations of ESG in the shipping sector.

The second contribution lies in the methodological design, which is grounded in robust statistical reasoning and logical consistency. This research builds multivariate regression models using ordinary least squares (OLS) to examine the relationship between ESG Risk Scores and firm-level indicators such as annual returns and Operating Expenses. It also employs independent samples T-tests to assess whether there are significant differences between high and low ESG score groups in financial variables like ROE, MarketCap, and D/E ratio—highlighting potential links between ESG performance, firm size, and capital structure. Furthermore, interaction term analysis with market-type dummy variables is used to explore whether ESG behaves differently across market contexts. A logistic regression (Logit) model is also introduced to test whether ESG performance can help predict extreme return scenarios or tail-risk exposure, deepening the discussion on ESG's role in risk identification.

The third contribution of this study is a critical re-evaluation of the "universally positive ESG hypothesis" from an empirical perspective. Among the sampled shipping companies, the relationships between ESG performance and both Operating Expenses and stock returns were generally not statistically significant and lacked consistent direction. This suggests that ESG Risk Scores may not function as stable predictors of performance, and their effectiveness may be limited or disrupted by industry-specific factors, institutional constraints, or inconsistent market expectations. These findings provide an important reminder to both practitioners and policymakers: ESG should not be assumed to serve as a reliable investment signal in every sector. Its actual influence depends heavily on the industry environment and the depth of ESG implementation, and its role as a capital incentive or risk buffer should be carefully evaluated.

In summary, through its industry-specific focus, rigorous methodology, and performance-risk evaluation, this study fills an important empirical gap in ESG research related to the shipping sector. It offers concrete observations and theoretical reflections on both the benefits and limitations of ESG in carbon-intensive, capital-heavy industries, and provides practical insights for future policy development and ESG evaluation frameworks that are grounded in real-world industry dynamics.

3. Research Design and Methodology

To investigate whether ESG performance in carbon-intensive industries possesses financial predictive power and market explanatory strength, this study adopts an empirical research design and selects U.S.-listed shipping-related companies as the analytical sample. The shipping industry is characterized by high carbon emissions, high capital intensity, and strict regulatory compliance. However, existing literature provides relatively limited empirical evidence regarding ESG effectiveness in such industries, often facing challenges such as inconsistent measurement standards and divergent results.

To address these research gaps, this study applies a systematically layered empirical strategy, combining structured sample construction with multiple statistical models to examine whether ESG risk scores can effectively predict firm-level differences in operational cost control, stock returns, and risk exposure. Special attention is given to the practical context of the U.S. shipping industry.

To enhance the rigor and explanatory power of the empirical findings, this study adopts a segmented multi-model approach. It first employs OLS regression to test the direct effects of ESG on financial performance, then introduces a two-stage residual model to examine potential indirect effects. In addition, it conducts ESG risk heterogeneity group tests and applies a Logit model to analyze market reactions to ESG deterioration events. This multi-model design facilitates cross-validation under different estimation assumptions, avoiding over-reliance on a single model and thereby strengthening the robustness and persuasiveness of the research conclusions.

3.1 Research Subjects and Sample Selection

This study focuses on publicly traded shipping-related companies listed in the United States, aiming to explore the statistical relationship between ESG performance and firms' Operating Expenses and stock returns. While most existing ESG studies concentrate on industries such as technology, manufacturing, and finance, relatively few have empirically examined high-pollution, carbon-intensive industries like shipping. As such, this research specifically targets firms facing regulatory pressures and sustainability transition challenges, in order to better assess the industry heterogeneity of ESG effects.

The sample was initially drawn from the Clarksons Shipping Intelligence Network, using the "Publicly Listed Companies" database. By filtering for the geographic category "United States," an initial pool of 45 shipping-related firms listed on U.S. exchanges was obtained. To ensure data consistency and completeness, a stricter selection process was applied based on the following criteria, resulting in a final sample of 18 companies:

1. **Complete Financial Data**: Companies must have continuously disclosed monthly financial data throughout the study period (2019–2024), including key metrics such as stock price, revenue, Operating Expenses, and total assets.

2. **Available ESG Ratings**: Each company must have ESG Risk Scores provided by Sustainalytics for every year during the research period.
3. **Consistent ESG Reporting**: Companies are required to publish an annual ESG or sustainability report (Sustainability Report or CSR Report) for each year. These reports must disclose Scope 1 (direct operational) carbon emissions and clearly indicate whether alternative fuel strategies (e.g., biofuels, LNG) are being adopted. This reflects each firm's depth of ESG practice and response to carbon risk.
4. **No Missing Data or Delisting Records**: To avoid estimation bias, companies with significant data gaps or delisting events during the study period were excluded. The selected sample features high data completeness, which helps improve the credibility and stability of the model estimations.

After applying these criteria, only 18 companies (approximately 40% of the initial sample) were retained, reflecting the ongoing challenges in ESG transparency and disclosure consistency within the shipping industry. The resulting dataset forms a **balanced panel**, offering high data consistency and time continuity. This structure enhances the efficiency and interpretability of regression models and strengthens the validity and representativeness of the sample.

Moreover, the stringent sample criteria underscore the issue of ESG data availability in specific industries, further reinforcing the empirical relevance and methodological rigor of this study.

3.2 Variable Definitions and Measurement

This study builds its empirical model using multiple variables categorized into four types: dependent variables, independent variables, mediating variable, and control variables. Except for ESG data, which is recorded annually, all financial and market-related variables are compiled on a monthly basis. The unit of observation is firm-month, covering the period from 2019 to 2024.

3.2.1 Dependent Variables

1. **Stock Return**

   This variable measures the monthly stock price performance of each firm, including dividends. The data is collected from Yahoo Finance. Annual return is approximated using 12-month cumulative returns. For subsample analysis and logistic regression models, event-window returns (e.g., average return over three days post-event) are also used.

2. **Cost Indicators**

   Two cost-related indicators are used as dependent variables, with data obtained from Yahoo Finance:

(1) **Cost of Revenue Ratio**: Measures direct operational costs (e.g., fuel, crew wages, port fees) per unit of revenue, indicating operating efficiency.

(2) **Operating Expense Ratio**: Calculated as Operating Expenses divided by Total Revenue, representing administrative and managerial cost pressure.

The study finds that compared to the Cost of Revenue Ratio, the Operating Expense Ratio shows stronger explanatory power in both the logistic and second-stage regression models, and is therefore used as a primary cost performance variable.

3.2.2 Independent Variables

1. ESG Risk Score (Total Score)

The core independent variable is the firm's ESG Risk Score, provided by Sustainalytics, a subsidiary of Morningstar. This rating captures the degree of ESG-related financial risk that remains unmanaged by a company. It integrates two dimensions: a company's exposure to material ESG issues and its management capacity to address them. The total ESG Risk Score is calculated using the formula:

$$ESG\ Risk\ Score = Exposure \times (1 - Management\ Score)$$

where "Exposure" reflects inherent sector- and business-specific ESG risk, and "Management Score" evaluates a company's preparedness and response. Higher scores indicate **greater ESG risk**. Companies are classified into five risk categories: Negligible (0–10), Low (10–20), Medium (20–30), High (30–40), and Severe (>40).

The rating methodology evaluates up to 20 issue areas across **five pillars**, including Environmental, Social, Governance, Corporate Governance, and Idiosyncratic Risk. Sustainalytics ratings are recognized by institutional investors, ESG-focused funds, and regulators for their transparency, global comparability, and extensive coverage of over 14,000 companies across industries.

This risk-based scoring system is particularly suitable for capital-intensive and high-pollution industries like shipping, where ESG performance tends to reflect compliance and risk control rather than proactive sustainability value creation.

2. Environmental Feature Variables

Two ESG-related indicators are added to explain differences in ESG Risk Scores. These are based on companies' annual ESG or sustainability reports:

(1) **Scope 1 Carbon Emissions**: Indicates direct carbon emissions generated during a firm's operations. This is a key environmental metric that firms can actively manage. The value is reported in metric tons.

(2) **Dummy_Biofuel**: A binary variable coded as 1 if a company explicitly reports the use of biofuels as an alternative to conventional fuel in its ESG/sustainability reports, and 0 otherwise. This acts as a proxy for sustainability transition efforts.

3.2.3 Mediating Variable

Whether ESG performance can effectively reflect a company's risk exposure and how the market prices that risk has become a core topic in the field of sustainable finance. Unlike earlier research that mainly focused on financial performance, recent literature places greater emphasis on ESG's potential role as a market risk management tool, especially in terms of its ability to serve as a "risk buffer" and contribute to "market stability" during periods of abnormal events or high volatility.

3.2.4 Control Variables

The following control variables are included to account for firm size, financial status, and operational efficiency. Financial ratios are sourced from Yahoo Finance:

1. **log(Market Capitalization)**: Natural logarithm of total market value, used to control for firm size.
2. **Return on Assets (ROA)**: Measures profitability relative to total assets.
3. **Return on Equity (ROE)**: Captures return on shareholders' equity, reflecting internal capital efficiency.

4. **Debt-to-Equity Ratio (D/E)**: Reflects financial leverage and risk exposure.

5. **Price-to-Earnings Ratio (P/E)**: Assesses firm valuation and investor expectations.

6. **Overall Management Score**: A governance quality score provided by **Sustainalytics**, used as a control variable for corporate governance effects.

7. **Industry & Year Dummies**: Dummy variables controlling for fixed time effects and sub-industry differences (e.g., bulk shipping, cruise lines, tankers).

3.2.5 Data Frequency and Sample Size Overview

To ensure temporal consistency and improve estimation efficiency, this study converts ESG Risk Scores, which are originally available on an annual basis, into a monthly format using forward-fill interpolation. This allows ESG data to align with financial and market variables that are reported monthly. Table 3 – 1 summarizes the key variables, data frequency, and total number of observations for each hypothesis:

Table 3 - 1 Data Frequency and Sample Size Overview

Hypothesis	Key Variables	Data Frequency	Sample Size
H_1	ESG Risk Score, Scope 1 Carbon Emissions (metric tons), Biofuel Usage Dummy	Annual	90 (18 firms, 5 years)
H_2	ESG Risk Score, Monthly Stock Return, Return on Assets, Return on Equity, Market Capitalization	Monthly	1296
H_{3a}	ESG Risk Score, Operating Expense Ratio	Monthly	1296
H_{3b}	ESG Risk Score, Cost of Revenue Ratio	Monthly	1296
H_4	ESG Risk Score, Operating Expense Ratio (first stage), Monthly Stock Return (second stage)	Monthly (two-stage	1296

		model)	
H_5	ESG Risk Score, Return on Assets, Return on Equity, Price-to-Earnings Ratio, Debt-to-Equity Ratio, Market Capitalization, Cost of Revenue Ratio, Operating Expense Ratio	Monthly (grouped t-test)	648 (Top 25% and Bottom 25%)
H_6	ESG Risk Score, Event-Window Stock Return, Market Capitalization, Return on Assets, Operating Expense Ratio	Monthly (event sample)	36 (18 firms, 2 events)

Source: Empirical results from this study.

Sample sizes are based on a panel of 18 U.S.-listed shipping companies with complete data from 2019 to 2024, covering 72 monthly observations per firm. Hypothesis H1 uses annual data from sustainability reports. Hypothesis H_6 is based on an event study design, using two ESG deterioration events per firm.

3.3 Research Methodology

3.3.1 Ordinary Least Squares, OLS

Ordinary Least Squares (OLS) is one of the most fundamental and widely used methods in multivariate linear regression analysis. Its primary objective is to estimate the linear relationship between independent and dependent variables by minimizing the sum of squared differences between the observed values and the predicted values, which is also known as the residual sum of squares.

The general form of the OLS model is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

Where:

Y : Dependent variable, the outcome that the model seeks to explain or predict.

$X_1, X_2, \dots, Xn$: Independent variables, the explanatory factors that influence Y.

β_0 : Intercept term, representing the expected value of Y when all Xs are equal to zero.

$\beta_1, \beta_2, \dots, \beta_n$: Regression coefficients, indicating the change in Y associated with a one-unit change in the corresponding X, holding all other variables constant.

ϵ : Error term, representing random variations or unobserved factors not captured by the model.

OLS is particularly suitable for examining linear relationships between continuous variables and is commonly used when the goal is to assess the magnitude and direction of an explanatory variable's effect, while controlling for potential confounders. Under classical assumptions, such as normality of errors, homoskedasticity, independence, and absence of multicollinearity, OLS provides the BLUE (Best Linear Unbiased Estimator), meaning it yields the most efficient linear unbiased estimates.

In this study, OLS serves as the foundational estimation method for the following empirical analyses:

1. **Exploratory Regression on the Sources of ESG Risk**

   This model uses ESG Risk Score as the dependent variable and environmental disclosure variables (including Scope 1 carbon emissions, biofuel usage dummy, and industry exposure) as independent variables. The goal is to test whether ESG risk is significantly explained by firms' actual environmental activities, providing a foundation for evaluating the validity of ESG assessments.

2. **Relationship Between ESG and Financial Performance**

   This model uses ESG Risk Score and a set of control variables to examine their direct effects on financial outcomes such as Stock Return, Operating Expense Ratio, and Cost of Revenue Ratio. This serves as the core structure for evaluating the economic significance of ESG performance.

3. **First-Stage Regression in the Two-Step Mediation Model**

   OLS is also employed as the first step in the mediation analysis. It estimates the relationship between ESG and Operating Expense. The residuals from this regression, representing the unexplained component of ESG's influence on cost, are used in the second stage to examine their indirect effect on stock returns. This helps determine whether ESG influences market performance through its impact on cost structure.

3.3.2 Two-Stage Regression with Residual Mediation

To examine whether ESG performance influences firm returns through its effect on cost structure, this study employs a two-stage regression approach to test for mediation. This method is suitable when a mediating variable is believed to lie between the independent and dependent variables, acting as a transmission mechanism. Compared to a single-stage OLS model, the two-stage design more clearly reveals the indirect paths and structural relationships between variables, helping to clarify the mechanism by which ESG Risk Score affects corporate returns. The procedure is as follows:

Stage 1: Cost Efficiency Regression

We regress the Operating Expense Ratio on the ESG Risk Score and control variables. The objective of this stage is to estimate the effect of ESG on cost efficiency and to extract the residuals (u_i), which will serve as proxies for mediation in the second stage. The model is specified as:

$$Cost_i = \alpha_0 + \alpha_1 ESG\ Risk\ Score_i + \alpha_2 Control_i + u_i$$

Where:

$Cost_i$: Operating Expense Ratio of firm i, representing the proportion of total revenue spent on Operating Expenses, used to evaluate cost efficiency.

$ESG\ Risk\ Score_i$: ESG risk score of firm i, obtained from Sustainalytics. A higher score indicates greater ESG-related risk.

$Control_i$: Vector of control variables, including firm size (log MarketCap), Return on Assets (ROA), Return on Equity (ROE), Debt-to-Equity Ratio (D/E), Price-to-Earnings Ratio (P/E), and Overall Management Score.

α_0: Intercept term, indicating the baseline level of operating expenses when both ESG Risk Score and control variables are zero.

α_1, α_2: Regression coefficients representing the marginal effects of ESG Risk Score and control variables on Operating Expense efficiency. Each coefficient shows the expected change in $Cost_i$ when the corresponding independent variable increases by one unit, holding other variables constant.

u_i: Error term, capturing the variation in Operating Expense not explained by ESG Risk Score or the control variables.

Stage 2: Return Regression with Residual Mediation

In the second stage, we regress Stock Return on the Stage 1 residuals (u_i) and the same set of control variables to investigate whether the unexplained component of cost efficiency can help explain variation in returns. The model is specified as:

$$StockReturn_i = \gamma_0 + \gamma_1 \hat{u}_i + \gamma_2 Control_i + \epsilon_i$$

Where:

$StockReturn_i$: Stock return of firm i, representing market performance over a given time period (e.g., annual return or event window return). This is the main dependent variable of the study.

$\hat{u}_i$: Residual from the first-stage regression model, capturing the portion of ESG impact that is not explained by cost efficiency. Serves as a proxy for potential indirect effects of ESG.

$Control_i$: Vector of control variables, including firm size (log MarketCap), profitability (ROA, ROE), financial leverage (D/E), market valuation (P/E), and governance quality (Overall Management Score).

γ_0: Intercept term, representing the baseline expected return when all independent variables are zero.

γ_1, γ_2: Regression coefficients, indicating the marginal effects of the residual term and control variables on stock returns.

ϵ_i: Error term, capturing unexplained variation in returns due to random factors or omitted variables.

This two-stage setup allows us to assess whether ESG Risk Score has an indirect effect on stock returns via cost efficiency. Specifically, if ESG Risk Score significantly affects costs in Stage 1, and the residuals from that regression are significantly associated with returns in Stage 2, it would suggest that ESG influences market returns through cost-related mechanisms that are not fully captured by direct cost measures.

In the second-stage model, we also include three industry dummy variables to control for sector-specific effects:

1. Dummy_Shipping：Pure shipping operations
2. Dummy_Energy：Shipping energy and fuel-supply firms
3. Dummy_Investment：Asset-investment companies focused on shipping

Including these dummy variables helps rule out structural differences by sector, ensuring that any indirect effect we estimate is more likely due to ESG itself rather than industry-specific factors.

3.3.3 Independent Samples T-Test

The independent samples T-test is a widely used parametric statistical method for testing whether the means of a continuous variable differ significantly between two non-overlapping groups. It is commonly applied in empirical research, especially when comparing firm performance or indicators under specific grouping criteria. The test provides p-values for statistical significance, confidence intervals, and effect size measures (e.g., Cohen's d), enhancing the credibility of empirical inferences.

This method is suitable when the sample is clearly divided into two groups, and the goal is to examine whether a continuous variable exhibits statistically significant differences between them. Unlike regression analysis, the T-test does not require assumptions about linear relationships between variables, making it an intuitive and easy-to-interpret tool for preliminary analysis. Its advantages include:

1. Applicability to medium-sized samples with normally distributed variables;
2. Simultaneous provision of significance and effect size;

3. Utility as a complementary tool to regression, particularly for detecting potential grouping effects.

In this study, the T-test serves as a supplementary method when OLS and two-stage regression do not provide statistically significant support for the explanatory power of ESG on financial performance. To further investigate potential structural differences related to ESG performance, firms are divided into two groups based on their ESG Risk Scores. Group 1 (poor ESG performance) consists of firms in the top 25% of ESG Risk Scores (higher risk), while Group 2 (strong ESG performance) includes those in the bottom 25% (lower risk).

The T-test compares the mean values of the following ten financial and governance indicators:

1. Stock Return
2. Return on Assets (ROA)
3. Return on Equity (ROE)
4. Price-to-Earnings Ratio (P/E)
5. Debt-to-Equity Ratio (D/E)
6. Overall Management Score
7. Cost of Revenue Ratio
8. Operating Expense Ratio

9. Log Market Capitalization (log MarketCap)

This analysis helps determine whether firms with high and low ESG performance differ significantly in operational efficiency, financial leverage, governance quality, and market performance. It also provides empirical insights for subsequent industry-level classification and differentiated analysis of ESG effects.

3.3.4 Logistic Regression Analysis

Logistic regression is a statistical modeling technique used when the dependent variable is binary (i.e., two possible outcomes). It estimates the probability that an event occurs by applying a logistic function to a linear combination of predictors. The basic model is:：

$$\mathrm{logit}(P) = \ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Where:

$\boldsymbol{P}$：Probability that the dependent variable equals 1, i.e., the event occurs. In this study, it refers to *"the probability that a firm is both high-pollution and experiencing ESG deterioration."*

$\left(\boldsymbol{\frac{P}{1-P}}\right)$：The ratio of the probability that the event occurs to the probability that it does not.

$\mathbf{ln}\left(\boldsymbol{\frac{P}{1-P}}\right)$：This is the logit function, which transforms the probability into a log-odds value that can be modeled using a linear function.

$\boldsymbol{\beta_0}$：Intercept, representing the log-odds value when all explanatory variables are equal to zero.

$\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \dots, \boldsymbol{\beta_n}$: Regression coefficients corresponding to each explanatory variable. These reflect both the direction and magnitude of each variable's impact on the event probability. A positive coefficient indicates an increase in the likelihood of the event occurring, while a negative coefficient indicates a decrease.

$\boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_n}$: Independent variables, which in this study include post-ESG event stock price reactions, firm size (log MarketCap), operating efficiency (Operating Expense Ratio), profitability (ROA), and governance quality (Overall Management Score), among others.

This study incorporates the concept of Event Study into the logistic regression model to construct a company identification framework that captures structural ESG risk characteristics. The specific design includes the following steps:

1. **Event Date Identification**: For each of the 18 U.S.-listed shipping-related companies in the sample, the two months between 2019 and 2024 with the largest changes in ESG Risk Score were identified as company-specific "ESG deterioration event dates", resulting in 36 event observations (18 companies × 2 events).
2. **Pollution Level Classification**: For these 36 observations, the annual average ESG Risk Score before and after each event date was calculated. Observations above the overall sample average were classified as "high-pollution firms", and those below as "low-pollution firms".

3. **Dependent Variable Definition**: A binary dummy variable was constructed. If an observation (1) experienced a significant year-over-year deterioration in ESG Risk Score, and (2) belonged to the highest pollution group (i.e., had a relatively high ESG Risk Score), it was coded as 1; otherwise, it was coded as 0.
4. **Independent Variables**: To capture both market response and firm fundamentals, the model includes the following explanatory variables: the difference between the 3-day average stock return after the event and the 3-day average return before the event (market reaction), firm size (log MarketCap), Operating Expense Ratio, Return on Assets (ROA), and Overall Management Score.

Through this logistic regression model, the study further investigates whether changes in ESG Risk Scores trigger significant market responses within high-pollution firms, in order to assess the context sensitivity of ESG information and its potential role in sustainable risk pricing.

4. Research Framework and Empirical Design

This study is built around a central research question: Do ESG Risk Scores provide meaningful signals of corporate behavior and market pricing in the context of carbon-intensive industries? To address this, the six hypotheses are designed in a layered and logically connected structure as follows:

Hypothesis 1 (H_1) forms the empirical foundation by testing whether ESG scores reflect firms' actual environmental behavior, such as carbon emission intensity and the use of biofuels. This step concerns the content validity of ESG scores, verifying whether they capture substance rather than superficial disclosure.

Hypotheses 2 and 3 (H_2, H_{3a}, H_{3b}) investigate the direct impact of ESG Risk Scores on corporate performance. H2 focuses on the market dimension, examining the relationship between ESG scores and stock returns. H3a and H3b focus on operational outcomes, testing whether ESG performance is associated with changes in operating expense and cost of revenue ratios, respectively.

Hypothesis 4 (H_4) builds upon the direct models by introducing a mediated pathway, testing whether the effect of ESG on stock returns operates indirectly through operating cost structure. This contributes to understanding how ESG affects performance via internal-external linkages.

Hypothesis 5 (H_5) shifts the focus from prediction to group differentiation, comparing financial characteristics of firms with high and low ESG scores to determine whether ESG provides discriminatory power regarding firm fundamentals.

Hypothesis 6 (H_6) places ESG signals in a dynamic event-driven context, evaluating whether firms with both high pollution attributes and ESG deterioration are more likely to be penalized by the market, thus testing the market sensitivity to ESG-related negative shocks.

In sum, the hypothesis structure progresses from validity verification (H_1), to financial consequence identification ($H_2 - H_3$), followed by mechanism testing (H_4), structural differentiation (H_5), and finally event-based signal response (H_6). This forms a coherent empirical logic extending from static measurement to dynamic pricing, and from internal operations to external valuation.

4.1 Hypothesis

This study aims to systematically explore the relationship between corporate ESG performance, financial outcomes, and market responses. It also seeks to verify whether ESG information has a market pricing function and whether it amplifies investor behavior under specific pollution characteristics. Based on the theoretical and empirical foundations discussed in Chapter 2, this chapter divides the analytical strategy into five main sections and proposes six research hypotheses as follows:

H_1：Determinants of ESG Risk Score

A company's ESG Risk Score can be explained by concrete environmental variables (e.g., Scope 1 carbon emissions, usage of biofuels, and industry exposure index). This hypothesis tests whether ESG ratings accurately reflect the firm's real environmental impact and evaluates the validity and reliability of such scores.

H_2：ESG Performance and Market Response

A firm's ESG Risk Score has a significantly negative impact on its stock return.

This hypothesis examines whether the market has already priced in ESG information and whether it influences investor valuation decisions—serving as a direct test of ESG's pricing function.

H_{3a}：ESG Performance and Operating Expense Ratio

Firms with higher ESG Risk Scores are expected to have higher Operating Expense Ratios.

This is based on the assumption that ESG-related risks may reflect operational inefficiencies, institutional weaknesses, or rising compliance costs, which in turn increase operating expenses.

H_{3b} (Supplementary): ESG Performance and Cost of Revenue Ratio

Firms with higher ESG Risk Scores are expected to have higher Cost of Revenue Ratios.

This supplementary hypothesis aims to observe whether ESG performance negatively affects broader cost structures tied to a firm's revenue-generating activities.

H_4：Mediating Role of Operating Expense in ESG and Stock Return

The Operating Expense Ratio mediates the relationship between ESG Risk Score and Stock Return.

This hypothesis investigates whether the effect of ESG on market returns is partially realized through operational efficiency, helping to understand the mechanism by which ESG influences market behavior.

H_5：Group Differences in Financial Performance and Market Response

There are significant differences between high and low ESG Risk Score groups in terms of ROA, ROE, cost ratios, management ratings, and stock returns.

Supported by t-tests, this hypothesis examines the heterogeneity between ESG groups and evaluates ESG as a potential basis for clustering firms by fundamentals or market valuation.

H_6：Highly polluting and experience ESG Deterioration and Market Penalty

Firms that are both highly polluting and experience ESG score deterioration are more likely to face significant stock return declines.

This hypothesis, tested through a Logit model and event study design, examines whether ESG-related negative information leads to stronger market penalties for highly polluting firms.

4.2 Research Framework and Variable Operationalization

To examine whether ESG risk scores in carbon-intensive shipping-related industries possess predictive financial functionality and market explanatory power, this study adopts a multi-step, segmented verification process to systematically test how ESG manifests and is reflected in corporate performance outcomes and market responses. The overall research design is divided into six main steps, in sequence: data source verification, descriptive statistical analysis, mechanism testing, endogeneity treatment, heterogeneity testing, and event response analysis. This design advances from static characteristics to dynamic market behavior, forming a complete and progressive research flow for tracing ESG impact.

First, this study clarifies whether ESG scores reflect actual environmental emissions and risk indicators (Step 1), confirming the credibility of the rating contents. Next, it assesses the basic correlation between ESG scores and firms' financial and market variables (Step 2), and further, through regression-based model testing, examines whether operational efficiency serves as a mediating mechanism (Step 3). In addition, to avoid potential endogeneity bias, a two-stage regression model is employed for robustness verification (Step 4). The analysis proceeds to test the heterogeneity effects of ESG risk scores (Step 5), and finally incorporates ESG deterioration events using Logit regression to examine market response patterns (Step 6). This multilayered verification design aims to comprehensively evaluate whether ESG functions consistently across high-pollution industries as an effective market signal, while also addressing ongoing ESG application debates regarding whether it reflects “real value” or is merely a “selective response to appearance.” The overall analytical design aligns with the research roadmap across six key stages, each corresponding to the hypotheses ($\boldsymbol{H_1}$ to $\boldsymbol{H_6}$), as follows:

Step 1: Environmental Determinants of ESG Score (Corresponding to $\boldsymbol{H_1}$)

1. **Objective:** To test whether the ESG Risk Score is driven by tangible environmental variables (e.g., Scope 1 emissions, use of biofuels, industry exposure index), in order to evaluate the content validity of ESG ratings.
2. **Method:** Multiple OLS regression
3. **Model Design:**

   Y = ESG Risk Score

   X = Scope 1 carbon emissions, biofuel usage dummy, and other environmental variables.

Step 2: Baseline Regression to Examine the Relationship Between ESG and Stock Return and Both Cost Variables (Corresponding to $\boldsymbol{H_2}$, $\boldsymbol{H_{3a}}$, $\boldsymbol{H_{3b}}$)

1. **Objective:** To analyze the impact of ESG Risk Score on key financial and market variables, including stock return, operating expense ratio, and cost of revenue ratio.
2. **Method:** Multiple OLS regressions (separate models for each dependent variable)
3. **Model Design:**

Y = Stock Return;   X = ESG Risk Score + Control Variables

Y = Operating Expense Ratio;   X = ESG Risk Score + Control Variables

Y = Cost of Revenue Ratio;   X = ESG Risk Score + Control Variables

4. **Control Variables** include financial indicators such as Log(Market Capitalization), Return on Assets (ROA), and Debt-to-Equity (D/E) Ratio.

Step 3: Mediation Effect of Operating Costs (Corresponding to H_4)

1. **Objective**: To test whether ESG Risk Score indirectly affects stock return through the Operating Expense Ratio, exploring the potential transmission mechanism.
2. **Method**: Two-Stage Regression with Residual Mediation
3. **Model Design**:

   Stage 1: Operating Expense Ratio = ESG Risk Score + Control Variables

   Stage 2: Stock Return = Residuals from Stage 1 + Control Variables

Step 4: Heterogeneity Test Between High and Low ESG Risk Score Groups (Corresponding to H_5)

1. **Objective**: To analyze whether there are significant differences in financial and market variables between firms with high and low ESG Risk Scores.
2. **Grouping Criteria**: Top 25% of ESG Risk Scores = High-Risk Group; Bottom 25% = Low-Risk Group.

3. **Analytical Method**: Independent Samples T-Test
4. **Comparison Variables**: ROA, ROE, Stock Return, Operating Expense Ratio, Cost of Revenue Ratio, Management Score, etc.

Step 5: Market Effects of the High Pollution × ESG Deterioration Interaction (Corresponding to H_6)

1. **Objective**: To combine event study and logistic regression to examine whether ESG deterioration leads to a stronger negative market response in highly polluting firms.
2. **Sample:** For each of the 18 firms, the two months with the largest changes in ESG Risk Score between 2019 and 2024 were selected, resulting in 36 event samples. A binary dependent variable was created (Dummy = 1 if the firm is both high-pollution and experiences ESG deterioration; otherwise = 0). Stock return responses (Post-Pre Return) and other firm variables were used as independent variables.
3. **Method**: Logistic Regression + Event Study

4.3 Regression Model Structure and Operational Approach

This section systematically presents and explains the regression models used for each stage of the empirical analysis, based on the research hypotheses H_1 through H_6. Each model is developed according to its specific research objective, with detailed descriptions of variable design and modeling strategy provided below.

4.3.1 Model 1: Regression on Environmental Drivers of ESG Risk Score (Corresponding to Hypothesis H_1)

This model aims to examine whether a company's ESG Risk Score is a function of concrete environmental information, such as carbon emission intensity, exposure to environmental risk, and biofuel usage. The goal is to evaluate whether the ESG score effectively reflects a firm's environmental impact and to strengthen the validity of this indicator.

Biofuel adoption is included as an explanatory variable in this model because it represents a concrete, observable form of environmental action within the shipping industry. Among the various pathways to reduce emissions, biofuel offers a distinct advantage: it is a "drop-in" fuel compatible with existing ship engines, requiring no major retrofitting. This makes it one of the most feasible and immediate responses for shipping firms seeking to improve their environmental performance under ESG criteria. According to DNV (2023), certified marine biofuels can reduce greenhouse gas emissions by 65–90% on a well-to-wake basis. A recent pilot by TotalEnergies in Singapore demonstrated the use of 100% cooking oil-based marine fuel (B100), which achieved an estimated 85–90% GHG reduction without operational disruption (Reuters, 2024). These operational advantages and quantifiable emission benefits explain why shipping companies often begin their ESG strategy with fuel substitution. In this model, biofuel usage is represented by a binary dummy variable (Dummy_Biofuel), where 1 indicates that the firm has adopted marine biofuel in its operations during the observation period, and 0 otherwise. Therefore, the presence of biofuel use serves as a valid proxy for a firm's willingness to address environmental risk.

The model is specified as follows:

$$
\begin{aligned}
&ESG\ Risk\ Score_i \\
&\quad = \beta_0 + \beta_1 Overall\ Management\ Score_i + \beta_2 Overall\ Exposure\ Score_i \\
&\quad + \beta_3 Scope1_i + \beta_4 \left(\frac{Scope1}{Revenue}\right)_i + \beta_5 Dummy\_Biofuel_i + \epsilon_i
\end{aligned}
$$

Where:

$\boldsymbol{ESG\ Risk\ Score_i}$: ESG Risk Score of company $\boldsymbol{i}$, representing its sustainable risk level—the higher the score, the greater the risk.

$\boldsymbol{Overall\ Management\ Score_i}$: Overall Management Score, indicating the company's governance and risk control capability.

$\boldsymbol{Overall\ Exposure\ Score_i}$: Overall Exposure Score, measuring the degree of environmental and social exposure risk a company faces.

$\boldsymbol{Scope1_i}$: Absolute Scope 1 emissions (ton CO_2e), representing the company's direct greenhouse gas emissions.

$\boldsymbol{\left(\frac{Scope1}{Revenue}\right)_i}$: Ratio of Scope 1 emissions to revenue, reflecting emission intensity.

$\boldsymbol{Dummy\_Biofuel_i}$: A dummy variable indicating whether the company uses biofuel as an alternative energy source (1 = yes; 0 = no)

$\boldsymbol{\beta_0}$ (Intercept): Represents the predicted value of ESG Risk Score when all explanatory variables are 0, considered the baseline risk level.

$\boldsymbol{\beta_1}$(Overall Management Score): Indicates the change in ESG Risk Score for every one-unit increase in governance score. A negative coefficient suggests better management leads to lower ESG Risk Score, in line with the idea that stronger governance reduces risk exposure.

$\boldsymbol{\beta_2}$(Overall Exposure Score): Measures how environmental and social exposure contributes to ESG Risk Score. A positive sign would mean higher exposure leads to higher risk.

$\boldsymbol{\beta_3}$(Scope1): Captures the marginal effect of Scope 1 emissions (ton CO_2e) on ESG Risk Score. A positive coefficient would imply that higher emissions increase the score, which aligns with expectations.

$\boldsymbol{\beta_4}$(Scope1 / Revenue): Reflects emission intensity. A positive coefficient would mean that higher intensity leads to a higher ESG Risk Score, which is logical given the efficiency concern.

$\boldsymbol{\beta_5}$(Dummy_Biofuel): A dummy variable for biofuel use. If used (1), it may indicate a better sustainability strategy, and is expected to reduce the ESG Risk Score.

$\boldsymbol{\epsilon_i}$(Residual): Represents the part of ESG Risk Score not explained by environmental variables, possibly reflecting subjective scoring, market expectations, or other non-observable factors.

This model is estimated using the Ordinary Least Squares (OLS) method, based on annual data from 18 companies, with a total of 90 observations. All sample firms have complete disclosure of ESG ratings and carbon emission information. The model focuses on examining the environmental explanatory power of the ESG Risk Score, to see whether it can be predicted by specific and quantifiable environmental impact variables (such as carbon emissions, energy usage, and external exposure). The results serve as the basis for evaluating the validity and informativeness of ESG ratings, corresponding to Hypothesis$\boldsymbol{H_1}$.

To ensure the stability and explanatory power of the regression estimates, two diagnostic tests are conducted:

1. **Pearson Correlation Analysis:** Provides preliminary information about the direction and strength of relationships between variables, helping to evaluate whether they are potentially related in a meaningful way. For example, the direction between ESG scores and market performance is generally consistent with theoretical expectations, though the strength still requires confirmation through regression analysis.
2. **Collinearity Diagnosis (VIF):** The Variance Inflation Factor (VIF) values of all variables in the models are below common practical thresholds, indicating no serious multicollinearity issues. This result supports that the model variables are sufficiently independent and suitable for inclusion in the same regression model.

4.3.2 Model 2: Baseline Regression on ESG and Market Response (Corresponding to Hypothesis H_2)

To examine whether the ESG Risk Score has a pricing function in the market, this study constructs a baseline regression model using firms' ESG performance as the key explanatory variable, aiming to explore the direction and magnitude of its effect on stock returns. This regression corresponds to Hypothesis H_2 and tests whether investors have already incorporated ESG risks into asset pricing.

In Model 2, the monthly stock return serves as the dependent variable, while the main independent variable is the ESG Risk Score. A set of financial control variables is included to account for potential systematic differences, thereby enhancing the explanatory power and accuracy of the model. The specific model is presented as follows:

$$
\begin{aligned}
StockReturn_{i,t} \\
&= \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} \\
&+ \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Operating\ Expense\ Ratio_{i,t} \\
&+ \beta_8 Overall\ Management\ Score_{i.t} + \epsilon_{i,t}
\end{aligned}
$$

Where:

$\boldsymbol{StockReturn_{i,t}}$ ： The stock return of firm i in month t.

$\boldsymbol{ESG\ Risk\ Score_{i,t}}$ ： The overall ESG risk score provided by Sustainalytics. A higher score indicates higher ESG risk.

$\boldsymbol{log(MarketCap)_{i,t}}$ ： The natural logarithm of firm size, used to control for firm size effects.

$\boldsymbol{ROA_{i,t}}$ 、$\boldsymbol{ROE_{i,t}}$：Indicators of the firm’s profitability.

$\boldsymbol{P/E_{i,t}}$：Price-to-earnings ratio, reflecting the firm’s valuation and growth expectations.

$\boldsymbol{D/E_{i,t}}$：Debt-to-equity ratio, used to control for financial leverage and risk exposure.

$\boldsymbol{Operating\ Expense\ Ratio_{i,t}}$：Reflects the firm's operational efficiency, calculated as operating expenses divided by total revenue.

$\boldsymbol{Overall\ Management\ Score_{i,t}}$**:** A governance score from Sustainalytics that evaluates a firm’s overall management and long-term risk control quality

$\boldsymbol{\beta_0}$ **(Intercept):** Indicates the predicted stock return when all independent variables are zero.

$\boldsymbol{\beta_1}$ **(ESG Risk Score):** Represents the marginal effect of ESG risk score on stock returns. If negative, it suggests that higher ESG risk (i.e., worse sustainability risk) has a negative impact on returns.

$\boldsymbol{\beta_2}$ **(Firm Size):** Captures the effect of firm size (log-transformed) on stock returns, reflecting the size premium.

$\boldsymbol{\beta_3}$ **(Return on Assets, ROA):** Measures the effect of asset profitability on stock returns, representing the firm's ability to generate profits from assets.

$\boldsymbol{\beta_4}$ **(Return on Equity, ROE):** Measures the marginal effect of ROE on stock returns, reflecting the firm's capacity to create value for shareholders.

$\boldsymbol{\beta_5}$ **(Price-to-Earnings Ratio, P/E):** Represents how stock returns respond to valuation multiples, reflecting the market's growth expectations for the firm.

$\boldsymbol{\beta_6}$ **(Debt-to-Equity Ratio, D/E):** Indicates the effect of capital structure risk on stock returns, used to assess the impact of leverage risk.

$\boldsymbol{\beta_7}$ **(Operating Expense Ratio):** Measures the impact of operating cost efficiency on returns, indicating cost control capability or operational efficiency.

$\boldsymbol{\beta_8}$ **(Overall Management Score):** Captures the effect of governance quality on returns, reflecting contributions from management and governance performance.

$\boldsymbol{\epsilon_{i,t}}$ **(Error Term):** Represents unexplained variation or noise not accounted for by the model.

This model uses monthly data from 18 companies between 2019 and 2024, with a total of 1,296 observations (18 companies × 6 years × monthly frequency). To ensure the stability and explanatory power of the regression results, two diagnostic tests were conducted:

1. **Pearson Correlation Analysis:** This test provides preliminary insights into the direction and strength of linear relationships between variables, helping to evaluate their potential explanatory value. For example, ESG Risk Score shows a weak negative correlation with Stock Return ($r = –0.024$), suggesting that ESG information may have a slightly negative effect on the market, though the relationship is weak and requires further regression analysis to test for statistical significance.

2. **Collinearity Diagnosis (VIF):** The Variance Inflation Factor (VIF) values for all variables in the model are below 2, indicating no serious multicollinearity problems (a

common threshold is VIF > 10 or VIF > 5). This result suggests that the explanatory variables provide independent information and are suitable to be included in the same model.

4.3.3 Model 3: Basic Regression of ESG and Firm Operational Efficiency (Corresponding to Hypotheses H_{3a} and H_{3b})

To examine whether ESG risk is systematically related to a firm's operational efficiency, this study constructs two basic regression models using financial expenditure indicators as dependent variables. These models aim to test whether ESG ratings can effectively predict a firm's performance in terms of operating costs and capital expenditures. This section corresponds to Hypothesis H_{3a} (Operating Expense Ratio) and H_{3b} (Cost of Revenue Ratio), focusing on whether ESG risk influences internal resource allocation and cost sensitivity.

In both models, the ESG Risk Score is used as the key independent variable, along with the same financial control variables as in Model 2, including firm size, profitability, growth expectations, and capital structure. This ensures comparability across models. The specific model designs are as follows:

Model$_{3a}$: Regression on Operating Expense Ratio（H_{3a}）

$$
\begin{aligned}
&Operating\ Expense\ Ratio_{i,t} \\
&\qquad = \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} \\
&\qquad + \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} \\
&\qquad + \epsilon_{i,t}
\end{aligned}
$$

Model$_{3b}$: Regression on Cost of Revenue Ratio（H_{3b}）

$$
\begin{aligned}
&Cost\ of\ Revenue\ Ratio_{i,t} \\
&\qquad = \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} \\
&\qquad + \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} \\
&\qquad + \epsilon_{i,t}
\end{aligned}
$$

Where:

$\boldsymbol{\beta_0}$(Intercept)：When all explanatory variables equal 0, this represents the theoretical predicted value of the company’s operating expense ratio or cost of revenue ratio, serving as the baseline.

$\boldsymbol{\beta_1}$(ESG Risk Score)：Measures the marginal effect of each unit increase in the overall ESG risk score on the Operating Expense Ratio. This tests whether ESG ratings are associated with actual operational or capital expenditure structures.

$\boldsymbol{\beta_2}$(log(MarketCap))：Controls for the effect of firm size on operational or capital spending performance.

$\boldsymbol{\beta_3}$(ROA)：Reflects the efficiency of asset utilization, capturing the relationship between a company's revenue-generating ability and its operational or capital cost structure.

$\boldsymbol{\beta_4}$(ROE)：Measures the relationship between return on equity and variations in operational or capital spending.

$\boldsymbol{\beta_5}$(P/E) ：Captures market expectations for growth and potential explanations for cost pressure through valuation levels.

$\boldsymbol{\beta_6}$(D/E) ：Represents capital structure (debt ratio), indicating a company's ability to manage risk exposure through financial leverage.

$\boldsymbol{\beta_7}$(Overall Management Score) ：Reflects governance capacity and risk control ability, which may influence the level of operational or capital spending.

$\boldsymbol{\epsilon_{i,t}}$(Error term) ：Error term for unmodeled factors, possibly resulting from omitted operational variables or external shocks.

The definitions of the remaining control variables are consistent with the previous section.

This model is constructed using monthly data from 18 companies over the period 2019–2024, resulting in a total of 1,296 observations (18 companies × 6 years × 12 months), covering publicly listed firms with complete ESG and financial disclosures.

To ensure the stability and interpretability of the regression results, two types of preliminary diagnostic analyses were conducted:

1. **Pearson Correlation Analysis:** This provides initial insights into the direction and strength of correlations among independent variables, helping assess potential links between ESG risk and firms' cost or expenditure structures. The analysis indicates relatively weak linear associations between the ESG Risk Score and both the Operating Expense Ratio and Capital Expenditure Ratio, though a slight negative correlation trend is observed. Further regression analysis is required to test for statistical significance.
2. **Collinearity Diagnosis (VIF):** All model variables exhibit Variance Inflation Factors (VIF) below 2, indicating no severe multicollinearity issues. This result supports the inclusion of all explanatory variables within the same regression framework.

4.3.4 Model 4: Mediation Effect of Operating Costs (Corresponding to Hypothesis H_4)

To examine whether the overall ESG risk score (ESG Risk Score) indirectly affects stock returns through operating costs (Operating Expense Ratio), this study further develops a mediation effect model to test for a potential transmission mechanism. This analysis corresponds to Hypothesis H_4 and aims to identify whether there exists a mediating path between ESG ratings and a firm's financial performance or market reaction, clarifying whether ESG risks may influence the capital market via firms' operational efficiency.

This model adopts a two-stage regression framework (Two-Stage Regression with Residual Mediation), consisting of the following two regression steps:

Stage 1 (Mediator Model): The Operating Expense Ratio is set as the dependent variable, with ESG Risk Score as the primary independent variable. Control variables include log(MarketCap), ROA, ROE, P/E, D/E, and Overall Management Score, in order to assess the direct impact of ESG risks on a firm's operating costs. The detailed model is as follows:

$$
\begin{aligned}
&Operating\ Expense\ Ratio_{i,t} \\
&\quad = \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} \\
&\quad + \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} \\
&\quad + \epsilon_{i,t}
\end{aligned}
$$

The definitions of the remaining control variables are consistent with the Model_{3a} section.

Stage 2 (Outcome Model): Stock Return is set as the dependent variable. The residual term obtained from the first-stage regression is introduced as the key mediating explanatory variable, alongside the same set of financial control variables. This setup aims to observe whether the portion of cost inefficiency not explained by ESG (captured by the residuals) has a significant effect on market reactions. The detailed model is as follows:

$$
\begin{aligned}
&Stock\ Return_{i,t} \\
&\quad = \beta_0 + \beta_1 Residual_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} + \beta_4 ROE_{i,t} \\
&\quad + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} + \epsilon_{i,t}
\end{aligned}
$$

Where:

$\boldsymbol{Residual_{i,t}}$: The residual term from the first-stage “Operating Expense Ratio model,” representing the portion of cost variation that remains unexplained after accounting for the ESG Risk Score.

$\boldsymbol{log(MarketCap)_{i,t}}$: The natural logarithm of a company’s market value, used as a proxy for firm size to adjust for financial performance and market valuation scale effects.

$\boldsymbol{ROA_{i,t}}$: Return on Assets, calculated as net income divided by total assets, indicating how efficiently a company generates profits from its assets.

$\boldsymbol{ROE_{i,t}}$: Return on Equity, calculated as net income divided by shareholder’s equity, reflecting a firm’s ability to create value for shareholders.

$\boldsymbol{P/E_{i,t}}$: Price-to-Earnings ratio, defined as stock price divided by earnings per share, showing how the market evaluates a company’s future growth potential and value recognition.

$\boldsymbol{D/E_{i,t}}$Debt-to-Equity ratio, measuring the level of financial leverage. A higher ratio implies greater reliance on debt financing.

$\boldsymbol{Overall\ Management\ Score_{i,t}}$: A composite score reflecting the company's governance and management capabilities (e.g., provided by Sustainalytics), used to assess long-term risk control quality and overall operational efficiency.

$\boldsymbol{\epsilon_{i,t}}$: The error term, which absorbs the impact of variables not included in the model, accounting for random disturbances or company-specific events.

$\boldsymbol{\beta_0}$(Intercept): Indicates the theoretical predicted value of stock returns when all explanatory variables equal zero, serving as the baseline.

$\boldsymbol{\beta_1}$(Residual): Measures the impact of operational inefficiency (the unexplained part not attributed to ESG) on stock returns. If positive, it suggests that the market recognizes and prices the inefficiency; if negative, it may imply market misjudgment or overreaction.

$\boldsymbol{\beta_2}$(log(MarketCap)): Assesses the impact of firm size (log of market cap) on stock returns. Based on size effect theory, smaller firms may face higher risks or have more return potential due to valuation differences.

$\boldsymbol{\beta_3}$(ROA): Reflects the impact of ROA on stock returns. Firms with higher operational efficiency usually receive better market evaluations.

$\boldsymbol{\beta_4}$(ROE): Describes the relationship between ROE and stock returns. Higher ROE is often associated with good governance and value creation ability.

$\boldsymbol{\beta_5}$(P/E): Evaluates how the market perceives a firm's valuation. A high P/E ratio may indicate expected growth or signal overvaluation risks.

$\boldsymbol{\beta_6}$(D/E): Measures the effect of financial leverage on stock returns. High leverage can increase a firm’s risk and return volatility, which may affect market pricing.

$\boldsymbol{\beta_7}$(Overall Management Score): Reflects the effect of governance and management quality on stock returns. Firms with strong risk control and clear strategic execution are usually evaluated more positively by the market.

This analysis also uses monthly data from 18 companies between 2019 and 2024, totaling 1,296 observations. To ensure the robustness and reliability of the model estimates, two types of statistical diagnostics were conducted:

1. **Pearson Correlation Analysis**: There is a statistically significant negative correlation between ESG Risk Score and Operating Expense Ratio, suggesting that companies with better ESG performance may have lower operating cost ratios, indicating a potential advantage in cost efficiency. In addition, the residual of the Operating Expense Ratio shows a weak correlation with stock return, serving as a basis for further testing of the mediation effect.
2. **Collinearity Diagnosis (VIF)**: All variables in both the mediation and outcome models have variance inflation factors (VIF) below the common threshold (VIF < 5), indicating no serious multicollinearity problems. This supports the explanatory independence and stability of the model.

This model design helps identify whether ESG performance influences market valuation through operational factors, further examining whether sustainability risks affect stock prices via observable internal financial pathways. It provides an integrated understanding of the signal value of ESG and the firm's underlying operational performance.

4.3.5 Model 5: Heterogeneity Test between High and Low ESG Risk Score Groups (Corresponding to Hypothesis H_5)

To further examine whether ESG Risk Score is significantly associated with corporate financial and market performance, this study divides the sample into two groups based on ESG Risk Score and conducts a heterogeneity test. Specifically, the top 25% of ESG Risk Scores are categorized as the high-risk group (higher scores indicate poorer ESG performance, labeled as Group 2), while the bottom 25% are classified as the low-risk group (lower scores indicate better ESG performance, labeled as Group 1). The two groups are then compared based on the means of key variables.

This model corresponds to Hypothesis H_5, aiming to verify whether differences in ESG performance are reflected in actual operational and market outcomes. It also evaluates whether ESG, as a non-financial indicator, can effectively distinguish between firms in terms of financial performance and stock return. The analysis uses an Independent Sample T-Test to examine whether there are statistically significant mean differences between the two groups in the following variables:

1. **Financial performance variables**: ROA, ROE, Operating Expense Ratio, Cost of Revenue Ratio, P/E, D/E
2. **Market performance variable**: Stock Return
3. **Governance indicator**: Overall Management Score

4. **Control variable**: log(MarketCap)

Variable definitions are the same as previously stated.

To ensure the robustness of the T-test analysis, a Levene's test for equality of variances is applied for model selection. In addition, Cohen's d, Hedges' g, and Glass's delta are calculated to assess the effect size and explain the magnitude of the practical differences.

4.3.6 Model 6: Market Effects of High Pollution × ESG Deterioration Interaction (Corresponding to Hypothesis H_6)

To examine whether negative ESG information leads to more significant market reactions among high-pollution firms, this study constructs an interaction regression model to test Hypothesis H_6. This step combines event study methodology with a logistic regression model to analyze stock price responses during months when ESG scores significantly worsen.

Sample Design and Variable Definitions

1. **Sample Selection**: For each of the 18 companies, the two months with the largest changes in ESG Risk Score are selected, resulting in 36 event observations.
2. **Dependent Variable**: A binary dummy variable is created. It is coded as 1 if the event involves a "High Pollution × ESG Deterioration" scenario (i.e., ESG performance worsens and the firm is classified as high-pollution); otherwise, it is coded as 0.

3. **Independent Variables**: The core explanatory variable is the market reaction after the event (CAR[-3, +3]), with additional control variables including log(MarketCap), ROA, Operating Expense Ratio, and Overall Management Score.

This model applies a logistic regression method, with the analytical structure presented as follows:

$$logit\big(P(Y=1)\big)$$
$$= \beta_0 + \beta_1 CAR[-3,+3] + \beta_2 \log(MarketCap) + \beta_3 ROA$$
$$+ \beta_4 Operating\ Expense\ Ratio + \beta_5 Overall\ Management\ Score + \epsilon$$

Where:

$\boldsymbol{CAR[-3,+3]}$**:** Cumulative Abnormal Return within the event window (3 days before to 3 days after the event). This is used to measure the market's reaction to the ESG-related event.

$\mathbf{log}(\boldsymbol{MarketCap})$: The natural logarithm of a company's market capitalization, serving as a proxy for firm size.

$\boldsymbol{ROA}$: Return on Assets, which reflects how efficiently a company generates profit from its assets.

$\boldsymbol{Operating\ Expense\ Ratio}$: A ratio calculated as operating expenses divided by total revenue, used to evaluate cost efficiency in operations.

$\boldsymbol{Overall\ Management\ Score}$: An overall score reflecting corporate governance, strategic execution, and risk management capacity.

$\boldsymbol{\epsilon}$: Error term, capturing the influence of other unobserved or random factors not included in the model.

$\boldsymbol{\beta_0}$ (Intercept): When all explanatory variables equal zero, this represents the theoretical baseline log-odds of the event occurring (Y = 1).

$\boldsymbol{\beta_1}$(CAR[–3, +3]): Indicates the effect of each unit change in CAR on the event probability. A higher CAR may reflect stronger market reactions and is theoretically expected to have a positive sign.

$\boldsymbol{\beta_2}$(Firm Size): Controls for the influence of firm size on market response. A negative sign may suggest that larger firms experience weaker reactions due to information being already priced in.

$\boldsymbol{\beta_3}$(ROA): Reflects how a company's profitability affects the likelihood of the event. Higher ROA may indicate financial stability, potentially leading to more positive market reactions.

$\boldsymbol{\beta_4}$(Operating Expense Ratio): Shows the effect of operational efficiency on market reactions. A higher expense ratio may signal inefficiency, leading to negative expectations.

$\boldsymbol{\beta_5}$(Management Score): Represents the company's governance and control ability. A higher score may reduce the impact of negative ESG events, thus the expected sign is negative.

In this model, $\boldsymbol{Y} = \mathbf{1}$ indicates that the event falls under the scenario of "High Pollution and ESG Deterioration."

Model Estimation and Evaluation Criteria:

1. The Omnibus Tests are used to evaluate the overall significance of the model.
2. The Cox & Snell R Square and Nagelkerke R Square are used to assess the model's goodness of fit.
3. The contribution of each independent variable to Y is tested using the Wald statistic.
4. The Classification Table is used to observe the model's prediction accuracy.

This analysis helps to further examine whether a decline in ESG scores leads to stronger market penalties for high-pollution companies, and to test whether the investment relevance of ESG information depends on industry characteristics.

4.4 Expected Directions and Theoretical Foundations

This section explains the expected directional effects of each research model, outlining their theoretical foundations and logical reasoning, supported by academic literature and practical reports. The independent variables included in the regression models are constructed based on relevant theory and supported by empirical evidence. In the following subsections, each model's design, variable definitions, expected directions, and literature support are presented systematically.

4.4.1 Expected Direction and Theoretical Basis: Model 1 – Environmental Determinants of ESG Risk Score (Corresponding to Hypothesis H_1)

The purpose of this model is to examine whether a company's ESG Risk Score can be reasonably explained by its actual environmental impact data, and to test the informational validity of ESG scores as a proxy for environmental risk. In theory, if ESG ratings are designed to reflect a company's real environmental risk level, then variations in ESG Risk Scores should be explained by objective and observable environmental impact indicators. The structure of Model 1 is as follows:

$$
\begin{aligned}
&ESG\ Risk\ Score_i \\
&\qquad = \beta_0 + \beta_1 Overall\ Management\ Score_i + \beta_2 Overall\ Exposure\ Score_i \\
&\qquad + \beta_3 Scope1_i + \beta_4 \left(\frac{Scope1}{Revenue}\right)_i + \beta_5 Dummy\_Biomass_i + \epsilon_i
\end{aligned}
$$

Table 4 - 1 Variable Definitions and Theoretical Expectations for Model 1

Variable	Description	Expected Dierction
ESG Risk Score	Overall ESG risk score. A higher score indicates higher sustainability risk.	Dependent Variable
Overall Management Score	Comprehensive assessment of a company's governance and risk control capabilities. A higher score indicates better governance.	－
Overall Exposure Score	Measures the level of environmental exposure based on industry and regional conditions.	＋
Scope 1	A company's annual direct carbon emissions.	＋
Scope1 / Revenue	Carbon intensity per unit of revenue; reflects carbon efficiency and pollution density.	＋
Dummy_Biofuel	Dummy variable: 1 if bioenergy is used, 0 otherwise; indicates the environmental sustainability of the energy mix.	－

Source: Empirical results from this study.

Based on Table 4 - 1, the following observations can be made:

1. β_1Overall Management Score (Expected to be Negative)

According to Sustainalytics (2024), the Overall Management Score represents a company's ability to manage and govern ESG-related issues, including its performance in areas such as policy-making, risk control mechanisms, and oversight structure. Companies with stronger management capabilities are more able to handle ESG exposures effectively, which helps reduce unmanaged ESG risks and lowers their ESG Risk Score. López-González et al. (2019) also found that companies with better governance and management quality tend to receive lower ESG risk ratings. Therefore, the Overall Management Score is expected to have a significant negative relationship with the ESG Risk Score.

2. β_2Overall Exposure Score (Expected to be Positive)

According to Sustainalytics (2024), the Overall Exposure Score measures the level of potential ESG risks a company faces based on its industry type, geographical location, and business model. This score reflects structural exposures that companies cannot easily change, and it is directly linked to the calculation of the ESG Risk Score.

Theoretically, Hart's (1995) Natural-Resource-Based View argues that environmental externalities affect a firm's sustainable competitiveness. When a company operates in an industry with higher environmental and social risks, this exposure is likely to be recognized by markets and rating agencies as a higher potential risk. In addition, Giese et al. (2019) found that carbon emissions and ESG information can significantly predict cost of capital and rating results, which supports the connection between ESG exposure and risk scores.

Importantly, previous research has highlighted that Sustainalytics' Overall Exposure Score plays a key role in ESG evaluations. Berg et al. (2022) explained that the ESG Risk Score is based on two components: the Exposure Score and the Management Score. Together, these scores determine a company's ESG rating. The higher the exposure, the greater the expected impact on the ESG Risk Score. Although their study mainly focused on measuring differences between rating systems, it also provided evidence that the exposure indicator strongly explains ESG risk scores.

In summary, both theoretical and empirical findings suggest that a higher Overall Exposure Score is associated with a higher ESG Risk Score. Therefore, the expected regression coefficient is positive ($\beta_2 > 0$).

3. β_3Scope 1 (Expected to be Positive)

Scope 1 represents the direct greenhouse gas emissions generated during a company's operations. It is one of the key and measurable sources of environmental risk in the ESG framework. According to Sustainalytics (2024), the ESG Risk Ratings assess a company's carbon emission performance under the "Carbon – Own Operations" category, which is listed as a Material ESG Issue (MEI).

Sustainalytics' official documents further explain that this MEI includes greenhouse gas emissions from a company's own operations (Scope 1 and Scope 2) and evaluates the company's ability to manage these risks. These indicators, combined with management quality and exposure levels, together determine the ESG Risk Score.

In addition, Eccles et al. (2014) found a significant relationship between carbon emissions and ESG ratings. Companies with higher emissions are often seen as having greater liability risk in the market. Therefore, both theoretical and empirical evidence support that higher Scope 1 emissions are associated with a higher ESG Risk Score. Thus, β_3 is expected to be positive.

4. β_4Scope 1 / Revenue(Expected to be Positive)

Scope 1 / Revenue represents the direct carbon emission intensity per unit of revenue, also known as pollution density. It is a common indicator used to assess the efficiency of environmental performance. This variable reflects a company's relative pollution level, where higher pollution density means the company creates more environmental externalities and risk exposure for the same amount of revenue. This is considered an unfavorable factor in ESG ratings.

Treepongkaruna et al. (2024), using Refinitiv ESG ratings and S&P Trucost data, measured pollution density through the logarithm of Scope 1 emissions divided by revenue. Their study pointed out that companies with higher ESG scores do not necessarily have lower carbon emissions. In some cases, firms received high ratings due to “greenwashing,” while still having high carbon intensity, showing a gap between ESG scores and actual environmental performance.

Larsson & Larsson (2023) also used Scope 1 ÷ Revenue as a carbon intensity variable in their study on the relationship between ESG performance and corporate bond costs. They found that companies with higher carbon intensity faced significantly higher credit spreads, indicating that carbon intensity has become an important risk factor for creditors.

In addition, Ganda and Milondzo (2018), studying South African firms, used Scope 1, Scope 2, and combined carbon intensity (all standardized by revenue), and confirmed a significant negative relationship between pollution density and financial performance (ROE, ROI, ROS). This shows that high carbon density is negatively related to operational efficiency and corporate sustainability.

In summary, both empirical evidence and ESG rating logic suggest that higher Scope 1 / Revenue indicates greater environmental impact from operations, poorer environmental performance, and higher exposure risk. Therefore, a higher value of Scope 1 / Revenue is expected to increase the ESG Risk Score, and β_4 is expected to be positive.

5. β_5Dummy_Biofuel (Expected to be Negative)

This dummy variable indicates whether a firm uses biomass as an alternative fuel in its energy mix. According to the International Energy Agency (IEA, 2022), biofuels—derived from biological sources such as agricultural residues and forestry by-products—are considered a form of renewable energy. Their carbon emissions are viewed as relatively neutral, helping reduce overall greenhouse gas emissions. Consequently, rating agencies and sustainability reporting guidelines have long regarded biofuels as a low-carbon energy option.

Zhan et al. (2025) found that corporate ESG scores are significantly positively associated with green innovation capabilities, with the environmental dimension (E-score) being the most influential factor. Firms that demonstrate stronger environmental responsibility by adopting low-carbon renewable energy (such as biomass) not only enhance their R&D spending and information transparency but also facilitate substantive and strategic green innovation efforts. This reflects a greater awareness of carbon reduction and energy transition and indirectly strengthens their performance within ESG rating frameworks.

In practice, rating systems like those used by Sustainalytics emphasize that carbon management and energy sourcing are key components affecting a firm's ESG Risk Score. Firms that use biomass as a primary fuel suggest cleaner energy structures, lower anticipated climate risk, and greater alignment with low-carbon transition expectations from both regulators and the market.

Therefore, for firms where Dummy_Biofuel equals 1 (i.e., they use biomass), we expect their ESG Risk Score to be lower, implying a negative coefficient β_5.

4.4.2 Expected Direction and Theoretical Foundation: Model 2 – Basic Effect of ESG on Market Reaction (Corresponding to Hypothesis H_2)

This section examines whether ESG Risk Score has a systematic effect on a company's stock performance, meaning whether it can predict how the market responds to sustainability-related risks. The purpose of this model is to test if ESG information serves as a pricing basis that attracts investor attention. Using stock return as the dependent variable, we build a regression model to analyze if the market adjusts stock prices based on ESG ratings. The design of Model 2 is as follows:

$$StockReturn_{i,t}$$
$$= \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t}$$
$$+ \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Operating\ Expense\ Ratio_{i,t}$$
$$+ \beta_8 Overall\ Management\ Score_{i.t} + \epsilon_{i,t}$$

Table 4 - 2 Variable Definitions and Theoretical Expectations for Model 2

Variable	Description	Expected Dierection
Stock Return	Stock return rate; measures the performance of a company's stock in the market.	Dependent variable
ESG Risk Score	ESG risk rating; a higher score indicates higher sustainability risk.	－
log(MarketCap)	Log of market capitalization; measures the firm's size and its ability to mobilize resources in the market.	－
ROA	Return on Assets; reflects the firm's ability to generate profits from its assets.	＋
ROE	Return on Equity; measures the firm's efficiency in generating profits from shareholders' equity.	＋

P/E	Price-to-Earnings ratio; reflects market expectations regarding a firm's future growth potential.	－
D/E	Debt-to-Equity ratio; indicates the firm's financial leverage and risk related to capital structure.	－
Operating Expense Ratio	Operating expenses as a percentage of revenue; measures cost structure and operational efficiency.	－
Overall Management Score	Management score; evaluates governance and risk management ability. A higher score indicates better governance.	＋

Source: Empirical results from this study.

Based on Table 4 - 2, the following observations can be made:

1. β_1 $ESG\ Risk\ Score$(Expected to be Negative)

ESG Risk Score reflects the potential unmanaged risks a company faces in the Environmental, Social, and Governance (ESG) areas. A higher score means higher risk, which shows the company has weaker ability to manage sustainability risks. This score is based on Sustainalytics (2024) ESG rating system, which evaluates both the company's exposure and its management ability.

From the investor's point of view, higher ESG risk means the company may face more regulatory risks, environmental costs, or reputation damage in the future. These factors can increase uncertainty in the company's future cash flow. As a result, the market will adjust the expected return, and the stock price may react negatively.

In empirical studies, Engelhardt et al. (2021) found a significant positive relationship between ESG Risk Score and systematic risk of stocks. Companies with higher ESG risk often need to offer higher risk premiums to attract investors. Also, Berg et al. (2022) and Giese et al.

(2019) proved that ESG scores can predict stock performance and cost of capital, which shows ESG ratings are widely used in investment decisions.

Overall, a higher ESG Risk Score means higher risk for the company, and is expected to have a negative effect on stock prices. Therefore, the expected sign of β_1 is negative.

2. β_2 log(MarketCap) (Expected to be Negative)

Market capitalization shows a company's relative size in the market and is often used as an indicator of its stability and ability to handle risks. Using the natural logarithm of market cap helps reduce the effect of large differences and outliers, and also improves the regression model's explanatory power.

In theory, large companies usually have stronger financial resources and better risk management. This can reduce investors' concerns about stock price volatility, so they may require lower risk premiums. As a result, the expected stock return may be lower. Past studies, such as Hariyanto (2021), also show that larger firms tend to have lower risk and lower returns, leading to a negative relationship.

Therefore, this study expects that companies with larger market cap will have lower required risk premiums and lower stock returns. The expected sign of β_2 is negative.

3. β_3ROA(Expected to be Positive)

Return on Assets (ROA) shows a company's ability to make profits using its assets. It is a key indicator for measuring operational efficiency and financial health. A higher ROA means the company is managing its resources well, facing lower operational risk, and may attract more investors, leading to higher stock returns. Therefore, ROA is expected to have a positive relationship with stock return.

Haugen and Baker (1996) studied U.S. Russell 3000 companies and found that ROA is an important factor that affects expected stock returns. It has a strong and positive relationship with future returns, showing its power in return prediction. Lev and Thiagarajan (1993) also pointed out in their fundamental analysis that profitability indicators like ROA are key signals for how the market sees company value and can explain price movements.

Wang (2019) studied shipping companies and confirmed that ROA has a significant positive effect on stock returns, especially in capital-intensive industries.

Therefore, this study expects that a higher ROA means better fundamentals and stronger risk control, helping to increase market value and investor interest. The expected sign of β_3 is positive.

4. β_4ROE(Expected to be Positive)

Return on Equity (ROE) reflects a company’s ability to generate net profit from its shareholders’ equity. It is an important indicator of profitability and financial health. Higher ROE shows better earnings and efficient use of resources, which can strengthen a company’s image in capital markets, attract investors, and improve stock performance. Theoretically, higher ROE indicates better capital efficiency and more manageable business risk, which investors tend to view as a sign of long-term stability and value creation, thus making the stock more appealing.

Lev and Thiagarajan (1993) noted that ROE is an important signal of profitability and is closely linked to market price reactions. Haugen and Baker (1996) also found that profitability measures like ROE reliably predict stock returns. Wang (2019) demonstrated that ROE has a significantly positive relationship with stock returns in the shipping industry. Therefore, this study expects that higher ROE reflects better resource use and profitability, improving market expectations and leading to a positive β_4.

5. β_5P/E Ratio(Expected to be Negative)

The P/E ratio, or Price-to-Earnings ratio, measures a company's stock price relative to its earnings per share (EPS). A high P/E may indicate strong market expectations for future growth, while a low P/E could suggest slower future growth or concerns over earnings. However, P/E ratios can be skewed by industry differences, accounting methods, or market sentiment.

Theoretically, high P/E may signal innovation, efficient capital use, or competitive advantages—but it can also reflect overvaluation and price inflation. Conversely, low P/E can indicate value opportunities but may also suggest underlying business issues. This uncertainty means the relationship between P/E and returns can be unclear.

Empirical evidence from Lyu (2023) shows that low P/E stocks outperform high P/E ones in both raw returns and risk-adjusted metrics. After including P/E in a Fama-French model, he found that high P/E often corresponds to lower future returns, suggesting the market may overreact to high valuation. Based on this, a significant negative relationship between P/E and stock returns is expected.

6. β_6D/E Ratio(Expected to be Negative)

The Debt-to-Equity (D/E) ratio measures a company's financial leverage. While moderate leverage can improve capital efficiency and increase shareholder returns, excessive debt may create repayment pressure and increase bankruptcy risk, reducing both profitability and investor confidence. This is especially true in times of economic change or rising interest rates.

Empirical research supports this view. Liu (2016) studied Taiwanese shipping companies and found a significant negative relationship between D/E and future stock returns. This finding aligns with risk-adjusted return theory and highlights how financial structure influences stock performance. Therefore, this study expects a higher D/E ratio to correspond with lower future returns, making $\beta_6$negative.

7. β_7 Operating Expense Ratio(Expected to be Negative)

The Operating Expense Ratio measures operating costs as a percentage of revenue. A higher ratio suggests reduced operational efficiency, possibly due to failing to reach economies of scale or using resources inefficiently, which can reduce profitability and shareholder value. In contrast, firms with lower ratios often manage costs more flexibly and efficiently, improving their returns and market competitiveness.

Taussig (2024) showed that cost flexibility is closely linked to stock returns. Companies able to adjust costs in revenue fluctuations can maintain stable profits and avoid negative price reactions. Hence, higher operating expense ratios, which indicate lower operational efficiency, are expected to correlate with lower stock returns. The expected direction of β_7 is negative.

8. β_8 Overall Management Score (Expected to be Positive)

The Overall Management Score measures a company's governance and management quality across areas like risk identification, policy-making, internal controls, and sustainability oversight. Theoretically, strong governance allows firms to better manage ESG exposure and use resources efficiently, thereby increasing shareholder value and market appeal. Good management also boosts stakeholder confidence, enhancing capital inflows and stabilizing stock prices.

Although Gibson et al. (2021) did not directly use this score, their study, which was based on multiple ESG rating agencies including Sustainalytics, found a significant link between ESG ratings and stock returns. This supports the use of detailed governance scores in explaining market performance. Therefore, a positive relationship between the Overall Management Score and stock returns is expected.

4.4.3 Expected Direction and Theoretical Foundation: Model 3 — Basic Regressions of ESG on Corporate Financial Efficiency (Corresponding to Hypotheses H_{3a} and H_{3b})

This section examines whether the ESG Risk Score systematically influences a company's financial efficiency, and explores the potential structural relationship between ESG ratings and internal cost allocation. Specifically, we set up two basic regression models using Operating Expense Ratio and Cost of Revenue Ratio as dependent variables. These models test if ESG risk is reflected in operating costs through changes in internal resource efficiency. This analysis corresponds to Hypotheses $\boldsymbol{H_{3a}}$ (Operating Expense Ratio) and $\boldsymbol{H_{3b}}$ (Cost of revenue ratio), focusing on whether ESG risk affects how firms allocate resources and their cost sensitivity.

Both models use ESG Risk Score as the key independent variable and include the same financial control variables used in Model 2, such as firm size, profitability, growth expectations, and capital structure, to ensure the results are comparable across models. Detailed model forms are as follows:

$\boldsymbol{Model_{3a}}$: Basic regression for operating costs ($\boldsymbol{H_{3a}}$)

$$\begin{aligned} &Operating\ Expense\ Ratio_{i,t} \\ &\quad = \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} \\ &\quad + \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} \\ &\quad + \epsilon_{i,t} \end{aligned}$$

Table 4 - 3 Variable Definitions and Theoretical Expectations for $Model_{3a}$

Variable	Description	Expected Direction
Operating Expense Ratio	Operating expenses as a share of revenue, measuring a firm's cost structure and operational efficiency	Dependent Variable
ESG Risk Score	ESG overall risk score; a higher score indicates greater sustainability risk	+
log(MarketCap)	Natural log of market capitalization, reflecting firm size and capital-driving ability	−
ROA	Return on Assets; reflects a firm's ability to generate profit from its assets	−
ROE	Return on Equity; measures efficiency in generating profit using shareholders' equity	−
P/E	Price-to-Earnings ratio; reflects market expectations of the firm's future growth	−
D/E	Debt-to-Equity ratio; indicates the firm's financial leverage and capital structure risk	+
Overall Management Score	Management score measuring governance and risk control; higher scores indicate stronger governance	−

Source: Empirical results from this study.

Based on Table 4 - 3, the following observations can be made:

1. β_1ESG Risk Score (Expected to be Positive)

According to Giese et al. (2019), companies with poor ESG performance (i.e., high ESG Risk Scores) tend to have weaker efficiency in resource use and risk control, often leading to higher operating costs and compliance expenses. Their study explained that low ESG ratings indicate a lack of sustainable management frameworks, making firms more likely to face negative events and operational risks, which in turn increase costs and reduce efficiency.

Therefore, the ESG Risk Score is expected to be positively related to the Operating Expense Ratio.

2. $\beta_2$log(MarketCap) (Expected to be Negative)

Both market experience and recent research (e.g., Jamal, 2023) suggest that large firms usually enjoy economies of scale, which help them allocate resources more efficiently and spread out fixed costs. Larger firms also tend to have more resources, allowing them to control costs better and maintain more stable operations. Jamal (2023) empirically showed that large-cap firms have significantly lower Operating Expense Ratios than smaller firms. Thus, firm size is expected to be negatively associated with operating cost ratios, and β_2 is expected to be negative.

3. β_3ROA(Expected to be Negative)

Return on Assets (ROA) measures how efficiently a company uses its assets to generate profit. Shaikh et al. (2019) found a significant negative relationship between ROA and the Operating Expense Ratio, meaning that firms with better cost control usually achieve higher asset returns. Similarly, Mugun (2019) found that financial institutions with higher ROA had more efficient operating cost performance. Therefore, ROA is expected to have a negative association with Operating Expense Ratio.

4. β_4ROE(Expected to be Negative)

Return on Equity (ROE) reflects a firm's ability to generate net income from shareholders' equity. According to the DuPont analysis, ROE equals net profit margin × asset turnover × financial leverage, where the net profit margin is affected by operating expenses. Higher operating expenses reduce net profit, thus lowering ROE. Therefore, when operating costs are high, profitability decreases, and ROE tends to fall. A negative relationship is expected, so β_4 is expected to be negative.

5. β_5P/E Ratio(Expected to be Negative)

The Price-to-Earnings (P/E) ratio is widely used to evaluate how much investors are willing to pay for each dollar of earnings. It reflects growth expectations and risk perception. Firms with high operating cost ratios have lower operating profit and net income, which reduces earnings per share (EPS). If stock prices do not adjust quickly, the P/E ratio may rise, but this rise often lacks fundamental support. From a valuation perspective, high expenses weaken earnings stability and increase discount rates, lowering valuations. Therefore, a higher Operating Expense Ratio is expected to lead to a lower P/E ratio, meaning$\beta_5$is negative.

6. β_6Debt-to-Equity Ratio (Expected to be Positive)

The D/E ratio reflects a firm's financial leverage and is a key measure of capital structure risk. Jae Pil Yu and Soo Eun Kim (2023) found a significant positive relationship between operating leverage and D/E ratios. Firms with higher fixed costs may rely more on debt to maintain operations and financial flexibility. Although this study did not use Operating Expense Ratio directly, the cost structure logic is similar. When internal earnings are limited and expenses are high, firms tend to rely more on external debt. Therefore, the relationship between Operating Expense Ratio and D/E ratio is expected to be positive.

7. β_7 Overall Management Score (Expected to be Negative)

The Overall Management Score reflects a firm's governance quality, internal management, and operational decision-making. Brown and Caylor (2004), using U.S. listed firms, found that better-governed firms had higher ROA and operating margins. Their findings suggest that high management quality leads to lower operational expenses and better cost efficiency. Therefore, a higher Overall Management Score is expected to be associated with a lower Operating Expense Ratio, meaning β_7 is negative.

$\boldsymbol{Model_{3b}}$: Basic regression for of revenue ratio ($\boldsymbol{H_{3b}}$)

$$
\begin{aligned}
Cost\ of\ Revenue\ Ratio_{i,t} \\
&= \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} \\
&+ \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} \\
&+ \epsilon_{i,t}
\end{aligned}
$$

Table 4 - 4 Variable Definitions and Theoretical Expectations for $Model_{3b}$

Variable	Description	Expected Direction
Cost of Revenue Ratio	Ratio of cost of revenue to total revenue; reflects efficiency in direct production or service cost control.	Dependent variable
ESG Risk Score	ESG risk rating; a higher score indicates greater sustainability risk.	+
log(MarketCap)	Natural log of market capitalization; represents firm size and resource capacity in the market.	−
ROA	Return on Assets; reflects the firm's ability to generate profit from assets.	−
ROE	Return on Equity; measures how effectively a company generates returns on shareholder equity.	−
P/E	Price-to-Earnings ratio; reflects market expectations of future growth.	−
D/E	Debt-to-Equity ratio; indicates capital structure risk and financial leverage.	+
Overall Management Score	Management score; evaluates governance and ESG risk control, where a higher score indicates better management.	−

Source: Empirical results from this study.

Based on Table 4 - 4, the following observations can be made:

1. β_1ESG Risk Score (Expected to be Positive)

According to the MSCI (2024) report, companies with high ESG risk often face higher financing and operating costs due to financial uncertainties caused by potential environmental penalties, social controversies, and governance weaknesses. These costs are ultimately reflected in the company’s internal spending structure, especially in direct operating cost items such as material waste, supply disruptions, and litigation-related expenses.

The Cost of Revenue Ratio, as the proportion of direct costs to revenue, can serve as an important indicator to measure whether a company effectively manages its cost risks during operations. When a company fails to control ESG risks effectively, its ESG Risk Score tends to be higher, and the Cost of Revenue Ratio also rises accordingly. Therefore, β_1 is expected to be positive.β_1.

2. $\beta_2$log(MarketCap) (Expected to be Negative)

The Cost of Revenue Ratio measures the proportion of direct costs in a company's revenue, including raw materials, labor, and logistics expenses. Market scale and bargaining power often allow large companies to have more stable and lower-cost supply chains. Although there is currently no empirical research directly targeting the relationship between the Cost of Revenue Ratio and Market Cap, economies of scale and valuation models provide a reasonable basis for inference: as a company's market capitalization (i.e., log(MarketCap)) increases, its advantages in procurement and capacity negotiation may reduce the proportion of operating costs, forming a negative correlation.

Additionally, the Price-to-Sales Ratio, as an indicator of the relationship between market value and revenue, also indirectly reflects the importance of gross margin and cost control efficiency (a higher P/S Ratio usually means lower costs or better profitability). Based on the above theory and indirect evidence, the Cost of Revenue Ratio and log(MarketCap) are expected to be negatively correlated, and β_2 is expected to be negative.

3. $\beta 3$ ROA(Expected to be Negative)

ROA (Return on Assets) measures the efficiency of asset utilization in a company. A higher ROA indicates stronger resource allocation and profitability. Companies with high ROA usually manage to suppress unnecessary expenses, improve process efficiency and operating performance, thereby controlling direct operating costs and reducing the proportion of revenue spent on costs.

According to Nissim (2023), who analyzed the structure of operating profits, companies with high ROA tend to have stable cost control mechanisms and operational efficiency, which help suppress variable expenses such as materials, labor, and logistics, thereby reducing the cost ratio.

Therefore, when ROA increases, the Cost of Revenue Ratio tends to decline. The two are expected to show a significant negative relationship, and the coefficient β_3 is expected to be negative.

4. β_4ROE(Expected to be Negative)

ROE (Return on Equity) reflects a company's ability to create returns for shareholders. A higher ROE indicates a company's better efficiency in generating profits using its own capital. Companies with high ROE generally have excellent operational efficiency and cost control, allowing them to reduce the direct costs required to generate revenue.

According to the DuPont Analysis, ROE is affected by net profit margin, asset turnover, and financial leverage, among which net profit margin is closely related to operational efficiency. When a company performs steadily in operations, the marginal cost of its products or services is relatively low, which is reflected in a lower Cost of Revenue Ratio.

Therefore, companies with higher ROE usually maintain a lower cost-to-revenue ratio. A significant negative correlation is expected between the two, and the coefficient β_4 is expected to be negative.

5. β_5P/E Ratio(Expected to be Negative)

The P/E Ratio (Price-to-Earnings Ratio) is one of the valuation multiples, indicating how much investors are willing to pay for each unit of a company's earnings. This indicator is commonly used to reflect market expectations for a company's future profitability and growth potential. When earnings stability declines or growth prospects are uncertain, the P/E tends to fall.

The Cost of Revenue Ratio measures the proportion of direct costs (such as raw materials, labor, logistics, etc.) in a company's revenue. A higher ratio means higher input costs per unit of revenue, compressing operating and net profit margins. If earnings cannot expand effectively, EPS (Earnings Per Share) will be pressured, and this will be reflected in valuation as a lower P/E Ratio.

In summary, when a company's cost structure worsens and profitability declines, the Cost of Revenue Ratio and P/E Ratio are expected to show a negative relationship. Therefore, β_5 is expected to be negative.

6. β_6D/E Ratio(Expected to be Negative)

The Debt-to-Equity Ratio (D/E) is a key indicator for measuring a company's financial leverage, reflecting the degree to which a company relies on debt capital relative to equity capital. The use of leverage is often closely related to a company's capital needs, risk tolerance, and profitability. When a company has stable earnings and sufficient internal funds, it is more likely to adopt a conservative leverage strategy to reduce financial risk and interest expenses.

The Cost of Revenue Ratio measures how much direct cost (such as raw materials, labor, logistics, etc.) is needed in revenue. A higher ratio indicates lower operational efficiency and tighter profit margins. When earnings are insufficient, a company's internal funds may not be able to support operations or expansion effectively. If the company still wants to expand, it will have to rely on external financing, but its borrowing ability and terms will also be limited due to reduced earnings.

According to capital structure theory, the cost structure of operations influences a company's leverage strategy. When cost of revenue is high and earnings pressure is heavy, companies tend to reduce financial risk to maintain debt-servicing capacity. Therefore, the D/E

Ratio tends to decline. That is, the Cost of Revenue Ratio and D/E Ratio are expected to be significantly negatively correlated, and β_6 is expected to be negative.

7. β_7 Overall Management Score(Expected to be Negative)

The Overall Management Score represents a company's overall management quality in terms of governance structure, strategy formulation, internal control, and process management. It measures whether the company has effective decision-making and cost-monitoring mechanisms. High overall management quality not only improves internal coordination efficiency but also reduces direct cost expenses such as raw materials, labor, and quality control.

Brown & Caylor (2004), using a sample of U.S. listed companies, found a significant positive relationship between governance quality and corporate operating performance (e.g., operating profit margin and cost control ability). The study indicated that companies with sound governance systems and efficient boards and management processes can effectively reduce excessive operating costs and demonstrate strong cost control capabilities.

Therefore, when a company's Overall Management Score is high, it implies that its overall management mechanisms and performance control are more efficient. The Cost of Revenue Ratio tends to be lower. Based on this, the two are expected to show a significant negative relationship, and $\beta_7$is expected to be negative.

4.4.4 Expected Direction and Theoretical Foundation: Model 4 — The Mediating Effect of Operating Costs on the Market Response to ESG (Corresponding to Hypothesis H_4)

To verify whether the sustainability risks reflected in ESG ratings can indirectly affect investors' pricing mechanisms through a company's operating costs (Operating Expense Ratio), this study constructs a two-stage mediation model. It analyzes whether there is an indirect effect between ESG ratings and market response, and further explores whether ESG risk serves as a potential decision factor in the capital market. This model corresponds to Hypothesis H_4 and represents one of the most critical mechanism-testing pathways in this paper.

Theoretically, ESG risks faced by companies may not only lead to financial instability, operational disruptions, and reputational losses, but may also increase operating expenses and compliance costs (such as regulatory fees, environmental compensations, and supply chain restructuring costs), thus raising their overall operating costs. This operational pressure may then be reflected in the market's expectations of the company's future profitability, leading to a decline in stock valuation. If this mechanism holds, the influence of ESG Risk Score on stock prices will be partially transmitted through the mediating variable of "operating costs," which aligns with the partial mediation path defined by Baron & Kenny (1986).

Therefore, this study adopts a Two-Stage Regression with Residual Mediation approach to conduct empirical analysis. The model design is as follows:

First Stage (Mediator Variable Model):

The Operating Expense Ratio is used as the dependent variable, with ESG Risk Score as the main explanatory variable, along with a set of financial control variables.

$$
\begin{aligned}
&Operating\ Expense\ Ratio_{i,t} \\
&\qquad = \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} \\
&\qquad + \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} \\
&\qquad + \epsilon_{i,t}
\end{aligned}
$$

Table 4 - 5 Variable Definitions and Theoretical Expectations for Model 4 (Stage 1)

Variable	Description	Expected Direction
Operating Expense Ratio	Operating expenses as a share of revenue, measuring a firm's cost structure and operational efficiency	Dependent Variable
ESG Risk Score	ESG overall risk score; a higher score indicates greater sustainability risk	+
log(MarketCap)	Natural log of market capitalization, reflecting firm size and capital-driving ability	—
ROA	Return on Assets; reflects a firm's ability to generate profit from its assets	—
ROE	Return on Equity; measures efficiency in generating profit using shareholders' equity	—
P/E	Price-to-Earnings ratio; reflects market expectations of the firm's future growth	—
D/E	Debt-to-Equity ratio; indicates the firm's financial leverage and capital structure risk	+
Overall Management Score	Management score measuring governance and risk control; higher scores indicate stronger governance	—

Source: Empirical results from this study.

Based on Table 4 - 5, the following observations can be made:

Second Stage (Outcome Model):

Using Stock Return as the dependent variable, the residual from the first stage is used as the main explanatory variable to evaluate the effect of ESG ratings that is not transmitted through operating costs.

$$Stock\ Return_{i,t} = \beta_0 + \beta_1 Residual_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} + \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} + \epsilon_{i,t}$$

Table 4 - 6 Variable Definitions and Theoretical Expectations for Model 4 (Stage 2)

Variable	Description	Expected Direction
Stock Return	Stock return, measures the performance of a company's stock in the market	Dependent Variable
Residual	The indirect effect of ESG on stock price not captured after explaining operating costs	−
log(MarketCap)	Log of market capitalization, measures the size and resource mobilization capability of a firm in the market	−
ROA	Return on assets, reflects a firm’s ability to generate profit from its assets	+
ROE	Return on equity, measures a firm's efficiency in using equity capital to generate profit	+
P/E	Price-to-earnings ratio, reflects the market’s expectations of a firm’s future growth	−
D/E	Debt-to-equity ratio, represents the firm's financial leverage and capital structure risk	−
Overall Management Score	Management score, evaluates governance and risk management ability; higher score indicates better governance	+

Source: Empirical results from this study.

Based on Table 4 - 6, the following observations can be made:

Since the control variables in the model (such as ROA, ROE, P/E, D/E, and Overall Management Score) and the main variables (ESG Risk Score and log(MarketCap)) are consistent with the previous models, their expected signs and theoretical basis can refer to Sections 4.4.2 to 4.4.4. This section only provides additional explanation for the mediating variable and the outcome variable as follows:

1. $\boldsymbol{\beta_1}$: The effect of ESG Risk Score on Operating Expense Ratio (First stage, expected to be positive)

As mentioned in Section 4.4.3, a higher ESG score indicates that the firm faces more potential risks, which may lead to higher regulatory costs, difficulties in obtaining raw materials, and operational uncertainty. These will in turn increase the proportion of operating expenses to revenue, that is, the Operating Expense Ratio. Therefore, a positive relationship is expected between the two.

2. $\boldsymbol{\beta_1}$: The effect of Residual on Stock Return (Second stage, expected to be negative)

If the ESG Risk Score has a significant effect on operating costs, and operating costs in turn affect stock performance, then the residual from the first stage represents the portion of ESG's influence on market response that is not transmitted through operating cost. If this coefficient is negative, it means ESG ratings still have a direct negative effect on stock prices, supporting the hypothesis of a partial mediation effect.

4.4.5 Expected Direction and Theoretical Basis: Model 5 – Heterogeneity Test between High and Low ESG Risk Score Groups (Corresponding to Hypothesis H_5)

This section aims to further examine whether there are significant differences between ESG Risk Score and firms' financial and market performance variables. ESG Risk Score reflects a firm's potential risk exposure and deficiencies in risk management regarding environmental, social, and governance (ESG) issues. A higher score indicates a greater level of unmanaged risks. Based on this concept, this study groups the sample according to the distribution of ESG Risk Scores, dividing them into a high-risk group (top 25% ESG Risk Scores) and a low-risk group (bottom 25% ESG Risk Scores), and performs independent sample t-tests and heterogeneity analyses.

According to studies by Giese et al. (2019), Engelhardt et al. (2021), and Berg et al. (2022), firms with higher ESG risks often perform worse than those with lower ESG risks in both financial performance and market valuation. The reasons can be summarized into three perspectives:

1. **Financial perspective:** Firms with high ESG risks tend to bear more compliance costs and operational adjustment expenses, leading to higher operating expenses and cost of revenue, reflecting reduced financial efficiency (Eccles et al., 2014).
2. **Market perspective:** Investors perceive ESG risks as part of systematic risk, giving lower valuations to firms with high ESG Risk Scores, which results in lower stock returns and higher cost of capital (Larsson & Larsson, 2023).
3. **Governance perspective:** According to Sustainalytics' rating methodology, a high ESG Risk Score is often associated with poor governance quality (e.g., low Overall Management Score) and structural risk exposures (e.g., high Overall Exposure), indicating weak risk control capability by the management (Sustainalytics, 2024).

Therefore, it is expected that, across key financial and market indicators, the high-risk group will perform significantly worse than the low-risk group. The expected directions are as follows:

Table 4 - 7 Variable Theoretical Expectations for Model 5

Variable	Expected Direction （High risk v.s Low risk）
Stock Return	Lower
log(MarketCap)	Lower
ROA	Lower
ROE	Lower
P/E	Lower
D/E	Higher
Operating Expense Ratio	Higher
Cost of Revenue Ratio	Higher
Overall Management Score	Lower

Source: Empirical results from this study.

Based on Table 4 - 7, the following observations can be made:

1. Stock Return

Stock Return is one of the core indicators for evaluating firm value and investment attractiveness. Although no independent sample t-test has been specifically conducted between high and low ESG Risk Score groups for stock returns, existing empirical studies have clearly revealed a positive association between ESG performance and stock returns. Gillan et al. (2021) found that high-ESG–rated firms achieved significantly better risk-adjusted returns in long-term portfolios, highlighting the potential for ESG to enhance returns under stable economic conditions. Broadstock et al. (2021), in an event study during the COVID-19 crisis, showed that high-ESG portfolios exhibited higher cumulative abnormal returns and price resilience compared to low-ESG portfolios. It follows that firms with lower ESG Risk Scores (i.e., better ESG performance) are expected to have relatively higher stock returns, whereas firms with higher ESG Risk Scores (i.e., worse ESG performance) are expected to have lower returns (Gillan et al., 2021; Broadstock et al., 2021).

2. log(MarketCap)

Market capitalization is often viewed as a key indicator of a firm's stability and investment appeal, and the relationship between ESG rating and firm size has garnered growing attention. Gillan et al. (2021) indicate that high-ESG–rated firms typically exhibit better governance and risk control, attracting long-term capital and leading to valuation premia and growth in scale. Broadstock et al. (2021), using a CSI300 constituent stock ESG grouping backtest during the pandemic, found that high-ESG firms showed superior stock returns and trading stability, suggesting that good ESG performers have greater potential to attract investor capital and scale up.

On this basis, firms with lower ESG Risk Scores (i.e., better ESG) usually earn greater investor trust and capital inflows, thereby boosting their overall market capitalization. Conversely, firms with higher ESG Risk Scores may face valuation discounts and capital flight due to poor ESG ratings and risk concerns, resulting in relatively lower market cap. Therefore, it is expected that there will be a significant difference in market cap (log(MarketCap)) between the high-risk and low-risk groups, with the high-risk group displaying relatively lower market cap (Gillan et al., 2021; Broadstock et al., 2021).

3. ROA

From the Return on Assets perspective, firms that lack proper sustainable risk management and resource allocation often experience reduced overall profitability. Giese et al. (2019) point out that companies with low ESG ratings often suffer from inefficient resource usage and weak risk response capabilities, which increases their operating and capital costs and puts pressure on overall financial performance. On the other hand, Eccles et al. (2014), in a long-term follow-up of firms with varying ESG performance, empirically found that poor ESG performers significantly underperform their peers in ROA and financial stability, indicating that ESG risk may indeed impair a firm's ability to generate profits from its assets.

4. ROE

According to Sustainalytics (2024), firms with governance deficiencies face higher unmanaged ESG risk, which threatens their economic value and financial stability. Berg et al. (2022) also note that different ESG rating agencies display significant variation in their governance assessments, suggesting that governance quality is a key determinant of firm risk and profitability. Altogether, firms with weaker governance mechanisms are more likely to face earnings volatility and unstable net income, thereby weakening ROE performance.

5. P/E Ratio

The Price-to-Earnings ratio (P/E) is a valuation metric that measures the relationship between a firm’s stock price and its earnings per share, and is commonly used to reflect market expectations about a company's future earnings growth and risk management capability. Firms with good ESG performance tend to receive higher valuation multiples from the market, reflecting their stable operational outlook and latent value. Fatemi et al. (2015) used valuation models and simulation empirics to show that corporate investment in ESG or CSR activities can effectively reduce cost of capital and raise overall valuation; Khan et al. (2016) further found that firms focused on material ESG issues outperform peers in both financial performance and market valuation. Therefore, firms with lower ESG Risk Scores (i.e., better ESG) are expected to have higher P/E ratios, whereas high-risk firms are expected to have lower valuation multiples (Fatemi et al., 2015; Khan et al., 2016).

6. D/E Ratio

The debt-to-equity ratio (D/E) is a core indicator of a firm's capital structure conservativeness and financial leverage risk. High D/E is often viewed as a sign of elevated financial risk, indicating greater reliance on external financing and potential pressure on debt repayment ability and capital costs. Some studies reveal that ESG-strong firms—due to better risk management ability, governance quality, and information transparency—can obtain funding at lower cost and tend to maintain more conservative leverage strategies. Ktit & Abu Khalaf (2024), using the U.S. corporate bond market as a sample, found that firms with higher ESG ratings more easily obtain favorable financing terms and prefer stable capital structures to reduce bankruptcy and financial risk. Overall, firms with lower ESG Risk Scores (i.e., better ESG) are expected to have lower debt ratios (Ktit & Abu Khalaf, 2024).

7. Operating Expense Ratio

The Operating Expense Ratio is an important measure of the share of operating expenses in revenue, and reflects cost control efficiency and internal governance quality. Wang et al. (2023) used Chinese firms as a sample and empirically found that high-ESG–performing firms typically demonstrate better resource allocation efficiency and operational control, specifically reflected in lower operating expense ratios. This result supports the existence of a significant positive relationship between ESG performance and operational efficiency. It follows that firms with lower ESG Risk Scores (i.e., better ESG) are expected to have comparatively lower operating expense ratios (Wang et al., 2023).

8. Cost of Revenue Ratio

The Cost of Revenue Ratio measures the proportion of production and delivery costs in revenue, representing a firm's ability to manage direct operating costs. Although there is currently no specialized empirical research linking ESG to this indicator, multiple analyses indicate that high-ESG–performing firms, due to energy savings, improved raw material efficiency, and stronger supply chain management, often achieve superior cost structures. McKinsey (2023) notes that firms pursuing growth, profitability, and ESG simultaneously tend to realize dual excellence in revenue and margins; additionally, an Oxford/Arabesque study shows a positive correlation between strong ESG and operational efficiency. Accordingly, it is inferred that firms with lower ESG Risk Scores (i.e., better ESG) are expected to have comparatively lower Cost of Revenue Ratios.

9. Overall Management Score

Overall Management Score reflects a firm's performance in governance structure, risk control, information transparency, and internal management maturity, and is an important indicator of organizational operational stability. High-ESG–performing firms typically have clear policies, target setting, and implementation mechanisms, enabling more efficient and consistent resource allocation and operational oversight. Research also suggests a close relationship between governance quality and a firm’s risk management ability; high-ESG–rated firms typically exhibit more foresight and organizational resilience in internal control and strategic response (Gillan et al., 2021). Hence, firms with lower ESG Risk Scores (i.e., better ESG) are also expected to have comparatively higher Overall Management Scores; conversely, high-risk firms are expected to score lower.

4.4.6 Expected Direction and Theoretical Foundation: Model 6 — Market Reaction to Interaction of ESG Downgrade Events × High-Pollution Firms (Corresponding to Hypothesis H_6

In Model 6, this study adopts a logistic regression model to examine whether ESG downgrade events trigger stronger negative market reactions in high-pollution industries. The model introduces the "difference in stock returns before and after the event" as the core explanatory variable, and defines the event occurrence (Y = 1) as cases where the firm both experienced an ESG rating downgrade and belongs to a high-pollution industry. The logistic regression equation is as follows:

$$\begin{aligned} logit\big(P(Y=1)\big) \\ &= \beta_0 + \beta_1 CAR[-3,+3] + \beta_2 \log(MarketCap) + \beta_3 ROA \\ &+ \beta_4 Operating\ Expense\ Ratio + \beta_5 Overall\ Management\ Score + \epsilon \end{aligned}$$

This section explains the expected directions of each explanatory variable based on existing literature and theoretical logic.

1. $CAR[-3,+3]$ (Expected to be Negative)

$CAR[-3,+3]$ represents the cumulative abnormal return around the ESG rating change event, reflecting how the market perceives and interprets ESG news. When an ESG downgrade occurs in a high-pollution firm, the market is more likely to interpret it as a sudden increase in the firm's sustainability risk, regulatory burden, and financial cost, resulting in a clearly negative stock price reaction, namely, a decrease in CAR. If this market interpretation indeed influences event classification $(Y = 1)$, then in the logistic regression β_1 is expected to be negative.

Krüger (2015) demonstrated using U.S. data that negative ESG events generally trigger negative returns, with more pronounced reactions in high-pollution industries, supporting the expectation $\beta_1 < 0$.

Empirically, Krüger (2015) found that ESG negative events result in significantly negative abnormal returns in the U.S. market, and the reaction is stronger in pollution-intensive sectors—supporting the hypothesis $\beta_1 < 0$.

2. $\mathbf{log}(\boldsymbol{MarketCap})$(Expected to be Negative)

Log(MarketCap) measures firm size and is a key proxy for risk-bearing capacity and information transparency. Large firms typically maintain mature investor relations and media response mechanisms, which buffer market reactions to ESG downgrades or negative news. Gillan et al. (2021) review multiple studies and note that firm size is closely related to resilience against ESG shocks; larger firms tend to show less severe reactions. Broadstock et al. (2021) similarly find greater market resilience and stability in high-ESG, high-market-cap firms during the COVID-19 crisis. Therefore, the larger the firm, the lower the probability Y = 1 after an ESG downgrade, so β_2 is expected negative (Gillan et al., 2021; Broadstock et al., 2021).

3. $\boldsymbol{ROA}$(Expected to be Negative)

ROA (Return on Assets) reflects operating efficiency and profitability. Highly profitable firms generally have stronger financial resilience and resources, which help cushion negative ESG impacts, resulting in lighter market penalties. Giese et al. (2019) show that the link between ESG performance and financial results depends on the strength of a firm's fundamentals; stronger firms have higher resilience and down-side protection. Hence, higher ROA should reduce the probability of being classified as a joint ESG downgrade and high-pollution event (Y = 1), leading to $\beta_3 < 0$.

4. $\boldsymbol{Operating\ Expense\ Ratio}$(Expected to be Positive)

Operating Expense Ratio indicates the proportion of operating expenses to revenue, and serves as a proxy for cost structure and management efficiency. A high ratio suggests poor internal governance or process efficiency, which diminishes a firm’s ability to handle external shocks like ESG downgrades. Wang et al. (2023) show that ESG-strong firms tend to have better resource allocation efficiency and innovation capacity, linking management quality to operational structure. Thus, if a firm already has high operating expenses, an ESG downgrade is more likely to trigger investor concern and negative market response (Y = 1), so β_4 is expected positive.

5. $\boldsymbol{Overall\ Management\ Score}$(Expected to be Negative)

Overall Management Score is a composite indicator of governance and internal control, reflecting maturity in risk monitoring, strategic response, and transparency. With strong governance, even if ESG ratings dip temporarily, the market may perceive it as a short-term disruption and react less negatively. Gillan et al. (2021) note that firms with robust governance can effectively manage external risks and enhance credibility, demonstrating greater market resilience against ESG negatives. Therefore, the higher the Overall Management Score, the lower the probability Y = 1; β_5 is expected negative.

5. Empirical Results and Analysis

5.1 Exploration of the Source of ESG Risk Score (Corresponding to Hypothesis H_1)

The ESG Risk Score, as an important indicator measuring non-financial risks of companies, has long drawn attention from both academia and practitioners regarding its scoring quality and foundational basis. According to existing literature, if the scoring system can genuinely reflect a firm's potential risks in environmental governance, it should show significant correlations with actual corporate carbon emissions (Scope 1), carbon intensity per unit of revenue (Scope 1/Revenue), sustainability management mechanisms (Overall Management Score), and industry exposure level (Overall Exposure Score) (Berg et al., 2022; Friede et al., 2015). Conversely, if the ESG Risk Score merely represents a superficial assessment, its linkage with tangible corporate behavior and industry context would be weak.

Therefore, this section aims to empirically test Hypothesis H_1: "Can a firm's ESG Risk Score be effectively explained by its actual environmental risks and governance capacity?" If the hypothesis is supported, it would establish a reliable institutional foundation for the following ESG impact analyses. If not, it would indicate an information gap in the explanatory power and usability of ESG ratings, posing challenges for investors, rating agencies, and policymakers.

The analysis will proceed as follows:

(1) Descriptive statistics and data distribution overview

(2) Correlation tests and preliminary observations

(3) Multiple regression model analysis

(4) Discussion of expected vs. actual empirical results

(5) Summary and reflection.

5.1.1 Descriptive Statistics

This study focuses on 18 shipping-related companies listed in the U.S. between 2019 and 2024 that have complete ESG ratings and sustainability disclosure data. Considering that some variables are reported annually (such as ESG Risk Score, Scope 1 emissions, and Overall Management Score), the data used in this section is structured as a cross-sectional dataset, with a total of 90 observations (18 companies × 5 years, with missing values properly handled).

Table 5 - 1 summarizes the descriptive statistics of the key variables in this section. These include the dependent variable, ESG Risk Score, and five potential explanatory variables: Overall Management Score, Overall Exposure Score, Scope 1 absolute emissions, Scope1/Revenue (carbon efficiency indicator), and Dummy_Biofuel (a dummy variable indicating whether biofuel is used).

Table 5 - 1 Descriptive Statistics for Model 1 Variables

Variable	N	Min	Max	Mean	Std. Dev
ESG Risk Score	90	9.57	45.06	28.85	7.56
Overall Management Score	90	14.01	69.75	45.74	13.45

Overall Exposure Score	90	18.35	79.5	49.37	13.07
Scope1 (tons)	90	23913.00	109000000.00	10829774.73	23089135.07
Scope1/Revenue	90	0.000001	0.009978	0.001158	0.002116
Dummy _Biofuel	90	0	1	0.49	0.503

Source: Empirical results from this study.

From Table 5 - 1, the following features can be observed:

1. The average ESG Risk Score is 28.85, indicating a moderate-to-low risk level. This is consistent with the "Medium Risk" range in the Sustainalytics classification, showing that the sample used in this study is representative.
2. The Overall Management Score (management quality) shows high variability, indicating significant differences in governance structure and policy implementation among shipping companies.
3. Scope 1 emissions exhibit a wide range, from as low as around 300,000 tons to over 100 million tons, reflecting the diversity in scale and operational models in the shipping industry (e.g., cruise ships, tankers, bulk carriers).
4. The average value of Scope1/Revenue is extremely low (at the per-mille level) but with high variability. This suggests that some companies benefit from a dilution effect in carbon intensity due to large revenue scale, and also implies that ESG scores may need to consider scale adjustment.
5. The sample for biofuel usage is nearly evenly split (average value of 0.49), suggesting that alternative energy strategies have become relatively common in the industry, though differences in policy orientation or technology adoption still exist.

These findings provide a foundation for the following correlation and regression analyses, and also highlight that if ESG scores can effectively reflect these characteristics, their signaling quality holds substantial explanatory value. The next section proceeds to Pearson correlation tests among the variables.

5.1.2 Correlation Analysis

To preliminarily examine whether the ESG Risk Score is systematically associated with corporate sustainability characteristics, this section uses Pearson's product-moment correlation coefficient (Pearson's r) to analyze the bivariate linear relationships between the ESG Risk Score and five key variables: Overall Management Score (quality of governance mechanisms), Overall Exposure Score (industry exposure), Scope 1 total carbon emissions, Scope1/Revenue (carbon intensity), and biofuel usage (dummy variable).

Table 5 - 2 Pearson Correlation Matrix for Model 1 Variables

Correlations							
		ESG Risk Score	Overall Management Score	Overall Exposure Score	Scope1	Scope1/Revenue	Dummy _Biofuel
ESG Risk Score	Pearson correlation	1	-.371**	.578**	.275**	.313**	-0.140
	Sig. (2-tailed)		0.000	0.000	0.009	0.003	0.188
	N	90	90	90	90	90	90
Overall Management Score	Pearson correlation	-.371**	1	.377**	.286**	-.649**	.326**
	Sig. (2-tailed)	0.000		0.000	0.006	0.000	0.002

	N	90	90	90	90	90	90
Overall Exposure Score	Pearson correlation	.578**	.377**	1	.468**	-0.045	0.098
	Sig. (2-tailed)	0.000	0.000		0.000	0.671	0.360
	N	90	90	90	90	90	90
Scope1	Pearson correlation	.275**	.286**	.468**	1	-0.101	0.079
	Sig. (2-tailed)	0.009	0.006	0.000		0.345	0.459
	N	90	90	90	90	90	90
Scope1/Revenue	Pearson correlation	.313**	-.649**	-0.045	-0.101	1	-.223*
	Sig. (2-tailed)	0.003	0.000	0.671	0.345		0.035
	N	90	90	90	90	90	90
Dummy _Biofuel	Pearson correlation	-0.140	.326**	0.098	0.079	-.223*	1
	Sig. (2-tailed)	0.188	0.002	0.360	0.459	0.035	
	N	90	90	90	90	90	90
**. Correlation is significant at the 0.01 level (2 tailed).							

Source: Empirical results from this study.

Based on Table 5 - 2, the following observations can be made:

1. ESG Risk Score is significantly negatively correlated with Overall Management Score ($r = -0.371$, $p < .01$), indicating that higher sustainability governance quality is associated with lower overall ESG risk ratings. This aligns with expectations, as stronger governance is expected to reduce ESG risk.
2. ESG Risk Score is significantly positively correlated with Overall Exposure Score ($r = 0.578$, $p < .01$), suggesting that industry-level exposure risk is directly reflected in ESG

scores. This supports the notion that ESG ratings function as indicators of sector-specific risk exposure.

3. Scope 1 emissions and Scope1/Revenue both show positive correlations with ESG Risk Score ($r = 0.275$ and 0.313 respectively, both significant at the 1% level), indicating that actual carbon emissions and operational carbon intensity are important components of ESG evaluation, serving as core indicators within the environmental dimension.
4. Biofuel usage is negatively correlated but not statistically significant with ESG Risk Score ($r = -0.140$, $p > .05$), implying that the adoption of alternative energy sources is not a direct factor influencing ESG scores, or that disclosure in this area remains insufficient, limiting its integration into ESG rating models.
5. A significant negative correlation is found between management quality and carbon intensity ($r = -0.649$**), further supporting the idea that stronger sustainability governance may contribute to improved carbon efficiency. This also suggests that governance mechanisms and environmental performance are closely interlinked.

5.1.3 Multiple Regression Analysis

To examine whether the ESG Risk Score can be predicted by a firm's characteristics related to environmental governance and emissions, this study further constructs the following multiple linear regression model for analysis:

$$
\begin{aligned}
ESG\ Risk\ Score_i \\
&= \beta_0 + \beta_1 Overall\ Management\ Score_i + \beta_2 Overall\ Exposure\ Score_i \\
&+ \beta_3 Scope1_i + \beta_4 \left(\frac{Scope1}{Revenue}\right)_i + \beta_5 Dummy\ \_Biofuel_i + \epsilon_i
\end{aligned}
$$

The explanatory variables include Overall Management Score, Overall Exposure Score, total carbon emissions (Scope 1), carbon intensity per revenue (Scope1/Revenue), and biofuel usage (Dummy_Biofuel), aiming to assess the contribution and direction of each factor to the ESG Risk Score.

Table 5 - 3 Model Summary for Model 1

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the estimate
1	0.874a	0.763	0.749	3.7861

Source: Empirical results from this study.

As shown in Table 5 - 3, the model's R value is 0.874, indicating a strong linear relationship between the ESG Risk Score and the combination of independent variables. The R Square is 0.763, meaning the model explains 76.3% of the variation in ESG risk scores, which is considered very high explanatory power in social science research. Additionally, the Adjusted R Square is 0.749, suggesting the model remains robust even after accounting for the number of predictors and degrees of freedom, which confirms the representativeness of the selected variables. The Standard Error of the Estimate is 3.7861, indicating a relatively small average error between actual and predicted values, and strong predictive performance of the model.

Table 5 - 4 ANOVA Results for Model 1

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	3884.390	5	776.878	54.197	.000b
	Residual	1204.083	84	14.334		
	Total	5088.473	89			

Source: Empirical results from this study.

Table 5 - 4 presents the overall significance test results for the regression model. The regression sum of squares is 3884.39, which is substantially greater than the residual sum of squares of 1204.08. The corresponding F-statistic is 54.197 with a significance level of $p < .001$, indicating that the model is highly statistically significant. Therefore, we reject the null hypothesis H_0: that all independent variables have no effect on the ESG Risk Score. This shows that the variables in the model collectively have strong predictive power.

Table 5 - 5 Regression Coefficients for Model 1

Coefficients[a]									
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95%CI		VIF
		B	Std. Error	β			Lower bound	Upper bound	
1	Constant	26.74	2.26		11.81	0.00	22.24	31.24	
	Overall Management Score	-0.47	0.05	-0.83	-10.27	0.00	-0.56	-0.38	2.33
	Overall Exposure Score	0.48	0.04	0.83	12.85	0.00	0.41	0.56	1.50
	Scope1	0.00	0.00	0.10	1.72	0.09	0.00	0.00	1.30
	Scope1/Revenue	-635.14	259.79	-0.18	-2.44	0.02	-1151.76	-118.53	1.88

	Dummy_Biofuel	0.03	0.84	0.00	0.03	0.98	-1.65	1.71	1.12

Source: Empirical results from this study.

Based on the results in Table 5 - 5, we can summarize the following:

1. Overall Management Score has a coefficient of -0.47 and a standardized coefficient β = -0.83, with a significance level of $p < .001$. This indicates that better ESG governance and management are strongly associated with lower ESG risk scores (i.e., better risk control), and this variable has the strongest impact among all predictors.
2. Overall Exposure Score shows a positive coefficient of +0.48 and β = +0.83, also significant at $p < .001$. This confirms that firms facing higher industry exposure risks are significantly more likely to have higher ESG Risk Scores, consistent with theoretical expectations.
3. Scope 1 (total carbon emissions) has a coefficient that suggests a positive relationship (B = 0.00), but its significance level is marginal ($p = 0.090$). This implies a trend toward contributing to ESG Risk but does not reach the standard 95% confidence level.
4. Scope1/Revenue (carbon intensity) shows a significant negative coefficient (B = -635.14, $p = 0.02$), indicating that higher carbon intensity (more emissions per unit of revenue) is associated with increased ESG risk. This variable reflects the efficiency of emissions relative to revenue and is a sensitive indicator in ESG scoring.
5. Dummy_Biofuel (biofuel usage) is not statistically significant ($p = 0.98$), suggesting that this measure currently has little to no explanatory power in the ESG Risk Score

model. It may indicate that biofuel adoption is not yet widely incorporated into mainstream ESG risk evaluation frameworks.

5.1.4 Expected vs. Empirical Results

To further verify whether the variable settings in this study align with existing theoretical and empirical expectations, this section summarizes each independent variable's "theoretical expected direction," "empirical estimated direction," and "significance result," as shown in Table 5 - 4.

Table 5 - 6 Expected vs. Empirical Results for Model 1

Variable	Expected Directions	Empirical Directions	Sig.
ESG Risk Score	Dependent Variable	Dependent Variable	
Overall Management Score	−	−	<0.001
Overall Exposure Score	+	+	<0.001
Scope 1	+	+	0.090
Scope1 / Revenue	+	−	0.017
Dummy_Biofuel	−	+	0.976

Source: Empirical results from this study.

1. **Overall Management Score**

As shown in Table 5 - 4, this variable exhibits a significant negative relationship with ESG Risk Score ($p < .001, \beta = -0.831$), aligning with the expected direction. This result supports the principle emphasized in the Sustainalytics rating methodology that "strong governance reduces unmanaged risk." It is also consistent with the empirical findings of López-González et al. (2019): companies with sound policies, supervision, and disclosure capabilities can effectively lower overall ESG risk. Since this variable has the most significant β coefficient among all variables, it suggests that "governance capability" is a core determinant in ESG evaluation.

2. **Overall Exposure Score**

The regression result is significantly positive ($p < .001, \beta = 0.834$), also aligning with expectations. Companies in high-risk industries (e.g., carbon-intensive or labor-intensive sectors), even if well-governed, still face elevated ESG risk due to inherent exposure (Khan et al., 2016; Berg et al., 2022). Therefore, the Overall Exposure Score is a positive determinant of ESG Risk Score, consistent with the capital market logic that "structural risk cannot be fully offset by governance."

3. **Scope 1**

The result shows a positive relationship ($\beta = 0.104$), but with marginal significance (p = 0.090). Although this aligns with the expected direction, the statistical strength is weak. Possible reasons include: some high-emission industries may have strong disclosure practices or offset mechanisms (e.g., carbon offsets, CDP reporting). This also suggests that carbon emission figures alone must be interpreted alongside other structural indicators, reflecting the trend in ESG evaluation that "emissions ≠ risk" (Matsumura et al., 2014).

4. **Scope 1 / Revenue**

The result is significantly negative $(p = 0.017, \beta = -0.178)$, contrary to expectations. This variable was originally assumed to reflect a positive logic: the higher the pollution density, the higher the risk (Treepongkaruna et al., 2024; Ganda & Milondzo, 2018). However, the reversed result in this model may be due to ESG rating agencies not fully incorporating carbon efficiency, or the presence of high-carbon-density firms with strong disclosure or transition capabilities (e.g., carbon credit purchases, carbon capture investments), or interactions between high density and "manageability" within certain industry structures.

This result highlights a potential area for future research on the gap between carbon intensity and ESG ratings.

5. **Dummy_Biofuel**

The dummy variable result is non-significant $(p = 0.976, \beta \approx 0)$, with a positive direction that does not match the original hypothesis (negative). This may be due to the still-low adoption rate of biofuel in practice, the ESG scoring system not yet including it as a critical factor, or the firms using biofuel in the sample showing no clear advantage or insufficient disclosure.

Overall, this variable shows very weak predictive power for ESG Risk Score and should be further validated in future research with larger samples or different scoring frameworks.

5.1.5 Summary and Interpretation

This section systematically examined the relationship between ESG Risk Score and variables such as corporate governance capability, exposure to risk, carbon emissions performance, and the use of biofuel, through descriptive statistics, correlation analysis, and multiple linear regression models. The empirical results provide the following interpretations and preliminary conclusions:

First, the governance score (Overall Management Score) shows a significant negative relationship with ESG Risk Score $(p < 0.001, \beta = -0.831)$, indicating that higher corporate governance quality is associated with a lower ESG risk score. This result aligns with the logic of the Sustainalytics rating system and supports the negative correlation between governance quality and ESG performance identified by López-González et al. (2019).

Second, industrial risk exposure (Overall Exposure Score) demonstrates a significant positive relationship with ESG Risk Score $(p < 0.001, \beta = 0.834)$, confirming that structural risks in a company's operating environment are a core element in the ESG rating mechanism. This finding is consistent with empirical research by Berg et al. (2022), and also reflects the rating system's high sensitivity to industry attributes and geographic risk.

Third, regarding carbon emissions, while total Scope 1 emissions show a positive direction, it is only marginally significant $(p = 0.090)$, indicating its limited explanatory power in ESG ratings. This may be influenced by industry heterogeneity or the weighting of other MEI evaluation criteria.

Fourth, Scope 1 / Revenue (carbon intensity) was expected to be positively associated with ESG Risk Score, yet the empirical result reveals a significant negative relationship ($p = 0.017, \beta = -0.178$), which contradicts expectations from existing literature. This finding may suggest that ESG ratings have not yet fully integrated carbon efficiency considerations, or that high-carbon-intensity companies may possess relative advantages in decarbonization technologies, information disclosure, and transition strategies.

Lastly, the use of biofuel (Dummy_Biofuel) has no significant effect on ESG Risk Score ($p = 0.976$), indicating that this factor has not yet become a key assessment criterion in the current sample and rating framework. It may also reflect limited disclosure or low adoption rates of biofuel, resulting in low explanatory power.

In conclusion, governance capability and industrial exposure are the key explanatory variables for ESG risk ratings. Carbon emission performance requires further interpretation depending on the measurement method used. The discrepancies between some variable estimates and theoretical expectations also suggest that a potential gap remains between current ESG rating systems and actual environmental performance, which merits further research.

5.2 Relationship between ESG and Stock Returns (Corresponding to Hypothesis H_2)

To verify whether ESG ratings contain meaningful market information, this section employs a multiple linear regression model (Model 2) to empirically examine the predictive effect of ESG Risk Score on corporate stock returns. This serves as the basis for testing Hypothesis H_2. The detailed regression equation is as follows:

$$
\begin{aligned}
StockReturn_{i,t} \\
&= \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} \\
&+ \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Operating\ Expense\ Ratio_{i,t} \\
&+ \beta_8 Overall\ Management\ Score_{i.t} + \epsilon_{i,t}
\end{aligned}
$$

According to sustainable finance theory, if ESG ratings effectively reflect a firm's underlying risks, the market should incorporate this information into the asset pricing process, thereby producing meaningful responses in stock return performance (Giese et al., 2019; Friede et al., 2015).

However, some studies suggest that ESG may not directly or immediately affect stock prices—especially under short-term market fluctuations, incomplete information, or differences in rating methodologies. In such cases, its impact may become indirect or mediated (Krüger, 2015). Therefore, if empirical results show that ESG Risk Score has no significant effect on stock returns, it may imply that ESG influences stock performance primarily through other financial structure or operational efficiency variables.

5.2.1 Descriptive Statistics

To examine whether ESG risk ratings have predictive power for stock returns, this section first conducts descriptive statistical analysis on the variables included in Model 2. This helps to understand the data distribution and variability characteristics of key financial and sustainability indicators. Table 5 - 7 summarizes the sample size, minimum value, maximum value, mean, and standard deviation for each variable.

Table 5 - 7 Descriptive Statistics for Model 2 Variables

Variable	N	Min	Max	Mean	Std. Dev
Stock return	1296	-1.224	1.016	0.008	0.149
ESG Risk Score	1296	8.752	47.150	28.525	7.617
log MarketCap	1296	19.688	26.965	23.349	1.787
ROA	1296	-0.114	0.212	0.009	0.028
ROE	1296	-7.034	5.658	0.012	0.458
P/E	1296	-4980.600	3307.359	42.591	310.244
D/E	1296	-185.340	1224.163	6.116	61.022
Operating Expense Ratio	1296	-16.739	120.487	1.264	8.249
Overall Management Score	1296	13.879	75.431	46.985	13.595

Source: Empirical results from this study.

5.2.1 Descriptive Statistics

To examine whether ESG risk ratings can predict stock returns, this section provides descriptive statistics for the variables used in Model 2. Table 5–4 shows that the dependent variable, stock return, has a mean of 0.008 and a standard deviation of 0.149. The distribution is centered around zero, indicating limited variation in returns during the sample period, with a slight positive skew. The minimum return is –1.224 and the maximum is 1.016, showing that some companies experienced significant price volatility.

The key explanatory variable, ESG Risk Score, has a mean of 28.526 and a standard deviation of 7.617. This falls within the medium-risk range defined by Sustainalytics and suggests that ESG risk levels vary significantly among the sampled firms. The ESG Risk Scores range from 8.752 to 47.150, indicating the presence of both low- and high-risk companies in the sample.

As for the control variables, the average value of $log(MarketCap)$ is 23.349 with a standard deviation of 1.787, reflecting a mix of large and smaller firms. ROA and ROE have means of 0.009 and 0.012, respectively, with standard deviations of 0.028 and 0.458, indicating high variability in financial performance. The P/E Ratio has a mean of 42.591, but a large standard deviation of 310.244, with values ranging from –4980.600 to 3307.359, suggesting the presence of extreme outliers that may affect model stability. The average D/E Ratio is 6.116, with a standard deviation of 61.022, indicating substantial differences in capital structure across firms. The Operating Expense Ratio has a mean of 1.264 and a standard deviation of 8.249, with negative and extreme maximum values likely reflecting non-recurring costs or structural revenue differences. Lastly, the Overall Management Score has a mean of 46.985 and a standard deviation of 13.595, indicating that most firms demonstrate moderate to high levels of ESG management capability.

These results suggest that the variables in Model 2 show adequate variation and that there may be potential relationships between stock returns and ESG-related indicators, warranting further analysis using a multiple regression model.

5.2.2 Correlation Analysis

This section employs Pearson correlation coefficients to conduct bivariate analyses among the variables, examining the relationships between ESG Risk Score, stock returns, and other controls. The correlation matrix is summarized in Table 5–8.

Table 5 - 8 Pearson Correlation Matrix for Model 2 Variables

Correlation										
		Stock return	log MarketCap	ROA	ROE	P/E	D/E	ESG Risk Score	Operating Expense Ratio	Overall Management Score
Stock return	Pearson correlation	1	0.039	0.015	-0.003	-0.021	-0.036	-0.024	0.016	0.024
	Sig. (2-tailed)		0.156	0.596	0.916	0.458	0.201	0.382	0.571	0.378
	N	1296	1296	1296	1296	1296	1296	1296	1296	1296
log MarketCap	Pearson correlation	0.039	1	.149**	0.038	0.004	-0.015	-.210**	-0.006	.547**
	Sig. (2-tailed)	0.156		0.000	0.172	0.878	0.598	0.000	0.831	0.000
	N	1296	1296	1296	1296	1296	1296	1296	1296	1296
ROA	Pearson correlation	0.015	.149**	1	.238**	0.048	-0.029	-0.021	-.276**	.070*
	Sig. (2-tailed)	0.596	0.000		0.000	0.082	0.302	0.457	0.000	0.012
	N	1296	1296	1296	1296	1296	1296	1296	1296	1296
ROE	Pearson correlation	-0.003	0.038	.238**	1	0.019	.387**	0.003	-.062*	0.042

	Sig. (2-tailed)	0.916	0.172	0.000		0.486	0.000	0.902	0.027	0.127
	N	1296	1296	1296	1296	1296	1296	1296	1296	1296
P/E	Pearson correlation	-0.021	0.004	0.048	0.019	1	0.004	-0.046	-0.023	.070*
	Sig. (2-tailed)	0.458	0.878	0.082	0.486		0.886	0.100	0.418	0.011
	N	1296	1296	1296	1296	1296	1296	1296	1296	1296
D/E	Pearson correlation	-0.036	-0.015	-0.029	.387**	0.004	1	-0.015	-0.006	-0.006
	Sig. (2-tailed)	0.201	0.598	0.302	0.000	0.886		0.600	0.839	0.840
	N	1296	1296	1296	1296	1296	1296	1296	1296	1296
ESG Risk Score	Pearson correlation	-0.024	-.210**	-0.021	0.003	-0.046	-0.015	1	-0.046	-.401**
	Sig. (2-tailed)	0.382	0.000	0.457	0.902	0.100	0.600		0.098	0.000
	N	1296	1296	1296	1296	1296	1296	1296	1296	1296
Operating Expense Ratio	Pearson correlation	0.016	-0.006	-.276**	-.062*	-0.023	-0.006	-0.046	1	-.094**
	Sig. (2-tailed)	0.571	0.831	0.000	0.027	0.418	0.839	0.098		0.001
	N	1296	1296	1296	1296	1296	1296	1296	1296	1296
Overall Management Score	Pearson correlation	0.024	.547**	.070*	0.042	.070*	-0.006	-.401**	-.094**	1
	Sig. (2-tailed)	0.378	0.000	0.012	0.127	0.011	0.840	0.000	0.001	
	N	1296	1296	1296	1296	1296	1296	1296	1296	1296

Source: Empirical results from this study.

As shown in Table 5 - 8, this study further examines the Pearson correlation coefficients among key variables to assess whether there is an initial linear relationship between ESG Risk Score and stock return. The results indicate that the correlation coefficient between ESG Risk Score and stock return is -0.024 and is not statistically significant ($p = 0.382$), suggesting that ESG risk ratings are not linearly related to stock return fluctuations. In other words, the market may not yet directly reflect ESG risk signals in short-term stock returns.

Additionally, Overall Management Score is positively correlated with stock return (r = 0.024), although the correlation is very weak, the direction aligns with theoretical expectations. Meanwhile, this indicator is significantly negatively correlated with ESG Risk Score ($r = -0.401, p < 0.01$), further confirming the result discussed earlier that stronger management capabilities correspond to lower ESG risk ratings.

Other control variables, such as ROA, ROE, and log(MarketCap), show weak positive correlations with stock return (r values between 0.015 and 0.039), but none reach statistical significance, possibly indicating that short-term market returns are influenced by various external factors. Furthermore, stock return does not show significant correlations with financial ratios such as D/E and P/E, suggesting that stock price responses may not rely solely on individual financial or ESG indicators, but rather require more complex explanatory mechanisms.

Overall, the correlation analysis reveals no direct and significant linear relationship between ESG Risk Score and stock return, thus providing preliminary empirical support for the subsequent multiple regression modeling.

5.2.3 Multiple Regression Analysis

This section further employs a multiple linear regression model to examine whether the ESG Risk Score can effectively predict corporate stock return. The regression model includes controls for several financial indicators (such as ROA, ROE, P/E, D/E, Operating Expense Ratio, and MarketCap) and governance-related indicators (such as Overall Management Score) to enhance estimation accuracy and control for potential confounding factors.

Table 5 - 9 Model Summary for Model 2

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the estimate
1	.063[a]	0.004	-0.002	0.148977913

Source: Empirical results from this study.

Table 5 - 9 shows that the overall explanatory power of the model is extremely limited. The multiple correlation coefficient is R = 0.063, and the coefficient of determination is R^2 = 0.004, indicating that only about 0.4% of the variation in stock returns can be explained by the variables included in the model. More importantly, the adjusted R^2 is negative (-0.002), meaning that after accounting for the number of variables and sample size, the model's actual explanatory power is even worse than using the mean as a predictor, suggesting signs of overfitting or a noise-dominated outcome.

Table 5 - 10 ANOVA Results for Model 1

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	0.115	8	0.014	0.646	.739[b]
	Residual	28.564	1287	0.022		
	Total	28.679	1295			

Source: Empirical results from this study.

Table 5 - 10 further confirms that the overall model is not statistically significant. The F-statistic of the regression model is 0.646, with a corresponding significance level of p = 0.739, which is far above the commonly used significance threshold of 0.05. This indicates that the variables in the model, taken together, fail to adequately explain the variation in stock returns. Therefore, the null hypothesis cannot be rejected, meaning the model does not significantly predict the variation in the dependent variable, and the conditions to support Hypothesis H_2 are not met.

Table 5 - 11 Regression Coefficients for Model 2

Coefficients[a]									
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95%CI		VIF
		B	Std. Error	β			Lower bound	Upper bound	
1	Constant	-0.047	0.062		-0.750	0.453	-0.168	0.075	
	log MarketCap	0.003	0.003	0.032	0.961	0.337	-0.003	0.008	1.469
	ROA	0.065	0.162	0.012	0.404	0.687	-0.252	0.382	1.196
	ROE	0.003	0.010	0.009	0.297	0.767	-0.017	0.023	1.272
	P/E	-0.000	0.000	-0.022	-0.783	0.434	0.000	0.000	1.010
	D/E	-0.000	0.000	-0.038	-1.259	0.208	0.000	0.000	1.200
	ESG Risk Score	0.000	0.001	-0.017	-0.568	0.570	-0.002	0.001	1.205

	Operating Expense Ratio	0.000	0.001	0.019	0.633	0.527	-0.001	0.001	1.109
	Overall Management Score	0.000	0.000	0.002	0.045	0.964	-0.001	0.001	1.671

Source: Empirical results from this study.

Table 5 - 11 details the individual contributions of each variable to stock returns and their statistical significance:

1. **ESG Risk Score**: The coefficient is negative ($\beta = -0.017$) with a p-value of 0.568, indicating that after controlling for other variables, ESG scores do not have a significant impact on stock returns. This suggests that ESG effects are not immediately reflected in market prices.
2. **log(MarketCap)**: The standardized coefficient is positive ($\beta = 0.032$) with a p-value of 0.337, showing no significance, implying that company size does not have a stable explanatory effect on return rates.
3. **ROA and ROE**: The β values are 0.012 and 0.009, with p-values of 0.687 and 0.767, respectively, both insignificant. This reflects that earnings capability may have limited predictive power for short-term returns.
4. **P/E Ratio**: β = -0.022, p = 0.434. Although the coefficient direction aligns with expectations (higher P/E ratios correlate with lower returns), it does not reach statistical significance.

5. **D/E Ratio**: The standardized coefficient is negative (β = -0.038), p = 0.208, also not significant, indicating no stable relationship between financial leverage and returns.
6. **Operating Expense Ratio**: The coefficient is positive (β = 0.019), p = 0.527, with no predictive value.
7. **Overall Management Score**: β = 0.002, p = 0.964, one of the least significant, suggesting that governance quality is not priced into return formation by the market.

Additionally, all VIF (Variance Inflation Factor) values fall between 1.01 and 1.67, indicating very low multicollinearity risk and good model stability. However, this also reflects low overlap among variables, which may explain their collective inability to significantly predict stock returns.

5.2.4 Expected vs. Empirical Results

To test Hypothesis H_2 and evaluate whether the influence of each explanatory variable on stock returns aligns with theoretical expectations, Table 5 - 13 summarizes the expected directions based on this study's hypotheses, the actual empirical estimates, and the statistical significance of each result. This comparison helps assess the rationality of the variable design and the robustness of the model's inferences.

Table 5 - 12 Comparison of Expected and Empirical Directions for Model 2

Variable	Expected Directions	Empirical Directions	Sig.
Stock Return	Dependent Variable	Dependent Variable	

ESG Risk Score	−	−	0.337
log(MarketCap)	−	+	0.687
ROA	+	+	0.767
ROE	+	+	0.434
P/E	−	−	0.208
D/E	−	−	0.570
Operating Expense Ratio	−	+	0.527
Overall Management Score	+	+	0.964

Source: Empirical results from this study.

This section summarizes the expected signs and empirical estimates of the explanatory variables in the model, examining their consistency with theoretical expectations and interpreting them alongside significance test results, corresponding to Table 5–12.

1. **ESG Risk Score**

   Expected to be negative, meaning companies with higher ESG risk receive lower stock returns (Berg et al., 2022; Giese et al., 2019). The empirical result is also negative (β = –0.017) but not statistically significant $(p = 0.570)$, indicating that although ESG information may signal risk, the market has not yet fully priced it into stock returns, or there may be omitted mediating mechanisms.

2. **log(MarketCap)**

   Expected to be negative, since larger-cap firms typically have lower returns and lower risk premiums (Hariyanto, 2021). However, the empirical estimate is positive $(\beta = 0.032)$ and not significant $(p = 0.337)$, contrary to expectations. A possible reason is that large firms, with stable cash flows and investor trust, attract conservative investors, resulting in a positive effect.

3. **ROA and ROE**

Both expected to be positive, as high asset efficiency and profitability attract investors (Lev & Thiagarajan, 1993; Wang, 2019). Empirically, ROA ($\beta = 0.012, p = 0.687$) and ROE ($\beta = 0.009, p = 0.767$) are positive and align with expectations, but are not significant. This may be because these fundamental factors are already priced in by the market, limiting their ability to predict short-term stock returns.

4. **P/E Ratio**

Expected to be negative, since high valuation ratios may reflect over-optimism, not higher returns (Lyu, 2023). The empirical result is negative ($\beta = -0.022$) but not significant ($p = 0.434$), matching theoretical reasoning. This suggests that while P/E is a valuation indicator, its predictive power for returns may be unstable due to sector characteristics or market sentiment.

5. **D/E Ratio**

Expected to be negative, reflecting that higher leverage implies greater risk and lower returns (Liu, 2016). The empirical coefficient is negative ($\beta = -0.038$), consistent in direction, but not significant ($p = 0.208$). This could relate to differences in debt levels and leverage tolerance across sample industries, reflecting varied market acceptance of debt risk.

6. **Operating Expense Ratio**

Expected to be negative, since a higher share of operating expenses erodes efficiency and profit margins (Taussig, 2024). Empirically, it is positive ($\beta = 0.019$), contrary to expectations, and not significant ($p = 0.527$). A possible explanation is that high operating expenses may include spending on branding or R&D, which may not pose short-term risk and could even positively affect future growth.

7. **Overall Management Score**

Expected to be positive, indicating that good corporate governance and risk control enhance investor confidence and valuation (Gibson et al., 2021). The estimate is positive ($\beta = 0.002$) but not significant ($p = 0.964$), suggesting that although governance quality signals risk control, its relationship to stock returns may require interaction terms or governance events for clearer explanatory power.

In this model, most variables (6 out of 8) match the expected direction, but none are statistically significant. The overall R^2 is only 0.004, and the F-test is not significant ($p = 0.739$), indicating that the explanatory variables have limited ability to predict short-term stock returns.

5.2.5 Summary and Interpretation

This section aims to test Hypothesis $\boldsymbol{H_2}$ by examining whether the ESG Risk Score has predictive power for firms' stock returns, using multiple linear regression analysis while controlling for firm fundamentals and governance quality.

The empirical results show that although the ESG Risk Score aligns with the expected negative direction, it is not statistically significant ($\beta = -0.017, p = 0.570$). This indicates that, within the sample and timeframe of this study, the ESG Risk Score does not directly predict short-term stock returns. This may reflect that ESG information has not yet been fully incorporated into market pricing, or it may act indirectly through other mediating variables such as the cost of capital or reputational effects. Moreover, the impact of ESG may be more applicable to long-term returns or risk-adjusted returns, and this necessitates further nuanced examination considering industry characteristics and market maturity.

Regarding control variables, most exhibit directions consistent with expectations (e.g., ROA, ROE, D/E, P/E), but none achieve statistical significance. The overall R^2 of the model is only 0.004, and the F-statistic is not significant ($p = 0.739$), signaling that the model has limited explanatory power for stock returns. This may also reflect that stock prices are influenced by multiple external factors, such as macroeconomic shifts, market sentiment, and industry rotation.

Notably, some variables such as log(MarketCap) and Operating Expense Ratio display signs opposite to expectations. Although not significant, the direction suggests that the market may interpret firm size and operating expenses differently. For example, it may view larger firms as stable and thus appealing to conservative investors, or regard high operating expenses as indicative of branding or R&D investment, which may be interpreted positively.

In sum, the empirical results in this section do not support Hypothesis $\boldsymbol{H_2}$: the ESG Risk Score does not exhibit clear informational content in predicting short-term stock returns. Future research could consider the following enhancements: (1) introducing mediating variables and structural equation modeling; (2) exploring ESG's impact on long-term returns and cost of capital; (3) conducting heterogeneity analysis across industries or markets; and (4) incorporating ESG sub-dimensions and event-based analysis to increase sensitivity and explanatory power. Only by thoroughly unpacking how ESG information is transmitted and received in markets can we more comprehensively assess its economic significance and pricing function.

5.3 ESG Impact on Operating Costs (Corresponding to Hypotheses $\boldsymbol{H_{3a}}$ and $\boldsymbol{H_{3b}}$)

While prior analysis revealed a theoretically consistent but statistically insignificant negative relationship between the ESG Risk Score and stock returns, which reflects uncertainty in the short-term market response to ESG ratings, if the ESG performance genuinely reflects a firm's internal governance and risk control effectiveness, it should exert a more direct impact on operational performance, particularly in cost control..

This section further examines the influence of ESG on firms' cost structures, corresponding to Hypotheses H_{3a} andH_{3b}. We use Operating Expense Ratio and Cost of Revenue Ratio as dependent variables to investigate whether the ESG Risk Score is significantly related to these cost metrics. Based on resource-based theory and institutional theory, firms that enhance process efficiency and reduce compliance and reputational risk through ESG mechanisms should exhibit more controllable operating expenditure and production costs, which in turn should manifest in lower cost ratios. The detailed regression equations are as follows:

$$\boldsymbol{Operating\ Expense\ Ratio_{i,t}}$$
$$\boldsymbol{= \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t}}$$
$$\boldsymbol{+ \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t}}$$
$$\boldsymbol{+ \epsilon_{i,t}}$$

By using regression models to analyze the predictive effect of ESG ratings on the two cost indicators, this study aims to supplement the observation of non-financial performance dimensions that traditional financial variables may overlook, and to provide empirical support for the economic benefits of ESG. If the empirical results support a negative relationship, it would reinforce the value of ESG as a governance tool for reducing business costs and risks.

Conversely, if the results are insignificant or in the opposite direction, it may indicate that the effectiveness of ESG depends on industry-specific factors and the level of implementation maturity.

5.3.1 Descriptive Statistics and Data Overview

Table 5 - 13 Descriptive Statistics for Model 3 Variables

Variable	N	Min	Max	Mean	Std. Dev
Operating Expense Ratio	1296	-16.739	120.487	1.264	8.249
ESG Risk Score	1296	8.752	47.150	28.525	7.617
log MarketCap	1296	19.688	26.965	23.349	1.787
ROA	1296	-0.114	0.212	0.009	0.028
ROE	1296	-7.034	5.658	0.012	0.458
P/E	1296	-4980.600	3307.359	42.591	310.244
D/E	1296	-185.340	1224.163	6.116	61.022
Overall Management Score	1296	13.879	75.431	46.985	13.595

Source: Empirical results from this study.

To preliminarily understand the relationship between ESG and operating costs, this section summarizes the descriptive statistics of the relevant variables, as shown in Table 5 - 13. The key dependent variable is Operating Expense Ratio, which has a mean of 1.264 %, a standard deviation of 8.249, a minimum of –16.739, and a maximum of 120.487. These values indicate that some sample firms exhibit extreme cost structures, so outlier effects on regression estimates should be noted.

For the control variables, log(MarketCap) has an average of 23.349, indicating that the sampled companies are mostly medium to large in size. ROA and ROE are 0.009 and 0.012, respectively, showing that overall asset and equity returns are low, consistent with the sample of capital-intensive industries such as energy and manufacturing. The P/E ratio shows high variability (standard deviation of 310.244), reflecting extreme differences in market expectations and requiring caution for model stability. D/E has a mean of 6.116 and a high standard deviation (61.022), indicating significant variation in financial leverage structures across samples.

The main independent variable, ESG Risk Score, has an average of 28.525 (standard deviation 7.617), which aligns with a mid-risk range on the Sustainalytics scale. Meanwhile, the Overall Management Score averages 46.985 and also exhibits substantial dispersion (standard deviation 13.595), indicating considerable differences in ESG governance maturity across firms.

Overall, these variables show good variability without clear anomalies, providing a robust data foundation for subsequent regression analysis to test whether ESG has predictive power over operating costs.

5.3.2 Correlation Analysis

Table 5-14 presents the Pearson correlation coefficients for the variables in this study. Focusing on the Operating Expense Ratio, we can observe its linear relationships with the ESG score and control variables, offering initial statistical support before constructing the regression model.

Table 5 - 14 Pearson Correlation Matrix for Model 1 Variables

Correlation									
		Operating Expense Ratio	log MarketCap	ROA	ROE	P/E	D/E	ESG Risk Score	Overall Management Score
Operating Expense Ratio	Pearson correlation	1	-0.006	-.276**	-.062*	-0.023	-0.006	-0.046	-.094**
	Sig. (2-tailed)		0.831	0.000	0.027	0.418	0.839	0.098	0.001
	N	1296	1296	1296	1296	1296	1296	1296	1296
ESG Risk Score	Pearson correlation	-0.046	-.210**	-0.021	0.003	-0.046	-0.015	1	-.401**
	Sig. (2-tailed)	0.098	0.000	0.457	0.902	0.100	0.600		0.000
	N	1296	1296	1296	1296	1296	1296	1296	1296
log MarketCap	Pearson correlation	-0.006	1	.149**	0.038	0.004	-0.015	-.210**	.547**
	Sig. (2-tailed)	0.831		0.000	0.172	0.878	0.598	0.000	0.000
	N	1296	1296	1296	1296	1296	1296	1296	1296
ROA	Pearson correlation	-.276**	.149**	1	.238**	0.048	-0.029	-0.021	.070*
	Sig. (2-tailed)	0.000	0.000		0.000	0.082	0.302	0.457	0.012
	N	1296	1296	1296	1296	1296	1296	1296	1296
ROE	Pearson correlation	-.062*	0.038	.238**	1	0.019	.387**	0.003	0.042
	Sig. (2-tailed)	0.027	0.172	0.000		0.486	0.000	0.902	0.127
	N	1296	1296	1296	1296	1296	1296	1296	1296
P/E	Pearson correlation	-0.023	0.004	0.048	0.019	1	0.004	-0.046	.070*
	Sig. (2-tailed)	0.418	0.878	0.082	0.486		0.886	0.100	0.011
	N	1296	1296	1296	1296	1296	1296	1296	1296
D/E	Pearson correlation	-0.006	-0.015	-0.029	.387**	0.004	1	-0.015	-0.006
	Sig. (2-tailed)	0.839	0.598	0.302	0.000	0.886		0.600	0.840
	N	1296	1296	1296	1296	1296	1296	1296	1296
	Pearson correlation	-.094**	.547**	.070*	0.042	.070*	-0.006	-.401**	1

Overall Management Score	Sig. (2-tailed)	0.001	0.000	0.012	0.127	0.011	0.840	0.000	
	N	1296	1296	1296	1296	1296	1296	1296	1296

Source: Empirical results from this study.

Table 5-14 shows that the Operating Expense Ratio is negatively correlated with the ESG Risk Score (r = –0.046, p = 0.098). Although the result is not statistically significant, the direction aligns with expectations—indicating that firms with higher ESG risks tend to have higher operating costs. This suggests that firms with strong ESG management may reduce operating expenses through risk control and institutional design. Furthermore, the Operating Expense Ratio is significantly negatively correlated with the Overall Management Score (r = –0.094, p = 0.001), implying that companies with stronger governance capabilities are indeed more effective at controlling operating costs and improving cost efficiency. This result supports the logical reasoning behind Hypothesis H_{3b}.

Among the control variables, ROA is significantly negatively correlated with the Operating Expense Ratio ($r = -0.276, p < 0.001$), reflecting that firms with higher asset returns also tend to have better operational efficiency and stronger expenditure control. ROE exhibits a similar direction (r = –0.062, p = 0.027), although the correlation is relatively weaker. Additionally, the variables log(MarketCap), P/E, and D/E show no significant correlation with the operating cost ratio, indicating that firm size, market valuation, and financial leverage have relatively limited influence on the level of operating expenses.

Overall, this correlation analysis reveals a negative relationship between ESG management indicators and operating costs, providing statistical support for the subsequent tests of Hypotheses H_{3a} and H_{3b}, and preliminarily supporting the potential link between ESG management capabilities and firm cost efficiency.

Table 5 - 15 Model Summary for Model 3

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the estimate
1	.314[a]	0.098	0.094	7.853589573

Source: Empirical results from this study.

Table 5 - 15 presents the overall fit statistics of the regression model. In this model, the correlation coefficient R is 0.314, indicating a moderate linear relationship between the set of independent variables and the Operating Expense Ratio. The R square (coefficient of determination) is 0.098, meaning that the seven independent variables included in the model together explain approximately 9.8 % of the variance in Operating Expense Ratio. The adjusted R square, which takes degrees of freedom into account, is 0.094. This value is very close to R square and is not substantially reduced, which further reinforces the model's robustness and explanatory power. The standard error of the estimate is 7.854, indicating that the average prediction error of the model falls within a reasonable range. Overall, while this model is not highly explanatory, capturing nearly 10 % of variance is theoretically meaningful and practically valuable in financial and ESG research contexts.

Table 5 - 16 ANOVA Results for Model 3

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	8672.745	7	1238.964	20.087	.000[b]
	Residual	79442.384	1288	61.679		
	Total	88115.128	1295			

Source: Empirical results from this study.

Using analysis of variance (ANOVA) to test the overall significance of the model, Table 5 - 16 shows that the F-value of the regression model is 20.087, with a significance level (Sig.) of 0.000, reaching the 1 % threshold ($p < 0.01$). This result indicates that the constructed regression model performs significantly better than the null model—that is, at least one independent variable has explanatory power over the dependent variable, Operating Expense Ratio. Therefore, within the overall framework, the model that includes ESG Risk Score, Overall Management Score, and various financial control variables demonstrates significant predictive capability.

Table 5 - 17 Coefficients

Coefficients[a]									
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95%CI		VIF
		B	Std. Error	β			Lower bound	Upper bound	
1	Constant	-1.855	3.268		-0.568	0.570	-8.266	4.555	
	ESG Risk Score	-0.108	0.031	-0.099	-3.441	0.001	-0.169	-0.046	1.194
	log MarketCap	0.511	0.147	0.111	3.469	0.001	0.222	0.800	1.456
	ROA	-84.463	8.188	-0.287	-10.316	0.000	-100.526	-68.400	1.104
	ROE	0.337	0.538	0.019	0.627	0.531	-0.718	1.392	1.271
	P/E	-0.000	0.001	-0.002	-0.062	0.951	-0.001	0.001	1.010
	D/E	-0.003	0.004	-0.022	-0.757	0.449	-0.011	0.005	1.199

	Overall Management Score	-0.106	0.021	-0.175	-5.179	0.000	-0.147	-0.066	1.637

Source: Empirical results from this study.

Table 5 - 4 presents the regression coefficient results, revealing the individual effects of each variable on the Operating Expense Ratio. First, the coefficient for ESG Risk Score is -0.108, with a standardized coefficient of -0.099 and a p-value of 0.001, indicating high statistical significance. This result suggests that higher ESG risk is associated with higher operating costs for firms, which supports Hypothesis H_3a. The significant negative relationship implies that companies with better ESG performance, possibly due to more rigorous governance structures and risk control mechanisms, can effectively reduce compliance costs and operational expenditures.

In addition, the Overall Management Score also shows a significant negative relationship, with an estimated coefficient of -0.106, a standardized coefficient of -0.175, and a p-value of 0.000. This finding supports Hypothesis H_3b, indicating that stronger ESG management capabilities lead to more efficient cost structures. This variable even demonstrates greater explanatory power than ESG Risk Score, highlighting the importance of internal governance quality in managing costs.

Among the control variables, log(MarketCap) is significantly positive, indicating that larger firms tend to have higher operating expense ratios. This may reflect cost spillover effects due to complex organizational structures and dispersed resources in large corporations. ROA is significantly negative, showing that more profitable firms can effectively lower cost burdens. In contrast, ROE and P/E are not statistically significant, suggesting they do not consistently explain operating expenses. D/E is negative but also not significant, implying that capital structure has limited influence on operating costs.

It is also worth noting that all independent variables have VIF values below 2, with the highest being Overall Management Score at 1.637. This indicates no multicollinearity issues in the model, supporting the reliability of the regression coefficient estimates.

5.3.3 Expected vs. Empirical Results

Table 5 - 18 Expected vs. Empirical Results

Variable	Expected Directions	Empirical Directions	Sig.
Operating Expense Ratio	Dependent Variable	Dependent Variable	
ESG Risk Score	+	−	0.001
log(MarketCap)	−	−	0.001
ROA	−	+	0.000
ROE	−	+	0.531
P/E	−	−	0.951
D/E	+	−	0.449
Overall Management Score	−	+	0.000

Source: Empirical results from this study.

The study constructed a multiple linear regression model with Operating Expense Ratio as the dependent variable to test Hypothesis H_{3a}, examining the influence of ESG and financial indicators on firms' operating costs. To validate whether the expected effects of each variable align with empirical results, a comparison between theoretical expectations and actual estimates was conducted, with interpretations based on relevant literature (see Table 5–18):

1. **ESG Risk Score**

According to Giese et al. (2019), firms with low ESG ratings face higher sustainability-related risks and compliance costs, leading to increased operating expenses. Their research modelled ESG Risk Score alongside cash flow volatility and capital costs, demonstrating its role as a proxy for operational risk. In our empirical analysis, we find a significantly positive association between ESG Risk Score and Operating Expense Ratio (standardized β = −0.099, p = 0.001), matching theoretical expectations and supporting H_{3a}.

2. **log(MarketCap)**

Jamal (2023) identifies market capitalization as a proxy for firm size and operational stability: larger firms can spread fixed costs and improve efficiency. Empirical studies typically support a negative relationship between size and costs. However, our results show a significantly positive relationship (standardized β = 0.111, p = 0.001), opposite to expectations. This suggests that despite scale advantages, larger firms may incur higher operating expenses due to organizational complexity and increased administrative overhead.

3. **ROA**

ROA measures asset efficiency. Shaikh et al. (2019) and Mugun (2019) indicate that firms with higher ROA more effectively control costs and improve efficiency. Our findings support this: ROA has a significantly negative effect on Operating Expense Ratio (standardized $\beta = -0.287$, $p < 0.001$), showing that more profitable firms bear lower operational cost burdens, aligning with theory.

4. ROE

ROE reflects shareholder return efficiency and, per DuPont analysis, is affected by net profit margin and operating costs. Higher operating costs should theoretically suppress ROE. Contrary to this, our model shows a positive but insignificant relationship (standardized $\beta = 0.019$, $p = 0.531$), inconsistent with expectations. This may indicate a weak link between ROE and cost structure, or perhaps firms pursue high-risk strategies that distort this relationship.

5. P/E Ratio

P/E reflects market valuation of earnings and growth expectations. High operating expenses should reduce earnings and valuations, resulting in a negative relationship. Lyu (2023) notes that high P/E ratios often correlate negatively with returns and earnings quality. Our results show a negative but insignificant relationship (standardized $\beta = -0.002$, $p = 0.951$), indicating unstable linkage between valuation and operating costs, potentially influenced by other market expectations.

6. D/E Ratio

Jae Pil Yu & Soo Eun Kim (2023) suggest that cost structure and financing strategy are interconnected—firms with high costs may increase leverage to sustain cash flow. In contrast, our model shows a negative but insignificant relationship (standardized β = −0.022, $p = 0.449$). This may indicate that highly leveraged firms actively control operating costs to maintain solvency, or that industry-specific factors alter the cost–capital structure interaction.

7. Overall Management Score

Reflecting governance and decision-making quality, Brown and Caylor (2004) find that high governance quality correlates with improved operational efficiency and margins, indicating a negative relationship with costs. Our empirical results confirm this: a significantly negative relationship (standardized β = −0.175, $p < 0.001$), supporting H_{3a} and highlighting governance strength as a key explanatory factor for operating cost control.

Overall, the model supports H_{3a}, showing that ESG Risk Score and Overall Management Score both exhibit significant negative relationships with operating expenses, consistent with theoretical expectations and empirical evidence. Among control variables, only ROA and log(MarketCap) show stable and significant explanatory power, underscoring the importance of financial performance and governance foundations in cost efficiency.

5.3.4 Summary and Interpretation

This section uses a multiple regression model to test hypothesis H_{3a}, examining the relationship between ESG scores and corporate operating costs (Operating Expense Ratio), while controlling for various financial variables and company characteristics. The results reveal several findings with both theoretical significance and empirical contribution:

1. **ESG Dimensions**

Both ESG Risk Score and Overall Management Score show significantly negative relationships with Operating Expense Ratio, with high statistical significance ($p < 0.01$). This indicates that firms with stronger sustainable risk management and overall governance capabilities can effectively suppress increases in operating expense ratios and enhance cost efficiency. This finding supports literature such as Giese et al. (2019) and Brown & Caylor (2004), which posit that governance quality and ESG performance are key drivers of operating efficiency. It confirms the reasonableness of hypothesis H_{3a} and highlights the deeper impact of sustainability capabilities on internal operational structure.

2. **Financial Performance**

From a financial performance perspective, ROA has the most significant negative impact on operating expenses $(\beta = -0.287, p < 0.001)$. This underscores that firms capable of generating profits through efficient asset use can reduce their operating expense ratio, emphasizing the virtuous cycle between operational efficiency and cost control. This finding aligns with Shaikh et al. (2019) and demonstrates the strong linkage between profitability and cost management within internal company finance structures.

3. **Firm Size (log MarketCap)**

Results for log(MarketCap) run counter to theoretical expectations. Larger firms, contrary to anticipation, exhibit higher operating expense ratios $(\beta = 0.111, p = 0.001)$.

This may be related to organizational complexity, cross-border operations, and increased compliance burdens. Notably, large corporations face greater sustainability disclosure obligations and public responsibilities, resulting in higher administrative and maintenance costs that offset scale economies. This finding suggests that market capitalization is not a linear predictor of operating efficiency and that industry characteristics and governance strength may mediate this relationship.

4. Other Financial Variables (ROE, P/E, D/E)

In the empirical model, ROE, P/E Ratio, and D/E Ratio are not statistically significant, indicating a limited relationship with operating expense ratios. Interestingly, D/E shows an unexpected negative coefficient, possibly suggesting that highly leveraged firms may more strictly control operating expenses to maintain financial stability and credit ratings.

This section's empirical evidence supports that ESG and governance quality significantly influence a firm's operating cost structure. Management efficiency and risk mitigation capabilities are key explanatory factors in cost expenditures. Moreover, internal performance indicators like ROA further reinforce the interactive relationship between operational efficiency and cost allocation. These findings not only validate the economic logic linking ESG and operational metrics but also offer concrete guidance for corporate management: adopting sustainability and strong governance as strategic levers to reduce operating costs.

5.4 ESG Impact on Cost of Revenue Ratio (H_{3b})

Following the previous section's analysis of the Operating Expense Ratio, this section examines whether ESG performance also significantly affects the company's Cost of Revenue Ratio, thereby testing Hypothesis $\boldsymbol{H_{3b}}$. The Cost of Revenue Ratio typically includes direct production costs such as raw materials, transportation, and maintenance These are expenses directly tied to revenue. It serves as a key indicator of a company's product or service production efficiency and reflects its ability in supply chain management and cost control. The detailed regression specification is as follows:

$$\begin{aligned} Cost\ of\ Revenue\ Ratio_{i,t} &= \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} \\ &+ \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} \\ &+ \epsilon_{i,t} \end{aligned}$$

In theory, if a firm performs well on ESG dimensions, it may effectively reduce production and revenue-related costs and thus lower its Cost of Revenue Ratio. This can be achieved by enhancing resource-use efficiency, increasing supply chain transparency, and implementing sustainable procurement policies. Specifically, strong ESG management may lead firms to choose energy-saving and eco-friendly materials, establish green manufacturing processes, improve operational safety, and boost labor efficiency. These practices help optimize the overall cost structure.

Firms with superior ESG performance often possess better risk management capabilities and supply chain resilience, allowing them to maintain lower marginal costs and steady delivery efficiency in the face of external shocks (such as raw material price fluctuations or regulatory changes). Therefore, the higher a firm's ESG score, the more likely it is to exhibit a negative impact on its Cost of Revenue Ratio.

To test this theoretical expectation, we will next conduct descriptive statistics, correlation analysis, and multiple regression to investigate whether ESG Risk Score and Overall Management Score can significantly predict firms' cost-of-revenue structure, and to further analyze their relative influence and robustness.

5.4.1 Descriptive Statistics

Table 5 - 19 Descriptive Statistics for $Model_{3b}$ Variables

Variable	N	Min	Max	Mean	Std. Dev
Cost of Revenue Ratio	1296	-9.161	64.792	1.388	5.344
ESG Risk Score	1296	8.752	47.150	28.525	7.617
log MarketCap	1296	19.688	26.965	23.349	1.787
ROA	1296	-0.114	0.212	0.009	0.028
ROE	1296	-7.034	5.658	0.012	0.458

P/E	1296	-4980.600	3307.359	42.591	310.244
D/E	1296	-185.340	1224.163	6.116	61.022
Overall Management Score	1296	13.879	75.431	46.985	13.595

Source: Empirical results from this study.

Table 5 - 19 presents descriptive statistics for the primary variables in this study's sample, including Cost of Revenue Ratio, ESG Risk Score, log(MarketCap), ROA, ROE, P/E, D/E, and Overall Management Score. The total sample size is 1,296 observations, spanning various industries and company sizes, thereby offering heterogeneity and representativeness for subsequent empirical analysis.

Cost of Revenue Ratio has a mean of 1.388 and a standard deviation of 5.344, indicating substantial differences among firms. Its maximum value is 64.792 and minimum is –9.161, reflecting a skewed distribution that may result from accounting recognition methods or industry-specific cost structures. Compared to the Operating Expense Ratio analyzed in the previous section, this ratio shows slightly less volatility, though its extreme values warrant further consideration regarding their influence on regression outcomes.

ESG Risk Score has a mean of 28.525 with a standard deviation of 7.617, ranging from 8.752 to 47.150. This demonstrates clear segmentation among firms in terms of ESG risk exposure. As the core independent variable for testing hypothesis $H_{3\beta}$, this score is expected to inversely relate to cost efficiency.

Overall Management Score averages 46.985 with a standard deviation of 13.595, a minimum of 13.879, and a maximum of 75.431. Its distribution is comparatively more concentrated than the ESG Risk Score, reflecting more moderate variation in overall governance capability. Since this score encompasses governance systems, risk management, and strategic planning, it serves as an auxiliary variable to assess how internal management mechanisms influence cost structure.

Among control variables, log(MarketCap) averages 23.349 (standard deviation 1.787), indicating a stable distribution of firm sizes in the sample. Profitability metrics such as ROA (mean = 0.009) and ROE (mean = 0.012) suggest modest overall earnings power with relatively stable distributions. Their standard deviations are 0.028 and 0.458, respectively. Notably, the P/E Ratio (mean = 42.591) and D/E Ratio (mean = 6.116) exhibit very large standard deviations (310.244 and 61.022), indicating that some firms may be in extreme growth or highly leveraged conditions, potentially affecting model stability.

In summary, the sample displays pronounced cross-sectional variation in industry, scale, and governance capacity, providing a sound empirical basis for further investigation into the impact of ESG scores on cost-of-revenue ratios.

5.4.2 Correlation Analysis

To further examine the linear relationships between each variable and the Cost of Revenue Ratio, this section adopts Pearson's product-moment correlation coefficient. The results are summarized in Table 5 - 22. Overall, most variables show directions of association that are consistent with theoretical expectations, and several variables reach statistical significance, indicating their potential explanatory power regarding firms' cost-of-revenue structures.

Table 5 - 20 Pearson Correlation Matrix for $Model_{3b}$ Variables

Correlation									
		Cost of Revenue Ratio	log MarketCap	ROA	ROE	P/E	D/E	ESG Risk Score	Overall Management Score
Cost of Revenue Ratio	Pearson correlation	1	-0.005	-.295**	-.065*	-0.024	-0.007	-0.048	-.089**
	Sig. (2-tailed)		0.860	0.000	0.020	0.395	0.796	0.085	0.001
	N	1296	1296	1296	1296	1296	1296	1296	1296
ESG Risk Score	Pearson correlation	-0.048	-.210**	-0.021	0.003	-0.046	-0.015	1	-.401**
	Sig. (2-tailed)	0.085	0.000	0.457	0.902	0.100	0.600		0.000
	N	1296	1296	1296	1296	1296	1296	1296	1296
log MarketCap	Pearson correlation	-0.005	1	.149**	0.038	0.004	-0.015	-.210**	.547**
	Sig. (2-tailed)	0.860		0.000	0.172	0.878	0.598	0.000	0.000
	N	1296	1296	1296	1296	1296	1296	1296	1296
ROA	Pearson correlation	-.295**	.149**	1	.238**	0.048	-0.029	-0.021	.070*
	Sig. (2-tailed)	0.000	0.000		0.000	0.082	0.302	0.457	0.012
	N	1296	1296	1296	1296	1296	1296	1296	1296
ROE	Pearson correlation	-.065*	0.038	.238**	1	0.019	.387**	0.003	0.042
	Sig. (2-tailed)	0.020	0.172	0.000		0.486	0.000	0.902	0.127
	N	1296	1296	1296	1296	1296	1296	1296	1296
P/E	Pearson correlation	-0.024	0.004	0.048	0.019	1	0.004	-0.046	.070*
	Sig. (2-tailed)	0.395	0.878	0.082	0.486		0.886	0.100	0.011
	N	1296	1296	1296	1296	1296	1296	1296	1296
D/E	Pearson correlation	-0.007	-0.015	-0.029	.387**	0.004	1	-0.015	-0.006

	Sig. (2-tailed)	0.796	0.598	0.302	0.000	0.886		0.600	0.840
	N	1296	1296	1296	1296	1296	1296	1296	1296
Overall Management Score	Pearson correlation	-.089**	.547**	.070*	0.042	.070*	-0.006	-.401**	1
	Sig. (2-tailed)	0.001	0.000	0.012	0.127	0.011	0.840	0.000	
	N	1296	1296	1296	1296	1296	1296	1296	1296

Source: Empirical results from this study.

Table 5 - 20 first shows that the ESG Risk Score has a negative correlation with the Cost of Revenue Ratio (r = –0.048), although this relationship is not statistically significant (p = 0.085). This result deviates from the expected positive relationship and may be explained by the fact that companies with higher ESG risk scores may have already made provisions or adjustments affecting cost items, so the effect is not clearly reflected in revenue-cost structure in the short term.

Second, regarding firm size, log(MarketCap) shows virtually no correlation with the Cost of Revenue Ratio (r = –0.005, p = 0.860), indicating that company size does not have a significant linear influence on the ratio. A possible reason is that cost structure is more heavily influenced by industry characteristics, and a single size metric may not fully explain that heterogeneity.

Among profitability metrics, ROA exhibits a significant negative correlation with the Cost of Revenue Ratio $(r = -0.295, p < 0.001)$, making it the most significant relationship in this analysis. This result aligns with theoretical expectations and supports the use of Cost of Revenue Ratio as an indirect indicator of operational efficiency and asset utilization. Similarly, ROE also shows a significant negative correlation with the ratio $(r = -0.065, p = 0.020)$, suggesting a link between return on equity and revenue-cost control.

Although the P/E Ratio has a negative correlation with the Cost of Revenue Ratio (r = –0.024), this is not statistically significant $(p = 0.395)$, indicating that market valuation multiples and revenue costs do not have a clear direct relationship. This result may be due to multiple factors—such as growth expectations, risk, and investor sentiment—influencing valuation, which weakens its connection with cost indicators.

Debt-to-Equity Ratio (D/E) also shows no significant correlation with the Cost of Revenue Ratio $(r = -0.007, p = 0.796)$, possibly reflecting that capital structure and revenue-cost control logic do not always align. Especially given varying debt policies and financial strategies across industries, leverage may not consistently explain revenue-cost allocation behavior.

Regarding ESG management capacity, the Overall Management Score has a significant negative correlation with the Cost of Revenue Ratio (r = –0.089, p = 0.001), in line with expectations. This variable reflects a company’s comprehensive governance structure, control processes, and strategic execution under the ESG framework. Firms with higher overall management scores tend to have lower revenue-cost ratios, indirectly confirming that management capacity aids in controlling revenue-side costs and improving resource efficiency.

In summary, ROA and the Overall Management Score are the variables most significantly correlated with the Cost of Revenue Ratio, supporting the notion that profitability and governance quality are consistently and negatively associated with revenue-cost structure. These findings provide a solid basis for subsequent multiple regression analysis.

5.4.3 Multiple Regression Analysis

Table 5 - 21 Model Summary for $Model_{3b}$

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the estimate
1	.329[a]	0.109	0.104	5.059

Source: Empirical results from this study.

This model's multiple correlation coefficient (R) is 0.329, indicating a moderately positive relationship between the independent variables and the Cost of Revenue Ratio.The coefficient of determination R^2 = 0.109, meaning that the variables included in the model explain approximately 10.9% of the variance in the Cost of Revenue Ratio.

The adjusted R^2 is 0.104, only slightly lower, suggesting that the model is not overfitted and remains statistically sound. The Standard Error of the Estimate is 5.059, representing the average level of prediction error, which falls within an acceptable range.

Table 5 - 22 ANOVA Results for $Model_{3b}$

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	4014.309	7	573.473	22.406	.000[b]
	Residual	32965.611	1288	25.594		
	Total	36979.920	1295			

Source: Empirical results from this study.

Table 5 – 22 ANOVA analysis shows that the overall F value of the model is 22.406, with a corresponding significance level of $p < 0.001$, indicating that the regression model is highly significant in statistical terms. The null hypothesis that "all regression coefficients are equal to zero" can be rejected, meaning that at least one variable in the model has a significant impact on the Cost of Revenue Ratio.

Table 5 - 23 Regression Coefficients for $Model_{3b}$

Coefficients[a]									
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95%CI		VIF
		B	Std. Error	β			Lower bound	Upper bound	
1	Constant	-0.752	2.105		-0.357	0.721	-4.882	3.378	
	ESG Risk Score	-0.069	0.020	-0.099	-3.445	0.001	-0.109	-0.030	1.194
	log MarketCap	0.332	0.095	0.111	3.497	0.000	0.146	0.518	1.456
	ROA	-58.629	5.274	-0.307	-11.116	0.000	-68.976	-48.281	1.104
	ROE	0.250	0.346	0.021	0.722	0.471	-0.430	0.929	1.271
	P/E	-0.000	0.000	-0.002	-0.087	0.931	-0.001	0.001	1.010
	D/E	-0.002	0.003	-0.025	-0.869	0.385	-0.007	0.003	1.199
	Overall Management Score	-0.066	0.013	-0.168	-5.005	0.000	-0.092	-0.040	1.637

Source: Empirical results from this study.

Table 5 – 23 shows that in this regression analysis, the regression coefficient of ESG Risk Score is negative and statistically significant ($p = 0.001$). Although the direction is consistent with the original theoretical expectation, the result reveals an intriguing phenomenon:

firms with higher ESG risk scores tend to exhibit a lower Cost of Revenue Ratio. This outcome may reflect factors such as industry heterogeneity, accounting recognition strategies, or distortions in governance frameworks, suggesting that high-ESG-risk firms may not yet bear the expected compliance or environmental costs in the short term. Further analysis by industry is warranted to explore this finding.

The coefficient of log(MarketCap) is significantly positive, indicating that larger firms tend to have higher Cost of Revenue Ratios, which contradicts the prior hypothesis. This may be due to the fact that large firms, because of their product portfolios, operational diversity, or broader resource allocation, are more prone to diminishing marginal returns in cost allocation. Complex structures of fixed assets and human resource distribution may also maintain their overall costs at a higher level, suggesting that economies of scale and cost efficiency may not have a linear relationship.

The regression result for ROA shows a significant negative relationship (standardized coefficient $\beta = -0.307$, $p < 0.001$), which aligns with theoretical expectations. ROA represents a firm's ability to generate profits from its assets. When ROA is higher, indicating improved resource allocation efficiency, firms are usually better at controlling costs and thus reduce their Cost of Revenue Ratio. This result further confirms that ROA is a key indicator of operational efficiency and cost control.

In contrast, ROE, P/E, and D/E do not reach statistical significance, suggesting that after controlling for other financial and size-related variables, their impacts on the Cost of Revenue Ratio are not significant. This could be because these indicators are more affected by profit distribution policies, capital structure strategies, and market expectations, making them less directly reflective of cost allocation.

Lastly, the Overall Management Score shows a significant negative relationship (standardized coefficient $\beta = -0.168$, $p < 0.001$), indicating that firms with stronger governance capabilities can reduce their Cost of Revenue Ratio by optimizing internal processes, strengthening control systems, and integrating resources. This highlights the central role of management quality in enhancing operational efficiency and controlling costs. Overall, there is no obvious multicollinearity among the variables, as all VIF values are below 2, further ensuring the robustness and explanatory power of the regression results.

5.4.4 Expected vs. Empirical Results

Table 5 - 24 Comparison of Expected and Empirical Directions for $Model_{3b}$

Variable	Expected Directions	Empirical Directions	Sig.
Cost of Revenue Ratio	Dependent Variable	Dependent Variable	
ESG Risk Score	+	−	0.001
log(MarketCap)	−	+	0.000
ROA	−	−	0.000
ROE	−	+	0.471
P/E	−	−	0.931

D/E	+	−	0.385
Overall Management Score	−	−	0.000

Source: Empirical results from this study.

1. **ESG Risk Score**

Theoretically, firms with higher ESG risk should face increased cost pressure due to potential regulatory fines, supply chain disruptions, and operational uncertainties, which would raise their Cost of Revenue Ratio. However, empirical results (Table 5 - 24) show that firms with high ESG risk scores actually exhibit lower direct revenue costs. This may be because some high-risk firms aggressively cut spending under cost-maximization strategies, or because industry-specific factors distort the relationship between ESG scores and actual expenses, indicating a reverse phenomenon.

2. **log(MarketCap)**

Larger firms are expected to benefit from economies of scale, such as in bargaining, procurement, and resource allocation, which should result in lower cost ratios. Yet, empirical evidence shows that larger firms have higher Cost of Revenue Ratios. This may stem from business diversification, global operations, or a higher share of production expenditures, which elevate direct operating costs relative to revenue.

3. **ROA**

Consistent with expectations, firms with higher ROA, which indicates efficient use of assets, also exhibit leaner cost structures and effectively lower their direct cost ratio. This aligns with findings from Nissim (2023) and similar studies.

4. **ROE**

Although ROE theoretically reflects overall profitability and operational efficiency, it does not have a significant effect on the Cost of Revenue Ratio when controlling for multiple variables. This suggests a weak link between shareholder return efficiency and direct revenue costs.

5. **P/E Ratio**

The P/E ratio reflects earnings expectations and market valuation, but its relationship with direct operating costs becomes insignificant once financial and governance variables are controlled. This may be due to valuation multiples being heavily influenced by external market factors rather than pure cost efficiency.

6. **D/E Ratio**

While theory suggests cost pressures may influence capital structure choices, empirical results indicate that debt-to-equity ratio does not significantly explain the Cost of Revenue Ratio. This suggests that leverage strategies are more influenced by industry characteristics or capital market conditions.

7. **Overall Management Score**

In line with expectations, firms with stronger governance quality have advantages in process and resource allocation and effectively suppress their direct revenue cost ratio. This finding supports Brown & Caylor (2004) on the link between governance quality and operational performance, and underscores the importance of governance mechanisms in cost control.

This comparison table shows that most core variables align with expectations, but the relationships involving ESG Risk Score and log(MarketCap) are reversed, indicating that the actual effects of ESG scores and firm size on cost structure are more complex and warrant further analysis by industry and governance characteristics.

5.4.5 Summary and Interpretation

This section employs descriptive statistics, correlation analysis, and multiple regression models to deeply examine the relationship between ESG scores and the Cost of Revenue Ratio, thereby testing Hypothesis H_{3b}. The key findings and interpretations are as follows:

First, descriptive statistics indicate that the average Cost of Revenue Ratio among sample firms is 1.388%, with notable volatility (standard deviation of 5.344), showing significant variations in direct revenue cost structures across companies. Further Pearson correlation analysis reveals a significant negative correlation between Cost of Revenue Ratio and ESG Risk Score, ROA, and Overall Management Score. This preliminarily supports the influence of ESG and governance quality on direct operating costs.

Multiple regression results further confirm this trend. The overall model has an $R^2 = 0.109$ (Adjusted $R^2 = 0.104$), and the F-test is significant ($p < 0.001$), indicating strong statistical predictive power. At the variable level, both ESG Risk Score and Overall Management Score show significant negative relationships, meaning that firms with higher ESG risk or weaker governance tend to have lower Cost of Revenue Ratios—contrary to conventional expectations.

The ESG Risk Score coefficient is negative ($\beta = -0.099$, $p = 0.001$), which contradicts theoretical expectations. This inverse relationship may arise from mismatches between industry characteristics and ESG scoring methods. For example, some high-ESG-risk firms might operate in resource-intensive industries where costs are concentrated in capital expenditure or R&D instead of direct operating costs. Alternatively, firms may temporarily reduce or outsource direct costs in response to ESG criticism, causing estimation bias.

Additionally, log(MarketCap) is positively and significantly associated with Cost of Revenue Ratio ($\beta = 0.111$, $p = 0.001$), again opposite to expected direction. This suggests larger firms may exhibit higher direct cost ratios, potentially due to diversified operations, complex global supply chains, or accounting classification—such as including manufacturing costs under Cost of Revenue—thereby inflating the ratio.

ROA is significantly negatively related to Cost of Revenue Ratio ($\beta = -0.307$, $p < 0.001$), clearly demonstrating the link between operational efficiency and direct cost control. In contrast, ROE, P/E, and D/E are not statistically significant, suggesting that after controlling for governance and operational efficiency, these financial indicators have limited explanatory power for revenue-cost ratios and should be viewed as indirect variables or background conditions.

Finally, Overall Management Score is significantly negative ($\beta = -0.168$, $p < 0.001$), indicating that overall governance quality plays a critical role in controlling direct costs. Firms with sound process controls, decision-making mechanisms, and risk management are more likely to reduce unnecessary expenditure and waste through internal systems, enhancing resource-use efficiency.

In summary, while the empirical results for ESG and firm size do not align with expectations, the effects of operational efficiency (ROA) and governance quality (Overall Management Score) are significant and consistent. They underscore internal management and efficiency improvement as core strategies for reducing revenue-related costs. The inverse relationship between ESG Risk Score and direct costs suggests that scoring models, industry characteristics, and accounting standards may interfere with the findings. Future research should further investigate heterogeneity in ESG–cost transmission mechanisms across industries.

5.5 Two-Stage Regression Analysis

Following the previous section's examination of the relationship between ESG performance and operating costs, this section further tests whether ESG risk indirectly affects firms' stock returns through an operating cost mediation mechanism. It aims to examine Hypothesis H_4: that ESG Risk Score influences shareholder returns indirectly via Operating Expense Ratio.

Specifically, this section investigates whether ESG performance, through its impact on operating cost structure, indirectly affects market performance. Based on the previously specified model design, a two-stage regression is employed to handle the potential mediation effect. In the first stage, a regression model is constructed with ESG Score predicting Operating Expense Ratio (OER). In the second stage, the residuals from that regression are used as a mediator variable in the main model explaining Stock Return.

Although prior analyses (Section 5.3) included two cost-structure metrics, the Operating Expense Ratio (OER) and Cost of Revenue Ratio (COR), this section selects OER as the core mediator variable based on three reasons:

1. OER is more widely used in financial literature as a comprehensive measure of firm governance and operational efficiency, covering general administrative expenses, personnel, and process costs. It better reflects actual implementation of ESG-related

institutional designs, resource management, and governance mechanisms, and shows high relevance to sustainability management quality.

2. Empirical evidence (Section 5.3) indicates a significant negative relationship between ESG Risk Score and OER, and a strong negative relationship between Overall Management Score and OER, validating its suitability as a mediator variable. By contrast, COR demonstrates weaker associations with ESG or governance variables.
3. In mediation modeling logic, OER better represents the mechanism through which ESG impacts market performance. Firms with strong sustainability practices and governance frameworks improve operational cost control, which enhances earnings quality and reduces risk, This ultimately reinforcing shareholder value.

Thus, considering theoretical rationale, statistical significance, and model consistency, this section uses OER as the mediator variable in the two-stage regression model to test whether ESG performance indirectly influences shareholder returns through operational cost efficiency.

First Stage (Mediation Variable Model):

In the first stage, “Operating Expense Ratio” serves as the dependent variable, with ESG Risk Score as the main explanatory variable, alongside controls for firm-level financial characteristics (such as size, ROA, ROE, P/E ratio, financial leverage, and Overall Management Score). The regression model is as follows:

$$Operating\ Expense\ Ratio_{i,t}$$
$$= \beta_0 + \beta_1 ESG\ Risk\ Score_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t}$$
$$+ \beta_4 ROE_{i,t} + \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t}$$
$$+ \epsilon_{i,t}$$

This regression was completed in Section 5.3. Its results indicate that ESG Risk Score has a statistically significant positive effect on Operating Expense Ratio ($p < 0.01$), consistent with expectations. It shows that firms with poorer ESG performance typically bear higher operating costs. This finding also confirms the necessary condition for mediation.

Second Stage (Outcome Model):

In the second stage, the residuals from the first-stage regression on Operating Expense Ratio are used as an instrumental variable. These residuals are included in the model explaining Stock Return to determine whether ESG indirectly affects market performance via operating costs. The model is structured as follows:

$$Stock\ Return_{i,t}$$
$$= \beta_0 + \beta_1 Residual_{i,t} + \beta_2 log(MarketCap)_{i,t} + \beta_3 ROA_{i,t} + \beta_4 ROE_{i,t}$$
$$+ \beta_5 P/E_{i,t} + \beta_6 D/E_{i,t} + \beta_7 Overall\ Management\ Score_{i,t} + \epsilon_{i,t}$$

In this model, if $\boldsymbol{\beta_1}$ is statistically significant, it indicates that operating costs serve as a mediating variable between ESG and stock returns. In other words, the impact of ESG performance on market returns may not be direct, but instead realized indirectly through increases or reductions in operating expenses. The residual term is used here instead of the direct variable to address potential endogeneity and reverse causality issues between ESG Score and stock returns, thereby enhancing the consistency of the model estimation.

5.5.1 Descriptive Statistics

Table 5 - 25 Descriptive Statistics for Model 4 Variables

Variable	N	Min	Max	Mean	Std. Dev
Stock return	1296	-1.224	1.016	0.008	0.149
residual	1296	-22.650	110.917	0.000	7.832
log MarketCap	1296	19.688	26.965	23.349	1.787
ROA	1296	-0.114	0.212	0.009	0.028
ROE	1296	-7.034	5.658	0.012	0.458
P/E	1296	-4980.600	3307.359	42.591	310.244
D/E	1296	-185.340	1224.163	6.116	61.022
Overall Management Score	1296	13.879	75.431	46.985	13.595

Source: Empirical results from this study.

Table 5 – 25 presents the descriptive statistics of the variables included in the two-stage regression analysis of this study, including the independent variable residual (from the first-stage OER model), the dependent variable Stock Return, and each control variable (log(MarketCap), ROA, ROE, P/E, D/E, and Overall Management Score). The table includes the sample size, minimum, maximum, mean, and standard deviation for each indicator.

For the dependent variable, the average value of Stock Return is 0.008, with a standard deviation of 0.149, indicating that the overall sample shows a slight positive return, but there are significant differences between individual firms. The maximum reaches 1.016, and the minimum is -1.224, showing that some companies experienced extreme fluctuations and changes in stock prices.

As the mediating variable, residual (from the first-stage model) has a mean of 0, and the standard deviation is 7.832, indicating that there are still differences between ESG and operating cost structures that cannot be fully explained, and this may provide further explanatory power for stock return.

Among the control variables, the mean of log(MarketCap) is 23.349, showing that most sample companies are medium to large-sized listed firms. The standard deviation is 1.787, showing a certain level of variation in market capitalization. ROA (mean = 0.009) and ROE (mean = 0.012) reflect that the overall profitability of sample firms is generally low, possibly influenced by recent industry cycles and the pressure of ESG-related costs.

The mean of P/E Ratio is 42.591, but the standard deviation is as high as 310.244, showing that some sample companies have extremely high valuation multiples, and this should be paid special attention to in the subsequent empirical tests for its potential influence on model stability. The D/E Ratio (mean = 6.116) reflects a wide distribution of financial leverage strategies among firms, with a large gap between the minimum and maximum values, possibly due to the inclusion of diverse industries in the sample.

Finally, the average Overall Management Score is 46.985, with a standard deviation of 13.595, indicating significant differences among companies in terms of governance and management quality, which helps explain the potential differences in operating efficiency and stock performance. Overall, the descriptive statistics in this section show that the sample distribution is diverse, and the potential relationships between variables offer room for theoretical and practical analysis, providing statistical support and rationality for the subsequent two-stage empirical model.

5.5.2 Correlation Analysis

Table 5 - 26 Pearson Correlation Matrix for Model 4 Variables

Correlation									
		Stock return	residual	log MarketCap	ROA	ROE	P/E	D/E	Overall Management Score
Stock return	Pearson correlation	1	0.018	0.039	0.015	-0.003	-0.021	-0.036	0.024
	Sig. (2-tailed)		0.527	0.156	0.596	0.916	0.458	0.201	0.378
	N	1296	1296	1296	1296	1296	1296	1296	1296
residual	Pearson correlation	0.018	1	0.000	0.000	0.000	0.000	0.000	0.000
	Sig. (2-tailed)	0.527		1.000	1.000	1.000	1.000	1.000	1.000
	N	1296	1296	1296	1296	1296	1296	1296	1296
log MarketCap	Pearson correlation	0.039	0.000	1	.149**	0.038	0.004	-0.015	.547**
	Sig. (2-tailed)	0.156	1.000		0.000	0.172	0.878	0.598	0.000

	N	1296	1296	1296	1296	1296	1296	1296	1296
ROA	Pearson correlation	0.015	0.000	.149**	1	.238**	0.048	-0.029	.070*
	Sig. (2-tailed)	0.596	1.000	0.000		0.000	0.082	0.302	0.012
	N	1296	1296	1296	1296	1296	1296	1296	1296
ROE	Pearson correlation	-0.003	0.000	0.038	.238**	1	0.019	.387**	0.042
	Sig. (2-tailed)	0.916	1.000	0.172	0.000		0.486	0.000	0.127
	N	1296	1296	1296	1296	1296	1296	1296	1296
P/E	Pearson correlation	-0.021	0.000	0.004	0.048	0.019	1	0.004	.070*
	Sig. (2-tailed)	0.458	1.000	0.878	0.082	0.486		0.886	0.011
	N	1296	1296	1296	1296	1296	1296	1296	1296
D/E	Pearson correlation	-0.036	0.000	-0.015	-0.029	.387**	0.004	1	-0.006
	Sig. (2-tailed)	0.201	1.000	0.598	0.302	0.000	0.886		0.840
	N	1296	1296	1296	1296	1296	1296	1296	1296
Overall Management Score	Pearson correlation	0.024	0.000	.547**	.070*	0.042	.070*	-0.006	1
	Sig. (2-tailed)	0.378	1.000	0.000	0.012	0.127	0.011	0.840	
	N	1296	1296	1296	1296	1296	1296	1296	1296

Source: Empirical results from this study.

Table 5 – 26 shows that in the correlation analysis of the second stage variables, this study uses Pearson correlation coefficients to test the linear relationships between each independent variable and Stock Return. According to the results, the residual (from the first-stage operating expense model) has a correlation coefficient of 0.018 with Stock Return, which is not statistically significant (p = 0.527), indicating that its linear influence is unclear. However, this does not necessarily mean it loses its effect in a multivariate regression, since mediation

effects might emerge after controlling for other confounding factors. Further regression analysis is therefore required.

Regarding control variables, log(MarketCap) shows a positive but non-significant correlation with Stock Return ($r = 0.039$, $p = 0.156$), indicating no obvious simple linear relationship between firm size and stock returns. ROA has a correlation of 0.015 with Stock Return ($p = 0.596$), also non-significant, while ROE is near zero ($r = –0.003$, $p = 0.916$), further supporting the lack of stable linkage between return on equity and market performance in this sample period. The correlation coefficients for P/E and D/E are –0.021 and –0.036 respectively, both non-significant, indicating that valuation multiples and leverage levels do not necessarily exhibit a direct linear relationship with returns.

In contrast, the Overall Management Score has a low positive correlation with Stock Return ($r = 0.024$), but it is also not statistically significant ($p = 0.378$), suggesting that management quality does not have a noticeable effect on return rates before controlling for other variables.

In summary, from a univariate correlation perspective, Stock Return does not exhibit significant correlations with most financial or governance variables. This highlights that the current stage of model analysis should rely more on multivariate regression to clarify the true causal relationships and mediation effects after controlling for confounders, particularly regarding the mediating role of the residual.

5.5.3 Multiple Regression Analysis

This section aims to test whether the first-stage residual has a statistically significant effect on Stock Return in the second-stage model, in order to verify the indirect effect of ESG through operating efficiency on performance.

Table 5 - 27 Model Summary for Model 4

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the estimate
1	.061[a]	0.004	-0.002	0.148943120

Source: Empirical results from this study.

In Table 5–27, the R value is 0.061, indicating that the linear relationship between the explanatory variables and the dependent variable (Stock Return) is extremely weak. The R Square is only 0.004, suggesting that all the independent variables (including the Residual and control variables) can explain only about 0.4% of the variation in stock returns. The adjusted R^2 is –0.002, which means that after accounting for the number of variables, the explanatory power of the model is not only poor but even negative—implying that the model may be "overfitted" to the sample data and unable to generalize effectively.

The Standard Error of the estimate is 0.1489, further indicating a relatively high level of prediction error.

These results suggest that even with the inclusion of the residual from the first-stage model and financial control variables, the overall explanatory power for stock return remains very weak. This implies that the hypothesis of an indirect ESG effect on market returns lacks empirical support.

Table 5 - 28 ANOVA Results for Model 4

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	0.106	7	0.015	0.682	.687[b]
	Residual	28.573	1288	0.022		
	Total	28.679	1295			

Source: Empirical results from this study.

Table 5 - 28 tests whether the overall model is statistically significant. The results show an F-value of 0.682, indicating that the model's explained variance relative to error variance is not significant. The significance level (Sig.) is 0.687, which is well above conventional thresholds of 0.05 or 0.1.

This means that the entire regression model is not significant. In other words, we cannot demonstrate that the group of independent variables in the model collectively has a linear effect on the dependent variable (stock return). This finding aligns with the previously reported R^2 result and further confirms the limitations of this two-stage model specification.

Table 5 - 29 Regression Coefficients for Model 4

Coefficients[a]									
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95%CI		VIF
		B	Std. Error	β			Lower bound	Upper bound	
1	Constant	-0.061	0.058		-1.064	0.287	-0.175	0.052	
	residual	0.000	0.001	0.018	0.633	0.527	-0.001	0.001	1.000

	log MarketCap	0.003	0.003	0.034	1.019	0.308	-0.003	0.008	1.456
	ROA	0.037	0.155	0.007	0.239	0.811	-0.267	0.342	1.104
	ROE	0.003	0.010	0.009	0.289	0.773	-0.017	0.023	1.270
	P/E	-0.000	0.000	-0.022	-0.772	0.440	0.000	0.000	1.009
	D/E	-0.000	0.000	-0.038	-1.256	0.210	0.000	0.000	1.198
	Overall Management Score	-0.000	0.000	0.006	0.186	0.852	-0.001	0.001	1.438

Source: Empirical results from this study.

Table 5 - 29 lists the direction, magnitude, and significance of each explanatory variable's effect on stock return:

The coefficient of the residual term is 0.000, with a standardized coefficient $\beta = 0.001$, a t-value of only 0.633, and a p-value of 0.527. This is not statistically significant at any conventional level, indicating that the estimation error from the first-stage ESG-to-operating-efficiency model does not explain stock return.

All control variables, including log(MarketCap), ROA, ROE, P/E, D/E, and Overall Management Score, also show non-significant coefficients, with p-values all above 0.1. This suggests that under the current model specification, these traditional financial indicators are also unable to effectively predict stock return within the sample.

All VIF values are below 2, with the highest being 1.456 for log(MarketCap), indicating no significant multicollinearity issues among the variables. Thus, the model specification is statistically stable, and the results can be considered valid. However, due to the low explanatory power of the independent variables, the overall model results are not statistically significant.

5.5.4 Expected vs. Empirical Results

Table 5 - 30 Comparison of Expected and Empirical Directions for Model 4

Variable	Expected Directions	Empirical Directions	Sig.
Stock Return	Dependent Variable	Dependent Variable	
Residual	−	+	0.527
log(MarketCap)	−	+	0.308
ROA	+	+	0.811
ROE	+	+	0.773
P/E	−	−	0.440
D/E	−	−	0.210
Overall Management Score	+	+	0.852

Source: Empirical results from this study.

This section further aligns the expected directions with empirical results for each variable in the second-stage model predicting Stock Return, and incorporates related literature to strengthen the theoretical foundation of the hypothesis.

Table 5 - 30 shows that in this study's design, the second-stage model uses stock return as the dependent variable to test whether ESG affects market response indirectly through operating efficiency. This indirect effect is represented by the residual from the first-stage model, capturing whether a firm's operating efficiency exceeds or falls short of what the ESG score implies. Theoretically, if the negative impact of ESG on efficiency is overestimated, the residual would be positive. This would indicate that actual efficiency exceeds expectations, which should theoretically enhance market valuation. Hence, the expected correlation between the residual and stock return is negative.

However, empirical results show that the residual's effect on stock return is positive but not statistically significant ($p = 0.527$), indicating that deviations between ESG and operating efficiency are not effectively translated into price differences by the market. In other words, even if some firms outperform the efficiency implied by their ESG score, the market does not significantly adjust their stock return accordingly.

Similarly, the firm-size variable log(MarketCap) is theoretically expected to be negative, based on the "Small Firm Effect": smaller firms typically demand higher returns due to greater risk. But in this study, the variable shows a positive (though non-significant) result ($p = 0.308$), possibly due to a predominance of larger firms in the sample or insufficient control for risk variation, resulting in inconsistency with theoretical expectations.

Moreover, ROA, ROE, P/E ratio, D/E ratio, and Overall Management Score are all expected to positively correlate with stock return, as they represent operating efficiency, valuation attractiveness, capital structure stability, and governance quality—all indicators of overall financial health. However, none of these variables attain statistical significance in the model: ROA and ROE coefficients are positive but minimal, with p-values of 0.811 and 0.773 respectively; P/E ratio has $p = 0.440$ and shows no market sensitivity; D/E ratio is negative (contrary to expectation) but not significant ($p = 0.210$); and Overall Management Score coefficient is also not statistically significant ($p = 0.852$), indicating that governance performance may not manifest in short-term market pricing.

In summary, while most variables align directionally with theoretical expectations, none are statistically significant. This indicates that the proposed mechanism, where ESG improves market return via enhanced operating efficiency, lacks empirical support in this study. Market returns may be influenced by a broader, dynamic array of non-financial and macro factors such as economic conditions, industry rotation, and geopolitical risk. These factors may limit the ability of linear mediation models to fully capture the determinants of stock return.

5.6 Financial Heterogeneity Tests by High/Low ESG Groups (Corresponding to Hypothesis H_5)

To verify whether ESG Risk Score can serve as a structural explanatory factor for corporate financial and market performance, this section conducts comparative tests on the financial indicators of firms with high and low ESG performance, empirically examining the validity of hypothesis H_5. The study groups samples based on ESG Risk Score distribution, dividing them into high ESG risk (top 25%) and low ESG risk (bottom 25%) groups, and uses independent-samples t-tests to compare their performance on various financial and operational metrics.

The ESG Risk Score reflects a firm's unmanaged exposure in environmental, social, and governance dimensions. A higher score indicates greater embedded risks and potentially inferior governance quality. Theoretically, firms with higher ESG risk incur greater compliance burdens and operational risks, which not only impact cost structure and financial efficiency but may also lead to lower market valuations, restricted access to capital, or weak stock performance. Research by Giese et al. (2019), Berg et al. (2022), and Sustainalytics (2024) collectively finds that high ESG Risk Scores are often associated with elevated operating expenses, diminished profitability, valuation discounts, and weak governance frameworks.

Therefore, we expect that in terms of financial variables such as Return on Assets (ROA), Return on Equity (ROE), Price-to-Earnings Ratio (P/E), Debt-to-Equity Ratio (D/E), Operating Expense Ratio, and Cost of Revenue Ratio, high ESG risk firms will significantly underperform low ESG risk firms. If statistical tests support this difference, it would further confirm the effectiveness of ESG scoring as a tool for assessing corporate financial structure and risk.

5.6.1 Descriptive Statistics

Table 5 - 31 Descriptive Statistics for Model 5 Variables

Group		N	Mean	Std. Dev	Std. Error of the mean
Stock return	1	342	0.00586365	0.141974164	0.007677084
	2	278	0.00539140	0.144413017	0.008661317
ROA	1	342	0.00783082	0.031057266	0.001679385
	2	278	0.01205435	0.020904230	0.001253752
ROE	1	342	0.00792427	0.111112691	0.006008286
	2	278	0.01891510	0.077704644	0.004660415
P/E	1	342	47.31596451	140.517999803	7.598343208
	2	278	-5.45892505	500.748883194	30.032922224
D/E	1	342	2.73138789	4.495306583	0.243078341
	2	278	1.90308709	1.648188133	0.098851755

ESG Risk Score	1	342	19.56578202	3.868313457	0.209174435
	2	278	39.63804456	3.372322700	0.202258475
Overall Management Score	1	342	54.70073426	7.661856215	0.414305735
	2	278	39.51717143	15.670124837	0.939831633
Cost of Revenue Ratio	1	342	1.72891413	5.590255561	0.302286401
	2	278	0.69797972	0.241760489	0.014499831
Operating Expense Ratio	1	342	1.51689666	6.055125072	0.327423665
	2	278	0.08581836	0.072405695	0.004342605
log MarketCap	1	342	23.78592020	0.794642897	0.042969367
	2	278	22.78214583	2.460211656	0.147553690

Source: Empirical results from this study.

Prior to conducting heterogeneity tests between high- and low-ESG Risk Score groups, Table 5 - 4 summarizes descriptive statistics of key financial and market indicators for the two groups. Group 1 (high risk) comprises the top 25% of firms based on ESG Risk Score, while Group 2 (low risk) includes the bottom 25%.

Overall, the two groups exhibit significant mean differences across multiple financial variables, suggesting a potential association between ESG scores and firm financial characteristics.

First, in terms of financial performance, the low-risk group shows higher returns: ROA (M = 0.0121) and ROE (M = 0.0189) exceed those of the high-risk group (ROA = 0.0078, ROE = 0.0079), indicating that firms with better ESG performance have superior efficiency in asset and equity returns. Additionally, the high-risk group's average P/E is negative with extremely high variance, likely influenced by outliers or low valuation by investors, whereas the low-risk group averages a P/E of 5.46, reflecting more favorable earnings outlook.

Regarding capital structure, the low-risk group's average D/E is 1.90, which is well below the high-risk group's 2.73. This suggests that firms with strong ESG tend to use more conservative financial leverage, with relatively lower capital structure risk.

For efficiency metrics, the high-risk group exhibits higher direct and indirect operating costs: Cost of Revenue Ratio (M = 1.73) and Operating Expense Ratio (M = 1.52), compared to the low-risk group (M = 0.70 and 0.086), indicating that firms with weak ESG performance generally face higher operational costs due to less efficient resource allocation and internal control.

Governance measures also differ markedly. The low-risk group's average Overall Management Score is 46.98, which is significantly lower than the high-risk group's 54.70. This further supports the close link between ESG scores and internal governance quality.

Additionally, log(MarketCap) shows that firms in the low-risk group generally have smaller market capitalization (M = 22.78), while the high-risk group is somewhat larger (M = 23.79), aligning with literature suggesting that larger firms tend to receive higher ESG ratings (Gillan et al., 2021).

Overall, these preliminary descriptive statistics demonstrate structural differences across most variables between high- and low-ESG Risk Score groups, providing a solid basis for subsequent t-tests and effect size analyses, and supporting hypothesis H_5's contention that ESG is associated with financial heterogeneity.

5.6.2 Analysis of Financial and Market Performance Heterogeneity between High- and Low-ESG Groups

Table 5 - 32 Independent Sample T Test for Model 5

Independent Sample T Test										
		Levene's Test for Equity of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig.(2-tailed)	Mean Difference	Std. Error Difference	95% CI	
									Lower	Upper
Stock return	Equal variance assumed	0.728	0.394	0.041	618	0.967	0.000	0.012	-0.022	0.023
	Equal variance not assumed			0.041	588.268	0.967	0.000	0.012	-0.022	0.023
ROA	Equal variance assumed	23.064	0.000	-1.938	618	0.053	-0.004	0.002	-0.009	0.000
	Equal variance not assumed			-2.015	598.258	0.044	-0.004	0.002	-0.008	0.000
ROE	Equal variance assumed	35.047	0.000	-1.395	618	0.164	-0.011	0.008	-0.026	0.004
	Equal variance not assumed			-1.445	605.113	0.149	-0.011	0.008	-0.026	0.004
P/E	Equal variance assumed	3.581	0.059	1.861	618	0.063	52.775	28.354	-2.907	108.457
	Equal variance not assumed			1.704	312.556	0.089	52.775	30.979	-8.179	113.729
D/E	Equal variance assumed	25.042	0.000	2.917	618	0.004	0.828	0.284	0.271	1.386
	Equal variance not assumed			3.157	448.029	0.002	0.828	0.262	0.313	1.344
Overall Management Score	Equal variance assumed	316.379	0.000	15.753	618	0.000	15.184	0.964	13.291	17.076
	Equal variance not assumed			14.783	383.360	0.000	15.184	1.027	13.164	17.203
Cost of Revenue Ratio	Equal variance assumed	40.319	0.000	3.072	618	0.002	1.031	0.336	0.372	1.690
	Equal variance not assumed			3.407	342.569	0.001	1.031	0.303	0.436	1.626
Operating Expense Ratio	Equal variance assumed	61.938	0.000	3.940	618	0.000	1.431	0.363	0.718	2.144
	Equal variance not assumed			4.370	341.120	0.000	1.431	0.327	0.787	2.075
log MarketCap	Equal variance assumed	849.989	0.000	7.104	618	0.000	1.004	0.141	0.726	1.281
	Equal variance not assumed			6.531	324.080	0.000	1.004	0.154	0.701	1.306

Source: Empirical results from this study.

To examine whether the ESG Risk Score effectively differentiates firms in terms of financial and market performance, this study conducted independent-samples t-tests comparing the high-risk group (top 25%) and the low-risk group (bottom 25%). The results show that the ESG Risk Score itself significantly differs between the two groups ($t = -68.019$, $p < .001$), confirming the validity of the grouping. Further comparisons, as presented in Table 5 - 32, reveal the following:

For the two indicators reflecting operating cost and efficiency, both the Cost of Revenue Ratio ($t = 3.072$, $p = .002$) and Operating Expense Ratio ($t = 3.940$, $p < .001$) are statistically significant, showing that the high-risk ESG group has significantly higher ratios. This indicates comparatively weaker cost-control ability.

Regarding capital structure, the D/E Ratio is significantly higher in the high-risk group than in the low-risk group ($t = 2.917$, $p = .004$), implying that high-risk firms depend more on external financing and bear greater financial risk.

In terms of corporate governance and managerial quality, the Overall Management Score also differs significantly ($t = 15.753$, $p < .001$), supporting that high ESG-risk firms have weaker governance structures and risk-control capability.

Concerning market size, log(MarketCap) shows a significant difference as well ($t = 7.104$, $p < .001$); the mean values indicate that the high-risk group has a significantly larger market capitalization, which contradicts the Small-Firm Premium theory. This suggests that large firms with poor risk control may be included in the high ESG-risk group.

However, some financial performance variables do not reach statistical significance. Although ROA and ROE align in direction, their p-values are .053 and .164 respectively, indicating marginal or non-significance, possibly due to earnings volatility and variation within the sample. The P/E Ratio, under Levene's test for equal variances, is marginally insignificant ($p = .059$), and shows marginal significance ($p = .063$) when assuming equal variances. This suggests that the market's valuation reaction to ESG signals requires further confirmation.

In summary, the high- and low-ESG groups demonstrate significant heterogeneity in governance quality, operational efficiency, financial leverage, and certain market-structure indicators, supporting hypothesis H_5. These findings show that ESR Risk Score indeed contains fundamental signals, effectively distinguishing firms according to risk exposure and financial structure characteristics.

Table 5 - 33 Effect Sizes for Independent Samples Test

Independent Samples Effect Sizes					
		Standardizer[a]	Point Estimate	95% CI	
				Lower	Upper
Stock return	Cohen's d	0.143072448	0.003	-0.155	0.162
	Hedges correction	0.143246373	0.003	-0.155	0.161
	Glass's delta	0.144413017	0.003	-0.155	0.162
ROA	Cohen's d	0.026983100	-0.157	-0.315	0.002
	Hedges correction	0.027015902	-0.156	-0.315	0.002
	Glass's delta	0.020904230	-0.202	-0.361	-0.043
ROE	Cohen's d	0.097563567	-0.113	-0.271	0.046
	Hedges correction	0.097682170	-0.113	-0.271	0.046
	Glass's delta	0.077704644	-0.141	-0.300	0.017
P/E	Cohen's d	351.121057396	0.150	-0.008	0.309

	Hedges correction	351.547894647	0.150	-0.008	0.308
	Glass's delta	500.748883194	0.105	-0.053	0.264
D/E	Cohen's d	3.516795254	0.236	0.077	0.394
	Hedges correction	3.521070416	0.235	0.077	0.394
	Glass's delta	1.648188133	0.503	0.338	0.666
Overall Management Score	Cohen's d	11.935384754	1.272	1.098	1.445
	Hedges correction	11.949893900	1.271	1.097	1.443
	Glass's delta	15.670124837	0.969	0.791	1.146
Cost of Revenue Ratio	Cohen's d	4.155700758	0.248	0.089	0.407
	Hedges correction	4.160752599	0.248	0.089	0.406
	Glass's delta	0.241760489	4.264	3.875	4.652
Operating Expense Ratio	Cohen's d	4.498122624	0.318	0.159	0.477
	Hedges correction	4.503590727	0.318	0.159	0.477
	Glass's delta	0.072405695	19.765	18.111	21.416
log MarketCap	Cohen's d	1.749668770	0.574	0.412	0.735
	Hedges correction	1.751795739	0.573	0.411	0.734
	Glass's delta	2.460211656	0.408	0.246	0.570

Source: Empirical results from this study.

To assess whether the ESG Risk Score can discriminate firms based on fundamental differences, this study performed independent-samples t-tests and effect-size comparisons between firms in the top 25% (high ESG risk group) and bottom 25% (low ESG risk group) of ESG Risk Scores. The results are summarized in Table 5 – 33:

1. **Financial performance indicators**: Although the low ESG risk group showed higher average ROA and ROE, neither difference reached statistical significance ($p > 0.05$), and effect sizes were small (ROA Cohen’s d = –0.157; ROE = –0.113). These results suggest that while governance risk is related to operational efficiency, the differences in these metrics within this sample were not sufficient to produce significant contrasts.

2. **Capital structure indicator**: The D/E Ratio was significantly higher in the high ESG risk group ($p = 0.004$), with a moderate effect size (Cohen's $d = 0.236$). This indicates that firms with higher ESG risk tend to rely more heavily on leverage, suggesting greater financial risk.
3. **Valuation and firm size indicators**: P/E Ratio did not reach the 5% significance threshold ($p = 0.063$), but log(MarketCap) did ($p < 0.001$) with a moderate-to-large effect size (Cohen's $d = 0.574$). This suggests that high ESG risk firms are smaller in size, which is consistent with the theory of a "Small-Firm ESG Risk Effect."
4. **Operating efficiency indicators**: Both Operating Expense Ratio and Cost of Revenue Ratio were significantly lower in the low-risk group ($p < 0.001$ and $p = 0.002$, respectively), with moderate effect sizes ($d = 0.318$ and 0.248). This indicates that firms with lower ESG risk generally have better cost control and resource efficiency.
5. **Core ESG discriminative variables**: ESG Risk Score and Overall Management Score both showed very strong statistical differences between the groups (both $p < 0.001$). Effect sizes were extremely large for ESG Risk Score (Cohen's $d = –5.493$; Glass's delta $= –5.952$) and substantial for Overall Management Score (Cohen's $d = 1.272$; Glass's delta $= 0.969$). This confirms that firms in the high ESG risk group indeed exhibit poor governance and high risk exposure, demonstrating strong discriminative capacity.

Overall, the results support hypothesis H_5: ESG Risk Score effectively differentiates firms across multiple financial and operational variables. In particular, the statistical significance and effect sizes for operating costs, firm size, and governance score highlight the practical value of ESG ratings in risk identification and firm screening.

5.6.3 Expected vs. Empirical Results

Table 5 - 34 Comparison of Expected and Empirical Directions for Model 5

Variable	Expected Direction (High vs. Low Risk)	Empirical Direction (High vs. Low Risk)	Sig. ($\alpha = 0.05$)
Stock Return	Lower	Lower	0.967
ROA	Lower	Lower	0.044
ROE	Lower	Lower	0.149
P/E	Lower	Higher	0.089
D/E	Higher	Higher	0.002
Cost of Revenue Ratio	Higher	Higher	0.000
Operating Expense Ratio	Higher	Higher	0.000
Overall Management Score	Lower	Lower	0.001
log(MarketCap)	Lower	Lower	0.000

Source: Empirical results from this study.

To verify whether ESG Risk Score embodies fundamentals that reflect in firms' financial and market performance, this section aligns the theoretical expectations with empirical outcomes for each dependent variable, based on Table 5 – 34. Overall, except for a few minor deviations, the sample results largely match the expected direction, supporting the viability of ESG Risk Score as a discriminating criterion of firm heterogeneity.

1. **Stock Return**: The theory predicts firms with higher ESG Risk Score will earn lower returns, due to risk not being internalized and valuation discounts (Gillan et al., 2021;

Broadstock et al., 2021). The empirical result aligns in direction but is not significant (p = 0.967), possibly due to short-term market volatility obscuring long-term trends.

2. **ROA and ROE (profitability)**: It is anticipated that firms with better ESG performance, due to resource allocation efficiency and governance advantages, will exhibit higher ROA and ROE (Giese et al., 2019; Eccles et al., 2014; Sustainalytics, 2024). ROA reaches statistical significance (p = 0.044), while ROE aligns in direction but is not significant (p = 0.149).

3. **P/E Ratio**: Firms with good ESG scores are expected to enjoy valuation premiums and thus higher P/E (Fatemi et al., 2015; Khan et al., 2016). However, empirically the high ESG-risk group shows higher P/E (opposite direction), and this is not significant (p = 0.089), possibly due to earnings instability or market mispricing.

4. **D/E Ratio (leverage)**: Good ESG firms are expected to have more conservative capital structures and lower leverage (Ktit & Abu Khalaf, 2024). The empirical result matches the expected direction and is significant (p = 0.002), supporting the hypothesis.

5. **Cost of Revenue and Operating Expense Ratios**: Theoretically, firms with strong ESG performance are more efficient in cost control (Wang et al., 2023; McKinsey, 2023), so both ratios should be lower. Empirical results align and are significant (p = 0.000), confirming high ESG-risk firms bear greater cost pressure.

6. **log(MarketCap)**: ESG excellence is believed to attract long-term capital and investor support, fostering growth (Gillan et al., 2021; Broadstock et al., 2021). Empirically, the high ESG-risk group has significantly lower market value ($p = 0.000$), matching expectations.
7. **Overall Management Score**: This variable reflects governance and internal control capabilities. Firms with lower ESG Risk Score are expected to have higher scores (Sustainalytics, 2024). The empirical result matches expected direction and is significant ($p = 0.001$).

In summary, among the 10 dependent variables, 8 align directionally with expectations, of which 6 are statistically significant. Only P/E shows a deviation in direction but not significantly. These findings indicate that ESG Risk Score effectively differentiates firm quality and risk across multiple dimensions, providing empirical support for hypothesis H_5.

5.6.4 Summary and Interpretation

This section uses independent-samples t-tests to examine whether firms grouped by ESG Risk Score exhibit significant heterogeneity in key financial and market variables, thus testing Hypothesis H_5. The results show that the high-risk (high ESG Risk Score) group and low-risk (low ESG Risk Score) group differ significantly on most variables: specifically, ROA, D/E, Cost of Revenue Ratio, Operating Expense Ratio, Overall Management Score, and log(MarketCap) all show statistically significant differences ($p < 0.05$). This supports the validity of using ESG Risk Score for risk-based grouping.

Further comparing empirical and theoretical directions, eight out of ten variables move in the expected direction, with six being statistically significant. This indicates that variations in ESG performance indeed affect firms' cost structure, governance efficiency, scale, and financial stability. Notably, the significant differences in operating expenses and cost of revenue ratios suggest that firms with better ESG performance enjoy improved cost control and operational efficiency. Differences in market value and overall management score were also significant, indicating that the market and rating agencies place higher valuation and governance recognition on firms with superior ESG performance.

Although the P/E Ratio deviates from the expected direction and is not statistically significant, this may reflect lagging market expectations or distorted valuations due to earnings volatility. Still, the overall pattern demonstrates that the ESG Risk Score does differentiate firms in fundamental dimensions. This verifies that the ESG Risk Score not only serves as a rating tool but also carries meaningful financial implications and strategic reference value. These findings support H_5: ESG heterogeneity is reflected in firms' financial structure and market valuations, reinforcing the link between ESG metrics and capital market responses established in this study.

5.7 Does Market Reaction Intensify Due to ESG Deterioration Combined with High-Pollution Attributes? (Testing Hypothesis H_6)

This section aims to examine whether a deterioration in ESG performance triggers a stronger negative market reaction among high-pollution companies, thereby testing Hypothesis H_6. Considering that ESG risk events may have asymmetric market impacts, especially within high-pollution industries, investors may be more sensitive and reactive to ESG deterioration in such contexts.

To investigate this, the study integrates the event study approach with a logistic regression framework to observe how the market responds to the interaction between high-pollution firm status and ESG score deterioration. The detailed regression model is as follows:

$$\begin{aligned} \boldsymbol{logit}\big(P(Y=1)\big) \\ &= \beta_0 + \beta_1 CAR[-3,+3] + \beta_2 \log(MarketCap) + \beta_3 ROA \\ &+ \beta_4 Operating\ Expense\ Ratio + \beta_5 Overall\ Management\ Score + \epsilon \end{aligned}$$

The sample includes the two months with the most significant changes in ESG Risk Score for each of the 18 firms, resulting in a total of 36 observed events. The dependent variable is a dummy variable: if the event simultaneously satisfies "high pollution level" and "ESG rating deterioration," it is coded as 1; otherwise, it is coded as 0.

The core independent variable is the market reaction following the event, quantified as CAR[–3,+3], the difference between the average stock return over the three trading days following the event and the average stock return over the three trading days preceding the event.

In addition to the core variable CAR, several control variables are included. Selection of control variables follows the logic of the statistical models in Sections 5.3 to 5.5, focusing on variables that have demonstrated stable significance in earlier empirical results or possess strong theoretical justification. These include:

1. **log(MarketCap): Reflecting firm size and information transmission speed**

   Market capitalization is a common control variable in event studies. Large firms often exhibit different patterns of abnormal return due to more complete disclosure systems, higher liquidity, and broader market coverage (Barber & Lyon, 1997). Furthermore, earlier analyses in Sections 5.3 to 5.6 consistently show that log(MarketCap) has stable correlations with ESG scores and financial indicators, suggesting its important role in the governance-market impact pathway. It is therefore included as a control.

2. **ROA: Representing operating efficiency and risk resilience**

   Return on Assets is a comprehensive measure of financial performance. High-ROA firms are typically more efficient and resilient, better able to absorb the operational and market shocks stemming from ESG risks (Eccles et al., 2014; Giese et al., 2019). Including ROA as a control helps to isolate the specific ESG × industry effect by filtering out internal efficiency noise.

3. **Operating Expense Ratio (OER): Reflecting cost control and ESG response capability**

   OER measures operating expenses per unit of revenue, including selling, administrative, and management costs. It is closely related to governance maturity, procedural resilience, and the firm's ability to absorb external shocks (Wang et al., 2023). Compared with Cost of Revenue Ratio, which reflects only production and direct costs, OER better captures whether a company can respond to ESG deterioration events through internal adjustments or cost shifting. Empirical results in Sections 5.4 and 5.5 show that OER is consistently significant and directionally stable, whereas COR is not. Thus, OER is chosen here for its theoretical justification and empirical relevance.

4. **Overall Management Score: Reflecting governance level and ESG integration capacity**

   This variable captures overall performance in policy design, risk control, information transparency, and internal governance maturity, which are core dimensions of ESG rating methodology. High governance firms typically show less severe abnormal returns in response to ESG negative events due to stronger risk controls and greater market trust. It has been consistently significant in earlier models and carries strong practical implications, so it is included as a control to avoid misattribution of governance effects.

In summary, the variable selection in this model is not driven by data availability or randomness, but by continuity in model logic from previous sections, theoretical completeness, and empirical significance. Controlling for these factors allows the model to focus purely on the interactive effect of ESG deterioration and high-pollution attributes on market reaction, ensuring the result's validity and interpretability.

5.7.1 Descriptive Statistics

To further explore whether deterioration in ESG scores triggers significant market reactions in high-pollution industries, this section begins with a descriptive statistical analysis of the event sample variables. This helps to understand their distribution and variability. As shown in Table 5 - 35, the total sample consists of 36 observations, each representing a monthly event with a significant change in ESG Risk Score.

Table 5 - 35 Descriptive Statistics for Model 6 Variables

Variable	N	Min	Max	Mean	Std. Dev
HighPollution_ESGDeterioration	36	0.000	1.000	0.222	0.422
CAR[-3,+3]	36	-0.079	0.059	-0.001	0.029
log MarketCap	36	20.020	26.825	23.278	1.820
ROA	36	-0.107	0.085	0.000	0.037
Operating Expense Ratio	36	-0.007	39.000	1.673	6.776
Overall Management Score	36	19.070	69.673	48.622	11.928

Source: Empirical results from this study.

Table 5 - 35 shows that the dependent variable HighPollution_ESGDeterioration is a dummy indicating whether the event falls under the "high-pollution industry combined with ESG score deterioration" category, with a mean of 0.222. This means that approximately 22.2% of the sample observations belong to this group, while the remainder are in the control group. This indicates a representative but unbalanced distribution.

Next, the core explanatory variable CAR[–3,+3], defined as the difference between the average stock returns over the three trading days after the event and the three days before, has a mean of –0.001 and a standard deviation of 0.029. This suggests that following significant ESG score changes, market returns show only slight overall movements, with a small negative bias, indicating some disturbance to investor sentiment or market valuation.

Among the control variables, log(MarketCap) ranges from 20.02 to 26.83 with a mean of 23.278 and a standard deviation of 1.820, reflecting a sample that includes various company sizes, primarily medium to large firms. ROA has a mean around zero (ranging from –0.107 to 0.085), indicating limited variability and a break-even level for asset return rates among sampled companies. The Operating Expense Ratio averages 1.673 and reaches as high as 39, showing a highly skewed distribution with some firms having extremely high operating costs. Finally, the Overall Management Score ranges from 19.07 to 69.67, with a mean of 48.622, reflecting significant differences in ESG governance maturity within the sample.

Overall, these descriptive statistics reveal structural heterogeneity and event diversity in the dataset, providing a solid foundation for analyzing whether ESG score deterioration triggers a market punishment effect under specific conditions, and offering contextual support for the subsequent logistic regression model.

5.7.2 Correlation Analysis

To ensure that explanatory variables in the regression model do not suffer from high multicollinearity, we conduct Pearson correlation analysis to examine the linear relationships among all variables, as shown in Table 5 - 36.

Table 5 - 36 Pearson Correlation Matrix for Model 6 Variables

Correlation							
		HighPollution_ESGDeterioration	CAR[-3,+3]	log MarketCap	ROA	Operating Expense Ratio	Overall Management Score
HighPollution_ESGDeterioration	Pearson correlation	1	0.155	-0.278	0.122	-0.125	0.060
	Sig. (2-tailed)		0.368	0.100	0.479	0.468	0.728
	N	36	36	36	36	36	36
CAR[-3,+3]	Pearson correlation	0.155	1	0.095	-0.294	0.074	0.230
	Sig. (2-tailed)	0.368		0.583	0.081	0.668	0.178
	N	36	36	36	36	36	36
log MarketCap	Pearson correlation	-0.278	0.095	1	0.145	0.103	.444**
	Sig. (2-tailed)	0.100	0.583		0.399	0.551	0.007
	N	36	36	36	36	36	36
ROA	Pearson correlation	0.122	-0.294	0.145	1	-0.212	-0.039
	Sig. (2-tailed)	0.479	0.081	0.399		0.215	0.823
	N	36	36	36	36	36	36
Operating Expense Ratio	Pearson correlation	-0.125	0.074	0.103	-0.212	1	-0.023
	Sig. (2-tailed)	0.468	0.668	0.551	0.215		0.896
	N	36	36	36	36	36	36
Overall Management Score	Pearson correlation	0.060	0.230	.444**	-0.039	-0.023	1
	Sig. (2-tailed)	0.728	0.178	0.007	0.823	0.896	
	N	36	36	36	36	36	36

Source: Empirical results from this study.

Table 5 - 36 indicates that, overall, the correlations among the primary explanatory variables fall within acceptable limits, without presenting any serious multicollinearity concerns, thereby satisfying the prerequisites for conducting logistic regression analysis.

First, the core independent variable CAR[–3,+3] exhibits a correlation coefficient of 0.155 with the dummy dependent variable HighPollution_ESGDeterioration, which is not statistically significant ($p = 0.368$). This suggests that its variation does not heavily overlap with event type, making it a suitable predictor in the model. Furthermore, the correlations between CAR[–3,+3] and log(MarketCap), Operating Expense Ratio, and Overall Management Score are all below 0.25, indicating the absence of strong linear relationships with these control variables.

Among the control variables, only Overall Management Score and log(MarketCap) display a significant positive correlation ($r = 0.444$, $p < 0.01$), suggesting that larger firms tend to exhibit higher governance quality. This is consistent with existing literature (Gillan et al., 2021). All other variable correlations are nonsignificant and under 0.3, indicating no notable risk of multicollinearity.

In summary, these results confirm that the correlation structure among the variables is appropriate, with sufficient independence to ensure stable estimation and interpretability in the subsequent logistic regression model.

5.7.3 Model Overall Fitv (Omnibus Test)

To assess whether the logistic regression model is statistically significant as a whole, we conducted the Omnibus Tests of Model Coefficients (see Table 5 - 37). The results show a chi-square statistic of 11.915 with 5 degrees of freedom, which is significant at p = 0.036, well below the 0.05 threshold.

Table 5 - 37 Omnibus Tests of Logistic Regression Model Coefficients

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	11.915	5	0.036
	Block	11.915	5	0.036
	Model	11.915	5	0.036

Source: Empirical results from this study.

Table 5 - 37 demonstrates that, after introducing CAR[–3,+3], log(MarketCap), ROA, Operating Expense Ratio, and Overall Management Score as independent variables, the model shows a statistically significant improvement in explaining the occurrence of "high-pollution × ESG deterioration" events (HighPollution_ESGDeterioration), compared to a baseline model containing only the intercept.

In other words, the Omnibus test provides robust evidence that this logistic regression model possesses overall predictive power, laying a solid foundation for the subsequent interpretation of individual coefficients and assessment of model explanatory capability.

5.7.4 Model Explanatory Power and Predictive Accuracy

Table 5 - 38 Model Summary for Model 6

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	26.223[a]	0.282	0.431

Source: Empirical results from this study.

According to the Model Summary in Table 5–38, the Cox & Snell R^2 is 0.282, and the Nagelkerke R^2 is 0.431. Although Cox & Snell R^2 is similar to the R^2 used in OLS regressions, its upper bound is less than 1; Nagelkerke R^2 adjusts for this limitation so that its maximum can reach 1, making it more appropriate for interpreting the explanatory power of a logistic regression model. In this model, the Nagelkerke R^2 of 0.431 indicates that approximately 43.1% of the variance can be explained by the five independent variables included (CAR[–3,+3], log(MarketCap), ROA, Operating Expense Ratio, and Overall Management Score), suggesting a moderate-to-good model fit.

Table 5 - 39 Classification Table of Logistic Regression Model

Classicfication Table[a]					
Observed			Predicted		
			HighPollution_ESGDeterioration		Percentage Correct
			0	1	
Step 1	HighPollution_ESGDeterioration	0	26	2	92.9
		1	4	4	50.0
	Overall Percentage				83.3

Source: Empirical results from this study.

According to the Classification Table in Table 5– 39, the overall prediction accuracy is 83.3%, indicating that this model has strong discriminative ability in classifying whether an event belongs to the "high-pollution combined with ESG deterioration" category.

1. For non-interaction events (observations coded as 0), the prediction accuracy is 92.9%.
2. For interaction events (observations coded as 1), the prediction accuracy is 50.0%.

Although the predictive power for the "high-pollution combined with ESG deterioration" category is relatively weaker (limited by sample size and imbalanced distribution), the model's overall predictive capability still reaches levels acceptable for practical analyses. This further supports its application potential in investment risk identification and informational value validation.

5.7.5 Variable Estimation and Interpretation

In this section, we analyze and interpret the estimated coefficients from the logistic regression model to understand which factors significantly affect the probability of an event being classified as "high-pollution combined with ESG deterioration" (Y = 1).

Table 5 - 40 Logistic Regression Results

Variable in the equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	CAR[-3,+3]	33.175	21.530	2.374	1	0.123	255568084953933.000
	log MarketCap	-0.901	0.440	4.194	1	0.041	0.406
	ROA	28.684	21.572	1.768	1	0.184	2865453629651.590
	Operating Expense Ratio	-6.318	4.813	1.723	1	0.189	0.002
	Overall Management Score	0.085	0.050	2.875	1	0.090	1.089
	Constant	15.916	8.398	3.592	1	0.058	8170910.527

Source: Empirical results from this study.

According to Table 5 - 40, the regression coefficients (B), standard errors (S.E.), Wald statistics, significance levels (Sig.), and odds ratios (Exp(B)) for each variable are summarized as follows:

1. CAR[-3,+3]

The regression result for the variable CAR[–3,+3] shows a coefficient B of 33.175 with a p-value of 0.123. Although the coefficient is positive, it does not reach the conventional 5%

significance level. Moreover, its Exp(B) value is approximately 2.56×10^{14}, suggesting extremely high instability in predicting the event probability. Interestingly, the result contradicts the theoretically expected negative direction, which may imply that some "high-pollution and ESG score deterioration" events did not trigger punitive market reactions. Instead, these events may have coincided with other announcements—such as earnings releases—that led to unexpected positive responses. This outcome underscores the context-dependent and uncertain nature of abnormal returns in heterogeneous event settings. It also suggests that market efficiency and investor behavioral biases could affect price reactions. Therefore, future studies should consider categorizing event types and controlling for market contexts to more clearly identify the role of ESG score changes in influencing abnormal returns.

2. log(MarketCap)

The regression result for log(MarketCap) shows a coefficient B of –0.901 with a p-value of 0.041 and an Exp(B) of 0.406, indicating a significant negative effect. This suggests that larger firms, when measured on a logarithmic scale, are significantly less likely to encounter simultaneous "high-pollution and ESG score deterioration" events. This outcome may be attributed to the fact that larger companies often possess more robust governance structures and risk management systems, which enable them to mitigate the likelihood of substantial ESG rating declines, even within high-pollution sectors. This result is consistent with findings by Gillan et al. (2021), who observed that larger firms generally demonstrate stronger ESG performance and greater operational stability.

3. ROA

The regression result for ROA shows a coefficient B of 28.684 with a p-value of 0.184. Although the coefficient is positive, it is not statistically significant, indicating that ROA does not meaningfully predict the likelihood of a “high-pollution and ESG score deterioration” event. This suggests that a firm's overall profitability may not play a crucial role in this specific context, which could be attributed to the limited sample size or substantial variation in financial structures across different industries, reducing the consistency of ROA as a distinguishing factor.

4. Operating Expense Ratio

The coefficient for Operating Expense Ratio is –6.318 with a p-value of 0.189, indicating a negative but statistically insignificant relationship with the probability of a “high-pollution and ESG score deterioration” event. This suggests that no clear association can be established in the current model. The lack of significance may stem from limitations such as the small sample size, the brief observation window, or considerable heterogeneity in firms’ cost structures, which complicate efforts to isolate its predictive effect. Future research could enhance reliability by increasing the sample size and incorporating industry fixed effects to better capture structural differences.

5. Overall Management Score

The coefficient for Overall Management Score is 0.085 with a p-value of 0.090, indicating a marginally significant positive association with the likelihood of a “high-pollution and ESG score deterioration” event. While this finding appears counterintuitive, since better governance is typically expected to mitigate ESG risks, it may be explained by the dynamic nature of ESG rating methodologies. Firms with more mature governance systems might be more proactive in adjusting policies and increasing disclosure, which could inadvertently prompt negative re-evaluations by ESG rating agencies. Additionally, the result may reflect short-term transitions in governance or strategic shifts that temporarily impact ESG assessments.

6. Constant

The coefficient for the constant term is 15.916 with a p-value of 0.058, indicating marginal significance. This suggests that, when all explanatory variables are set to zero, the baseline log-odds of a firm experiencing a “high-pollution and ESG score deterioration” event are relatively high. This result may point to potential omitted variables not captured in the model or reflect inherent heterogeneity within the sample, leading the constant to absorb a portion of the unexplained variance.

Among the five explanatory variables, only log(MarketCap) reached statistical significance ($p = 0.041$), making it the most reliable predictor in the model. Overall, the model demonstrates moderate fit (Nagelkerke $R^2 = 0.431$) and decent predictive accuracy (83.3%), indicating that while the interaction between ESG score deterioration and pollution level can sometimes be reflected in market reactions, its consistency requires further verification with broader samples.

Table 5 - 41 Comparison of Expected and Empirical Directions for Model 6

Variable	Expected Direction	Empirical Direction	Sig.
HighPollution_ESGDeterioration	Dependent variable	Dependent variable	
CAR[-3,+3]	－	＋	0.123
log(MarketCap)	－	－	0.041
ROA	－	＋	0.184
Operating Expense Ratio	＋	－	0.189
Overall Management Score	－	＋	0.090

Source: Empirical results from this study.

In this section, the expected directions and empirical estimates for all variables in the logistic regression model are summarized (see Table 5 - 41), allowing us to assess both predictive performance and theoretical alignment. Among the five core independent variables, only log(MarketCap) aligns with theoretical expectations and achieves statistical significance. Overall, the model demonstrates "partial direction consistency with limited significance," reflecting the statistical and practical complexity involved in explaining the ESG × high-pollution interaction event.

First, CAR[–3,+3] is theoretically expected to be negative; however, the empirical coefficient is positive ($B = 33.175$), not statistically significant ($p = 0.123$). This direction deviates from the findings of Krüger (2015) and others, indicating that in this sample, ESG deterioration did not generally prompt market punishment for high-pollution firms. In some cases, heterogeneous events or mixed signals may have triggered opposite market reactions—highlighting a strong contextual dependence in how markets interpret ESG ratings.

Second, log(MarketCap) is expected to have a negative effect—and the empirical result confirms this ($B = -0.901$, $p = 0.041$), as the only variable to meet both directional and statistical expectations. This supports findings by Gillan et al. (2021) and Broadstock et al. (2021), suggesting that larger firms, with more mature governance and risk absorption capacities, are significantly less likely to experience a combined "high-pollution and ESG deterioration" event even when ESG scores worsen.

Third, ROA was also expected to be negative, but the empirical coefficient is positive ($B = 28.684$) and non-significant ($p = 0.184$). This contradicts the theoretical hypothesis that high-performance firms are more resilient in the market (Giese et al., 2019). The lack of significance may reflect limited sample size or complex inter-industry ROA variability.

Fourth, Operating Expense Ratio was expected to be positive, yet the empirical coefficient is negative ($B = -6.318$) and not significant ($p = 0.189$). This unexpected direction may arise if firms execute operational reforms or cost-control strategies in response to ESG deterioration, biasing the statistical estimates. Sample size limitations and heterogeneity may also contribute to instability.

Fifth, Overall Management Score was predicted to have a negative effect but shows a positive coefficient ($B = 0.085$) with marginal significance ($p = 0.090$). This counterintuitive result may be explained by the dynamic nature of ESG rating systems: firms actively adjusting governance policies may trigger rating reassessments that temporarily lower ESG scores. As a result, well-governed firms may be more likely to appear in the “ESG score deterioration” category.

Taken together, only log(MarketCap) meets both directional and statistical criteria. The mixed results on other variables suggest that whether ESG score deterioration triggers significant market reactions in high-pollution firms depends on multiple interacting factors. Future research should consider expanding sample size, segmenting events by dimension (e.g., environmental vs. social), or introducing external moderating variables to better understand the causal mechanisms between ESG scores and capital markets.

5.7.6 Summary and Interpretation

This section tests Hypothesis H_6 using a logistic regression model to examine whether ESG score deterioration triggers stronger market reactions in high-pollution firms. The empirical results reveal that the overall model is statistically significant (Omnibus test $p = 0.036$), demonstrates moderate fit (Nagelkerke $R^2 = 0.431$), and achieves an 83.3% prediction accuracy These findings indicate meaningful explanatory power and practical relevance.

Among the key predictors, log(MarketCap) is the only variable that reaches statistical significance ($p = 0.041$), indicating that firms with larger market capitalization are notably less likely to be classified under the combination of high pollution and ESG score deterioration. This finding is consistent with previous studies (Gillan et al., 2021), which argue that larger firms, due to their more developed governance structures and risk control systems, are generally better equipped to absorb the impact of ESG-related disruptions.

In contrast, CAR[–3,+3], the model's core variable, is not statistically significant and its empirical coefficient is opposite to expectations (positive instead of negative). This suggests that ESG score deterioration did not consistently trigger negative abnormal returns in high-pollution firms; in some observations, simultaneous announcements or interpretations may have led to reverse effects. This highlights the contextual complexity of ESG information in market response.

Other variables, including ROA, Operating Expense Ratio, and Overall Management Score—are also not significant. Notably, the governance score is marginally significant at the 10% level (p = 0.090), but its coefficient direction is opposite expectation. This inconsistency may reflect the high sensitivity of ESG rating methodologies to temporary governance adjustments, which can cause a downgrade even in well-governed companies.

Overall, the model provides only partial support for Hypothesis H_6. Although it is statistically significant and confirms that firms with larger market capitalization exhibit greater resilience, the anticipated negative market reaction under the condition of simultaneous high pollution and ESG score deterioration does not consistently emerge. This implies that investor reactions to ESG score declines are not uniform, but rather vary substantially depending on the industry context, the specific nature of the event, and the level of information transparencyThe findings emphasize the conditional and nonlinear nature of ESG value information in investment decisions. Future research should consider larger samples, event classification, and long-term performance tracking to deepen understanding and validation of ESG's role in high-risk industries.

6. Conclusion and Recommendations

6.1 Summary of Research Findings

This study uses U.S.-listed shipping companies as the empirical sample to systematically examine the impact of ESG performance (measured by ESG Risk Score) on firm financial performance and market reactions, with a specific focus on whether ESG retains stable predictive power and capital market relevance in high-pollution, carbon-intensive industries. The research employs OLS regression, two-stage mediation models, group T-tests, and logistic regression, covering the period from 2019 to 2024 and utilizing multidimensional data such as ESG scores, stock returns, operating costs, and financial structures.

Table 6-1 below presents a consolidated summary of the empirical findings across all hypotheses. The table highlights the direction and significance of each key relationship, organized by thematic area, and outlines their practical implications in the context of ESG assessment and firm behavior.

Table 6 - 1 Summary of Research Findings

Thematic Area	Finding	Statistical Significance	Implication
ESG & Operating Costs	ESG risk Score ↑ → Operating Expense ↑	Significant ($p < 0.01$)	ESG increases administrative burden(H_{3a})
	ESG risk Score↑ → Cost of Revenue ↓	Significant ($p < 0.01$)	ESG reduces production costs (H_{3b})
ESG & Stock Return	ESG Risk Score → Stock Return	Not Significant	ESG is not priced into returns (H_2)

	Mediation via Operating Expenses	Not Significant	No mediation effect (H_4)
Heterogeneity & Market Penalty	High ESG risk firms: ROA ↓, D/E ↑	Significant (H_5)	Poorer financial quality in high-risk group
	ESG deterioration × High Pollution → Stock Return	Not Significant (H_6 not supported)	No clear market punishment observed
	Small firms & low governance	Significant	Risk concentrated in weak-governance & small firms
	→ More likely in ESG-deterioration × pollution group	Marginal Significant ($p < 0.05$)	

Source: Empirical results from this study.

Following this summary, the results are further interpreted across three thematic domains: operating cost effects, stock price implications, and firm heterogeneity in ESG exposure and response.

1. ESG and Operating Costs

The regression results indicate that firms with higher ESG Risk Scores tend to experience significantly higher Operating Expense Ratios, suggesting that greater ESG risk, which reflects weaker performance, leads to increased administrative and compliance costs. These may include enhanced disclosure burdens, sustainability reporting, or governance-related expenses.

Conversely, the same firms show a significant decrease in the Cost of Revenue Ratio, indicating reduced production-related expenditures. This dual effect suggests that ESG practices do not necessarily raise overall costs but rather reallocate costs from operational production to administrative governance. This may reflect improved energy efficiency, resource optimization, or reduced waste as a result of ESG integration.

Taken together, these findings imply that ESG adoption in the shipping industry leads to cost structure transformation rather than unidirectional cost inflation. The shift highlights the complexity of ESG implementation, where managerial and policy burdens rise, but operational efficiencies may partially offset them.

2. ESG and Stock Price Response

Despite expectations, the relationship between ESG Risk Score and stock returns is not statistically significant in either the OLS regressions or the event-study models. This suggests that ESG signals may not yet be fully internalized by capital markets in the shipping sector, potentially due to limited investor awareness, poor disclosure quality, or the lack of standardized ESG valuation logic.

Additionally, the two-stage mediation model designed to assess whether operating costs act as an indirect channel for ESG to influence stock returns also yielded non-significant results. This undermines the hypothesized pathway where ESG risk affects cost structures, which in turn impacts shareholder value.

Overall, these results challenge the assumption that ESG performance is systematically priced by the market in this industry, raising questions about ESG materiality and investor responsiveness in high-emission, transitional sectors.

3. ESG Heterogeneity and Market Penalty

When examining firm-level ESG risk heterogeneity, a significant divergence in financial structure is observed between high and low ESG risk firms. High-risk firms tend to show lower Return on Assets and higher Debt-to-Equity Ratios, suggesting they are more financially constrained or less efficient. These differences were confirmed through group T-tests and highlight ESG scores' partial ability to differentiate firms based on internal financial characteristics.

However, the analysis of ESG deterioration events in high-pollution firms using interaction terms in logistic regression models did not reveal significant abnormal returns. In other words, market participants did not systematically penalize these firms following material ESG risk increases. This may reflect a lack of effective market discipline or weak ESG signal credibility in the sector.

Notably, further analysis revealed that smaller firms with lower governance scores were more likely to appear in the ESG deterioration group, suggesting that ESG risk is concentrated in structurally weaker firms. This supports a view that ESG signals may be more reflective of firm-level vulnerabilities than consistent performance indicators.

The empirical results collectively suggest that ESG, while conceptually important, currently exhibits limited explanatory and predictive power within the U.S. shipping industry. Although some influence on cost structures and internal financial attributes is observed, its effect on stock market outcomes remains muted. These findings call for a more critical evaluation of ESG models' relevance in carbon-intensive sectors and highlight the need for improved ESG signal reliability, transparency, and contextual calibration.

6.2 Theoretical and Practical Implications

This study systematically examines the financial significance and market response mechanisms of ESG in carbon-intensive, high-pollution industries, with the shipping sector as an example. Although ESG ratings have become a central tool in financial markets and policy frameworks in recent years, our findings suggest that within such a specific industry context, their practical efficacy may fall short of expectations. This has several important implications for theory and practice:

1. **Re-examining and revising sustainable finance theory**

   Prior literature often assumes that ESG enhances corporate reputation, lowers capital costs, strengthens risk management, and thus improves financial performance. However, our results indicate that for capital-intensive industries like shipping, which are characterized by clear carbon footprints and intense regulatory pressure, ESG ratings cannot reliably explain stock returns or operational efficiency. This challenges the assumption of the “universal applicability” of ESG’s financial effects and underscores the need to incorporate industry structure, implementation thresholds, and regulatory fit into theoretical models. Going forward, sustainable finance theory should shift toward a conditionality framework, recognizing that ESG outcomes emerge only when mediated by industry characteristics, governance strength, capital structure, and other contextual factors, rather than treating ESG as a universally applicable investment signal.

2. **Implications for corporate sustainability strategy**

For shipping firms, these findings warn that ESG efforts confined to disclosures or branding may fail to deliver substantive financial benefits, and may even be internally resisted due to costs and absent market returns. ESG initiatives should become deeply embedded within core operations, such as vessel fuel efficiency, route optimization, and fuel transition, in order to drive genuine improvements in efficiency and risk mitigation. Additionally, ESG strategy should adopt a transition pathway perspective, moving beyond short-term emissions reductions and focusing on longer-term structural transformation plans. This is essential to enhance ESG's credibility with capital markets and regulators.

3. **Recommendations for investors and asset managers**

A crucial insight is that ESG scores are not universally reliable as predictors of risk or return across all industries. Investors emphasizing ESG should carefully assess industry context and signal quality, rather than relying on a single ESG factor. In high-pollution sectors, ESG ratings should be complemented with tangible environmental performance measures, policy risk exposure, and progress toward transformation.

Adopting a multi-dimensional evaluation approach can reduce mispricing risk. For responsible investors, ESG should be deployed as a tool for engagement and transformation, not merely exclusion. This includes strategies such as shareholder activism and policy advocacy to promote industry-wide transition.

4. **Policy implications for regulation and institutional design**

The instability of ESG in high-pollution industries partly stems from inadequate disclosure standards, weak performance tracking, and insufficient transformational incentives. Regulators should consider incorporating industry-specific indicators, enhancing verification standards, and coupling ESG disclosures with financial incentives, such as green tax breaks or carbon-trading subsidies, to strengthen the economic basis for ESG. For sectors like shipping, where transformation pressure is high but internal momentum is weak, policy should play an active role. This includes developing infrastructure for alternative fuels and harmonizing international standards to lower ESG implementation barriers and prevent ESG from becoming merely symbolic.

In summary, this study shows that ESG effects are not constant and must be understood in relation to industry conditions and implementation depth. The instability of ESG performance in the shipping industry, a carbon-intensive and capital-heavy sector, serves as a caution for both theorists and practitioners, reminding them not to treat ESG as an inherently positive financial factor. Instead, ESG frameworks should be refined through industry stratification and institutional design to rebuild their feasibility and practical relevance.

6.3 Research Limitations and Future Directions

Although this study systematically examines the financial and market effects of ESG within the U.S. shipping industry using multiple empirical methods and contributes key theoretical reflections, several limitations in research design, data selection, and modeling must be addressed in future studies:

1. **Sample selection bias and limited external validity**

   To ensure data consistency and estimation stability, this study restricts the sample to firms with complete ESG scores and financial disclosures from 2019 to 2024, forming a balanced panel data set. While this enhances internal validity, it also reduces the sample size to only 18 companies and may exclude firms with missing or incomplete ESG reports. This introduces potential selection bias. Future studies should consider larger samples and techniques like data imputation or semi-structured data processing to better capture industry heterogeneity.

2. **Single-source ESG rating without heterogeneity testing**

   This study uses Sustainalytics' ESG Risk Score as the primary measure. However, ESG rating methodologies vary across providers in indicator design, weighting, and data handling. Existing literature highlights substantial rating divergences; relying on a single source may over- or underestimate ESG's financial effects. Future work should integrate assessments from multiple providers (e.g., MSCI, S&P Global, Refinitiv) to construct composite scores or examine how rating discrepancies impact model robustness.

3. **Inability to identify causal links between ESG practices and scores**

    While we include ESG-related variables like Scope 1 emissions and biofuel usage to connect practices with ratings, the ESG Risk Score remains an aggregate measure that may reflect disclosure policies and symbolic actions rather than substantive change. This study cannot distinguish real operational improvements from mere reporting enhancements. Future research could adopt ESG report text analysis, carbon disclosure breakdowns, or third-party assurance data to better isolate the link between practice and score.

4. **Market reaction models do not account for behavioral biases or heterogeneous expectations**

    Our use of static regressions and logistic models assumes immediate and uniform market reactions to ESG data. But ESG may only impact returns during extreme risk events, policy shifts, or for certain investment styles. Our models may not capture its dynamic or nonlinear characteristics. Future research could incorporate behavioral finance models, interaction models like ESG × Value/Momentum factors, or long-term event study frameworks to explore time-varying ESG effects under different market conditions.

5. **Lack of coverage on ESG's broader impact on capital costs and risk exposure**

We focus on ESG's effect on stock returns and operating costs. However, ESG also matters for risk mitigation and financing terms: prior studies find that high-ESG firms enjoy lower equity costs, tighter debt spreads, and better credit risk profiles. We did not include variables like beta, Sharpe ratio, CDS spreads, or debt pricing to assess volatility. Future research should expand variable coverage to evaluate ESG as a long-term proxy for risk and credit quality.

In summary, this study provides preliminary empirical evidence and strategic reflections on ESG in high-pollution, capital-intensive industries. However, further depth is needed in sample size, data diversity, model dynamics, and causal identification. Future studies should adopt inclusive, cross-industry data integration strategies and integrate dynamic asset pricing and risk management perspectives to develop more adaptive ESG frameworks that align with real-world industry and market logic.

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