Original Research Article

Quantifying Financial Disparities in Corporate Sustainability: Predictive Modeling using Support Vector Machines and Regression Analysis

Aarush Arun

Novi High School, 24062 Taft Rd, Novi, MI, 48375, United States

ABSTRACT

As the world becomes increasingly aware of climate change and recognizes the need for environmental, social, and governance (ESG) consciousness, it has become necessary to balance economic and private sector growth with ecological sustainability. Hence, many efforts have been made to categorize businesses by their sustainability performance, aiming to incentivize sustainable corporate practices. Yet, despite this, it is actively debated whether being a sustainable company is beneficial to companies in terms of profit and economic growth. This paper examines the structural differences and associations between being a corporate sustainability leader and key financial metrics, including stock performance, profit, and growth. This study utilizes the Corporate Knights Global 100, a ranking of the world's 100 most sustainable public companies with revenue exceeding 1 billion USD. By employing rigorous nonparametric statistical testing, subsequent False Discovery Rate corrections, and predictive modeling using Support Vector Machines, this study compares these highly ranked firms against their unranked peers. Despite potentially strengthening a company's brand image by striving to be at the forefront of corporate sustainability, findings suggest that ranked companies are generally associated with inferior financial performance compared to their unranked peers, raising questions about the potential trade-offs of ESG leadership.

Keywords: Corporate Sustainability; ESG; Finance; Economics; Global 100; Financial Analysis; Predictive Modeling

INTRODUCTION

Climate change and global warming present fundamental threats to humans and society, affecting all aspects of both human and natural systems (1). It has been deemed a "threat multiplier," having the potential to reduce and reverse generations of human progress and innovation (2). International Agreements, such as the Paris Agreement, aim to limit global warming to below 2°C (3). Around this time, individuals began making noticeable changes in their lives to reduce their carbon footprint in various ways, such as recycling and opting for eco-friendly transportation like walking or biking. It was clear to individuals that these issues would play a massive role in society for years to come.

Yet while individuals were adjusting their habits, businesses and corporations saw no reason to strive for sustainability at the time. From a purely financial perspective, there was no incentive for them to invest time and money in becoming a sustainable corporation. It

Corresponding author: Aarush Arun, E-mail: aarushrcb@gmail.com.

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wasn't until 2004, when the United Nations published the famous "Who Cares Wins" report, that corporations had reason to strive for sustainability (4). This report marked the first time that investors could categorize corporate sustainability into three significant parts: environmental, social, and governance (ESG) impacts. This gave companies a clear reason to strive for sustainability, as doing so would, in theory, improve stock performance. By 2010, corporate sustainability had shifted from being seen as helpful to essential, as millions around the world responded with immediate backlash on social media over corporate sustainability issues.

Since then, ESG has become a typical framework used by investors to evaluate a company's sustainability and societal impact. The idea encourages corporations to remain diligent in their sustainability efforts, as failing to do so is often associated with declines in company stock and revenue performance (5). From another perspective, ESG also provides a straightforward method for companies to assess and manage risks associated with their environmental footprint and social and corporate governance practices. This, in turn, helps companies avoid regulatory fines and pushes for innovation across industries.

However, ESG has faced criticism from many individuals, who typically argue that ESG is either not measurable, not feasible, not desirable (as it is a distraction), or not helpful to company performance (6). Although many retaliate with arguments of rising stock performance or increased revenue once ESG is implemented, it is unclear whether ESG is truly correlated with company financial performance, and whether being at the pinnacle of corporate sustainability is more beneficial than being casually involved in sustainability efforts.

METHODS AND MATERIALS

This study aimed to compare the top 100 sustainable companies, as identified in a reputable published list, with industry peers that are not ranked on the list, measuring key financial metrics that significantly relate to being ranked versus not being ranked on the list. The study characterizes the financial structure of firms that achieve top ESG rankings, clarifying which types of firms tend to be represented in widely cited sustainability indices.

The Corporate Knights Global 100 is an in-depth ranking of public companies with revenues over 1 billion USD based on their sustainability and environmental impact. Since 2005, Corporate Knights has ranked corporations by a rigorous analysis. The methodology of the rankings is primarily based on 25 key performance indicators (7). This study analyzes the Corporate Knights Global 100 since 2016 and each company's financial data to assess relationships between being at the pinnacle of corporate sustainability and financial performance and metrics. The study also analyzes the stock performance of Corporate Knights Global 100 companies for each year a company appears on the list. The raw data used were gathered from the Corporate Knights website, where a free Excel file is available for each year, detailing the top 100 companies and the methodology used to rank them. For the purposes of this study, companies with incomplete financial data due to corporate changes, such as mergers or bankruptcy, were omitted.

Financial data for the ranked companies were pulled from Yahoo Finance using the Python "yfinance" library. In addition, the financial data from 367 similar companies that never appeared on the list from 2016 to 2025 were drawn using the same methodology. These companies serve as the control group during the analysis. Companies were selected according to three primary criteria. All selected firms are publicly traded and have annual revenue exceeding $1 billion USD, consistent with the minimum revenue threshold used by Corporate Knights in Global 100 eligibility. Unranked firms were selected by GICS sector: approximately 30-40 unranked companies were identified for each sector to ensure proportional representation. Companies with significant amounts of incomplete financial data across key metrics were excluded to ensure data integrity. All firms were confirmed not to have appeared on the Global 100 between 2016 and 2025. Market capitalization was not used as an explicit matching criterion; however, company size was controlled for in subsequent analyses using revenue-residual regression. Geographic distribution was not constrained during the selection of the control group, consistent with the scope of the Global 100. The financial information included over 30 unique metrics, such as total revenue, gross profit, net income, diluted earnings per share (EPS), and EBITDA, and spanned the period from 2021 to 2025. Although financial data were limited for previous years (2016 - 2020), 2021 to 2025 provided sufficient data for the analysis, and the years in which companies were ranked were carefully compared with the available financial data for those years. Stock performance was used as a metric from 2016 to 2025, as historical price data were consistently available throughout this window. Additionally, since stock performance is generally evaluated as a reflection of long-term market and investor valuation, this longer

time period was selected to better reflect broader market trends. Data analysis was performed using the "pandas" Python library (8). It should be noted that the difference in time windows between stock performance (2016-2025) and other financial metrics (2021-2025) represents a structural asymmetry in the dataset. Stock performance associations are based on longer time periods and may reflect differences in the market environment compared to other financial metrics. Therefore, comparisons across these two categories of metrics should be interpreted with this limitation in mind.

To identify the relationship between being a ranked or an extremely high ESG score company and financial performance, this study contrasts years where a company is ranked versus not ranked to observe changes in key financial metrics. This study also runs tests comparing companies ranked in a given year with those not ranked in the same year to observe how ranked companies perform relative to their unranked competitors. To maintain fairness in comparisons, Global Industry Classification Standard (GICS) sectors are utilized as needed to ensure that companies are directly compared with their competitors and peers in the same industry, thereby eliminating the risk of industry-wide growth or decline skewing the analysis (9).

Table 1 presents the overall composition of the ranked dataset used in this study. The table is sorted by GICS sector and shows essential metrics for each sector.

Table 2 presents the overall composition of the unranked dataset used in this study. The companies in this dataset have not been ranked in the Corporate Knights Global 100 from 2016 to 2025, and are competitors to many of the companies that have been ranked during this time period. The table is of a similar format to Table 1, other than the exclusion of the "Average Rank" column. Note that there is a noticeable discrepancy in the average revenue of ranked and unranked companies, despite being close competitors and peers in their respective spaces. This critical observation is likely to have a notable impact on the interpretation of results later.

To prevent any spillover or look-ahead bias in the analysis, ranked companies were omitted in years where they did not appear on the top 100 list. Unranked companies were included for the full span of 2016-2025. Additionally, data preprocessing was strictly designed to align a firm's presence in the Global 100 with that exact fiscal year's financial performance. This ensures that there is temporal alignment in the analysis and that the data is structurally sound. Once again, all years in which a "ranked" company did not appear on the Global 100 list were discounted from future analysis, as they did not reflect an accurate representation of a "non-ranked company."

All data and code necessary to reproduce the analyses in this paper are available at: https://github.com/aarusharun1/esg_analysis.

Table 1. *Sector-level composition and revenue characteristics of Corporate Knights Global 100 ranked companies included in the analysis (2016–2025)*

GICS Sector	Company Count	Average 2024 Revenue (Billion USD)	Median 2024 Revenue (Billion USD)	Number of Countries Represented	Average Rank
Communication Services	17	34.51	10.12	11	58
Consumer Discretionary	32	38.34	11.34	16	53
Consumer Staples	23	25.14	19.04	14	57
Energy	7	42.95	23.73	6	31
Financials	52	27.92	14.45	19	57
Health Care	36	23.51	12.88	11	65
Industrials	24	14.90	6.95	15	26
Information Technology	40	37.79	9.55	15	52
Materials	16	17.09	11.65	9	44
Real Estate	9	12.81	4.13	7	49
Utilities	19	25.87	6.17	10	34

Table 2. *Sector-level composition and revenue characteristics of unranked peer companies comprising the control group (2016–2025)*

GICS Sector	Company Count	Average 2024 Revenue (Billion USD)	Median 2024 Revenue (Billion USD)	Number of Countries Represented
Communication Services	34	58.00	45.43	13
Consumer Discretionary	38	86.42	36.66	8
Consumer Staples	36	61.74	22.37	9
Energy	33	82.68	27.83	11
Financials	35	58.81	53.51	12
Health Care	33	94.52	54.07	8
Industrials	32	29.53	22.27	6
Information Technology	34	49.37	25.45	8
Materials	32	27.67	15.79	10
Real Estate	29	3.75	2.98	4
Utilities	31	19.44	13.19	6

RESULTS

The analysis conducted to answer the research question was divided into multiple parts to gather more accurate and precise information on different aspects of the dataset. Each analysis is intended to collect data and draw conclusions on either separate parts of the dataset or various aspects of the research question.

To begin with, an analysis was conducted to determine the association between being a ranked company and financial performance relative to other companies that were unranked in the same year. To maintain a fair comparison, the test was run separately for each of the 11 GICS sectors, comparing the median value of significant financial metrics for ranked and unranked companies.

The use of parametric tests relies on the assumption that the data is in the shape of a normal distribution. Since real-world financial data is essentially always non-normal, statistical significance was primarily evaluated using the nonparametric Mann-Whitney U (MWU) test to remove the assumption of normally distributed data. This allows for greater confidence in the validity of the analysis as potential non-normality is no longer a concern.

Since numerous tests were run, issues arose regarding the necessity of correction to counteract the negative effects of multiple hypothesis testing. To prevent potential errors in the conclusions drawn by the MWU tests, a Benjamini-Hochberg False Discovery Rate (FDR) correction was applied to the MWU test results (10). This ensures that the data and metrics obtained are accurate representations of which metrics remain significant after correction for potential errors regarding multiple hypothesis testing.

Figure 1 illustrates the percentage difference in sector-level median outcomes between ranked and unranked firms, where negative values indicate a lower value for ranked companies and positive values indicate a higher value for ranked companies. Only metrics that were found to be statistically significant after applying the FDR correction are displayed in the figure ($q < 0.05$). Note that the Real Estate sector was excluded from this comparison due to the absence of significant metrics. Once again, metrics deemed to be statistically insignificant after the implementation of the FDR correction were omitted.

The analysis indicates that metrics such as gross profit, diluted EPS, net income, operating income, and total revenue were all significantly lower for ranked companies in most sectors. In addition, sectors such as consumer staples, energy, and materials saw nearly all metrics statistically significant in the negative direction. This suggests that, in most cases, being a ranked company is associated with inferior financial performance compared to unranked competitors. The practical significance of these differences is considerable. Lower operating

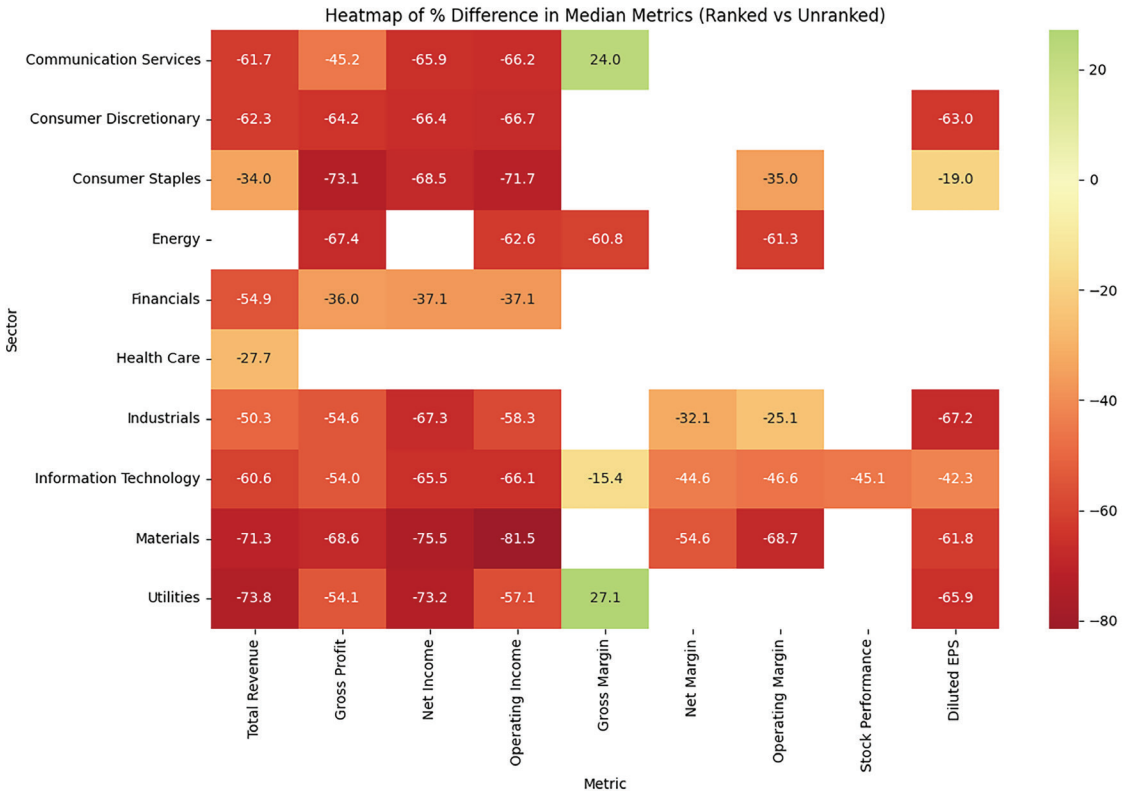

Figure 1. *Heatmap of sector-level percentage differences in median financial metrics between ranked and unranked firms; only FDR-corrected statistically significant results are shown ($q < 0.05$).*

margin and income indicate that the business retains less profit per dollar of revenue after operating expenses. This may reflect the elevated costs that are associated with maintaining top-tier sustainability standards. Additionally, similar associations with other metrics, such as net income and diluted EPS, indicate that ranked firms generate lower final profits and lower per-share value for investors, relative to unranked peers. These differences represent substantive divergences in financial structure that could influence investment decisions and long-term firm valuation.

Upon examining the data, however, one key discrepancy was observed: the difference between the average and median total revenue of ranked companies compared to unranked companies. This then raised the question: Was the observed difference in key metrics simply a reflection of company size? If this were the case, it would lead to many significant differences in the interpretations of the results. Although this study has already carefully included ratios as key metrics, such as gross margin, net margin, and stock performance, further analysis of this interesting phenomenon was desired. To test this, the initial analysis was repeated with a control for company size. As total revenue is essentially a measure of a company's size, this study proceeded with the analysis using total revenue as the metric for control. The revenue of each company was regressed out from each metric, measuring the difference in residuals of other metrics.

Figure 2 illustrates the percentage changes in financial metrics for companies by sector. Metrics that were found to be insignificant after controlling for company size have been omitted. Statistical significance for this figure was calculated using the residual values for each metric, after regressing out total revenue. For a metric to be considered statistically significant, it must have passed the FDR correction to account for multiple hypothesis testing. Only metrics with statistical significance in both the original and the controlled analysis are shown in the diagram, indicating that a majority of metrics remain statistically significant even after accounting for company size. Total Revenue was not residualized and was evaluated using the raw-metric FDR result. Results suggest that many metrics remain significant in

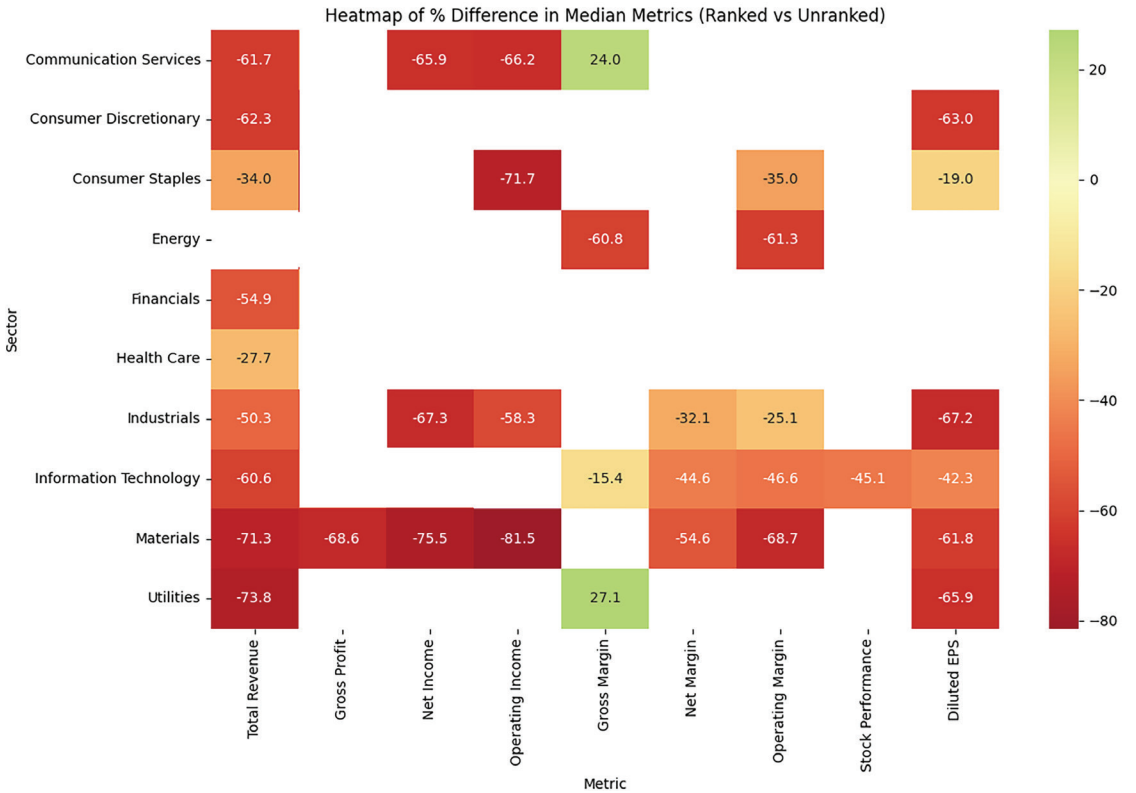

Figure 2. *Heatmap of the percent difference in raw median metrics of ranked versus unranked companies, utilizing FDR-corrected p-values from MWU tests, and controlled for company size.*

the negative direction across most sectors, specifically in sectors such as consumer staples and materials. This provides more substantial evidence that being a ranked company is associated with lower financial metrics compared to competitors in the same sector. Additionally, the persistence of these associations after controlling for company size strengthens their practical implications. Even among firms of similar size, a ranked firm is associated with lower financial metrics, such as operating income, operating margin, and diluted EPS, when compared to industry peers.

To ensure the robustness of the findings from the MWU tests, a secondary analysis was also conducted using Welch's t-tests. Welch's t-tests account for potential unequal variances in data between ranked and unranked firms. After applying the same FDR corrections and revenue normalizations, the results remain broadly consistent with the associations identified by the MWU test. Specifically, metrics like operating income, diluted EPS, and operating margin exhibit very similar overarching trends across tests, even when evaluating differences in the mean rather than the median. This consistency serves as an indicator of the validity and rigor of the analysis and further validates the associations observed by this analysis.

Although the preceding analysis addresses the relationship between being a top sustainability corporation and financial metrics, the study still sought to identify the specific metrics that are most strongly associated with ESG rankings. In essence, this study intended to determine which financial metrics have the strongest power to predict whether a company is ranked and what the specific rank is.

To answer this, a multivariate analysis was performed to find which metrics are most strongly correlated with ESG ranking. The model developed aims to predict a company's rank and therefore uses the dataset of ranked companies only. The model identified the best-performing metrics in terms of R^2, RMSE, and BIC. Hence, the metrics displayed in Table 3 were selected because they are the best-performing metrics according to the model. Metrics were added one at a time in the order that gave the greatest model improvement.

Table 3. *Multivariate regression model performance by variable combination, evaluated using R^2, RMSE, and BIC; bolded row indicates the optimal model specification.*

Factors	R^2	RMSE	BIC
GICS Sector	0.1443	26.540	8859.7
GICS Sector + Diluted EPS	0.4696	20.732	2568.9
GICS Sector, Diluted EPS, & Full-Time Employees	**0.5417**	**19.152**	**2055.1**
GICS Sector, Diluted EPS, Full-Time Employees, & Country	0.5727	18.494	2169.4

Table 3 presents the performance, as determined by R^2, RMSE, and BIC, of various metric combinations according to the model. Once again, the metrics included in the table are the best-performing metrics, added in order. The bolded row shows the combination of metrics that produces the most effective results. The increase in BIC between rows 3 and 4 of the table shows that the improvement in model fit does not outweigh the negative effect of the model's additional complexity. Therefore, BIC is often treated as a metric that indicates a model's true strength, leading to the selection of the row with the lowest BIC in the table as the most efficient model. The substantial decrease in BIC from 8859.7 to 2055.1 over the first three iterations confirms that each additional variable added yields significant predictive improvement rather than overfitting. The fact that the optimal BIC combination excludes the "Country" variable suggests that a company's sustainability rank is strongly tied to its core business framework, rather than its geographic location.

Results indicate that sector, EPS, and employees are the strongest predictors of a company's rank in the selected model. Note that the model explains a significant portion of the variance in the data, indicating a relationship between these metrics and a company's ranking. This is indicated by the R^2 value shown in the table: an R^2 of 0.5417 indicates that 54.17% of the data's variance is explained by these three characteristics alone. In the context of ESG ranking prediction, sustainability rankings are influenced by various non-financial qualitative factors that aren't captured in financial data. Therefore, the R^2 value of 0.54 indicates a meaningful explanation of variance, but one that is still incomplete. The RMSE value of 19.152 indicates that the model's rank predictions deviate from actual ranks by 19 positions on average, reflecting the inherent noise in predicting qualitatively determined ranking purely from quantitative metrics. The decrease in RMSE as the first three variables are added indicates that each variable substantially increases the model's precision. This suggests that top-tier sustainability leaders share key distinct structural similarities, showing that ESG rankings may be partially anchored in core business characteristics like industry, workforce size, and bottom-line profitability.

Although the previous model enabled the identification of the strongest predictors of a company's rank, this study sought to validate these findings using an alternative approach. The multivariate regression analysis predicts a company's numerical rank; however, it doesn't directly address whether or not a company is ranked in the first place, which is a crucial part of this study's research question. Therefore, a Support Vector Machine (SVM) model was created, enabling a supervised machine learning classification method in this analysis (11). It is important to note that, unlike the regression model, the SVM model predicts whether a company is ranked or unranked. This means that slight discrepancies in the results are expected.

The SVM model was trained on 17 key features that included absolute financial metrics (total revenue, gross profit, net income, operating income, and diluted EPS), ratio-based and margin metrics (gross margin, net margin, operating margin, stock performance, and year-over-year growth rates for all five absolute financial metrics), and organizational characteristics (GICS sector, country, and full-time employee count). No feature selection or dimensionality reduction was applied prior to training the model. One-hot encoding was used on categorical features like Country and GICS Sector. All numeric features were standardized using a sklearn "StandardScaler" to ensure comparability across variables of different sizes (12).

The kernel used for the SVM model was an RBF (radial basis function) kernel. The key benefit presented by the RBF kernel is that it enables the model to map input features into an infinite-dimensional space, creating flexible, curved decision boundaries that a linear kernel

cannot. The RBF kernel allows for higher classification accuracy on non-linear data, which is what real-world financial data tends to be. Hyperparameters were set to sklearn default values (C = 1.0, gamma = 'scale'), which are well-established baseline specifications for RBF kernel SVM models.

The dataset was partitioned into an 80/20 train-test split, using standardized values for all metrics to ensure the predictive validity of the model. Stratified splitting was used to prevent class imbalances from affecting the predictive integrity of the model. Model performance was assessed exclusively on the testing set, ensuring that the model refrains from overfitting to improve accuracy. Performance was analyzed using both a confusion matrix and the area under a receiver operating characteristic curve (AUC-ROC).

Table 4. *Confusion matrix for the RBF-kernel SVM classifier distinguishing ranked from unranked firms on the held-out test set (n = 348).*

n = 348	Predicted No	Predicted Yes
Actually No	237	66
Actually Yes	16	29

This model achieved a relatively strong accuracy, as indicated by the confusion matrix in Table 4. The model performs exceptionally well at minimizing false negatives (high negative predictive value); however, the model predicts a substantial number of false positives (low precision). This disparity is expected as it reflects the natural imbalance between ranked and unranked firms. The Global 100 represents an elite group that is, by nature, small, meaning that they are naturally underrepresented relative to unranked peers. In the current situation, it is not entirely clear whether false positives or false negatives are preferred; therefore, the model's sensitivity has not been adjusted.

To better visualize the false positive and negative rates of the SVM model, a Receiver Operating Characteristic (ROC) curve for the model is shown in Figure 3. The ROC curve indicates a strong Area Under the Curve (AUC) value of 0.8032. This indicates that, given a randomly selected ranked firm and a randomly selected unranked firm, the model correctly identifies which is which approximately 80% of the time based solely on financial metrics. The AUC value exceeds the model's accuracy score because AUC evaluates classification performance across all possible decision thresholds, whereas accuracy depends on a single threshold. The curve visually indicates that the results are better than chance, as the AUC value is substantial.

The model's misclassifications likely reflect two main sources of ambiguity. First, misclassifications may simply occur because certain firms exhibit financial profiles atypical of their ESG status. For example, there are outlier firms that are financially successful despite being ranked, due to factors beyond those captured by the model, and vice versa. Second, the financial metrics on which the model was trained may not fully capture ESG selection criteria, as qualitative factors often affect a company's sustainability ranking.

Since the model performed with notable accuracy, observing the weightings of different metrics in the model was the next step. This provides a clear understanding of which metrics are most significant in determining whether a company is ranked or unranked. The absolute values of the coefficients were used because they provide the clearest interpretation of which financial metrics are most significant for predicting whether a company is ranked.

The primary classification model employed the use of an RBF-kernel SVM for higher accuracy and robustness.

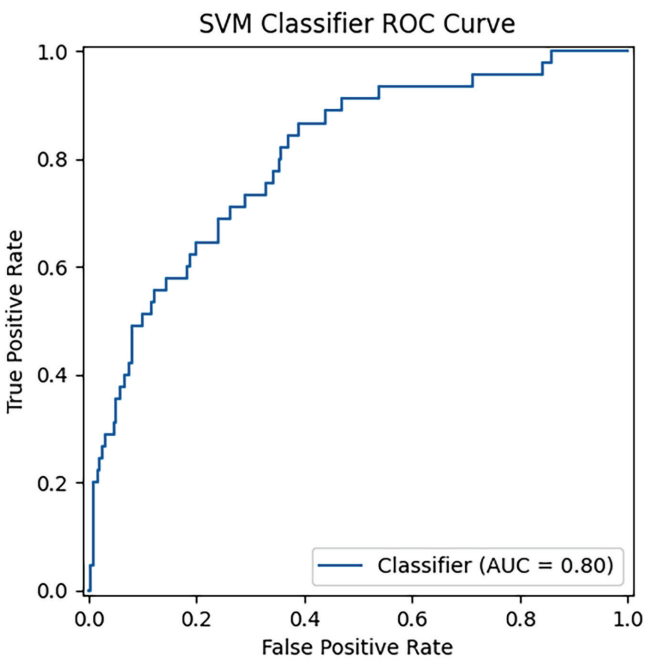

Figure 3. *Receiver operating characteristic (ROC) curve for the RBF-kernel SVM classifier, with an area under the curve (AUC) of 0.80.*

However, feature contributions as coefficients cannot be drawn from RBF models. Hence, an additional linear SVM model was trained on the same preprocessed feature space to allow for coefficient interpretability.

As linear SVMs produce explicit weightings for each metric, the magnitude (absolute value) of each coefficient reflects the relative contribution and importance in the prediction model, providing a more interpretable indication of which metrics are most relevant in the prediction of whether a company is ranked or unranked. To improve interpretability and validate the analysis, the linear SVM model was calibrated using a five-fold cross-validation technique.

As shown in Figure 4, operating income, gross profit, and total revenue are key metrics in determining whether a company is ranked or unranked. From this, the same phenomenon is observed: metrics that are strongly correlated to company size are significant. However, as seen in previous analyses, many metrics are still important when accounting for company size. Further down the list, it can be seen that metrics such as operating margin, gross margin, and stock performance make significant contributions to the model. Note that metrics that have the term "YoY Growth" refer to the year-over-year growth rate as a percentage. The margin and YoY Growth metrics are normalized for company size and are independent of total revenue.

DISCUSSION

Overall, the analyses show that in the majority of sectors, the percent difference between ranked and unranked firms for most financial metrics, including stock performance, is negative. This indicates that companies with high ESG scores are associated with being financially worse off than their competitors. This was particularly evident in sectors such as Information Technology and Financials, where highly significant negative correlations between being a ranked company and financial performance were found. An exception to this is the Real Estate sector, which showed almost no correlation with being ranked versus being unranked. This suggests that ESG ranking is not significantly associated with financial metrics in the Real Estate sector.

This correlation may reflect factors such as the time and capital investment required to reach the pinnacle of corporate sustainability. This may also be related to the observation that most ranked companies are small- or mid-cap companies, which naturally have higher failure rates in global markets. Larger companies often find it more challenging to achieve this level of sustainability, as their leadership may struggle to control every minor aspect of such large businesses. To reach the top 100 list, meticulous effort is required, and often it is not feasible

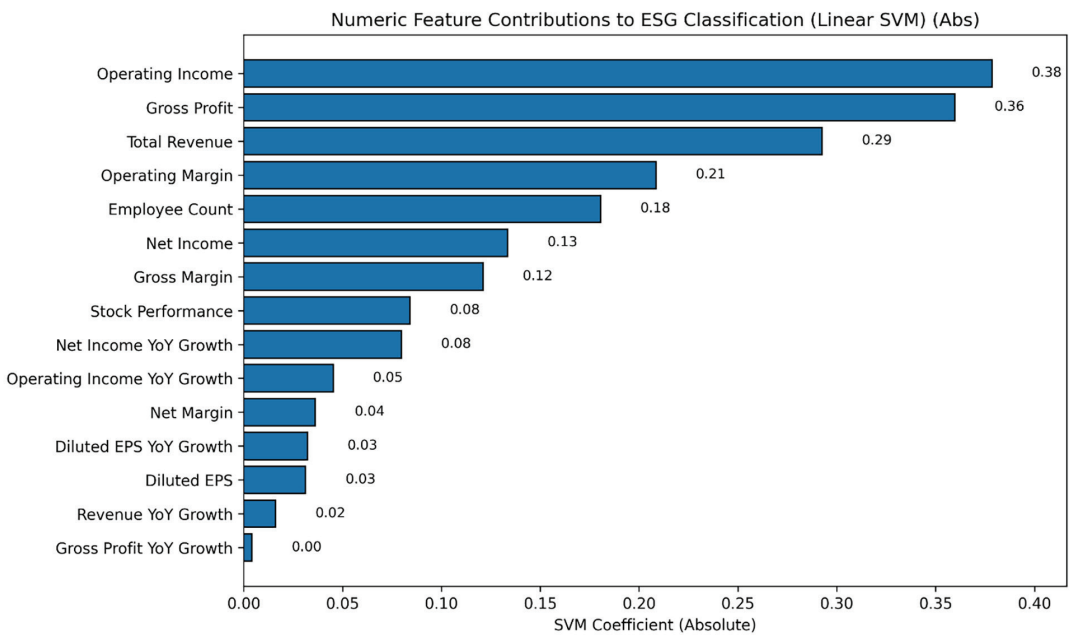

Figure 4. *Ranked absolute coefficient values from a cross-validated linear SVM model, indicating the relative contribution of each financial metric to classifying firms as ranked or unranked.*

for large-cap companies to achieve this (13).

In addition, variables like sector, EPS, employees, and country are strong predictors of whether a company is ranked or unranked. This can also potentially be explained by the discrepancies in company size that were stated earlier, as metrics like employee count are a direct reflection of a company's size.

Another key result was a negative association between stock performance and ranked companies, relative to their competitors as a group. This suggests that ranked status is not systematically associated with superior stock performance compared with peers, contrary to what some may have believed. From the SVM model alone, meaningful conclusions can be drawn, such as how positive stock performance generally corresponds to a lower probability of being a ranked company. However, it is important to note the structural asymmetry in the time coverage of financial metrics when interpreting the results. Since stock performance spans a longer time period than the other financial data, cross-metric comparisons involving stock performance should be analyzed with this limitation in mind. Setting aside this methodological consideration, net income and gross margin seem to be among the best predictors, other than company size, of whether a company is ranked or unranked. Additionally, the SVM model can be used to support the overall conclusion that large companies are generally associated with a lower likelihood of being ranked than smaller companies, as seen by the consistent negative relationships between being ranked and metrics like employee count and total revenue.

A key limitation of this study is its observational design. Comparing ranked and unranked firms does not constitute a true treatment-control analysis, due to the lack of a counterfactual. Ranked and unranked firms are likely structurally different from one another in ways beyond the scope of this model, such as geography, age, governance structure, and leadership. Furthermore, ESG ranking itself can be viewed as an outcome of other aspects of a corporation, introducing selection bias and potential endogeneity concerns. As a result, the analyses cannot isolate a causal effect of ESG ranking on financial performance.

Accordingly, the findings must strictly be interpreted and viewed as statistical associations between sustainability leaders and financial characteristics, rather than a direct causal impact of ESG leadership on financials. This study does not make any claims or associations between more general corporate sustainability efforts and financials; instead, it characterizes the observable financial patterns associated with firms identified as top sustainability leaders.

Although incorporating basic sustainability considerations could potentially boost a company's ESG score and stock value, sustainability leadership is not systematically associated with higher financial or stock performance.

CONCLUSION

Corporate sustainability is an increasingly important aspect of contemporary society, designed to address environmental issues such as climate change and pollution. ESG ratings were created with the intention of integrating corporate sustainability into investment decisions, emphasizing the importance of businesses remaining environmentally conscious. As many efforts have been made to place importance on corporate sustainability, such as ESG ratings and the Corporate Knights Global 100, it remains debated whether these metrics correlate with corporate financial performance.

This paper analyzes the relationship between companies' sustainability and their financial performance. In particular, the study aims to quantify the association between financial performance and the attainment of the pinnacle of corporate sustainability, as identified by the Corporate Knights Global 100.

It was determined that, in most cases, companies with top-tier ESG rankings tend to exhibit lower financial performance compared to competitors in their sector. While basic sustainability may be associated with stronger company stock and financial performance, a negative association was observed when companies exceeded this basic threshold.

These findings have meaningful implications for investors and corporations. For investors, this study signals that top-tier sustainability leaders should not be assumed to have superior financial performance; in fact, the observed associations support the contrary. Additionally, for corporations, the observed relationships raise questions about the financial trade-offs of becoming a global sustainability leader, particularly in sectors such as materials and information technology, where negative associations were most prevalent. It is important to reiterate that the study's findings represent statistical associations and should not be interpreted as evidence of causal relationships.

While current data shows financial trade-offs associated with top-tier corporate sustainability, encouraging sustainable practices may lead to shifts

in market behaviors over time. Future research can further analyze the relationships between basic ESG considerations and financial metrics, rather than focusing on corporate sustainability leaders. Additionally, research can be conducted on the potential associations of greenwashing and other deceptive ESG practices on both short-term and long-term financial performance.

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CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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