

A MACHINE LEARNING BASED APPROACH TO IDENTIFY KEY DRIVERS FOR IMPROVING CORPORATE'S ESG RATINGS

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ABSTRACT

Investors increasingly non-financial factors as part of their risk analysis process and growth assessments of corporates. Machine learning (ML) models for predicting ESG scores are an extremely useful tool to help investors make more informed decisions on their portfolios. Such a tool with wide-encompassing alternative data can be useful to the investors. The use of such datasets and machine learning models for ESG ratings can continuously improve the accuracy and reliability of those models. Using machine learning algorithms to identify key drivers of ESG ratings is an effective way of improving portfolio performance. Although the current state of ESG ratings is relatively static, data collection and mapping methodologies are evolving. As more data becomes available, the noise in ESG factors will become less important.

This unique document provides a machine learning algorithm for predicting an ESG rating based on a company's financial and non-financial attributes. The financial and non-financial attributes of corporations are extracted from Moody's Orbis and Ratings from S&P. The objective here is to predict the ESG rating of companies where the ESG rating is not easily accessible. At the same time, this approach would allow investors to have a suitable framework for investments based on ESG ratings. With the latest financial and non-financial disclosure by a corporate an ESG score can be predicted which can be used to identify its riskiness with a corresponding increase/decrease of ESG score.

Keywords: ESG Investing, ML model, Socially responsible investing, Sustainable investing, Green finance.

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1. INTRODUCTION

The corporate social responsibility (CSR) initiatives and their influence on corporate financial performance have been actively researched (Francesco et al., 2018). The term encompasses how the company contributes to the preservation of the environment, for instance, by reducing air pollutant emission, issuing green bonds, and participating in other activities, which can help solve the problem of climate change. Moreover, environmental, social, and governance (ESG) initiatives cover social issues, such as caring for employees by providing good work conditions, effective human capital management, and health and safety programs. Additionally, corporate governance is implied in ESG activities. ESG refers to the three central factors in measuring the sustainability and societal impact of a company or a business. These criteria have proven to be influential on performance due to increased scrutiny on companies to comply with sustainable business models. The central factors are as below:

Environmental:

Environmental considerations include the contribution of a business or government to climate change through greenhouse gas emissions, as well as waste management and energy efficiency. As a result of renewed efforts to address global warming, it is becoming increasingly important to reduce emissions and decarbonize.

Social

Social aspects include human rights, labor standards in the supply chain, any exposure to illegal child labor, and more common issues such as respect for workplace health and safety. A social score is impacted positively if a company is well integrated with its local community and therefore has a 'social license' to operate with consent.

Governance

Governance means a set of rules or principles that define the rights, responsibilities, and expectations between the different stakeholders in corporate governance. A well-defined corporate governance system can be used to balance or align interests across stakeholders and can be used as a tool to support a business's long-term strategy.

ML models have proven to be highly effective in predicting ESG Ratings. They can be trained on extensive structured data with a range of features. Using a model for ESG will help



investors and analysts make informed decisions. In addition to predicting ESG ratings, it can also predict the future performance of a company (Valeria et al., 2021).

One approach to build an ML model for ESG ratings is to collect two weeks' worth of news data from various sources. This is computationally expensive because it includes over 37,000 different news articles. Then, the machine learning algorithm produces predictions based on these features. This model contains positive and negative prediction rules. Each rule contains two features and a range of time intervals. The second step is to determine whether the feature should be analyzed for all stocks or just a particular one.

A key problem in analyzing ESG data is the lack of a standard taxonomy for the different ESG factors. This means that data providers must make model selections and must control for factors such as country, sector, and risk. These factors affect the prediction accuracy of ESG ratings and pillar scores. However, machine learning algorithms can help to reduce noise and improve the accuracy of ESG ratings and pillar scores. This can help sustainable investors to identify companies that may not have the data needed to meet sustainability commitments.

To develop an ML-model for ESG ratings, we have extracted different data components that make up a company's ESG profile. Then, we have attempted to create various ML-based predictive models based on these attributes and combine it with a corresponding index. As a next step we compared various models to existing ESG scores and make an informed investment decision based on those. This also gives us an indication of the champion model that can be selected from all other models. This model gives us a clear idea of how different companies perform in an industry/sector.

By the time we have built a champion ML model, we also have a clearer idea of which attributes are important that will be included in the final model. This robust ESG-ML model provides a meaningful ESG rating.

The data derived from these sources can be standardized to allow for more accurate and meaningful predictions. ML models can be useful in predicting ESG ratings; at the same time, they can be applied to questions related to ESG. In addition to ESG rating, these ML models can be used for responsible investment in a specific area, such as environmental issues. The results show that a particular model can accurately identify which stocks are more sustainable and which are less. The data analyzed in this way will help investors make an informed decision regarding which ESG stocks to buy. They will also help managers improve their ESG Reporting.

In predicting ESG ratings, the data should encompass a suitable and comprehensive peer universe. It should also cover the entire spectrum of ESG. Only then these models should be



able to provide a consistent and credible representation of a company. However, the social pillar of ESG has some gaps. Some of the companies have not published all of their ESG reports. This leads to gaps in the model.

Corporates should have an internal ratings system for ESG and should not rely compositely on external agency. There is variation in data providers' ESG ratings. The lack of standardization and lack of transparency in these data sources makes it difficult for companies to use these metrics to make decisions. Regardless, ESG metrics have a wide range of uses, from measuring a company's environmental performance to influencing investment decisions. These data providers use different methodologies to measure ESG, which can result in wide variations in scores. ESG ratings are complex and have limited correlations. It is difficult to accurately evaluate the correlation between ratings when they vary greatly, especially when there is no standardization across the providers. There are three factors that contribute to the variation: scope, measurement, and weights. These factors are interconnected and can lead to different results. So a robust internal rating model that is calibrated periodically is the need of the day and has been tested in the paper.

Non-financial data for ESG rating models can be used to make better rating models and hence better investment decisions. There are numerous data providers who supply non-financial data for ESG rating models. These providers offer a range of data including private and quasi-public data. They also sell raw data. The data providers' methodological choices are crucial to the quality of their ratings. Some providers use in-house statistical models to estimate data that is not reported. One of the biggest challenges of ESG scoring is the sheer size of the input variables. There is a huge range of variables to consider, from the volume of coverage to the influence of the source. Here we test various non financial data for building the ratings models in the paper.

2. LITERATURE STUDY

Valeria et al. (2021) used ESG scores from Bloomberg to study the role of structural variables adopting a machine learning approach. They used the balance sheet data for a sample of the Euro Stoxx 600 index constituents and studied how this data explains the Bloomberg ESG scores. They found that financial statement elements provide a powerful tool for explaining the ESG rating using machine learning. In another study (Recoo Ciciretti et al., 2022), they examined whether the ESG investment reduces the risk of contagion between equity



mutual funds. They measured the impact of fire-sale spillovers, spreading across the financial system, on funds ranked on ESG aspects. In the event of de-leveraging of funds, the fallout from the fire sale spreads throughout the network because of the mutual assets of the funds. They observed that the vulnerability of funds to contagion decreases as the level of ESG compliance increases.

Furthermore, they found that the average relative loss is lower for funds classified higher than for funds classified low. Xian Lin et al. [2022] has worked on the application of machine learning models for predictions on cross-border merger and acquisition decisions with ESG features from a sustainable development and ecosystem perspective. They used AdaBoost to train several low-ranking classifiers to achieve a robust decision-making model with a large financial transaction database of 215,160 transactions. The results achieved an 80.1% prediction accuracy, using the AdaBoost model, thanks to a 10-step cross-validation. They found differences between the predictive features of mergers and acquisitions (M&A) and the different characteristics of sustainable development. Caterina De Lucia et al.(2020) has developed a machine learning model for publicly owned enterprises in Europe. Their findings suggest that ML accurately predicts key metrics such as Return on Assets (ROA) and Return on Equity (ROE), and indicate, through the ordered logistic regression model, the existence of a positive relationship between ESG practices and the financial indicators. They also found that the existing relationship becomes more apparent when firms invest in environmental innovation, employment, productivity, diversity and equal opportunities policies. In a different work by Carmine de Franco et al. (2018), they designed an ML algorithm which identifies the models between ESG profiles and financial performance for companies in a broad investment universe. The algorithm consisted of a set of regularly updated rules that map regions to the ESG characteristics of high-dimensional space for excess yield prediction. The final predictions are converted into scores. These scores are used to design simple strategies that filter the investing universe for equities with a positive rating.

Ng and Rezaee (2020) investigated whether and how business sustainability performance and disclosure factors affect stock price informativeness (SPI). Fiaschi et al. (2020) conducted a study to evaluate and overcome the limitations of ESG scores. Rajesh et al. (2021) found in his research, the mean differences in the CSR strategy scores and the ESG scores of firms in select developed economies such as US, UK, Japan, and Australia, representing different geographical regions globally. Champagne et al. (2021) examined whether non-financial ratings are related to the likelihood of adverse environmental, social, and governance (ESG) events occurring and therefore serve as an indicator of ESG risk. Bannier et al. (2022) studied the



relationship between corporate social responsibility and credit risk for U.S. and European firms over the period 2003 to 2018 and found that only environmental aspects are negatively related to various measures of credit risk for U.S. firms. For European companies, environmental and social aspects are adversely associated with credit risk. Jarjir et al. (2020s) ; concluded that a risk premium is associated with market-assessed non-financial ratings (i.e., environmental, social and governance (ESG) ratings). You and Managi (2022) investigated whether the information disclosure of Environmental, Social, Governance (ESG) criteria is more crucial than actions for the financial performance of firms by using two different ratings with more than 1,000,000 samples and results showed that disclosure is more important for profits while action is more critical in Tobin's Q and Intangible Value Assessment (IVA) scores. Wong et al. (2021) showed that ESG certification reduces a company's cost of capital, while Tobin's Q certification increases substantially. Broadstock et al. (2020) the study provided evidence of a non-linear relationship between the adoption of ESG policies and the innovativeness of enterprises. Chen and Yang (2020) revealed that investors respond excessively to environmental rather than social or governance factors. Li et al. (2022) concluded that higher ESG scores, reduce the risk of business failure. Barros et al. (2022) investigated that whether mergers and acquisitions (M&A) operations impact firms' performances on triple ESG pillars (environment, social, and governance) and provided evidence that M&A deals have a positive impact on the ESG score of firms. Sabbaghi (2022) provided empirical studies of asymmetric volatility in ESG holdings. Wong and Zhang (2022) found that Empirical results advance signalling theory and resource-based view by providing evidence that corporate reputation is considered a valuable intangible asset by investors and adverse ESG disclosure via media channels have a significant and negative impact on firm valuation. Avramov et al. (2021) analyzed asset pricing and the portfolio impact of a significant impediment to sustainable investment: uncertainty around the company's ESG profile.

Targeted studies were carried out on a smaller group of corporate entities. Egorova et al. (2022") Demonstrated that enterprises in the Information Technology (IT) sector have significant weaknesses in their ESG components and reporting. Huang et al. (2022) has demonstrated that natural disasters have an impact on the environmental, social and governance (ESG) disclosure policies of the companies located near disaster areas. They found that companies with a higher percentage of local institutional ownership are more likely to increase ESG disclosure following nearby disasters. Feng et al. [2022] studied the relationship between ESG scores and the risk of falling stock prices, finding a statistically and economically significant negative relationship for Chinese firms. Singhania and Saini (2022) noted that a



systematic approach using ESG structures could serve as a reference point for the business sector in India and lead to sustainable development goals (SDGs). Ng and Rezaee (2020), Becker et al. (2021) Top of page analysed the impact of the Financial Sustainability Disclosure Regulation (SFDR) on mutual funds and retail investors in the EU. The results showed that the allocated funds increase their sustainability rating after the policy was implemented.

3. DATA AND METHODOLOGY

ESG Rating Data: NIFTY100 ESG Index is designed to reflect the performance of companies within NIFTY 100 index, based on Environmental, Social and Governance (ESG) scores. The weight of each constituent in the index is tilted based on ESG score assigned to the company, i.e., the constituent weight is derived from its free float market capitalization and ESG score. To form part of the NIFTY100 ESG Index, stocks should qualify the following eligibility criteria: Stocks should form part of NIFTY 100 Companies and should have an ESG score. However, companies engaged in the business of tobacco, alcohol, controversial weapons and gambling operations has been excluded.

Sample: For the purpose of the study, a sample of 90 companies included in National Stock Exchange (NSE) - 100 ESG Index. Of the total companies, GlaxoSmithKline Consumer Healthcare Ltd has been merged with Hindustan Unilever Ltd (HUL) and the data of Cummins India Ltd, Emami Ltd., Oil India Ltd. Steel Authority of India Ltd (SAIL), and Vodafone Idea Ltd was not available from the sources of data collection. Therefore, effectively the sample of the study constitutes 84 companies. The data have been collected for the year 2021.

Sources of Data: ESG Disclosure scores have been collected from www.s&pglobal.com. The S&P Global ESG Scores is an environmental, social and governance data set that provides company level, dimension level, and criteria level scores based on the S&P Global Corporate Sustainability Assessment (CSA) process, an annual evaluation of companies' sustainability practices. data pertaining to women's participation on board and in Key executive position has been collected from www.goodreturn.in. Data for financial ratio and other corporate attributes was extracted from Moody's Orbis. Moody's Orbis contains information on companies across the world and focuses on private company information containing information on companies in comparable formats. It has information on close to 400 million companies and entities across the globe. 41 million of these have detailed financial information.

Around 47 attributes were available in Orbis. Key fields extracted from Orbis include:



- Operating revenue
 - Number of employees
 - P/L before tax
 - Cash flows
 - Total Assets
 - Current Ratio
 - ROE
 - Number of publications
- BVD Independence Indicator: This field contains the BVD independence indicator which indicates independence with respect to shareholding as follows:
1. A+: Indicator A+ identifies Independent Companies and it is attached to any company with known recorded shareholders, none of which having more than 25% of direct or total ownership
 2. B+: Indicator B+ is attached to any company with a known record shareholder none of which with an ownership percentage (direct, total or calculated total) over 50% but with one or more shareholders with ownership percentages above 25%
 3. C+: Indicator C+ is attached to any company with a recorded shareholder with a total or a calculated total ownership over 50%.
 4. D: Indicator D is allocated to any company with a recorded shareholder with a direct ownership of over 50%
 5. U: Companies with an unknown degree of ownership concentration.

3.1. Data Preparation:

Data for 84 corporates was extracted from S & P and Moody's Orbis. Around 47 corporate level attributes were available. Single Factor analysis was carried out. Pearson Correlation and VIF score were calculated to check for multicollinearity. Finally, 8 variables were shortlisted and included in the final Machine Learning model. The final correlation matrix for the selected variables is as follows:



Table 1: Correlation Matrix

| | PL | NPUB | OPREV | NCURRDIR | NWOMEN | PRMAR | NCOMP | Score |
|----------|----|--------|--------|----------|---------|---------|---------|---------|
| PL | 1 | 0.1306 | 0.4993 | 0.1977 | -0.0421 | 0.1939 | 0.1582 | 0.1685 |
| NPUB | | 1 | 0.4381 | 0.1047 | 0.0827 | -0.2708 | 0.0044 | 0.2801 |
| OPREV | | | 1 | 0.1451 | 0.1459 | -0.1821 | -0.1571 | 0.2209 |
| NCURRDIR | | | | 1 | 0.0319 | 0.1218 | -0.1023 | 0.2799 |
| NWOMEN | | | | | 1 | -0.0474 | -0.2969 | 0.3008 |
| PRMAR | | | | | | 1 | 0.0146 | -0.2148 |
| NCOMP | | | | | | | 1 | -0.1879 |

Where,

PL= P/L before tax USD Last avail. yr,

NPUB=Number of publications,

OPREV= Operating revenue (Turnover) (m USD),

NCURRDIR= Number of current directors and managers,

NWOMEN= Number of women directors,

PRMAR= Profit Margin (%),

NCOMP=Number of companies in corporate group,

Score=ESG Score.

ESG score is positively correlated to all the selected variables except Profit Margin and number of companies in the corporate group. This behavior is intuitive. The increase in profit margin will not translate into improvement of the ESG score. Also, as the increase in the number of subsidiaries in a group of companies, it is difficult to have corresponding increase ESG as synergies with time.

With respect to the BVD independence indicator, average ESG distribution is as follows: With the decrease in independence from A+ to D the ESG Score also decreases with the exception of BVD Grade C+ for which ESG score is less than D. This exception could be because of small sample size of corporates in grade C+(6) as compared to grade D(27).

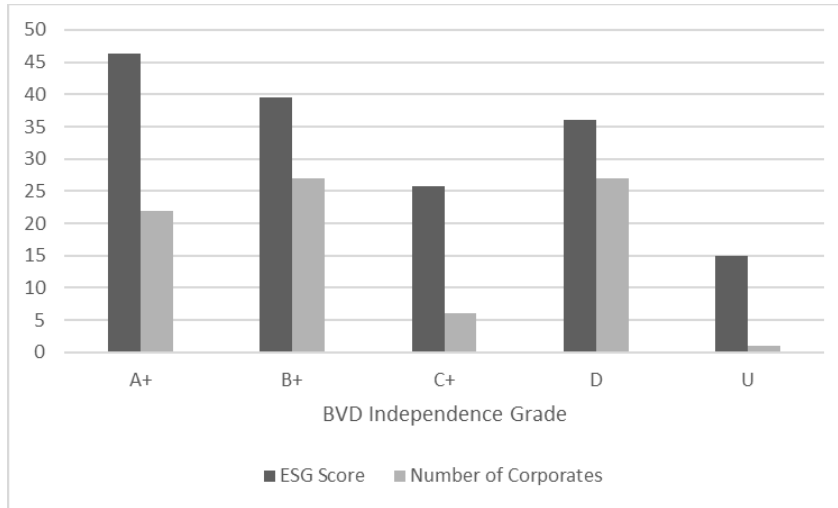


Figure 1: Distribution of BVD independence grade

Machine learning techniques are used to develop the ESG Score Model. Multiple machine learning model viz. Gradient boosting, neural network, forest, decision tree, linear regression and ensemble of these models were developed using the shortlisted variables. For the final model, Gradient Boosting was selected based on the goodness of fit statistic (RMSE).

4. RESULTS

Due to small sample size k-fold cross validation was performed (with k=5). A highly predictable model is developed with an RMSE of 3.47. The comparison can be summarized in the tables as follows: The gradient Boosting model gave the best fit with an RMSE of 3.47. The variable importance of the model is as follows:

Table 2: Model Comparison

| Model | RMSE |
|-------------------|-------|
| Gradient Boosting | 3.47 |
| Ensemble model | 16.12 |
| Neural Network | 18.05 |
| Forest | 19.15 |
| Decision Tree | 20.22 |
| Linear Regression | 22.59 |



Table 3: Variable importance for gradient boosting model

| Variable | Importance |
|------------------------------------------|------------|
| Operating revenue (Turnover) (m USD) | 1 |
| Profit Margin (%) | 2 |
| P/L before tax USD Last avail. year | 3 |
| Number of publications | 4 |
| Number of companies in corporate group | 5 |
| Number of women directors | 6 |
| BVD Independence Indicator | 7 |
| Number of current directors and managers | 8 |

5. CONCLUSION

Several organizations have turned to artificial intelligence (AI) systems to overcome the challenges involved with analyzing ESG data. Artificial Intelligence can enable companies to evaluate risks, find hidden opportunities, and perform complex tasks. It can also allow sustainable investors to filter through mountains of data to identify opportunities and potential risks.

The author successfully developed a machine learning model to predict the ESG score for corporate entities. An RMSE value of 3.47 using Gradient boosting algorithm shows high goodness of fit. This approach of predicting ESG scores for other corporates where such scores are not available can be used while making ESG investments. Based on the predicted ESG score, a strategy can be developed using a cutoff value of such score.

ESG ratings are not meant to be used as an indicator of a company's true performance. However, they can influence a company's decision making and reputation. These ratings can help companies become more environmentally and socially sustainable, contributing to a more socially just economy. ESG ratings are becoming increasingly important to investors, particularly those interested in sustainable economic growth. Since the data for analysis is based on information from publicly available sources, including annual reports and other disclosures, the scoring model is easy to use. In addition to helping investors determine whether companies are performing well on ESG metrics, these reports provide information on competitors and the



environment. MSCI rates companies on ten-point scales for environmental, social, and governance factors. This includes controversial business activities such as tobacco production and weapons manufacturing. The weightings are applied to the data to derive an overall ESG rating. The underlying methodology behind ESG measures is highly complex, but the results of this analysis are useful and provide a more nuanced picture of a company's performance. There are some drawbacks of ESG ratings, though. One common drawback is the lack of consistency among rating providers. Some ESG provider score companies differently, and this creates uncertainty for investors. Additionally, ESG scores are not a complete picture. ML based ratings models help us to uncover some of these facts.

Machine learning algorithms can be used to analyses data and measure the performance of companies. They can identify indicators that contribute to efficient portfolios. They can also measure the performance of companies by comparing their performance with their peers. In addition, these algorithms can help companies to determine whether their ESG programs are effective. They can also help to identify companies that may not have the data needed to meet sustainability commitments.

A common concern among investors is the lack of consistency in the data. For instance, a company may have a lower ESG score than its peers in one industry but have a higher score in another. Some providers also issue different ratings on the same company. Internal rating model can help bridge this gap.

6. DISCUSSIONS

Developing a proactive ESG rating for corporates is critical for the organizations because of regulatory and financial needs. It involves a series of steps. They must establish an approach and strategic plan and companies should develop and manage disclosure. Finally, companies must implement best practices to improve their ESG ratings. Companies need to work with different stakeholders to design a focused set of ESG targets and indicators. Companies should also establish a clear process and establish a system for monitoring ratings. This includes a system for archiving and auditing. A company must participate in multiple ESG ratings. This would help to drive strategic decision-making and access lower capital costs. It would also help to improve shareholder relations. Companies should participate in ratings that align with their ESG goals and investment philosophy. This will also help to build a relationship with the ratings analyst team. A rating model like the presented in the paper can help organizations improve the EST ratings.



Also, such rating monitoring should be monitored timely update. it should not be a onetime activity. It would also help to ensure that the company is aware of ESG milestones and updates. It also includes a comprehensive ESG Risk Rating scorecard. This tool can also be used to develop a formal ESG risk register. We wish to extent out work with more data sources and re validate the ratings periodically.

As an extension of this model, Machine learning algorithms can also integrate unstructured data from public companies to form ESG scores. These metrics are used to evaluate a company's sustainability and are used by investors to decide which companies to invest in. In addition, the predicted ESG ratings can be used for companies that are not covered by rating agencies.

REFERENCES

“Avramov, D., Cheng, S., Lioui, A., and Tarelli, A. (2021). Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*”

“Banner, C. E., Bofinger, Y., and Rock, B. (2022). Corporate social responsibility and credit risk. *Finance Research Letters*, 44(November 2020).”

“Barros, V., Matos, P. V., Sarmiento, J. M., and Vieira, P. R. (2022). M&A activity as a driver for better ESG performance. *Technological Forecasting and Social Change*, 175(November 2021):121338.”

“Becker, M. G., Martin, F., and Walter, A. (2021). Fostering the Power of ESG Transparency: The Effect of Sustainability Labels on Mutual Funds and Individual Investors. *SSRN Electronic Journal*, (November 2021):1–6.”

“Broadstock, D. C., Matousek, R., Meyer, M., and Tzeremes, N. G. (2020). Does corporate social responsibility impact firms' innovation capacity? The indirect link between environmental & social governance implementation and innovation performance. *Journal of Business Research*, 119(July 2019):99–110.”

“Champagne, C., Coggins, F., and Sodjahin, A. (2021). Can extra-financial ratings serve as an indicator of ESG risk? *Global Finance Journal*, (March):100638.”

“Chen, H. Y. and Yang, S. S. (2020). Do Investors exaggerate corporate ESG information? Evidence of the ESG momentum effect in the Taiwanese market. *Pacific Basin Finance Journal*, 63(October 2019):101407.”

“Egorova, A. A., Grishunin, S. V., and Karminsky, A. M. (2022). The Impact of ESG factors on the performance of Information Technology Companies. *Procedia Computer Science*, 199:339–345.”

“Feng, J., Goodell, J. W., and Shen, D. (2021). ESG rating and stock price crash risk: Evidence from China. *Finance Research Letters*, (September):102476.”

“Gangi, F., Mustilli, M. and Varrone, N. (2018). The impact of corporate social responsibility (CSR) knowledge on corporate financial performance: evidence from the European banking industry. *Journal of Knowledge Management*.”



“Fiaschi, D., Giuliani, E., Nieri, F., and Salvati, N. (2020). How bad is your company? Measuring corporate wrongdoing beyond the magic of ESG metrics. *Business Horizons*, 63(3):287–299.”

“Huang, Q., Li, Y., Lin, M., and McBrayer, G. A. (2022). Natural disasters, risk salience, and corporate ESG disclosure. *Journal of Corporate Finance*, 72(December 2021):102152.”

“Jarjir, S. L., Nasreddine, A., and Desban, M. (2020). Corporate social responsibility as a common risk factor. *Global Finance Journal*, (December 2019):100577.”

“Li, H., Zhang, X., and Zhao, Y. (2022). ESG and Firm's Default Risk. *Finance Research Letters*, (January):102713.”

“Ng, A. C. and Rezaee, Z. (2020). Business sustainability factors and stock price informativeness. *Journal of Corporate Finance*, 64(November 2019):101688.”

“Rajesh, R., Rajeev, A., and Rajendran, C. (2021). Corporate social performances of firms in select developed economies: A comparative study. *Socio-Economic Planning Sciences*, (November):101194.”

“Sabbaghi, O. (2022). The impact of news on the volatility of ESG firms. *Global Finance Journal*, 51(December 2019):100570.”

“Singhania, D. M. and Saini, D. N. (2022). Systems approach to environment, social and governance (ESG): Case of Reliance industries. *Sustainable Operations and Computers*, 3(November 2021):103–117.”

“Wong, J. B. and Zhang, Q. (2022). Stock market reactions to adverse ESG disclosure via media channels. *British Accounting Review*, 54(1):101045.”

“Wong, W. C., Batten, J. A., Ahmad, A. H., Mohamed-Arshad, S. B., Nordin, S., and Adzis, A. A. (2021). Does ESG certification add firm value? *Finance Research Letters*, 39(November 2019):101593.”

“Yoo, S. and Managi, S. (2022). Disclosure or action: Evaluating ESG behavior towards financial performance. *Finance Research Letters*, 44(November 2020):102108.”

“Valeria D'Amato, Rita D'Ecclesia and Susanna Levantesi(2021). Fundamental ratios as predictors of ESG scores: a machine learning approach. <https://link.springer.com/article/10.1007/s10203-021-00364-5>.”

“Roy Cerqueti, Rocco Ciciretti, Ambrogio Dalò and Marco Nicolosi(2022). Mitigating Contagion Risk by ESG Investing. <https://www.mdpi.com/2071-1050/14/7/3805>.”

“Xiangjun Hong, Xian Lin, Laitan Fang, Yuchen Gao and Ruipeng Li(2022). Application of Machine Learning Models for Predictions on Cross-Border Merger and Acquisition Decisions with ESG Characteristics from an Ecosystem and Sustainable Development Perspective. <https://www.mdpi.com/2071-1050/14/5/2838>.”

“Caterina De Lucia, Pasquale Pazienza and Mark Bartlett. Does Good ESG Lead to Better Financial Performances by Firms? *Machine Learning and Logistic Regression Models of Public Enterprises in Europe*.”

“Vincent Margot, Christophe Geissler, Carmine de Franco and Bruno Monnier. ESG Investments: Filtering versus Machine Learning Approaches <https://arxiv.org/abs/2002.07477>.”



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