Deciphering the Global ESG Landscape: India's Sector-Specific Trends and Impact on Market Capitalization

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Abstract

As the consideration of non-financial metrics in stakeholder decision making has significantly grown over time, the ESG framework or Environmental (E), Social (S), and Governance (G) pillars have become key contributors of overall financial performance and positioning of firms. This paper depicts the global ESG landscape, while estimating India's position in the same through examining the impact of ESG scores on the market capitalization of Nifty500 companies from 2019 to 2022. We do this by using an unbalanced panel data set of 144, 154, 207 and 441 companies for the years 2019, 2020, 2021 and 2022. The findings of our paper reveal that Indian Nifty500 firms with higher ESG scores tend to have larger market capitalization, but with each of the 11 sectors showcasing differing results, consisting of positive, negative, and absent relationships between sectoral ESG and individual E, S, and G scores, and their market capitalization. The study further highlights that although company turnover significantly naturally influences market capitalization in the Nifty500 dataset, the debt-to-equity ratio did not have a significant impact over the four years. The lack of existing dataset for Nifty500 ESG scores over a larger period of time suggests the presence of research gaps in identifying the position of developing ESG markets, such as India, in the global ESG landscape, and necessitates potential scope for further research into sector-specific, time-invariant, and ESG divergence factors to estimate the same.

1 Introduction

Environmental, Social, and Governance (ESG) regulations and philosophies have phenomenally evolved over the past few years, transitioning from a choice to a global revolution in driving responsible investment practices and long-term financial performances aligned with broader societal needs and expectations. This is seen especially through a necessity for firms to adapt to factors ranging from environmental degradation to demographic challenges, to position themselves better at enhancing long-term value creation and foster financial performance through incorporating non-financial factors.

The integration of Environmental, Social and Governance (ESG) factors and the materiality of ESG metrics into investment decisions has led to a predicted surge in ESG aligned institutional investments to upwards of 33.9 trillion USD in 2026 (PwC, 2022). This burgeoning realization and prediction of sustainability challenges and regulatory mandates have helped India aspire to be a potential competitor in the nascent niche of ESG investing landscape, enhancing the role of business in society by integrating non-financial factors to investment decision making that also contribute to a sustainable future. Such a holistic metric is driven by the understanding that environmental, social, and governmental risks can be translated to financial losses.

A meta-analysis by Whelan et al (2021) at the NYU Stern Center for Sustainable Business and Rockfeller Asset Management reports that ESG drives better financial performance, indicating that companies with strong ESG profiles tend to have better financial. Additionally, a recent paper by Kalia et al (2022) revealed light on how current studies on existing ESG scores and practices on financial performances are mostly limited to developed geographies (Galbreath, 2013; Kiriu and Nozaki, 2020), with very limited research conducted on emerging markets.

This paper thus seeks to explore India's position as a nation at a cririal stepping point in ESG integration (Patnaik et al, 2022) in the global ESG Landscape, examining how ESG scores of Indian ESG reporting companies influence Market Capitalization. The study ranges over a span of four years from 2019 to 2022, and draws global data from Refinitiv Workspace, and India Nifty500 data on 144, 154, 207 and 441 companies for the years 2019, 2020, 2021 and 2022, from CMIE Prowess. The Nifty500 Index consists of the top 500 Indian companies listed on the National Stock Exchange of India (NSE), representing about 91.8 percent of the free float market capitalization NSE listed stocks (NSE, 2024). Additionally, it also inspect individual E,S,G, and sectoral changes across 11 sectors according to the GICS framework, identifying possible differences and trends that may affect market capitalization. Through this analysis, we aim to enhance and contribute to a current literature gap on ESG scores affecting market capitalization, especially in the context of the Indian Markets, wherein ESG research is in its developmental stage.

The following sections in the paper are stated as follows: Section 2 assesses the Global ESG Landscape from 2019 to 2022, as well as estimating India's position in the same. Section 3 outlines our quantitative analysis, while Section 4 states the results obtained. Lastly, Section 5 lays out the conclusion by summarising the findings of the study, addressing a need for further research in the area this paper wishes to explore.

2 Assessing the Global ESG Landscape and estimating India's Position

Although the importance of ESG principles and scoring is set to witness a boom in India as companies recognise the importance of aligning sustainability with profits and executive strategies, it is quite newly developed and amassed into the Indian markets as recently stated in the Economic Times (Khanna, 2024). Therefore, examining the genesis of pre-existing global ESG players is crucial for understanding India's specific landscape in ESG reporting and adoption. Thus, we present a brief landscape of global ESG trends before focusing on India.

2.1 Global ESG Landscape

The time period between 2019 and 2022 has seen an overall increase in average ESG scores, as visualised by the distribution in Figure 1. Particularly, North America is found to have the lowest percentage increase in average ESG scores at 8.09 percent, with Africa showing the greatest percentage increase of 27.03 percent. To explore the cause behind such a trend, we look at Figure 2, which states the number of ESG reporting companies across continents, to assess the sample size effect on ESG score averages. Africa has the lowest number of ESG disclosing companies across the four years, while Asia possesses the highest. Percentage change-wise, Asia is seen to depict the highest increase in the number of ESG reporting countries from 2361 to 4080 companies, at 72.81 percent over the four years, with Africa following in from 132 to 194 companies, at 46.97 percent. South America is seen to be the only continent with a decrease in ESG disclosing companies from 263 to 236, of 10.27 percent. Interestingly, although Africa possesses the second highest percentage increase in number of ESG reporting companies, and highest in average ESG scores, the limited sample size could render the results inconclusive, suggesting a need for further study into Africa's economic landscape in comparison to other continents, serving as a separate topic of research.

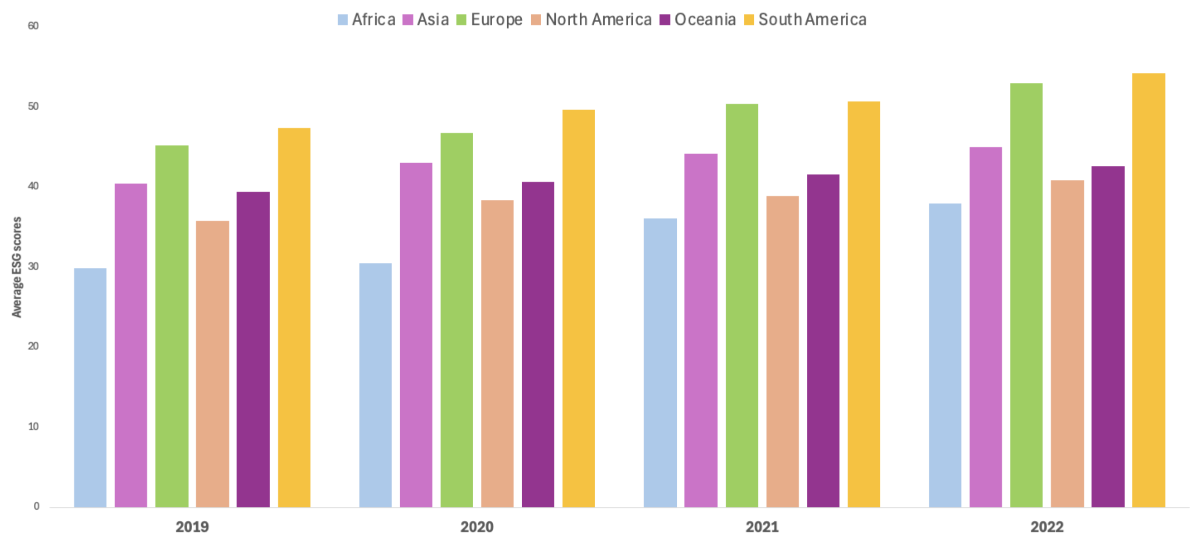


Figure 1: Average ESG Scores across Continents from 2019-22

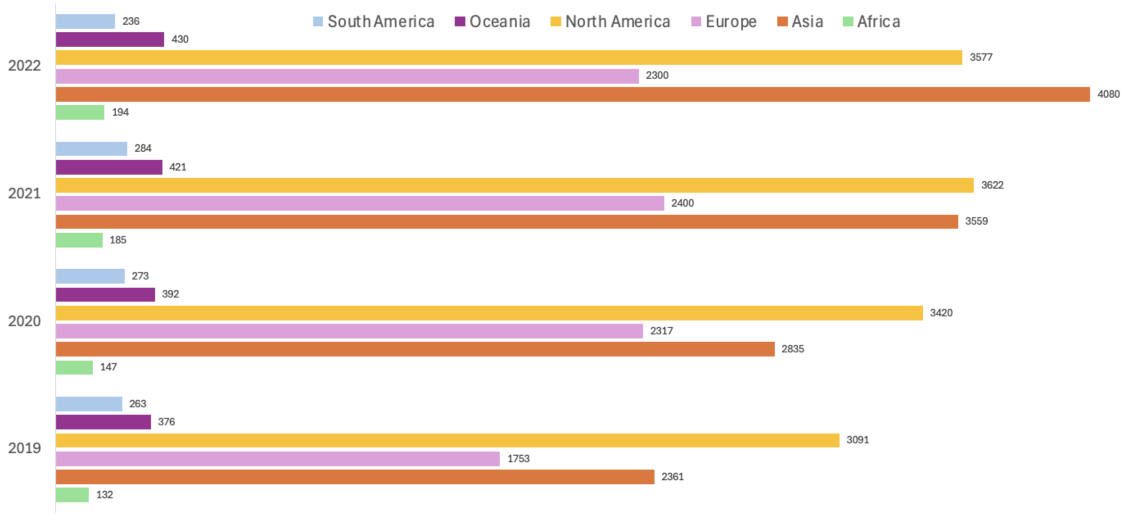


Figure 2: Number of ESG reporting companies across Continents from 2019-22

2.2 GICS Sectors Segregation

The average continent wise ESG scores reported by companies depicted in Figure 1 can be further classified according to the Global Industry Classification Standard (GICS) Framework created by MSCI and S&P Dow Jones Indices. The GICS Framework is made up of 11 primary sectors: Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate, and Utilities (MSCI, 2023).

The data represented in Table 1 denotes the number of ESG reporting companies around the world through the 11 sectors. Through the data, it is evident that there is an upward trend in ESG reporting companies across the four years, depicting an increased awareness of reporting regulations and practices. Additionally, the percentage changes differ significantly for each sector, with Information Technology showing a 54.3 percent increase in number of ESG reporting companies from 2019, followed by Materials at 49.7 percent. On the other hand, the Utilities sector shows the lowest positive change 18.9 percent, followed by the Energy sector at 20 percent.

Figure 3 denotes the average ESG, and their individual component (E, S, and G) scores for the year 2019. Although the Utilities sector shows the lowest positive change in the ESG reporting companies as stated above, it shows the highest average ESG scores of 48.08 in 2019, with its individual E and G scores only being the highest across the 11 sectors at 45.48 and 54.04 respectively. It continues to lead with the highest average ESG score, leading not only in terms of E and G scores, but also in terms of S scores in the year 2022. This highlights the sectors commitment to being ESG compliant. Similarly, Information Technology has the second lowest average ESG score of 44.47, while showing the highest percentage increase in ESG reporting companies over the four years. The Health Care sector has been struggling with the lowest ESG from 2019 to 2022 across the two figures, despite witnessing the highest increase in the ESG score across the 11 sectors from 2019 to 2022. It has also obtained the lowest scores in the individual E, S and G pillars.

Table 1: Percentage Change in No of ESG reporting companies across GICS sectors

GICS Sectors	2019	2020	2021	2022	% Change
Communication Services	358	430	456	457	27.65
Consumer Discretionary	644	744	815	853	32.45
Consumer Staples	550	649	735	746	35.64
Energy	410	467	518	492	20
Financials	1313	1453	1634	1644	25.21
Health Care	863	1073	1180	1206	39.75
Industrials	1230	1463	1638	1769	43.82
Information Technology	779	1008	1136	1202	54.30
Materials	748	873	1004	1120	49.73
Real Estate	786	896	994	977	24.30
Utilities	295	328	361	351	18.98

Additionally, the Health Care sector has shown a considerable amount of disparity between its scores across pillars, with the social pillar having a score as high as 43.69 and the environmental pillar having a score as low as 19.91 as of 2019. A possible hypothesis for the low environmental score could be the abundance of medical waste generated across the years, especially during the Covid -19 pandemic. Additionally, the pandemic may have triggered healthcare resource utilization at significant levels, such as high water and energy utilization, leaving a carbon footprint (Poucke et al, 2024). Similar trends can be found for the year 2022 in Figure 4, highlighting the fact that this sector has been struggling to incorporate sustainable environmental practices in its decision making process. Sectors like Real Estate and Consumer Staples have less disparity which translates to a relatively higher average ESG score of 47.62 and 48 respectively as of 2022.

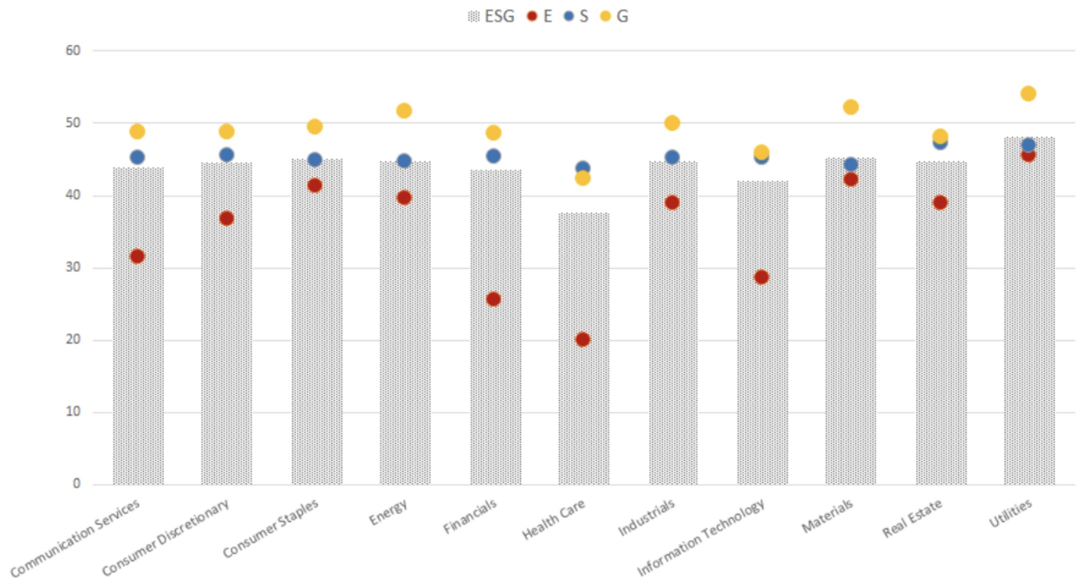


Figure 3: Average ESG and E,S,G Scores Worldwide in 2019

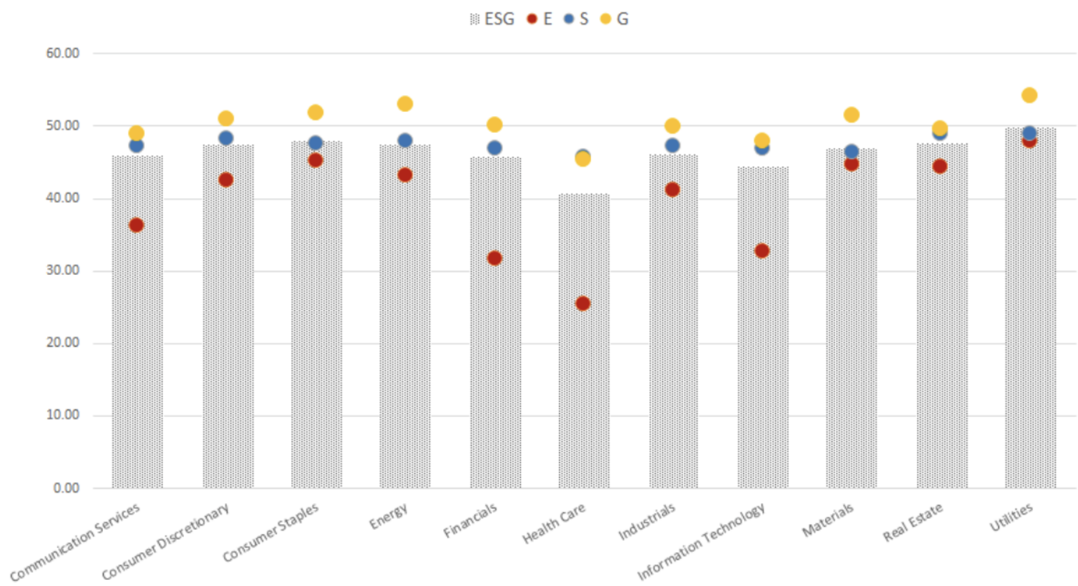


Figure 4: Average ESG and E,S,G Scores Worldwide in 2022

On examining the Global ESG Landscape, we further approach and estimate India's Position with respect to the same across the four years, as a focus on developing ESG frameworks aligned to pre-existing international standards is a critical step to adopt ESG practices in Indian businesses in the future. Therefore, we shift the analysis's focus to India's position within this emerging industry, exploring sector wise ESG performance from 2019 to 2022.

2.3 India's Position

India's position in ESG compliance as compared to that worldwide, serves as a crucial metric to carry forward India's vision of becoming a leader in ESG and sustainability, especially after the introduction of the 2023 Business Responsibility and Sustainability Report Core by the Securities Exchange Board of India (SEBI) stating mandatory ESG disclosure and compliance for the top 1000 listed entities by market capitalization (Gupta, 2023). Among the 94 ESG reporting countries around the world as of 2022, India secures a position of being the 62nd with an average ESG score of 41.58. This is a significant downfall, as India ranked 26th among the 87 ESG reporting countries as of 2019 with an average ESG score of 50.94.

Additionally, although India was comfortably in the top 30 percent amongst the ESG reporting countries, it now barely makes it to the top 70 percent. Specifically addressing E,S, and G scores (with 2019 data denoted in brackets), it can be found that India secures 60th (38th), 64th (22nd), and 66th (45th) positions respectively across 94 (87) ESG reporting countries as of 2022. By therefore assessing India's current standing, we can further estimate relationships and economic measures that can be taken to enhance its position in the Global ESG Landscape.

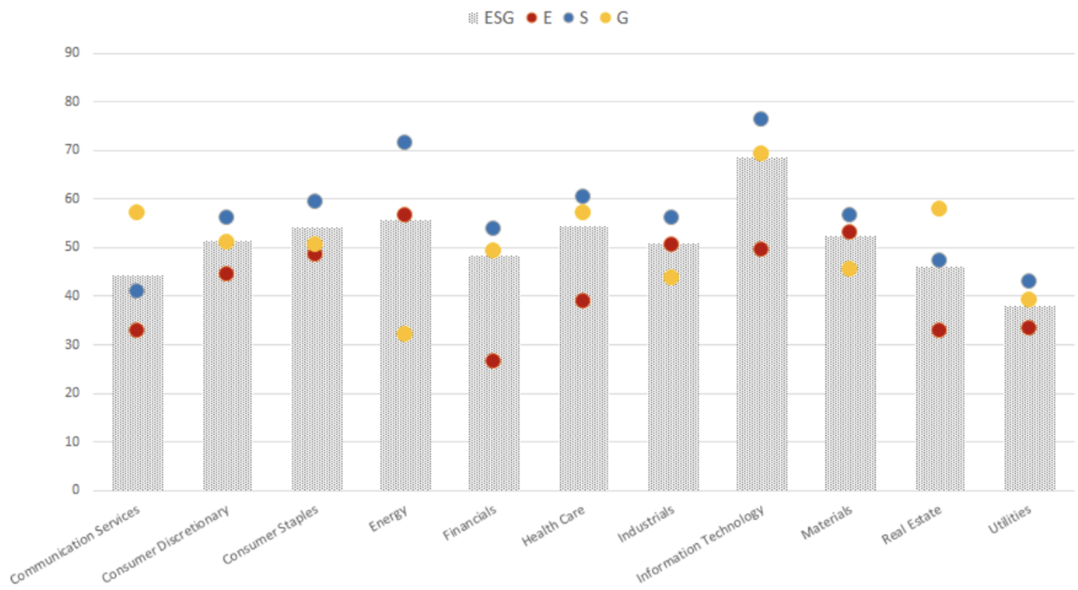


Figure 5: Average ESG Scores across GICS sectors in India in 2019

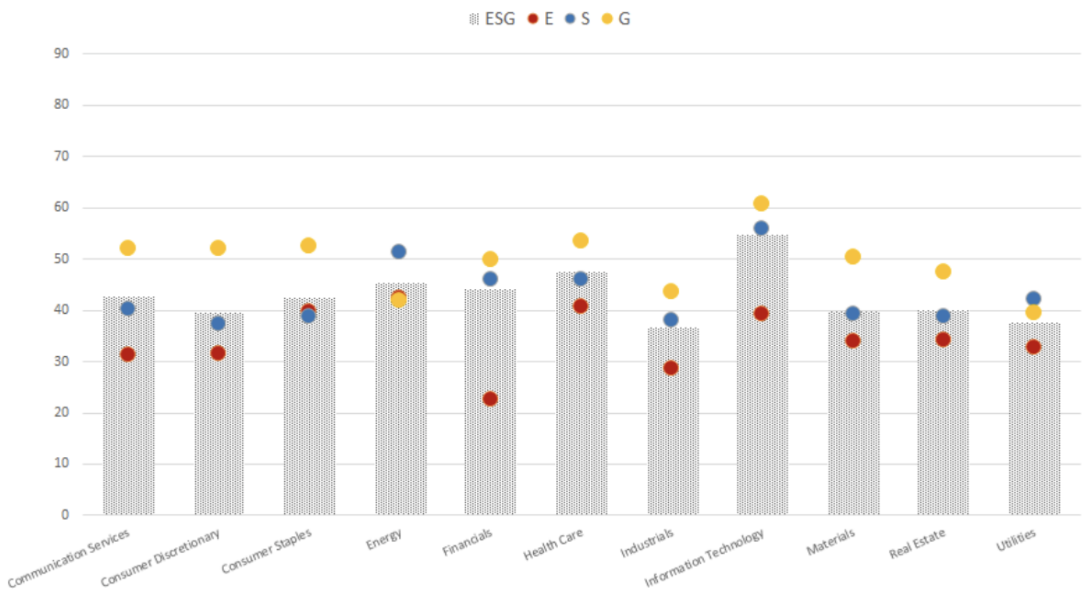


Figure 6: Average ESG Scores across GICS sectors in India in 2022

Through Figure 5 and Figure 6, we try to understand the sector specific trends in ESG performance from the year 2019 to 2022, while giving attention to the evolution of Environmental, Social, and Governance scores. It is clearly evident from the above graphs that the average ESG scores across all the sectors have gone down from the periods taken into consideration. This trend might be attributed to various factors, including the increase in the number of reporting companies from 157 to 702 during the four year period following SEBI's disclosure mandates (Gupta, 2023).

The Information Technology sector continues to be the leader in ESG performance, especially in the Social and Governance pillars, with the Financials sector showcasing a relatively stable ESG performance with moderate declines in all the three pillars. Enhancing environmental practices and social impact measures could improve sector's ESG performance, as they seem to be the most affected ones. An example of this is the Industrials sector, experiencing a sharp plunge reducing its ESG performance by 28 percent from 50.89 to 36.59. Additionally, another possible reason could be the increase in the number of reporting companies in this sector from 17 to 132 companies, which is the second highest among the 11 sectors, denoting the sector has a highly populated and crucial as part of India's economy.

Noticeably, the Energy sector has managed to secure the highest average score in the Environmental pillar in all the four years despite experiencing a decline in its score highlighting the importance that this sector gives to environmental responsibility and investor appeal. On the contrary, the Financials sector has continuously obtained the lowest score in this pillar, calling the need to analyse ESG controversy scores and combined scores in future research. The Real Estate sector has shown a relatively stable Environmental performance. Particularly, we find that the Real Estate sector along with the Health Care sector are the only two sectors to witness a growth in the Environmental score. The Social pillar is found to be a relative weakness for most of the sectors, with significant declines observed. Almost all the sectors have witnessed significant drops in the Social scores, with Consumer Discretionary and the Consumer Staples sectors facing the most significant drops.

Additionally, the Communication Services and the Utilities sector suffered lower drops in their average scores in the Social pillar. The Governance pillar has shown mixed results across the sectors, where there is a general trend of improvement over the years in most sectors. The Energy and the Materials sector has shown significant progress in the Governance pillar which reflects an improvement in transparency and accountability. However, what is confounding is that the Energy sector, despite witnessing a significant increase in the Governance score by 30 percent from 32.07 to 41.94, is found to still have the second lowest Governance score among the 11 sectors. Conversely, the Real Estate sector experienced a decline in the Governance score, highlighting the challenges in corporate governance practices.

We further explore these Indian sectoral ESG variations through the box-plots shown in Figure 7 and 8, showing the distribution of ESG scores across GICS sectors in India for the years 2019 and 2022 respectively. The box-plots show us that the Utilities sector is the only sector experiencing an increase in median ESG scores, while the other 10 sectors experience a fall. The Information Technology sector continues to lead in ESG performance with overall distribution shifting upward, indicating a sustained and focused change in the ESG practices. Consumer Staples, Utilities, and Financials sectors are the only three sectors witnessing a significant reduction of 15.56, 5.11 and 3.51 units respectively in the interquartile range from 2019 to 2022, indicating lower variability and lower disparity, hence promoting data reliability.

On the contrary, sectors like Information Technology, Communication Services, and Health Care have witnessed an increase in their inter-quartile ranges by 4.27, 2.41 and 2.02 respectively indicating that ESG scores within these sectors are more spread out, indicating greater diversity in the ESG performance. The other sectors show mixed results with the overall distribution remaining mostly unchanged, indicating possible obstacles in ESG adoption in various sectors, such as differences in regulatory parameters across sectors.

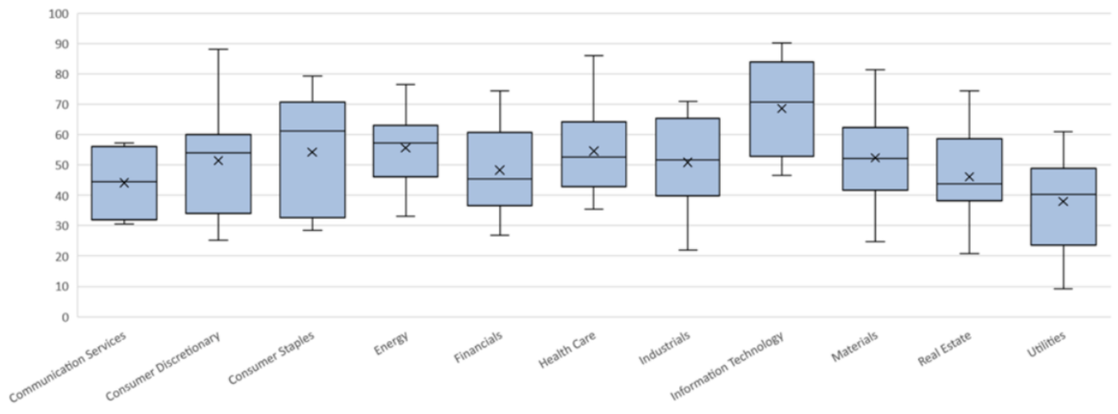


Figure 7: Distribution of ESG Scores Across Sectors in India in 2019

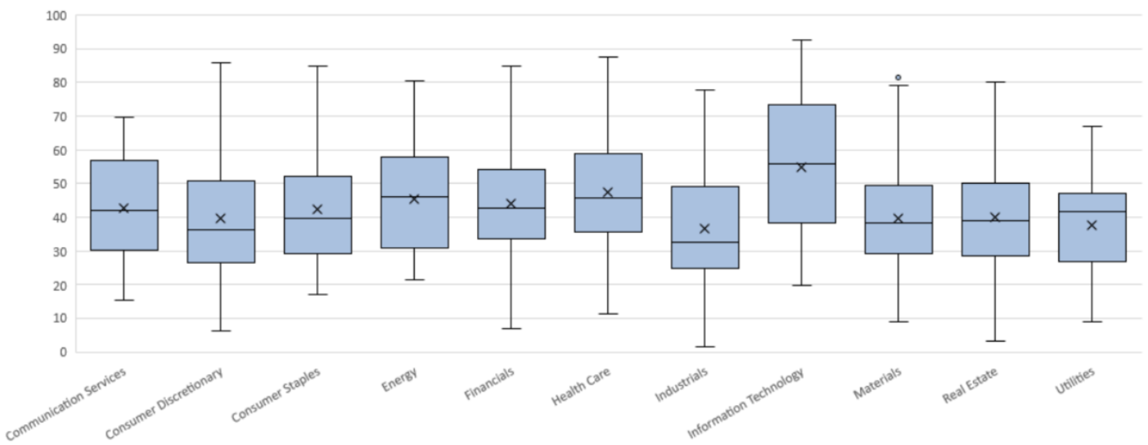


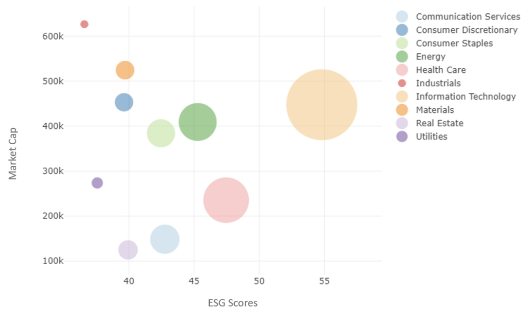
Figure 8: Distribution of ESG Scores Across Sectors in India in 2022

Our research above therefore shows evidence that India's ESG landscape is outlined by striking sector wise variations. Some sectors have showcased their leadership in ESG integration, while others have reflected the need for targeted efforts to combat sector specific challenges. Hence, to further estimate India's position amongst the Global ESG Landscape and see potential quantitative factors affecting the same, we explore the relationship between ESG Scores and market capitalization values (in millions of USD) through quantitative analysis in the latter section.

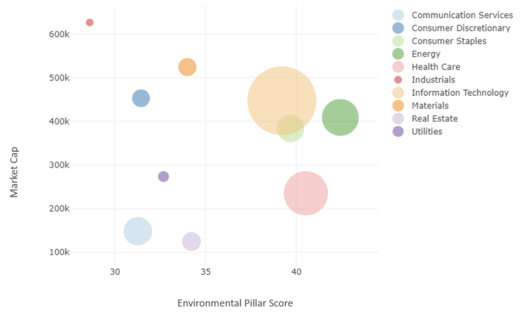
3 Quantitative Analysis

3.1 Panel Data Analysis

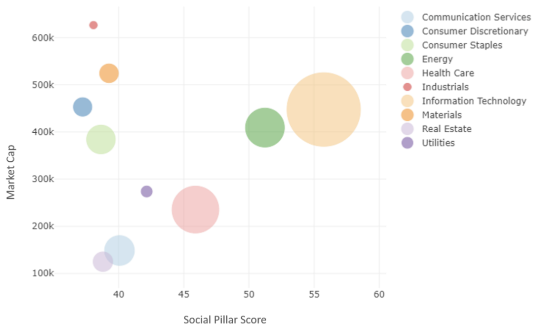
Prior to conducting the Panel Data analysis, we attempt to showcase a *prima facie* relationship in between ESG scores and market capitalization of Indian companies in 2022 through bubble plots. The bubble plots in figure 9 exhibit the relationship in between



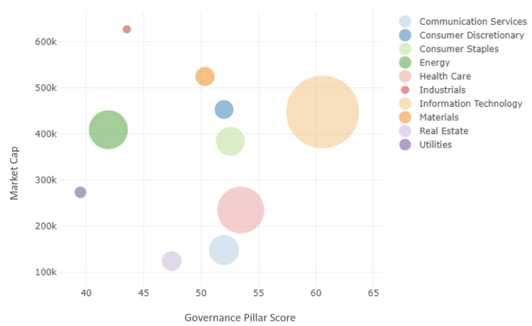
(a) Relationship between Market Capitalization (millions of USD) and ESG Scores Across Sectors in India in 2022



(b) Relationship between Market Capitalization (millions of USD) and E Scores Across Sectors in India in 2022



(c) Relationship between Market Capitalization (millions of USD) and S Scores Across Sectors in India in 2022



(d) Relationship between Market Capitalization (millions of USD) and G Scores Across Sectors in India in 2022

Figure 9: Relationship between Market Capitalization and ESG Scores Across Sectors in India in 2022

ESG and individual E,S,G scores, and market capitalization for the year 2022, with the bubble size representing the ESG score of the particular sector. At a first glance, Graph (a) depicts that there might be a potential correlation amongst some sectoral ESG scores, and their market capitalization. This would however require further statistical analysis, carried out in the latter sections of the paper. Additionally, sectoral outliers such as Industrials can be seen, possessing the highest market capitalization in 2022, but the lowest overall sectoral ESG score. To understand this interplay further, we look at individual E,S and G scores to understand specific effects pillar scores may have on market capitalization, in addition to the overall ESG scores. Furthermore, Graph (b) depicts a rather scattered relationship in between market capitalization and E scores in India, showing that there isn't a strong linear correlation amongst the same. Similar relationships can be seen across Graphs (c) and (d), showing that additional statistical analysis is crucial to estimate the relationship even further and solidify the findings of the paper.

To further attempt to examine the above relationships statistically, our study examines a dataset of Nifty 500 companies in India over a four-year period from 2019 to 2022 to investigate the relationship between ESG scores and market capitalization. The market capitalization of these companies vary from \$15.6 million to \$21 billion. We employ a panel regression framework in our research, which is well-suited for analysing data that spans multiple time periods for the same entities. Given the varying presence of these companies throughout the study period, we have an unbalanced panel dataset with 144, 154, 207 and 441 companies for the years 2019, 2020, 2021 and 2022.

Our dependent variable is the market capitalization of the companies, whereas our key independent variables are the ESG scores, both consolidated and disaggregated into Environmental (E), Social (S), and Governance (G) pillars. The ESG scores and the E, S, and G pillar scores were taken from Refinitiv Workspace. These scores range from 0 to 100, reflecting a firm's ESG performance relative to industry peers.

To account for firm-level heterogeneity, we control for two firm-specific factors:

1. **Turnover**: A measure of the total revenue or sales generated by the company, reflecting its operational scale and market activity. The reason behind choosing turnover as a variable is because of it's directness and simplicity in measuring the financial and growth performance of a company, thus allowing us to correlate ESG scores and a company's growth potential in its crudest form.

2. **Debt to Equity ratio**: A measure of the amount of debt used by the company to finance itself, against shareholder equity. The reason behind choosing this variable is again, its descriptiveness and simplicity as a key indicator of financial stability. Through this, we can correlate ESG scores and a company's financial stability in a comprehensive and understandable manner.

The market capitalization, debt-to-equity ratio, and turnover data were taken from CMIE Prowess. Additionally, we include sectoral dummy variables for 11 sectors as part of the GICS framework to control for sector-specific effects and solidify our findings.

We employ three different models: Pooled Ordinary Least Squares (OLS), Fixed Effect model, and Random Effect Model. Using the variables stated in Table 2, we then select the best model among them based on statistical criteria.

Table 2: Variable Description

Variable	Description
market_cap	CMIE Prowess Market Capitalization
esg_score	Refinitiv ESG score
e_score	Refinitiv Environmental score
s_score	Refinitiv Social score
g_score	Refinitiv Governance score
turnover	CMIE Prowess company turnover
debt_to_equity	CMIE Prowess Debt to Equity ratio

3.1.1 Pooled OLS Model Analysis

The equation derived and used in our Pooled OLS Model analysis is specified as follows:

$$\text{market\_cap}_{it} = \beta_0 + \beta_1 \text{esg\_score}_{it} + \beta_2 \text{turnover}_{it} + \beta_3 \text{debt\_to\_equity}_{it} + \epsilon_{it}$$

3.1.2 Fixed Effect Model Analysis

In addition to these variables we add 10 sectoral dummy variables for the 11 sectors of GICS to control for sector specific effects. The equation for the same is derived as follows:

$$\begin{aligned}\text{market\_cap}_{it} &= \beta_0 + \beta_1 \text{esg\_score}_{it} + \beta_2 \text{turnover}_{it} \\ &\quad + \beta_3 \text{debt\_to\_equity}_{it} + \sum_j \beta_j \text{sector\_dummy}_{jit} + \epsilon_{it}\end{aligned}$$

To capture potential temporal effects, we include time fixed effects. These account for macroeconomic factors or events impacting all firms across the board during specific periods. The equation for this Time Fixed Effects Model is as follows:

$$\begin{aligned}\text{market\_cap}_{it} &= \beta_0 + \beta_1 \text{esg\_score}_{it} + \beta_2 \text{turnover}_{it} + \beta_3 \text{debt\_to\_equity}_{it} \\ &\quad + \sum_j \beta_j \text{sector\_dummy}_{jit} + \sum_l \beta_l \text{time\_dummy}_{lit} + \epsilon_{it}\end{aligned}$$

3.1.3 Random Effect Model Analysis

To account for both firm-level and sector-level variability, we also fit a Random Effect model to include sectoral dummy variables. This model is specified as follows (u_i represents the random effect capturing firm-level variability):

$$\begin{aligned}\text{market\_cap}_{it} &= \beta_0 + \beta_1 \text{esg\_score}_{it} + \beta_2 \text{turnover}_{it} + \beta_3 \text{debt\_to\_equity}_{it} \\ &\quad + \sum_j \beta_j \text{sector\_dummy}_{jit} + u_i + \epsilon_{it}\end{aligned}$$

To verify the three models, we also ran corresponding statistical tests to verify which model among the three models is the best fit to our research.

3.1.4 Tests

The tests used to compare between the Pooled OLS, Sector Fixed Effect, Time Fixed Effect, and Random Effect model are as follows:

1. **Restricted F Test**

   The restricted F-test is a statistical tool used to determine whether individual differences significantly influence the outcome in panel data analysis. This test helps to decide if a simple pooled OLS model, which ignores individual variations, is adequate or if a more complex model, such as a fixed effects model, is necessary to account for these differences (Blackwell, 2008). Essentially, the test compares whether the assumption of no individual effects (null hypothesis) holds or if there is evidence to suggest that individual factors impact the outcome (alternative hypothesis).

   The restricted F-test results indicate that there is no significant evidence of individual effects in the data. Based on the F-test results, with an F-value of 0.76693 and a p-value of 0.998, we fail to reject the null hypothesis that there are no individual differences influencing the outcome. This implies that a simple pooled OLS model, which assumes homogeneity across individuals, is appropriate for analysing this dataset. In other words, the variations observed between individuals do not appear to be statistically significant enough to warrant the use of a more complex model like sector fixed effects.

The F-test results strongly support the inclusion of time fixed effects in the model. With an F-value of 5.8007 and a highly significant p-value of 2.307e-10, we further reject the null hypothesis that there are no time effects. This indicates that factors varying over time have a significant impact on market capitalization, making it essential to incorporate time fixed effects in our research to accurately capture these changes.

2. **Breusch–Pagan LM Test**

   The Breusch-Pagan Lagrange Multiplier test helps determine whether a random effects model is necessary for panel data analysis. This test checks if there are significant variations between different entities (like individuals or companies) in the data. If the test indicates significant difference (null hypothesis is rejected), a random effects model is preferred as it accounts for these variations (Breusch and Pagan, 1979). If the test indicates no significant difference (null hypothesis is not rejected), a simpler pooled OLS model might be sufficient.

   The Breusch-Pagan test results strongly suggest the presence of random effects in the data. With a chi-squared value of 689.75 and a p-value less than 2.2e-16, we reject the null hypothesis of no random effects. This implies that a random effects model is more appropriate than a pooled OLS model as it can effectively account for the observed variations across different entities.

3. **Hausman Test**

   The Hausman test is used to determine whether a fixed effects or random effects model is more suitable for panel data analysis. This test examines if the individual-specific effects are correlated with the explanatory variables (Durbin, 1954). If the test indicates that these individual effects are correlated with the explanatory variables (null hypothesis is rejected), a fixed effects model is preferred as it controls for these unobserved effects. If the test suggests no correlation (null hypothesis is not rejected), a random effects model is generally more efficient as it provides more precise estimates.

   Based on the Hausman test results, with a chi-squared value of 11.73 and a p-value of 0.4676, we fail to reject the null hypothesis that the random effects model is consistent. Therefore, the random effects model is appropriate for this dataset, as the differences in coefficients between the sector fixed effects and random effects models are not statistically significant. The Hausman test results thus support the use of a random effects model. With a chi-squared value of 1.2812 and a p-value of 1, we fail to reject the null hypothesis that the random effects model is consistent. This indicates that there is no significant difference between the time fixed and random effects models, suggesting that the random effects model is a suitable and efficient choice for analysing the data.

4 Results

In the Pooled OLS model without sector or time fixed effects, ESG scores show a positive and statistically significant relationship with market capitalization. This suggests that firms with higher ESG scores tend to have larger market capitalization. Turnover also significantly and positively influences market capitalization, indicating that higher turnover is associated with larger market-capitalized firms. However, debt-to-equity ratio does not have a significant impact on market capitalization, suggesting its limited explanatory power in determining market capitalization.

In the Time Fixed Effects model with sector dummies, the ESG score continues to show a positive and statistically significant relationship with market capitalization, although the size of the effect is reduced compared to the Pooled model. This suggests that while ESG scores remain a relevant factor influencing market capitalization, their impact can be partially explained by time-invariant unobserved factors captured by the time fixed effects. Turnover remains a significant positive predictor of market capitalization, while debt-to-equity continues to be insignificant.

In the Random Effects model with sector dummies, the positive and statistically significant relationship between ESG scores and market capitalization persists, with a size similar to the Time Fixed Effects model. This suggests that ESG scores are a relevant factor influencing market capitalization positively across companies, even after accounting for unobserved firm-specific effects captured by the random effects. Turnover remains a significant positive predictor of market capitalization, while debt-to-equity again shows no significant impact.

After conducting all 3 tests, which are the Restricted F-Test, Breusch Pagan Test and the Hausman Test, it suggests that the Random Effect Model should be considered. The model effectively accounts for unobserved individual heterogeneity without introducing the complexities of the fixed effects model. The individual ESG components (Environmental, Social, and Governance) all positively and significantly impact market capitalization across all three model specifications. While examining trends in ESG scores offers valuable insights into the dynamic relationship between ESG and market capitalization, a comprehensive understanding requires considering additional firm-specific characteristics.

The results of the REM in Table 3 show that there is a negative and statistically significant correlation in between ESG scores and Market Cap in companies in the Consumer Discretionary, Financials, Health care, Materials, and Real Estate sectors respectively. The essay's findings on the Real Estate sector can be seen globally through Erol et al (2023)'s research on ESG dynamics in the Real Estate sector in the USA, the UK, Australia, Canada, and Japan, showing that REIT policies on improving ESG scores (particularly environmental pillar scores) in the sector involve high financial costs that drain capital, as well as lead to decreasing market capitalization and returns.

The essay's sector-specific results further depict a positive correlation in between ESG scores in the Energy Sector and market capitalization according to Table 3, indicating that a single unit increase in ESG scores in the sector would lead to an increase in 7581.2462 units of market capitalization while being statistically significant. Although there is inconclusive research conducted specifically on this relationship in the Energy sector in Indian companies and those part of Nifty500, the findings significantly align with Serban et al (2022)'s research on ESG scores impact on Sector-wise market capitalization for a dataset of 5557 companies globally, indicating that ESG scores showed the greatest direct and positive impact on market capitalization in the Energy Sector, similar to the findings of our paper. However, this would require additional research that remains outside the scope of this paper.

Table 3: Models with ESG score as main independent variable of interest

	Pooled OLS	**Sector FE**	**Time FE**	**REM**
ESG_Scores	195.730	248.93	165.884	165.571
	(6.077e-09)***	(4.18e-06)***	(1.128e-06)***	(9.332e-07)***
Turnover	395.006	429.787	393.770	393.462
	(2.2e-16)***	(2.2e-16)***	(2.2e-16)***	(2.2e-16)***
Debt-to-Equity	-28.740	-11.591	-15.897	-17.516
	(0.419220)	(0.80061)	(0.64906)	(0.61513)
SectorCommunication_Services		-10126.481	-6197.638	-6147.755
		(0.08243).	(0.11598)	(0.11829)
SectorConsumer_Discretionary		-5931.533	-5679.430	-5503.661
		(0.18592)	(0.05556).	(0.06258).
SectorConsumer_Staples		7332.867	2233.678	2460.306
		(0.12805)	(0.48852)	(0.44371)
SectorEnergy		9667.902	7356.455	7558.844
		(0.06677).	(0.03656)*	(0.03095)*
SectorFinancials		-7640.675	-5409.467	-5279.295
		(0.06445).	(0.05019).	(0.05526).
SectorHealth_Care		-7915.914	-7054.137	-6949.199
		(0.08545).	(0.02324)*	(0.02491)*
SectorIndustrials		-4066.814	-4586.716	-4406.545
		(0.33558)	(0.10990)*	(0.12325)
SectorInformation_Technology		5165.672	5320.818	5523.592
		(0.29124)	(0.11349)	(0.09918)
SectorMaterials		-7159.082	-6415.203	-6318.316
		(0.08365).	(0.02374)*	(0.02543)*
SectorReal_Estate		-5998.592	-7614.053	-7337.565
		(0.26896)	(0.03597)*	(0.04155)*
Constant	-5067.110			-123.076
R^2	0.35258	0.422022	0.39311	0.39269
Adjusted R^2	0.35052	-0.14383	0.38266	0.38422

The table depicts estimated coefficients from a pooled OLS, sector fixed effects (Sector FE), time fixed effects (Time FE), and random effects model (REM), with standard errors shown in parentheses. ESG score is the main independent variable of interest, and control variables consist of sector dummies, turnover, and debt-to-equity ratio, with the Communication Services sector serving as the baseline. Sector fixed effects included in the table accounts for unobserved heterogeneity across the sectors, while the time fixed effects model controls for factors relating to time. The significance levels are shown by .,*,**,and ***, at 15, 10, 5, and 1 percent levels respectively. The adjusted R^2 and R^2 values are stated at the bottom, depicting the model's proportion of variance after adjusting for predictors.

In summary, while the Pooled OLS model provides valuable insights into the relationship between ESG scores and market capitalization, it is important to consider its limitations. The positive and significant relationship between ESG scores and market capitalization suggests that firms with higher ESG scores tend to have larger market capitalization. This is further supported by Kalia et al (2022)'s research However, the model also highlights that turnover significantly influences market capitalization, while the debt-to-equity ratio does not have a significant impact. To gain a more comprehensive understanding of the factors influencing market capitalization, it is essential to consider additional analyses, such as those accounting for sector-specific or time-invariant factors, as demonstrated in the Time Fixed Effects and Random Effects models. These models help refine our understanding of the dynamic relationship between ESG scores and market capitalization in India, by accounting for unobserved heterogeneity across firms and over the four years.

5 Conclusion

Through our paper, we initially dived into the global distribution of Environment, Social, and Governance (ESG) scores and the number of ESG reporting companies, to understand the global ESG landscape at a glance. We further delved into estimating India's position as part of this landscape, by exploring relationships with market capitalisation across GICS sectors in India. Our study therefore aimed to understand the prominence of the use of such non financial metrics globally, and whether they resulted in different financial trends for Indian sectors.

Our analysis involved utilising an unbalanced panel data over a four year period, implementing a Pooled OLS, Fixed effects model (FEM), and Random effects model (REM) to draw relationships in between ESG, and individual Environmental (E), Social (S), Governmental (G) scores. The findings reveal a significant positive relationship in between ESG scores and market capitalization, aligning with the global trend that ESG scores have gained as as an important metric in gaining investor attraction and enhancing firm reputation, thus affecting profitability. This research in India's landscape additionally carries forward a trend similar to previous global trends as famously found by Friede and Bassen (2015), showing the positve stable trend in between ESG and corporate financial performance.

Our study's strength lies in depicting both sector-wise global ESG trends, and the specificity of India's landscape over 2019-22, showcasing the position of a developing ESG market, thus filling the research gaps as mentioned by Ruan and Li (2021), and Ting et al (2019) on ESG practices affecting financial performance in emerging ESG markets. However, the four year gap proves to be an evident limitation to our study, not capturing possible long term trends and implications in ESG scores and market capitalization. Additionally, the Nifty500 dataset obtained is from 144, 154, 207 and 441 companies for the years 2019, 2020, 2021 and 2022. Therefore, not all companies are included every year. Furthermore, this lack of data due to a lower time period may be the reason for the model showing turnover to significantly influence market capitalization positively, but showing no significant relationship between debt-to-equity ratios and market capitalization. The non significant values in the models depict that further analysis is required in different methodological approaches accounting for time-invariant and sector-specific factors, and additional variables such as firm age could be utilised, thus providing scope to further enhance our model.

Furthermore, despite the ongoing development in ESG in emerging markets, there are issues with the nascent nature of ESG rating agencies themselves, which are yet to be resolved due to lack of standardisation and comparability. A case study to support the above statement would be the ESG divergence for the Chevron Corporation in 2022, as part of the Energy Sector. Sustainalytics provided the Chevron Corporation with a ranking of 43.0, placing it in its 'highest risk' category. However, MSCI in the same year placed Chevron between 4.2 and 5.7, positioning it under 'average', instead of utilising 'laggard' as their worst risk category (Bitutsky, 2022). This highlights the significant subjectivity of rating metrics, and the influence the rating can have on investment decisions. Further research should therefore be conducted at a global and country level, to explore the concept of ESG rating divergence identified by Berg et al (2022), Tayan et al (2022), and more.

In conclusion, the global ESG landscape is distinguished by significant heterogeneity due to varying levels of adoption and regulation across different regions and industries, thus making the process of identifying a country's positioning in the global ESG landscape challenging. This evolving research necessitates further academic exploration, especially in countries as sector-wise and financially diverse as India.

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6 Appendix

Table 4: Correlation Matrix

	Market cap	ESG Scores	E	S	G	Turnover	Debt to Equity ratio
Market cap	1						
ESG Scores	0.327	1					
E	0.260	0.783	1				
S	0.334	0.869	0.665	1			
G	0.173	0.647	0.259	0.313	1		
Turnover	0.573	0.314	0.238	0.326	0.139	1	
Debt to equity ratio	0.005	-0.004	-0.014	-0.002	0.013	0.052	1

Table 5: Comparison of ESG Scores Across Sectors in India (2019 vs 2022)

GICS Sectors	2019 Q1	2019 Median/Q2	2019 Q3	2019 IQR	2022 Q1	2022 Median/Q2	2022 Q3	2022 IQR	Change in IQR
Communication Services	31.97	44.51	56.11	24.14	30.36	41.96	56.91	26.55	2.41
Consumer Discretionary	34.14	54.02	60	25.86	26.68	36.15	50.72	24.04	-1.82
Consumer Staples	32.55	61.08	70.74	38.19	29.37	39.81	52	22.63	-15.56
Energy	46.21	57.24	63.03	16.82	30.78	45.93	57.73	26.95	10.13
Financials	36.54	45.29	60.73	24.19	33.49	42.78	54.17	20.68	-3.51
Health Care	42.84	52.7	64.15	21.31	35.51	45.69	58.84	23.33	2.02
Industrials	39.89	51.73	65.37	25.48	24.88	32.68	49.07	24.19	-1.29
Information Technology	52.8	70.59	83.95	31.15	38.3	55.92	73.72	35.42	4.27
Materials	41.73	52.16	62.34	20.61	29.18	38.27	49.56	20.38	-0.23
Real Estate	38.22	43.78	58.73	20.51	28.53	39.03	50.24	21.71	1.2
Utilities	23.68	40.34	48.91	25.23	26.92	41.76	47.04	20.12	-5.11

Table 6: ESG, P Value, Adj. R-Squared, E, P Value, Adj. R-Squared, S, P Value, Adj. R-Squared, G, P Value, Adj. R-Squared

	ESG	P Value	Adj. R-Squared	E	P Value	Adj. R-Squared	S	P Value	Adj. R-Squared	G	P Value	Adj. R-Squared
1 India	340.24	2E-16	0.1278	279.12	2E-16	0.1268	301.69	2E-16	0.1383	89.93	0.00104	0.01385
2 Financials	250.4	0.0478	0.02927	461.6	2.36E-05	0.1575	289.8	0.0163	0.04741	13.24	0.8712	-0.009831
3 Communication Services	557.2	0.0429	0.149	480.9	0.0231	0.1941	351.2	0.19	0.03831	407.7	0.0352	0.1635
4 Consumer Discretionary	276.18	3.54E-06	0.2351	226.41	3.12E-06	0.2376	257.83	4.02E-07	0.2758	69.75	0.209	0.0007723
5 Consumer Staples	476.11	6.76E-07	0.3475	366.81	5.31E-06	0.2992	397.56	1.25E-06	0.3335	203.29	0.0264	0.06864
6 Energy	1993.5	0.00826	0.3221	954.7	1.12E-01	0.09729	1288.3	0.0252	0.2305	825.2	0.14	0.07681
7 Health Care	172.8	0.000549	0.1917	142.43	1.17E-04	0.236	146.09	0.000507	0.194	43.36	0.283	0.003351
8 Industrials	202.6	3.21E-06	0.1477	208.66	7.00E-10	0.2487	177.49	1.84E-06	0.1547	4.215	0.9095	-0.007592
9 Materials	256.51	1.35E-14	0.3456	190.91	4.95E-12	0.288	188.1	4.34E-12	0.2893	68.18	0.00789	0.04315
10 Information Technology	620.7	6.17E-03	0.1637	766	8.92E-04	0.2409	437.8	1.33E-02	0.1317	416	0.0606	0.06739
11 Real Estate	154.69	8.66E-04	0.2607	122.58	1.40E-03	0.241	147.63	4.29E-04	0.2889	63.06	0.114	0.04467
12 Utilities	488	7.72E-03	0.2587	398.1	3.81E-03	0.3034	448.1	3.33E-04	0.4405	-102.1	0.36255	-0.006113

Table 7: Models with Environmental Pillar Score as the main independent variable of interest

	Pooled OLS	**Sector FE**	**Time FE**	**REM**
Environmental_Pillar_Scores	117.460	159.359	103.600	103.779
	(1.764e-06)***	(0.0001256)***	(6.069e-05)***	(5.257e-05)***
Turnover	410.003	436.992	401.125	400.653
	(2.2e-16)***	(2.2e-16)***	(2.2e-16)***	(2.2e-16)***
Debt_to_Equity	-28.647	-15.980	-16.803	-18.225
	(0.4235)	(0.7293989)	(0.63191)	(0.60236)
SectorCommunication_Services		-8020.330	-4829.911	-4784.548
		(0.1704418)	(0.22162)	(0.22528)
SectorConsumer_Discretionary		-4400.219	-4649.917	-4468.181
		(0.3273090)	(0.11679)	(0.13038)
SectorConsumer_Staples		9232.247	3271.994	3487.728
		(0.0549053).	(0.30944)	(0.27663)
SectorEnergy		10809.935	7991.259	8168.871
		(0.0395491)*	(0.02344)*	(0.01996)*
SectorFinancials		-4439.295	-3141.780	-3019.186
		(0.2899160)	(0.25974)	(0.27771)
SectorHealth_Care		-5949.928	-5480.161	-5389.425
		(0.1941483)	(0.07607).	(0.08082).
SectorIndustrials		-3173.378	-3947.486	-3786.737
		(0.4539342)	(0.16929)	(0.18588)
SectorInformation_Technology		9136.730	8231.241	8412.397
		(0.0577992).	(0.01268)*	(0.01051)*
SectorMaterials		-6288.002	-5774.380	-5689.467
		(0.1298640)	(0.04915)*	(0.04439)*
SectorReal_Estate		-4235.395	-6551.173	-6300.416
		(0.4357023)	(0.07106).	(0.08012).
Constant	-548.737			2355.920
R^2	0.34499	0.41232	0.38811	0.38776
Adjusted R^2	0.3429	-0.15941	0.37757	0.37922

The table depicts estimated coefficients from a pooled OLS, sector fixed effects (Sector FE), time fixed effects (Time FE), and random effects model (REM), with standard errors shown in parentheses. Environmental Pillar (E) score is the main independent variable of interest, and control variables consist of sector dummies, turnover, and debt-to-equity ratio, with the Communication Services sector serving as the baseline. Sector fixed effects included in the table accounts for unobserved heterogeneity across the sectors, while the time fixed effects model controls for factors relating to time. The significance levels are shown by .,*,**,and ***, at 15, 10, 5, and 1 percent levels respectively. The adjusted R^2 and R^2 values are stated at the bottom, depicting the model's proportion of variance after adjusting for predictors.

Table 8: Models with Social Pillar Score as the main independent variable of interest

	Pooled OLS	**Sector FE**	**Time FE**	**REM**
Social_Pillar_Scores	171.747	226.951	136.824	135.855
	(4.493e-09)***	(8.589e-07)***	(3.117e-06)***	(3.031e-06)***
Turnover	393.006	430.763	394.928	394.785
	(2.2e-16)***	(2.2e-16)***	(2.2e-16)***	(2.2e-16)***
Debt_to_Equity	-29.015	-11.361	-16.381	-18.019
	(0.414636)	(0.80388)	(0.63947)	(0.60545)
Sector_Communication_Services		-7857.448	-4501.509	-4454.077
		(0.17499)	(0.25336)	(0.25777)
Sector_Consumer_Discretionary		-5057.637	-4688.280	-4498.503
		(0.25603)	(0.11269)	(0.12667)
Sector_Consumer_Staples		9276.638	3711.746	3970.692
		(0.05090).	(0.24595)	(0.21256)
Sector_Energy		9069.923	7420.469	7659.385
		(0.08504).	(0.03517)*	(0.02896)*
Sector_Financials		-6900.400	-4627.933	-4487.043
		(0.09346).	(0.09344).	(0.10299)
Sector_Health_Care		-6371.605	-5794.096	-5672.947
		(0.16016)	(0.06019).	(0.06505).
Sector_Industrials		-2891.965	-3580.820	-3383.229
		(0.48962)	(0.21010)	(0.23490)
Sector_Information_Technology		6767.004	6598.431	6833.568
		(0.15927)	(0.04705)*	(0.03894)*
Sector_Materials		-6138.425	-5433.930	-5320.029
		(0.13446)	(0.05427).	(0.05877).
Sector_Real_Estate		-4629.333	-6332.168	-6003.899
		(0.38964)	(0.07980).	(0.09405).
Constant	-4337.436			-52.776
R^2	0.35298	0.42389	0.39181	0.39125
Adjusted R^2	0.35092	-0.13659	0.38133	0.38276

The table depicts estimated coefficients from a pooled OLS, sector fixed effects (Sector FE), time fixed effects (Time FE), and random effects model (REM), with standard errors shown in parentheses. Social Pillar (S) score is the main independent variable of interest, and control variables consist of sector dummies, turnover, and debt-to-equity ratio, with the Communication Services sector serving as the baseline. Sector fixed effects included in the table accounts for unobserved heterogeneity across the sectors, while the time fixed effects model controls for factors relating to time. The significance levels are shown by .,*,**,and ***, at 15, 10, 5, and 1 percent levels respectively. The adjusted R^2 and R^2 values are stated at the bottom, depicting the model's proportion of variance after adjusting for predictors.

Table 9: Models with Governance Pillar Score as the main independent variable of interest

	Pooled OLS	Sector FE	Time FE	REM
Governance_Pillar_Scores	88.239	109.888	90.216	90.043
	(0.0004077)***	(0.006605)**	(0.0004036)***	(0.0003842)***
Turnover	423.650	462.055	417.437	416.979
	(2.2e-16)***	(2.2e-16)***	(2.2e-16)***	(2.2e-16)***
Debt_to_Equity	-34.040	-15.309	-18.281	-19.696
	(0.3440956)	(0.742251)	(0.6029431)	(0.5741880)
SectorCommunication_Services		-10470.778	-7348.057	-7298.077
		(0.079034).	(0.0670539).	(0.0683728).
SectorConsumer_Discretionary		-5744.693	-6195.906	-5997.125
		(0.209774)	(0.0403001)*	(0.0463004)*
SectorConsumer_Staples		8324.735	2292.448	2519.658
		(0.091186).	(0.4834852)	(0.4394998)
SectorEnergy		12080.695	8601.435	8779.045
		(0.023062)*	(0.0146771)*	(0.0123340)*
SectorFinancials		-8200.470	-6107.968	-5983.740
		(0.052071).	(0.0296642)*	(0.0325948)*
SectorHealth_Care		-6579.431	-7046.439	-6951.270
		(0.159660)	(0.0256242)*	(0.0272250)*
SectorIndustrials		-3319.363	-4566.073	-4401.580
		(0.439409)	(0.1153621)	(0.1277621)
SectorInformation_Technology		7085.189	5859.372	6047.613
		(0.155009)	(0.0858441).	(0.0752457).
SectorMaterials		-6197.662	-6327.849	-6239.794
		(0.139751)	(0.0272671)*	(0.0289686)*
SectorReal_Estate		-5578.979	-7853.653	-7601.827
		(0.314073)	(0.0329070)*	(0.0374192)*
Constant	-369.631			3213.114
R^2	0.33776	0.40325	0.38576	0.38533
Adjusted R^2	0.33565	-0.17731	0.37518	0.37676

The table depicts estimated coefficients from a pooled OLS, sector fixed effects (Sector FE), time fixed effects (Time FE), and random effects model (REM), with standard errors shown in parentheses. Government Pillar (G) score is the main independent variable of interest, and control variables consist of sector dummies, turnover, and debt-to-equity ratio, with the Communication Services sector serving as the baseline. Sector fixed effects included in the table accounts for unobserved heterogeneity across the sectors, while the time fixed effects model controls for factors relating to time. The significance levels are shown by .,*,**,and ***, at 15, 10, 5, and 1 percent levels respectively. The adjusted R^2 and R^2 values are stated at the bottom, depicting the model's proportion of variance after adjusting for predictors.