Are Developing Country Firms Facing a Downward Bias in ESG Scores?

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Abstract

Policymakers in emerging economies are increasingly concerned that global ESG scoring firms based in developed countries are 'unfairly punishing' their companies by assigning lower scores compared to those in developed countries. This study investigates and provides empirical evidence supporting this concern. Using panel regression analysis on a comprehensive cross-country sample of 7,904 listed firms from 2002 to 2022 across 50 countries, we find that corporate ESG scores in developing economies are significantly lower – 57% lower for raw ESG scores and 23% lower for standardized ESG scores – than those in developed economies. Further analysis indicates that this disparity is linked to institutional bias and measurement issues within ESG scoring firms, stemming from information asymmetry. Our empirical evidence also suggests that ESG scoring firms can mitigate these information problems by incorporating analyst coverage and experience into their algorithms. This study, therefore, contributes to the ongoing debate on the subjectivity of the global rating industry by demonstrating that the biases affecting the credibility of corporate credit and corporate governance ratings also extend to corporate ESG scores.

Keywords: Institutional Theory; Theory of Human Needs; Information Asymmetry; ESG; Financial Analyst; Developing Country

JEL Codes: D82; G24; I31; O16; P48

1. Introduction

Since the introduction of the United Nations Sustainable Development Goals (SDGs) in 2015, sustainability has taken centre stage, especially in light of the global financial crisis of 2007-08, growing climate concerns and the more recent COVID-19 pandemic.[1] This emphasis on sustainability has spurred the growth and demand of ESG rating providers such as Refinitiv, Sustainalytics, MSCI, and Bloomberg. These ESG rating firms quantify a company's environmental, social, and governance (ESG) performance and sell their ESG scores to various users. However, unlike credit rating agencies, the lack of transparency and a standardised framework has cast doubt on the accuracy of these scores, leading investors, businesses, and regulators to question their credibility (Larcker et al., 2022).[2] Adding to this controversy is a growing concern that ESG raters may be intentionally assigning lower scores to companies in developing countries.[3]

This development is concerning as it discourages the inflow of capital investments based on sustainability criteria, thus, preventing them from having the desired effect in the countries where it is most needed (UNCTAD, 2023).[4] One plausible explanation is that the ESG scoring agencies, headquartered in the United States (US) and Europe, rarely consider the cultural and contextual distinctions between developed and developing nations (UNEP Finance Initiative, 2010). For instance, employment generation, community development, and access to basic services that improve social equity could be more critical than environmental goals in developing countries. Thus, a failure to capture these nuances may introduce biases in ESG scores (GIS, 2024; SEBI, 2022, 2023). While these biases have been examined in the context of credit ratings and corporate governance ratings (Almeida et al., 2017; De Moor et al., 2018; Black et al., 2017, 2023), this study marks the first attempt to explain why firms in developing countries may receive lower ESG scores from two perspectives: institutional bias of ESG raters and measurement issues.

For this purpose, we integrate DiMaggio and Powell's (1991) institutional theory with human needs theories (Maslow, 1943, 1954; Deci and Ryan, 1985; Ryan and Deci, 2017) to explain why ESG scores are lower in developing countries. The institutional theory highlights how differences in political systems, labour and education systems, national cultures, and legal origins shape corporate social performance (Ioannou and Serafeim, 2012; Liang and Renneboog, 2017). However, this theory alone cannot fully explain the ESG score variations between developed and developing countries. Differences in SDG priorities lead to different ESG priorities in policymaking. According to the human needs theory, these variations arise because developing countries often

[1] See, ESG awareness is an enduring legacy of the global financial crisis. Accessed on July 1, 2024.
[2] See, Sustainability Institute, ERM (2023). "Rate the Raters 2023: ESG Ratings at a Crossroads". Accessed on January 19, 2024.
[3] See, ESG scoring 'unfairly punishing' emerging economies. Accessed on January 19, 2024.
[4] See, Are ESG data demands hurting emerging markets? Accessed on July 1, 2024.

prioritise fundamental needs such as poverty alleviation and infrastructure development. Failure to recognise these distinctions may result in lower ESG scores for firms in developing countries. Standardising ESG scores, as done with sovereign ESG scores, might address institutional bias but won't resolve measurement issues in ESG rating systems.

As the availability and access to ESG-related information are crucial for reliable ESG scores (Larcker et al., 2022), ESG scores are strongly correlated with the quantity of ESG disclosures (Raghunandhan and Rajagopal, 2022). Thus, lower disclosures in developing countries (Black et al., 2023) could result in lower ESG scores for developing country firms. Furthermore, as most ESG raters are based primarily in the US or Europe (Widyawati, 2020), information asymmetry arising from the geographic distance between the firm and the rating agencies (Ayers et al., 2011) would hamper their ability to assess the reliability of the ESG related information, whatsoever, obtained from the developing country firms. Accordingly, if the poor disclosures and information asymmetry are the sources of the downward bias, we conjecture that analyst characteristics like the extent of analyst coverage of a firm and analyst experience in covering the firm could provide credible signals to ESG raters regarding the reliability of ESG disclosures of the developing country firms. This is because financial analysts incorporate sustainability-related information into their forecasts and recommendations (Ioannou and Serafeim, 2015; Luo et al., 2015; Kopita and Petrou, 2024).[5] However, analyst forecasts and recommendations would not serve the purpose because they are meant to assess the ability of the firm to maximise shareholder wealth and analysts are known to provide over-optimistic forecasts in developing countries due to the investment banking pressure (Lai and Teo, 2008) and aggressive "numbers game" (De Moura et al., 2023).

To test the above propositions, we use a global sample of non-financial firms and classify them as either developing or developed based on the United Nations designation of the country where their securities are primarily traded.[6] Accordingly, the *DVPG* dummy takes a value of one if the firm is from a developing country as per the aforementioned criteria, else zero. Next, we obtain their raw ESG scores (*RESG*) from the Refinitiv database,[7] along with additional financial and non-financial information from the WorldScope, BoardEx, and I/B/E/S databases. To address potential endogeneity caused by sample selection bias and omitted variables, we included firm-level controls in all our regression models and employed an entropy-balanced sample of firms from both developed and developing countries, following the procedure outlined in Hainmueller (2012) and Shroff et al. (2017).[8]

[5] Rajgopal (2023) notes that "ESG can be viewed as a set of signals that a good analyst would have looked for anyway."
[6] Following the procedure laid down in De Moura et al., (2023), we find that our classification of countries into developed and developing successfully captures 84% of the institutional differences between these two groups of countries.
[7] We consider the ESG scores from Refinitiv since it is has the largest global coverage of firms and is widely used (Basu et al., 2022; Drempetic et al., 2020; Dyck et al., 2019).
[8] The results of the balancing procedure are presented in Appendix D.

Panel regression analysis reveals that the raw ESG score (*RESG*) of firms in developing countries is 57% lower than in developed countries. This confirms that the systematic bias observed in credit ratings (Almeida et al., 2017) and governance ratings (Witt et al., 2022) towards firms in developing countries, persists even in the case of ESG scores. This finding aligns with the predictions of institutional theory. Notably, the differences are more pronounced in the Environment (*RENV*) and Governance (*RGOV*) components, at 56% and 51% respectively, compared to the Social (*RSOC*) component at 28%. In line with the theory of human needs, these variations in component scores reflect the institutional priorities in developing countries, which focus more on promoting social equity over governance or environmental concerns (GIS, 2024; SEBI, 2022, 2023).

Next, to demonstrate that ESG raters' measurement issues may contribute to the downward bias in corporate ESG scores in developing countries, we eliminate the effect of institutional bias by standardizing the *RESG* scores with respect to country-industry-year median *RESG* scores.[9] If institutional biases were the only source of the difference in ESG scores between firms in developed and developing countries, we would expect no difference in the standardized ESG scores (*SESG*) between these groups. However, the differences persist, with standardized ESG scores (*SESG*) being 23% lower in developing countries, and the respective component scores being lower by 20% (*SENV*), 16% (*SSOC*), and 21% (*SGOV*). This finding indicates that the differences in ESG scores between firms in developed and developing countries are not solely due to institutional biases but are also attributable to the measurement issues faced by ESG raters when assessing firms in developing countries.

Our empirical analysis suggests that endogeneity issues, particularly those arising from reverse causality, are unlikely. Entropy balancing helps address endogeneity from self-selection, and we perform additional tests to tackle endogeneity concerns related to omitted variable bias and measurement errors. The first test that we perform to address omitted variable bias is the Impact Threshold Confounding Variables (ITCV) analysis (Frank, 2000; Larcker and Rusticus, 2010) and observe that the omitted variable problem is not severe enough to invalidate our regression results. The second test that we perform to address the omitted variable problem is a Difference-in-Difference (DiD) analysis structured around the passage of mandatory ESG disclosures, considering a two-year before and after time window (Christensen et al., 2022).

If developing country firms were indeed performing poorly on ESG metrics and the ESG scores were rightly capturing it, we would expect the lower ESG scores for developing countries to persist even after mandatory disclosures. On the other hand, if the lower ESG scores are due to institutional bias and/or measurement problems of ESG raters, then we would expect the lower ESG

[9] This is done by subtracting the country-industry-year median *RESG* scores from the firm's *RESG* scores and dividing the resultant figure by the standard deviation of the county-industry-year *RESG* scores.

ratings for developing firms to disappear after the passage of the mandatory disclosure requirements. Our regression results indicate that the *RESG* scores increased in developing countries after mandatory disclosures which confirms the existence of institutional bias. If institutional bias was the only reason for lower ESG scores for developing country firms, then the *SESG* scores should also increase after mandatory adoption. However, we find that there is no such increase in the *SESG* scores. This confirms that institutional bias is not the only source of difference in ESG scores between developed and developing countries and that standardising ESG scores at the country-industry level has incremental information content. This also confirms that measurement problems of the ESG raters are contributing to a downward bias in ESG scores for developing country firms. Furthermore, the DiD analysis also addresses endogeneity concerns related to measurement error, if any, that may be driving our regression estimates.

We then test whether ESG raters can overcome this bias by considering the extent of analyst coverage and analyst experience as credibility signals for the reliability of corporate ESG information in developing countries. We conduct this analysis by following the procedure as in Fernandes et al. (2013) and find that the difference in standardized ESG (*SESG*) scores between developed and developing countries disappears when analyst coverage and experience are introduced in the regression models. We also observe a similar pattern for the *SESG* component scores – *SENV*, *SSOC* and *SGOV*.

Therefore, our empirical results suggest that ESG scoring agencies can mitigate their scoring biases by using financial analyst coverage and experience as positive indicators of the reliability of sustainability-related information for firms in developing economies, leading to more accurate ESG scores for these firms. We conduct additional tests to confirm the robustness of our findings. First, using the IMF classification for developed and developing countries, we find that our results remain consistent. Second, switching from median-adjusted to country-industry-mean-adjusted ESG scores does not alter our conclusions.

Overall, our study makes significant contributions to multiple strands of literature. First, we expand the existing literature exploring how the institutional environment shapes sustainable business practices. While previous studies (Ioannou and Serafeim, 2012; Cai et al., 2016; Liang and Renneboog, 2017) have predominantly used DiMaggio and Powell's institutional theory (1991) to explain variations in corporate ESG performance across countries, we enrich the literature by integrating insights from human needs theories (Maslow, 1943, 1954; Deci and Ryan, 1985; Ryan and Deci, 2017). Furthermore, we consider an integration of these institutional factors and adopt the developed and developing classification which is more meaningful from a policy perspective. By doing so, we emphasize that differing priorities in policymaking between developed and developing countries are crucial in understanding disparities in corporate social performance.

Second, our research contributes to discussions on the subjective nature of the global rating industry. Previous studies have shown how institutional biases and measurement problems affect the credibility of corporate credit ratings and corporate governance ratings, resulting in lower ratings for firms in developing countries (Borensztein et al., 2013; Almeida et al., 2017; Duong et al., 2016; Fuchs and Gehring, 2017; De Moor et al., 2018; Black et al., 2017, 2023; Witt et al., 2022). Building on this, we demonstrate that corporate ESG scores are similarly affected by institutional biases and measurement issues, including challenges in quantifying qualitative information and the imposition of benchmarks from developed countries onto developing ones.

Lastly, we contribute to the literature on geographic distance and information asymmetry in finance. While previous studies have explored how information asymmetry due to geographic distance affects investment decision-making (Malloy, 2005; Butler, 2008; Ayers et al., 2011; Kim et al., 2016), our study is among the first to show that ESG raters also encounter such information challenges. Additional analysis reveals that ESG raters may mitigate these issues by relying on financial analyst coverage and experience as indicators of the reliability of sustainability information from firms in developing countries.

2. Relevant Literature, Theoretical Background and Hypothesis Development

2.1. Evolution of ESG Scores

With the growing importance of non-financial information in investors' decision-making process, ESG factors began capturing investors' attention in the 1990s, leading to the rise of socially responsible investing (SRI). However, early ESG scores, often based on self-reported data, lacked standardization and transparency (Michelson et al., 2004). Therefore, SRI in the 1990s involved negative screening to avoid investing in companies deemed unethical, for example, companies engaged in the alcohol, tobacco or gambling business (Sparkes and Cowton, 2004). Since this approach did not encourage non-ethical companies to adopt responsible business practices (Heinkel et al., 2001), there was a significant push in the 2000s towards standardization of ESG metrics by the Global Reporting Initiative (GRI) and the United Nations Principles for Responsible Investment (UNPRI) (Renneboog et al., 2008). This led to positive screening or "best-in-class" practices and the integration of ESG factors into mainstream investment strategies of asset managers and institutional investors (Statman and Glushkov, 2009). More so, the global financial crisis further increased investor focus on sustainability (Galbreath, 2013), encouraging the development of sophisticated ESG scoring methodologies using extensive data sets and analytics by major scoring agencies such as MSCI, Sustainalytics, and FTSE Russell (Berg et al., 2022).

2.2. Significance of ESG Scores in Decision Making

Today, ESG scoring agencies process voluminous amounts of data from various sources on firms' environmental, sustainability and governance performance and make sustainability measurable.

These scores assess a company's management issues like pollution, climate action, employee satisfaction, gender diversity, corruption and entrenchment. Further, by benchmarking business practices on sustainability, ESG scores guide companies towards continuous improvement and help in mitigating negative incidents (Eccles et al., 2015). Thus, institutional investors, particularly signatories to the Principles of Responsible Investment (PRI) initiative, sovereign wealth funds and pension funds use commercially available corporate ESG scores to incorporate sustainability into their investment strategy (UNCTAD, 2020). Further, government agencies are increasingly relying on these ESG scores to guide policymaking in promoting responsible corporate business conduct (OECD, 2020). However, Larcker et al. (2022) argue that the notion of ESG scores measuring ESG performance is a myth due to issues with the construction of such metrics. Therefore, investors have questioned the reliance of SRI funds on ESG metrics as a proxy for sustainability performance (Avetisyan and Hockerts, 2017; Widyawati, 2020). Despite these concerns, ESG scores remain influential in shaping global trade and investment, meriting further empirical investigation.

2.3. Criticism and Geopolitics of ESG Scores

The failure to recognize the priorities of developing country firms has a deep-rooted history, starting with sovereign credit ratings. After the 2008 financial crisis, sovereign credit ratings were criticized for being overly optimistic about their home countries and other regions with stronger economic, geopolitical, and cultural ties, disregarding economic fundamentals (Fuchs and Gehring, 2017; De Moor et al., 2018). Large developing nations, despite their significant economic growth, often receive unfairly low credit ratings that do not reflect their economic fundamentals, affecting their firms via the sovereign ceiling channel (Borensztein et al., 2013; Almeida et al., 2017).[10] [11] Similarly, commercial corporate governance ratings based on developed economy norms, are ineffective for emerging markets (Bhagat et al., 2008; Duong et al., 2016). This bias results in lower ratings for firms in developing economies (Khanna and Paleppu, 2010; Witt et al., 2022), limiting their usefulness in assessing global corporate governance (Black et al., 2017; Black et al., 2023).

As with commercial corporate governance ratings, one major issue with ESG scores is the lack of transparency in the methodologies used by ESG scoring agencies. While some agencies disclose more information about their methods, crucial details necessary for meaningful interpretation and accurate comparison are still not fully transparent (Busch et al., 2016). Additionally, the absence of a standardized framework for ESG metrics leads to differences in data collection methods, incompatible data formats, and varying levels of quality control, making it difficult to draw accurate conclusions (Berg et al., 2022; Chatterji et al., 2016; Christensen et al., 2022; Semenova and Hassel, 2015). Moreover, various measurement issues have been recognized, such as a tendency towards

[10] See India's ratings don't reflect economy's fundamentals: CEA
[11] See Moody's politically biased credit outlook cut won't affect China's long-term upward growth trend: experts

favouring larger companies (Drempetic et al., 2020), which could potentially mislead investors (Cheng et al., 2015; Kim and Yoon, 2024).

Hence, regulators in advanced economies endorse the supervision of ESG raters.[12] [13] However, regulatory authorities in developing countries raise an overlooked yet important issue relevant to emerging markets. The consultation paper released by the Securities Exchange Board of India (SEBI) in February 2023 highlights that the existing ESG scoring providers fail to factor in the domestic context when assessing and grading the environmental and social issues because ESG issues plaguing emerging markets are completely different from developed countries (SEBI, 2023). A similar viewpoint has been put forth by the economies of the African Union (GIS, 2024). For example, concerns like generating employment in smaller towns, fostering gender diversity among employees, and promoting inclusive development hold greater priority than pollution and climate-related issues here. Hence, for climate issues, as developing countries are not the primary contributors to global greenhouse gas emissions, the resource constraints make it difficult for them to implement stringent climate policies and pollution norms at the cost of economic growth (Cai et al., 2016; UNCTAD, 2021). Thus, most of the metrics considered in assessing the environmental pillar are of less priority in developing countries than in developed countries. This leads to an overall lower ESG score for developing country firms by design (OECD, 2023).

2.4. ESG Scores Through the Lens of Institutional Theory and Human Needs Theory

The institutional theory by DiMaggio and Powell (1991) posits that organizations conform to societal norms to gain legitimacy and support. Therefore, this theory emphasizes that external institutions are instrumental in shaping organizational behaviour and practices. Accordingly, in stakeholder-oriented economies, like France and Germany, socially responsible businesses are held in high regard whereas in shareholder-oriented economies, like the US, economically responsible businesses are held in higher regard (Maignan, 2001). This difference in stakeholder pressure influences managerial incentives to act in a socially responsible manner (Maignan and Ralston, 2002). Hence, whether firms conduct their businesses in a socially responsible manner is driven by nation-level institutions (Jackson and Apostolakou, 2010) and the institutionalized norms of corporate behaviour (Campbell, 2007; Jamali et al., 2020).

Subsequent studies have provided empirical evidence in support of the institutional theory of corporate social responsibility. In a cross-country study spanning 2,787 firms across 42 countries from 2002 to 2008, Ioannou and Serafeim (2012) report that political systems, labour and education systems, and national cultures drive corporate social performance (CSP). They observe that CSP is negatively affected by increasing national corruption and power distance, leftist ideology, laws

[12] See Sustainable finance: Council agrees negotiating mandate on ESG ratings
[13] See UK set to unveil regulatory regime for ESG ratings industry

promoting competition, and higher levels of shareholder protection, but is positively influenced by strong labour unions. Liang and Renneboog (2017), studying 23,000 companies in 114 countries, find that legal origin significantly explains CSP differences, with firms in civil law countries with stronger stakeholder protection scoring higher on ESG metrics than those in common law countries with stronger shareholder protection. Notably, Cai et al. (2016) demonstrate that country-level characteristics matter more than firm-level characteristics in explaining sustainability as measured by commercial ESG scores. Using 2,632 unique firms across 36 countries from 2006 to 2011, they find that country-level characteristics such as economic development, culture, and institutions explain 13.4% of the variation in ESG scores while firm-level characteristics explain only 6.7% of the variation in ESG scores. While these studies highlight the importance of cross-country differences in shaping corporate ESG outcomes, they fail to address the question of whether ESG scores are different between developed and developing countries. This is important because the different set of challenges facing developing countries leads to differences in policymaking between developed and developing countries.

To investigate this question, we draw inspiration from the nexus between the theories of human needs (Maslow, 1943, 1954; Deci and Ryan, 1985; Ryan and Deci, 2017) and the institutional theory. The human needs theory has been highly influential in developmental economics and is the foundation of the basic needs movement which sets priorities for governments and organizations in framing development policies (United Nations, 2010). By prioritizing the eradication of poverty and hunger, the first two goals of the UN SDGs, released in 2015, focus on lower-level needs which is still a problem in many developing countries. These lower-level needs are critical in many developing countries, affecting their ESG priorities. For example, in India, the emphasis on employment generation, gender diversity and promoting inclusive development highlights the priority of addressing the fundamental socio-economic issues before moving focus to the more advanced sustainability issues related to climate, environment and bio-diversity relevant to developed markets (SEBI 2022, 2023). Similar concerns have been raised by countries of the African Union (GIS, 2024).

Integrating this perspective with the institutional theory suggests that corporate ESG priorities also differ between developed and developing countries. Since the sustainability framework underpinning international ESG scores is based on institutional norms established in developed economies, firms in developing countries, that are focused on addressing local priorities and challenges, may not prioritize adhering to these norms for better ESG scores. Consequently, firms in developing countries could receive lower rankings on ESG criteria compared to their counterparts in developed nations.

Empirically, addressing the institutional differences from a developing versus developed perspective eliminates the issue of co-dependence among country attributes (Leuz et al., 2003).

Practically, categorizing countries as either developed or developing is a more accurate depiction of reality compared to any other arbitrary classification. First, institutions (e.g., World Bank, IMF, UN) providing funding assistance to countries fix the covenants in the assistance programs according to the development status as to whether a country is developed, developing or in transition. Second, investors (i.e., foreign institutional investors, pension funds) managing global portfolios diversify their portfolios across geographical regions by following a similar classification of countries. Accordingly, the first hypothesis is stated as follows:

H1: *ESG Scores of firms in developing countries are lower than their developed counterparts.*

2.5. Refinitiv ESG Scoring Methodology and Standardized ESG Scores

Liang and Renneboog (2017) reflect that the ESG rating providers rate companies relative to their industry peers across international markets making the scores independent of the local institutional environment. Similarly, Refinitiv uses industry averages as the benchmark for environmental and social scores, but national averages for governance scores (Basu et al., 2022). This global benchmarking approach leads to variations in ESG scores across countries (Ioannou and Serafaim, 2012; Cai et al., 2016; Liang and Renneboog, 2017). If the difference in ESG scores between developed and developing countries is simply an aggregation problem, then deriving country-wise industry-adjusted ESG scores would remove the differences.[14] However, we argue that aggregation ranking is not the sole cause as the institutional theory explains only the incentives for a firm to adopt sustainable business practices. The extensive number of input variables required to quantify sustainability practices makes the ESG scores susceptible to distortion from measurement issues and other information problems faced by the ESG raters themselves.[15]

Furthermore, as ESG scores are influenced by the volume of voluntary ESG-related disclosures (Raghunandan and Rajgopal, 2022), availability and access to information becomes a key factor in determining the reliability of ESG scores (Larcker et al., 2022). As disclosures are poorer in developing countries (Black et al., 2023), ESG information availability is also poor. Therefore, if poor disclosures are the source of the difference in ESG scores between developed and developing countries, then we would expect firms in developing countries to have lower scores than firms in developed countries even after standardization. This would result in a downward bias in the ESG scores of firms in developing countries. We test this assertion using hypothesis, H2, stated below.

H2: *There exists a downward bias in ESG scores of firms in developing countries.*

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[14] Gratcheva et al. (2021) show that adjusting for income levels removes the differences in the sovereign ESG scores between high-income and low-income countries.

[15] From a social planning perspective, Campbell (1979) warns that "the more any quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor".

2.6. The Role of Financial Analysts

Geographic distance is an important source of information asymmetry for market participants as it limits information access and analysis (Ayers et al, 2011; Kim et al. 2016). Most of the commercial ESG scoring agencies are based out of Europe and USA, which increases the geographic distance between the ESG raters and firms in developing countries (Widyawati, 2020). Further, the lack of institutional familiarity adds an additional layer of opacity for the ESG raters. This leads to an interesting question of how ESG raters could overcome this information disadvantage.

To understand this, we consider the pivotal role played by financial analysts as information intermediaries. Of late, financial analysts who specialise in security valuations and recommendations (Bradshaw et al., 2017), have started incorporating sustainability-related information in their analyses (Ioannou and Serafeim, 2015; Luo et al., 2015; Kopita and Petrou, 2024). Thus, financial analysts have been found to influence the sustainability disclosure practices of firms which in turn influences their ESG performance (Benlemlih et al., 2023; Qian et al., 2019).[16]

Recognizing that analyst coverage and experience can reduce information asymmetry and lower information acquisition costs (Chen et al., 2015), we argue that ESG raters in developed countries can provide more accurate and fairer sustainability scores for firms in developing countries by leveraging extensive analyst coverage and experience. While we acknowledge that ESG raters could infer such cues from analyst coverage in developed countries as well, the higher information asymmetry in developing countries (Black et al., 2023) makes analyst coverage and experience a crucial signal in developing countries. Thus, ESG raters could overcome the downward bias in their ESG scoring methodology by incorporating analyst characteristics like analyst coverage and analyst experience.[17]

H3: *The downward bias in ESG Scores of firms in developing countries is mitigated by analyst coverage and analyst experience.*

3. Data, Covariates and Descriptive Analysis

3.1. Sample Selection

Our sample includes all publicly traded non-financial firms with annual data from 2002 to 2022. We source corporate ESG performance measures from the Refinitiv (Version 2) database,[18] formerly known as ASSET4 of Thomson Reuters, which is widely used due to its extensive global coverage and accessibility for both investors and scholars (Basu et al., 2022; Drempetic et al., 2020; Dyck et

[16] Rajgopal (2023) argues that "ESG can be viewed as a set of signals that a good analyst would have looked for anyway."
[17] Analyst forecasts and recommendations would not serve the purpose for two reasons: First, analyst forecasts and recommendations are meant to provide estimates of future earnings based on past performance and current expectations. Second, analysts are known to collude with the management in developing countries by providing over-optimistic forecasts due to the investment banking pressure (Lai and Teo, 2008) and weak institutional environment (De Moura et al., 2023).
[18] See Thomson Reuters to sell Refinitiv to London Stock Exchange Group (accessed 17 January 2024).

al., 2019). The Refinitiv ESG score reflects a firm's commitment to environmental, social, and governance dimensions, evaluated through 178 metrics and the Refinitiv ESG controversy score.[19] Annual financial data is sourced from the Worldscope database and analysts' information from the I/B/E/S detail files. Firms are classified as 'developed' or 'developing' based on the United Nations' 2018 classification,[20] depending on the market where its primary security is traded.

To maintain sample homogeneity, we exclude firms from the financial, utility, transportation, public administration, and non-classifiable sectors based on their SIC codes, as well as firms with missing primary quote information. After merging Worldscope data with Refinitiv ESG, our dataset is reduced to 63,624 observations. Further filtering for country and industry-adjusted ESG scores, which requires at least six observations per country-industry-year group, and eliminating observations with missing data for the computation of key variables, leaves us with 54,023 observations from 7,904 firms across 50 countries. Country-wise distribution of firms presented in Table 1 shows that our sample includes 2,690 firms (34%) from developing countries and 5,214 firms (66%) from developed countries, with significant representation from the United States (46% of developed countries), China (30% of developing countries), and India (18% of developing countries). To mitigate the impact of outliers, we winsorized all continuous variables at their 1st and 99th percentiles.

<Insert Table 1 Here>

3.2. Covariates

3.2.1. Raw ESG Scores and Standardized ESG Scores

The dependent variables of interest in our study are the raw ESG scores (*RESG*) and the standardized ESG scores (*SESG*). *RESG* represents the raw ESG scores from Refinitiv for company *i* in the year *t*. Likewise, *RENV*, *RSOC* and *RGOV* represent the raw component scores from Refinitiv. The *RENV* reflects the company's performance on resource use, emissions and innovation related aspects. The *RSOC* reflects the company's performance in the workforce, human rights, community and product responsibility related aspects. The *RGOV* reflects the company's performance in management, shareholders and CSR strategy related issues. These scores provide a comprehensive assessment of the overall and category-wise sustainability performance, but they are not the raw scores collected by Refinitiv.

The pillar scores (*RENV, RSOC* and *RGOV*) are first normalised category-wise using percentile ranking to eliminate outliers. Refinitiv considers the industry group based on the TRBC

[19] There are three subcategories within the environmental pillar: innovation, emissions, and resource utilisation – containing a total of 19, 22, and 20 indicators respectively. Workforce, human rights, community, and product responsibility are the four subcategories of the social pillar, each of which has 29, 8, 14, and 12 indicators, respectively. The three subcategories comprising the governance pillar—management, shareholders, and CSR strategy—are measured by 34, 12, and 8 indicators, respectively.

[20] Available at: [World Economic Situation and Prospects 2018 | Department of Economic and Social Affairs (un.org)](un.org) (accessed 17 January 2024)

codes (The Refinitiv Business Classification) as the peer group for the *RENV* and *RSOC* scores and the country of incorporation as the benchmark for the *RGOV* scores. This technique scales the pillar scores between 0 and 1. Then, the final ESG score *(RESG)* is calculated as the weighted average of percentile-ranked pillar scores, also ranging between 0 and 1.[21]

The percentile ranking technique eliminates outliers but causes information loss by making data points equidistant, thereby masking the magnitude of score differences between companies. Second, since the peer group for *ENV* and *SOC* is the TRBC group, the *RENV* and *RSOC* scores ignore the country-specific priorities on the *E* and *S* pillars. Similarly, since the country of incorporation is the benchmark for the *GOV* component, the *RGOV* score ignores the industry-specific differences in governance practices. Therefore, these limitations are reflected in the overall ESG Score (*RESG*) as well.

To overcome this limitation, we standardise the overall ESG score and the respective pillar scores using the country-industry-year benchmark. Accordingly, the standardised ESG score (*SESG*) is measured as the difference between the firm-year *RESG* score and the median of the country-industry-year *RESG* score divided by the standard deviation of the country-industry-year *RESG* score. Similarly, *SENV*, *SSOC* and *SGOV* represent the standardized component scores relating to the *E*, *S* and *G* pillars respectively.

Standardizing the ESG scores in this manner has two important advantages: First, it accounts for the industry-specific and country-specific differences, addressing institutional priorities for environmental and social aspects. Second, taking care of the institutional differences, helps us to isolate the measurement and information problems of ESG raters in scoring firms across countries.[22]

3.2.2. United Nations Classification of Developed and Developing Countries

The United Nations (UN) categorizes nations based on their development status based on metrics like per capita gross national income (GNI), human assets index, economic vulnerability index, and various other factors (United Nations, 2018, 2024). Our independent variable of interest is *DVPG*, an indicator variable which takes value 1 if a firm belongs to a developing country as per the UN 2018 classification, else zero.

To verify that the *DVPG* dummy reflects the major institutional differences, we follow De Moura et al. (2023) and regress the *DVPG* dummy on the four latent country factors that measure country-level economic, social, regulatory, and political systems, as proposed by Isidro et al. (2020).

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[21] Refer to the ESG scoring methodology booklet issued by LSEG in Dec 2023 for additional details. Environmental, social & governance scores guide (lseg.com)

[22] However, we acknowledge that the problem of equidistant data points in the normalised ESG scores provided by Refinitiv could persist in the standardised scores as well since we have applied the standardisation process to the normalised scores provided by Refinitiv. This may be overcome by applying the standardisation process over the raw data points used by Refinitiv as inputs to the percentile ranking methodology. Due to the lack of access to this data, we are unable to perform this procedure.

The regression analysis reveals that the *DVPG* dummy alone explains 84% of the variation in these factor variables. Next, we regress the *DVPG* dummy on 21 of the 72 country-level variables in Isidro et al. (2020) that change over time and find that the *DVPG* dummy explains almost 95% of the variation in these time-varying country-specific attributes. As a further robustness check, we regress the *DVPG* on the entire set of 72 attributes and make similar observations.[23] Hence, the classification of countries as developed and developing captures all the important institutional differences.

3.2.2 Analyst Coverage and Experience

In line with the literature, we measure analyst coverage (*COVR*) as the logarithm of (1 + number of analysts following the firm) during the year and analyst experience (*EXP*) as the logarithm of (1 + number of years that the firm has been followed by analysts). To represent earnings forecasts, we use analysts' forecast error *(FEEPS)*, forecast walkdown *(WLKDN)* and negative earnings surprises *(NSURP)*. We use the mean of analysts' recommendation *(RAVG)* and change in analysts' mean recommendation *(RCHG)* to capture variations in the analysts' recommendations.

3.2.3. Control Variables

We include several firm-specific control variables suggested in prior studies (Cai et al., 2016; Chen et al., 2020; Dyck et al., 2019). First, we control for *SIZE* (Ln(Total Assets)), profitability (*ROA*), financial slack (*CASH*) and working capital (*LIQ*) because larger companies that are more profitable, have higher cash holdings and better liquidity, exhibit better sustainability performance. Next, since firms with a greater degree of product differentiation exhibit better ESG performance, we use R&D intensity as an indicator of product differentiation. Further, we include leverage *(LEV)* and performance (*TQ*) to control for the effect of credit constraints and performance respectively. We include capital expenditure (*CAPEXP*) as an indicator of resource allocation since higher *CAPEX* would strain the company's resources thereby limiting the funds available for ESG initiatives. Next, we control for *GROWTH* (change in sales scaled by assets) since an aggressive growth strategy could be an indicator of compromise on ESG initiatives. Finally, we control for stability and risk through stock price volatility (*VOL*) and financial health through a dividend payment dummy (*DIV*).

A detailed description of all the variables in the study is presented in Appendix A. Our univariate regression analysis presented in Appendix B confirms that these control variables are significant predictors of both *RESG* and *SESG* and their respective individual components.

3.3. Descriptive Analysis

Table 2 provides summary statistics of all variables in the study, highlighting differences between developed and developing countries. The mean of the ESG score *(RESG)* is similar in both groups, as are the *RENV* and *RSOC* scores. Only the *RGOV* score differs between these groups. Nevertheless,

[23] These results are available on request.

the mean differences presented in Table 3 suggest statistically significant differences in corporate ESG scores between these groups due to institutional differences and/or measurement problems of ESG raters. The *SESG* scores, the standardized version of *RESG* by country-industry-year median also present significant differences (see Table 2 and Table 3). The same trend can be observed in the standardized component scores – *RENV, RSOC* and *RGOV*. These observations indicate that measurement problems of the ESG raters might be causing a downward bias in the ESG scores of developing countries.

<Insert Tables 2 and 3 Here>

Next, analyst related metrics also exhibit a systemic difference between developing and developed countries. While the forecast error (*FEEPS*) is higher in developed than in developing countries, the revision in forecasts (*WLKDN*) and negative surprises in earnings (*NSURP*) are higher in developing countries than in developed countries. Analysts' recommendations (*RAVG*) are slightly more optimistic in developing countries, but the change in recommendation (*RCHG*) is less favourable in developing countries suggesting that analysts are more likely to downgrade a recommendation in the future in developing countries than in developed countries. These patterns suggest that the weak institutional environment results in analysts colluding with the management and providing optimistic forecasts initially which later leads to revisions and negative surprises (De Moura et al., 2023). Therefore, analyst recommendations and forecasts might not eliminate the measurement problems of the ESG raters in developing countries. Further, analysts' coverage (*COVR*) is higher in developed countries (6 analysts per firm) than in developing countries (4 analysts per firm). Also, the experience of analysts (*EXP*) is higher in developed (2.16 years) than in developing countries (1.43 years).[24]

Additionally, firms in developing countries have lower liquidity (*LIQ*) and poor product differentiation (*RDEXP*), but are larger in size (*SIZE*) and more profitable (*ROA*), hold more cash (*CASH*), pay more dividends (*DIV*) and have more volatile returns (*VOL*). However, the leverage (*LEV*) levels and growth prospects (*GROWTH*) are similar between firms in developed and developing countries. Additionally, the correlation matrix presented in Appendix C confirms that the pairwise correlations amongst the control variables are within acceptable limits, thus eliminating concerns of multicollinearity.

4. Empirical Results and Discussion

4.1. Empirical Model

We consider the following baseline model to test our hypotheses:

$$ESG_{i,t} = \alpha_0 + \beta_1 DVPG_{i,t} + Controls_{i,t-1} + IndFE + YearFE + \varepsilon_{it} \quad (1)$$

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[24] As the analyst coverage and analyst experience are computed by the natural logarithm(1+analysts following) and natural logarithm(1+experience), we calculate the exponential of the mean values and subtract by one to arrive at these figures.

In Eq. (1), *DVPG* represents the developing dummy. *Controls* represents the control variables as described in Section 3.2.3 and are lagged by one year. It includes *SIZE* (Ln (Total Assets)), financial slack (*CASH*), product differentiation (*RDEXP*), profitability (*ROA*), leverage (*LEV*), performance (*TQ*), working capital (*LIQ*), capital expenditure (*CAPEXP*), stock price volatility (*VOL*), dividend payment dummy (*DIV*) and *GROWTH* (change in sales by assets). *IndFE* and *YearFE* represent industry and year fixed effects. *ESG* is the dependent variable and denotes *RESG* and its components (*RENV*, *RSOC* and *RGOV*) when testing H1. When doing so, if β_1 is negative, it confirms our first hypothesis that corporate ESG scores are lower in developing countries than in developed countries due to institutional differences or measurement problems of ESG raters or both. To test H2, we replace *ESG* in Eq. (1) with the standardised ESG score (*SESG*) and the standardised component scores (*SENV*, S*SOC* and *SGOV*). In doing so, if β_1 remains negative, it means that the lower corporate ESG scores for developing country firms are due to the measurement problems of the ESG raters.

Since firms in developing countries differ from firms in developed countries on several firm-specific attributes (Table 2), we consider an entropy-balanced sample of firms from developed and developing countries to address sample selection issues and eliminate self-selection bias. First, we match firms on all the firm-specific attributes considered in our study (i.e., *Controls*) and arrive at an entropy-balanced sample, following the procedure as in Haimueller (2012) and Shroff et al. (2017). The results of the balancing procedure across three moments (mean, variance and skewness) are presented in Appendix D. The panel regression analysis is carried out with this entropy-balanced sample. In line with prior research (Cai et al., 2016; Liang and Renneboog, 2017), we do not control for firm-fixed effects since the it is highly collinear with the *DVPG* dummy. Further, as the *DVPG* dummy captures the institutional differences to the extent of 95%, we do not include country-fixed effects in our regression model to avoid multicollinearity issues that would eliminate the *DVPG* dummy from the regression.

Next, to show that ESG raters can overcome the downward bias in corporate ESG scores if they incorporate analyst characteristics in their measurement, we adopt the procedure as in Fernandes et al. (2013) and modify our baseline model to include analyst coverage (*COVR*) and experience (*EXP*) as additional controls:

$$SESG_{i,t} = \alpha_0 + \beta_1 DVPG_{i,t} + \beta_2 COVR_{i,t-1} + \beta_3 EXP_{i,t-1} + IndFE + YearFE + \varepsilon_{it} \quad (2)$$

When analyst coverage (*COVR*) and experience (*EXP*) are included in Eq. (2), we expect β_1 to be insignificant and β_2 and β_3 to be significant. This would support our proposition that ESG raters can overcome the bias in ESG scores by relying on analyst coverage of a firm (*COVR*) and the analyst experience in covering a firm (*EXP)* as it helps them overcome measurement problems caused by information asymmetry.[25] Since sustainability scores are based on qualitative information, we do not expect ESG raters to pay attention to the forecasts and recommendations for the firms covered by analysts. Thus, when analysts' earnings forecasts (*FEEPS, WLKDN, NSURP*) and analysts' recommendations (*RAVG, RCHG*) are included in the model, we expect the coefficient on $DVPG$ (β_1) to remain significant suggesting that once the information environment is improved by analyst coverage in developing country firms, the earnings forecasts and recommendations are of little consequence to the ESG raters.

4.2. Test of H1

H1 predicts that corporate ESG scores (*RESG*) are lower in developing countries compared to developed countries. The panel regression results indicate that the *DVPG* dummy is negative and significant in the *RESG*, *RENV*, *RSOC* and *RGOV* regressions suggesting that corporate ESG scores are lower in developing countries (see columns 2 to 5 of Table 4). In terms of economic significance, *RESG* scores in developing countries are lower by 57% than in developed countries, when measured with respect to the standard deviation (see Mitton, 2022).[26] In a similar fashion, the *RENV* scores are 56% lower, *RSOC* scores are 28% lower, and *RGOV* scores are 51% lower in developing country firms compared to their counterparts in developed countries. The break-up of the component scores suggests that the lower ESG scores in developing countries are driven by the lower environmental and governance scores.

<Insert Table 4 Here>

This finding is in line with the theory of human needs that environmental and governance aspects of sustainability take a back seat in developing countries. For example, in developing countries, addressing basic needs like employment generation may take precedence over environmental concerns, especially in industries where there is a trade-off between pollution and job creation. Similarly, the necessity to sustain growth can justify higher fossil fuel usage, resulting in lower *RENV* scores and *RGOV* scores compared to *RSOC* scores. Overall, empirical tests provide strong support for hypothesis, H1.

4.3. Test of H2

Since the differences in corporate ESG scores may also be driven by measurement problems of ESG raters, H2 posits that there is a downward bias in the ESG scores of firms in developing countries. To investigate this, we standardize the ESG score by subtracting a firm's *RESG* score from the country-industry-year-median *RESG* score and dividing it by the country-industry-year standard deviation of

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[25] Fernandes et al. (2013) find that the difference in equity pay between US and non-US CEOs is primarily due to institutional investor presence. Initially, they show a compensation difference between US and non-US CEOs. However, when controlling for institutional ownership, the difference in equity pay between US and non-US CEOs disappears.

[26] Economic significance with respect to standard deviation is calculated by dividing the regression coefficient by the standard deviation of the dependent variable (Mitton, 2022). The standard deviation of the ESG scores for the entire sample is provided in Appendix E.

RESG score. Regressing this standardized ESG (*SESG*) score on *DVPG* and a set of firm-level controls reveals that the coefficient of *DVPG* remains negative and significant (see Column 6 of Table 4). Regarding the component scores, the *DVPG* dummy also remains negative and significant in regression estimates employing *SENV*, *SSOC*, and *SGOV* as dependent variables, respectively.

In terms of economic significance, *SESG* scores in developing countries are lower by 23% than in developed countries, when measured with respect to the standard deviation. With respect to the component scores, *SENV*, *SGOV* and *SSOC* scores in developing countries are lower by 20%, 21% and 16% than in developed countries respectively. These findings confirm that the challenges in measuring qualitative information are more pronounced for ESG scores, resulting in a downward bias in the corporate ESG scores of firms in developing countries, thus, confirming H2.

4.4. Test of H3

H3 proposes that incorporating analyst coverage and experience into the computation of ESG scores by scoring agencies could address the ESG bias problem. The empirical investigation of this proposition is presented in Table 5. Panel A presents the results with respect to standardised ESG scores (*SESG*). Following the empirical design of Fernandes et al. (2013), if analyst coverage and experience mitigates the bias in ESG scores, then the coefficient on *DVPG* would become insignificant when *COVR* and *EXP* are introduced in the model. Accordingly, in column 5, when analyst coverage (*COVR*) and experience (*EXP*) are included in the model, the *DVPG* coefficient reduces in magnitude to 5.7% and becomes insignificant. This suggests that the incorporation of analyst coverage and analyst experience when constructing the ESG scores can help the ESG raters overcome the measurement problems and reduce the bias when assigning sustainability scores to firms in developing countries. Next, in line with our prediction that analyst forecasts and recommendations do not affect the ESG scores in developing countries, we find that when earnings forecasts (*FEEPS, WLKDN, NSURP*) and analysts' recommendations (RCHG, RAVG) are incorporated into the model, the coefficient on *DVPG* remains negative and statistically significant (see Columns 3 and 4).

<Insert Table 5 Here>

These results are consistent with the notion that ESG raters can rely on analyst coverage and experience as a credible signal to overcome information asymmetry and transparency in developing country firms. The observation that the *DVPG* coefficient remains significant when analyst forecasts and recommendations are included in the model is consistent with our prediction that once a firm is covered by analysts, their forecasts and recommendations are of little consequence to ESG scores. This is because sustainability scores primarily involve quantifying qualitative information unlike analyst forecasts and recommendations which are largely based on the financial information related to the firm.

Further, we also investigate whether analyst coverage and experience are effective in addressing biases related to the individual components, i.e., *SENV, SSOC*, and *SGOV*. This analysis is presented in Panels B, C and D of Table 5. The results in these panels are reflective of the main results in Panel A. Regardless of whether ESG scoring agencies assess environmental, social, or governance factors in developing market firms, the importance of analyst coverage and experience for ESG raters in overcoming information challenges associated with these firms remains crucial.

4.5. Mitigating Endogeneity Concern

Endogeneity in regression-based empirical research may arise due to four issues: self-selection, reverse causality, omitted variables and measurement error (Hill et al., 2021; Roberts and Whited, 2013; Wooldrige, 2010). We addressed the self-selection issue by employing an entropy-balancing procedure (Hainmueller, 2012) and performing our regression analysis with the entropy-balanced sample. Reverse causality is not an issue in our context, as ESG scores do not influence the *DVPG* variable. However, omitted variable bias and measurement error remain a concern even after the inclusion of numerous firm-specific controls. Therefore, we perform tests to address endogeneity concerns arising due to omitted variables and measurement errors.

4.5.1 Endogeneity Due to Omitted Variables

We perform two tests to address the omitted variable bias problem: Impact Threshold of Confounding Variables (ITCV) analysis (Frank, 2000) and a Difference-in-Difference (DiD) analysis structured around the passage of mandatory ESG disclosures around the world (Christensen et al., 2022).

The first procedure, the ITCV analysis, evaluates the severity of the omitted variable issue necessary to invalidate our findings (Frank, 2000; Larcker and Rusticus, 2010). Omitted variable bias is significant when an unobserved variable, correlated with both the independent (x) and dependent (y) variables, undermines the results. According to Frank (2000), the ITCV is defined as the minimum product of the partial correlations between the confounding variable and both the y- and x-variables needed to invalidate the conclusions. A high ITCV, coupled with the control variables having an impact score lower than the ITCV, indicates that the omitted variable bias is insufficient to invalidate the OLS regression results.[27]

When performing the ITCV analysis using the natural logarithm of total assets as a proxy for size, we find that size has an impact score greater than the ITCV value for the *DVPG* dummy. This suggests that size may be confounding the effect of the *DVPG* dummy on *RESG* and *SESG* scores. Since ESG scores depend on data availability and larger firms can produce more ESG data, ESG scores are often highly correlated with firm size (Drempetic et al., 2020). To address this issue, we measure the size of a firm relative to its industry size within a given country and year for the ITCV

[27] The impact score of a control variable is defined as the magnitude of the product of the partial correlations of the control variable with the x- and y-variables (Larcker and Rusticus, 2010).

analysis. Relative size (*RSIZE*) is calculated as the total assets of a firm in a given year divided by the sum of the total assets of all firms in the same industry and year. We use this measure of size in our regression analyses for the ITCV test.

The results of ITCV analysis are presented for both the *RESG* and *SESG* regressions along with the component scores in Table 6. The ITCV values for the *DVPG* dummy in *RESG* and *SESG* regressions are 0.055 and .015 respectively (Columns 2 and 6). This indicates that the unobserved confounding variable must have a minimum correlation of 0.2345 with *RESG* and 0.1225 with *SESG* respectively to invalidate the regression inferences.[28] Next, we calculate the impact score of each control variable. In the *RESG* and *SESG* regressions, *DIV* and *VOL* have the highest impact scores of 0.031 and 0.015 respectively, which are lower than or equal to the reported ITCV values of the *DVPG* dummy in these regressions (Columns 2 and 6). Except for the *SENV* and *SSOC* regressions (Columns 7 and 8), we observe that the impact scores of the control variables in the remaining regressions are lower than the respective ITCV values. This confirms that the omitted variable problem is not severe enough to invalidate our regression findings and hence our inferences are robust to omitted variable bias.

<Insert Table 6 Here>

The second procedure involves a DiD analysis around the passage of mandatory ESG disclosures (Christensen et al., 2022). For example, developing country firms could indeed be performing poorly on ESG parameters and the ESG raters might be correctly capturing the differences, thereby invalidating our claim that institutional biases and measurement problems of the ESG raters are driving the differences in ESG scores.

To rule out this possibility due to unobservable variables, we construct a Difference-in-Difference (DID) model around the implementation of mandatory ESG disclosures in various countries considering a two-year before and after time window. We identify mandatory ESG disclosures at the country level following Krueger et al. (2024). If ESG raters provided lower ESG scores to developing country firms because the developing country firms were indeed performing poorly, then we would expect developing country firms to perform poorly even after ESG disclosures became mandatory. On the other hand, if the developing country firms were receiving poorer ESG scores due to institutional biases and/or measurement problems of ESG raters, we would expect the difference in ESG scores between developed and developing country firms to become insignificant.

To test this proposition, we modify the baseline model in Eq. (1) as follows:

$$ESG_{i,t} = \alpha_0 + \beta_1 DVPG_{i,t} \times MAN + Controls_{i,t-1} + IndFE + YearFE + \varepsilon_{it} \quad (3)$$

[28] Correlation is square root of ITCV (Frank, 2000).

Here, *MAN* takes the value 1 if a country has mandated ESG disclosures in year *t*, else 0. For the regressions with raw ESG scores as provided by Refinitiv (*RESG*), we replace *ESG* with *RESG* and for regressions with standardised ESG scores (*SESG*), we replace *ESG* with *SESG*. The regression results are presented in Table 7. In the *RESG* regressions, we find *MAN* to be negative and significant suggesting that mandatory ESG disclosures led to a decline in ESG scores in the immediate aftermath of its implementation. Contrary to our expectation, the interaction term *DVPG* × *MAN* is positive and significant in the *RESG* regressions suggesting that after mandatory ESG disclosures in developing country firms, ESG scores for developing country firms increased at a higher rate compared to developed country firms (Column 2). A similar trend can be observed with respect to the component scores – *RENV, RSOC* and *RGOV* – in Columns 3 to 5. An increase in the *RESG* scores in response to mandatory disclosures does not indicate any substantive changes in the ESG behaviour of the firm and is only indicative of an underlying institutional bias that resulted in lower ESG scores in the pre-disclosure period.

<Insert Table 7 Here>

If institutional bias is the only source of difference in ESG scores between developed and developing countries, then we would expect the positive and significant coefficient on the interaction term *DVPG* × *MAN* to exist in the *SESG* regressions as well. However, in the *SESG* regressions, we find that the interaction term *DVPG* × *MAN* becomes insignificant suggesting that the difference in ESG scores between developed and developing countries becomes insignificant in the post-disclosure period (Column 6). This finding is indicative of two pieces of information: first, since the *SESG* scores represent the raw ESG scores that have been standardized at the country level, a different impact of mandatory disclosure on *RESG* and *SESG* between developed and developing countries confirms that *SESG* has incremental information content over and above the raw ESG scores presented by Refinitiv. Therefore, this result validates the necessity to standardise the ESG scores at the country level before using them for decision-making. Second, the differential impact also highlights that institutional bias is not the only source of lower ESG scores in developing countries and confirms that the measurement problems of the ESG raters due to information asymmetry are the real cause of lower ESG scores here, resulting in a downward bias.

Overall, these findings validate our claims and confirm that there is a downward bias in corporate ESG scores towards developing countries, i.e., developing country firms have lower ESG scores only because they are from developing countries and not because they are underperforming the developed country firms on ESG issues.

4.5.2 Endogeneity Due to Measurement Error

Measurement error refers to the possibility that the dependent and/or independent variable in our study could be capturing an unobserved phenomenon rather than the observed phenomenon, thereby invalidating our findings (Hill et al., 2021). This concern is also addressed by the DiD analysis performed using mandatory ESG disclosures as an exogenous shock because mandatory ESG disclosures have a first-order effect on ESG disclosures through the information channel (Christensen et al., 2022). Overall, our results are robust to endogeneity concerns due to measurement error.

4.6 Robustness Checks

To further substantiate our findings, we conduct the following robustness checks.

4.6.1 Alternate Classification of Developed and Developing Countries

Since different international agencies have their own criteria for classifying nations as developed and developing, we first repeat our empirical tests with an alternate classification of firms into developed and developing as per the International Monetary Fund (IMF) criteria. The regression results confirm that irrespective of the classification criteria adopted, developing country firms have lower ESG scores than developed country firms due to differing institutional priorities in meeting sustainability goals and the measurement problems of the ESG raters.[29]

4.6.2 Alternate Method of Standardisation

Next, in our main analysis, we have considered standardised ESG scores with respect to country-industry-median. As coverage of firms varies widely across countries, it could be possible that the country-industry-median ESG scores are different from the country-industry-mean ESG scores. To address this concern, we repeat the standardization process using the country-industry-mean rather than the country-industry-median. Our regression results suggest that the main empirical predictions regarding the downward bias in ESG scores of developing country firms remain qualitatively unchanged even when we use country-industry-mean for standardisation.[30]

4.6.3 Issue of Cross-listed Firms

Lastly, by excluding cross-listed firms from our sample, we recognize that firms from developing countries listed in developed markets might not face the same information challenges as their non-cross-listed peers (Del Bosco and Misani, 2016). This could impact the influence of the *DVPG* dummy on ESG scores. To address this concern, we included cross-listed firms in our sample and repeated the analysis. Our regression results show that, even with cross-listed firms included, developing country firms still experience a downward bias in ESG scores.[31]

5. Conclusion

Using a global sample of firms from 50 developed and developing countries, we demonstrate that corporate ESG scores are systematically lower in developing countries relative to their developed counterparts. We find that the lower ESG scores for developing firms are not only due to the inherent

[29] Results of this analysis are available upon request.
[30] Results of this analysis are available upon request.
[31] Results of this analysis are available upon request.

institutional biases against developing countries but also due to the measurement problems of the ESG raters arising from information asymmetry.

Since the bias stems from measurement issues faced by ESG raters due to the geographical distance that limits their access to information about firms in developing countries (Ayers et al., 2011; Widyawati, 2020), we also propose a solution to this problem. Financial analysts have a larger presence than ESG analysts in developing economies and readily incorporate sustainability-related information into their forecasts and recommendations (Ioannou and Serafeim, 2015; Luo et al., 2015; Kopita and Petrou, 2024). Thus, we provide empirical evidence which shows that ESG raters could rely on analyst coverage and experience to overcome their information asymmetry when assigning ESG scores to developing country firms. This may mitigate the subjectivity in ESG scores and ensure that ESG raters are assigning ESG scores based on actual ESG behaviour and not disclosures.

From a policy perspective, our findings using a developed and developing classification of countries, underscore the systematic tendency for corporate ESG scores to be lower for developing country firms compared to their developed counterparts. Interestingly, this discrepancy is not only caused by varying prioritization of environmental and social issues but also by the information acquisition challenges faced by ESG raters. Hence, stakeholders should be aware of these factors when interpreting ESG scores in emerging economies. To overcome this bias, we suggest that ESG raters incorporate analyst coverage and experience when assigning ESG scores to developing country firms. This would ensure that funds intended to promote sustainable business practices are effectively allocated to achieve global sustainability goals.

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Table 1
Country-wise Distribution of RESG and SESG Scores

Country	No. of Firms	No. of Firm-years	*RESG* Mean	*RESG* Standard Deviation	*SESG* Mean	*SESG* Standard Deviation
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Developing Countries						
Argentina	33	169	0.347	0.193	0.009	0.812
Bermuda	8	32	0.418	0.227	0.004	0.800
Brazil	61	393	0.495	0.218	–0.061	0.881
Chile	16	120	0.516	0.237	–0.029	0.839
China	808	3348	0.342	0.169	0.093	0.966
Colombia	8	61	0.579	0.149	0.024	0.830
Egypt	8	42	0.281	0.100	–0.189	0.800
Hong Kong	99	889	0.435	0.182	0.063	0.894
India	502	1764	0.476	0.183	0.066	0.952
Indonesia	45	360	0.459	0.202	–0.025	0.882
Israel	14	111	0.380	0.239	–0.224	0.845
Korea (South)	134	1225	0.464	0.251	–0.111	0.944
Kuwait	4	14	0.366	0.238	0.000	0.734
Malaysia	297	933	0.420	0.173	0.029	0.919
Mexico	62	280	0.478	0.228	–0.049	0.842
Morocco	18	25	0.348	0.124	–0.109	0.799
Peru	11	67	0.408	0.218	–0.053	0.845
Philippines	16	141	0.477	0.201	–0.027	0.850
Qatar	8	32	0.275	0.146	0.000	0.718
Russia	28	307	0.443	0.159	–0.030	0.901
Saudi Arabia	24	130	0.290	0.212	0.110	0.858
Singapore	46	428	0.427	0.186	–0.031	0.827
South Africa	94	838	0.519	0.178	–0.057	0.877
Taiwan	135	1317	0.463	0.230	0.019	0.941
Thailand	124	462	0.509	0.176	–0.060	0.877
Turkey	58	291	0.557	0.215	–0.067	0.839
United Arab Emirates	19	46	0.337	0.167	0.004	0.776
Vietnam	10	24	0.374	0.197	0.145	0.887
Total	**2,690**	**13,849**				
Developed Countries						
Australia	362	2755	0.372	0.192	0.073	0.938
Austria	10	47	0.522	0.192	0.039	0.782
Belgium	24	174	0.538	0.185	–0.104	0.820
Canada	305	2011	0.402	0.197	0.073	0.935
Denmark	36	185	0.551	0.150	–0.041	0.828
Finland	61	393	0.552	0.183	–0.049	0.832
France	151	1217	0.567	0.204	–0.076	0.902
Germany	218	1345	0.521	0.221	–0.043	0.913
Greece	12	79	0.551	0.160	–0.031	0.801
Ireland	16	120	0.531	0.181	0.071	0.864
Italy	94	469	0.581	0.178	–0.008	0.888
Japan	447	6558	0.444	0.213	–0.025	0.972

Netherlands	39	185	0.574	0.166	0.048	0.822
New Zealand	29	173	0.388	0.149	0.022	0.875
Norway	48	219	0.528	0.190	–0.020	0.840
Poland	26	201	0.402	0.166	0.004	0.786
Portugal	11	77	0.638	0.151	–0.010	0.750
Spain	54	425	0.640	0.185	–0.017	0.877
Sweden	234	957	0.479	0.208	0.002	0.905
Switzerland	120	787	0.489	0.229	0.039	0.927
United Kingdom	520	3754	0.478	0.189	0.003	0.935
United States	2397	18043	0.415	0.196	0.099	0.988
Total	**5,214**	**40,174**				
Sample Total	**7,904**	**54,023**				

Notes: This table reports summary statistics of *RESG* and *SESG* scores by countries. The sample is based on the annual data of firms from 50 developed and developing countries from 2002 to 2022.

Table 2
Summary Statistics

Variables	Country Classification	Mean	Standard Deviation	Median	Minimum	Maximum
(1)	(2)	(3)	(4)	(5)	(6)	(7)
			ESG Scores			
RESG	Developed	0.442	0.205	0.428	0.004	0.956
	Developing	0.432	0.205	0.428	0.007	0.942
RENV	Developed	0.363	0.289	0.343	0.000	0.991
	Developing	0.387	0.260	0.376	0.000	0.988
RSOC	Developed	0.502	0.223	0.507	0.001	0.994
	Developing	0.490	0.221	0.490	0.003	0.980
RGOV	Developed	0.445	0.235	0.421	0.002	0.982
	Developing	0.422	0.251	0.411	0.001	0.984
SESG	Developed	0.045	0.959	0.000	–3.739	3.735
	Developing	0.015	0.921	0.000	–3.037	3.586
SENV	Developed	0.124	0.979	0.000	–3.507	4.899
	Developing	0.038	0.928	0.000	–2.971	3.528
SSOC	Developed	–0.016	0.955	0.000	–3.170	3.044
	Developing	–0.001	0.921	0.000	–2.843	2.754
SGOV	Developed	0.058	0.958	0.000	–3.127	3.675
	Developing	0.032	0.926	0.000	–3.041	3.789
			Analyst Forecasts, Recommendations and Characteristics			
FEEPS	Developed	0.105	0.368	0.010	0.000	2.562
	Developing	0.034	0.102	0.011	0.000	2.562
WLKDN	Developed	0.648	0.478	1.000	0.000	1.000
	Developing	0.807	0.395	1.000	0.000	1.000
NSURP	Developed	0.508	0.500	1.000	0.000	1.000
	Developing	0.633	0.482	1.000	0.000	1.000
RCHG	Developed	–0.118	0.737	0.000	–1.000	1.000
	Developing	–0.178	0.713	0.000	–1.000	1.000
RAVG	Developed	3.463	0.652	3.500	1.000	5.000
	Developing	3.620	0.691	3.667	1.000	5.000
COVR	Developed	1.982	0.795	2.079	0.000	3.932
	Developing	1.706	1.008	1.792	0.000	3.951
EXP	Developed	0.888	0.550	0.847	0.000	2.708
	Developing	0.376	0.339	0.405	0.000	2.079
			Control Variables			
LIQ	Developed	0.174	0.203	0.141	–0.253	0.759
	Developing	0.148	0.191	0.130	–0.253	0.759
RDEXP	Developed	0.027	0.055	0.001	0.000	0.297
	Developing	0.011	0.024	0.000	0.000	0.297
TQ	Developed	2.036	1.570	1.497	0.621	9.991
	Developing	1.964	1.705	1.333	0.621	9.991
LEV	Developed	0.249	0.185	0.235	0.000	0.803
	Developing	0.254	0.176	0.245	0.000	0.803
SIZE	Developed	22.666	2.691	22.155	17.990	30.946
	Developing	25.078	2.524	24.683	17.990	30.946
ROA	Developed	0.031	0.115	0.042	–0.507	0.300
	Developing	0.055	0.080	0.047	–0.507	0.300
GROWTH	Developed	0.090	0.287	0.052	–0.595	1.613
	Developing	0.100	0.290	0.064	–0.595	1.613
CASH	Developed	0.156	0.162	0.102	0.002	0.765

	Developing	0.163	0.128	0.130	0.002	0.765
CAPEXP	Developed	0.045	0.043	0.033	0.000	0.233
	Developing	0.049	0.044	0.037	0.000	0.233
DIV	Developed	0.114	0.317	0.000	0.000	1.000
	Developing	0.480	0.500	0.000	0.000	1.000
VOL	Developed	0.289	0.102	0.268	0.124	0.577
	Developing	0.298	0.087	0.293	0.124	0.577

Notes: This table reports summary statistics for all variables used in the multivariate analysis. All variables are winsorised at their 1st and 99th percentiles. The sample is based on the annual data of firms over 50 developed and developing countries from 2002 to 2022.

Table 3
Difference of ESG Scores between Developed and Developing Countries

Variables	Mean		Difference
	Developed	Developing	(2) – (3)
(1)	(2)	(3)	(4)
Panel A: Raw ESG Scores			
RESG	0.443	0.432	0.010***
RENV	0.363	0.387	–0.024***
RSOC	0.502	0.490	0.012***
RGOV	0.445	0.422	0.023***
Panel B: Standardized ESG Scores			
SESG	0.045	0.015	0.030***
SENV	0.123	0.037	0.086***
SSOC	–0.016	–0.001	–0.015
SGOV	0.058	0.032	0.026***

Notes: This table presents the *t*-test results comparing ESG scores between developed and developing countries. All variables have been winsorized at the 1st and 99th percentiles. Panel A shows the differences in raw ESG scores, while Panel B displays the differences in standardized ESG scores. Column (4) provides the *t*-test results for the ESG score differences between developed and developing countries. The sample includes annual data from firms in over 50 developed and developing countries spanning from 2002 to 2022. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively, and # indicates 10% significance level of a one-tailed *t*-test. *t*-statistics are given in parentheses.

Table 4
Multivariate Regressions of ESG Scores

Variables	Raw Scores				Standardized Scores			
	RESG	*RENV*	*RSOC*	*RGOV*	*SESG*	*SENV*	*SSOC*	*SGOV*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DVPG	–0.116***	–0.158***	–0.063***	–0.122***	–0.219***	–0.192***	–0.152***	–0.201***
	(–13.850)	(–16.445)	(–6.438)	(–11.653)	(–5.154)	(–4.737)	(–3.407)	(–5.087)
LIQ	–0.141***	–0.188***	–0.099***	–0.139***	–0.744***	–0.725***	–0.568***	–0.688***
	(–4.915)	(–5.652)	(–2.823)	(–4.122)	(–4.908)	(–5.286)	(–3.697)	(–4.561)
RDEXP	0.868***	1.183***	0.559***	0.868***	4.212***	4.058***	2.368***	4.303***
	(5.882)	(6.736)	(3.108)	(5.031)	(5.296)	(5.332)	(2.946)	(5.471)
TQ	0.002	–0.002	0.002	0.005*	0.025**	0.021	0.011	0.033***
	(1.012)	(–0.567)	(0.624)	(1.799)	(2.151)	(1.584)	(0.911)	(2.850)
LEV	0.048*	0.062**	0.025	0.051*	0.274**	0.286**	0.196	0.156
	(1.887)	(2.158)	(0.838)	(1.672)	(2.221)	(2.451)	(1.463)	(1.333)
SIZE	0.014***	0.025***	0.007***	0.010***	0.036***	0.028***	0.034***	0.031***
	(8.939)	(14.526)	(3.878)	(4.987)	(4.496)	(3.806)	(3.803)	(4.115)
ROA	0.137***	0.083	0.077*	0.197***	0.270	0.435*	0.187	0.173
	(3.368)	(1.608)	(1.664)	(3.813)	(1.346)	(1.835)	(0.977)	(0.776)
GROWTH	–0.037***	–0.032***	–0.013*	–0.055***	–0.004	0.028	–0.012	0.011
	(–6.035)	(–4.070)	(–1.739)	(–5.600)	(–0.116)	(0.706)	(–0.298)	(0.297)
CASH	–0.069*	–0.056	–0.036	–0.126***	0.022	–0.165	0.111	–0.025
	(–1.876)	(–1.301)	(–0.874)	(–2.892)	(0.114)	(–0.865)	(0.619)	(–0.127)
CAPEXP	–0.042	–0.033	–0.020	0.018	0.578	0.046	0.049	0.887**
	(–0.546)	(–0.366)	(–0.204)	(0.183)	(1.401)	(0.112)	(0.111)	(2.187)
DIV	0.072***	0.077***	0.018**	0.107***	0.095***	0.086**	0.049	0.074**
	(10.427)	(9.167)	(2.327)	(12.079)	(2.710)	(2.379)	(1.415)	(2.111)
VOL	–0.547***	–0.685***	–0.336***	–0.610***	–1.948***	–1.640***	–1.177***	–1.870***
	(–12.870)	(–13.967)	(–7.056)	(–10.986)	(–8.186)	(–7.339)	(–5.027)	(–8.185)
Constant	0.323***	0.089*	0.468***	0.420***	–0.195	–0.026	–0.406*	–0.096
	(7.436)	(1.828)	(10.164)	(7.516)	(–0.966)	(–0.130)	(–1.825)	(–0.489)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,804	45,801	45,804	45,801	45,804	45,608	45,804	45,799
Ad. R-squared	0.322	0.371	0.107	0.297	0.111	0.107	0.057	0.104

Notes: This table presents entropy-balanced multivariate regression estimates, with ESG scores as the dependent variable and the *DVPG* dummy variable as the independent variable of primary interest. All variables have been winsorized at the 1st and 99th percentiles. Columns (2) to (5) show models using raw ESG scores as the dependent variable, while columns (6) to (9) display models using standardized ESG scores. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Table 5
Multivariate Regressions of Standardized ESG Scores with Analyst Variables

Panel A: SESG on Analyst Forecasts, Recommendations and Characteristics

Variables	*SESG*			
(1)	(2)	(3)	(4)	(5)
DVPG	–0.219***	–0.127**	–0.195***	0.057
	(–5.154)	(–2.473)	(–4.263)	(1.047)
FEEPS		0.141***		
		(3.105)		
WLKDN		0.015		
		(0.598)		
NSURP		–0.041		
		(–1.530)		
RCHG			–0.082***	
			(–6.017)	
RAVG			0.035	
			(1.631)	
COVR				0.234***
				(11.235)
EXP				0.146***
				(3.841)
Constant	–0.195	–0.145	–0.074	–0.389
	(–0.966)	(–0.611)	(–0.323)	(–1.613)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	45,804	35,103	37,552	35,257
Adjusted R-squared	0.111	0.129	0.118	0.169

Panel B: SENV on Analyst Forecasts, Recommendations and Characteristics

Variables	*SENV*			
DVPG	–0.192***	–0.109**	–0.170***	0.086
	(–4.737)	(–2.207)	(–3.937)	(1.368)
FEEPS		0.085		
		(1.525)		
WLKDN		0.034		
		(1.223)		
NSURP		–0.051*		
		(–1.877)		
RCHG			–0.070***	
			(–4.527)	
RAVG			0.037*	
			(1.653)	
COVR				0.216***
				(10.306)
EXP				0.190***
				(4.409)
Constant	–0.026	0.089	0.043	–0.185
	(–0.130)	(0.366)	(0.184)	(–0.780)

Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	45,608	34,955	37,371	35,108
Adjusted R-squared	0.107	0.121	0.113	0.159

Panel C: SSOC on Analyst Forecasts, Recommendations and Characteristics				
Variables	*SSOC*			
DVPG	–0.152***	–0.093*	–0.129***	–0.003
	(–3.407)	(–1.744)	(–2.728)	(–0.054)
FEEPS		0.124***		
		(2.843)		
WLKDN		–0.027		
		(–1.000)		
NSURP		–0.009		
		(–0.341)		
RCHG			–0.047***	
			(–3.014)	
RAVG			0.014	
			(0.678)	
COVR				0.141***
				(6.700)
EXP				0.045
				(1.061)
Constant	–0.406*	–0.443	–0.270	–0.556**
	(–1.825)	(–1.642)	(–1.175)	(–1.984)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	45,804	35,103	37,552	35,257
Adjusted R-squared	0.057	0.071	0.061	0.082

Panel D: SGOV on Analyst Forecasts, Recommendations and Characteristics				
Variables	*SGOV*			
DVPG	–0.201***	–0.124***	–0.182***	0.032
	(–5.087)	(–2.650)	(–4.255)	(0.631)
FEEPS		0.118**		
		(2.402)		
WLKDN		0.027		
		(1.010)		
NSURP		–0.051*		
		(–1.916)		
RCHG			–0.075***	
			(–5.326)	
RAVG			0.038*	
			(1.846)	
COVR				0.205***
				(9.979)
EXP				0.116***

				(3.108)
Constant	–0.096	–0.074	–0.055	–0.280
	(–0.489)	(–0.319)	(–0.241)	(–1.201)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	45,799	35,100	37,547	35,254
Adjusted R-squared	0.104	0.123	0.109	0.153

Notes: This table presents multivariate regression estimates using an entropy-balanced sample with standardized ESG scores as the dependent variable and the *DVPG* dummy variable as the key independent variable. Additional control variables related to analysts' information are included: earnings forecast metrics (analysts forecast error of EPS (*FEEPS*), analysts walk down of EPS forecast (*WLKDN*), and negative surprise of EPS forecast (*NSURP*)), recommendation metrics (change of recommendation (*RCHG*) and average of recommendation (*RAVG*)), and analysts' characteristics (analyst coverage (*COVR*) and experience (*EXP*)). Columns (2) to (5) report the regression results, with Column (2) presenting the baseline model. Panel A shows the multivariate model with *SESG* as the dependent variable, Panel B shows the multivariate model with *SENV* as the dependent variable, Panel C shows the multivariate model with *SSOC* as the dependent variable and Panel D shows the multivariate model with *SGOV* as the dependent variable. All variables are winsorized at the 1st and 99th percentiles. The sample includes annual data of firms in from 50 developed and developing countries from 2002 to 2022. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Table 6
Impact of Unobservable Confounding Variables

Variables	Raw Scores				Standardized Scores			
	RESG	*RENV*	*RSOC*	*RGOV*	*SESG*	*SENV*	*SSOC*	*SGOV*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ITCV (DVPG)	0.055	0.061	0.020	0.046	0.015	0.012	0.006	0.015
Impact Scores								
RSIZE	0.012	0.011	0.006	0.012	0.012	0.010	0.007	0.011
LIQ	0.003	0.003	0.001	0.003	0.003	0.003	0.002	0.003
RDEXP	–0.014	–0.009	–0.006	–0.015	–0.011	–0.009	–0.005	–0.011
TQ	0.000	–0.001	–0.000	0.001	0.000	0.000	–0.000	0.000
LEV	0.001	0.000	0.000	0.001	0.001	0.001	0.000	0.001
ROA	0.005	0.006	0.003	0.004	0.005	0.004	0.004	0.004
GROWTH	–0.001	–0.001	–0.001	–0.001	–0.001	–0.000	–0.000	–0.000
CASH	–0.002	–0.002	–0.004	–0.002	–0.001	–0.001	–0.000	–0.001
CAPEXP	–0.001	0.000	0.000	–0.001	0.000	–0.000	–0.000	0.000
DIV	**0.031**	**0.040**	–0.008	**0.040**	–0.014	**–0.017**	–0.008	–0.013
VOL	–0.024	–0.023	**–0.013**	–0.022	**–0.015**	–0.013	**–0.009**	**–0.015**

Notes: This table presents the Impact Threshold for Confounding Variable (ITCV) analysis for regression results presented in Table 4. The first row shows the ITCV values of the DVPG dummy for respective models. The following rows display the impact scores for the control variables. Columns (2) to (5) presents models using raw ESG scores as the dependent variable, while Columns (6) to (9) presents models with standardized ESG scores as the dependent variable.

Table 7
Effect of Mandatory ESG Disclosures

Variables	Raw Scores				Standardized Scores			
	RESG	*RENV*	*RSOC*	*RGOV*	*SESG*	*SENV*	*SSOC*	*SGOV*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DVPG	–0.204***	–0.245***	–0.052***	–0.292***	–0.324***	–0.334***	0.004	–0.346***
	(–9.345)	(–8.578)	(–2.800)	(–10.590)	(–2.950)	(–3.215)	(0.032)	(–3.064)
MAN	–0.069***	–0.041	–0.071***	–0.101***	–0.016	–0.104	0.078	–0.126
	(–3.354)	(–1.528)	(–3.107)	(–3.419)	(–0.178)	(–1.092)	(0.657)	(–1.386)
DVPG* × *MAN	**0.050****	**0.030**	**0.058****	**0.070****	**0.020**	**0.014**	**–0.077**	**0.016**
	(1.991)	(0.920)	(2.147)	(2.004)	(0.170)	(0.113)	(–0.520)	(0.139)
Constant	0.161	0.170	0.477***	–0.030	–1.684***	–1.438***	–0.529	–1.094**
	(1.321)	(1.090)	(3.800)	(–0.201)	(–3.280)	(–3.009)	(–1.036)	(–2.131)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,482	2,482	2,482	2,482	2,482	2,479	2,482	2,482
Ad. R-squared	0.379	0.371	0.181	0.357	0.162	0.148	0.068	0.141

Notes: This table presents the results of a difference-in-difference (DiD) analysis examining the effect of mandatory ESG disclosure. The multivariate regressions use raw and standardized ESG scores as dependent variables, with the *DVPG* dummy variable as the independent variable of interest. Columns (2) to (5) feature models with raw ESG scores as the dependent variable, while Columns (6) to (9) present models with standardized ESG scores as the dependent variable. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Appendix A

Variable Definition

Variables	Definitions
RESG	Firm's overall raw ESG score obtained from Refinitiv.
RENV	Firm's individual raw environmental score obtained from Refinitiv.
RSOC	Firm's individual raw social score obtained from Refinitiv.
RGOV	Firm's individual raw governance score obtained from Refinitiv.
SESG	Firm's standardized ESG score measured as the difference between firm-year ESG score and the median of country-industry-year ESG score divided by the standard deviation of country-industry-year ESG score.
SENV	Firm's standardized environment score measured as the difference between firm-year environment score and the median of country-industry-year environment score divided by the standard deviation of country-industry-year environment score.
SSOC	Firm's standardized social score measured as the difference between firm-year social score and the median of country-industry-year social score divided by the standard deviation of country-industry-year social score.
SGOV	Firm's standardized governance score measured as the difference between firm-year governance score and the median of country-industry-year governance score divided by the standard deviation of country-industry-year governance score.
DVPG	Indicator variable equals one if the country is classified as developing country by the United Nations' 2018 classification, and zero otherwise. https://www.un.org/development/desa/dpad/wp–content/uploads/sites/45/publication/WESP2018_Full_Web–1.pdf
FEEPS	Analysts' forecast error of EPS of the firm in the fiscal year end in consideration.
WLKDN	Indicator variable equals one if the calculated walkdown (analysts' first forecast minus last forecast, scaled by total assets and finally multiplied by 1000) of each firm-year is above the median of country-industry-year, and zero otherwise.
SURP	The difference between firm's actual EPS and the median of analysts' *EPS* forecast, scaled by the stock price at the beginning of the fiscal year.
NSURP	An indicator which equals one (and zero otherwise) if firm's *SURP* is negative.
RECOM	Categorical variable with the value if 1, 2, 3, 4, 5, which indicates the analyst issues "strong sell", "sell", "still", "buy", "strong buy" recommendations.
RAVG	Mean of analyst *RECOM* for all analysts who cover a firm over a year.
RCHG	The difference between the *RAVG* in the next year ($t + 1$) and the *RAVG* in the current period (t).
COVR	Logarithm of the number of analysts following the firm during the year.
EXP	Logarithm of analyst's firm-specific experience measured as the number of prior years he has issued annual earnings forecasts for a given firm. The variable is averaged across analysts following the firm.
LIQ	The ratio of the difference between current asset and current liabilities over total assets at the end of fiscal year.
RDEXP	The ratio of R&D expenditure over total assets at the end of fiscal year.
TQ	The ratio of the sum of total assets and market capitalization minus common equity over total assets at the end of fiscal year.
LEV	The ratio of total debt to total assets at the end of fiscal year.
SIZE	Firm size calculated as the natural log of the firm's assets at of the end of fiscal year.
RSIZE	The total assets of a firm in a given year divided by the sum of the total assets of all firms in the same industry and year.
ROA	Return on assets (income before extraordinary items divided by average total assets.
GROWTH	Change in sales scaled by lagged total sales.

CASH	The percentage of cash and short-term investments over total assets.
CAPEXP	The ratio of capital expenditure to total assets at the end of fiscal year.
DIV	An indicator which equals one (and zero otherwise) if the firm has dividend payout at the end of fiscal year.
VOL	Stock price volatility obtained from Worldscope.

Appendix B
Univariate Regressions of ESG Scores

Variables	Raw Scores				Standardized Scores			
	RESG	*RENV*	*RSOC*	*RGOV*	*SESG*	*SENV*	*SSOC*	*SGOV*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LIQ	–0.170***	–0.286***	–0.106***	–0.150***	–0.589***	–0.603***	–0.366***	–0.523***
	(–35.693)	(–43.750)	(–20.328)	(–26.689)	(–26.296)	(–26.194)	(–16.447)	(–23.281)
RDEXP	–0.142***	–0.626***	–0.175***	0.100***	–0.250***	–0.270***	–0.607***	–0.148***
	(–7.046)	(–22.557)	(–8.004)	(4.237)	(–3.012)	(–4.935)	(–7.337)	(–2.761)
TQ	–0.007***	–0.024***	–0.006***	0.001	–0.006**	0.004*	–0.019***	0.003
	(–11.444)	(–29.713)	(–9.085)	(1.043)	(–2.453)	(1.711)	(–7.343)	(1.216)
LEV	0.113***	0.173***	0.066***	0.113***	0.443***	0.474***	0.254***	0.379***
	(21.434)	(23.926)	(11.611)	(18.367)	(18.042)	(18.809)	(10.449)	(15.432)
SIZE	0.021***	0.040***	0.009***	0.015***	0.064***	0.052***	0.041***	0.064***
	(64.371)	(95.946)	(25.701)	(39.054)	(42.036)	(33.050)	(26.524)	(41.957)
ROA	0.220***	0.304***	0.158***	0.195***	0.817***	0.712***	0.560***	0.752***
	(23.509)	(23.598)	(15.509)	(17.804)	(18.691)	(15.863)	(12.916)	(17.165)
GROWTH	–0.073***	–0.109***	–0.045***	–0.067***	–0.138***	–0.113***	–0.142***	–0.090***
	(–21.208)	(–23.141)	(–12.026)	(–16.774)	(–8.602)	(–6.847)	(–8.966)	(–5.618)
CASH	–0.186***	–0.350***	–0.156***	–0.138***	–0.566***	–0.545***	–0.397***	–0.480***
	(–29.755)	(–40.971)	(–22.948)	(–18.741)	(–19.295)	(–18.052)	(–13.649)	(–16.308)
CAPEXP	–0.189***	0.008	0.053**	–0.302***	0.015	–0.240**	–0.200**	0.310***
	(–8.625)	(0.274)	(2.412)	(–11.780)	(0.147)	(–2.502)	(–2.140)	(3.309)
DIV	0.080***	0.132***	0.014***	0.097***	0.080***	0.037***	0.057***	0.062***
	(34.359)	(41.375)	(5.494)	(35.577)	(7.286)	(3.295)	(5.253)	(5.621)
VOL	–0.630***	–0.874***	–0.405***	–0.632***	–1.936***	–1.700***	–1.313***	–1.792***
	(–75.314)	(–76.072)	(–43.220)	(–64.011)	(–48.637)	(–41.603)	(–32.704)	(–44.848)

Notes: This table reports univariate regression estimates employing raw and standardized ESG scores as dependent. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Appendix C
Correlation Matrix

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FEEPS	(1)	1.000								
WLKDN	(2)	0.033	1.000							
NSURP	(3)	0.049	0.681	1.000						
RCHG	(4)	–0.012	–0.058	–0.045	1.000					
RAVG	(5)	–0.029	–0.051	–0.042	0.372	1.000				
COVR	(6)	–0.079	0.019	–0.038	–0.204	–0.055	1.000			
EXP	(7)	–0.125	–0.063	–0.103	0.034	–0.037	0.352	1.000		
LIQ	(8)	–0.058	–0.049	–0.054	0.039	0.041	0.001	0.070	1.000	
RDEXP	(9)	–0.040	–0.049	–0.058	0.026	0.033	0.103	0.123	0.387	1.000
TQ	(10)	–0.065	–0.115	–0.113	0.006	0.033	0.105	0.067	0.279	0.322
LEV	(11)	0.023	0.069	0.072	–0.001	–0.041	–0.008	0.058	–0.415	–0.184
SIZE	(12)	–0.153	–0.001	0.025	–0.087	0.001	0.150	–0.139	–0.153	–0.147
ROA	(13)	–0.086	–0.189	–0.200	–0.019	0.035	0.089	0.032	0.075	–0.210
GROWTH	(14)	–0.052	–0.167	–0.172	0.035	0.102	–0.017	–0.017	0.070	0.106
CASH	(15)	–0.050	–0.063	–0.058	0.014	0.035	0.030	–0.006	0.674	0.517
CAPEXP	(16)	–0.042	0.020	0.034	–0.048	0.038	0.038	–0.046	–0.237	–0.150
DIV	(17)	0.045	0.054	0.066	–0.063	–0.013	–0.008	–0.283	–0.156	–0.143
VOL	(18)	0.089	0.027	0.051	0.007	0.063	–0.114	–0.111	0.225	0.218
		(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
TQ	(10)	1.000								
LEV	(11)	–0.193	1.000							
SIZE	(12)	–0.261	0.076	1.000						
ROA	(13)	0.316	–0.217	0.048	1.000					
GROWTH	(14)	0.176	–0.055	–0.066	0.107	1.000				
CASH	(15)	0.402	–0.336	–0.113	–0.021	0.100	1.000			
CAPEXP	(16)	–0.037	0.040	0.015	0.020	0.051	–0.185	1.000		
DIV	(17)	–0.112	0.062	0.182	0.023	–0.048	–0.084	–0.004	1.000	
VOL	(18)	0.040	–0.073	–0.209	–0.288	0.143	0.273	0.101	–0.089	1.000

Notes: This appendix table reports corelation metrics for all control variables used in the multivariate analysis. All variables are winsorised at their 1st and 99th percentiles. The sample is based on the annual data of firms over 50 developed and developing countries from 2002 to 2022.

Appendix D
Descriptive Statistics of Entropy Balanced Sample

Variables	Treat Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Before Entropy Balancing						
LIQ	0.148	0.036	0.389	0.174	0.041	0.756
RDEXP	0.011	0.001	4.382	0.027	0.003	3.087
TQ	1.964	2.907	2.724	2.036	2.464	2.756
LEV	0.254	0.031	0.501	0.249	0.034	0.639
SIZE	25.080	6.372	0.560	22.670	7.241	0.680
ROA	0.055	0.006	–0.845	0.031	0.013	–2.172
GROWTH	0.100	0.084	1.678	0.090	0.082	2.323
CASH	0.163	0.016	1.538	0.156	0.026	1.859
CAPEXP	0.049	0.002	1.529	0.045	0.002	2.099
DIV	0.480	0.250	0.078	0.114	0.101	2.436
VOL	0.298	0.008	0.377	0.289	0.011	0.944
After Entropy Balancing						
LIQ	0.148	0.036	0.389	0.148	0.036	0.389
RDEXP	0.011	0.001	4.382	0.011	0.001	4.383
TQ	1.964	2.907	2.724	1.964	2.907	2.724
LEV	0.254	0.031	0.501	0.254	0.031	0.501
SIZE	25.080	6.372	0.560	25.080	6.372	0.560
ROA	0.055	0.006	–0.845	0.055	0.006	–0.845
GROWTH	0.100	0.084	1.678	0.100	0.084	1.678
CASH	0.163	0.016	1.538	0.163	0.016	1.538
CAPEXP	0.049	0.002	1.529	0.049	0.002	1.529
DIV	0.480	0.250	0.078	0.480	0.250	0.078
VOL	0.298	0.008	0.377	0.298	0.008	0.377

Note: This table reports the summary statistics before and after entropy-balanced matching. All variables have been winsorized at the 1st and 99th percentiles. The sample comprises annual data of firms over 50 developed and developing countries from 2002 to 2022.

Appendix E
Summary Statistics – Entire Sample

Variables	Number of observations	Mean	Standard Deviation	Median	Minimum	Maximum
(1)	(2)	(3)	(4)	(5)	(6)	(7)
			ESG Scores			
RESG	54,023	0.440	0.205	0.428	0.004	0.956
RENV	54,018	0.369	0.282	0.352	0.000	0.991
RSOC	54,023	0.499	0.223	0.502	0.001	0.994
RGOV	54,018	0.439	0.239	0.419	0.001	0.984
SESG	54,023	0.038	0.949	0.000	–3.739	3.735
SENV	53,662	0.102	0.967	0.000	–3.507	4.899
SSOC	54,023	–0.012	0.947	0.000	–3.170	3.044
SGOV	54,016	0.051	0.950	0.000	–3.127	3.789
			Analyst Forecasts, Recommendations and Characteristics			
FEEPS	36,484	0.092	0.338	0.010	0.000	2.562
WLKDN	54,023	0.689	0.463	1.000	0.000	1.000
NSURP	36,484	0.529	0.499	1.000	0.000	1.000
RCHG	39,207	–0.132	0.732	0.000	–1.000	1.000
RAVG	39,207	3.500	0.665	3.500	1.000	5.000
COVR	36,645	1.934	0.843	2.079	0.000	3.951
EXP	43,633	0.776	0.553	0.693	0.000	2.708
			Control Variables			
LIQ	54,023	0.167	0.200	0.138	–0.253	0.759
RDEXP	54,023	0.023	0.049	0.001	0.000	0.297
TQ	54,023	2.017	1.606	1.456	0.621	9.991
LEV	54,023	0.250	0.183	0.237	0.000	0.803
SIZE	54,023	23.285	2.851	22.847	17.990	30.946
ROA	54,023	0.037	0.108	0.043	–0.507	0.300
GROWTH	54,023	0.093	0.288	0.055	–0.595	1.613
CASH	54,023	0.158	0.154	0.111	0.002	0.765
CAPEXP	54,023	0.046	0.044	0.034	0.000	0.233
DIV	54,023	0.208	0.406	0.000	0.000	1.000
VOL	54,023	0.291	0.099	0.275	0.124	0.577

Notes: This table reports summary statistics for all variables used in the multivariate analysis. All variables are winsorised at their 1st and 99th percentiles. The sample is based on the annual data of firms over 50 developed and developing countries from 2002 to 2022.