Biodiversity Risk Disclosure and Analyst Forecasts

Abstract

Does the disclosure of biodiversity information affect analyst forecast accuracy? This question is important in light of recent initiatives by academics and global policymakers to raise awareness about biodiversity. Biodiversity is a key component of natural capital and fosters economic development and societal wellbeing (Heal, 2020; Dasgupta, 2024). While the natural resources literature has long underscored economic aspects of biodiversity, researchers are just beginning to study financial implications. In this study, we examine the relationship between biodiversity information disclosure and analyst forecast accuracy. Using data from publicly listed U.S. firms from 2000 to 2023, we find a significant negative relationship between biodiversity information disclosures and analyst forecast errors. While biodiversity disclosures generally contribute to reducing forecast errors, we observe that the combined effect of strong environmental performance alongside these disclosures can paradoxically lead to increased inaccuracies in forecasts. Our findings highlight the crucial role of biodiversity information for sophisticated market participants, such as analysts. However, as firms grapple with the evolving factors that influence biodiversity disclosures, analysts may inadvertently overestimate the benefits associated with high environmental performance, resulting in potential inaccuracies in their forecasting efforts.

Keywords: Biodiversity; Financial Accounting; Disclosure; Natural Capital; Analyst Forecast Accuracy

JEL Classification: G12; G14; G30; M41; Q51; Q57

The authors have no conflicts of interest to declare.

I. Introduction

Business decisions often depend on the abundance of natural capital—the natural and environmental benefits present in a given location, including biodiversity. Some business decisions hinge directly on biodiversity, as in the pharmaceutical industry (see Heal (2020)). But even if a particular business does not immediately rely on biodiversity, it may have a detectable exposure to biodiversity risk. Biodiversity is a global public good which unregulated market will under-provide (Barrett (2007)). Nevertheless, society can elicit provision by various channels that raise awareness, including public pressure, social norms, and media attention (Dannenberg et al. (2024); Zhang and Khanna (2024)). Recent initiatives to highlight biodiversity risk by academics and global policymakers represent a key step towards raising public awareness of biodiversity. While evidence suggests that investors are relatively slow to incorporate biodiversity risk (Giglio et al. (2023); Garel et al. (2024)), finance and accounting theory indicates that the disclosure of such risk is valuable. It is imperative to understand the perceived financial value of biodiversity risk disclosure using standard financial accounting frameworks. If the perceived value is significant, this reassures policymakers that investors and other stock market participants take biodiversity seriously. By contrast, if disclosure value appears negligible, this will spur policymakers to raise investor awareness about biodiversity risk. In order to address this issue, therefore, we examine whether biodiversity risk disclosure affects the accuracy of analyst forecasts.

We may expect a negligible impact, given the recency with which biodiversity has garnered attention among finance professionals and researchers—as well as the relatively small percentage of firms that disclose. If biodiversity awareness follows the path of climate change awareness, markets shall in the medium term possess good biodiversity risk metrics and other information that aid investor decision making. Thus, we feel it is important to provide a benchmark in order to

assess whether and to what extent biodiversity disclosure is already making an impact on analyst forecasts.

Prior studies document the role of firms' disclosure in lowering information asymmetry and improving analyst forecasts (Lang and Lundholm (1996); Byard and Shaw (2003); Francis et al. (2005)). Nonfinancial information such as corporate social responsibility (CSR) and environmental, social and governance (ESG) disclosures significantly improve analysts' forecast accuracy (Cormier and Magnan (2014); Dhaliwal et al. (2014); Bernardi and Stark (2018)). Increased voluntary disclosure related to environmental issues improves transparency, reduces uncertainty, and provides better insights into a company's operational resilience, regulatory risks, and stakeholder expectations. Accordingly, biodiversity disclosures can provide relevant information about a firm's dependence on natural resource extraction and ecosystem services. Biodiversity disclosures can also indicate a company's commitment to innovation in sustainable practices, reducing habitat destruction and negative impacts on climate. By integrating biodiversity considerations, analysts can be better informed of firms' potential risks and opportunities and make more accurate forecasts about firms' operational efficiency, future earnings, and fundamental valuation. Thus, our main research question: Does biodiversity disclosure affect analyst forecast accuracy?

We join three ongoing research conversations. One important conversation involves recent studies on biodiversity finance. Karolyi and Tobin-de la Puente (2023) summarize outstanding issues in biodiversity finance, distinguish it from climate finance, and call for research in this area. Flammer et al. (2023) tackle the conundrum of how to finance biodiversity conservation. Using proprietary data on biodiversity-related deals, they document an interesting dichotomy: smaller projects with high expected returns are more often financed by private capital, while larger projects

tend to have a blend of private and public capital. Giglio et al. (2023) conduct a systematic study of firm exposure to biodiversity risk at both the aggregate and firm level, based on textual analysis and surveys. The authors document substantial variation in industry-level biodiversity risk and provide some evidence that biodiversity risk is related to stock prices. Flammer et al. (2024) study the sustainability implications of blended finance, where public and philanthropic funding are used to encourage private capital. The authors highlight the importance of concessionally, the extent to which the blended investment subsidizes the venture. They discover a positive relationship between projects' concessionally and several key variables, including the projects' sustainability im- pact, political risk, and information asymmetry. Garel et al. (2024) analyze the corporate biodiversity footprint (CBF), which measures the firm-level impact of biodiversity. The authors document mixed evidence on CBF: while it does not explain the cross-section of returns in their sample, they discern the emergence of a premium in the wake of important 2021 biodiversity announcements—the establishment up of the Taskforce on Nature-related Financial Disclosures, and the Kunming Declaration. We add to this prescient literature by analyzing implications for cost of capital and analyst forecasts.

The second conversation concerns the ways in which environmental policy can be encouraged by norms and public pressure. A natural contention is that biodiversity disclosure should not matter for market-based firms in the absence of regulation. Without regulation, firms do not internalize biodiversity and therefore we should not expect any effect. By contrast, recent natural resources literature emphasizes non-regulatory avenues both to impel policy action and to actuate firms' environmentally conscious decisions in the absence of regulation. In particular, norms and public pressure can impel governments and firms to foster environmental

protection.[1]Araujo et al. (2024) illustrate the power of media and public attention to reduce environmental damage. They focus on the annual forest fires in the Amazon, which went viral in August 2019. Preserving the Amazon's forests is an important goal under the Paris Agreement and the United Nations Sustainable Development Goals. The authors utilize a difference-in-differences approach to compare fires in Brazil, Peru, and Bolivia. They show that increased public attention reduced fires by 22% and avoided nearly 25 million tons of CO2 emissions. This finding is striking because the Brazilian administration was openly opposed to conservation but still acted because of the surge in public attention. Kruse et al. (2024) study whether markets respond to firms' climate actions. They use the Paris Agreement as a quasi-natural experiment and document a 10% average increase in cumulative abnormal returns for firms that earn large revenues from green goods and services. The authors conclude that financial markets respond well to the creation of new environmental markets. Zhang and Khanna (2024) study how public pressure can affect firms who do not participate in voluntary environmentally friendly activities. They show that voluntary activities are more effective when there are high costs to being publicly scrutinized, which lowers the number of free riders and improves environmental quality. Their model also explains empirical results for voluntary pollution abatement programs.

Social norms also play an outsize role in environmental behavior. An environmental policy may appear inefficient when considering individual firms, but can become efficient if one firm's choice to be environmentally aware influences others to do likewise. Dannenberg et al. (2024) emphasize the importance of social norms in environmental behavior. The authors conclude that influencing norms is a powerful tool for environmental policymakers. We add to this literature by

[1] For instances of public pronouncements on biodiversity, see the UN statements at https://www.un.org/en/climatechange/science/climate-issues/biodiversity and the listing of biodiversity preservation as UN Sustainable Development Goal 15: https://sdgs.un.org/goals/goal15.

studying another setting where social norms and public pressure are important for environmental policy.

Third important conversation concerns research on the implications of disclosure about corporate social responsibility (CSR) and climate risk. Dhaliwal et al. (2012) analyze the impact of CSR disclosure on the cost of capital, using firm-level data. The authors document a negative relation between CSR and the cost of capital, especially in countries that are stakeholder oriented. Dhaliwal et al. (2014) parse the relation between disclosure of nonfinancial information and analyst forecast accuracy, documenting a positive relationship between issuance of stand-alone CSR reports and forecast accuracy. Once again, this relationship is more pronounced in stakeholder-oriented countries. Dhanda and Malik (2020) assess the role of carbon management on emission disclosure and find that effective carbon managing firms are more likely to disclose information about emissions. Ilhan et al. (2023) study the implications of climate risk disclosure in financial markets, using a mix of survey and observational data on institutional investors. They present evidence that institutional investors value climate risk disclosure. Besides these papers, there is a relatively new literature that examines whether disclosure regulation increases firm biodiversity disclosure (Bhattacharyyam and Yang (2019)), and whether biodiversity disclosure is linked to gender diversity on corporate boards (Haque and Jones (2020)). We extend the accounting disclosure frameworks utilized by Dhaliwal et al. (2012) and Dhaliwal et al. (2014), who both examine firm-level data in multiple countries. Our main innovation to this valuable research stream is to include implications of disclosure of biodiversity risk. Our study contributes to the literature by documenting evidence on how biodiversity-related information disclosure helps reduce information asymmetry for the firms, resulting in improved analyst forecast accuracy. Attention to biodiversity risk is just beginning to grow in business circles, so we expect many results to be quite

muted. Additionally, our work adds value by providing a benchmark for future research on biodiversity, and by opening a window to view biodiversity disclosure's impact on business.

II. Methodology

We analyze whether voluntary disclosure of biodiversity information has a discernible impact on investors and financial market participants. We use a financial accounting framework on disclosure to parse the impact of biodiversity risk on analyst forecast precision. To measure biodiversity risk disclosure, we incorporate an index from the database constructed by Giglio et al. (2023).[2] The main variable is "BIODIS", a scoring variable computed from the 10-K statements of firms. If a 10-K statement contains at least two biodiversity- related sentences, the score is "1", otherwise it is zero. Our main empirical framework uses a least squares regression to determine the association between biodiversity disclosure BIODIS and analyst forecast accuracy. For our research question—testing the link between biodiversity disclosure and analyst forecast accuracy—we develop the model of Hope (2003) and estimate the following equation:

$$
\begin{aligned}
FERROR_1 = {} & \alpha_0 + \beta_1 SIZE_{i,t} + \beta_2 LEVERAGE_{i,t} + + \beta_3 BM_{i,t+} + \beta_4 RETVAR_{i,t} \\
& + \beta_5 FHORIZON_{i,t} + \beta_6 ANANO_{i,t} + \beta_7 AACCQ_{i,t} + \beta_8 AUDQ_{i,t} + \beta_9 LOSS_{i,t} \\
& + \beta_{10} FAGE_{i,t} + \beta_{11} TANGB_{i,t} + \beta_{12} ENVIRON_{i,t} + \beta_{13} FFIN_{i,t} + \beta_{12} BIODIS_{i,t} \\
& + \beta_{13} BIODIS\ X\ ENVIRON_{i,t} + Year_Indicators_{\ i,t} \\
& + Industry_Indicators_{i,t} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)
\end{aligned}
$$

We use a standard set of control variables in expression (1). In keeping with previous literature on analyst forecasts (Dhaliwal et al. (2012)), we use analyst forecast error as an inverse measure of forecast accuracy. We compute analyst forecast error (FERROR) as the average of absolute errors of all forecasts made in the year for earnings, scaled by the stock price at the

[2] We thank Giglio et al. (2023) for graciously making these data available.

beginning of the year. We use three types of forecast errors - the forecast error for the forecast made in year t for the earnings of year t+1, the forecast made in year t for the earnings of year t+2, and the forecast made in year t for the earnings of year t+3.

We control for various firm-specific characteristics that previous literature documents as determinants of analyst forecast accuracy. The control variables are: SIZE (the natural log of a firm's market value of equity); LEVERAGE (long-term debt divided by total assets); BM (the ratio of the book value of equity to the market value of equity); RETVAR (the variability of stock return, measured as the standard deviation of daily stock returns over the past year); ACCQ (whether the firm follows the UG GAAP); AUDQ (whether the firm is audited by one of the Big Four audit firms); and TANGB (natural logarithm of net property, plant, and equipment). We measure the firm's financial opacity, FFIN, in similar manner to Bhattacharya et al. (2003), DeFond and Hung (2003), and Leuz et al. (2003). Financial opacity is the absolute value of scaled accruals averaged over the previous three years. Beyond these variables, we control other variables that have been found significant for analyst forecasting, such as: LOSS (whether the firm reports net loss); FHORIZON (forecast horizon estimated as the length of time between the forecasting date and the earnings announcement date); and ANANO (the natural logarithm of the number of analysts following the firm throughout the year).

We also include a role for firms' environmental performance and test the joint effects of biodiversity disclosure and environmental performance on analyst forecast errors. Therefore, our model uses an interaction term of BIODIS with environmental performance. We measure firms' environmental performance scores, ENVIRON, using the MSCI Environmental Pillar score. The environmental pillar score is calculated based on four key themes: climate change, natural capital, pollution and waste, and environmental opportunities. Each theme includes several key rating

areas. The environmental score is estimated by using a total of 13 critical areas of these four themes. We also control industry- and year-fixed effects. We conduct robustness tests using firm-fixed effect model. In light of our research question, our key explanatory variables are BIODIS and the interaction variables with ENVIRON. We expect a negative, statistically significant coefficient for the variable BIODIS. A negative coefficient for BIODIS implies fewer forecast errors (higher forecast accuracy) as disclosure increases. Appendix A provides the definitions of the variables. In our regression model, the standard errors are clustered by firms, which control for within-firm correlation over time.

III. Data Description and Empirical Tests

We utilize data from several sources. We collect environmental performance and climate risk information from MSCI's ESG database. MSCI contains the ESG scores based on three pillar ratings: environmental pillar, social pillar, and governance pillar. These three pillars provide ratings measuring a firm's resilience to financially material environmental, societal, and governance risks and opportunities. MSCI has coverage for global firms from 2007 to the present. We use the industry-adjusted weighted average scores of the three pillars: environment, social, and governance. We also use only the environmental pillar score, carbon emission, and climate change theme scores for robustness tests and additional analysis. These detailed scoring on various environmental theme data are available from 2013. We utilize the biodiversity disclosure dataset of Giglio et al. (2023), which provides measures of biodiversity exposure at the firm and aggregate level from 2001 to 2023. Firm characteristics variable information is collected from COMPUSTAT North America, which contains publicly listed company financial data from 1950 to present. Additionally, we collect the analyst forecast data from the IBES database. IBES provides analyst forecasting estimates and company guidance for more than 23,400 public companies. The stock

returns data are collected from CRSP. CRSP contains daily and monthly stock price data for over 32,000 active and inactive securities with primary listings on the NYSE, NYSE American, NASDAQ, NYSE Arca, and Cboe BZX exchanges. Stock price data are available for NYSE firms from 1925 to 2023. For NASDAQ firms.

Given the nascent stage of research on biodiversity risk, we propose a basic null hypothesis for the informativeness of biodiversity disclosure. After testing the hypothesis, we assess the economic mechanism underlying the relationships between biodiversity disclosure and analyst forecast precision.

Hypothesis 1: Biodiversity disclosure is not associated with analyst forecast accuracy.

Our hypothesis reflects the widespread lack of awareness about biodiversity risk (see Giglio et al. (2023)). We note that another approach to formulate the hypotheses would have been to aver that despite the lack of information and awareness about biodiversity risk, biodiversity concerns may overlap with other environmental concerns. This approach builds on theories from previous environmental disclosure—CSR and ESG reporting, say —to motivate a negative association between biodiversity disclosure and analyst forecast accuracy. Given the nascent character of biodiversity risk disclosure, however, we thought that such associations would start to arise in the future, as awareness of biodiversity risk unfolded. While there is a growing body of accounting and finance literature on CSR and ESG disclosure, the concept of biodiversity risk is new to the financial world. Stock market participants and stakeholders may consider biodiversity risk less important than other environmental issues like carbon emissions and climate change.

Several ESG and CSR databases are well-accepted and widely used in the literature, such as Asset4, MSCI ESG, KLD, Sustainalytics, CSRHUB, Bloomberg, and Refinitiv (Martiny et al. (2024)). The disclosure measurements of ESG and CSR are also common in the literature.

However, the biodiversity performance metrics and biodiversity risk disclosure measurement are yet to be established. We utilize disclosure data from Giglio et al. (2023), an early systematic paper on biodiversity risk.

IV. Main Results and Discussions

We construct our dataset by combining information from several sources: biodiversity disclosure from Giglio et al. (2023); environmental and climate change strategy scores from MSCI; firms' financial variables from COMPUSTAT; stock prices from CRSP; and analyst forecast data from IBES. Table 1 Panel A shows the sample distribution by year. The sample size is significantly lower in earlier years, from 2000 to 2011, due to the smaller amount of firm coverage in the MSCI ESG database. Panel B presents the sample distribution by industry, which shows that the majority of firms are in manufacturing.

[Table 1]

Table 2 reports descriptive statistics for our variables of interest. Analyst forecast errors (FERROR) are larger for forecasts of longer horizons. The environmental score has a mean value of 4.407. The environmental scores range from zero to ten, and the higher the scores, the better the firm is doing in terms of environmental performance and dealing with climate change risks. The mean value of biodiversity disclosures is slightly above 0.04, implying that only 4% of our firm-year observations have biodiversity risk disclosures.

[Table 2]

Table 3 presents the correlation matrix for the variables. Forecast errors are highly correlated, while large firms have fewer forecast errors. Moreover, loss firms have more forecast errors. However, there is no significant correlation between forecast errors and environmental

scores, as well as biodiversity disclosures. We find that biodiversity disclosure is positively correlated with accounting and audit quality.

[Table 3]

Table 4 displays regression results for biodiversity risk disclosures and analyst forecast errors. The sample includes publicly listed firms in the U.S. from 2000 to 2023. We find that biodiversity disclosure has a significant negative impact on analyst forecast errors. The negative association is stronger for the forecast errors when analysts project further into the future. Thus, our findings imply that biodiversity risk disclosures improve the information environment for the analysts, allowing them to more accurately assess a company's performance and risk exposures. Additionally, we find that firms' environmental performance and biodiversity disclosures jointly increase analyst forecast errors, as evidenced by the significant coefficient for the interaction variable, BIODIS × ENVIRON.

The finding that firms with better environmental performance, combined with biodiversity disclosure, may increase analysts' forecast errors can stem from several factors. The interplay between biodiversity information disclosure and environmental performance can be intricate. Analysts may struggle to accurately model the relationship between enhanced environmental efforts and their direct financial impacts, leading to errors in forecasting. Also, factors influencing biodiversity disclosures may be evolving over time. Analysts may also overestimate the benefits of strong environmental performance. Thus, the complexities, uncertainties, and challenges in assessing their impacts can paradoxically create increased forecast errors among analysts.

Our analyses also show negative and significant coefficients for firm size across all models, indicating that larger firms might experience smaller FERROR. Also, LEVERAGE, BM, and RETVAR have positive associations with FERROR.

[Table 4]

Table 5 reports the regression results with firm-fixed effects. The adjusted R-squared values improved significantly after controlling for firm-fixed effects. Although, the result is not significant in column 1 where the forecast error is measured based on one-year ahead forecasts. BIODIS variables are significant in columns 2 and 3, suggesting the significant impact of biodiversity information disclosure in reducing forecast errors when analysts project for future years. Overall, the findings are robust, highlighting the importance of biodiversity disclosure in improving the information environment for the analysts. When companies disclose their biodiversity risks, they provide analysts with clearer insights into potential ecological challenges that could affect business operations. This transparency helps analysts make more informed predictions about future performance.

[Table 5]

A potential concern regarding our sample is that it is not evenly distributed in earlier years due to the limited coverage of environmental information in the MSCI data. Biodiversity has gained increasing importance in recent years, particularly following the directives from the UN's COP meetings, including the Kunming-Montreal Global Biodiversity Framework. Advocacy from scientists, NGOs, and activists has also elevated biodiversity as a critical focus area for both conservation and sustainable development. We, therefore, conduct a sub-sample analysis that includes data from the years 2012 to 2023. We document similar findings for the BIODIS and BIODISXENVIRON variables. Untabulated results indicate weaker findings in analyses from prior years. To summarize, we find that biodiversity risk disclosure reduces analysts' forecast errors, and these findings are more pronounced in recent years.

[Table 6]

V. Additional Analysis

Our novel findings in this study document the informativeness of biodiversity information disclosed by the firms. Understanding the rationale behind biodiversity disclosures may extend our understanding further in this area. Prior literature suggests that firms should disclose more to enhance transparency, meet stakeholder expectations, manage risks, and align with sustainability goals (Dhaliwal et al., 2012, 2014). Factors such as firm size, industry sector, financial solvency, as well as biodiversity risk exposure, can significantly influence the level and quality of biodiversity disclosures. We further examine the firm characteristics and their role in biodiversity disclosure. Table 7 shows the regression results of firms' three types of biodiversity footprints (Scope 1, Scope 2, and Scope 3) and biodiversity information disclosures. The biodiversity footprints data are collected from the Iceberg Data Lab (IDL). We find a significant negative coefficient for the CBF_Scope_1 variable, indicating that firms with a more direct biodiversity footprint and risk exposure disclose less. Firms with higher Scope 1 CBF might engage in less biodiversity disclosure due to fear of negative perceptions, resource and risk exposures. This situation underscores the need for companies to adopt a more integrated approach to environmental impact by recognizing the interplay between environmental performance and biodiversity conservation.

[Table 7]

We conduct additional analysis by checking firms' ability to manage their biodiversity and land use risks, and this risk management affects biodiversity information disclosure. Table 8 presents the regression results of the biodiversity land use exposure scores and biodiversity information disclosures. The biodiversity land use exposure scores are collected from the MSCI ESG database, which evaluates the company's ability to manage its exposure to biodiversity and

land use risks. Our results show that firms with better quality biodiversity and land use risk management disclose more biodiversity information. However, the result weakens after controlling for firm-fixed effects.

[Table 8]

VI. Conclusions

In recent years, both global policymakers and social media have voiced concern about planetary boundaries and biodiversity depletion. Moreover, finance research has started to grow in this often-neglected area. We analyze whether the disclosure of biodiversity risk affects analyst forecast accuracy. Our analysis is important because if disclosure has an impact, it indicates that financial markets and investors are effectively processing information about biodiversity risk. Such a result should hearten environmentalists and policymakers. By contrast, if disclosure has no impact, this should spur environmentalists and policymakers to raise awareness of biodiversity risk. In either case, our work helps to open a window into the impact of biodiversity risk on business.

Going into the study, we find a significant negative relationship between biodiversity information disclosures and analyst forecast errors for publicly listed firms in the U.S. from 2000 to 2023. The findings indicate that enhanced biodiversity disclosures improve the information environment, enabling analysts to make more accurate assessments of company performance and risk exposures. Specifically, the negative association with forecast errors is stronger for long-term projections, underscoring the value of timely and relevant ecological information in forecasting scenarios. Moreover, while biodiversity disclosures generally aid in reducing forecast errors, the interaction between strong environmental performance and biodiversity disclosure can lead to increased forecast errors. This complexity arises from the challenges analysts face in accurately modeling the relationship between enhanced environmental efforts and financial outcomes. As

firms navigate evolving factors influencing biodiversity disclosures, analysts may overestimate the benefits of high environmental performance, creating potential inaccuracies in forecasts. Our study provides a useful benchmark for subsequent research, as biodiversity-related information disclosure improves the information environment for market participants and stakeholders, and analysts incorporate biodiversity information in their forecasts. Given the significant impact of biodiversity disclosures on reducing analyst forecast errors, policymakers should encourage firms to adopt standardized reporting for biodiversity information. Regulations that mandate transparency in environmental disclosure may include biodiversity metrics, facilitating more informed decision-making for the investors, analysts, and stakeholders.

References

Araujo, R., Costa, F., Garg, T., 2024. Going Viral: Public attention and Environmental Action in the Amazon. *Journal of the Association of Environmental and Resource Economists* 11, 1605–1627.

Barrett, S., 2007. Why Cooperate? The Incentive to Supply Global Public Goods. Oxford University Press.

Bernardi, C., Stark, A., 2018. Environmental, social and governance disclosure, integrated reporting, and the accuracy of analyst forecasts. *The British Accounting Review* 50, 16–31.

Bhattacharya, U., Daouk, H., Welker, M., 2003. The world price of earnings opacity. *The Accounting Review* 78, 641–678.

Bhattacharyyam, A., Yang, H., 2019. Biodiversity disclosure in Australia: Effect of GRI and Institutional factors. *Australasian Journal of Environmental Management* 26, 347–369.

Byard, D., Shaw, K., 2003. Corporate disclosure quality and properties of analysts' information environment. *Journal of Accounting, Auditing & Finance* 18, 355–378.

Cormier, D., Magnan, M., 2014. The impact of social responsibility disclosure and governance on financial analysts' information environment. *Corporate Governance* 14, 467–484.

Dannenberg, A., Gutsche, G., Batzke, M., Christens, S., Engler, D., Mankat, F., Moller, S., Weingartner, E., Ernst, A., Lumkowsky, M., von Wangenheim, G., Hornung, G., Ziegler, A., 2024. The Effects of Norms on Environmental Behavior. *Review of Environmental Economics and Policy* 18, 165–187.

Dasgupta, P., 2024. The Economics of Biodiversity: The Dasgupta Review. Cambridge University Press, Cambridge, UK.

DeFond, M.L., Hung, M., 2003. An empirical analysis of analysts' cash flow forecasts. *Journal of Accounting and Economics* 35, 73–100.

Dhaliwal, D., Li, O., Tsang, A., Yang, Y., 2014. Corporate social responsibility disclosure and the cost of equity capital: The roles of stakeholder orientation and financial transparency. *Journal of Accounting and Public Policy* 33, 328–355.

Dhaliwal, D., Radhakrishnan, S., Tsang, A., Yang, Y., 2012. Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The Accounting Review* 87, 723–759.

Dhanda, K., Malik, M., 2020. Carbon management strategy and carbon disclosures: An exploratory study. *Business and Society Review* 125, 225–239.

Flammer, C., Giroux, T., Heal, G., 2023. Biodiversity Finance. Technical Report. ECGI Working Paper Series in Finance 901/2023.

Flammer, C., Giroux, T., Heal, G., 2024. Blended Finance. Technical Report. ECGI Finance Working Paper 973/2024.

Francis, J., Khurana, I., Pereira, R., 2005. Disclosure incentives and effects on cost of capital around the world. *The Accounting Review* 80, 1125–1162.

Garel, A., Romec, A., Sautner, Z., Wagner, A., 2024. Do investors care about biodiversity? Review of Finance, forthcoming, https://doi.org/10.1093/rof/rfae010.

Giglio, S., Kuchler, T., Stroebel, J., Zeng, X., 2023. Biodiversity Risk. Technical Report. NBER Working Paper 31137.

Haque, F., Jones, M., 2020. European Firms' Corporate Biodiversity Disclosures and Board Gender Diversity from 2002 to 2016. *The British Accounting Review* 52, 100893.

Heal, G., 2020. The Economic Case for Protecting Biodiversity. Technical Report. NBER Working Paper 27963.

Hope, O., 2003. Accounting policy disclosures and analysts' forecasts. *Contemporary Accounting Research 20, 295–321.*

Ilhan, E., Krueger, P., Sautner, Z., Starks, L., 2023. Climate risk disclosure and institutional investors. *Review of Financial Studies* 36, 2617–2650.

Karolyi, G., Tobin-de la Puente, J., 2023. Biodiversity finance: A call for research into financing nature. *Financial Management* 52, 231–251.

Kruse, T., Mohnen, M., Sato, M., 2024. Do Financial Markets Respond to Green Opportunities? *Journal of the Association of Environmental and Resource Economists* 11, 549–576.

Lang, M., Lundholm, R., 1996. Corporate disclosure policy and analyst behavior. *Accounting Review* 71, 467–492.

Leuz, C., Nanda, D., Wysocki, P., 2003. Investor protection and earnings management: An international comparison. *Journal of Financial Economics* 69, 505–527.

Martiny, A., Taglialatela, J., Testa, F., Iraldo, F., 2024. Determinants of environmental social and governance (ESG) performance: A systematic literature review. *Journal of Cleaner Production* 456, 142213.

Zhang, R., Khanna, N., 2024. Public Pressure and the Heterogeneous Effects of Voluntary Pollution Abatement. *Journal of the Association of Environmental and Resource Economists* 11, 719–754.

Table 1: Sample Distributions

This table presents the distribution of the sample used in this study. The sample consists of publicly listed firms in the U.S. from 2000 to 2023. Panel A reports the distribution by year. Panel B shows the distribution by industries. Industries are defined by the first digit of the SIC codes. We collect firm financial variables from COMPUSTAT, stock price data from CRSP, and the firm's environmental performance from the MSCI ESG database. We collect forecast-related information from the IBES dataset, and the biodiversity disclosure measures from the database of Giglio et al. (2023).

Panel A: Sample Distribution by Year

Year	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
2000	105	0.48%	105	0.48%
2001	138	0.63%	243	1.11%
2002	150	0.69%	393	1.8%
2003	198	0.91%	591	2.71%
2004	228	1.05%	819	3.76%
2005	264	1.21%	1,083	4.97%
2006	321	1.47%	1,404	6.44%
2007	318	1.46%	1,722	7.9%
2008	326	1.5%	2,048	9.4%
2009	320	1.47%	2,368	10.86%
2010	317	1.45%	2,685	12.32%
2011	339	1.56%	3,024	13.87%
2012	1,353	6.21%	4,377	20.08%
2013	1,421	6.52%	5,798	26.6%
2014	1,507	6.91%	7,305	33.51%
2015	878	4.03%	8,183	37.54%
2016	1,571	7.21%	9,754	44.75%
2017	1,566	7.18%	11,320	51.93%
2018	1,593	7.31%	12,913	59.24%
2019	1,638	7.51%	14,551	66.75%
2020	1,703	7.81%	16,254	74.57%
2021	1,812	8.31%	18,066	82.88%
2022	1,903	8.73%	19,969	91.61%
2023	1,829	8.39%	21,798	100%

Panel B: Sample Distribution by Industry

Industry	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Agriculture, and forestry	31	0.14%	31	0.14%
Constructions	418	1.92%	449	2.06%
Finance, insurance, real estate	3,731	17.12%	4,180	19.18%
Manufacturing	8,900	40.83%	13,080	60.01%
Mining	799	3.67%	13,879	63.67%
Public administration	48	0.22%	13,927	63.89%
Retail trade	1,497	6.87%	15,424	70.76%
Service	3,684	16.9%	19,108	87.66%
Transportations	2,022	9.28%	21,130	96.94%
Wholesale trade	668	3.06%	21,798	100%

Table 2: Descriptive Statistics

This table presents the descriptive statistics of the variables used in this study. The sample consists of publicly listed firms in the U.S. from 2000 to 2023. We collect firm financial variables from COMPUSTAT, stock price data from CRSP, the firm's environmental performance from the MSCI ESG, and analyst forecast data from the IBES datasets. The biodiversity disclosure measures are collected from the database of Giglio et al. (2023).

Variable	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
FERROR (t=1)	0.0338	0.7041	0.0025	0.0074	0.0219
FERROR (t=2)	0.0539	1.7960	0.0040	0.0115	0.0324
FERROR (t=3)	0.0743	2.2727	0.0051	0.0145	0.0428
SIZE	8.2278	1.5434	7.0755	8.0936	9.2338
LEVERAGE	0.2328	0.2214	0.0524	0.2007	0.3480
BM	0.4368	0.4160	0.1891	0.3632	0.6080
RETVAR	0.0241	0.0130	0.0155	0.0206	0.0291
FHORIZON	15.7457	10.3336	7	13	21
ANANO	2.1297	0.8025	1.6094	2.1972	2.7726
ACCQ	0.9867	0.1144	1	1	1
AUDQ	0.8840	0.3203	1	1	1
LOSS	0.2172	0.4124	0	0	0
FAGE	15.0734	10.2361	6	15	22
TANG	6.0357	2.1479	4.5782	5.9751	7.4851
ENVIRON	4.4072	2.2282	2.82	4.4	6
FFIN	0.0999	2.0738	0.0238	0.0420	0.0707
BIODIS	0.0438	0.2047	0	0	0

Table 3: Correlation Matrix

The table presents a correlation matrix for the variables. The sample comprises US public firms from 2000 to 2023. We collect firm financial variables from COMPUSTAT, stock price data from CRSP, the firm's environmental performance from the MSCI ESG, and analyst forecast data from the IBES datasets. The biodiversity disclosure measures are from Giglio et al. (2023). *, **, *** indicate the statistical significance of the correlation coefficient at 0.01, 0.05, and 0.10 levels. Appendix A provides variable definitions.

	FERROR (t=1)	FERROR (t=2)	FERROR (t=3)	SIZE	LEVERAGE	BM	RETVAR	FHORIZON
FERROR (t=2)	0.995***							
FERROR (t=3)	0.996***	0.999***						
SIZE	-0.049***	-0.037***	-0.049***					
LEVERAGE	0.003	-0.002	-0.006	0.080***				
BM	0.059***	0.045***	0.053***	-0.249***	-0.221***			
RETVAR	0.302***	0.335***	0.344***	-0.303***	0.060***	0.065***		
FHORIZON	0.001	-0.002	-0.002	-0.012*	0.014**	-0.006	0.012*	
ANANO	-0.023***	-0.015**	-0.024**	0.684***	0.086***	-0.208***	-0.120***	-0.016*
ACCQ	0.002	0.002	0.002	-0.021***	0.034***	0.001	0.037***	-0.010
AUDQ	0.000	0.002	0.001	0.283***	0.129***	-0.072***	-0.061***	0.029***
LOSS	0.050***	0.037***	0.042***	-0.292***	0.065***	0.024***	0.482***	0.013*
FAGE	-0.037***	-0.039***	-0.055***	0.211***	0.026***	0.074***	-0.216***	0.006
TANG	-0.021***	-0.019***	-0.029***	0.689***	0.241***	0.053***	-0.246***	-0.023***
ENVIRON	-0.005	-0.002	-0.006	0.219***	0.088***	-0.149***	-0.021***	0.039***
FFIN	0.005	0.003	0.027***	-0.029***	-0.015*	0.020***	0.070***	-0.009
BIODIS	0.005	0.002	0.000	0.008	0.067***	0.113***	0.010	-0.005
	ANANO	ACCQ	AUDQ	LOSS	FAGE	TANG	ENVIRON	FFIN
ACCQ	0.029***							
AUDQ	0.264***	-0.023***						
LOSS	-0.077***	-0.011*	-0.002					
FAGE	-0.033***	-0.045***	-0.006	-0.280***				
TANG	0.459***	0.038***	0.237***	-0.275***	0.314***			
ENVIRON	0.186***	-0.028***	0.171***	0.042***	-0.030***	0.095***		
FFIN	-0.003	0.002	-0.000	0.043***	-0.039***	-0.039***	0.012	
BIODIS	-0.004	0.015**	0.018***	0.008	-0.007	0.184***	-0.036***	-0.004

Table 4: Biodiversity Information Disclosure and Analyst Forecast

This table reports the regression results of biodiversity disclosure and analyst forecasts. The dependent variable of the first model is the analyst forecast error for the forecast made in year t for the earnings of year t+1. The second model's forecast error is the forecast made in year t for the earnings of year t+2, and the third model is for the forecast made in year t for the earnings of year t+3. The sample consists of publicly listed firms in the U.S. from 2000 to 2023. We collect firm financial variables from COMPUSTAT, stock price data from CRSP, the firm's environmental performance from the MSCI ESG, and analyst forecast data from the IBES datasets. The biodiversity disclosure measures are from Giglio et al. (2023). Appendix A provides the variable definitions.

Dependent Variable =	**FERROR (t=1)**			**FERROR (t=2)**			**FERROR (t=3)**		
	Estimate	t Stat	P Value	Estimate	t Stat	P Value	Estimate	t Stat	P Value
Intercept	-0.0898	-2.6	0.0095	-0.0138	-0.36	0.7180	0.0330	0.85	0.3929
SIZE	-0.0082	-3.14	0.0018	-0.0134	-5.53	<.0001	-0.0201	-5.44	<.0001
LEVERAGE	0.0308	3.86	0.0001	0.0377	4.9	<.0001	0.0485	4.2	<.0001
BM	0.0464	2.64	0.0084	0.0513	3.84	0.0001	0.0595	3.43	0.0006
RETVAR	1.5030	7.07	<.0001	1.8447	7.18	<.0001	2.0205	5.58	<.0001
FHORIZON	0.0000	-0.16	0.8763	-0.0001	-0.8	0.4253	0.0000	-0.03	0.9756
ANANO	0.0010	0.5	0.618	0.0023	0.88	0.3771	0.0076	1.55	0.1221
ACCQ	0.0335	2.6	0.0094	0.0309	2.15	0.0315	0.0177	1.75	0.0801
AUDQ	-0.0032	-0.77	0.4423	-0.0018	-0.43	0.6682	-0.0026	-0.29	0.7711
LOSS	0.0131	5.81	<.0001	0.0303	9.73	<.0001	0.0441	8.51	<.0001
FAGE	-0.0001	-0.71	0.4781	0.0000	-0.16	0.8768	0.0001	0.45	0.6493
TANGB	0.0053	2.83	0.0047	0.0084	4.97	<.0001	0.0085	3.47	0.0006
ENVIRON	0.0005	1.01	0.3105	0.0005	0.79	0.4306	-0.0010	-1.16	0.2449
FFIN	0.0006	0.36	0.7178	-0.0005	-1.29	0.1982	0.0070	0.69	0.4914
BIODIS	-0.0245	-1.85	0.0643	-0.0338	-2.48	0.0134	-0.0704	-3.52	0.0004
BIODIS X ENVIRON	0.0070	2.03	0.0423	0.0092	2.71	0.0068	0.0151	2.87	0.0042
Adjusted R^2	15.37%			23.29%			28.55%		
Year-Fixed Effects	Yes			Yes			Yes		
Industry-Fixed Effects	Yes			Yes			Yes		
SE Clusters by Firms	Yes			Yes			Yes		

Table 5: Biodiversity Information Disclosure and Analyst Forecast – Firm Fixed Effect Model

This table reports the regression results of biodiversity disclosure and analyst forecasts controlling firm-fixed effects. The dependent variable of the first model is the analyst forecast error for the forecast made in year t for the earnings of year t+1. The second model's forecast error is the forecast made in year t for the earnings of year t+2, and the third model is for the forecast made in year t for the earnings of year t+3. The sample consists of publicly listed firms in the U.S. from 2000 to 2023. We collect firm financial variables from COMPUSTAT, stock price data from CRSP, the firm's environmental performance from the MSCI ESG, and analyst forecast data from the IBES datasets. The biodiversity disclosure measures are from Giglio et al. (2023). Appendix A provides the variable definitions.

Dependent Variable =	**FERROR (t=1)**			**FERROR (t=2)**			**FERROR (t=3)**		
	Estimate	t Stat	P Value	Estimate	t Stat	P Value	Estimate	t Stat	P Value
Intercept	10.9175	1.44	0.1503	15.5988	1.78	0.0747	30.3730	3.03	0.0025
SIZE	-2.4905	-4.74	<.0001	-3.6652	-5.49	<.0001	-5.6954	-6.3	<.0001
LEVERAGE	3.2565	2.92	0.0035	4.5295	2.72	0.0067	6.6181	2.74	0.0061
BM	3.9363	2.5	0.0125	5.4169	3.23	0.0012	4.6267	2.46	0.0141
RETVAR	14.7658	3.6	0.0003	42.1613	3.56	0.0004	26.0614	2.88	0.0039
FHORIZON	-0.0070	-0.48	0.6345	-0.0064	-0.37	0.7093	-0.0075	-0.39	0.6937
ANANO	-0.2562	-0.5	0.6177	-0.4964	-0.76	0.4467	-0.4329	-0.52	0.6039
ACCQ	0.7391	1.04	0.3002	3.1255	3.49	0.0005	2.6864	2.47	0.0136
AUDQ	-0.7931	-0.98	0.3255	-1.3329	-1.51	0.1321	-1.5388	-0.98	0.3259
LOSS	1.1716	1.75	0.0801	2.9362	3.77	0.0002	3.7699	4.33	<.0001
TANGB	1.0094	2.84	0.0045	1.5426	3.46	0.0006	2.3307	3.81	0.0001
ENVIRON	0.1508	2.16	0.0306	0.1947	2.19	0.0289	0.0939	0.89	0.3757
FFIN	0.8788	1.06	0.2870	0.1085	0.1	0.9212	1.1679	0.6	0.5518
BIODIS	-2.2892	-1.44	0.1489	-4.5542	-2.02	0.0436	-4.9339	-2.47	0.0136
BIODIS X ENVIRON	0.5779	2.07	0.0386	0.9685	2.26	0.0240	1.1979	2.92	0.0036
Adjusted R^2	42.62%			51.21%			54.68%		
Firm-Fixed Effects	Yes			Yes			Yes		
Year-Fixed Effects	Yes			Yes			Yes		
SE Clusters by Firms	Yes			Yes			Yes		

Table 6: Biodiversity Information Disclosure and Analyst Forecast – Sub Sample Analysis for Later Years

This table reports the regression results of biodiversity disclosure and analyst forecasts for a sub-sample of later years. The dependent variable of the first model is the analyst forecast error for the forecast made in year t for the earnings of year t+1. The second model's forecast error is the forecast made in year t for the earnings of year t+2, and the third model is for the forecast made in year t for the earnings of year t+3. The sample consists of publicly listed firms in the U.S. from 2012 to 2023. We collect firm financial variables from COMPUSTAT, stock price data from CRSP, the firm's environmental performance from the MSCI ESG, and analyst forecast data from the IBES datasets. The biodiversity disclosure measures are from Giglio et al. (2023). Appendix A provides the variable definitions.

Dependent Variable =	**FERROR (t=1)**			**FERROR (t=2)**			**FERROR (t=3)**		
	Estimate	t Stat	P Value	Estimate	t Stat	P Value	Estimate	t Stat	P Value
Intercept	-0.0548	-1.7	0.0892	-0.0331	-0.75	0.4508	0.0448	1.43	0.1534
SIZE	-0.0082	-3.05	0.0023	-0.0138	-5.61	<.0001	-0.0211	-5.63	<.0001
LEVERAGE	0.0324	3.75	0.0002	0.0397	4.74	<.0001	0.0507	4.16	<.0001
BM	0.0475	2.57	0.0103	0.0517	3.68	0.0002	0.0585	3.18	0.0015
RETVAR	1.5681	6.28	<.0001	1.8485	6.38	<.0001	2.0037	5.25	<.0001
FHORIZON	0.0000	-0.12	0.9072	-0.0001	-0.58	0.5599	0.0000	-0.07	0.9475
ANANO	0.0011	0.51	0.6102	0.0029	1.09	0.2744	0.0089	1.75	0.0803
ACCQ	0.0427	3.2	0.0014	0.0408	1.48	0.1404	0.0000	0.03	0.9810
AUDQ	-0.0036	-0.84	0.4022	-0.0022	-0.52	0.6058	-0.0028	-0.3	0.7606
LOSS	0.0135	5.73	<.0001	0.0305	9.43	<.0001	0.0447	8.28	<.0001
FAGE	-0.0001	-0.45	0.6536	0.0000	0.16	0.8725	0.0002	0.74	0.4624
TANGB	0.0056	2.84	0.0046	0.0086	4.84	<.0001	0.0087	3.35	0.0008
ENVIRON	0.0004	0.81	0.4191	0.0004	0.68	0.4967	-0.0012	-1.31	0.1904
FFIN	0.0006	0.37	0.7111	-0.0004	-1.26	0.2074	0.0068	0.67	0.5026
BIODIS	-0.0264	-1.82	0.0684	-0.0375	-2.5	0.0124	-0.0776	-3.49	0.0005
BIODIS X ENVIRON	0.0077	2.07	0.0386	0.0105	2.84	0.0046	0.0172	2.91	0.0037
Adjusted R^2	15.05%			22.55%			27.70%		
Year-Fixed Effects	Yes			Yes			Yes		
Industry-Fixed Effects	Yes			Yes			Yes		
SE Clusters by Firms	Yes			Yes			Yes		

Table 7: Biodiversity Footprints and Biodiversity Information Disclosure

This table reports the regression results of firms' three types of biodiversity footprints and biodiversity information disclosures. The sample consists of publicly listed firms in the U.S. from 2018 to 2023. We collect firm financial variables from COMPUSTAT, stock price data from CRSP, the firm's environmental performance from the MSCI ESG, and analyst forecast data from the IBES datasets. The biodiversity disclosure measures are from Giglio et al. (2023), and the biodiversity footprints data are from the Iceberg Data Lab (IDL). Appendix A provides the variable definitions.

Dependent Variable =	**BIODIS**			**BIODIS**			**BIODIS**		
	Estimate	t Stat	P Value	Estimate	t Stat	P Value	Estimate	t Stat	P Value
Intercept	0.0917	1.35	0.1775	0.0619	0.91	0.3621	-0.1608	-0.8	0.4224
CBF_Scope_1	-0.0001	-2.76	0.0061	-0.0001	-1.83	0.0684	-0.0001	-1.04	0.2976
CBF_Scope_2	0.0001	1.94	0.0531	0.0002	3.76	0.0002	0.0000	-0.65	0.5144
CBF_Scope_3	0.0000	1.36	0.1734	0.0000	-0.93	0.3543	0.0000	0.75	0.4547
SIZE	-0.0311	-3.95	<.0001	-0.0218	-2.77	0.0059	0.0171	0.87	0.3835
LEVERAGE	-0.0004	-0.03	0.9783	0.0039	0.26	0.7924	0.0351	0.58	0.5615
BM	0.0130	0.53	0.5954	0.0010	0.04	0.9666	0.0062	0.29	0.7737
ROE	0.0483	0.87	0.3856	0.1124	2.03	0.0430	0.0902	1.15	0.2495
CASH_HOLD	-0.0543	-1.15	0.2517	-0.0977	-2.18	0.0296	-0.0397	-0.54	0.5918
TANGB	0.0343	5.01	<.0001	0.0137	2.59	0.0100	-0.0031	-0.28	0.7829
Adjusted R^2	9.57%			16.9%			69.90%		
Firm-Fixed Effects	No			No			Yes		
Year-Fixed Effects	Yes			Yes			Yes		
Industry-Fixed Effects	No			Yes			No		
SE Clusters by Firms	Yes			Yes			Yes		

Table 8: Biodiversity Land Use Exposure and Biodiversity Information Disclosure

This table reports the regression results of firms' biodiversity land use exposure scores and biodiversity information disclosures. The sample consists of publicly listed firms in the U.S. from 2013 to 2023. We collect firm financial variables from COMPUSTAT, stock price data from CRSP, the firm's environmental performance from the MSCI ESG, and analyst forecast data from the IBES datasets. The biodiversity disclosure measures are from Giglio et al. (2023), and the biodiversity land use exposure scores are from the MSCI ESG database. Appendix A provides the variable definitions.

Dependent Variable =	**BIODIS**			**BIODIS**			**BIODIS**		
	Estimate	t Stat	P Value	Estimate	t Stat	P Value	Estimate	t Stat	P Value
Intercept	-0.0533	-2.02	0.0434	-0.1033	-0.86	0.3899	0.0292	0.35	0.7297
BIO_LAND_USE	0.0454	11.65	<.0001	0.0349	7.59	<.0001	0.0052	1.06	0.2905
SIZE	-0.0092	-2.43	0.0151	-0.0099	-2.66	0.0078	-0.0037	-0.74	0.4592
LEVERAGE	-0.0011	-0.09	0.9307	0.0013	0.11	0.912	-0.0134	-0.63	0.5306
BM	0.0419	4.22	<.0001	0.0234	2.29	0.0223	-0.0059	-0.41	0.6803
ROE	0.0007	0.06	0.949	0.0018	0.19	0.8521	-0.0058	-0.9	0.3696
CASH_HOLD	0.0217	1.16	0.2465	0.0392	1.95	0.0514	0.0107	0.62	0.5345
TANGB	0.0099	3.29	0.001	0.0079	2.65	0.008	0.0012	0.18	0.8551
Adjusted R^2	18.10%			22.62%			75.31%		
Firm-Fixed Effects	No			No			Yes		
Year-Fixed Effects	Yes			Yes			Yes		
Industry-Fixed Effects	No			Yes			No		
SE Clusters by Firms	Yes			Yes			Yes		

Appendix A: Variable Definitions

Variables	Variable Definition	Variable Construction	Data Source
Dependent Variables			
FERROR	Analyst Forecast Errors	The average of the absolute errors of all forecasts made in the year for earnings, scaled by the stock price at the beginning	IBES and COMPUSTAT
Explanatory Variables			
SIZE	Firm Size	The natural log of market value of equity	COMPUSTAT
LEVERAGE	Leverage Ratio	Long-term debt divided by total assets	COMPUSTAT
BM	Book to Market Ratio	The ratio of the book value of equity to the market value of equity	COMPUSTAT
RETVAR	Stock Returns Volatility	The variability of stock returns measured as the standard deviation of daily stock returns over the past one year	CRSP
FHORIZON	Analyst Forecast Horizon	The length of time between the forecasting date and the earnings announcement date	IBES
ANANO	No. of Analysts Following the Firm	The natural log of the number of analysts following the firm throughout the year	IBES
ACCQ	Accounting Quality	A dummy variable value is one if the firm follows the UG GAAP, otherwise zero	COMPUSTAT
AUDQ	Audit Quality	A dummy variable is one if the firm is audited by one of the Big Four audit firms	COMPUSTAT
LOSS	Loss Firm	A dummy variable value of 1 if a firm reports net loss during the year, otherwise zero	COMPUSTAT
FAGE	Firm Listing Age	Difference between the fiscal year and the year a firm listed on the stock exchange	COMPUSTAT
TANGB	Tangibility of Assets	The natural log of net property, plant, and equipment	COMPUSTAT
ENVIRON	Environmental Performance	Environmental pillar scores	MSCI ESG
FFIN	Financial Opacity or Accruals	The absolute value of scaled accruals averaged over the previous three years	COMPUSTAT
BIODIS	Biodiversity Disclosure	Biodiversity disclosure scores developed by Giglio et al., 2023	Giglio et al. (2023)