Ecological Economics 236 (2025) 108662

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Noisy biodiversity: The impact of ESG biodiversity ratings on asset prices

Wei Xin[a,b], Lewis Grant[b,c], Ben Groom[d,e,*], Chendi Zhang[a,b]

[a] Department of Finance and Accounting, University of Exeter Business School, UK
[b] Exeter Sustainable Finance Centre, University of Exeter, UK
[c] Federated Hermes, United Kingdom
[d] Dragon Capital Chair of Biodiversity Economics, LEEP Institute, Department of Economics, University of Exeter Business School, UK
[e] Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science, UK

ARTICLE INFO

JEL codes:
G12
G14
G23
Q56
Q57

Keywords:
ESG
Biodiversity
Nature
Disclosure
Finance
Asset Pricing
Risk

ABSTRACT

The biodiversity components of ESG ratings are analysed to understand whether this disclosure mechanism can affect investment decisions, improve outcomes for biodiversity or lead to better management of nature-based risks. We analyse the relationship between stock returns and firms' biodiversity ratings and how biodiversity ratings are related to firm characteristics. We conclude that biodiversity ratings are largely uncorrelated to firm characteristics other than via firm size, and do not predict stock returns. Analysis of operating performance sheds light on why: returns on assets and profit margins are not affected by biodiversity ratings. Systematic risk, idiosyncratic risk and firm valuation are also not influenced by overall biodiversity performance. The effect is heterogeneous across industries: biodiversity ratings predict negative returns in metals and mining but positive returns in utilities. Further, institutional investors and sell-side analysts ignore biodiversity ratings in their decision-making. A suite of tests suggests that biodiversity as measured in ESG ratings does not provide useful additional information for financial decision makers. It is difficult to see how, on its own at least, the measurement and disclosure of biodiversity via ESG ratings currently helps achieve any target related to biodiversity and nature recovery or improves the management of nature-based risks.

1. Introduction

Biodiversity - the biological variety and variability of life on Earth- has been shown to be an important aspect of natural capital, an important cultural ecosystem service and to underpin supporting, provisioning and regulatory ecosystem services (Dasgupta, 2021). This close connection between the economy and nature means that economic activity impacts biodiversity and natural capital but is also exposed to nature-based risks. While resource-based sectors are directly at risk from the collapse of natural systems, the relationship between economy, finance and nature is often complicated such that ostensibly unrelated activities (e.g. pain-killers in livestock agriculture) can have disastrous effects on nature (the loss of vultures in India) which cause feedback to human well-being (infant mortality via pathogens transported by increasing rat populations) (Frank and Sudarshan, 2022). These impacts on, and economic values of, biodiversity are rarely reflected in market transactions. Likewise, given the complexity of these relationships, the risks to assets and returns are also typically absent or incompletely represented in financial valuations. As a result, the so-called "double-materiality" (Boissinot et al., 2022) of biodiversity risks and impacts have little effect on decisions in the financial sector. In the absence of distinct regulatory interventions to internalise nature-based impacts or risks, voluntary disclosure mechanisms, such as ESG or the Task Force for Nature-related Financial Disclosures (TNFD), are currently being proposed to address these materiality and externality issues in the Financial Sector. The idea behind these instruments is that they will induce a movement of capital away from activities that are harmful to nature and prices (risk premia) will properly reflect nature-based risks thereafter. In this paper, we test this theory of change directly by examining the extent to which risks and impacts associated with biodiversity are reflected in financial markets via one of the chief disclosure mechanisms for environmental risks: ESG ratings. Specifically, we examine the predictive power of the biodiversity rating component in the overall E of the ESG score on the performance assessed by ESG data on stock future returns. We then use a range of analyses at different levels of governance to explain the mechanisms behind the extent of the associations between biodiversity scores and returns. Overall, we find that biodiversity performance in ESG data is not

* Corresponding author at: Dragon Capital Chair of Biodiversity Economics, LEEP Institute, Department of Economics, University of Exeter Business School, UK.
E-mail address: B.D.Groom@exeter.ac.uk (B. Groom).

https://doi.org/10.1016/j.ecolecon.2025.108662
Received 14 August 2023; Received in revised form 28 April 2025; Accepted 29 April 2025
Available online 14 May 2025

associated with firms' characteristics, stock future returns, and firms' operating performance. Neither do other financial participants, including institutional investors and sell-side analysts, take biodiversity performance into account in their professional activities. Our findings suggest that the biodiversity component of E in ESG is unlikely to achieve much in terms of shifting capital away from harmful activities or insulating companies from natural capital risks.

The findings are important because absent price or quantity regulation on biodiversity loss, ESG ratings are one of the chief mechanisms through which it is thought that this otherwise non-marketed factor and its associated environmental externalities can be internalised in the financial investment sector. Disclosure, it is hoped, will provide an impetus for investors to reorient their investments away from the risks associated with environmental degradation or, via companies' management capabilities, reduce the impacts of company or portfolio-level activities on the environment. Disclosure mechanisms such as ESG are intended to affect the capital flows from both the demand and supply sides. On the one hand, the information delivered by disclosures of this sort of increase investors' attention to the environment and natural-related risks with the hope that they will prefer more environmentally friendly stocks. On the supply side, these mechanisms encourage firms to better internalise externalities with the hope that they can capitalize on this demand, perhaps by issuing”greener” securities, attracting more investment and reducing their cost of capital. Such adjustments to portfolios would be socially valuable since otherwise non-marketed environmental assets, particularly biodiversity, have public good properties and play an important role in regulating and supporting both the environment the broader economy (Dasgupta, 2021, ch. 4).[1] Globally, ecosystem services (e.g. pollination, water quality, climate regulation etc.) are worth an estimated USD 125–140 trillion (US dollars) per year, i.e. more than one and a half times the size of the global GDP. (OECD, 2019). The financial sector currently does not reflect these wider economic values and as a consequence fails to allocate capital in a way that improves or sustains social well-being (Dasgupta, 2021).

Voluntary disclosure of nature-based risks may only be taken up by a limited number of firms and financial institutions since it may be perceived as costly in many cases, either in terms of reputation or due to the corrective measures required to improve ratings. Nevertheless, it is frequently argued that ESG ratings can provide a win-win outcome for both firms' financial performance and external responsibility (see for example: Benabou and Tirole, 2010; Fatemi et al., 2015; Flammer, 2021).[2] Provided there is a close relationship between the ESG ratings and impacts on biodiversity on the ground, then the pursuit of better returns in the financial markets will reduce both the impacts on biodiversity and the vulnerability of returns to biodiversity and nature-based risks: so-called double materiality associated with finance and biodiversity (Boissinot et al., 2022).

Our work contributes to a nascent literature that considers the way in which the risks associated with nature and biodiversity can be measured and whether or not different agents in the financial sector respond. Giglio et al. (2023) measure biodiversity risk using textual analysis of media reports on biodiversity and 10 k reports (using a dictionary of terms). They also conduct expert surveys. In this sense, their research question concerns responses to positive or negative events that are newsworthy. They find that media reported shocks are priced-in to some extent by equities at the industry level, but not by municipal bonds. The 10 k and expert survey analysis yield similar results. Beyond this, Agarwala et al. (2022) model the downgrading of sovereign bonds associated with growing nature-based risks, while more generally Johnson et al. (2021) model the loss in GDP arising from catastrophic losses of ecosystem services such as forest, fisheries and agriculture and find losses between 5 and 20 % in GDP by 2030.

We use alternative measures of biodiversity risk drawn from MSCI's ESG ratings metric: their biodiversity measure which contributes to the overall E score for a firm. This biodiversity metric is constructed by experts within MSCI via analysis of firm activities, industry structures, supply chains and geographical data. This measure is likely to be closely related to the biodiversity and nature-based risks that companies face day to day and perceive in reality. The Management and Exposure measures, which make up the overall biodiversity score, are also likely to provide a closer link to the actual impacts that firms have on biodiversity and the actions they take to address them. This measure of biodiversity risk is arguably more concrete than previous measures and is certainly more central to decision-making in the financial sector. The measure also allows the analysis of day-to-day risks over time, rather than the shocks central to the analysis of (e.g. Giglio et al., 2023). Our analysis looks at the relationship between the MSCI biodiversity ratings metric, its management and exposure components, and firm-level data, including firm characteristics, future stock returns, and betas. Importantly, we find no significant (statistically or economically) significant relationship between stock returns and biodiversity measures. Various aspects of firm returns are evaluated in this way with the same insignificant results.

We have thoroughly reviewed the growing body of literature on biodiversity and asset pricing, with particular attention to recent studies featured in the biodiversity special issue of *Ecological Economics*. Perhaps the most closely related research to this is Garel et al. (2023) who also look at biodiversity risk and stock returns using the Corporate Biodiversity Footprint by IDL as well as the MSCI ESG disclosure metric. Their results show that pricing has changed in the recent time period, especially after COP15 in the Kunming-Montreal agreement, potentially an indication of anticipated transition risk, and in contrast with our findings. In addition, Coqueret et al. (2025) study the pricing of biodiversity risks by constructing portfolios sorted on firms' biodiversity footprint intensities using Iceberg Data Lab data. They find the emergence of a biodiversity risk premium after 2021. While both studies focus on the asset pricing implications of biodiversity, our study differs in purpose and approach. We use biodiversity scores from MSCI ESG ratings, which are widely adopted financial disclosure tools, to examine whether biodiversity-related information embedded in existing ESG ratings is effectively delivered to the market and reflected in firm valuation and professional financial activities, rather than to create new asset pricing factors.

To investigate further, we make several additional contributions. First, we evaluate the separate components of the MSCI biodiversity metric: management and exposure. Second, we unpack our results and explore the mechanisms behind them by looking at different aspects of firm returns: systematic risk (firm betas), and over-valuation (Tobin's Q). Third we analyse market participant behaviour: sell-side analysts and institutional investors. The aforementioned papers are, nevertheless, highly complementary to ours in that they address the pressing issue of the extent to which the financial sector reflects nature-based risks, and whether disclosure mechanisms can be effective in addressing the double material risks associated with biodiversity.[3]

We conduct a series of tests to investigate the extent to which these various theoretical mechanisms are borne out in the data. We focus on the way in which biodiversity is measured within ESG data and investigate whether ESG delivers biodiversity information properly and how

[1] The Dasgupta Review (Dasgupta P'astor et al., 2021) argues that the economy is embedded in the environment and hence reliant on the biosphere rather than a separate and independent entity. Ecosystem services delivered by biodiversity, such as crop pollination, water purification, flood protection and carbon sequestration, are vital to human well-being.

[2] See also Gillan et al. (2021) and P'astor et al. (2021) for a review.

[3] Other contributions in this area include Flammer et al. (2023), which looks at how biodiversity conservation can be financed, and Cherief et al. (2022) who look at biodiversity risks from natural disasters/acute shocks and corporate bond spreads.

this information affects the financial market. First, to know what types of companies tend to rank higher in biodiversity performance, we conduct tests on firms' characteristics and their biodiversity scores. We find no clear connection here (See Section 5). Second, to show whether ESG ratings could lead capital to move away from the biodiversity-harmful areas, we conduct stock return analyses based on portfolios sorted by ESG biodiversity scores in the market (See Section 6). Our results show that biodiversity scores do not predict stock future returns. We extend the analysis further (Section 7), focusing on the potential mechanisms behind the null results. Specifically, we analyse the relationship between firms' biodiversity scores and their operating performance and find no clear connection. Institutional investors and sell-side analysts also tend to ignore the biodiversity performance of firms in their portfolio holding and earning forecast activities.

Overall, our finding indicates that the relationship between the biodiversity measurement of ESG ratings and firms' fundamentals is weak. Such information delivery does not have a significant impact on either the firm's stock performance or operating performance. Financial market participants, including institutional investors and sell-side analysts, do not treat it as important information in their professional activities. In short, the results cast doubt on the ability of disclosure mechanisms as they are currently constructed to properly internalise the external costs of biodiversity and nature loss. Arguably ESG also fails to reflect societal nature-based risk as a distinct factor either on the demand side or the sell side. The results suggest that instruments other than ESG disclosures are needed to ensure that societal objectives with regard to Nature and biodiversity are met.

2. Background

The emerging literature provides mixed evidence on how ESG and other similar disclosure mechanisms affect the movement of capital. Theoretical arguments suggest that stock returns of high-ESG-rated firms could be affected by time-varying investor demand (e.g. Fama and French, 2007; Pedersen et al., 2021; P'astor et al., 2021; Bansal et al., 2022). Luo and Bhattacharya (2006) have argued that higher corporate social responsibility (CSR) ratings increase customer loyalty, leading to firms having more pricing power. Further, Albuquerque et al. (2019) show that CSR decreases systematic risk (and hence reduces cost of capital) and increases firm value, suggesting some potentially positive outcomes from environmental disclosure-type instruments. Such stocks also perform better during the financial crisis due to higher socal capital (Lins et al., 2017). However, so-called"sin" stocks and firms with high carbon emissions have been shown to have higher risk-adjusted returns as investors require a premium for holding such stocks (Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2020). In relation to portfolio management, some studies show that many fund managers who publicly commit to responsible investment goals do little to improve the ESG performance of their portfolios (Kim and Yoon, 2020; Brandon et al., 2021). So, the evidence on ESG as an effective instrument from a financial perspective is somewhat limited, making it difficult to gauge its effectiveness as an instrument of change for the environment, social and governance aspects that ratings try to capture. Overall, the evidence of the effectiveness of such initiatives and instruments is mixed. It is not clear that higher returns or lower returns arise from higher ratings, or that positive impacts on the environment and nature or better risk management follow from disclosure or higher ratings.

The emphasis on biodiversity and nature-based risks is growing and some ESG ratings reflect biodiversity directly in their assessment of the E component of ESG. Following on from the review above, questions remain as to how well ESG ratings can affect the allocation of capital away from biodiversity-impactful activities, cause firms to move away from activities with biodiversity-based risks or promote engagement with firms that perform poorly with regard to biodiversity and nature. Indeed, an even more basic question is, can biodiversity and nature be measured and properly reflected in the E of ESG in a way that affects decision-making, by investors, portfolio managers or by firms themselves? These are important policy questions as national and international commitments to stop biodiversity loss come into effect (e.g. the UK Environment Act) or are binding in international law (e.g. the Kunming-Montreal agreement of the Convention on Biodiversity). For example, the EU's recently published Biodiversity Strategy addresses biodiversity risk. The strategy aims to conserve 30 % of land and marine environments in Europe and restore degraded ecosystems through tree planting, pesticide control and river restoration. The 15th UN Conference of Parties for the Convention on Biological Diversity in Kunming in 2022 (COP15), and then Montreal (COP 16) determined the post-2020 framework for biodiversity conservation, with the 30 by 30 target agreed by the majority of parties: 30 % protected areas on land and in marine environments by 2030(IPBES, 2019b). Action is needed to meet these commitments and prevent biodiversity loss. Steffen et al. (2015) argue that we are beyond the"safe space" for human survival in the dimension of biodiversity, which could lead to tipping points in the valuable global public goods that biodiversity supports within which economic activity is embedded Dasgupta (2021). In addition, there are strong links between biodiversity and climate change since on the one hand degradation of critical carbon-sink ecosystems, such as forests, wetlands and peatlands, is shown to reduce the planet's carbon-absorbing capacity (IPBES, 2019b), yet on the other, nature-based solutions to climate are potentially very cost-effective (Groom and Venmans, 2023). The understanding of the importance of nature and biodiversity to human well-being and economic activity is growing and recognized in globally significant reports such as the Dasgupta Review and reports by the International Panel on Biodiversity and Ecosystem Services (e.g. IPBES, 2019a). In light of this, attempts have been made in the financial sector to encourage nature-based disclosures among companies and financial institutions. For example, the Task Force on Climate-related Financial Disclosures (TCFD) provides guidance to all market participants on the disclosure of information on the financial implications of climate-related risks. Following this framework, the Taskforce on Nature-related Financial Disclosures (TNFD) is now being developed aiming to establish a disclosure framework for nature-related risks. Beyond these direct disclosure mechanisms, the Natural Capital Finance Alliance (NCFA) was launched at the UN Conference on Sustainable Development in 2012 to integrate natural capital considerations into financial products and services, and to work towards their inclusion in financial accounting, disclosure and reporting. The policy landscape is emerging with regard to biodiversity.

In addition to these initiatives, a number of biodiversity footprinting tools have emerged that allow firms and financial institutions, even central banks to evaluate and disclose their biodiversity and nature-based risks. These tools focus on a variety of aspects of biodiversity using different metrics and try to measure the impact of biodiversity on business or how business impacts biodiversity. Some focus on companies' products and services, providing a detailed analysis of how they are affected by degradation in biodiversity (Agrobiodiversity Index (ABD) and Product Biodiversity Footprint (PBF)). Others focus on supply chains, the sector as a whole or portfolios (Biodiversity Footprint Financial Institutions (BFFI) and LIFE Key (LIFE)). However, because of the difficulties in biodiversity measurement and the complexity of the models that assess the impact of biodiversity on business, most of the tools are still under development with limited coverage.

The most widely used biodiversity measurement is provided by ESG (Environment, Social and Governance) raters. This makes a financial analysis of biodiversity using ESG ratings the natural starting point of any discussion of the efficacy of disclosure mechanisms. As a disclosur mechanism, ESG is an approach to evaluating the extent to which a corporation aligns with environmental, social and governance goals. These goals may or may not be aligned with the pursuit of profits on behalf of the shareholders. Different ESG ratings provide signals for taking into account non-financial issues and related risks. Biodiversity is treated as a key issue under the Environment Category by most of the

ESG rating systems (For example, KLD (MSCI Stats), Sustainalytics, Vigeo Eris (Moody's), RobecoSAM (S&P Global), Asset4 (Refinitiv)).

With biodiversity widely recognized as an important component of environmental issues (the E) by ESG raters, the question remains as to how important biodiversity is as a component of this disclosure-based instrument. Could measurement of biodiversity in ESG move capital away from biodiversity-harmful areas or encourage engagement?

If so, what is the mechanism through which investors are led to invest in biodiversity-friendly areas? Is it because the biodiversity component has some predictive power on the stock returns? Or rather that it helps investors recognize whether a firm is a good or bad investment choice does 'biodiversity' as a component of ESG signal something about the firm's characteristics and fundamental performance? Finally, if the biodiversity rating does tell investors something about the firm and future stock returns, do financial market participants and companies have the incentive to track biodiversity measurement to raise returns or reduce risk? These questions address the overarching issue of how effective ESG disclosure can be in achieving agreed targets for nature and biodiversity recovery, and through which mechanism. These are the hypotheses that we test in this paper.

3. Environment and biodiversity in ESG metrics

We obtain stock-level ESG data from MSCI'S ESG Research, formerly known as KLD. This database is extensive and is widely used in finance literature. For our purposes, we focus on the US Russell 3000 stocks contained therein.[4] Environment (E), Social (S), and Governance (G) are the three pillars of the MSCI ESG data, each of which contains 10 themes. Each theme contains a series of relevant key issues. A firm's ESG score, and rating are generated from the firm's performance across a subset of a total of 37 different key issues. MSCI identify key issues that are relevant to an industry if it is likely that companies in this industry will incur substantial costs in connection with it or could capitalize on it for profit. The key issue is reassigned to each industry annually.

The performance of a firm on a specific key issue determines its key issue score. The key issue score is constructed by an *Exposure score* item and a *Management score*. The *Exposure score* measures how exposed the company is to the key issue, while the *Management score* shows how the company manages the key issue. For the purpose of our analysis, we have focused on the Biodiversity & Land Use key issue.

According to the rules of the MSCI ESG ratings, *Biodiversity & Land Use Score* (we use the term *biodiversity score* for short in this paper) is a combination of *biodiversity Exposure Score* and *biodiversity Management Score*: a company with high exposure must also have powerful management, whereas a company with limited exposure can have a more modest approach. Conversely, a highly exposed company with poor management will score worse than a company with the same management practices but with lower exposure to the risk. In other words, a higher *biodiversity exposure* indicates a lower biodiversity score, while a higher *biodiversity management* increases the biodiversity score.

Biodiversity exposure measures how a specific company is exposed to biodiversity risk based on a granular breakdown of its business, including the core product or business segments, the locations of its operations, and other relevant measures such as outsourced production or reliance on government contracts. Higher *biodiversity exposure* indicates that the company has a higher biodiversity risk. Further, *biodiversity management* is calculated based on the analysis of the extent to which a company has developed strategies and demonstrated a strong track record of performance in managing its specific level of biodiversity risks or opportunities. Higher biodiversity management indicates that the company has a stronger management of biodiversity risk. One important thing that needs to be noticed is that though the biodiversity exposure scores are provided to all the companies in the MSCI ESG universe, the biodiversity management scores are only available in firms in a specific group of industries. As a result, the coverage of biodiversity management score and biodiversity score (which is a combination of exposure and management) is not the MSCI ESG universe but only on specific groups of industries. The possible limitation brought by such methodology is discussed by Grant et al. (2023).

For the key issue of Biodiversity & Land Use, the industry level average *Exposure score* of Oil & Gas Exploration & Production is 7.34, indicating that the firms in this industry are highly exposed to the biodiversity issue based on their locations and products, while Road & Rail Transport industry only receives a 2.76 *Exposure score* on average. Such differences in the *Exposure score* of two industries tell investors about the difference of industry level biodiversity risk due to differences in their products and services, the location of company operations; and the nature of those operations. On the other hand, Oil & Gas Exploration & Production have an average *Management score* of 3.70, while Road & Rail Transport has a relatively higher *Management score* of 4.85. In relation to biodiversity, the management score relates mainly to companies' strategies & policies, targets & implementation, and demonstrated performance. Higher management scores in the Road & Rail Transport industry imply that these firms have a greater capacity to manage biodiversity risk. To score well on a key issue, management needs to be commensurate with the level of exposure: a company with high exposure must also have very strong management, whereas a company with limited exposure can have a more modest approach. Conversely, a highly exposed company with poor management will score worse than a company with the same management practices but with lower exposure to risk. Using the same example above, the overall biodiversity score of Oil & Gas Exploration & Production firms is only 3.34, while Road & Rail Transport is scored at 8.78. The huge difference between these two industries is mainly due to different levels of exposure to biodiversity given that their management performance is similar. Although almost all firms face exposures in key issues, not all of them have a *Management score*. According to the rules of the MSCI ESG ratings, each key issue is only materially relevant to a subset of industries, and while *Exposure scores* are provided for all firms, *Management scores* - and by extension final key issue scores - are only determined for companies in these industries. Otherwise, the key issue score will be set to be missing as a result.[5]

To further produce three pillar scores and final ESG scores, MSCI constructs *weight* for each key issue on an industry level. It takes into account both the contribution of industry, relative to all other industries, to the negative or positive impact on the environment or society; and the timeline within which we expect that risk or opportunity for companies in the industry to materialize. Higher contributions and shorter timelines will increase the weight of the key issues in a specific industry.

4. Data and methodology

The sample period of our research is from 2013 January to 2020 December, which is a result of matching MSCI ESG and CRSP/

[4] Transparency is a key issue with measurements of biodiversity impact and risk. The scientific documentation for ICEBURG labs and the MSA metrics is publicly available. There are issues of fungibility andinterpretation that beset all metrics of biodiversity impact and risk. Indeed, MSA is one among nearly 600 eligible metrics for biodiversity (Burgess et al., 2024). Our view is that the coverage of MSCI and Refinitiv approaches, while potentially less transparent, merits the kind of investigation that we undertake here to complement and broaden previous analyses.

[5] Grant et al. (2023) provide more details of the structure of the biodiversity metric in the MSCI and Sustainalytics ratings.

COMPUSTAT datasets. The MSCI ESG dataset provides the key biodiversity metrics that we are interested in, while CRSP and COMPUSTAT data provide stock returns and firm characteristics. We map these datasets mainly depending on ticker and cusip identifiers.[6]

4.1. Biodiversity data

We collect biodiversity score data from the MSCI ESG Score dataset, which provides monthly firm-level ESG score data. The scores that are related to biodiversity aspects in MSCI ESG data are measured by the *Biodiversity & Land Use Score* key issue, which is under the Environment pillar and Natural Capital theme. *Biodiversity & Land Use Score* is relevant to companies whose operations risk having a high negative impact on fragile ecosystems. The exposure component of this score, *Biodiversity & Land Use Exposure Score*, captures the extent to which a company's business is vulnerable to the ESG risk covered by this Key Issue. Examples of criteria assessed include the products and services a company provides; the location of company operations; and the nature of those operations. A higher exposure score indicates that the company has a higher risk related to biodiversity and land use, which decreases the overall *Biodiversity & Land Use Score* as a result. On the other hand, *Biodiversity & Land Use Management Score* measures how well a company *manages* biodiversity and land use risks. These metrics are grouped into the following broad categories: Strategies & Policies, Targets & Implementation, and Demonstrated Performance. The higher the management score, the better the management, which leads to a higher overall *Biodiversity & Land Use Score*.

The summary statistics of the three types of biodiversity metrics in MSCI ESG rating are provided in Panel A and of Table A. The average biodiversity score in our sample is 3.25 with a standard deviation of 2.23. We further present the number of firms in our sample in Panel E of Table A. There are 3146 firms and 51,765 firm-month observations in our full sample. The geographic distribution of the firms is shown in Table A2. California has the highest number of firms with the biodiversity exposure measure while Texas locates the most firms that are considered to be biodiversity material by the MSCI ESG rating. The full sample distribution for firms with biodiversity exposure is also slightly different from the sample that is biodiversity material. For example, 22 out of 61 firms (36 %) in Colorado are considered to be biodiversity material so they are given a biodiversity management score and biodiversity score. On the other hand, only 5 of 167 firms (3 %) in New York have a biodiversity management and biodiversity score.

4.2. Equity data

Stock-level data in our paper is obtained from the Center for Research on Security Prices (CRSP) and COMPUSTAT. From CRSP, we obtain the monthly stock returns, stock prices, and Standard Industry Classification (SIC) codes. We use COMPUSTAT to obtain various firm characteristics. In addition, all asset pricing factors except the liquidity factor come from Professor Kenneth French's data library. The liquidity factor is obtained from Professor Lubos Paster's website.

4.3. Institutional investor holding and analyst forecast

The Thomson Institutional (13f) Holdings shows the stock-level institutional holdings data, which provides quarterly snapshots of investor portfolio positions including manager id, report date, cusip and ticker of the stock, number of shares held, stock price, and number of shares outstanding, etc. We also use the institution-type data from Professor Brian Bushee's website.

We obtain annual forecast values on earnings per share (EPS) and actual values from Thomson Reuters' Institutional Brokers Estimate System (I/B/E/S) guidance database. We follow the analyst literature and impose several restrictions on our sample to filter for potential entry errors and mitigate the influence of outliers. First, we exclude forecasts with an absolute forecast error greater than one (Lim, 2001; Bernhardt et al., 2006). Second, we restrict our sample to forecasts issued for firms with an average share price greater than $1 (Chen and Jiang, 2006; Cen et al., 2013; Malmendier and Shanthikumar, 2014). To ensure that our consensus measurement is not biased by firms followed by a few analysts, we only include forecasts for firms covered by at least five analysts (Hilary and Hsu, 2013). Further, we keep forecasts with a maximum horizon of six months and a minimum horizon of one month from the earnings announcement date. This choice decreases the potential noise that could be introduced by stale forecasts and information leakage (Jackson, 2005; Jegadeesh et al., 2004).

5. Biodiversity scores and firm characteristics

In this section, we focus on the hypothesis we made in the introduction and analyse how biodiversity works in ESG ratings. Based on our first hypothesis, biodiversity performance provided by ESG ratings could be able to lead capital away from biodiversity-harmful areas. We first test this hypothesis by examining how biodiversity performance measurement is related to the firm's characteristics. The logic to start with is straightforward: if a firm's performance on the biodiversity score properly informs investors whether a firm is good or bad for biodiversity conservation, then in principle the score can affect decisions by investors that are interested in this characteristic and thereby influence the allocation of capital. Due to the heterogeneity of firms and their characteristics, we need to first show whether biodiversity performance is related to some specific fundamentals of firms so that investors could use biodiversity scores as an instrument to find out a group of firms with specific characteristics.

Further, we need to test whether biodiversity performance has the ability to lead capital move to a specific direction. In doing so, it should contain some information on further stock returns. Investors will have the incentive to follow biodiversity performance provided by ESG ratings if such a strategy could benefit them in future returns. So, it is necessary to examine how biodiversity performance affects future stock returns to present the mechanism of how it has an impact on capital flows.

Finally, after testing all the hypotheses above, it is still unclear how financial participants incorporate the information provided by the biodiversity measurements. That is, institutional investors and sell-side analysis may not treat biodiversity scores as information that could have an impact on stock return even if it works well. To get the whole picture of how biodiversity in ESG works in the financial market, we examine the reaction from these financial market participants in our analysis.

There are lots of different dimensions of ESG scores, and each of them is measured using different fundamental metrics. It is important to show what investors could get from ESG scores and their components. In other words, what are these ESG scores capturing for a company? Are they related to companies' fundamentals somehow? Some metrics in ESG, especially in key issues under the Environmental pillar, are sometimes closely related to other factors such as geographic information of firms. In this section, we investigate how three types of biodiversity scores are related to a series of firms' characteristics.

To start with, we investigate whether low biodiversity score firms are different from high biodiversity score firms in size and B/M ratio, which are two important characteristics that are related to firm performance and stock returns. In Table 2, we present the summary statistics of the firm's characteristics including biodiversity scores, firm size, and firm B/M ratio across five biodiversity portfolios. We present the average firm

[6] We also use ESG data from Thomson Refinitiv and conduct all the tests across the paper. The sample sizes are smaller, and the rating is discrete (3 levels) not continuous, and the results for stock returns and firm performances are similar to the results for the MSCI rating. The results using the Refinitiv data are available on request.

size and B/M ratio for each portfolio sorted based on one of the biodiversity scores in each panel. As is shown in Table 2, the size and B/M ratio do not change much across portfolios in all three panels, indicating that moving investment from firms in the lowest to the highest quintile does not change the target firm's characteristics in any discernible way.

To further check how a firm's biodiversity performance is related to its different characteristics, we regress biodiversity scores on a series of firm-level variables, comprising *Size*, *B/M Ratio*, *ROE*, *Leverage*, *INVEST/A*, *HHI*, *LOGPPE*, *R&D*, *CASH*, *SALESGR*, and *EPSGR*. We show the results in Table 3. Not surprisingly, biodiversity exposure is negatively correlated with firm size. Firms with larger sizes may have a better capability to diversify product and services so that their biodiversity exposure level would decrease. In addition, capital expenditure normalised for asset levels and plant, property and equipment are both positively correlated with the firm-level biodiversity exposure. These findings indicate that higher value of physical assets such as plants, properties and equipment could lead the firm to be more exposed to the biodiversity key issue. Further, we find that capital expenditure normalised for assets is also associated with a firm's biodiversity management score. Higher capital expenditure is associated with higher (better) biodiversity management scores. Last, higher earnings are also positively associated with higher biodiversity management scores. The results suggest that firms with higher capital expenditure and earnings have the ability to develop better exposure management strategies and management performance in general, including with regard to the measured biodiversity-related aspects of their operations.

In sum, these findings show firm-level characteristics are typically not associated with the firms' biodiversity performance, a conclusion that does not vary across portfolios aside from with regard to size, capital investment and earnings. These general measures of size reflect the type of firms that perform better in relation to biodiversity scores in ESG metrics. There are many reasons why this might be the case, including better management in general or the higher level of exposure that larger and growing firms have to the public and other scrutiny.

6. Are there returns to better biodiversity scores?

Based on the previous section, there is a minimal difference in the characteristics of firms with high and low biodiversity performance as measured by the MSCI index. However, biodiversity scores may be materially important in another sense: financial performance. In this section, we discuss whether biodiversity scores predict future stock returns. Specifically, we show how biodiversity scores affect stocks' future returns at the market and subindustry levels. We also provide evidence on any statistical association between biodiversity scores and stock returns. Finally, we show the relationship between firms' biodiversity scores and their performance.

To find out whether biodiversity scores could predict future stock returns, we first sort all stocks using their biodiversity score and construct portfolios each month to divide stocks with different levels of biodiversity score into different groups. Specifically, we use the $BiodiversityScore_{t-1}$ as the portfolio construction information. Specifically, in each month t, we first sort all the stocks in the market using their $BiodiversityScore_{t-1}$ in the previous month $t-1$. We then assemble stock portfolios reflecting quintiles of the score distribution from the lowest (portfolio 1) to the highest (portfolio 5). To avoid group separation bias, we excluded all the firms with the missing value of biodiversity scores last month. We further repeat the portfolio construction process using the components of the biodiversity score: *Biodiversity Exposure Score* and *Biodiversity Management Score*. The descriptive statistics of our sample using different biodiversity scores are reported in Table 1. As discussed in the previous section, most of the firms in MSCI's ESG dataset have biodiversity exposure scores while only about one tenth of these firms have a measure of biodiversity management score. The overall biodiversity score is only estimated when a firm has both its biodiversity exposure score, and biodiversity management scores are

Table 1
Summary statistics.

Variable	N Observation	Mean	SD	p25	p50	p75
Panel A: Biodiversity Scores						
Biodiversity Exposure	113,075	3.25	2.23	1.80	2.50	3.80
Biodiversity Management	20,376	3.25	1.50	2.00	3.40	4.30
Biodiversity Score	20,376	3.25	1.94	1.90	3.10	4.50
Panel B: Firm-Level Variables						
SIZE	51,765	14.75	1.65	13.59	14.60	15.80
B/M	51,765	0.83	0.85	0.41	0.68	1.05
ROE	51,765	0.04	0.55	0.00	0.10	0.20
LEV	51,765	0.30	0.25	0.12	0.28	0.41
INVEST/A	51,765	0.05	0.06	0.01	0.03	0.06
HHI	51,765	0.16	0.09	0.11	0.14	0.19
LNPPE	51,765	5.78	2.30	4.35	5.79	7.28
R&D	51,765	0.05	0.11	0.00	0.00	0.04
CASH	51,765	0.53	1.48	0.03	0.10	0.32
SALEGROWTH	51,765	−0.01	0.16	−0.05	0.00	0.05
EPSGROWTH	51,765	0.20	2.27	−0.51	0.15	0.93
ROA	17,784	0.00	0.17	0.00	0.04	0.08
EARNING	17,784	0.01	0.16	0.00	0.04	0.06
MARGIN PROFIT	17,559	−0.22	1.72	0.00	0.06	0.11
TOBINQ	51,651	2.37	1.82	1.24	1.71	2.76
FIRM BETA	52,137	1.17	2.40	0.47	1.10	1.76
IDIOSYNCRATIC RISK	51,675	0.30	0.16	0.18	0.26	0.37
Panel C: Time Series Variables						
MKTRF	96	1.26	4.16	−0.15	1.48	3.50
SMB	96	0.04	2.50	−2.00	0.28	1.43
HML	96	−0.57	2.84	−2.08	−0.54	0.56
MOM	96	0.22	3.66	−1.94	0.31	2.09

Variable	N Observation	Mean	SD	p25	p50	p75
Panel D: Institutional Investors-Level Variables						
Portfolio Size	14,936	8.93	2.31	7.37	9.02	10.48
Portfolio Concentration (in thousand)	14,936	1774	5292	463.2	606,1	1254
No. of States	14,936	41.20	10.09	37.00	45.00	48.00
No. of Companies	14,936	1588	1220	595	1364	2440
No. of Other Institutional Investor	14,936	2386	667.10	2009	2484	2938
Panel E: Analyst-Level Variables						
Forecast Horizon	46,432	3.24	1.62	2.00	3.00	5.00
No. of Companies	46,432	19.24	6.84	15.00	19.00	23.00
Company Experience	46,432	1.64	0.88	1.10	1.79	2.40
General Experience	46,432	2.72	0.30	2.56	2.77	2.94
Broker Size	46,432	19.32	11.83	9.00	18.00	28.00
No. of Industries	46,432	7.29	4.08	4.00	7.00	10.00
All Star	46,432	0.11	0.32	0.00	0.00	0.00
Lagged AFE	46,432	0.01	0.01	0.00	0.00	0.01

Panel F: Summary Statistics for Number of Firms Per Year						
Variable	Total Number of Firms	Mean	SD	p25	p50	p75
Biodiversity Score	429	239.25	14.45	229	237	250

(*continued on next page*)

Table 1 (*continued*)

Panel D: Institutional Investors-Level Variables						
Variable	N Observation	Mean	SD	p25	p50	p75
Biodiversity Exposure	3146	1339	1192	229	1285	2442
Biodiversity Management	429	239.25	14.45	229	237	250

This table presents summary statistics for the various datasets used in the paper. Panel A presents the biodiversity performance variables including the biodiversity score, biodiversity exposure, and biodiversity management Panel B shows firm-level descriptive characteristics. Panel C illustrates presents the time series variables including the Fama-French three factors and the momentum factor. In Panel D, we present institutional investor-level variables and Panel E presents the sell-side analyst variables. Panel F shows the summary statistics for the number of firms per year in our sample period. All variables are defined in Table A1.

non-missing.

Next, we analyse the performance of five sorted portfolios in month *t*. If the biodiversity score predicts stocks' future returns, we should find a significant difference between the performance of the lowest portfolio and the highest portfolio. We report the value-weighted excess return of five portfolios sorted by three categories of biodiversity scores in Table 4. We also present the return difference between the lowest portfolio and the highest portfolio in each category in the last row. Portfolio Excess returns are calculated by the difference between the value-weighted raw return across all stocks in the portfolio and the risk free rate in the same month. The excess return differences are negative in column (1) and (3) and positive in column (2). The interpretation of the signs is that there is a negative effect of adjusting portfolios from lowest to highest overall biodiversity score and this is composed of a negative effect of better management, and a negative effect of lower exposure.

Table 2
Firm characteristics in five biodiversity scores sorted portfolios.

Panel A: Biodiversity Score Sorted Portfolios			
Portfolio	Biodiversity Score	Size	B/M Ratio
1	0.928	15.434	0.799
2	2.155	14.960	1.323
3	3.007	15.065	1.008
4	4.146	15.538	0.931
5	6.049	14.506	0.840
Panel B: Biodiversity Exposure Sorted Portfolios			
Portfolio	Biodiversity Score	Size	B/M Ratio
1	2.638	14.130	0.812
2	4.080	16.416	1.380
3	4.919	15.536	0.979
4	5.689	14.336	0.961
5	7.242	15.206	0.833
Panel C: Biodiversity Management Sorted Portfolios			
Portfolio	Biodiversity Score	Size	B/M Ratio
1	1.271	15.803	1.102
2	2.499	14.725	0.957
3	3.222	14.020	0.909
4	3.728	14.741	1.008
5	4.808	16.187	0.933

This table reports performance estimates and characteristics of portfolios constructed by sorting firms into quintiles based on biodiversity score, biodiversity exposure, and biodiversity management. We show the average biodiversity performance, size and book-to-market ratio. In Panel A, we present the performance estimates of the portfolio sorted based on biodiversity exposure. Panel B and Panel C report the portfolio characteristics of portfolios sorted by biodiversity management and biodiversity score, respectively. All variables are defined in Table A1. Each panel reports the characteristics of the full sample from January 2013 to December 2020.

Table 3
Determinants of biodiversity scores.

Variables	Biodiversity Exposure	Biodiversity Management	Biodiversity Score
Size	−0.068**	0.247	0.891**
	(−3.06)	(0.77)	(2.71)
Bm	−0.014	0.156	0.559
	(−0.79)	(0.64)	(1.91)
ROE	0.012	−0.314*	−0.168
	(0.55)	(−2.57)	(−1.09)
lev	0.077	−0.172	−0.155
	(1.34)	(−0.41)	(−0.33)
INVEST/A	0.906*	2.550**	2.345*
	(2.29)	(2.67)	(2.10)
HHI	0.030	0.725	0.745
	(0.17)	(0.63)	(0.45)
lnppe	0.055**	−0.290	−0.920**
	(3.17)	(−1.01)	(−2.92)
lRD	−0.048	−13.881	−5.854
	(−0.25)	(−0.95)	(−0.38)
lCASH	0.010	−1.232	−0.356
	(0.84)	(−1.88)	(−0.46)
lSALEGROWTH	0.145	0.026	−0.511
	(1.99)	(0.08)	(−0.58)
lEPSGROWTH	0.008	0.027**	−0.013
	(1.07)	(3.30)	(−1.68)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	3132	488	488
Adj-R Square	0.850	0.177	0.336

This table presents the estimates from a regression between biodiversity performance and a series of firm-level characteristics. The independent variable is one of the following variables: biodiversity performance: biodiversity score, biodiversity exposure, and biodiversity management. We choose a series of one-year lagged firm-level characteristics as the dependent variables: SIZE is the log of the firm market capitalization. B/M is the Book-to-Market ratio of the firm. ROE is the return-on-equity of the firm, which is defined as the net income divided by the stockholder equity. LEV is the firm leverage, which equals the sum of debt in current liabilities and long-term debt divided by the value of total assets. INVEST/A is relative capital expenditure, which is the capital expenditure over total assets. HHI is the Herfindahl index of the business segments of a company with weights proportional to revenues. LNPPE is the natural logarithm of plant, property and equipment (in $ million); R&D is defined as R&D expenditure over total assets. CASH is the ratio of cash and marketable securities to the total asset net of cash and marketable securities. SALEGROWTH is the difference between sales in the current year and sales in the previous year. EPSGROWTH is defined as the difference between earnings per share this year and the earnings per share in the last year. All variables are defined in Table A1. *t*-statistics are reported in parentheses below the estimates are clustered at the year- and firm-level. The estimation period is from 2013 to 2020. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Nevertheless, the magnitudes of these effects are small and, sample sizes notwithstanding, the difference between the lowest and the highest portfolio in all categories is insignificant: biodiversity scores do not predict future stock returns.

In Table 5, we go further and estimate the factor-adjusted return of portfolios sorted by biodiversity scores. Specifically, we measure the portfolio factor adjusted returns using the CAPM model, the Fama-French three-factor model, Carhart four-factor model, and a combined six-factor model using Carhart four factors and short- and long-term reversal factors.[7]

According to the estimates shown in Table 5, the monthly return differences of the highest and the lowest biodiversity sorted portfolios using three biodiversity scores range from −0.043 % to 0.084 % across three score categories. Our finding regarding the factor-adjusted return of portfolios is consistent with the previous conclusion that the

[7] We only present the results based on the Carhart-Four-Factor-Model for brevity. The results using all other models above are quantitatively similar.

Table 4
Excess return of biodiversity sorted portfolio.

Portfolio	Biodiversity Exposure	Biodiversity Management	Biodiversity Score
Low	−0.069	−0.054	−0.065
	(−0.55)	(−0.54)	(−0.68)
2	0.009	−0.175	0.051
	(0.18)	(−1.27)	(0.24)
3	−0.130	0.128	−0.220**
	(−1.02)	(1.09)	(−2.39)
4	0.086	−0.199**	−0.017
	(0.81)	(−2.09)	(−0.16)
High	0.001	0.042	−0.059
	(0.01)	(0.31)	(−0.62)
High-Low	0.070	0.096	0.006
	(0.41)	(0.49)	(0.04)
Total No. Firms	3146	429	429

This table reports performance estimates from various zero-cost trading strategies. In particular, we sort stocks into quintiles based on their biodiversity performance: biodiversity score, biodiversity exposure, and biodiversity management. The "Low" portfolio is a value-weighted portfolio of the quintile of stocks with the lowest biodiversity performance. The "High" portfolio is a value-weighted portfolio of the quintile of stocks with the highest biodiversity performance. Portfolios 2 to 4 represent the value-weighted portfolios of the remaining firms sorted into terciles based on their biodiversity performance. The trading strategy consists of buying stocks in the top quintile and selling stocks in the bottom quintile. Component returns are those of the US firms in the MSCI ESG sample during the sample period. We report the industry-adjusted return of five portfolios sorted by each of the three biodiversity performances in each column. We further present the High-Low difference of the excess return between the "High" and "Low" portfolios and the number of firms in our sample at the bottom of each column. All variables are defined in Table A1. *t*-statistics are computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from 2013 to 2020. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 5
Carhart-four-factor-model adjusted returns of 5 biodiversity sorted portfolios.

Portfolio	Biodiversity Exposure	Biodiversity Management	Biodiversity Score
Low	0.029	0.026	−0.055
	(0.21)	(0.23)	(−0.55)
2	−0.007	−0.126	0.104
	(−0.13)	(−0.92)	(0.45)
3	−0.060	0.067	−0.237**
	(−0.53)	(0.46)	(−2.06)
4	0.022	−0.268**	−0.025
	(0.20)	(−2.57)	(−0.26)
High	−0.014	0.110	0.016
	(−0.10)	(0.90)	(0.17)
High-Low	−0.043	0.084	0.071
	(−0.21)	(0.47)	(0.44)
Total No. Firms	3146	429	429

This table reports performance estimates from various zero-cost trading strategies. In particular, we sort stocks into quintiles based on their biodiversity performance: biodiversity score, biodiversity exposure, and biodiversity management. The "Low" portfolio is a value-weighted portfolio of the quintile of stocks with the lowest biodiversity performance. The "High" portfolio is a value-weighted portfolio of the stocks with the highest biodiversity performance. Portfolios 2 to 4 represent the value-weighted portfolios of the remaining firms sorted into terciles based on their biodiversity performance. The trading strategy consists of buying stocks in the top quintile and selling stocks in the bottom quintile. Component returns are those of the US firms in the MSCI ESG sample during the sample period. We report the Carhart-four-factor adjusted industry-level demeaned return, namely market factor (RMRF), size factor (SMB), value factor (HML), and momentum factor (MOM), of five portfolios in each column. We further present the High-Low difference of the factor–adjusted return between the "High" and "Low" portfolios, the number of firms in our sample at the bottom of each column, and the total number of firms. All variables are defined in Table A1. *t*-statistics are computed using Newey- West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from 2013 to 2020. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

biodiversity measurement of stocks does not predict future stock returns.

One of the potential problems of our analysis up to now is that some industries may drive insignificant differences because of the data coverage of biodiversity scores. The factor-adjusted returns for each of the five portfolios in Table 5 also indicate that most of the portfolios that contain biodiversity scores present a lower performance relative to the benchmark. To further investigate this observation, we conduct an industry-level analysis of biodiversity portfolios instead of using the full sample in Table 6.[8] Specifically, we group all the stocks in our sample into different industries based on their GICS industry code[9] and sort stocks into five portfolios based on biodiversity scores following our main methodology in each industry. We then estimate the factor-adjusted returns for each portfolio and calculate the difference between the highest and the lowest biodiversity scores portfolio in each industry. Because of the limited coverage of biodiversity management score (and hence biodiversity score), there are only seven different industries in which the firms have scores in all three types of biodiversity scores in MSCI's ESG data, namely: Energy Equipment & Services; Integrated Oil; Gas, Metals and Mining - Non-Precious Metals; Metals and Mining - Precious Metals; Oil & Gas Exploration & Production; Oil & Gas Refining; Marketing; Transportation & Storage; and Utilities. Most of these industries are related to extractives; to avoid the bias due to the industry-level performance, we applied industry-adjusted return instead of excess return in Table 6.

Consistent with the previous findings, the return difference between the Highest and the Lowest biodiversity scoring portfolios remains insignificant in most of the seven industries for all three types of biodiversity scores. The negative performance of portfolios in Energy Equipment & Services and Oil & Gas related industries also explains the negative performance of the overall portfolio in Table 5.

The coverage of biodiversity exposure score is much larger in the dataset. There are 61 out of 88 industries where firms' biodiversity exposures are estimated. We conduct similar industry-level analyses on biodiversity exposure-based portfolios. However, only four out of 61 industries[10] show a significant difference between the Highest and the Lowest portfolios while others remain insignificant.

So far, we show that the biodiversity scores do not predict future stock returns. However, the sorting methodology could only tell the statistical relationship between the ranking of biodiversity scores of stocks in the full sample and its future stock returns. We further conduct regressions using several different models to explore statistical relationship between biodiversity scores and stock returns by including a series of firm-level characteristics. Specifically, we estimate the following model:

$$r_{i,t+1} = \alpha_i + \beta Biodiversity_{i,t} + \gamma X_{i,t} + \epsilon_{i,t+1} \tag{1}$$

where $r_{i,t+1}$ is the raw return for stock i on time $t+1$, $Biodiversity_{i,t}$ is one

[8] We only show the industry-level Carhart four-factor-model portfolio performance results in Table 6. Results based on other models are quantitatively similar.

[9] MSCI's ESG data provide industry information of each stock in the dataset based on the GICS industry code. There are in total 88 different industries contained in MSCI's ESG data. We directly use their data in our industry-level analysis.

[10] These four industries are Household Durables, Hotels & Travel, Commercial Services & Supplies, and Broadcasting, Cable & Satellite. These four industries only account for a limited size of the market which do not have a significant impact on the total result.

Table 6
Industry level carhart four-factor-model adjusted returns of 5 biodiversity sorted portfolios.

Biodiversity Score-sorted Portfolios Four Factor Alphas Difference in Seven Industries			
	High-Low Carhart-four-factor Alpha		
Industry	Biodiversity Exposure	Bioidiversity Management	Biodiversity Score
Energy Equipment & Services	−0.697	−0.998	0.061
	(−1.07)	(−1.46)	(0.11)
Integrated Oil & Gas	−2.219	−2.320	−1.387
	(−1.62)	(−1.38)	(−1.14)
Metals and Mining - Non-Precious Metals	0.191	−0.249	−1.848**
	(0.21)	(−0.33)	(−2.05)
Metals and Mining - Precious Metals	0.376	1.190**	1.535*
	(0.40)	(2.44)	(1.88)
Oil & Gas Exploration & Production	−0.127	0.196	−0.088
	(−0.26)	(0.43)	(−0.20)
Oil & Gas Refining, Marketing, Transportation & Storage	0.667	0.867	0.954*
	(0.64)	(0.91)	(1.88)
Utilities	0.069	0.594	1.040**
	(0.12)	(1.28)	(2.30)
No. of Periods	95	95	95

This table reports performance estimates of portfolios based on biodiversity performance at the industry level. In particular, we sort stocks into quintiles based on their biodiversity performance within each industry: biodiversity score, biodiversity exposure, and biodiversity management. The "Low" portfolio is a value-weighted portfolio of the quintile of stocks with the lowest biodiversity performance in each industry. The "High" portfolio is a value-weighted portfolio of the quintile of stocks with the highest biodiversity performance in each industry. Portfolios 2 to 4 represent the value-weighted portfolios of the remaining firms sorted into terciles based on their biodiversity performance in each industry. The trading strategy consists of buying stocks in the top quintile and selling stocks in the bottom quintile. Component returns are those of the US firms in the MSCI ESG sample during the sample period. We first calculate the industry-adjusted return for each portfolio and then further adjust it using the Carhart-four-factor model. We report the High-Low adjusted return generated by the trading strategy in each industry. All variables are defined in Table A1. *t*-statistics are computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from 2013 to 2020. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

of the three biodiversity scores for stock i on time t. $X_{i,t}$ represent a series of firm-level characteristics of stock i on time t, including the log of the size; the book-to-market ratio; the book leverage of the company; the firm's capital expenditures divided by the book value of its assets; the Herfindahl concentration index of firms with respect to different business segments, based on each segment's revenues; the natural logarithm, of the firm's property, plant, and equipment; firm's R&D expense over the total asset in the previous year; the ratio of cash and marketable securities to total assets net of cash and marketable securities in the previous year; the dollar change in annual earnings per share, normalised by the firm's equity price. All the variables are defined in Table A1. To eliminate the impact of outliers, we winsorize all the firm-level controls at the 1 % level on both sides.

Fama-MacBeth is a widely used regression model in asset pricing research to correct the cross-sectional correlation. Following most of the asset pricing papers, we directly run cross-sectional regressions across assets using our estimated stock-level characteristics, in addition to our biodiversity variable. We then take the average of the coefficients and calculate the t-statistics based on the distribution of the coefficients in our Fama- MacBeth regressions (see Addoum and Kumar, 2016; Addoum and Kacperczyk, 2021; Cuculiza et al., 2023; Sautner et al., 2023a, 2023b). In our analysis in Table 7. To further address the effect of biodiversity performance on the stock return, we generate a series of dummy variables in our regression model as dependent variables to clearly show how different rankings of biodiversity performance affect the stock returns. Specifically, we generate High-Score Dummy as an indicator equals 1 if the firm is in the top quintile of stocks sorted by biodiversity performance. We also construct a series of Quntile Dummy-based biodiversity performances. Quintile Dummy X (X = 1,2,3,4,5) equals 1 if the stock ranks in the Xth quintile portfolio sorted by the biodiversity performance, and zero otherwise. We omit Quintile Dummy 1 so coefficients represent variation relative to this omitted category. Industry and time-fixed effects are also controlled in our regression. The Fama-MacBeth regression results are shown in columns (1) to (3) and panel regression results are shown in columns (4) to (6) in all three panels in Table 7.

All the coefficients of the independent variables of interest are insignificant in Table 7, which shows that none of the three biodiversity scores generate significant future stock returns when considering firm-level characteristics.

The inclusion of firm characteristics and fixed effects is an attempt to estimate the association of the biodiversity ratings on returns. The identifying assumption would be that the firm-level characteristics and fixed effects control for the unobservable characteristics correlated with the biodiversity rating over time and in the cross-section. To the extent that this assumption is true, the estimates can be considered associative, controlling for observable firm characteristics.

7. Why biodiversity scores do not affect stock returns

There are several explanations behind the insignificant relationship between biodiversity scores and stock returns. The first possible explanation is that biodiversity scores are unrelated to firms' performance. If the key issue of biodiversity rarely affects firms' fundamentals, then we should see an insignificant relationship between the firms' future stock returns and biodiversity scores. Second, since biodiversity scores are not strongly associated with characteristics that are closely related to firm performance, one important interpretation of this finding could be that moving investment from low to high biodiversity-scoring firms could result in investment in firms with similar characteristics, which generate similar stock returns. Finally, we cannot rule out one final interpretation, that the firm's systematic risk is simply not affected by its biodiversity score. According to CAPM theory, systematic risk is the key risk that could generate a stock return. If biodiversity scores have no relationship with systematic risk, then it would be no surprise to find that biodiversity scores fail to predict future stock returns. Further, investors may pay only limited attention to biodiversity risk because they cannot get enough information from the market that increases their awareness of the importance of biodiversity. For example, if institutional investors do not show any holding preference across firms with different levels of biodiversity scores, and the sell-side analysts also do not incorporate biodiversity information into their earnings forecasts, investors in the market will hardly get any useful information that links biodiversity scores to stock returns. In this section, we will investigate the possible explanations above and show why biodiversity scores do not affect stock returns.

7.1. Firm's profitability, risk and Tobin'Q

We first regress the firm's performance on biodiversity scores and firm characteristics following Eq. (5) by replacing the dependent variable using the firm's profitability (e.g. return-on-asset, firm earnings and firm profit margin), firm's systematic and idiosyncratic risk, and Tobin's Q. The panel regression results are shown in Table 8.[11]

According to the coefficients in Table 8, there is no strong

[11] The results from the Fama-MacBeth regression are quantitatively similar

Table 7
Biodiversity scores and stock return regression estimates.

Panel A: Biodiversity Exposure and Stock Returns

	Fama-MacBeth			Pooled Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Exposure	−0.009			−0.008		
	(−0.06)			(−0.10)		
High-Score Dummy		−0.745			0.001	
		(−1.10)			(0.00)	
Quntile 2 Dummy			−2.391			−0.057
			(−1.13)			(−0.58)
Quntile 3 Dummy			−3.116			0.211
			(−1.21)			(0.65)
Quntile 4 Dummy			−3.448			0.000
			(−1.31)			(0.00)
Quntile 5 Dummy			−3.145			0.049
			(−1.17)			(0.08)
Control Variables	YES	YES	YES	YES	YES	YES
Year-month FE	NO	NO	NO	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Observations	51,765	51,765	51,765	51,765	51,765	51,765
Adj-R Square				0.191	0.191	0.191
Avg-R Square	0.310	0.305	0.331			

Panel B: Biodiversity Management and Stock Returns

	Fama-MacBeth			Pooled Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Management	0.021			0.080		
	(0.16)			(0.86)		
High-Score Dummy		−0.258			−8.865***	
		(−0.98)			(−8.67)	
Quntile 2 Dummy			−0.254			−0.161
			(−1.02)			(−0.43)
Quntile 3 Dummy			−0.326			−0.318
			(−0.64)			(−0.79)
Quntile 4 Dummy			0.042			1.317**
			(0.12)			(3.57)
Quntile 5 Dummy			−0.353			−8.978***
			(−0.99)			(−9.84)
Control Variables	YES	YES	YES	YES	YES	YES
Year-month FE	NO	NO	NO	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Observations	7254	7254	7254	7254	7254	7254
Adj-R Square				0.294	0.295	0.294
Avg-R Square	0.394	0.385	0.405			

Panel C: Biodiversity Score and Stock Returns

	Fama-MacBeth			Pooled Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Score	0.022			0.084		
	(0.23)			(0.84)		
High-Score Dummy		−0.091			−0.066	
		(−0.37)			(−0.24)	
Quntile 2 Dummy			0.124			0.320
			(0.43)			(1.31)
Quntile 3 Dummy			0.054			0.187
			(0.12)			(0.46)
Quntile 4 Dummy			1.227			0.529
			(1.56)			(0.73)
Quntile 5 Dummy			−0.026			−0.123
			(−0.04)			(−0.16)
Control Variables	YES	YES	YES	YES	YES	YES
Year-month FE	NO	NO	NO	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Observations	7254	7254	7254	7254	7254	7254
Adj-R Square				0.294	0.294	0.294
Avg-R Square	0.396	0.389	0.418			

This table reports estimates from predictive Fama-MacBeth (1973) regressions and panel regression. We regress a stock's monthly excess return on our main independent variable and the following controls: SIZE, B/M, ROE, LEV, INVEST/A, HHI, LNPPE, R&D, CASH, SALEGROWTH, and EPSGROWTH. Our main independent variable is biodiversity performance: biodiversity score, biodiversity exposure, and biodiversity management. High-Score Dummy is an indicator equals 1 if the firm is in the top quintile of stocks sorted by biodiversity performance. We also construct a series of Quntile Dummy-based firms' biodiversity performance. Quntile Dummy X (X = 1,2,3,4,5) equals 1 if the stock ranks in the Xth quintile portfolio sorted by the biodiversity performance, and zero otherwise. We omit Quintile Dummy 1 so coefficients represent variation relative to this omitted category. Panel A reports the regression estimates of the biodiversity exposure. In Panel B and Panel C, we report the regression estimates of biodiversity management and biodiversity score, respectively. We report the time-series average of cross-sectional adjusted 2. All variables are defined in Table A1. Standard errors are clustered at the firm and time levels and *t*-statistics are reported in parentheses below the estimates. We include both time- and industry-fixed effects in our regression. The estimation period is from 2013 to 2020. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 8
Biodiversity scores, firm profitability, risk and Tobin's Q.

Panel A: Biodiversity Exposure, Firm Profitability, Risk and Tobin's Q						
Dependent Variable	ROA	Earning	Profit Margin	Firm Beta	Idiosyncratic Risk	Tobin's Q
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Exposure	0.006	0.002	0.072***	0.024	0.003	−0.012
	(1.64)	(0.89)	(5.08)	(1.09)	(1.24)	(−0.45)
Control Variables	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Observations	17,784	17,784	17,559	52,137	51,675	51,651
Adj-R Square	0.624	0.335	0.632	0.040	0.417	0.391
Panel B: Biodiversity Management, Firm Profitability, Risk and Tobin's Q						
Dependent Variable	ROA	Earning	Profit Margin	Firm Beta	Idiosyncratic Risk	Tobin's Q
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Exposure	0.006**	0.008	0.016	0.023	−0.002	−0.010
	(3.10)	(1.13)	(1.26)	(0.57)	(−0.51)	(−0.49)
Control Variables	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Observations	2494	2494	2487	7259	7134	7113
Adj-R Square	0.424	0.391	0.768	0.151	0.544	0.517
Panel C: Biodiversity Score, Firm Profitability, Risk and Tobin's Q						
Dependent Variable	ROA	Earning	Profit Margin	Firm Beta	Idiosyncratic Risk	Tobin's Q
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Exposure	−0.002	0.007	−0.013	−0.008	−0.005	−0.011
	(−0.42)	(1.32)	(−1.21)	(−0.25)	(−1.46)	(−0.74)
Control Variables	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Observations	2494	2494	2487	7259	7134	7113
Adj-R Square	0.423	0.391	0.768	0.151	0.545	0.517

This table reports estimates from panel regressions. We regress a series of variables on our biodiversity performance (biodiversity score, biodiversity exposure, and biodiversity management) and the following control variables: SIZE, B/M, ROE, LEV, INVEST/A, HHI, LNPPE, R&D, CASH, SALEGROWTH, and EPSGROWTH. We first regress a series of measures on firm profitability on biodiversity performance including a firm's ROA, earnings, and profit margin. Further, we use firms' systematic risks and idiosyncratic risks as the dependent variables in our regression. Finally, Tobin's Q is regressed on the firm's biodiversity performance. All variables are defined in Table A1. Standard errors are clustered at the firm and time levels and t-statistics are reported in parentheses below the estimates. *t*-statistics are reported in parentheses below the estimates are clustered at the time- and firm-level. We include both time- and industry-fixed effects in our regression. The estimation period is from 2013 to 2020. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

relationship between biodiversity scores and firms' performance. Though biodiversity exposure and biodiversity management scores have some statistically significant prediction power on some of the performance estimates, these two sub-scores of biodiversity are not crucial enough to attract investors' attention when making decisions in practice, which, as a result, does not affect investment in general enough to generate significant stock return difference.

According to the CAPM theory, the return of a stock is affected by its systematic risk but not overall volatility. Investors could diversify away from the idiosyncratic risk of stocks so that only those risks that cannot be avoided matter when pricing the stock. In this case, the systematic risk will determine the stock return.

The coefficients between biodiversity scores and firm beta and idiosyncratic risk in our regression indicate that a firm's systematic risk and idiosyncratic risk are unaffected by its biodiversity performance in ESG. The coefficients in columns (4) and (5) across all three panels in Table 8 are not significant.

Another possible mechanism between firms' biodiversity performances and stock returns is from investors' misreaction. Since neither of the risks above is affected by the biodiversity scores, we then test whether investors tend to overvalue or undervalue the stock based on their biodiversity performance. In column (6) of Table 8, we test the regression between biodiversity scores and firm Tobin's Q, which indicates whether the stock is misvalued by the market. The coefficients of all three-biodiversity score categories are all insignificant, indicating that investors are not driven by firms' biodiversity performance in the valuation process.

Overall, our analysis shows that the firm's profitability and firm's risk, are not affected by the firm's biodiversity performance, which explains the insignificant relationship between biodiversity scores and stock returns. Further, investors are not affected by firms' biodiversity performance in their investment strategy since firms' misevaluation is not related to their biodiversity performance.

7.2. Reactions from financial market participants

So far, we have shown the relationship between biodiversity scores and firm-level characteristics that may have an impact on their return such as performance and systematic risk. Next, we will discuss why investors in the market do not react to biodiversity-related information. In this section, we mainly focus on two main information providers in the financial market: institutional investors and sell-side analysts. Investors

Table 9
Biodiversity scores and stock institutional ownership.

	Dependent Variable: Stock IO					
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Exposure	0.005*	0.005*				
	(1.79)	(1.79)				
Biodiversity Management			0.007*	0.007*		
			(2.12)	(2.12)		
Biodiversity Score					−0.000	−0.000
					(−0.05)	(−0.05)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Institutional Investor Controls	No	Yes	No	Yes	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,936	14,936	15,041	15,041	15,041	15,041
Adj-R Square	0.931	0.931	0.932	0.932	0.931	0.931

This table reports panel regression model estimates between a stock's institutional ownership and its biodiversity performance The dependent variable institutional ownership is defined as the ratio between the institutional holding value of a stock and its total market capitalization. Our main independent variable is the biodiversity performance: biodivesity score, biodiversity exposure, and biodiversity management. We control a series of firm control variables: the average log market capitalization of firms across all months last year, the book-to-market ratio of firms last year, and the firm's leverage the previous year. We also include a loss indicator that equals one if the firm experienced a loss last year. The dividend yield of a firm last year and a no dividend yield indicator equals one if the firm did not issue a dividend last year. We further include institutional-level controls in our regression: the portfolio size, portfolio concentration, the number of different states represented in the institution's portfolio, the number of different firms present in the institution's portfolio, and the total number of institutions in each state in quarter t. In our regression, we control for firm, and time-fixed effects. All variables are defined in Table A1. *t*-statistics are reported in parentheses below the estimates are clustered at the time- and firm-level. The estimation period is from 2013 to 2020. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

may not price biodiversity because there is no signal on the market showing that biodiversity matters to the stock return.

7.2.1. Biodiversity and stock institutional ownership

An important explanation to the abnormal stock return is that some investors may shun companies with specific characteristics, risk sharing would be limited, and idiosyncratic risk could be priced (e.g., Merton et al., 1987; Hong and Kacperczyk, 2009). If the extent of such divestment is high, one would expect to see significant pricing effects. We test this possibility by looking at the relationship between stock institutional ownership and biodiversity scores. Formally, we estimate the following pooled regression model:

$$IO_{i,j,t} = \alpha_i + \beta Biodiversity_{i,t-1} + \gamma X_{i,t-1} + \theta Z_{j,t-1} + \mu_t + \delta_j + \eta_i + \epsilon_{i,t} \quad (2)$$

We consider ownership effects based on biodiversity scores, $X_{i,t-1}$ is a series of firm controls, and $Z_{j,t-1}$ are institutional investors controls. All regressions include quarter and firm fixed effects. We report our results on Institutional Ownership (IO) in Table 9. In columns (1) and (2), we report how stocks' IO changes related to biodiversity exposure. Our results here show that institutional investors slightly increase their holding of market shares of firms according to their biodiversity exposure. Similar evidence is also presented in columns (3) and (4) for coefficients of biodiversity management. However, higher IO does not lead to a limitation on risk sharing, which means that there is no pricing in idiosyncratic risk when stocks' IOs are increased. So, there is no evidence showing that the difference in IO of stocks with different biodiversity scores could lead to their different stock return performance. Similar results are also found in the biodiversity score, which is presented in the last two columns in Table 9.

Since there is a large heterogeneity in the awareness of biodiversity risk across different types of institutions, it is necessary to analysis how different institutions react to a firm's biodiversity risk differently. We provide evidence by analysing the firm's institutional ownership by different types of institutions in Table 10. Specifically, following Bushee (1998), we separate institutions into eight types and show how the biodiversity performance of firms affects their institutional investors among these different types: Bank Trust, Insurance Company, Investment Company, Independent Investment Advisor, Corporate (private) Pension Fund, Public Pension Fund, University and Foundation Endowments, and Miscellaneous. We find that firms with higher biodiversity exposure have higher ownership held by the bank trust. This could be explained by the more expertise in risk management by banks. Further, insurance companies prefer those firms with better biodiversity management to avoid the potential risk brought by biodiversity. As a result, the combined biodiversity score decreases the firm's ownership by banks but increases the firm's ownership by insurance companies. The non-significant coefficients of IO on other types of institutions indicate that though some heterogeneity effects exist among different institutions, these effects are still too small to generate a significant preference from institutional investors.

Overall, our findings on institutional ownership and biodiversity scores are consistent with our previous finding that the biodiversity performance of stocks does not predict their future returns. Another implication of the results in Table 9 is that institutional investors in general do not consider the biodiversity performance of stocks in their portfolio construction. They show an indifferent preference for stocks with different biodiversity scores.

7.2.2. Biodiversity and analysts forecast accuracy

Further, it is necessary to examine whether sell-side analysts react to biodiversity information when they make earningsforecasts because analysts provide important information to the financial market and could have a huge impact on investors' investment decisions. Investors tend to change their portfolio holdings according to sell-side analysts' forecasts and recommendations. Thus, we test whether analysts' forecast error changes with firms' biodiversity performance. We calculate the analyst forecast error using a performance measure similar to Clement (1999). In particular, we use the proportional median absolute forecast error (PMAFE) to compare an analyst's absolute forecast error to the median absolute forecast error of other analysts that cover the same firm at the same time. The measure is as follows:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \widehat{AFE}_{j,t}}{\widehat{AFE}_{j,t}} \quad (3)$$

for analyst *i*, firm *j*, at time *t*. $AFE_{i,j,t}$ is defined as $\left|\frac{Forecast\ Value_{i,j,t} - Actual\ Value_{j,t}}{Price_{j,t-1}}\right|$, where $\widehat{AFE}_{j,t}$ is the median absolute error for firm *j* at time *t*. An advantage of using this measure is that it accounts for firm × time-fixed effects. Then, we estimate how biodiversity scores affect analysts' forecast errors using the following regression:

$$PMAFE_{i,j,t} = \alpha_i + \beta Biodiversity_{i,t-1} + \gamma X_{i,t-1} + \theta Z_{j,t-1} + \mu_t + \delta_j + \eta_i + \epsilon_{i,t} \quad (4)$$

We show how the biodiversity performance of a stock in a previous period affects analyst forecast accuracy. $X_{i,t-1}$ is a series of firm control variables and $Z_{j,t-1}$ is a series of analyst control variables. All results are presented in Table 11. We find that all coefficients across six columns in Table 11 are insignificant, which indicates that none of the three biodiversity scores affect analysts' forecast accuracy. Combined with the previous finding in Table 8 that biodiversity scores do not affect firm earnings, our results in Table 11 show that sell-side analysts' forecast

Table 10
Biodiversity scores and stock institutional ownership by type.

Panel A: Biodiversity Exposure and Institutional Ownership-Results by Eight Types of Institutions

	Dependent Variable: Stock IO							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Institution Type	Bank Trust	Insurance Company	Investment Company	Independent Investment Advisor	Corporate Pension Fund	Public Pension Fund	University and Foundation Endowments	Miscellaneous
Biodiversity Exposure	0.003**	−0.000	−0.001	0.001	0.001	0.000	−0.000	0.001
	(2.97)	(−0.62)	(−0.81)	(0.32)	(0.94)	(0.36)	(−0.29)	(0.80)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1765	1763	1765	1767	1446	1763	1294	1765
Adj-R Square	0.820	0.837	0.836	0.910	0.922	0.802	0.754	0.677

Panel B: Biodiversity Management and Institutional Ownership-Results by Eight Types of Institutions

	Dependent Variable: Stock IO							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Institution Type	Bank Trust	Insurance Company	Investment Company	Independent Investment Advisor	Corporate Pension Fund	Public Pension Fund	University and Foundation Endowments	Miscellaneous
Biodiversity Mgmt	0.001	0.001*	0.002	0.003	−0.000	0.000	0.000	0.000
	(0.93)	(1.97)	(1.52)	(0.96)	(−0.58)	(0.19)	(0.67)	(0.04)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1777	1775	1777	1779	1458	1775	1303	1777
Adj-R Square	0.816	0.838	0.835	0.911	0.921	0.802	0.753	0.680

Panel C: Biodiversity Score and Institutional Ownership-Results by Eight Types of Institutions

				Dependent Variable: Stock IO				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Institution Type	Bank Trust	Insurance Company	Investment Company	Independent Investment Advisor	Corporate Pension Fund	Public Pension Fund	University and Foundation Endowments	Miscellaneous
Biodiversity Score	−0.002*	0.001*	0.002	−0.000	−0.001	−0.000	0.000	−0.000
	(−1.76)	(1.90)	(1.32)	(−0.01)	(−0.94)	(−0.14)	(0.57)	(−0.41)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1777	1775	1777	1779	1458	1775	1303	1777
Adj-R Square	0.817	0.838	0.836	0.911	0.922	0.802	0.753	0.680

This table reports panel regression model estimates between a stock's institutional ownership by eight types of institution and its biodiversity performance. We use the same variables as Table 9 in the analysis. We separate institutional investors into eight types following Bushee (1998): Bank Trust, Insurance Company, Investment Company, Independent Investment Advisor, Corporate (Private) Pension Fund, Public Pension Fund, University and Foundation Endowments, and Miscellaneous. All the variables are following Table 9. We report the results for biodiversity exposure on Panel A. In Panel B and Panel C, we present the results for biodiversity management and biodiversity score, respectively. In our regression, we control for firm- and time-fixed effects. All variables are defined in Table A1. *t*-statistics are reported in parentheses below the estimates are clustered at the time- and firm-level. The estimation period is from 2013 to 2020. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

accuracy is not affected by firms' biodiversity performance. As a result, investors do not receive a signal from the market showing that biodiversity should be considered when making investment decisions. Thus, it is not surprising to find that there is no significant return difference generated by biodiversity scores.

To sum up, we discuss the possible explanation from other financial market participants on the non-significant return difference generated by biodiversity scores in this section. Based on what we find, neither institutional investors nor sell-side analysts react to biodiversity information from the professional side, which makes the market signal vague for investors pricing the biodiversity performance of stock into returns,

8. Conclusion

This paper studies the relationship between firm-level biodiversity performance and stock returns. Motivated by the previous literature showing that biodiversity is important to economic development, the financial sector influences biodiversity risks and impacts and disclosure mechanisms can influence outcomes, we investigate whether biodiversity risk is priced in the financial market. We find that biodiversity performance measured in the MSCI's ESG data is not closely related to firm characteristics and has little predictive power on firms' future stock returns. To understand the channel behind the insignificant connection, we conduct a series of tests focusing on the possible explanation. First, we show that firms' biodiversity performance is not a determinant of their future returns because firms' fundamentals such as return-on-asset,

Table 11
Biodiversity scores and analyst forecast error.

Biodiversity Scores and Analyst Forecast Error						
	Dependent Variable: PMAFE					
	(1)	(2)	(3)	(4)	(5)	(6)
BIO_Expsoure	−0.014	−0.027				
	(−1.15)	(−1.58)				
BIO_Management			−0.016	0.002		
			(−1.51)	(0.18)		
BIO_SCORE					−0.011	0.008
					(−1.54)	(0.76)
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	Yes	No	Yes	No	Yes
N Observations	46,479	46,432	13,603	13,600	13,603	13,600
Adj R-Square	0.041	0.085	0.022	0.029	0.022	0.029

The table examines whether analysts forecast accuracy changes with stocks' temperature sensitivity. We follow Clement (1999) and create the proportional mean absolute error (PMAFE). The main independent variable is the firm's biodiversity performance including biodiversity score, biodiversity exposure, and biodiversity management. The analyst-level controls include Forecast Horizon, which is the number of months between the forecast date and the actual earnings announcement date. It controls for potential time trends in forecasts such as "walk-downs" to beatable forecasts before earnings announcements (Richardson et al., 2004). No. Companies are the number of firms an analyst follows during a year. Firm Experience is the number of years an analyst has covered a firm. General Experience is the number of years between the forecast issued for a company and the first forecast of the analyst in the I/B/E/S database. Broker Size is the number of analysts who are employed at an analyst's brokerage firm. All Star is a dummy variable equal to one if the analyst is ranked first, second, third, or runner-up in the Institutional Investor magazine the previous year. It captures an analyst's ability and reputation. No. Industries is the number of Fama-French 48 Industries that an analyst follows. Lagged AFE (LAFE) is an analyst's absolute forecast error for a firm during the previous period. The analyst, firm, and time-fixed effects are included in the model. All variables are defined in Table A1. *t*-statistics are reported in parentheses below the estimates are clustered at the time- and firm-level. The estimation period is from 2013 to 2020. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

earnings, and profit margin are not affected by their biodiversity ratings. As these metrics are key factors in the valuation of the stock, biodiversity performance as a result has no strong effect on firms' future stock returns. Second, the systematic risk and Tobin's Q of a firm are unaffected by its biodiversity performance, which indicates that the stock return is unlikely to be influenced by the biodiversity performance metrics. Finally, other financial market participants including institutional investors and sell-side analysts do not take the biodiversity performance of firms into account in their financial activities, which leads to the lack of financial market signals to other investors to be aware of the biodiversity risk. Overall, our paper shows that the biodiversity performance of firms as measured by the biodiversity, management and exposure components of the E in the MSCI ESG rating does not predict future stock returns. Similar results are found for the Refinitiv ratings treatment of biodiversity.

In addition to the financial intuition, we mentioned above, we also contribute to the research in biodiversity and finance in the following way. First, our findings suggest that the current metrics of biodiversity in the market are not of a high quality, which may overlook key information in evaluating the biodiversity performance of firms. It is necessary to develop high-quality biodiversity tools to enable the financial sector (investors, analysts, fund managers and other market participants) to allocate capital more effectively and internalise external costs. Further, our results indicate that, although the biodiversity ratings performance does not affect a firm's future stock return, it is in principle costless for investors who have a concern about biodiversity to move their investments to those firms that are more friendly to biodiversity (Bolton et al., 2022; Bolton et al., 2020).

Again, for this logic to hold and positive biodiversity/risk outcomes to arise, the metrics for biodiversity need to measure real risks and outcomes associated with biodiversity and nature in a consistent way over space and time.

There are, of course, some limitations to our research. For example, due to data availability, we can only construct biodiversity portfolios with a limited number of firms that concentrate on a series of specific industries. In further research, it would be worthwhile to examine how specific groups of investors or corporate managers understand biodiversity risks and whether their better awareness of biodiversity risks could lead to different financial outcomes. Also, a potential weakness, our analysis is largely ex post analysis, which may have no bearing on optimism. Finally, the lack of influence of the biodiversity ratings could reflect the fundamentally non-marketed, public good nature of biodiversity which means that its values fail to register in any particular firm's returns. Furthermore, if the main risks are associated with uncertain and unprecedented tipping points in the future, rather than the marginal day-to-day risks that unfold unseen, again measurement and disclosure may fail to capture these complex aspects of the connection between the real economy and the natural world. This invisible and ambiguous aspect of biodiversity in supply chains and production may be the fundamental cause for the lack of influence of biodiversity disclosure in the financial sector, distinct from the effect of previously experienced economic catastrophes, which are typically reflected in equity prices (Barro and Ursua, 2008). If so, a more forward- looking and regulatory approach to biodiversity is to be recommended to draw clear lines in the sand to address the economic and financial consequences of biodiversity risk.

CRediT authorship contribution statement

Wei Xin: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Lewis Grant:** Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Ben Groom:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Chendi Zhang:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

None.

Acknowledgements

This research was made possible by the UKRI/NERC funded project entitled BIOESG (NE/X016560/1) and was also supported by the

BIOPATH research programme funded by the Swedish Foundation for Strategic Environmental Research MISTRA (F 2022/1448) and the Dragon Capital Chair in Biodiversity Economics. The authors would like to thank the participants of the 23rd BIOECON conference held at the University of Exeter. WX thanks the participants of EAERE 2024 for helpful comments and suggestions. We are especially grateful to Tim Kalmey (ZEW – Leibniz Centre for European Economic Research) for his thoughtful discussion and feedback on an earlier version of this paper. Finally, we thank the editors and the reviewers for expediting the review process and for excellent comments. The usual disclaimer applies.

Appendix A. Appendix

Table A1
Variable Definitions.

Biodiversity Scores	
Variable	
Biodiversity Score	Biodiversity & Land Use Score under the Environment pillar and Natural Capital theme in MSCI ESG dataset. Source: MSCI ESG data
Biodiversity Exposure	Biodiversity & Land Use Exposure Score under the Environment pillar and Natural Capital theme in MSCI ESG dataset. Source: MSCI ESG data
Biodiversity Management	Biodiversity & Land Use Management Score under the Environment pillar and Natural Capital theme in MSCI ESG dataset. Source: MSCI ESG data
Firm-Level Variables	
SIZE	Natural logarithm of total assets (ATQ). Source: COMPUSTAT
B/M	The total assets (ATQ) divided by the sum of market equity (PRCCQ \$\times\$ CSHOQ), short-term debt (DLCQ), and long-term debt (DLTTQ). Source: COMPUSTAT
ROE	The net income (NI) divided by the lagged stockholders equity (SEQ). Source: COMPUSTAT
LEV	The sum of short-term debt (DLCQ) and long-term debt (DLTTQ) divided by total assets (ATQ). Source: COMPUSTAT
INVEST/A	the CAPEX(CAPX) divided by book value of assets (AT). Source: COMPUSTAT
HHI	Herfindahl index of the business segments of a company with weights proportional to revenues. Source: COMPUSTAT
LNPPE	The natural logarithm of plant, property & equipment (in $ million) (PPENT). Source: COMPUSTAT
R&D	R&D expenditure [XRD] over total assets [AT]. We set missing values to zero following the prior literature. Source: COMPUSTAT
CASH	The ratio of cash and marketable securities [CHE] to total assets [AT] net of cash and marketable securities. Source: COMPUSTAT
SALEGROWTH	Difference between sales(SALE) over total asset (AT) in the current year and previous year. Source: COMPUSTAT
EPSGROWTH	Difference between earnings per share (EPSFI) this year and last year. Source: COMPUSTAT
ROA	The sum of net income (NIQ), depreciation and amortization (DPQ), income taxes (TXTQ), and total interest and related expenses (XINTQ) divided by the total asset last quarter (ATQ). Source: COMPUSTAT
EARNING YIELD	The ratio between earnings per share (EPSFI) and the lagged price (PRCC_F). Source: COMPUSTAT
MARGIN PROFIT	The net income (NI) divided by the amount of sale (SALE). Source: COMPUSTAT
TOBINQ	The ratio of the market value of equity (fiscal year-end price [PRCC_F] times number of shares outstanding [CSHO]) plus book value of debt (total assets [AT] less book value of equity [CEQ]) to total assets [AT]. Source:COMPUSTAT
FIRM BETA	The estimated coefficients on market excess return in the daily regression of firm excess return on market excess return. Source: CRSP

Panel C: Time Series Variables	
MKTRF	The monthly return on the value-weighted stock market net of the risk free rate. Source: Fama French Library
SMB	The monthly return on the portfolio long small-cap stocks and short large-cap stocks. Source: Fama French Library
HML	The monthly return on the portfolio long value stocks and short growth stocks. Source: Fama French Library
MOM	The monthly return on the portfolio long 12-month stock winners and short 12-month past losers. Source: Fama French Library
Panel D: Institutional Investors-Level Variables	
Institutional Ownership	The ratio between the holding value of a stock in one institutional investor's portfolio and the total market value of the stock. Source: Thomson 13F
Portoflio Size	The market value of the total institutional portfolio. Source: Thomson 13F
Portfolio Concentration	The Herfindahl index computed using the portfolio weights. Source: Thomson 13F
No. of States	The number of different states represented in the institution's portfolio in a quarter. Source: Thomson 13F and COMPUSTAT.
No. of Companies	The number of different firms present in the institution's portfolio in a quarter. Source: Thomson 13F
No. of Other Institutional Investor	The total number of other institutions in the same state in a quarter. Source: Thomson 13F, Nelson's Directory of Investment Managers, and the U.S. Securities and Exchange Commission.
Panel E: Analyst-Level Variables	
Forecast Horizon	The number of months between the forecast date and the actual value announcement. Source: I/B/E/S
No. of Companies	The number of companies an analyst follows during a year. Source: I/B/E/S
Company Experience	The number of years an analyst has covered a specific firm. Source: I/B/E/S
General Experience	The number of years since an analyst issued a forecast for a firm and her/his first forecast in the I/B/E/S database. Source: I/B/E/S
Broker Size	The number of analysts employed by an analyst's brokerage firm. Source: I/B/E/S
No. of Industries	The number of Fama-French 48 industries followed by an analyst. Source: I/B/E/S
All Star	A dummy variable equals one if an analyst is ranked first, second, third, or runner-up in the Institutional Investor magazine in the previous year. Source: \citep{Jannati et al., 2023}
Lagged AFE	Lagged absolute forecast error issued by the specific analyst on the specific firm. Source: I/B/E/S

Table A2
Sample geographic distribution.

Panel A: Geographic Distribution of Firms with Biodiversity Exposure Score

State	No. of Observations	Total Number of Firms	Average Number of Firms Per Year	State	No. of Observations	Total Number of Firms	Average Number of Firms Per Year
Alabama	417	14	9	Montana	62	2	2
Arizona	1116	35	29	Nebraska	294	10	9
Arkansas	384	13	10	Nevada	599	22	19
California	10,479	396	317	New Hampshire	235	6	5
Colorado	1858	61	40	New Jersey	2277	74	62
Connecticut	1377	48	41	New Mexico	33	1	1
Delaware	315	11	8	New York	4945	167	142
District of Columbia	257	7	5	North Carolina	1556	56	44
Florida	2527	85	69	North Dakota	62	2	2
Georgia	1801	64	55	Ohio	2450	83	73
Hawaii	227	7	7	Oklahoma	1023	23	16
Idaho	264	8	5	Oregon	310	11	10
Illinois	3680	116	102	Pennsylvania	2967	103	83
Indiana	1051	36	31	Rhode Island	198	6	6
Iowa	435	16	14	South Carolina	350	12	11
Kansas	445	14	11	South Dakota	157	5	5
Kentucky	395	15	12	Tennessee	1012	40	29
Louisiana	421	13	8	Texas	8740	256	150
Maine	137	5	4	Utah	392	17	11
Maryland	931	33	30	Vermont	33	1	1
Massachusetts	3774	146	120	Virginia	1899	71	61
Michigan	1241	43	38	Washington	1038	39	33
Minnesota	1291	43	40	West Virginia	128	4	4
Mississippi	196	7	6	Wisconsin	1110	40	36
Missouri	925	33	28	Wyoming	40	1	1

Panel B: Geographic Distribution of Firms with Biodiversity Management Score and Biodiversity Score

State	No. of Observations	Total Number of Firms	Average Number of Firms Per Year	State	No. of Observations	Total Number of Firms	Average Number of Firms Per Year
Alabama	138	3	2	Missouri	107	3	3
Arizona	172	3	2	Nevada	29	1	1
Arkansas	89	2	1	New Hampshire	70	1	1
California	635	11	8	New Jersey	340	5	4
Colorado	754	22	11	New York	419	5	5
Connecticut	73	2	1	North Carolina	142	4	2
Delaware	84	1	1	North Dakota	29	1	1
District of Columbia	60	1	1	Ohio	257	7	5
Florida	235	4	3	Oklahoma	860	17	12
Georgia	89	2	1	Oregon	14	1	1
Idaho	162	2	2	Pennsylvania	400	12	6
Illinois	421	8	6	South Dakota	29	2	2
Indiana	84	1	1	Tennessee	107	3	2
Kansas	101	2	1	Texas	4561	107	60
Louisiana	108	2	2	Utah	33	2	1
Massachusetts	49	1	1	Virginia	71	3	3
Michigan	52	1	1	Washington	39	1	1
Minnesota	31	2	2	Wyoming	40	1	1

This table reports the geographic distribution of the firm sample in our paper. We describe the summary statistics of the number of firms in each state in our sample. Specifically, we report the total number of observations, the total number of firms, and the average number of firms per year for each type of biodiversity performance (biodiversity exposure, biodiversity management and biodiversity score) in each state. In Panel A, we present the summary statistics for firms with biodiversity exposure scores and firms with biodiversity management scores and biodiversity scores are summarized in Panel B.

Data availability

The authors do not have permission to share data.

References

Addoum, P., Kacperczyk, M., 2021. Do investors care about carbon risk? J. Financ. Econ. 142, 517–549.

Addoum, J.M., Kumar, A., 2016. Political sentiment and predictable returns. Rev. Financ. Stud. 29, 3471–3518.

Agarwala, M., Burke, M., Klusak, P., Kraemer, M., Volz, U., 2022. Nature Loss and Sovereign Credit Ratings. Working Paper 06,. Bennett Institute for Public Policy.

Albuquerque, R., Koskinen, Y., Zhang, C., 2019. Corporate social responsibility and firm risk: theory and empirical evidence. Manag. Sci. 65, 4451–4469.

Bansal, R., Wu, D., Yaron, A., 2022. Socially responsible investing in good and bad times. Rev. Financ. Stud. 35, 2067–2099.

Barro, R.J., Ursua, J.F., 2008. Macroeconomic crises since 1870. Brook. Pap. Econ. Act. 39, 255–350.

Benabou, R., Tirole, J., 2010. Individual and corporate social responsibility. Economica 77, 1–19.

Bernhardt, D., Campello, M., Kutsoati, E., 2006. Who herds? J. Financ. Econ. 80, 657–675.

Boissinot, J., Goulard, S., Le Calvar, T., Salin, M., Svartzman, R., Weber, P.F., 2022. Aligning financial and monetary policies with the concept of double materiality: rationales, proposals and challenges. In: INSPIRE Policy Briefing Paper, 5.

Bolton, P., Kacperczyk, M.T., 2020. Carbon premium around the world. In: Tech. Rep. DP14567, CEPR Discussion Paper available at SSRN https://ssrn.com/abstract=3594188.

Bolton, P., Despres, M., Da Silva, L.A.P., Samama, F., Svartzman, R., et al., 2020. The Green Swan. BIS Books.

Bolton, P., Kacperczyk, M., Samama, F., 2022. Net-zero carbon portfolio alignment. Financ. Anal. J. 78, 19–33.

Brandon, R.G., Glossner, S., Krueger, P., Matos, P., Steffen, T., 2021. Do responsible investors invest responsibly?. In: Tech. Rep., ECGI Working Paper Series in Finance.

Burgess, N.D., Ali, N., Bedford, J., Bhola, N., Brooks, S., Cierna, A., Correa, R., Harris, M., Hargey, A., Hughes, J., et al., 2024. Global metrics for terrestrial biodiversity. Annu. Rev. Environ. Resour. 49, 673–709.

Bushee, B.J., 1998. The influence of institutional investors on myopic r&d investment behavior. Account. Rev. 305–333.

Cen, L., Hilary, G., Wei, K.J., 2013. The role of anchoring bias in the equity market: evidence from analysts' earnings forecasts and stock returns. J. Financ. Quant. Anal. 48, 47–76.

Chen, Q., Jiang, W., 2006. Analysts' weighting of private and public information. Rev. Financ. Stud. 19, 319–355.

Cherief, A., Sekine, T., Stagnol, L., 2022. The Market Effect of Acute Biodiversity Risk: The Case of Corporate Bonds. SSRN.

Clement, M.B., 1999. Analyst forecast accuracy: do ability, resources, and portfolio complexity matter? J. Account. Econ. 27, 285–303.

Coqueret, G., Giroux, T., Zerbib, O.D., 2025. The biodiversity premium. Ecol. Econ. 228, 108435.

Cuculiza, C., Kumar, A., Xin, W., Zhang, C., 2023. Temperature sensitivity, mispricing, and predictable returns. In: Mispricing, and Predictable Returns (March 29, 2023).

Dasgupta, P., 2021. The Economics of Biodiversity: The Dasgupta Review. HM Treasury.

Fama, E.F., French, K.R., 2007. Disagreement, tastes, and asset prices. J. Financ. Econ. 83, 667–689.

Fatemi, A., Fooladi, I., Tehranian, H., 2015. Valuation effects of corporate social responsibility. J. Bank. Financ. 59, 182–192.

Flammer, C., 2021. Corporate green bonds. J. Financ. Econ. 142, 499–516.

Flammer, C., Giroux, T., Heal, G., 2023. Biodiversity Finance. Working Paper 31022,. National Bureau of Economic Research.

Frank, E.G., Sudarshan, A., 2022. The social costs of keystone species collapse: evidence from the decline of vultures in India. In: Tech. rep., Working Paper.

Garel, A., Romec, A., Sautner, Z., Wagner, A.F., 2023. Do investors care about biodiversity? Rev. Finance 28, 1151–1186.

Giglio, S., Kuchler, T., Stroebel, J., Zeng, X., 2023. Biodiversity Risk. Working Paper 31137,. National Bureau of Economic Research.

Gillan, S.L., Koch, A., Starks, L.T., 2021. Firms and social responsibility: a review of ESG and CSR research in corporate finance. Finance 66.

Grant, L., Groom, B., Xin, W., Zhang, C., 2023. The Mechanics of Biodiversity in ESG. Working Paper.

Groom, B., Venmans, F., 2023. The social value of offsets. Nature 619, 768–773.

Hilary, G., Hsu, C., 2013. Analyst forecast consistency. J. Financ. 68, 271–297.

Hong, H., Kacperczyk, M., 2009. The price of sin: the effects of social norms on markets. J. Financ. Econ. 93, 15–36.

IPBES, 2019a. Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services.

IPBES, 2019b. The Global Assessment Report on Biodiversity and Ecosystem Services.

Jackson, A.R., 2005. Trade generation, reputation, and sell-side analysts. J. Financ. 60, 673–717.

Jannati, S., Kumar, A., Niessen-Ruenzi, A., Wolfers, J., 2023. In-Group Bias in Financial Markets. Working Paper (Available at SSRN 2884218).

Jegadeesh, N., Kim, J., Krische, S.D., Lee, C.M., 2004. Analyzing the analysts: when do recommendations add value? J. Financ. 59, 1083–1124.

Johnson, J.A., Ruta, G., Baldos, U., Cervigni, R., Chonabayashi, S., Corong, E., Gavryliuk, O., Gerber, J., Hertel, T., Nootenboom, C., Polasky, S., 2021. The Economic Case for Nature: A Global Earth-Economy Model to Assess Development Policy Pathways. Report 35882. World Bank, © World Bank, Washington, DC. http://hdl.handle.net/10986/35882. License: CC BY 3.0 IGO.

Kim, S., Yoon, A., 2020. Analyzing Active Managers' Commitment to ESG: Evidence from United Nations Principles for Responsible Investment. Available at SSRN 3555984.

Lim, T., 2001. Rationality and analysts' forecast bias. J. Financ. 56, 369–385.

Lins, K.V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: the value of corporate social responsibility during the financial crisis. J. Financ. 72, 1785–1824.

Luo, X., Bhattacharya, C.B., 2006. Corporate social responsibility, customer satisfaction, and market value. J. Mark. 70, 1–18.

Malmendier, U., Shanthikumar, D., 2014. Do security analysts speak in two tongues? Rev. Financ. Stud. 27, 1287–1322.

Merton, R.C., et al., 1987. A Simple Model of Capital Market Equilibrium with Incomplete Information.

OECD, 2019. Biodiversity: Finance and the Economic and Business Case for Action.

P'astor, L., Stambaugh, R.F., Taylor, L.A., 2021. Sustainable investing in equilibrium. J. Financ. Econ. 142, 550–571.

Pedersen, L.H., Fitzgibbons, S., Pomorski, L., 2021. Responsible investing: the ESG efficient frontier. J. Financ. Econ. 142, 572–597.

Richardson, S., Teoh, S.H., Wysocki, P.D., 2004. The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. Contemp. Account. Res. 21 (4), 885–924.

Sautner, Z., Van Lent, L., Vilkov, G., Zhang, R., 2023a. Firm-level climate change exposure. J. Financ. 78, 1449–1498.

Sautner, Z., Van Lent, L., Vilkov, G., Zhang, R., 2023b. Pricing climate change exposure. Manag. Sci. 69, 7540–7561.

Steffen, W., Richardson, K., Rockstrom, J., Cornell, S.E., Fetzer, I., Bennett, E.M., Biggs, R., Carpenter, S.R., De Vries, W., De Wit, C.A., et al., 2015. Planetary boundaries: guiding human development on a changing planet. Science 347, 1259855.