Received: 6 February 2024 | Revised: 8 October 2024 | Accepted: 20 October 2024

DOI: 10.1002/bse.4039

RESEARCH ARTICLE

Business Strategy and the Environment WILEY

Biodiversity risk and firm performance: Evidence from US firms

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Funding information
National Economics University, Vietnam, Grant/Award Number: 02/HD-CBQT2023.02

Abstract

Biodiversity loss is considered as a critical global challenge with significant implications for ecosystems, economies, and societies. While the importance of biodiversity conservation is widely acknowledged, the extent to which biodiversity risk impacts firm performance remains an under-explored area of research. This paper examines how biodiversity risk affects firm performance using a new measure of firm-level biodiversity risk generated from textual analysis of firms' 10-K reports. Our multivariate analysis shows that biodiversity risk significantly hinders performance of firms in the United States during the 2001–2021 period. The finding holds well after controlling various confounding factors, using alternative variable measurements, model specifications, and correcting for endogeneity problems in the biodiversity risk-firm performance nexus. Besides decreasing sales growth and profitability, biodiversity risk increases in the cost of goods sold, as explained by the Cobb–Douglas production function. Interestingly, we find that the effect is stronger for firms in biodiversity-sensitive industries, weaker for firms with more product innovation, and remains insignificant for firms with top-tier performance. Our study provides policy and practical implications for businesses to mitigate biodiversity risk in this contemporary era of ecological degradation.

KEYWORDS
10-K reports, biodiversity risk, firm performance, natural capital, product innovation, United States

1 | INTRODUCTION

Biodiversity is the diversity of the living organisms in the ecosystems, including species and geneses, as well as their distribution (Kalhoro & Kyaw, 2024; Swingland, 2001). Biodiversity risk refers to the physical and regulatory risks related to biodiversity loss on economic activity and asset values (Giglio et al., 2023). As businesses are responsible for environmental pollution and environmental degradation, they have to face increasing biodiversity risk stemming from stakeholders' pressure to alleviate their negative impact on the ecosystem (Giglio et al., 2023; Houdet et al., 2012; Wagner, 2023). The economic impact of biodiversity risk is a modernly controversial issue (Dempsey, 2013; Panwar et al., 2023) but unfortunately remains under-researched in economics and finance literature. There are limited and ambiguous findings on how and whether biodiversity risk influences corporate decision-making and outcomes due to the lack of measurement of such a complex factor (Giglio et al., 2023). From a macro perspective, biodiversity and ecosystem degradation result in an estimated annual economic damage ranging from US$ 4 trillion to US$20 trillion (Kapnick, 2022), while approximately US$ 7.2 trillion of total enterprise value is reported exposed to unmanaged biodiversity risk (Carvalho et al., 2023). Only a few studies investigate the impact of biodiversity risk at firm level. For instances, Giglio et al. (2023) propose text-based measures of firm-level biodiversity risk and find that such a risk factor is not adequately priced by investors in the United States. Similar findings from the event study of Kalhoro and

Abbreviations: US$, United States Dollar; US, United States; SEC, Securities and Exchange Commission; RDT, Resource Dependence Theory; GICS, Global Industry Classification Standards; FE, Fixed effect; 2SLS/IV, Two-Stage Least Square/Instrumental Variable; PSM, Propensity Score Matching.

Kyaw (2024) surrounding biodiversity policy meetings further ensue that little is known about the economic significance of biodiversity risk.

Biodiversity risk belongs to a new and distinct category of risk which is different from climate change risk.[1] Indeed, there is a rich literature on how climate change risk is priced by investors (Bolton & Kacperczyk, 2021; Sautner et al., 2023), has significant economic impacts on corporate policies (Li et al., 2024; Mbanyele & Muchenje, 2022), and results in different economic outcomes (Pankratz et al., 2023). The embryonic biodiversity finance literature concentrates on market performance of stocks in reaction to biodiversity risk while the corporate finance aspect of biodiversity risk is unexplored. In general, biodiversity risk seems not fully priced by investors in the stock market (Giglio et al., 2023). While firms that manage their biodiversity risk exposure experience significant abnormal stock returns in days surrounding the 2021 Kunming Declaration on biodiversity protection and the United Nations' 2022 UN Biodiversity Conference (i.e., the COP15), there is no clear impact on stock returns of firms that do not manage their biodiversity risk well (Kalhoro & Kyaw, 2024). Interestingly, firm-level biodiversity footprint does not explain the cross-section of stock returns during 2019–2022, the 3-year period before the COP15 (Garel et al., 2024). Nedopil (2023) indicates that investors do not or cannot value the costs of biodiversity loss in their financial decision-making and the risks associated with biodiversity. From another perspective, Bassen et al. (2024) suggest that firms with better biodiversity management suffer less stock price crashes; however, the impact of those management practices on stock performance and the fundamental performance of firms are not investigated. These findings raise an intriguing yet unanswered question: Is the impact of biodiversity risk significant to corporate fundamental performance, given that the risk factor does not well materialize in the stock market? No attempts so far have been made to address the question.

This study answers the above research question. In this study, we explain the impact of biodiversity risk on firm's fundamental performance via the lens of the Cobb–Douglas production function where biodiversity serves as the natural capital inputs for production.[2] The Cobb–Douglas production function is a widely used economic model that represents the relationship between input and output factors in production processes. In this function, total output is modeled as a function of capital (K), labor (L), and technology (A). Changes in any of the inputs (i.e., K, L, or A) may impact total output of production. We modify the Cobb–Douglas production function by separating K into two different components: the natural capital that includes biodiversity (N) and the manufactured capital (M) that is non-natural. Because all economic activities depend on natural capital (Bastien-Olvera & Moore, 2021), the extractable natural resources are finite and decreasing. Under the impact of biodiversity loss, firms must deploy additional capital to maintain the optimal output, thus incur a higher cost of production, which negatively affects firm performance.

To empirically test this theoretical argument, we proxy biodiversity risk at the firm-level by novel text-based measures generated from 10-K reports of firms in the United States (Giglio et al., 2023). 10-K reporting is a mandatory annual filling required by the United States' Securities and Exchange Commission (SEC) for public firms. The reports provide detailed financial and non-financial information on a firm's financial performance, operations, and associated risks. Specifically, 10-K fillings include business overview, financial information, management's discussion and analysis, risk factors, corporate governance, legal proceedings, market and industry data, and other information. Using those text-based data, Giglio et al.'s (2023) measures of biodiversity risk capture corporate disclosure of biodiversity-related matters, including regulation, and present firm's sentiment toward biodiversity issues. The measures are available for a broad sample of firms in the United States, which encourages researchers to investigate the impact of biodiversity risk on a large sample setting compared to previous studies which focus on small surveys and case studies to draw inferences (Dana et al., 2012; Marco-Fondevila et al., 2018; Swanson, 1996). After merging Giglio et al.' (2023) dataset with the financial data of US firms, our final sample consists of 31,513 firm-year observations of 3376 US firms spanning from 2001 to 2021.

Using a high-dimensional fixed effect estimator, we find a significant negative impact of firm-level biodiversity risk on firm performance, meaning that the impact of biodiversity risk is economically significant from the corporate finance perspective. The finding holds well after intensively controlling for confounding factors at the firm level, industry level, and state level. We account for sample selection bias using the two-step Heckman selection estimator and a regression with Entropy Balancing weight. Causal inference of the newfound relationship is further reinforced with an instrumental approach in which we use internet users' attention to biodiversity and ecosystem issues as an exogenous instrument. The finding further survives additional robustness tests of alternative variable measurements for the dependent variable and the variable-of-interest. Further analysis indicates that the cost of goods sold increases significantly in response to an increase in biodiversity risk and contributes to decreased firm performance.[3] Nevertheless, we provide empirical evidence for two factors that influence the impact: industry's exposure to biodiversity risk and product innovation. Specifically, the effect is more pronounced for firms operating in industries with more exposure to biodiversity risk, and less pronounced if the firm is more inclined to the stage of product innovation in its product life cycle. Our findings have not been documented elsewhere in the literature.

Our study contributes to the existing biodiversity finance literature in three important ways. First, it sheds light on whether and how biodiversity risk is significant in influencing corporate finance. While

[1]Climate change risk (or in other names, carbon risk or carbon transition risk) is referred to as the financial vulnerability of firms to the transition from a carbon-intensive economy to a lower-carbon one (Nguyen & Phan, 2020).

[2]Costanza et al. (1997) define natural capital as "the stock of natural ecosystems that yields a flow of valuable ecosystem goods or services into the future". World Economic Forum (2020) estimates that about $44 trillion of economic value generation, which is equivalent to more than 50% of the world's gross domestic product, is dependent on natural capital.

[3]However, we do not find a significant impact of biodiversity risk on corporate operating expenses, suggesting that the impact of biodiversity risk only manifests in the production process. The results are available upon request.

other types of firm risks, for example, climate risk and political risk, seem to be more prominent and empirically proven relevant to firm performance, there is a missing link in the literature regarding how firm-level biodiversity risk affects firm performance. Our study offers novel empirical evidence on the impact of firm-level biodiversity risk on firm's fundamental performance, which has not been investigated before in the corporate finance literature. Given that previous studies suggest that biodiversity risk does not seem to be fully priced by investors in the financial market (Garel et al., 2024; Giglio et al., 2023; Kalhoro & Kyaw, 2024), our findings offer new insights on the important questions of whether and how the impact of biodiversity risk on firm's fundamental performance is economically significant. By combining the Cobb–Douglas production function to explain the impact of biodiversity risk on firm performance from a resource-based perspective, we lay a strong theoretical approach for future studies in this vein of research to examine the impact of biodiversity on corporate policy and outcomes.

Second, this current study is the first to explore how the impact of biodiversity risk on firm performance varies across firms and industries. In the context of increasing attention to climate change and the environment, biodiversity finance becomes a topical line of research, although still new and has abundant gaps to explore. As the identification of firms being exposed to biodiversity risk is complex, our study provides further evidence on how the economic impact of such a risk factor persists. One of the important questions that need to be addressed is whether biodiversity risk is more pronounced at the firm level or at the industry level. The former addresses firm-level exposure to both physical and regulatory biological diversity risk, while the latter refers to industry exposure to the transition to a regulated biodiversity status. Our findings answer this question and signify the role of industry exposure to biodiversity risk versus firm-level biodiversity risk to firm performance. Specifically, our empirical finding implies that the size of the negative effect of industry exposure to biodiversity risk (i.e., the transitional biodiversity risk) on firm performance is approximately four times larger than that of firm-level biodiversity risk. This study is the first to examine and compare the impact of biodiversity risk at the firm-level and the industry-level on firm performance. Specifically, we show that the impact of industry-level exposure to biodiversity risk is considerably larger than that at the firm-level, thus suggesting the spillover effect of the biodiversity transition from the macro environment to micro economic entity. This is in line with the findings of Ahmad and Karpuz (2024) that firms with higher biodiversity risk hold more cash than their counterparts, and the effect is stronger in industries highly exposed to biodiversity risk. The finding can serve as a reference for identification strategy of the impact of biodiversity risk in future studies in this embryonic line of research.

Third, we reveal the role of product innovation in alleviating the negative impact of biodiversity risk on firm performance. In this vein, our study adds new insights to the literature on the relationship between firm performance and product innovation (Artz et al., 2010; Chu et al., 2024; Cucculelli & Ermini, 2013; Ramadani et al., 2019). We extend the investigation to how product innovation influences the relationship between biodiversity risk and firm performance using the resource dependence theory. Our finding emphasizes the role of product innovation as a crucial stage of the business's product life cycle in forming the business strategy to mitigate firm-level exposure to biodiversity risk. This insight contributes to a deeper understanding of how firms can leverage product innovation to navigate the complex interplay between ecological challenges and economic performance.

The rest of the paper proceeds as follows. Section 2 is about literature review, theoretical framework, and hypothesis development. Section 3 discusses the research design and data used in this study. Section 4 reports and discusses the empirical results, including the baseline results, how we deal with the potential endogeneity problems, and results of sensitivity tests. We also conduct further analysis into the mechanisms through which the impact of biodiversity risk on firm performance is amplified or alleviated. Section 5 concludes the paper.

2 | THEORETICAL BACKGROUND

2.1 | Related studies

Theories to explain a relationship between biodiversity risk and firm performance can be dated back to the 1990s, namely, the natural resource-based theory of the firm (Barney, 1991; Hart, 1995). The theory states that a firm's long-term competitive advantage is dependent on its capability to manage environmental impacts. Carvalho et al. (2023) extend this view and propose a linkage between subsector-level biodiversity dependency risk and the long-term corporate strategic responses using an international sample of 11,812 firms from 41 countries during the 2004–2018 period. Their findings show that subsector-level biodiversity risk generally stimulates firms to adopt a biodiversity policy, but a substantial portion of firm value remains unmanaged against biodiversity risk. From the production perspective, Bastien-Olvera and Moore (2021) propose a specification of the Cobb–Douglas production function that incorporates ecosystem services as the natural capital input of the production process besides manufactured capital and human capital (i.e., labor input). Biodiversity loss affects the total production outputs via decreasing the natural capital inputs, thus increasing the welfare cost arising from the ecological effects of climate change.

A strand of literature empirically investigates how biodiversity-related factors affect corporate outcomes. Using a sample of 100 Fortune Global firms in 2013, 2016, and 2019, Elsayed (2023) suggests that corporate biodiversity disclosure practices exert a positive impact on firm financial performance. This means firms with good biodiversity disclosure practices enjoy better financial performance while those with poor biodiversity disclosure practices generally have lower financial performance. However, there is no direct study on how biodiversity risk affects firm performance. Contemporary research in environmental finance currently put a focus on the impact of climate change risk on stock returns, for example, in the works of Monasterolo and de Angelis (2020), Bolton and Kacperczyk (2021), Ilhan et al. (2021), Cevik and Miryugin (2023), Sautner et al. (2023), and Li et al. (2024). Some other studies investigate how macro-level climate change risk affects firm performance from the corporate finance perspective (Jayachandran et al., 2013; Pankratz et al., 2023). In general, those aforementioned studies agree on a negative impact of the risk associated with the transition to sustainability on firm performance and stock returns, but their coverage is limited to carbon policy, climate change exposure, or in a broader perspective (e.g., environmental performance). Overall, there is no prior study addressing the impact of biodiversity risk on firm performance, leaving a literature gap for investigation.

One final remark is that before the study of Giglio et al. (2023), there is no comprehensive measure of firm-level biodiversity risk in the literature. In fact, previous studies often rely on surveys, macro or sectoral data of biodiversity, and case studies to identify the impact of biodiversity on businesses (Bhattacharya & Managi, 2013; Carvalho et al., 2023; Marco-Fondevila et al., 2018; Swanson, 1996). Such approaches may be subject to either short study periods, potential small sample biases, or identification issues. Therefore, the firm-level biodiversity risk measures of Giglio et al. (2023) offer a new approach to evaluate the impact of biodiversity on corporate policy and outcomes.

2.2 | Theoretical consideration and hypothesis development

2.2.1 | The relationship between biodiversity risk and firm performance

Following Bastien-Olvera and Moore (2021), we employ the Cobb–Douglas production function to theoretically demonstrate the impact of biodiversity risk on corporate outcomes.[4] The Cobb–Douglas production function is a classic theoretical functional form that represents the relationship between the production inputs (e.g., capital, technology, and labor) and the outputs (e.g., total production) of a good or service. The function has been widely employed and tested using empirical data at firm level. We first start with a conventional Cobb–Douglas production function as follows:

$$Y_i = f(K_i, L_i) = A_i * K_i^{\alpha} * L_i^{\beta} \tag{1}$$

where Y_i is the total output of product i of the firm; K_i is capital stock needed for the production of product i, L_i is labor employment for product i, A_i is level of technology used in the production of product i, α_i and β_i are the output elasticities of K_i and L_i, respectively, assuming $0 < \alpha_i < 1$ and $0 < \beta_i < 1$.

If K is broadly defined as to contain both manufactured and national capital (i.e., natural resources), Equation (1) can be transformed to the following:

$$Y_i = A_i (M_I + N_i)^{\alpha} L_i^{\beta} \tag{2}$$

where M denotes non-natural (i.e., manufactured) capital and N denotes natural capital inputs, and $K = M + N$.

The production function in Equation (2) recognizes the role of natural capital (N) as a factor of production. A higher value of the elasticity α implies a higher percentage increase in the value of output per each percentage increase in capital. This modified production function allows us to analyze how changes in natural capital, such as biodiversity loss, influence total output. From Equation (2), we can have a preposition that, all else equal, a decrease in natural capital negatively affects total output Y. The decrease in natural capital may come from the biodiversity losses or new regulatory requirements from the government in environmental protection efforts. Under the reduction in natural capital inputs (i.e., lowering N), if the management wants to maintain the level of output to meet market demand, they must either increase non-natural capital input (M) or technological progress (A). This incurs additional costs of production and thus lowers financial performance. Based on this theoretical argument, we propose the following research hypothesis:

> **Hypothesis 1. (H1)**: Biodiversity risk negatively affects firm performance.

2.2.2 | The role of product innovation

The effect of biodiversity risk on firm performance is likely to be influenced by two following factors among others: product innovation and industry's exposure to biodiversity risk. This section is devoted to elaborating the theoretical aspect of general product innovation in how biodiversity risk affects firm performance.

Based on Equation (2), our modified Cobb–Douglas production function suggests that to maintain the level of output when natural capital inputs decrease, firms must incur additional costs to increase either in terms of non-natural capital input (P) or technological progress (A) to make up for the decrease in natural capital. In this case, firms are facing resource constraints due to increased biodiversity risk; thus, they cannot optimize performance given the constrained inputs. In these situations, firms must strategically shift to alternative resources and innovate their products to reduce their dependence on the reduced sources of inputs. This business strategy is well explained under the resource-dependence theory (RDT). According to RDT, firms depend on their environment for critical resources, which in turn influences their strategies and decision-making processes. In this context, biodiversity can be referred to as a critical external resource that a large portion of firms in the economy rely on, either directly or indirectly, for their operations and products. Biodiversity risk, therefore, exerts a negative impact on firm performance.

Product innovation is the process of creating and introducing new products to meet the changing needs of the market. Product innovation can mitigate this negative relationship by enabling firms to diversify their resource base, utilize alternative inputs, improve

[4]We adopt the Cobb–Douglas production function to ease the mathematical derivation. This choice of functional form does not lead to any loss in the generality of our theoretical implications. They can be inferred from another form of production function such as constant elasticity of substitution or translog.

resource efficiency, adapt to changing market demands, and enhance their reputation. Firms can choose to redesign their products to be less dependent on particular types of natural capital (*N*) and avoid the increased risks associated with tightening environmental regulations.[5] In this way, the impact of biodiversity risk on the natural inputs of firms can become less severe, thus alleviating its negative impact on total output, the cost of production, and firm performance. This argument is well explained from the production function perspective in which natural capital inputs play an important role in firm performance. Furthermore, firms that proactively address biodiversity concerns through innovative product development strategies do not only mitigate risks associated with ecosystem degradation but also position themselves as responsible and sustainable businesses in the eyes of customers (Carvalho et al., 2023).

This strategic approach to managing resource dependencies through product innovation can help firms maintain or even improve their performance in the face of biodiversity challenges, demonstrating how product innovation serves as a moderating factor in the relationship between biodiversity risk and firm performance. Understanding and effectively managing biodiversity risk is crucial for firms in an era where environmental considerations play an increasingly central role in shaping firm performance. Firms which fail to adapt to those changes are exposed more to the biodiversity risk stemming from consumers' penalties and regulatory intervention, thus affecting their performance. The role of product innovation aligns well with the current literature on the positive contribution of product innovation to firm performance (Artz et al., 2010; Chu et al., 2024; Corsino & Gabriele, 2011; Ramadani et al., 2019). We put out the following hypothesis:

> **Hypothesis 2. (H2)**: Product innovation helps mitigate the negative effect of biodiversity risk on firm performance.

2.2.3 | Industry's exposure to biodiversity risk

The RDT provides a valuable framework for understanding the impact of biodiversity risk on firm performance, particularly in industries with high exposure to biodiversity risk. Following the resource-based view, firms in industries with high exposure to biodiversity risk generally face greater uncertainty and potential disruption to their resource supply, which can significantly impact their performance. Therefore, industry's exposure to biodiversity risk plays a pivotal role in shaping the overall performance of a firm under the impact of biodiversity risk. During the contemporary era of increasing biodiversity awareness, industries that are heavily dependent on natural resources or engaging in ecosystem-degrading activities face higher risks stemming from reduction in natural, biodiversity capital inputs. Such heightened risks affect those firms' operational stability and supply chain dynamics. For example, industries such as agriculture, fisheries, food, and consumer products are particularly vulnerable to biodiversity-related disruptions, such as environmental disasters and shifts in the ecosystems. Consequently, environmental degradation and depletion of natural resources do not only affect one firm in an industry but can have a widespread impact on the whole industry. Specifically, decreasing supplies due to biodiversity risk might result in fiercer supply competition and increase the cost of operations, thus further hindering firm growth and fundamental performance in the industry. This can be referred to as the supply-side effect of biodiversity dependence at the industry level.

In addition, industries have higher ecological footprints and are put under tightened scrutiny from the market participants, regulators, and the public in general. More exposure to ecological concerns at the general industry level generated from changes in environmental protection regulations would affect the operations and performance of most firms in the high-exposure industries. Even firms with low exposure to physical biodiversity risk but residing in high-exposure industries might be affected by the regulatory transition toward sustainability. This mechanism relates to previous studies on how industry-level exposure to the environmental regulation risk affects corporate decision-making and outcomes (Balachandran & Nguyen, 2018; Cevik & Miryugin, 2023; Hoang, 2022; Matsumura et al., 2022; Phan et al., 2022; Xue et al., 2020). As such, we propose the following hypothesis:

> **Hypothesis 3. (H3):** Industry exposure intensifies the negative effect of biodiversity risk on firm performance.

Diagram 1 presents our theoretical framework as follows.

3 | DATA AND METHODOLOGY

3.1 | The empirical model

To investigate the impact of biodiversity risk on firm performance, we use the following empirical model:

$$PERF_{i,t} = \alpha + \beta \times BIODR_{i,t-1} + \sum_{t=1}^{n} CONTROL_{i,t-1} + \gamma_i + \delta_t + \varepsilon_{i,t} \qquad (3)$$

where $PERF_{i,t}$ is the proxy of performance of firm *i* during period *t*; $BIODR_{i,t-1}$ stands for firm-level biodiversity risk of firm *i* during period $t-1$; $\sum_{t=1}^{n} CONTROL_{i,t-1}$ is a vector of firm-level control variables of firm *i* during period $t-1$; γ_i and δ_t represent the firm- and year-fixed effects to control for potential confounding factors at the two dimensions; and $\varepsilon_{i,t}$ is the error term of the model. β is the coefficient-of-interest; we expected it to be negative and significant as per the hypothesis development of H1.

[5]A typical example is Beyond Meat, a leading producer of plant-based meat substitutes. Beyond Meat's plant-based meat alternatives are designed to reduce dependence on animal agriculture, which is resource-intensive and significantly contributes to environmental degradation. By offering meat substitutes made from plant-based ingredients, the company can mitigate risks associated with regulations targeting greenhouse gas emissions from livestock farming and deforestation for pastureland.

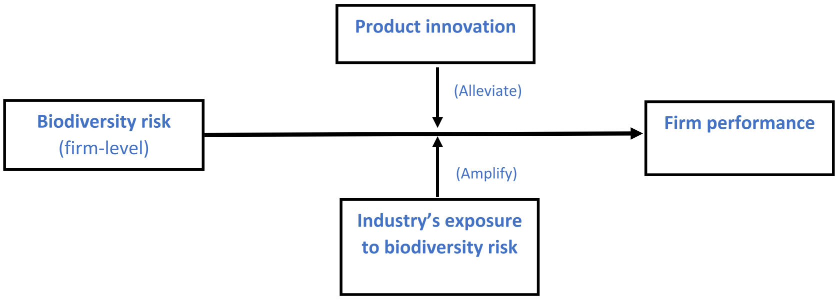

DIAGRAM 1 The conceptual framework.

TABLE 1 Variable descriptions and statistics.

Variable	Description	Source	Mean	SD	Min	Max
ROA	Net income scaled by average total assets	Bloomberg	0.002	0.242	−0.814	0.319
ROE	Net income scaled by average common equity	Bloomberg	0.021	0.961	−3.204	2.234
GROWTH	Changes in revenues scaled by lagged revenues	Bloomberg	0.178	0.707	−1.000	8.562
PBT_TA	Profit before tax scaled by average total assets	Bloomberg	0.016	0.293	−17.500	0.471
BIODR	Firm-level regulation-related biodiversity score generated from textual analysis of 10-K reports	Giglio et al. (2023)	0.018	0.134	0.000	1.000
BIODR_C	Firm-level biodiversity score that count the mentioning of biodiversity phrases in 10-K reports	Giglio et al. (2023)	0.027	0.163	0.000	1.000
BIODR_N	The number of negative biodiversity sentences minus the number of positive biodiversity sentences in 10-K reports	Giglio et al. (2023)	0.022	0.272	−6.000	8.000
FIRM SIZE	Natural logarithm of total assets	Bloomberg	5.450	3.041	−3.324	12.139
LEVERAGE	Debt-to-total assets ratio	Bloomberg	0.189	0.261	0.000	1.487
CAPEX	Capital expenditure scaled by lagged total assets	Bloomberg	0.064	0.126	0.000	0.882
PPE	The ratio of property, plant, and equipment to total assets	Bloomberg	0.251	0.281	0.000	0.959
CASH FLOW	Operating cash flows scaled by total assets	Bloomberg	−0.182	0.913	−6.895	0.413
NWC	Net working capital scaled by total assets	Bloomberg	−0.133	0.991	−7.866	1.630
CASH	Cash and cash equivalents scaled by total assets	Bloomberg	0.162	0.222	0.000	0.974
AUDITOR	Dummy variable that equals one if the auditor of the firm is a big four auditor, zero otherwise	Bloomberg	0.672	0.469	0.000	1.000
COGS	Cost of goods sold scaled by total sales	Bloomberg	0.603	0.218	0.225	0.968
IND_BIODRE	Industry-level biodiversity score	Giglio et al. (2023)	−0.014	0.038	−0.157	0.042
PRODUCT_INNO	Firm-level product innovation score generated from computational linguistic techniques and 10-K reports	Hoberg and Maksimovic (2022)	0.248	0.137	0.000	1.000
DISCLOSURE	Dummy variable that equals one if the firm is disclosing information related to biodiversity risk, zero otherwise	Giglio et al. (2023), and author's calculation	0.161	0.367	0.000	1.000
GGATTENTION	Natural logarithm of the number of Google searches related to biodiversity risk during a year	Giglio et al. (2023)	724.361	370.309	274.000	1844.000
NYT_BIONEWS	Natural logarithm of the number of New York Times articles related to biodiversity risk during a year	Giglio et al. (2023)	120.346	68.945	53.000	277.000
INDUSTRY	The GICS industry code of the firm	Bloomberg				
LOCATION	Firm location based on ZIP code	Bloomberg				

Following the finance and management literature (Bandiera et al., 2020; Bhagat & Bolton, 2008; Cevik & Miryugin, 2023; Dao & Ta, 2020; Jayachandran et al., 2013), we use the return-on-total assets ratio (ROA) as the main dependent variable. Alternative proxies for firm performance include the return-on-equity ratio (ROE) (Bennouri et al., 2018), sales growth (GROWTH) (Bandiera et al., 2020), and the pre-tax income to total assets ratio (PBT_ROA) for robustness check. While ROA shows how much after-tax income is generated given the total assets of firm and considered as the main proxy for firm performance in the finance literature, ROE is the ratio of profitability in regard to the common shareholders' equity but not considering the firm's liabilities. GROWTH describes another aspect of firm performance presented as the annual increase (decrease) in sales before any expenses. Furthermore, we use PBT_ROA as the pre-tax version of ROA to test the impact without considering the differences in corporate income tax rates across our sample. The higher the values of the performance variables, the better the financial performance of the firm.

To measure firm-level biodiversity risk, we employ Giglio et al.'s (2023) text-based measures of firm-specific biodiversity risk. The authors build a biodiversity dictionary to identify texts covering biodiversity-related topics. They use the dictionary and Python programming to quantify corporate biodiversity risk disclosure in the annual 10-Ks of US listed firms in three different measures: (i) the binary 10 K-Biodiversity-Regulation score that equals 1 if the firm is mentioning biodiversity risk in at least two sentences in their 10-Ks and one of them must be related to regulation, and 0 otherwise (BIODR); (ii) the binary10K-Biodiversity-Count Score identifies 10-Ks that contain at least two biodiversity-related sentences (BIODR_C); and (iii) the 10-K-Biodiversity-Negative Score constructed from sentiment analysis of biodiversity-related sentences in the 10-Ks, in which the score equals the count of negative-sentiment biodiversity-related sentences minus the count of positive-sentiment biodiversity-related-sentences (BIODR_N). In the construction of the three measures, 10-K's sentences with unrelated terms are excluded.

Control variables include firm size (FIRM SIZE), financial leverage (LEVERAGE), capital expenditure (CAPEX), fixed asset ratio (PPE), cash holding ratio (CASH), net working capital ratio (NWC), and an indicator that identifies auditor quality (AUDITOR). Table 1 presents the definition and summary statistics of variables used in this study.

To analyze the impact of biodiversity risk from the cost of production perspective, we use the cost of goods sold as the measure of cost of production. We calculate the cost of goods sold on total sales (COGS) and then regress COGS on BIODR to see which components of expenses change as a response to increased biodiversity risk at firm level. The finding from the test is expected to add insights to how biodiversity risk affects firm performance from the production cost perspective as explained in the modified Cobb–Douglas production function in the hypothesis development section.

3.2 | Data

We collect firm financial data of US listed firms from the Bloomberg database. Firm-level and industry-level biodiversity risk scores (Giglio et al., 2023) are available for the 2001–2021 period and collectible from https://biodiversityrisk.org. Firm-level product innovation score is obtainable from Hoberg and Maksimovic (2022).[6] We first exclude all financial firms from the sample and then exclude all the missing data after merging Bloomberg's data with the other datasets. Next, we eliminate all observations with data errors, such as observations with negative values of total assets, revenues, and fixed assets. The final panel data consist of 31,513 firm-year observations from 3376 US listed firms from 2001 to 2021. All continuous variables are winsorized by the first and the 99th percentiles to alleviate the impact of outliers in our sample. Table 2 presents the sample selection in our study.[7]

TABLE 2 Sample selection.

Data	Number of observations
Universe of listed firms in the US 2001–2021	236,865
After excluding financial (GICS sector code 40) and utilities firms (GICS sector code 55)	199,802
Merging with biodiversity risk dataset (Giglio et al., 2023), excluding all observation with missing biodiversity data	33,382
Final sample size after excluding missing financial data	31,513

Note: GICS, Global Industry Classification Standards.

Figures 1–3 illustrate the average values of biodiversity risk measures across different sectors. Sector classification follows the Global Industry Classification Standards (GICS). Industry classification data are from Bloomberg database. From the figures, we can see that energy, materials, utilities, and the real estate sectors are the sectors that are most exposed to biodiversity risk.

4 | EMPIRICAL RESULTS AND DISCUSSION

4.1 | Baseline results

Panel A of Table 3 reports the regression results of Model (3) using different model specifications from a reduced-form model to the full model specifications.

In all regression specifications in Panel A of Table 3, the coefficient of BIODR remains negative and statistically significant. Except for the reduced-form model (Column 1), the coefficient ranges from −0.039 to −0.030, while the coefficient is −0.032 in the full specification (Column 5). The results suggest that firm performance has a negative association with corporate biodiversity risk. More specifically, firms experience a decrease of 3.2 percentage points on average when exposed to biodiversity risk. Given that ROA has a mean of 0.002 (i.e., 0.2%) and ranges from −0.814 to 0.319 in our sample, the impact is economically significant at the firm level. This finding is generally in line with the detrimental effect of risks and uncertainty on financial performance in corporate finance literature (Gordon

[6]The data are accessible at Hoberg and Maksimovic's data library: https://faculty.marshall.usc.edu/Gerard-Hoberg/HobergMaxLifeCycles/index.html

[7]To test the baseline model under the present of potential sample selection bias, we employ the two-step Heckman selection estimator on the initial data sample rather than the final data set. Please refer to Section 4.2 for more details.

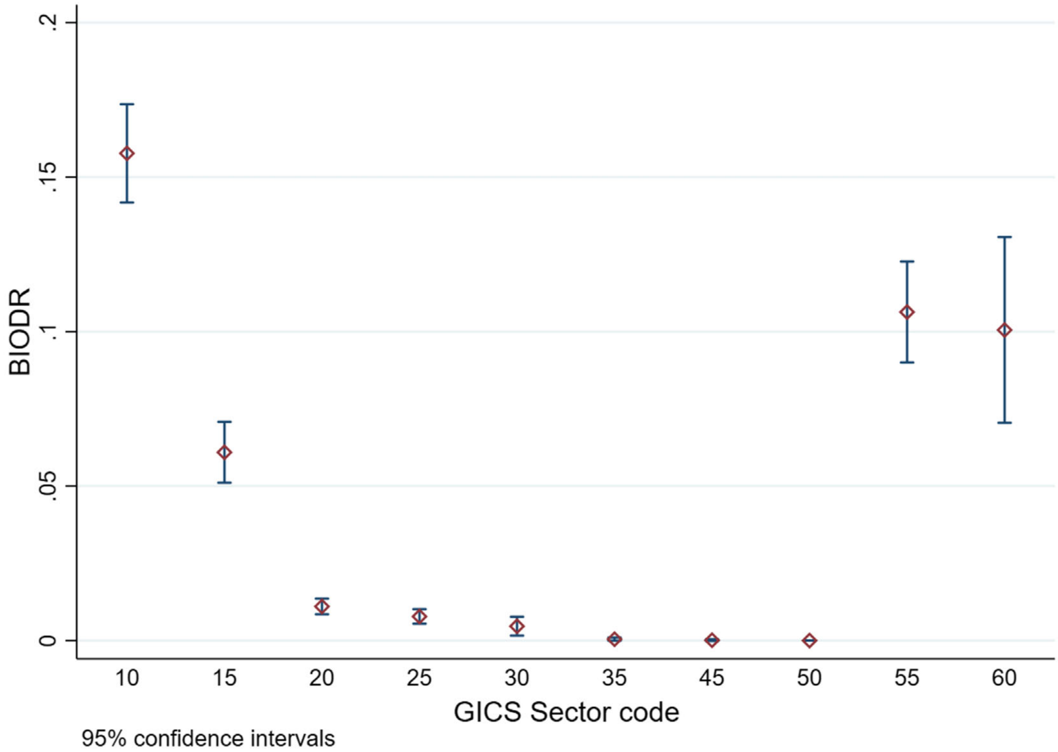

FIGURE 1 BIODR by GICS sector.Note: The GICS sector codes stand for 10 sectors: energy (10), materials (15), industrials (20), consumer discretionary (25), consumer staples (30), health care (35), information technology (45), communication services (50), utilities (55), and real estates (60). The financial sector (40) is excluded from our sample. BIODR, biodiversity risk; GICS, Global Industry Classification Standards.

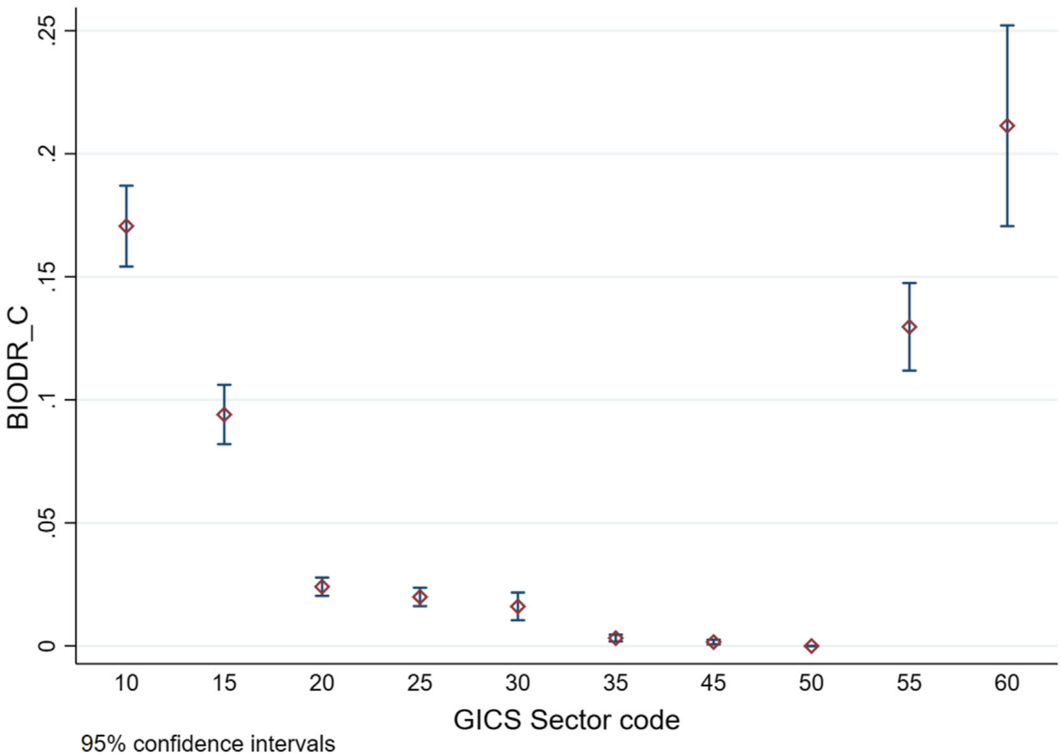

FIGURE 2 BIODR_C by GICS sector.Note: The GICS sector codes stand for 10 sectors: energy (10), materials (15), industrials (20), consumer discretionary (25), consumer staples (30), health care (35), information technology (45), communication services (50), utilities (55), and real estates (60). The financial sector (40) is excluded from our sample. BIODR, biodiversity risk; GICS, Global Industry Classification Standards.

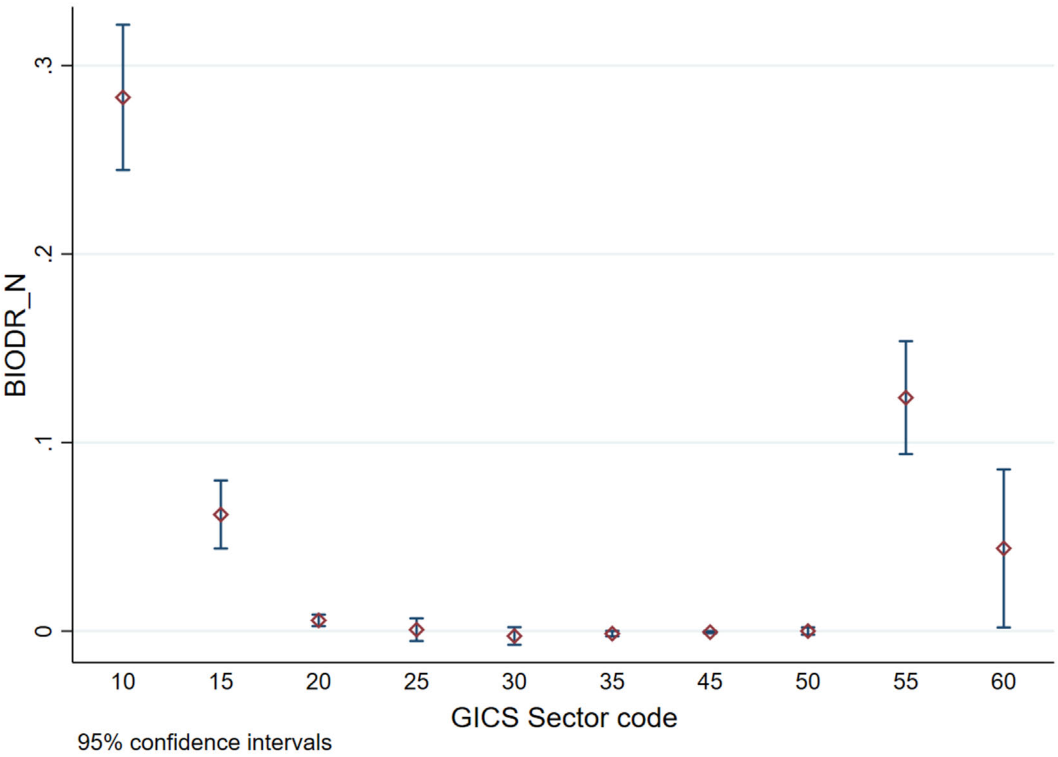

FIGURE 3 BIODR_N by GICS sector.Note: The GICS sector codes stand for 10 sectors: energy (10), materials (15), industrials (20), consumer discretionary (25), consumer staples (30), health care (35), information technology (45), communication services (50), utilities (55), and real estates (60). The financial sector (40) is excluded from our sample. BIODR, biodiversity risk; GICS, Global Industry Classification Standards.

et al., 2009; Huang et al., 2017; Iqbal et al., 2020). However, when considering the findings of previous studies regarding the market pricing of biodiversity risk (Garel et al., 2024; Giglio et al., 2023; Kalhoro & Kyaw, 2024), we suggest the impact of biodiversity risk manifests significantly at the firm-level accounting data, not as how it performs at the market level where the biodiversity risk factor is not fully priced.

Regarding our discussion on the modified Cobb–Douglas production function in Section 2.1, the impact of biodiversity risk on firm performance manifests in the increased cost of production due to biodiversity loss. To further elaborate this argument, we provide additional multivariate regression of cost of goods sold ratio (COGS) on biodiversity risk variable (BIODR). As discussed in Section 2.1, we expect to find the cost of goods sold (i.e., the cost of direct production) increases with biodiversity risk. The empirical results are presented in Panel B (Production cost analysis) of Table 3. The results support our argument from the Cobb–Douglas production function. Specifically, the coefficient of COGS in the cost analysis regression (Column 1, Panel B) is −0.145 (p-value <.01), suggesting a positive association between biodiversity risk and cost of goods sold, even after controlling for firm-specific traits and confounding factors in the time dimension. Firms that are exposed to biodiversity risk incur higher cost of goods sold than those that are less exposed to this category of risk. This implies that firms, in response to the heightened biodiversity risk, experience a notable rise in the expenses associated with acquiring inventories (i.e., inputs) for production. This increase in the cost of goods sold may be attributed to various factors, such as disruptions in the supply chain due to natural capital loss, increased costs of sourcing alternative materials, or expenses related to adapting operational standards to mitigate biodiversity risks.

To summarize, our empirical findings support Hypothesis 1 that biodiversity risk negatively affects firm performance. Section 4.2 deals with endogeneity problems and establishes causal inference for the newfound relationship.

4.2 | Dealing with endogeneity and selection bias

The baseline finding of this study needs further validation. In this section, we deal with the potential endogeneity and selection bias problems that may confound the outcomes of our empirical analysis.

4.2.1 | Addressing the potential selection bias

The construction of Giglio et al.'s (2023) biodiversity risk measures results in two firm groups: the firm group that discloses biodiversity information and the firm group that does not. Specifically, only 16.1% of public firms in the US listed firms in our data disclose enough information for the construction of firm-level biodiversity risk score by Giglio et al. (2023). Intuitively, a firm must disclose their risk factors in 10-K reports; however, the choice to disclose or not to disclose the

TABLE 3 The impact of biodiversity risk on firm performance.

Panel A. Baseline regression results.

	(1)	(2)	(3)	(4)	(5)
	Reduced-form regression	Regression without fixed effects	Regression with firm-fixed effect	Regression with year-fixed effect	Full model specification
VARIABLES	ROA	ROA	ROA	ROA	ROA
BIODR	−0.010*	−0.039***	−0.030***	−0.036***	−0.032***
	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)
FIRM SIZE		0.008***	−0.013***	0.009***	−0.026***
		(0.002)	(0.002)	(0.002)	(0.003)
LEVERAGE		0.001	0.046***	0.007	0.042***
		(0.009)	(0.013)	(0.009)	(0.014)
CAPEX		−0.131***	−0.004	−0.121***	0.035
		(0.025)	(0.026)	(0.025)	(0.026)
PPE		−0.030***	−0.089***	−0.033***	−0.094***
		(0.006)	(0.018)	(0.006)	(0.019)
CASH FLOW		0.911***	0.532***	0.909***	0.537***
		(0.070)	(0.082)	(0.071)	(0.082)
NWC		0.017	0.101***	0.012	0.100***
		(0.043)	(0.035)	(0.044)	(0.035)
CASH		−0.100***	−0.040*	−0.095***	−0.056**
		(0.021)	(0.023)	(0.021)	(0.023)
AUDITOR		−0.017***	−0.015***	−0.019***	−0.010**
		(0.004)	(0.005)	(0.004)	(0.005)
Constant	0.002	−0.072***	0.092***	−0.076***	0.182***
	(0.001)	(0.013)	(0.015)	(0.013)	(0.021)
Firm FE	No	No	Yes	No	Yes
Year FE	No	No	No	Yes	Yes
SE clustered by	firm, year	firm, year	firm, year	firm, year	firm, year
Observations	31,513	31,513	31,513	31,513	31,513
Adjusted *R*-squared	0.000	0.553	0.730	0.558	0.737

Panel B. Production cost analysis.

	(1)
VARIABLES	COGS
BIODR	0.145***
	(0.051)
Control variables	Yes
Firm FE	Yes
Year FE	Yes
SE clustered by	Firm, year
Observations	31,085
Adjusted *R*-squared	0.546

Note: Panel A reports the regression results of Model (3) and its specifications. Panel B reports the regression results of Cost of Goods Sold (COGS) on biodiversity risk (BIODR) and control variables. All variables' descriptions are in Table 1. Standard errors are clustered by firm and year. Numbers in parentheses are standard errors.

***Statistically significant at the 1% level.

**Statistically significant at the 5% level.

*Statistically significant at the 10% level.

TABLE 4 Endogeneity diagnostics.

Panel A. Heckman selection estimation			
	(1)	(2)	(3)
VARIABLES	ROA	DISCLOSURE	/mills
BIODR	−0.028***		
	(0.005)		
FIRM SIZE	−0.008***		
	(0.003)		
LEVERAGE	−0.003		
	(0.009)		
CAPEX	−0.107***		
	(0.022)		
PPE	−0.037***		
	(0.006)		
CASH FLOW	0.851***		
	(0.087)		
NWC	−0.053*		
	(0.029)		
CASH	−0.100***		
	(0.018)		
AUDITOR	−0.015***		
	(0.003)		
INDUSTRY		−0.001***	
		(0.000)	
LOCATION		−0.000***	
		(0.000)	
FIRM SIZE		0.177***	
		(0.001)	
NYT_BIODNEWS		−0.001***	
		(0.000)	
Lambda			−0.093***
			(0.012)
Observations	190,705	190,705	190,705

Panel B. Instrumental variable approach		
	(1)	(2)
	First stage	Second stage
VARIABLES	BIODR	ROA
GGATTENTION	0.000***	
	(0.000)	
BIODR		−1.174***
		(0.199)
FIRM SIZE	0.003***	0.013***
	(0.001)	(0.002)
LEVERAGE	−0.002	−0.032***
	(0.004)	(0.011)
CAPEX	0.130***	0.144***
	(0.028)	(0.046)

(Continues)

TABLE 4 (Continued)

Panel B. Instrumental variable approach		
	(1)	(2)
PPE	0.149***	0.130***
	(0.008)	(0.032)
CASH FLOW	−0.011***	0.562***
	(0.003)	(0.059)
NWC	0.007**	−0.167***
	(0.003)	(0.038)
CASH	0.018***	−0.106***
	(0.004)	(0.022)
AUDITOR	−0.009***	−0.035***
	(0.003)	(0.006)
Constant	−0.059***	−0.072***
	(0.005)	(0.011)
Kleibergen–Paap rk LM statistic	83.367***	
F statistic of excluded instruments	83.610***	
Anderson–Rubin 95% confidence interval	[−1.623, −0.836]	
Observations		28,505
R-squared		0.132

Panel C: Regression with entropy balancing weight		
	(1)	(2)
VARIABLES	ROA	ROA
BIODR	−0.016**	−0.019*
	(0.008)	(0.010)
FIRM SIZE	−0.021***	−0.021**
	(0.007)	(0.010)
LEVERAGE	0.034	0.068
	(0.028)	(0.041)
CAPEX	0.101***	0.143***
	(0.026)	(0.054)
PPE	−0.103***	−0.137**
	(0.033)	(0.069)
CASH FLOW	0.323***	0.244**
	(0.050)	(0.101)
NWC	0.035	0.034
	(0.024)	(0.028)
CASH	0.097**	0.180*
	(0.048)	(0.094)
AUDITOR	−0.001	−0.016
	(0.020)	(0.031)
Constant	0.194***	0.227**
	(0.066)	(0.104)
Firm FE	Yes	Yes
Year FE	Yes	Yes
SE clustered by	firm, year	firm, year
Weighting method		

(Continues)

TABLE 4 (Continued)

Panel C: Regression with entropy balancing weight		
	(1)	(2)
	Entropy balancing	Propensity score matching
Observations	27,973	1,026
Adjusted *R*-squared	0.499	0.372

Note: Panel A reports the two-step Heckman selection regression results. Panel B reports the 2SLS/IV regression results. Panel C reports the regression results of Model (1) using Entropy Balancing weight. All variables' descriptions are in Table 1. Standard errors are clustered by firm and year. Numbers in parentheses are standard errors.
***Statistically significant at the 1% level.
**Statistically significant at the 5% level.
*Statistically significant at the 10% level.

information depends on whether or not the risks are materialized to its business operations and on the regulatory enforcement regarding that required disclosure (Matsumura et al., 2022). Firms may self-select to disclose the information or not; thus, the model may be subjected to a selection bias. To overcome this limitation, we employ the two-step Heckman selection model. We model the choice of disclosing information as the function of firm location, firm size, firm's industry nature, and the public's attention to biodiversity issues. First, Giglio et al. (2023) show that different counties in the United States have different physical biodiversity scores, implying that geographic traits are factors that impact biodiversity risk. Second, larger firms tend to attract more attention (Hong et al., 2000) and be required to disclose more information. Third, different industries exhibit different exposure to biodiversity risk. Last but not least, maintaining biodiversity is a part of the sustainable development goals and attracts great attention from the public.[8] As public attention on biodiversity increases, it stimulates the country-level biodiversity exposure and drives government policy in this matter, thus increasing the transitional biodiversity risk. We proxy public attention on biodiversity issues using Giglio et al.'s (2023) New York Times Biodiversity News Index (NYT_BIONEWS), which is calculated as the difference between the daily count of negative biodiversity news and the daily count of positive biodiversity news. Those counts are constructed using sentiment analysis and their biodiversity dictionary. Panel A of Table 4 reports the two-step Heckman selection regression results.

In Panel A, Table 4, the coefficient of BIODR is −0.028 and significant at the 1% significance level, consistent with those in the baseline regression (see Table 3). The result suggests that our baseline finding holds after correcting for the sample selection bias.

[8]Biodiversity relates to the fourteenth and the fifteenth Sustainable Development Goals (Life Below Water and Life On Land, respectively) of the United Nations.

4.2.2 | Causal inference using the instrumental variable approach

To establish causal inference for the newfound relationship between biodiversity risk and firm performance, we employ the Two-Stage Least Square/Instrumental Variable (2SLS/IV) approach. We use the Google Biodiversity Attention Index (Giglio et al., 2023) as the instrument for firm-level biodiversity risk. This index is constructed using the Google website and counts the number of user searches for biodiversity terms such as "species loss," "ecosystem services," or "biodiversity loss" in each period. It represents the degree of how Google users care about ecosystem issues. Therefore, this instrument is no doubt exogenous to the model and does not have a direct impact on firm-level performance, thus satisfies the first condition of the exclusion restrictions. Moreover, the Google Biodiversity Attention Index is correlated with the firm-level biodiversity risk as they are both proxy for the increasing engagement of society to the endangered ecosystem. Due to these two reasons, the Google Biodiversity Attention Index (GGATTENTION) can serve as the instrument for firm-level biodiversity risk in our 2SLS/IV regression. Panel B of Table 4 reports the regression results.

In the first stage regression, the coefficient of GGATTENTION is positive and significant at 1% significance level, with the Kleibergen–Paap rk LM statistic of 83.367 and the *F* statistic of excluded instrument is 83.610, both with *p*-values smaller than .01. The results suggest that our instrument is not under identified or weakly identified, while strictly correlating with the instrumented variable, BIODR. In the second stage regression, the coefficient of the instrumented variable BIODR is negative and significant at 1% significance level and falls into the Anderson–Rubin 95% confidence interval, hence supporting the causal inference of biodiversity risk affecting firm performance.

4.2.3 | *Ceteris paribus* assumption with entropy balancing and propensity score matching (PSM)

To account for potential confounding factors and facilitate the *Ceteris Paribus* (i.e., all else equal) assumption in our analysis, we employ Entropy Balancing (Hainmueller, 2012) and PSM. Entropy Balancing is a statistical technique for alleviating bias in observational studies by balancing the distribution of covariates between treatment (BIODR = 1) and control groups (BIODR = 0). It minimizes the disparities in entropy between groups, ensuring comparability. This technique improves the validity of causal inference by addressing confounding factors, resulting in more accurate treatment effect estimates, and is considered doubly robust compared to the conventional PSM technique in some research designs (Zhao & Percival, 2017). Therefore, we apply Entropy Balancing method to match firms in treatment and control groups on the control variables. To further strengthen the findings, we employ another regression with weights using the PSM approach. We match each observation of the treated group (BIODR = 1) with an observation in the control group

TABLE 5 Sensitivity tests.

Panel A. Alternative variable measurements and sampling choices									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Alternative FEs	Interaction FEs	Excluding GFC period	Bootstrapping SE (1000 replications)	Alternative explanatory variable	Alternative explanatory variable	Alternative dependent variable	Alternative dependent variable	Alternative dependent variable
VARIABLES	ROA	ROA	ROA	ROA	ROA	ROA	ROE	GROWTH	PBT_ROA
BIODR	−0.033***	−0.023***	−0.036***	−0.032***			−0.111**	−0.071**	−0.058***
	(0.006)	(0.006)	(0.007)	(0.008)			(0.049)	(0.028)	(0.017)
BIODR_C					−0.021***				
					(0.005)				
BIODR_N						−0.008***			
						(0.003)			
FIRM SIZE	0.009***	0.008***	−0.023***	−0.026***	−0.026***	−0.026***	−0.056***	−0.078***	−0.031***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.016)	(0.011)	(0.005)
LEVERAGE	0.010	0.010	0.023**	0.042***	0.042***	0.042***	0.197**	−0.022	0.008
	(0.010)	(0.010)	(0.011)	(0.014)	(0.014)	(0.014)	(0.091)	(0.047)	(0.013)
CAPEX	−0.094***	−0.090***	0.056**	0.035	0.036	0.037	−0.119	0.673***	0.119***
	(0.025)	(0.024)	(0.024)	(0.027)	(0.026)	(0.026)	(0.117)	(0.122)	(0.032)
PPE	−0.046***	−0.052***	−0.118***	−0.094***	−0.094***	−0.093***	−0.219**	−0.295***	−0.174***
	(0.013)	(0.010)	(0.016)	(0.018)	(0.019)	(0.019)	(0.108)	(0.082)	(0.031)
CASH FLOW	0.890***	0.902***	0.374***	0.537***	0.537***	0.537***	0.348**	−0.954***	0.414***
	(0.083)	(0.085)	(0.031)	(0.082)	(0.082)	(0.082)	(0.137)	(0.189)	(0.056)
NWC	0.014	0.006	0.040***	0.100***	0.100***	0.100***	0.103*	0.052	−0.002
	(0.046)	(0.047)	(0.015)	(0.037)	(0.035)	(0.035)	(0.062)	(0.088)	(0.051)
CASH	−0.064***	−0.060***	−0.016	−0.056**	−0.056**	−0.056**	0.106	0.262***	0.002
	(0.019)	(0.019)	(0.015)	(0.023)	(0.023)	(0.023)	(0.080)	(0.095)	(0.023)
AUDITOR	−0.017***	−0.016***	−0.002	−0.010**	−0.010**	−0.010*	−0.043	0.039*	−0.016**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.030)	(0.022)	(0.007)
Constant	−0.082***	−0.079***	0.168***	0.182***	0.182***	0.181***	0.451***	0.756***	0.258***
	(0.016)	(0.011)	(0.020)	(0.021)	(0.021)	(0.021)	(0.122)	(0.095)	(0.035)
Firm FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No	No	No	No	No	No
State FE	Yes	No	No	No	No	No	No	No	No
Industry × year FE	No	Yes	No	No	No	No	No	No	No
State × year FE	No	Yes	No	No	No	No	No	No	No

(Continues)

TABLE 5 (Continued)

Panel A. Alternative variable measurements and sampling choices									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SE clustered by/bootstrap	Firm, year	Firm, year	Firm, year	Bootstrapping	Firm, year	Firm, year	Firm, year	Firm, year	Firm, year
Observations	31,513	31,426	26,685	31,513	31,513	31,513	31,507	31,029	31,513
Adjusted *R*-squared	0.566	0.587	0.764	0.765	0.737	0.737	0.139	0.228	0.634

Panel B. Quantile regression results.					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	ROA	ROA	ROA	ROA	ROA
	p10	p25	p50	p75	p90
BIODR	−0.090***	−0.038***	−0.008**	−0.005	−0.008
	(0.012)	(0.005)	(0.003)	(0.003)	(0.006)
FIRM SIZE	0.018***	0.010***	0.004***	−0.000	−0.004***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
LEVERAGE	−0.010	−0.021***	−0.024***	−0.018***	0.001
	(0.009)	(0.004)	(0.002)	(0.002)	(0.004)
CAPEX	−0.402***	−0.244***	−0.100***	−0.028***	0.025**
	(0.026)	(0.011)	(0.007)	(0.007)	(0.012)
PPE	0.005	−0.011**	−0.028***	−0.036***	−0.044***
	(0.010)	(0.004)	(0.003)	(0.003)	(0.005)
CASH FLOW	1.074***	0.958***	0.817***	0.693***	0.585***
	(0.010)	(0.004)	(0.003)	(0.003)	(0.005)
NWC	0.043***	0.028***	0.021***	0.024***	0.011**
	(0.010)	(0.004)	(0.003)	(0.003)	(0.005)
CASH	−0.259***	−0.189***	−0.110***	−0.033***	0.044***
	(0.012)	(0.005)	(0.003)	(0.003)	(0.006)
AUDITOR	−0.019***	−0.008***	−0.006***	−0.005***	−0.007**
	(0.006)	(0.003)	(0.002)	(0.002)	(0.003)
Constant	−0.229***	−0.112***	−0.026***	0.036***	0.098***
	(0.009)	(0.004)	(0.003)	(0.003)	(0.004)
Observations	31,513	31,513	31,513	31,513	31,513

Note: Panel A reports the regression results of sensitivity tests. Panel B reports the quantile regression results. All variables' descriptions are in Table 1. Standard errors are clustered by firm and year. Numbers in parentheses are standard errors.

***Statistically significant at the 1% level.

**Statistically significant at the 5% level.

*Statistically significant at the 10% level.

(BIODR = 0) using the nearest neighbor matching. The results of the matching procedure are presented in Appendix A1 and Appendix A2.

Table 4, Panel C, reports the regression results of Model (3) using Entropy Balancing and PSM weights. Consistent with our baseline results, the coefficient of BIODR in the regression is negative and significant in both model specifications, thus bolstering our confidence on the causal inference of the baseline finding under the *Ceteris Paribus* assumption.

4.3 | Sensitivity tests

We conduct several more sensitivity tests to ensure the reliability of our finding, including tests to address the omitted variable bias, sample selection, and potential measurement errors.

We use alternative fixed effect settings to account for potential confounding factors at the industry level and state level as biodiversity risk is industry sensitive and strongly related to the local ecosystem. To do that, we substitute the firm-fixed effect by the industry-fixed and state-fixed effects in Model (1) and re-estimate it. Furthermore, as the risk associated with biodiversity and ecosystem may vary over time, we adapt our model by using the interactions among industry, state, and year as the interaction fixed effects (i.e., Industry × Year and State × Year FEs). The regression results using these two fixed effect settings are reported in the first two columns of Panel A, Table 5.

In the next two tests, we account for the potential impact of the Global Financial Crisis (2008–2010) and sample selection on firm performance by excluding the 2008–2010 period and bootstrapping standard errors. The estimation results are in Columns (3) and (4) of Panel A, Table 5. Next, we use alternative variable measurements of firm-level biodiversity risk, including the 10 K-Biodiversity-Count Score (BIODR_C) and the 10 K-Biodiversity-Negative Score (BIODR_N), and alternative measures of firm performance, including ROE, GROWTH, and PBT_ROA, to re-estimate Model (3). The results of these tests are reported in Columns (5)–(9) of the panel.

Furthermore, we test how the impact of biodiversity risk varies at different quantiles of firm performance variable (ROA) by using the quantile estimator to re-estimate Model (3). We estimate Model (3) at five different quantiles $q = \{0.1, 0.25, 0.50, 0.75, 0.9\}$ to see whether the impact is uniform or varies at different levels of firm performance. Panel B of Table 5 reports the estimation results. We see that the coefficient of BIODR gradually decreases from -0.090 (p-value < .01) in the 10th percentile regression to -0.038 (p-value < .01) in the 25th percentile regression, and then to -0.008 (p-value < .05) in the 50th percentile regression before turning insignificant in the right tail of ROA's distribution. The findings suggest that the impact of firm-level biodiversity risk is not uniform on the whole sample but varies across different levels of firm performance. Firms in the right tail of distribution (i.e., firms with very high profitability) do not seem to be significantly affected by biodiversity risk, suggesting the resilience of this spectrum of firms to this new type of risk associated with their business operations. The results suggest that the relationship between performance and biodiversity risk is dynamic as higher performance creates a positive feedback loop that enhances corporate resilience and competitiveness in the long run.

Generally, the sensitivity test results are satisfactory. The coefficients of BIODR, BIODR_C, and BIODR_N are robustly negative and significant in all regression specifications from Column (1) to Column (9), thus suggesting that our baseline finding is not sensitive to choices of variable measurements, fixed effect settings, and sample selection.

4.4 | Mechanism tests

4.4.1 | Product innovation

Product innovation is the important first stage in the life cycle of an investment project. At this stage, firms concentrate on investing in R&D as their valuation increases. In other words, the more a firm exposes to this first stage of the product life cycle, the more capital spending for R&D (Hoberg & Maksimovic, 2022). Therefore, innovation in product design and development creates new growth opportunities and enhances projects' financial performance in the later stages. Previous studies in literature share similar views that product innovation has a positive impact on firm performance (Artz et al., 2010; Chu et al., 2024; Ramadani et al., 2019). During the stage of product innovation, by integrating sustainability practices and ecological concerns into product development and productions, firms can strategically reduce their exposure to biodiversity transition risk and sustain long-term growth. Such a conjecture is in line with our cost analysis (see Section 4.1) and the findings of Carvalho et al. (2023) who find evidence of firms strategically incorporating biodiversity risk into their production.[9] Based on this understanding, we predict that product innovation can play an important role in mitigating the negative impact of biodiversity risk on firm performance.

To proxy for product innovation, we employ a text-based measure of firm-level product innovation (PRODUCT_INNO) generated using computational linguistic methods on firm's 10-K reports (Hoberg & Maksimovic, 2022). The measure indicates the degree of a firm being exposed to early product innovation by identifying the first stage of investment project where the Tobin's Q is extremely sensitive to capital expenditure and R&D investments. We choose this general measure of product innovation instead of a specific green product innovation for two main reasons: (i) general product innovation can solve the natural capital input puzzle via improving efficiency and product design for productivity without a specific environmental focus; and (ii) there is no single comprehensive measure of green product innovation that can capture the degrees of "green" in all products of firms in our sample.

We argue that product innovation generates better products and enhances firm performance. We interact PRODUCT_INNO with

[9]Carvalho et al. (2023) investigate a sample of 11,812 international firms during 2004–2018. The sample period of Carvalho et al. (2023) fits well into our study period (2001–2021). Their findings support our conjecture that firms proactively and strategically consider biodiversity risk in product innovation.

TABLE 6 Mechanism tests.

	(1)	(2)	(3)	(4)
VARIABLES	ROA	ROA	ROA	ROA
BIODR	−0.081***	−0.058***	−0.029***	−0.026***
	(0.015)	(0.015)	(0.006)	(0.007)
PRODUCT_INNO	−0.105***	0.032*		
	(0.031)	(0.019)		
BIODR × PRODUCT_INNO	0.343***	0.235***		
	(0.077)	(0.071)		
IND_SCORE			−0.051*	
			(0.029)	
BIODR × IND_SCORE			−0.830***	−0.448***
			(0.148)	(0.157)
FIRM SIZE	0.008***	−0.031***	0.008***	−0.026***
	(0.002)	(0.003)	(0.002)	(0.003)
LEVERAGE	−0.002	0.038**	−0.000	0.042***
	(0.012)	(0.015)	(0.010)	(0.014)
CAPEX	−0.121***	0.028	−0.123***	0.034
	(0.026)	(0.027)	(0.025)	(0.026)
PPE	−0.047***	−0.095***	−0.029***	−0.093***
	(0.006)	(0.020)	(0.006)	(0.019)
CASH FLOW	0.889***	0.531***	0.911***	0.537***
	(0.083)	(0.091)	(0.071)	(0.082)
NWC	0.033	0.102***	0.017	0.100***
	(0.051)	(0.039)	(0.044)	(0.035)
CASH	−0.084***	−0.056**	−0.100***	−0.055**
	(0.020)	(0.025)	(0.021)	(0.023)
AUDITOR	−0.014***	−0.011**	−0.018***	−0.010**
	(0.004)	(0.005)	(0.004)	(0.005)
Constant	−0.041**	0.210***	−0.074***	0.184***
	(0.018)	(0.023)	(0.013)	(0.021)
Firm FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
SE clustered by	firm, year	firm, year	firm, year	f;irm, year
Observations	27,769	27,769	31,436	31,436
Adjusted *R*-squared	0.547	0.742	0.553	0.737

Note: This table reports the regression results of further analysis: product innovation and industry-level exposure to biodiversity risk. All variables' descriptions are in Table 1. Standard errors are clustered by firm and year. Numbers in parentheses are standard errors.
***Statistically significant at the 1% level.
**Statistically significant at the 5% level.
*Statistically significant at the 10% level.

BIODR in Model (1) and re-estimate the model; both variables are lagged by one period to demonstrate their impacts on the subsequent year's performance. Columns (1) and (2), Table 6, report the regression results with and without fixed effects.

The coefficient of the interaction term BIODR × PRODUCT_INNO is positive and significant at 1% significance level in both columns, suggesting that the impact of biodiversity risk on firm performance is weakened for firms with more product innovation. However, the size of the coefficient of BIODR is relatively small in comparison to that of BIODR × PRODUCT_INNO (−0.081 and −0.058 compared to 0.343 and 0.235, respectively), suggesting that product innovation may even reverse the negative impact of biodiversity risk on performance, hence support our Hypothesis 2 on the moderation of product innovation (H2).

4.4.2 | The industry-level exposure

To investigate the industry-level exposure to biodiversity risk, we draw on a holding-based measure of biodiversity risk exposure at the industry level (IND_BIODREE) proposed by Giglio et al. (2023) to test its role on how firm-level biodiversity risk affects firm performance. Following the discussion in Section 2.2, we expect that firms operating in an industry with a high degree of exposure to biodiversity risk may suffer even more from a biodiversity risk than a similar firm operating in a different industry. To test this conjecture, we include the interaction term between BIODR and IND_BIODRE into Model (1) and re-estimate the model. Columns (3) and (4) of Table 6 present the regression results with and without fixed effects.

In both Columns (3) and (4), Table 6, the coefficient of the interaction term BIODR × IND_BIODRE remains negative and significant at 1% significance level, suggesting an incremental effect of industry exposure to biodiversity risk on how firm-level biodiversity risk affects firm performance. Interestingly, the size of the interaction term's coefficient is much larger than that of the standalone BIODR variable (−0.830 and −0.448 compared to −0.029 and −0.026, respectively). Such a huge difference implies that the impact of biodiversity risk on firm performance majorly manifests at a more macro level than at the firm level. From a more macro perspective, the empirical evidence suggests a potential spillover effect of the biodiversity transition from the macro environment to micro (firm) behaviors. The finding is supported by Ahmad and Karpuz's (2024) results that the industry's exposure to biodiversity risk exerts an incremental effect on the firm-level impact of biodiversity risk on corporate cash holding. Despite biodiversity risk is related to but not the same as climate risk, this finding aligns with the discussion in the recent climate risk literature that climate risk is driven mainly by regulatory transition rather than firm-specific physical exposure to climate change (Salisu et al., 2023; Stroebel & Wurgler, 2021). Hence, Hypothesis 3 is supported.

In summary, our mechanism analysis yields interesting findings on how the impact of biodiversity risk on firm performance varies in the cross-section of firms and industries. The findings suggest the role of transitional biodiversity risk and product innovation in forming corporate outcomes in the United States.

5 | CONCLUSIONS AND IMPLICATIONS

There is growing awareness of the economic impact of biodiversity loss at the macro level and firm level. However, the literature on biodiversity risk is still in the early stages of development and lacks evidence on how such a risk factor exerts its impact on economic activities and corporate outcomes. This current study fills this gap in the literature and provides implications for businesses, investors, and policymakers in addressing a new type of risk associated with corporate ecological footprints and the transition to sustainability.

From the academic perspective, this study serves as the first academic reference that explores the relationship between biodiversity risk and firm performance. Our main finding suggests that biodiversity risk represents a material financial risk for firms. Our study suggests that while the biodiversity risk factor may not adequately explain the cross-section of stock returns (Giglio et al., 2023; Kalhoro & Kyaw, 2024), it still holds significant importance from the corporate finance perspective by exerting its strong impact on firm's financial performance. From there, we raise two questions for future research: Is biodiversity risk mispriced? and why so? Investigation into this direction may be beneficial to the new biodiversity finance literature and the wider literature of finance in general. Following this vein, future research can examine the mechanisms through which biodiversity risk affects firm performance, exploring potential mechanisms such as regulatory compliance costs, supply chain disruptions, reputational damage, and legal liabilities.

From a practitioner's perspective, firms that are exposed to biodiversity risk need to strategically incorporate biodiversity policy in their operations and product innovation to create sustainable growth opportunities in the long-term. By striking while the iron is hot, firms may alleviate the impact of the biodiversity transition when it is not yet formulated into an even larger economic impact. Nevertheless, investors should be aware of the evident impact of biodiversity risk at the firm level when making investing decisions. As Giglio et al. (2023) and Kalhoro and Kyaw (2024) show that investors do not seem to fully price biodiversity risk, our findings suggest the same risk factor is detrimental to firm performance; thus, it might affect future cash flows and valuations. A more thorough understanding of and attention to firm-level and industry-level biodiversity risk would help investors make more informed decisions when the biodiversity snowball starts to roll.

Our findings convey several policy implications. Policymakers should consider the impact of biodiversity risk at the firm level and industry level in policymaking, especially in the consideration of conservation finance programs to encourage firms moving toward sustainability. Because general firms' performance is likely affected by increasing biodiversity risk at both the firm level and industry level, economic growth in the economy might be slowed down. Supporting policies and conservation efforts from the government are required to improve biodiversity outcomes linked to economic activities. Moreover, policymakers should incorporate biodiversity risks into decision-making and policy development, rather than treating biodiversity as a separate issue. This could involve adapting macro-level and micro-level measures to better reflect natural capital, and mainstreaming biodiversity into economic strategies, plans, and projects.

As an empirical study, our study has two limitations. First, we do not consider the financial market performance of firms, but only focus on the corporate finance side of the impact of biodiversity risk. This limits the scope of the study to financial performance analysis using accounting data only. Investigating the impact of biodiversity risk on asset pricing (i.e., corporate bond and stocks) may provide new insights into how market values of assets change under the presence of increasing biodiversity risk. Second, the study only focuses on firms from the United States. Although our sample is more comprehensive than those of the previous studies in this line of research, future studies may need to revisit and expand our findings on different dimensions, such as green product innovation as a solution for mitigating the negative impact of biodiversity risk or expanding the scope of study to an international context to capture the cross-country variations on the impact of biodiversity risk.

ACKNOWLEDGMENTS

This research is funded by National Economics University, Vietnam, under the funding number 02/HD-CBQT2023.02.

CONFLICT OF INTEREST STATEMENT

The authors of this research have no conflict of interest. There is no relationship, financial or other interests that might influence our objectivity in conducting this research.

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How to cite this article: Bach, T. N., Hoang, K., & Le, T. (2025). Biodiversity risk and firm performance: Evidence from US firms. *Business Strategy and the Environment*, *34*(1), 1113–1132. https://doi.org/10.1002/bse.4039

APPENDIX A: APPENDICES

A.1 | Appendix A1. Entropy Balancing diagnostics

A.2 | Appendix A2. Propensity Score Matching diagnostics

a. Pre-match propensity scores of the treated group (BIODR = 1) versus the control group (BIODR = 0)
b. Post-match propensity scores of the treated group (BIODR = 1) versus the control group (BIODR = 0)

Before weighting						
Variable	Treat			Control		
	Mean	Variance	Skewness	Mean	Variance	Skewness
FIRM SIZE	8.100	2.272	−0.074	7.016	3.125	0.246
LEVERAGE	0.301	0.029	0.815	0.199	0.044	1.608
CAPEX	0.139	0.026	2.541	0.056	0.006	4.992
PPE	0.644	0.048	−0.685	0.242	0.051	1.202
CASH FLOW	0.101	0.007	−0.122	0.064	0.038	−11.120
CASH	0.069	0.010	3.630	0.154	0.029	2.046
NWC	0.010	0.014	4.964	0.026	0.037	−7.534
AUDITOR	0.888	0.100	−2.455	0.904	0.087	−2.745
After weighting						
Variable	Treat			Control		
	Mean	Variance	Skewness	Mean	Variance	Skewness
FIRM SIZE	8.100	2.272	−0.074	8.099	3.162	−0.125
LEVERAGE	0.301	0.029	0.815	0.301	0.041	1.149
CAPEX	0.139	0.026	2.541	0.139	0.024	2.602
PPE	0.644	0.048	−0.685	0.644	0.058	−0.993
CASH FLOW	0.101	0.007	−0.122	0.101	0.013	−10.310
CASH	0.069	0.010	3.630	0.069	0.012	3.791
NWC	0.010	0.014	4.964	0.010	0.014	3.093
AUDITOR	0.888	0.100	−2.455	0.888	0.100	−2.454