Biodiversity Physical Risk, Firm Performance, and Market Mispricing*

Yujun Huang† Anna Creti‡ Binghan Jiang§ Maria-Eugenia Sanin¶

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Abstract

This paper studies the asset pricing implications of biodiversity physical risk through studying the impact of a novel biodiversity index. A long-short portfolio constructed from firms with low versus high biodiversity physical risk within a given industry generates an average alpha of 2.5% per annum, and such alpha cannot be explained by existing common risk factors. We also document that the predictability of stock returns related to biodiversity physical risk is primarily due to the improper pricing of future cash flows, which is not predicted by financial analysts, by institutional investors, and even after the increase of global attention to biodiversity. We implicates the importance of considering "double materiality" during the evaluation of asset prices under biodiversity-related variables, especially the different impacts of physical and transition risk on asset prices.

Keywords: Biodiversity, physical risk, profitability, stock returns, market efficiency

JEL Classification: G1, G12, G14, Q57

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†CEC, University of Paris Dauphine - PSL

‡CEC, University of Paris Dauphine - PSL

§DRM, University of Paris Dauphine - PSL

¶Evry University, University of Paris-Saclay

1 Introduction

Since the last decade, people have been increasingly focusing on solving the problems of climate change and global warming. However, the body of scientific evidence supports the statement that climate change is one dimension of research; yet biodiversity issues are equally important. Scientists observe that the earth has suffered from a 69% loss of vertebrate species and an 83% loss of freshwater species from 1970 to 2018, but there is huge regional heterogeneity.[1]. In this context, several studies suggest that biodiversity loss may impact economic activity directly and indirectly. Specifically, Costanza et al. (1997) estimate that the whole biosphere provides an economic value of between 16 and 54 trillion dollars annually. This value was estimated for 1997 when the global gross GDP was 18 trillion dollars. To protect global biodiversity, countries and regions must cooperate by deciding the geographical priority areas, though only 11% of such areas are currently protected (Neugarten et al., 2024).

Biodiversity economic value includes firstly the value of species and habitats, which we call "direct value". Bartkowski, Lienhoop, and Hansjürgens (2015) argue that those values enter directly the utility function to provide well-being. Szabó and Ujhelyi (2024) also shows that the US National Park system leads to the augmentation of local employment and income levels, and such positive effects are driven by the increase of visitors rather than various public financing channels. Biodiversity also provides "indirect value". This kind of "indirect value" is hard to simulate and highly depends on the interaction of the whole ecosystem. However, researchers agree that biodiversity has positive impacts. For example, it favors agricultural output (Hector, 2011), fishery output (Worm et al., 2006), carbon storage (Strassburg et al., 2010; Chaplin-Kramer et al., 2015), human health (Wall, Nielsen, & Six, 2015), or assurance potential (Koellner & Schmitz, 2006).

To recapitulate, empirical evidence indicates biodiversity abundance generates economic profits. Higher biodiversity resilience reduces the uncertainty of expected cash flows from ecosystem services, thereby increasing the probability and economic value (Baumgärtner

[1]For instance, (WWF, 2022) shows that Latin America and the Caribbean countries have lost 94% of biodiversity in that same period while in Europe and Central Asia, biodiversity loss is estimated at 18%, Biodiversity loss represents 66% in Africa; 55% in Asia-Pacific; 20% in North America, respectively

& Strunz, 2014). Besides, this kind of effect expands across countries and sectors with ecosystem dynamics. (Cardinale et al., 2012; Hanley & Perrings, 2019; Giglio, Kuchler, Stroebel, & Wang, 2024).

However, the physical risk of long-run biodiversity loss and its impact on asset prices remain to be discussed. We refer to biodiversity physical risk to general climate-related physical risk, in which the mispricing is prevalent in the market. Specifically, we do not know (i) whether biodiversity loss is at the same level for all countries or regions; (ii) the average impact of biodiversity loss on firm-level future cash flows; (iii) and if so, should we expect that biodiversity physical risk to be a systematic risk factor and make it priced.[2]

To investigate those key research questions, we build a biodiversity Index for 35 leading economies worldwide over the last 50 years based on a scientific database called Ecological Footprint Initiative and compute a long-run trend of this index, we create a revenue decomposition strategy to compute firm-level biodiversity physical risk exposure. Specifically, we observe that the biodiversity index depends highly on country's natural location. For instance, Brazil, Canada, and Australia have the highest biodiversity eco-system, which means the biodiversity capacity far outweighs the destruction of biodiversity by nationals. Meanwhile, the investigation of long-term trend of biodiversity index in each country gives another picture. Except for some European countries, most of economy encounter a worsening biodiversity in average.

Second, we show that a value (equal)-weighted long-short portfolio constructed from firms with low versus high biodiversity physical risk within a given industry generates an average excess return (alpha) of approximately 2.5% per annum, and such excess return cannot be explained by existing common risk factors (e.g., MKT, HML, SMB, MOM, etc.). This alpha remains significant in a very long horizon, for two to four years.

Third, we document the return predictability phenomenon, indicating that information related to biodiversity physical risks is only partially priced into the market. Specifically, we document that firms with the low biodiversity physical risk compared to its industry-peers can generate 2.291% annual cumulative excess returns higher than firms with other

[2]For example, Krueger, Sautner, and Starks (2020) argue that investors and financial markets lack sufficient information of climate change to incorporate it into their cash flow or discount rate analysis.

level of biodiversity physical risk, and values -1.258% for firms with relative high risk.

Fourth, we show the reasons for the pricing error by running Fama-Macbeth regressions on biodiversity physical risk and firm-level profitability change. The results demonstrate that inaccurate forecasts of future cash flows primarily cause asset mispricing, which show that firms with the low biodiversity physical risk compared to its industry-peers generate more than 0.398% in future cash flows than others. This cash flow generation is economically larger when we sort firms with extreme low risk, valuing 1.289% per annum in average.

Fifth, we also document estimations across different industries characteristics. In short, we show that the industries with the highest sensitivity for biodiversity physical risk are Business Suppliers (Paper productions), Recreation (Tourism), Electronic Equipment, Food Products, Apparel (Textiles), Hotels and Restaurants, Construction, Materials, and Medical Equipment. Our results are partially consistent with the findings of Giglio, Kuchler, Stroebel, and Zeng (2023), but with some noticeable differences, especially for Energy and Chemicals industry. Moreover, we document that although the risk characteristics at he firm-level is sizable for predicting excess returns, if those firms are classified in the low biodiversity physical risk industries, the return predictability dilutes significantly, with approximately 4% decrease.

Sixth, we test whether the market is partially incorporate the biodiversity physical risk information into their prediction, or trading activities. The answer is simple: far away from complete. From the analysts' earning forecast and surprise estimation, we find that they are more sensitive to high risk firms' cash flow news rather than low risk firms. They efficiently downgrade the profitability change for high firms and there is no surprise in annual earning announcement. Meanwhile, they seem do not perceive which firms are more resilient, with insignificant upgrades and leave a significant gap of 0.5% annual profitability change as unpredicted. We do not find either any empirical evidence that institutional and retail investors adjust their portfolio weighting in response to the disclosure of biodiversity physical risk information, even in the period that people tend to focus more on biodiversity.

This paper systematically measures biodiversity physical risks at firm-level and contributes to several strands of literature. First of all, this paper differs from this strand of literature in the definitions of "acute physical risk" (e.g., Hurricanes (Ortega & Taspinar, 2018), Floods (Bakkensen & Barrage, 2017), Fires (Issler, Stanton, Vergara-Alert, & Wallace, 2020), and Thunderstorms (Braun, Braun, & Weigert, 2023)). For this type of physical risks, extreme events destroy the value of financial assets immediately, with a very high attention. Alok, Kumar, and Wermers (2020) document that the salience bias may cause the overreaction of the fund managers, and they will over-underweight the investments in the disaster zone. However, the perception of physical risk is considered local or regional.[3] In this paper, we show that biodiversity physical risk is persistent and generate a long-term negative impact worldwide, and short of market perception.

The second is the literature that studies the firm-value and asset-pricing consequences of chronic physical risk in particular, which either systematically affects future cash flow, thus increasing the cost of capital for firms (Balvers, Du, & Zhao, 2017), or affects the discount rates, especially in real estate investments (Giglio, Maggiori, Rao, Stroebel, & Weber, 2021). Our biodiversity physical risk measurement is consistent with many existent literature discussing the long-run effect of climate change, such as sea level rise (Bernstein, Gustafson, & Lewis, 2019; Murfin & Spiegel, 2020; Goldsmith-Pinkham, Gustafson, Lewis, & Schwert, 2023), global warning or abnormal temperature (Addoum, Ng, & Ortiz-Bobea, 2020, 2023; Pankratz, Bauer, & Derwall, 2023; Kumar, Xin, & Zhang, 2023), drought (Hong et al., 2019), etc.

This paper also contributes to the growing literature of biodiversity and finance. Despite its importance, biodiversity has not attracted much attention in finance, even if investors are trying to measure assets' exposure to biodiversity-related risks (Karolyi & Tobin-de la Puente, 2023). To our knowledge, there are only a few finance papers discussing biodiversity, and most existing literature focuses on biodiversity transition risk, its pricing, and how we could finance projects that contribute to biodiversity recovery. Garel, Romec, Sautner, and Wagner (2023) and Coqueret and Giroux (2023) use firm-level biodiversity footprint collected by the Iceberg Data lab to evaluate the biodiversity transition risk and its premium (referred to as the risk premium hypothesis). Flammer, Giroux, and Heal

[3]For instance, Hong, Li, and Xu (2019) find heterogeneity of vulnerability to drought across regions. Global warming intensify drought in most countries in northern hemisphere but reduces the severity of drought in countries in the southern hemisphere.

(2023) find that the lack of attention to biodiversity and financial management is due to the ambiguous evaluation methodology and the unbalance between risk and return, which restricts private financing. Regarding to the biodiversity physical risk, only Giglio et al. (2023) conduct 10-K and survey-based research on biodiversity physical risks. They widely document the exposure to biodiversity risk varies substantially across sectors. However, this evidence is incomplete because their results are based on subjective reporting rather than objective assessment.

Lastly, this paper contributes to the clarification of the importance of "Double Materiality," which needs to be taken into consideration for policymakers. Double Materiality shows not only the company's impacts on the climate (and other aspects of sustainability) but also the climate-related impacts on a company as material (TCFD, 2017; NFRD, 2017). Our results show perfectly the impact of physical risk is different from the transition risk. Transition risks are the risks of negative impacts on the natural capital. Negative impacts come from the large carbon or biodiversity footprint from both the consumption and production sides. Such negative effects on the climate can relate directly to higher policy and legal pressure (policy risks and legal risks), and to negative social image (reputational risks), etc. On the other hand, Bressan, uranović, Monasterolo, and Battiston (2024) argue that physical risks are the negative impacts of natural capital degradation or natural disasters on firms at the assets and facilities level. According to NGFS (2020), physical risks provoke negative impacts at the individual level (e.g., property damage, business disruption, loss of income) and on the aggregated level (e.g., capital depreciation, productivity changes, labor market frictions), and those effects generate financial risks through the interaction of economy and financial system feedback. One should be aware that a highly exposed firm (to physical risks) is not equally influenced by whether or not it hurts the climate, distinguishing the physical risks from the transition risks. For example, we can not expect that a firm that produces fossil fuels will be affected largely by the rising sea level, even if it contributes a large amount of carbon emissions[4]. Conversely, a fishery company is highly exposed to global warming even if it does not produce as much of a footprint as fossil fuel

[4]For instance, Garel et al. (2023) and Coqueret and Giroux (2023) document positive biodiversity transition risk premium.

companies.

The rest of this paper is organized as follows. In Section 2, we describe the data sample, the measurement of biodiversity risk, and present descriptive statistics. In Section 3, we report the asset pricing results of biodiversity physical risk. In Section 4, we explore the mechanisms through which biodiversity physical risk is associated with the return predictability. In Section 5, we conduct robustness checks. Section 6 concludes. Additional country level descriptions are provided in Appendix A. Details in data construction and explanations are provided in Appendix B. Robustness tests are further shown in Appendix C.

2 Data and Variables

2.1 Biodiversity Data

We extract the biodiversity dataset from the source Ecological Footprint Initiative[5] with two pillars: Bio-Capacity and Bio-Footprint[6]. The Bio-Capacity proxies the richness of the total biodiversity of a country, and the Bio-Footprint measures the damage imposed on such richness. each pillar covers differnt sub-categories: cropland, grazing land, built-up land, fishing grounds, forest products, and carbon uptake as components. The two pillars are monitored and updated yearly.[7]

We remove countries and regions with very small territories (e.g., Singapore and Hong Kong), with negligible population and economic size (e.g., Cayman Islands and Virgin Islands). The reason to do such treatment is that the value of biodiversity capacity could be dependent on the country's geographic location. For example, we expect that biodiversity conditions around the tropical forest (e.g., Brazil) are better than those around the desert

[5]Key sources include the International Energy Agency (IEA), the Food and Agriculture Organization (FAO) of the United Nations and its PopStat, ProdStat, TradeStat, ResourceStat, and FishStat databases, Sea Around US, UN Comtrade, Corine Land Cover, Global Agro-Ecological Zones (GAEZ), Global Land Cover (GLC), Global Carbon Budget, World Bank, International Monetary Fund, and Penn World Tables.

[6]The Bio-Capacity and the Bio-Footprint are measured in terms of global hectare, and computed by multiplying with an appropriate equivalence factor. Global hectare measures world average biological productivity for a given year.

[7]Although the measurement is constructed based on scientific research, robust results are also adaptable due to potential measurement changes, given that we do not yet have a comprehensive and standardized design.

(e.g., Egypt). Besides, countries with larger territories (e.g., the US and China) will have more extensive biodiversity. However, for the countries where the population is huge (e.g. China and India), Bio-Capacity per capita will naturally be lower.

Appendix A.1 presents the average Bio-Capacity and the average Bio-Footprint across countries and the results confirm our intuition. On the side of Bio-Footprint, we find that developed countries display more categories of damage (per person) to biodiversity than emerging countries. On the other hand, natural resource-rich countries have higher Bio-Capacity. We also summarize in Appendix A.1 the date countries sign for the international conventions. It reports that most countries participate in all three conventions (Protocols). However, Australia, Canada, and Chile join only the Convention on Biological Diversity. Colombia, Italy, New Zealand, and Poland are not involved in the Nagoya Protocol. The US did not sign any of these three.

We construct the biodiversity index as the variable aggregating at the country level, as follows:

$$\text{Biodiversity Index}_{c,t} = \frac{\text{Bio-Capacity}_{c,t}}{\text{Bio-Footprint}_{c,t}} \tag{1}$$

. The "Bio-Capacity" values the ecosystem's endowments to produce biomaterials and absorb human-generated wastes under current scenarios and techniques. The "Bio-Footprint" values the total Footprint as the ecological output of domestic production under the current situation, which harms the local biosphere. Both terms are expressed at the country level and change over time.[8] **We can define the balanced resilience of biodiversity when this ratio is equal to one, where demands on nature is the "Bio-Footprint" and supplies is the "Bio-Capacity".** A higher biodiversity index represents higher resilience and less vulnerability to biodiversity loss. The value of the index superior to one means that global biological resilience outweighs the destruction of biodiversity by production activities, and vice versa. Here, we closely follow Dasgupta (2021), as the author affirms: "ensure that our demands on nature do not exceed its supply and that we increase Nature's supply relative to its current level."

[8]Appendix A.2 presents the geographic distribution of countries with strong and weak resilience. The heat maps show the average Biodiversity Index for each country over two decades. Countries with strong resilience are colored green, those with weak resilience are red, and intermediate resilience is shown in yellow. The deeper the color, the larger the absolute average Biodiversity Index.

2.2 Measuring the Biodiversity Physical Risk

We construct a time series regression to measure the trend over time of the biodiversity index. This "Trend" term helps us capture the unexpected evolution of biodiversity across countries, and we use it to represent the long-run biodiversity risk.[9] We use a simple AR(1) model to identify the trends across the countries, with a time trend characteristic t.[10] The estimated coefficients β_0, β_1, and β_2 can differ from the country c. The coefficient for the trend, β_1, is our parameter of interest. We extract the trends on countries by running the over-lapping 30-year rolling regression of the index from the year $t-30$ up to the year $t-1$ to estimate the coefficient of trends for year $t-1$. This approach helps us capture unexpected biodiversity loss over 30 years, considering policy adjustments and initial differences in the biodiversity index. Thus, for each year t and each country c from 1974 to 2020, to get the trend β_1 from 2003 to 2020.[11]

$$\text{Biodiversity Index}_{c,t} = \beta_{0,c} + \beta_{1,c}t + \beta_{2,c}\text{Biodiversity Index}_{c,t-1} + \epsilon_{c,t} \tag{2}$$

Table 1 reports our average estimations of the draft (β_0) and trend (β_1) and their t-statistics over the period from $t-30$ to $t-1$. We take β_1 as the representative of one country's biodiversity risk. High β_1 means low risk, and verse versa. We do not report the coefficients of β_2 for brevity, but the estimated β_2 are statistically significant and inferior to one, confirming that there is no issue in terms of unit roots.

Our results show that there is heterogeneity in the trends of biodiversity across countries, which is consistent with the fact that not all countries are losing their biodiversity over time. For instance, India (8.212‰), South Africa (5.939‰), and Brazil (-4.615‰) are facing strong negative time trends in biodiversity, and these trends are statistically significant at the 1% level with t-statistics of 3.538, 3.129, and -2.486 respectively, while Denmark (6.395‰), Germany (4.635‰), and France (1.704‰) have significant in-

[9] As shown in Figure 1, the biodiversity index has been decreasing in the past decades in India, thus we expect that the impact of such risk on India's economy will become considerable over time.

[10] We confirm our model assumption using the Dickey-Fuller tests (Dickey & Fuller, 1979) for each country. The tests show that there are no issues with unit roots in our series.

[11] We also estimate the trends using data since the first record appears instead of running 30-year rolling regression. See Results in Appendix C.

creasing trends in terms of their biodiversity, with t-statistics of 2.860, 2.485, and 1.657 respectively.[12]

[Insert Table 1 here]

2.3 Properties of Biodiversity Physical Risk

Property 1: *Biodiversity physical risk is chronic*

In Section 2.1, we shed some light on the computation of the Biodiversity Index. Indeed, Biodiversity Loss is related to human damage and ecosystem resilience. Therefore, we assume that the biodiversity risk of a forest ecosystem does not increase irreversibly due to a wildfire because all these acute events are repaired in the short term. The real physical risk to biodiversity comes from *irreversible long-term damage*, which results in ecosystems becoming progressively less resilient.[13]

Property 2: *Biodiversity physical risk is heterogeneous across countries and regions*

From Appendix A.4 (a) we find that such positive trends appear primarily in European countries, showing that the European Union is in the most advanced position in the protection and reconstruction of biodiversity. Besides, North America has improved its performance since 2010. Appendix A.4 (b) shows that developed countries have been making more efforts to protect biodiversity given that OECD Membership countries have statistically significant higher average Biodiversity Trend. In Figure A.4 (c) we also show the Biodiversity Trend between 'bio-sufficient' (Biodiversity Index ¿ 1) and 'bio-deficit' (Biodiversity Index ¡ 1) countries. The index for the bio-deficit countries, has experienced an extreme increase since 2011.[14]

Property 3: *Biodiversity physical risk is exogenous*

[12]See also Appendix A.3, which shows the geographic distribution of the average biodiversity trend for each country. Both the numerical evidence and the geological distribution graph shows that the biodiversity ecosystem is worsening from a global point of view because negative trends outweigh positive ones.

[13]Our assumption is consistent with scientific research, such as Butchart et al. (2010); Chase, Blowes, Knight, Gerstner, and May (2020). In their papers, all indicators related to biodiversity are presented in the long-term.

[14]In 2010, the United Nations proposed the Strategic Plan for Biodiversity 2011-2020. One of its goals was to address the underlying causes of biodiversity loss by integrating biodiversity considerations across government and society. Since then, countries like China have introduced several government-led biodiversity protection plans.

As Lenton et al. (2008) and Solomon, Plattner, Knutti, and Friedlingstein (2009) point out referring to climate change, biodiversity physical risks measured at the county level are exogenous should not be affected by any individual establishment's limited local operations (Shi et al., 2021; Zheng et al., 2021). Thus our identification strategy is reliable.

2.4 Financial and Accounting Data

We extract our stock return data from CRSP/Compustat. Only primary stocks and common stocks with share code SHRCD=10 or 11 are included in our sample. We include live and dead stocks to make sure that there is no survivorship bias for the firms. Regarding the accounting variables, we extract our firm-level variables from the Compustat database.

We exclude the firms with Standard Industrial Classification (SIC) in the range of 4900-4999 and 6000-6999. The reason is multiple. First, these industries have different business operations or accounting measurements, compared to other sectors (Whited & Wu, 2006); Second, these sectors are in line with high transition risks instead of physical risks. As utilities and financial services bear the brunt of regulations (Bolton & Kacperczyk, 2021), we aim to distinguish the two different sources of risk in our study and focus specifically on physical risk. We also keep industries which have at least 10 observations over time. We drop observations with missing return described in Section 3.2.

We then collect revenue decomposition data from Factset Revere and merge them with biodiversity data. This step aims to attribute firms to countries with different biodiversity physical risks and to specify the firm-level biodiversity physical risk exposure. We winsorize independent variables at the 1% level except for excess returns. The final sample consists of 119 505 firm-year-month observations and 10 062 firm-year observations in Fama and French (1997) 48 industries from 2003 to 2021.

2.5 Summary Statistics

Table 2 presents pooled mean, median, standard deviation (SD), 25th percentile (P25), 75th percentile (P75), Minimum and Maximum value of the variables of interest, as well as the valid number of observations for each variable.[15]

Our main variable, Biodiversity Physical Exposure ($BioPhyRisk$), is the average of Biodiversity (Index) trend measurement decomposed in each country by the fraction of total revenues of firm i in the same year. We record and update this Biodiversity Physical Exposure for each firm at the end of each year. The Biodiversity Data are discussed in more detail in the Section 2.1. The average risk exposure is -6.47, suggesting that biodiversity degradation and its physical risks at firm level is non-negligible. Notice that negative $BioPhyRisk$ value represents positive exposure, and we show a positive $BioPhyRisk$ which equals to 5.81 only at the 75th percentile (P75) level, means that most of the firms are facing a worsening biodiversity across time. We have other firm-level variables. Profitability change is the yearly difference of return on asset (ROA), the net income scaled by total assets. $Vol6$ is the standard deviation of the excess stock returns over the past 6 months. $cumulret12$ is the cumulative return over the past 12 months, and is measured in percentage. Firm size ($firmsize$) is the natural logarithm of market capitalization. Book-to-Market ratio (BM) is total book value of equity divided by total market capitalization. Dividend-to-price ratio (dividend) is the total dividend paid over the 12 months, divided by the share price. Trading Volume (*logvol*) is the natural logarithm of trading volume. Price (*prc*) is the natural logarithm of stock price. Illiquid factor (*illiquid*) is the average absolute return over trading volume over the last 12 months,following Amihud (2002). We have a total of 10 062 firm-year observations with nonmissing biodiversity physical risk exposure.

[Insert Table 2 here]

3 Empirical Results

3.1 Biodiversity Alphas

To examine the relationship between biodiversity physical risks and the spectrum of stock returns, we create quintile portfolios based on firms' particular biodiversity physical risk

[15] Variables used in Robustness are summarized in Appendix C

exposures. For each year $t-1$, within each of the 48 industries identified by Fama and French (1997), we categorize enterprises into five groups based on their exposure, ranging from low to high. The industry-specific classification divides enterprises into equitable groupings within each sector. The low (high) quintile portfolio comprises enterprises with the lowest (highest) biodiversity risk exposures within each industry. Table 3 presents the average cross-sectional median of firm characteristics across five comparable portfolios.

[Insert Table 3 here]

After forming the five portfolios sorted by biodiversity physical risk exposure (from low to high), we compute the value-weighted monthly returns for each portfolio. Each portfolio is held for k months, where k ranges from 12 to 48 months. Following the methodology of Jegadeesh and Titman (1993), overlapping portfolios are constructed such that, for each quintile in month t, there are k portfolios spanning from month $t-k$ to $t-1$. The excess returns of these k portfolios are value-weighted to calculate the average return for each quintile portfolio in month t. We then examine how well the variation in average excess returns of the k-month overlapping portfolios sorted by biodiversity physical risk exposure can be explained by established common risk factors.

Specifically, we regress each portfolio's returns in excess of the US one-month treasury rate (as in (Fama & French, 2012)) with the capital asset pricing model (CAPM), the Fama-French three-factor model (Fama & French, 1996), the Fama-French five-factor model (Fama & French, 2015), the Carhart four-factor model (Carhart, 1997), the HXZ q-factor model (Hou, Xue, & Zhang, 2014).[16] Standard errors are corrected for heteroscedasticity and autocorrelation using the Newey and West (1987) estimator.

Table 4 presents the regression result for value-weighted 12-month overlapping portfolios within each quintile group. The final column in each table reports the portfolio derived from a long-short strategy, which involves longing firms with low biodiversity physical risk and shorting those with high biodiversity physical risk within their industry peers. Overall, the risk-adjusted alphas of the long-short portfolio based on biodiversity physical risk range from 20 to 44 basis points.

[16]Data on the Fama-French factors and the Carhart factors come from Kenneth French's website. Data on the I/A and ROE factors are provided by (Hou et al., 2014)

In addition, table 4 display a non-linear relationship between biodiversity physical risks and stock excess returns. In particular, compared with portfolio L, firms that encounter the greatest biodiversity physical risks (portfolio H) have much lower alphas while firms that encounter moderate biodiversity physical risks (portfolios 2 to 4) do not suffer from a vast decline in alphas. This suggests that negative biodiversity physical risk exposure trigger the strongest reactions.

We also regress long term overlapping portfolio returns on factor models. We test overlapping horizons to 24 months, 36 months and 48 months with both equal weighted and value weighted portfolios. We reported the long-short strategy portfolio alphas in table 5, results show that alphas of very long-term portfolio holding period remain significant.

[Insert Table 4 and 5 here]

3.2 Excess Stock Return Predictability

In this section, we rely on Fama-Mecbeth Fama and MacBeth (1973) regressions to examine the biodiversity physical risk-stock returns relation. We suppose that we hold our portfolio for one year, thus we compute the 12-month cumulative excess returns of portfolio. Our regression design is presented as follows:

$$\text{Excess Return}_{i,t} = \lambda_0 + \lambda_1 \mathbb{1}_{BioPhyRisk_{i,t-1}} + \phi' X_{i,t-1} + \mu_s + \epsilon_{i,t} \tag{3}$$

Specifically, the dependent variable, Excess $\text{Return}_{i,t}$, is firm i's excess return in year t, calculated as the firm's raw return in excess of the common risk free rate. The main independent variable, $\mathbb{1}_{BioPhyRisk_{i,t-1}}$ is a dummy variable that equals one if firm i's biodiversity physical exposure falls into the upper percentile (low risk) within its industry in year $t-1$, and zero otherwise. We control for the firm characteristics employed by Brennan, Chordia, and Subrahmanyam (1998) and Bolton and Kacperczyk (2021). $Vol6$ is the standard deviation of the excess stock returns over the past 6 months. $cumulret12$ is the cumulative return over the past 12 months, measured in percentage. Firm size ($firmsize$) is the natural logarithm of market capitalization. Book-to-Market ratio (BM) is total book value of equity divided by total market capitalization. Dividend-to-price ratio (dividend) is the total dividend paid from , divided by the share price. Trading Volume (*vol*) is the natural logarithm of trading volume at the end of the year $t-1$. Price (*prc*) is the natural logarithm of price at the end of the year $t-1$. Illiquid factor (*illiquid*) is the average absolute return over trading volume over the last 12 months, following Amihud (2002). I also take industry dummies μ_s based on Fama and French (1997) 48-industry classifications for controlling industry fixed effects. Standard errors are estimated using the Newey-West correction.

Table 6 report our estimation. We employ step-by-step additional controls from Columns (1) to Columns (4). For all five columns, the coefficients of the biodiversity risk are significantly positive at the 10% level or better. For example, in Column (4), a firm which encounters a lower biodiversity physical risk exposure that fall into the upper 20th percentile within the industry peers is linked to a higher cumulative return of 2.291% compared to firms fall into other quintile groups. Moreover, firms that encounter severe risk exposure, specifically within the bottom 20th percentile, face a significant decrease in cumulative return, amounting to -1.258%, as demonstrated in Column (5).

For the control variables, we find that book-to-market ratio positively predicts yearly stock returns. In contrast, a high dividend yield predicts negative returns. In addition, high realized volatility and return destroy the future returns. Illiquid factor, instead, has positive prediction power, which is consistent with the findings of (Amihud, 2002).

While in Table 6, we find that controls for firm characteristics that may affect stock returns. Motivated by the non-linear relationship between Biodiversity physical risks and stock excess returns, I examine how *extreme* low exposure are associated with asset prices. Thus, we re-run the Fama-Mecbeth regression by sorting our firms in 5th quintile based on their risk exposures. Using this idea, we consider that most of firms are suffering from biodiversity loss, and they share almost the same level of exposure, except for firms that operating in a improving biosphere.

Table 7 reports similar results compared to Table 6, which confirms that the *extreme* low exposure to the biodiversity physical risks scale the effects. For example, in Column (4), a firm which encounters a extreme lower biodiversity physical risk exposure (or even positive) that fall into the upper 5th percentile within the industry peers is linked to a higher cumulative return of 2.496% compared to firms fall into other quintile groups.

Meanwhile, firms that encounter most severe risk exposure, specifically within the bottom 95th percentile, face a insignificant decrease in cumulative return, amounting to -2.283%, as demonstrated in Column (5). The results show confirm the intuition that almost all companies have been affected by the decline in biodiversity over the past 30 years, and unless a company's operations are linked to the positive biodiversity trend, the company's returns will be affected broadly and profoundly, regardless of the company's exact exposure.

[Insert Table 6 and 7 here]

4 Mechanisms of Return Predictability

4.1 Firm Performance and Future Cash Flow

In this section, we analyze whether the physical risk of biodiversity over time affects the operating profits of firms. Typically, the market price of an asset is expressed as the discounted sum of the expected return on the asset. Thus, the market price of an asset depends to a large extent on the future income streams. The Efficient Market Hypothesis (Fama, 1970) proposes that when the investors correctly and promptly incorporate the information (here, the information is expressed in terms of the biodiversity risk), such information will not predict the returns of an asset. We assume that the lack of consensus among institutional investors on biodiversity risk is broad and persistent, which leads to a failure to reflect biodiversity risk in asset prices.

Following Fama and French (2000) and Hong et al. (2019), we measure change in firm-level profitability from year $t-1$ to t, which means that $\text{Profitability}_{i,t} = \text{NI}_{i,t}/\text{AT}_{i,t}$ - $\text{NI}_{i,t-1}/\text{AT}_{i,t-1}$. Where NI is the net operational income and AT is the total asset. We re-run this quintile sorting analysis using Fama-Mecbeth regressions.

$$\text{Profitability}_{i,t} = \lambda_0 + \lambda_1 \mathbb{1}_{BioPhyRisk_{i,t-1}} + \phi' X_{i,t-1} + \mu_s + \epsilon_{i,t} \quad (4)$$

We display our results in Table 8. $\text{Profitability}_{i,t}$ is our variable of interest. We keep the remaining regression sets as the same. Column (4) confirm that firms have very low biodiversity physical risks and attributed to the upper 20th quintile benefit from a 0.398%

higher profitability change from year $t-1$ to year t than their industry peers, respectively and significant at the 5% level. I also find similar results in Table 9, implying that *extreme* low biodiversity physical risk do associated with significant improved operating performance change, namely 1.289% higher than their industry peers.

Both Table 8 and Table 9 report that the spread in performance as driven by the sensitivity to unexpected biodiversity risk is clear-cut. The spread on the future performance of firms in upper quintile (L) relative to other risk groups (2, 3, 4 and H), is both significant in terms of future profitability and stock returns. In the real business cycle, we can expect that biodiversity physical risk can forecast the change in profitability of firms because the economic value of biodiversity is underestimated.

According to the Efficient Market Hypothesis (Fama, 1970), each kind of risk (physical or transition risks of biodiversity) should be priced immediately because it is related to the following year's profitability. Thus, in an efficient market, we can not expect that such a piece of public information (e.g. quintile for biodiversity physical risk exposure) can predict the stock returns for a long-term horizon. However, our empirical results show clearly the existence of excess returns and growth of profitability. To take a close look at how profitability change is linked to the spread of excess returns, we display the median value of Total assets/Net income of all firms (=24) as a multiplier to the magnitude of the difference in firm profitability is 0.4% as a fraction of total assets. Thus, we get the growth rate of net income as 9.6%. This matches well the results of Table 5, which shows the spread in excess stock returns between bottom quintile (H) and top quintile (L) adjusted by CAPM for 3-year holding period is 10.8% (0.3%*36).

[Insert Table 8 and 9 here]

4.2 Heterogeneity in Industrial Sensitivity

In Section 3.1, our model predicts a negative relationship between the biodiversity physical risk exposure and bunch of alphas when we only sort firms within their industrial peers. However, the such relationship is less clear in the presence of industrial risk exposure due to the conflicting forces of the cluster granularity. For example, Addoum et al. (2020) shows no evidence that temperature exposures impact firm-level profitability. However, they also show that extremely high and low temperatures affect different industries during different seasons, and those effects are mostly driven by consumption demand channels (Addoum et al., 2023). We question whether this conclusion is still valid in the case of biodiversity. To do so, We report the economic sector biodiversity physical risk exposure by re-estimating Equation (3) one-by-one for each industry, and get alphas for Fama and French (1997) 48 industries.

Based on the previous narrative, it is clear that the biodiversity physical risk exposure at the firm level is obtained from an approximate estimate of alphas. That is, whichever industry has a higher alphas indicates a greater exposure to risk in that industry. Figure 2 reports industry level alpha. We find that Business Suppliers (Paper productions), Recreation, Electronic Equipment, Food Products, Apparel, Restaurants, Construction Materials, and Medical Equipment industry have the largest exposure. On the opposite, Consumer Goods, Chemicals, Petroleum and Natural Gas seems benefit from destroying the biodiversity. Other industries are neither positively nor negatively exposed to the biodiversity physical risks.

[Insert Figure 2 here]

Our findings are primary consistent with the common sense of double materiality, especially when we take Energy or Chemicals into account. For example, even fossil-led energy development contributes to climate change, pollution and biodiversity destruction, the only risk source for this sector is transition risk, which means this industry is under more and more legal and transition-related policy pressure (local or global), alternatively saying, the transition risk of this industry should be very high. However, it does not mean that such industry are equally exposed to the degradation of biodiversity during the past years, and here we highlight that double materiality is important and policy makers should consider that separately.[17]

We also refer industrial sensitivity to Giglio et al. (2023), in which they analyze firm-level biodiversity physical risk exposure for all industries by using surveys to people in

[17] See Hsu, Li, and Tsou (2023); Bolton and Kacperczyk (2021); Garel et al. (2023), they show different aspects of firm-level emissions (e.g. carbon footprint, pollution emission, and biodiversity footprint). In particular, Energy and Chemicals are the most polluter, both in terms of total emission and density level.

academia or in profession.[18] To test their results, we assess return predictability by implementing dummy variable $IndLowRisk$ to conduct a placebo estimation. The treatment group includes sectors that are classified as sectors lowly exposed to biodiversity physical risk, and the control group includes sectors that are classified as sectors highly exposed to biodiversity physical risk.[19] Within each industry-level biodiversity physical risk group, we further sort stocks into 20th and 5th quintile portfolios according to their firm-level biodiversity physical risk exposure. The low (high) biodiversity physical risk and industrial biodiversity physical risk portfolios comprise the top (bottom) quintile of stocks based on the firm specific biodiversity physical risk and survey-based industry specific biodiversity physical risk, respectively. That is, we expect that the spread of excess returns for firm i between top and bottom quintile should be insignificantly predicted in sectors with low exposure to the biodiversity physical risk.

Table 10 reports the return predictability of biodiversity risk exposure with Fama-Macbeth regression. We employ step-by-step additional controls from Columns (1) to Columns (3) and from Columns (4) to Columns (6). For all four columns, the coefficients of interaction terms are negative. Column (3) shows that the difference, in terms of the excess return, between the firms with low biodiversity physical risk and rest of firms is -4.055% and not significant within the low risk industries. While for the high risk sectors, the difference is 3.263% and statistically significant at the 1% level. Column (4) to Column (6) report the estimation of *emtreme* low risk quintile, we have similar findings, but with a large scale of difference, meaning that the excess return is around -6% and significant for low risk industries, and 5% for high risk industries and statistically significant at the 1% level.

These results corroborate the huge finding that, in industries with low biodiversity

[18] They investigate biodiversity transition risk exposure from US firms' 10-K statements. In their paper, they have (1) 10K-Biodiversity-Count, (2) 10K-Biodiversity-Negative, (3) 10K-Biodiversity-Regulation Score, (4) Survey-Transition Score, (5) Survey-Physical Score, (6) Holding based score, and (7) CDP-Biodiversity Score, using different measurements. In this paper, we take only physical risk into consideration, and it is also the most weak scoring compared to others because it comes from the replies of the survey.

[19] In particular, we have Software & Services (4510), Tech. Hardw. & Equip. (4520), Semiconductors & Equip. (4530), Communication Services (5010), and Media & Entertainment (5020) in the low industrial risk group. And we gather all the rest of industries in the high industrial risk group.

exposure, returns do not fall (or even rise) even if a firm suffers a large biodiversity decline itself, due to industry characteristics. Combined with our results in Figure 2, we expect some industries to be more damaging to biodiversity, but not to suffer from the aftermath of the damage.

[Insert Table 10 here]

4.3 Analysts' Earnings Forecast and Surprise

The inferior operating performance change of firms encountering low BioPhyRisk documented in Section 4.1 can only account for their future inferior returns to the extent that they are not fully anticipated by the market. Utilizing analysts' earnings forecasts to proxy for investors' expectations, I test if investors revise their beliefs about the firms' future earnings after the publication of biodiversity physical risk related information. I follow Core, Guay, and Rusticus (2006) to study the relationship between the earnings forecasts and surprises and BioPhyRisk. To do so, I run the regression below:

$$\mathrm{FS}_{i,t} = \lambda_0 + \lambda_1 \mathbb{1}_{BioPhyRisk_{i,t-1}} + \phi^{'} X_{i,t-1} + \mu_s + \epsilon_{i,t} \tag{5}$$

where $\mathrm{FS}_{i,t}$ stands for earnings forecast or surprise for Profitability change from year $t-1$ to year t. The earnings forecast is the latest mean I/B/E/S analyst forecast for RoA before the earnings announcement in year t, minus acutal RoA in year $t-1$, similar way is employed for actual RoA change.[20] I calculate the earnings surprise as the actual RoA change minus the analyst forecast change. We test top 20th and 5th percentile case. I control a set of variables the same as in the previous sections except for past volatility, past cumulative return, and illiquid indicator since they can hardly affect forecasts.

We make this arrangement because most analyst reports are filed and updated for each fiscal quarter. But as we foresee, most analysts do not recognize the biodiversity physical risk of firms and its effects, we apply the latest earning forecast to ensure that analysts incorporate at the maximum level information that affect earnings.

[20] I test the latest median I/B/E/S analyst forecast and find similar results.

Table 11 illustrates the results. Columns (1) and (2) of Panel A show that analysts incorrectly make their forecasts (even they upgrade in a certain level) for profitability changes upon biodiversity physical risk. Columns (1) and (2) show that the actual profitability change exceed the consensus forecast by 0.375% (0.509%), which is economically meaningful and significant at the 1% level.

However, it is noteworthy that analysts still tend to estimate the impact of BioPhyRisk on firms' future earnings. Columns (3) to (4) of Panel A and B show that the earnings for firms within the bottom 20th quintile is somehow over-downgraded and significant at at the 1% level, and the forecast surprise is positive with no difference. Thus, financial analysts indeed partially incorporate some biodiversity physical related information into their valuation of firms, but only for firms which extremely suffer from the biodiversity physical risk and not for more common parties, whereas the tangible assets are affected to a greater extent and are more easily captured, especially for insurance companies Chichilnisky and Heal (1993).

[Insert Table 11 here]

4.4 Investment Behavior and Ownership

In this section, we turn to investigate how different types of institutional investors and retail investors react to Biodiversity Physical Risk. We hypothesize that both sophisticated institutional investors and unsophisticated retail investors should not be able to react for the value-destroying information of long-term biodiversity physical risk exposure. Thus there is very unlikely that each type of investors can adjust their holdings which responds to such information.[21]

We obtain institutional investors' holdings data from Thomson Reuters Institutional (13f) Holdings where institutional investors are categorized into banks, insurance companies, investment companies and their managers (mutual funds management companies),

[21]My assumptions are contrary to the assumptions of physical risk in the climate change category, in their articles they usually assume (and validate) that institutional investors are interested in extreme temperatures or climate change incorporated into their holdings. See, for example, Choi, Gao, and Jiang (2020); Krueger et al. (2020)

independent investment advisors, and all others (including pension funds and university endowments). We test our hypothesis through the following pooled panel regression with fixed effects:

$$\Delta Weight_{i,j,t} = \lambda_0 + \lambda_1 \mathbb{1}_{BioPhyRisk_{i,t-1}} + \phi^{'} X_{i,t-1} + \textit{Indusrty-YQ } FE_{i,t-1} + \epsilon_{i,t} \qquad (6)$$

where $\Delta Weight_{i,j,t}$ is the difference between the holding weight of different investors j in stock i in quarter Q of year t and that at the end of year $t-1$. We control for firm size, the dividend-to-price ratio, the book-to-market ratio, natural logarithm of stock price, natural logarithm of trading volume of firm i at the end of year $t-1$ and take industry-year-quarter fixed effects and cluster standard errors at the firm-year-quarter level.

The results are presented in Table 12. Overall, no type of investors exhibit an adjustment in their holdings in response to $BioPhyRisk$. Among all types of institutions, insurance and pension funds display the most positive response (but with no significance), increasing their holdings in the concurrent quarter, and which remain positive by 0.010% and 0.174% till the end of the year. In contrast, retail investors, mutual funds, independent institutions, and retail investors even react to the value-destroying information associated with $BioPhyRisk_{i,t-1}$ in the wrong direction.

Therefore, the stock market's no reaction to Biodiversity Physical Risk corresponds to the mispricing, although insurance companies and other institutional investors who focus on and care more about biodiversity risk and try to incorporate it.

[Insert Table 12 here]

4.5 Investors' Attention to Biodiversity

Previous Literature shows that the cross-sectional relationship between physical risk factor and stock returns is more sensitive during periods of high investor attention, which can be captured either by google trend searching volume index (SVI) (Da, Engelberg, & Gao, 2011; Choi et al., 2020), or by textual analysis of newspapers (Engle, Giglio, Kelly, Lee, & Stroebel, 2020; Giglio et al., 2023). However, those studies are high-frequent focusing on daily or monthly attentions. It is easy to understand because for acute physical risk, such as abnormal temperature, it often happens in a certain day or month than it comes back to normal. In our paper, we hypothesize that people care more and more biodiversity as the time goes by, but only in a long-run period, given it is unlikely that the loss of biodiversity will receive frequent social attention.

We employ google trend searching volume index (SVI) as a measurement of investors' attending to biodiversity physical risks.[22] We use key words provided by Giglio et al. (2023) as the definition of biodiversity physical risk, regarding 'biodiversity loss', combining with key words 'species loss' and 'ecosystem services'. We obtained monthly frequency US biodiversity physical risk SVI. We found that the SVI has a strong seasonality, we use classic Additive Decomposition model to obtain the long-term trend.

Figure 3 confirms our intuition and shows that there is an impressive increasing in the investors attention to biodiversity loss, expressively after the year 2015. To simplify our strategy, we choose the the time period that attention is above the mean value (after 2014) to separate our sample, as shown in Section 3.2. We find it is consistent with Nagoya Protocol (2015), and Paris agreement (2016) for the extent to which may lead to an increase of investors' attention to the biodiversity and related risks. [23]

Table 13 reports our estimation results. Column (3) demonstrates that the impact of low *BioPhyRisk* on excess returns is 3.653%, and remains still significant at 10% in periods of heightened investor attention (after 2015). Column (2) indicates that relative high *BioPhyRisk* are associated with a -1.762% lower return and significant at 1% level during low-attention periods. However, for high-attention periods, the market seems to price those stocks correctly, with only a -0.215% lower return and not statistically and economically significant.

To recapitulate, these results illustrate that market are enforcing to incorporate biodiversity physical risk information into asset prices, and this pricing is efficient for high

[22]The index represent search interest relative to the highest point on the chart for the specified region and time period. A value of 100 indicates peak popularity for the term, while a value of 50 means the term was half as popular. A score of 0 signifies insufficient data for each key word.

[23]We take also International Day for Biological Diversity (2015) into account given the theme is to establish a set of Sustainable Development Goals (SDGs) as part of the United Nations Development Agenda for the period of 2015-2030 and the relevance of biodiversity for the achievement of sustainable development.

BioPhyRisk group. Meanwhile, it is still partially for for low *BioPhyRisk* group. We link the estimations to results to those in Section 4.3, which show that financial analysts price high risk stocks more accurately than low risk stocks, and find the consistency across different mechanisms.[24]

[Insert Table 13 here]

5 Robustness Tests and Alternative Analyses

So far, we provide supporting empirical evidence on biodiversity physical risk is value-destroying, and the market inefficiently incorporates the future cash-flow associated with this type of risk into stock returns. Nevertheless, alternative explanations should be considered. Thus, We run different types of regressions described in this section to test the robustness of our main findings. All results are presented in Appendix C.

First, our risk factors (annual frequency) are correlated with macroeconomic phenomena (e.g., company earnings), and the impact that these risk factors may have on company earnings takes multiple quarters to be gradually reflected in share prices. In the short term, noise (e.g., momentum, market sentiment) may mask the factor signals, but noise interferes with the signals to a lesser extent over long time windows. As a result, we test one-month, three-month, and six-month cumulative excess returns. We further demonstrate that the impact of improving (or deteriorating) fundamentals is not immediately reflected in prices due to insufficient market interpretation resulting from incomplete disclosure of information in the short term.

Second, considering that biodiversity metrics are still wide discussion, we change the measure of risk associated with biodiversity. specifically, (1) we use only the estimated coefficient of the long-term trend in biodiversity capacity as a proxy for risk, replacing the biodiversity index in the main regression. (2) We also use regressions from the start year to t-1 to replace 30-year rolling regressions and obtain alternative risk estimates. (3) We add an AR(2) term to the regression to capture the autocorrelation of the biodiversity

[24]The point estimate in column (1) is virtually consistent with previous findings but of course the prediction varies since we have cut the sample period to calculate the standard errors.

series over a longer period of time. We find similar results, meaning that the low-risk group produces, relative to the other four high-risk groups, a 12-month cumulative stock return predictability.

Third, We use RoE, EBITDA, and NPM as alternative measures of profitability following Frankel and Lee (1998); Nissim and Penman (2001); Novy-Marx (2013). There are many other alternatives, like sales growth, or cost of goods sold divided by sales. We do not take those into account for brevity. We find that our baseline results remain robust, especially for firms with extreme low risk.

Lastly, the abnormal returns may stem from an omitted risk factor co-varying with biodiversity physical risk, such as carbon risks, ESG performance, and firm specific cliamte change exposure in documentations. This hypothesis is unlikely to be true because the our biodiversity physical risk is measured exogenously, and should be independent of different firm-level characteristics. Nevertheless, we test these confounding hypotheses by including mentioned variables in our regression. We find that the baseline results remain unchanged, demonstrating that our biodiversity physical risk is not diluted by other climate-related risk factors.

6 Conclusion

This paper studies how firm value and asset prices are affected by biodiversity physical risks, defined as the extent to which long-term biodiversity index unexpected loss related to the country-level trend estimation and de-composite in firms' operating locations. My sample is comprised of 10,062 firm-year observations of 1,274 public listed firms in the United States from 2003 through 2021.

We show that first, biodiversity physical risks reduce firm value. Stock excess returns decline up to twelve months (till the announcement of earnings for the concurrent year) following the publication of biodiversity physical risks related information. Second, we find this is primarily attributable to the misprediction of the cash-flow news. Further, the stock return–biodiversity physical risks relationship can be varied across industry sensitivity. Moreover, our biodiversity physical risks is universal and not incorporated, by financial analysts, by institutional investors, and by market even after the increase of global attention to biodiversity. Finally, the stock return predictability cannot be explained by confounding factors, such as immediate return decline followed by a return reversal, different measurements of biodiversity physical risk, different measurements of profitability, firm-level E scores, firm's Carbon footprint, and firm's climate change exposure.

Our results have potentially important implications. First, this paper emphasizes caution in studying biodiversity and finance. This caution is especially warranted because there exists a general losing trend of biodiversity across all countries. Second, this paper highlight the non-linear relationship between firm value, asset prices, and biodiversity-related variables. Moreover, this non-linear relationship has industry bias, country bias, and distinction bias between physical risk and transition risk. Third, in response to the escalating challenges of global biodiversity degradation and its impact, policymakers, firms and fund managers may consider to conduct long-term strategies, including how to mitigate spillover effects of global warming on biodiversity, to restore the whole Eco-Service system, and to conduct prospective biodiversity physical risk assessment. We leave all those topics for future research.

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Table 1: Biodiversity Index Trend Across Countries

This table reports the average value of the estimated trend from 2003 to 2020. The coefficients reported are the average value of the AR(1) regression from year $t-30$ to year $t-1$. We then rank these countries by their Trend estimations. We report only the estimates of constants and Trend with their t-statistics over time.

Country	Intercept	t-stat	Average Trend per year (‰)	t-stat
India	0.404	3.526	-8.212	-3.538
South Africa	0.306	3.474	-5.939	-3.129
Brazil	1.602	2.711	-4.615	-2.486
Colombia	0.863	2.699	-2.205	-2.204
Malaysia	0.323	2.322	-4.415	-2.081
Mexico	0.286	2.434	-3.477	-2.045
Sweden	0.827	3.549	-2.870	-2.009
Austria	0.290	2.520	-2.451	-1.825
Philippines	0.173	2.217	-2.019	-1.820
Australia	0.428	1.847	-3.255	-1.797
China	0.136	1.641	-3.717	-1.726
Finland	0.529	2.625	-2.875	-1.695
Indonesia	0.444	1.699	-4.275	-1.672
Norway	0.238	1.984	-1.617	-1.436
Egypt	0.077	1.818	-1.620	-1.412
Canada	0.503	2.301	-1.462	-1.345
Japan	0.054	2.081	-1.853	-1.280
Chile	0.275	1.688	-2.518	-1.222
New Zealand	0.240	1.423	-2.055	-1.177
Spain	0.329	4.218	-1.605	-1.135
Portugal	0.098	1.693	-1.971	-1.069
Netherlands	0.106	2.437	-1.253	-0.943
Greece	0.150	1.791	-2.258	-0.855
Korea, Republic of	0.049	1.196	-1.597	-0.808
Ireland	0.270	1.627	-2.999	-0.718
United States of America	0.105	1.746	-0.623	-0.459
Italy	0.084	1.817	-0.442	-0.257
Thailand	0.067	0.698	-0.444	0.131
Switzerland	0.197	2.774	0.566	0.517
Belgium	0.108	2.807	1.044	0.747
United Kingdom	0.095	2.294	2.152	1.361
Poland	0.170	2.952	2.071	1.373
France	0.168	2.349	1.704	1.657
Germany	0.139	3.115	4.635	2.485
Denmark	0.285	3.077	6.395	2.860

Table 2: Summary Statistics

This table reports the summary statistics of different classes of variables used in this paper. BioPhyRisk (measured in bps) is described in Section 2.5. This table also reports cross sectional firms' characteristics. Annual change in profitability ($Profchange$) is the yearly difference of return on asset (ROA), $Vol6$ is the standard deviation of the excess stock returns over the past 6 months. $cumulret12$ is the cumulative return over the past 12 months, and is measured in percentage. Firm size ($firmsize$) is the natural logarithm of market capitalization. Book-to-Market ratio (BM) is total book value of equity divided by total market capitalization. Dividend-to-price ratio ($dividend$) is the total dividend paid over the 12 months, divided by the share price. Trading Volume ($logvol$) is the natural logarithm of trading volume. Price (prc) is the natural logarithm of stock price. Illiquid factor ($illiquid$) is the average absolute return over trading volume over the last 12 months. We report the pooled mean, standard deviation (Std), 25th percentile (P25), median, and 75th percentile (P75). All variables are measured at the annual frequency.

Variables	Obs	Mean	SD	Min	Max	Median	P25	P75
BioPhyRisk	10062	-6.47	12.92	-42.40	25.88	-6.92	-17.97	5.81
Profchange	8675	-0.00	0.10	-0.44	0.40	0.00	-0.03	0.03
Vol6	9858	11.12	6.45	2.47	37.16	9.56	6.59	13.93
cumulret12	9658	17.74	44.05	-106.92	163.03	16.99	-5.69	39.56
firmsize	10062	7.14	2.00	2.59	12.00	7.14	5.82	8.42
BM	10062	0.48	0.38	0.03	2.23	0.39	0.22	0.63
dividend	10062	2.57	9.44	0.00	69.56	0.00	0.00	0.78
illiquid	9646	6.02	3.09	1.74	17.74	5.32	3.79	7.51
logvol	10062	15.78	1.75	11.13	19.65	15.83	14.78	16.95
prc	10062	3.08	1.15	-0.14	5.63	3.22	2.37	3.89

Table 3: Firm characteristics for biodiversity exposure sorted portfolios

This table reports the time-series average of the cross-sectional medians of firm characteristics for five biodiversity physical risk exposure sorted portfolios. Firm characteristics including biodiversity exposure, volatility for past 6 months, cumulative returns for past 12 months, firm size, book-to-market ratio, dividend-to-price ratio, illiquid, natural logarithm of trading volume, and natural logarithm of stock price.

	L	2	3	4	H
BiophyRisk	-4.198	-6.191	-7.357	-8.616	-10.765
vol6	9.845	9.489	9.638	9.760	9.725
cumulret12	16.019	15.957	15.953	16.490	15.581
firmsize	7.092	7.101	7.132	7.107	7.200
BM	0.417	0.391	0.388	0.383	0.405
dividend	0.000	0.006	0.011	0.002	0.000
illiquid	5.523	5.350	5.446	5.528	5.466
logvol	15.797	15.933	15.925	15.932	16.053
prc	3.186	3.240	3.247	3.259	3.222
observation	21569	24009	24016	24037	25874

Table 4: Factor alphas of biodiversity physical risk exposure sorted portfolios

The table reports biodiversity physical risk exposure sorted 12 month overlapping portfolio's returns in excess of the US one-month treasury rate with factor models. We report capital asset pricing model (CAPM), the Fama-French three-factor model (Fama & French, 1996), the Carhart four-factor model (Carhart, 1997), the Fama-French five-factor model (Fama & French, 2015), and HXZ factor model (Hou et al., 2014). Standard errors are corrected for heteroscedasticity and autocorrelation using the Newey and West (1987) estimator. We also report t-statistics for L-H long-short portfolios. The sample period is January 2003 to December 2021.

	L	2	3	4	H	L-H
			Panel A: CAPM			
MKT	0.763***	1.052***	0.992***	0.848***	1.104***	-0.340***
	(0.0594)	(0.0527)	(0.0624)	(0.0327)	(0.0343)	(0.0744)
Alpha	0.300***	0.0635	0.129	0.0507	0.0525	0.247**
	(0.0923)	(0.0745)	(0.0851)	(0.0670)	(0.0629)	(0.109)
			Panel B: FF 3			
MKT	0.783***	1.106***	0.980***	0.833***	1.088***	-0.305***
	(0.0482)	(0.0528)	(0.0514)	(0.0313)	(0.0388)	(0.0681)
SMB	-0.158	-0.0619	0.216**	-0.0750	0.0465	-0.204
	(0.120)	(0.0854)	(0.0965)	(0.0640)	(0.0792)	(0.124)
HML	0.0285	-0.252***	-0.121	0.147***	0.0463	-0.0178
	(0.0698)	(0.0445)	(0.0775)	(0.0532)	(0.0524)	(0.0971)
Alpha	0.306***	-0.0247	0.0920	0.0997	0.0694	0.237**
	(0.0894)	(0.0728)	(0.0868)	(0.0698)	(0.0663)	(0.116)
			Panel C: FF 3 + Carhart			
MKT	0.817***	1.142***	0.975***	0.840***	1.089***	-0.272***
	(0.038)	(0.025)	(0.051)	(0.025)	(0.037)	(0.057)
SMB	-0.065	0.035	0.202**	-0.058	0.049	-0.114
	(0.112)	(0.070)	(0.102)	(0.062)	(0.082)	(0.125)
HML	0.075	-0.204***	-0.128	0.155***	0.048	0.0269
	(0.067)	(0.043)	(0.081)	(0.056)	(0.051)	(0.097)
MOM	0.170***	0.177***	-0.027	0.032	0.005	0.165***
	(0.037)	(0.026)	(0.031)	(0.032)	(0.029)	(0.048)
Alpha	0.264***	-0.069	0.099	0.092	0.068	0.196*
	(0.079)	(0.048)	(0.082)	(0.064)	(0.064)	(0.110)
			Panel D: FF 5			
MKT	0.735***	1.079***	1.079***	0.836***	1.095***	-0.360***
	(0.0649)	(0.0650)	(0.0497)	(0.0436)	(0.0487)	(0.0925)
SMB	-0.133	-0.0482	0.158*	-0.0933	0.0343	-0.167
	(0.118)	(0.0859)	(0.0807)	(0.0692)	(0.0808)	(0.129)
HML	0.0635	-0.233***	-0.208**	0.106	0.0217	0.0417
	(0.0912)	(0.0554)	(0.0959)	(0.0681)	(0.0639)	(0.109)
RMW	-0.190	-0.108	0.383**	-0.0127	0.0148	-0.205
	(0.186)	(0.164)	(0.149)	(0.110)	(0.105)	(0.234)
CMA	-0.140	-0.0752	0.357**	0.181	0.109	-0.249
	(0.195)	(0.124)	(0.170)	(0.138)	(0.134)	(0.209)
Alpha	0.396***	0.0258	-0.0896	0.102	0.0604	0.335*
	(0.123)	(0.116)	(0.0969)	(0.0887)	(0.0891)	(0.171)
			Panel E: HXZ			
MKT	0.623***	1.110***	0.957***	0.751***	1.048***	-0.425***
	(0.0604)	(0.0670)	(0.0644)	(0.0522)	(0.0531)	(0.0910)
ME	-0.222*	-0.189*	0.0383	-0.0759	-0.0210	-0.201
	(0.132)	(0.104)	(0.109)	(0.0758)	(0.0937)	(0.130)
I/A	-0.279*	-0.158	0.138	0.194*	0.0795	-0.358*
	(0.155)	(0.132)	(0.161)	(0.116)	(0.105)	(0.183)
ROE	-0.518***	0.0553	-0.0650	-0.285***	-0.156	-0.362*
	(0.169)	(0.134)	(0.141)	(0.0929)	(0.114)	(0.191)
Alpha	0.604***	0.00928	0.185	0.250***	0.160*	0.444***
	(0.142)	(0.110)	(0.126)	(0.0937)	(0.0928)	(0.153)

Table 5: Long term portfolio Alphas

This table reports value (equal)-weighted biodiversity physical risk exposure sorted overlapping portfolios alphas on factor models for different holding horizons. We only report alphas for L-H long-short portfolio for brevity. Standard errors are corrected for heteroscedasticity and autocorrelation using the (Newey & West, 1987) estimator. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is January 2003 to December 2021.

Holding Horizon	CAPM	FF3	FF4	FF5	HXZ
	Panel A: Value-Weighted Portfolios				
2-year	0.273***	0.311***	0.278***	0.461***	0.588***
	(0.098)	(0.097)	(0.086)	(0.175)	(0.161)
3-year	0.320***	0.416***	0.384***	0.785***	0.618***
	(0.078)	(0.061)	(0.063)	(0.091)	(0.116)
4-year	0.254***	0.209***	0.205***	0.172***	0.131***
	(0.029)	(0.025)	(0.027)	(0.055)	(0.065)
	Panel B: Equal-Weighted Portfolios				
2-year	0.281***	0.164***	0.143***	0.031	0.216
	(0.094)	(0.079)	(0.069)	(0.090)	(0.170)
3-year	0.299***	0.234***	0.234***	0.218***	0.197***
	(0.047)	(0.043)	(0.043)	(0.053)	(0.096)
4-year	0.254***	0.209***	0.205***	0.172***	0.131***
	(0.029)	(0.025)	(0.027)	(0.055)	(0.065)

Table 6: Biodiversity Physical Risks and the Cross-section of Excess Stock Returns

This table reports estimation results of cross-sectional stock returns at time t on the biodiversity physical risk exposure estimated at the previous period. For columns (1) to (4), the main independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 20th within its industry at the end of the year $t-1$, and zero otherwise. For columns (5), we tested the opposite assignment of dummy variable. We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 2003 to 2021.

	Cumulative Excess Returns for 20th Percentile				
	(1)	(2)	(3)	(4)	(5)
BioPhyRisk_{low}	2.231*	2.177*	2.130**	2.291**	
	(1.060)	(1.051)	(0.832)	(0.844)	
BioPhyRisk_{high}					-1.258**
					(0.521)
firmsize	-1.251**	-0.480	-0.761	-0.861	-0.879
	(0.441)	(0.624)	(0.835)	(0.773)	(0.839)
BM	6.713***	4.863***	2.424	3.235**	3.391**
	(1.527)	(1.402)	(1.822)	(1.279)	(1.197)
dividend		-0.063***	-0.040	-0.055***	-0.056***
		(0.021)	(0.033)	(0.016)	(0.016)
logvol		0.473	0.406	0.773	0.777
		(0.894)	(1.002)	(0.997)	(1.034)
prc		-2.564***	-0.793	-1.182	-1.209
		(0.743)	(0.526)	(0.776)	(0.853)
vol6			-0.341***	-0.306***	-0.308***
			(0.090)	(0.073)	(0.079)
cumulret12			-0.051***	-0.052***	-0.052***
			(0.017)	(0.017)	(0.017)
illiquid			0.981***	0.763***	0.765***
			(0.169)	(0.195)	(0.207)
Obs.	9794	9794	9389	9389	9389
R^2	0.134	0.150	0.090	0.172	0.170
Industry FE	YES	YES	NO	YES	YES

Table 7: Biodiversity Physical Risks and the Cross-section of Excess Stock Returns

This table reports estimation results of cross-sectional stock returns at time t on the biodiversity physical risk exposure estimated at the previous period. For columns (1) to (4), the main independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 5th within its industry at the end of the year $t-1$, and zero otherwise. For columns (5), we tested the opposite assignment of dummy variable. We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 2003 to 2021.

	Cumulative Excess Returns for 5th Percentile				
	(1)	(2)	(3)	(4)	(5)
BioPhyRisk_{low}	3.004***	2.659**	2.458**	2.496**	
	(0.976)	(1.092)	(1.141)	(1.028)	
BioPhyRisk_{high}					-2.283
					(1.554)
firmsize	-1.279***	-0.555	-0.778	-0.877	-0.933
	(0.434)	(0.691)	(0.915)	(0.859)	(0.863)
BM	6.855***	4.986***	2.639	3.442**	3.446**
	(1.475)	(1.383)	(1.778)	(1.229)	(1.232)
dividend		-0.064***	-0.043	-0.058***	-0.059***
		(0.021)	(0.033)	(0.016)	(0.016)
logvol		0.512	0.420	0.779	0.800
		(0.938)	(1.051)	(1.054)	(1.043)
prc		-2.520***	-0.793	-1.188	-1.159
		(0.816)	(0.592)	(0.864)	(0.868)
vol6			-0.343***	-0.307***	-0.306***
			(0.094)	(0.077)	(0.083)
cumulret12			-0.051***	-0.052***	-0.053***
			(0.017)	(0.017)	(0.017)
illiquid			0.983***	0.761***	0.762***
			(0.182)	(0.209)	(0.208)
Obs.	9794	9794	9389	9389	9389
R^2	0.131	0.148	0.088	0.170	0.170
Industry FE	YES	YES	NO	YES	YES

Table 8: Biodiversity Physical Risks and the Cross-section of Firm's Profitability

This table reports estimation results of cross-sectional change in profitability at time t on the biodiversity physical risk exposure estimated at the previous period. For columns (1) to (4), the main independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 20th within its industry at the end of the year $t-1$, and zero otherwise. For columns (5), we tested the opposite assignment of dummy variable. We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 2003 to 2021.

	Annual Change in Profitability				
	(1)	(2)	(3)	(4)	(5)
BioPhyRisk_{low}	0.320**	0.309**	0.380*	0.398**	
	(0.140)	(0.131)	(0.189)	(0.156)	
BioPhyRisk_{high}					-0.220**
					(0.098)
firmsize	-0.221***	0.373***	0.690***	0.751***	0.782***
	(0.051)	(0.126)	(0.071)	(0.082)	(0.084)
BM	-2.405***	-2.944***	-3.040***	-2.965***	-2.952***
	(0.507)	(0.544)	(0.519)	(0.574)	(0.558)
dividend		-0.013***	-0.015***	-0.017***	-0.017***
		(0.004)	(0.005)	(0.003)	(0.003)
logvol		-0.053	-0.371***	-0.377***	-0.386***
		(0.097)	(0.058)	(0.066)	(0.070)
prc		-1.339***	-1.384***	-1.409***	-1.445***
		(0.202)	(0.143)	(0.133)	(0.148)
vol6			0.084***	0.092***	0.091***
			(0.013)	(0.015)	(0.015)
cumulret12			-0.002	-0.006*	-0.006*
			(0.003)	(0.003)	(0.003)
illiquid			-0.002	0.002	0.003
			(0.070)	(0.066)	(0.067)
Obs.	8675	8675	8327	8327	8327
R^2	0.075	0.090	0.052	0.107	0.106
Industry FE	YES	YES	NO	YES	YES

Table 9: Biodiversity Physical Risks and the Cross-section of Firm's Profitability

This table reports estimation results of cross-sectional change in profitability at time t on the biodiversity physical risk exposure estimated at the previous period. For columns (1) to (4), the main independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 5th within its industry at the end of the year $t-1$, and zero otherwise. For columns (5), we tested the opposite assignment of dummy variable. We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 2003 to 2021.

	Annual Change in Profitability				
	(1)	(2)	(3)	(4)	(5)
BioPhyRisk_{low}	1.192**	1.079**	1.170**	1.289***	
	(0.521)	(0.485)	(0.459)	(0.413)	
BioPhyRisk_{high}					-0.096
					(0.109)
firmsize	-0.213***	0.392***	0.705***	0.768***	0.767***
	(0.048)	(0.131)	(0.074)	(0.084)	(0.084)
BM	-2.367***	-2.913***	-2.980***	-2.908***	-2.942***
	(0.489)	(0.532)	(0.494)	(0.555)	(0.553)
dividend		-0.013***	-0.015***	-0.017***	-0.018***
		(0.004)	(0.005)	(0.003)	(0.003)
logvol		-0.064	-0.375***	-0.382***	-0.381***
		(0.100)	(0.062)	(0.070)	(0.070)
prc		-1.349***	-1.401***	-1.429***	-1.429***
		(0.206)	(0.149)	(0.143)	(0.155)
vol6			0.085***	0.093***	0.088***
			(0.014)	(0.015)	(0.015)
cumulret12			-0.001	-0.005*	-0.006*
			(0.003)	(0.003)	(0.003)
illiquid			-0.007	-0.002	0.005
			(0.072)	(0.069)	(0.066)
Obs.	8675	8675	8327	8327	8327
R^2	0.075	0.090	0.052	0.107	0.105
Industry FE	YES	YES	NO	YES	YES

Table 10: Further Analysis of Heterogeneity of Sub-Industry

This table reports estimation results of cross-sectional excess returns in year t on the biodiversity physical risk exposure estimated in year $t-1$. The independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 20th or 5th quintile within its industry at the end of the year $t-1$, and zero otherwise. We also create another dummy variable, IndLowRisk, that equals one if firm i is attributed into the low risk exposure industry. Thus, the main interaction variable, namely BioPhyRisk×IndLowRisk, is a dummy variable that equals one if firm i is within low risk industry and has low biodiversity physical risk exposure, and zero otherwise. The low risk industry classification draws on the survey-based research of Giglio et al. (2023). We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 2003 to 2021.

	Top 20th Percentile			Top 5th Percentile		
	(1)	(2)	(3)	(4)	(5)	(6)
IndLowRisk	0.180	-0.568	-0.307	-0.689	-1.304	-1.064
	(2.256)	(2.175)	(2.078)	(2.558)	(2.524)	(2.483)
BioPhyRisk	3.388***	3.186***	3.263***	5.885***	5.536***	4.733***
	(0.780)	(0.739)	(0.569)	(1.321)	(1.293)	(1.413)
BioPhyRisk×IndLowRisk	-4.737**	-4.119	-4.055	-6.486**	-6.341**	-4.008
	(2.184)	(2.616)	(2.733)	(2.403)	(2.405)	(2.401)
firmsize	-1.275**	-0.645	-1.007	-1.300**	-0.665	-0.965
	(0.481)	(0.593)	(0.756)	(0.465)	(0.630)	(0.771)
BM	6.618***	4.688***	3.210**	6.902***	4.961***	3.434**
	(1.586)	(1.503)	(1.295)	(1.540)	(1.479)	(1.312)
dividend		-0.056**	-0.051***		-0.059**	-0.054***
		(0.022)	(0.017)		(0.021)	(0.016)
logvol		0.635	0.930		0.629	0.869
		(0.837)	(0.959)		(0.854)	(0.967)
prc		-2.622***	-1.186		-2.612***	-1.248
		(0.863)	(0.887)		(0.880)	(0.893)
vol6			-0.308***			-0.290***
			(0.078)			(0.076)
cumulret12			-0.052***			-0.051***
			(0.017)			(0.017)
illiquid			0.756***			0.728***
			(0.198)			(0.213)
Obs.	9794	9794	9389	9794	9794	9389
R^2	0.141	0.157	0.179	0.138	0.154	0.175
Industry FE	YES	YES	YES	YES	YES	YES

Table 11: Earning Forecast and Earning Surprise

This table reports estimation results of cross-sectional I/B/E/S analystes' earning forecast in Panel A and earning surprise in Panel B in year t on the biodiversity physical risk exposure estimated in year $t-1$. For columns (1) and (2), the main independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 20th within its industry at the end of the year $t-1$, and zero otherwise. For columns (3) and (4), we tested the opposite assignment of dummy variable. We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 2003 to 2021.

	Panel A: Financial Analysts' Earning Forecast			
	(1)	(2)	(3)	(4)
BioPhyRisk_{low}	0.048	0.016		
	(0.126)	(0.125)		
BioPhyRisk_{high}			-1.007**	-0.730***
			(0.349)	(0.235)
firmsize	-0.157***	0.222	-0.138***	0.240
	(0.043)	(0.202)	(0.044)	(0.205)
BM	-2.301***	-1.747***	-2.072***	-1.464***
	(0.510)	(0.298)	(0.376)	(0.407)
dividend		-0.006		-0.016
		(0.018)		(0.021)
logvol		-0.015		-0.028
		(0.409)		(0.391)
prc		-0.455		-0.461
		(0.320)		(0.320)
Obs.	3389	3389	3389	3389
R^2	0.232	0.275	0.236	0.278
Industry FE	YES	YES	YES	YES
	Panel B: Financial Analysts' Earning Surprise			
	(1)	(2)	(3)	(4)
BioPhyRisk_{low}	0.375***	0.509***		
	(0.118)	(0.115)		
BioPhyRisk_{high}			0.404	0.091
			(0.249)	(0.166)
firmsize	0.002	0.027	-0.002	0.094
	(0.035)	(0.249)	(0.035)	(0.305)
BM	1.232**	0.818**	1.171**	0.852**
	(0.475)	(0.282)	(0.446)	(0.313)
dividend		0.007		0.007
		(0.011)		(0.010)
logvol		-0.224		-0.308
		(0.365)		(0.425)
prc		-0.117		-0.128
		(0.333)		(0.352)
Obs.	3389	3389	3389	3389
R^2	0.209	0.244	0.207	0.242
Industry FE	YES	YES	YES	YES

Table 12: Investors' Activities and Ownership

This table reports the results of investor-level Panel OLS regressions where the dependent variable is investor j's excess weight in stock i in quarter Q of year t. The main independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 20th within its industry at the end of the year $t-1$, and zero otherwise. All entries in the table reflect the regression coefficients and standard errors of BioPhyRisk. The control variables include firm i's firm size, the dividend-to-price ratio, the book-to-market ratio, the natural logarithm of stock price and natural logarithm of trading volume of firm i at the end of year $t-1$. I take industry-year-quarter fixed effects and cluster standard errors (given in parentheses) at the firm-year-quarter level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from $Q1$ of 2003 to $Q4$ of 2021.

	$Q1$	$Q2$	$Q3$	$Q4$
	(1)	(2)	(3)	(4)
Banks	-0.017	-0.022	0.033	0.009
	(0.051)	(0.069)	(0.087)	(0.101)
Insurance	0.030	0.027	0.046	0.010
	(0.022)	(0.038)	(0.047)	(0.061)
Mutual Funds	-0.011	-0.005	-0.019	-0.003
	(0.016)	(0.027)	(0.027)	(0.034)
Independent	0.051	-0.195	-0.335	-0.190
	(0.150)	(0.191)	(0.221)	(0.259)
Other Inst.	-0.053	0.195	0.275	0.174
	(0.153)	(0.199)	(0.232)	(0.267)
Retail Investors	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)

Table 13: Investors' attention to Biodiversity

This table reports estimation results of cross-sectional stock returns at time t on the biodiversity physical risk exposure estimated at the previous period in two separated sample period, namely 2003 to 2014, and 2015 to 2021. For columns (1) and (3), the main independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 20th within its industry at the end of the year $t-1$, and zero otherwise. For columns (2) and (4), we tested the opposite assignment of dummy variable. We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 2003 to 2021.

	2003 - 2014		2015 - 2021	
	(1)	(2)	(3)	(4)
BioPhyRisk_{low}	1.305		3.653*	
	(1.303)		(1.509)	
BioPhyRisk_{high}		-1.762***		-0.215
		(0.507)		(0.629)
firmsize	-0.026	0.036	-2.170	-2.322
	(0.679)	(0.676)	(2.026)	(2.124)
BM	2.900	3.081	3.346**	3.437**
	(3.227)	(3.018)	(0.966)	(0.959)
dividend	-0.051	-0.050	-0.055	-0.059
	(0.035)	(0.033)	(0.031)	(0.030)
logvol	-0.289	-0.330	2.540	2.620
	(0.846)	(0.842)	(1.962)	(2.034)
prc	-1.852*	-1.985*	0.134	0.294
	(0.979)	(0.971)	(1.248)	(1.333)
vol6	-0.397***	-0.400***	-0.107	-0.106
	(0.087)	(0.090)	(0.089)	(0.087)
cumulret12	-0.021	-0.020	-0.098***	-0.099***
	(0.049)	(0.049)	(0.013)	(0.013)
illiquid	0.688**	0.684*	0.783	0.794
	(0.302)	(0.313)	(0.539)	(0.547)
Obs.	5881	5881	3508	3508
R^2	0.186	0.183	0.145	0.143
Industry FE	YES	YES	YES	YES

Figure 1: Two Examples of Biodiversity Evolution

This figure illustrates the time series evolution of the biodiversity index for two selected Countries: India and Denmark. The red dashed line presents the fitted line over time. The sample period is from 1961 to 2020.

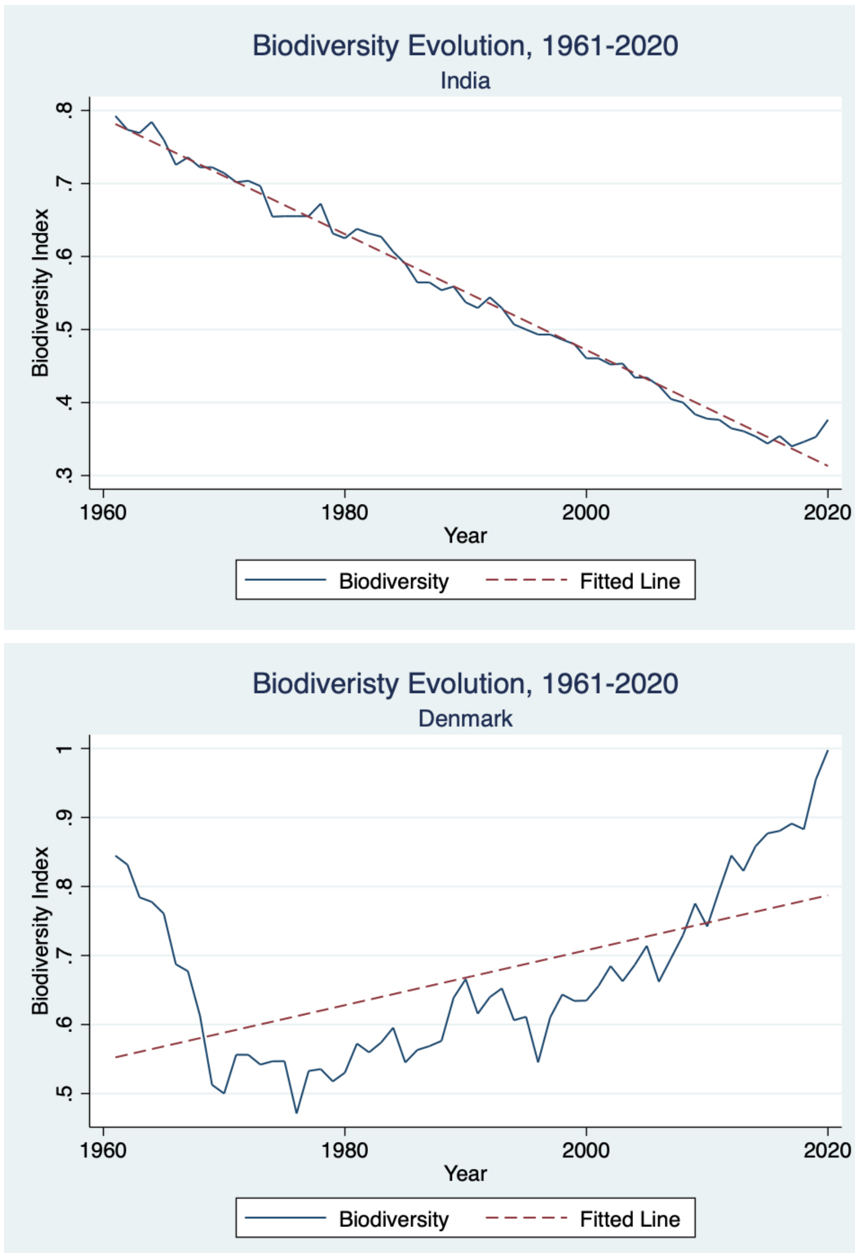


Figure 2: Heterogeneity and Industrial Sensitivity

This Figure reports the Fama and French (1996) 3-factor alpha of the long-short portfolio. For each industry at the end of year $t-1$, we sort firms into quintile portfolios based on its biodiversity physical risk and hold the portfolios for 12 months (namely 1 year). We construct overlapping portfolio following Jegadeesh and Titman (1993). Reported is the excess return spread on Fama and French (1997) 48-industry classification and the estimated intervals at 95% level. The sample period is from 2003 to 2021.

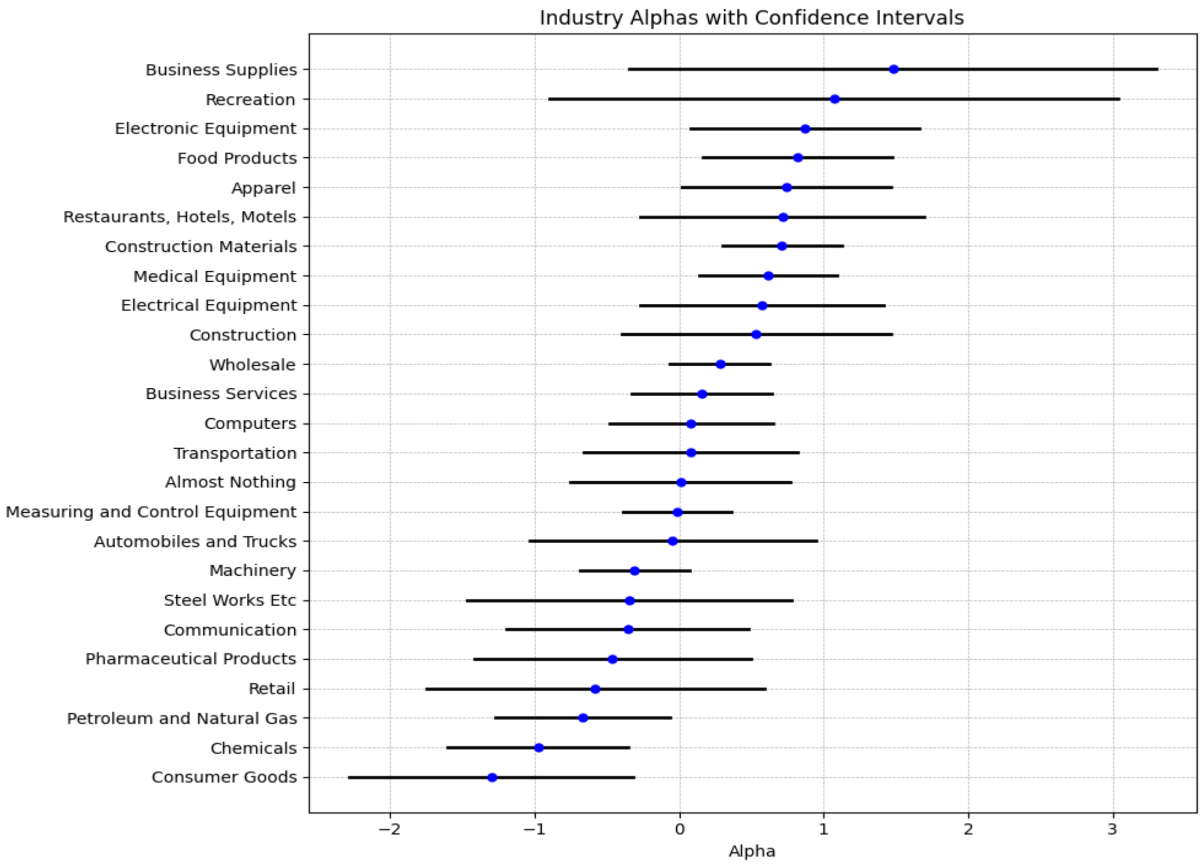
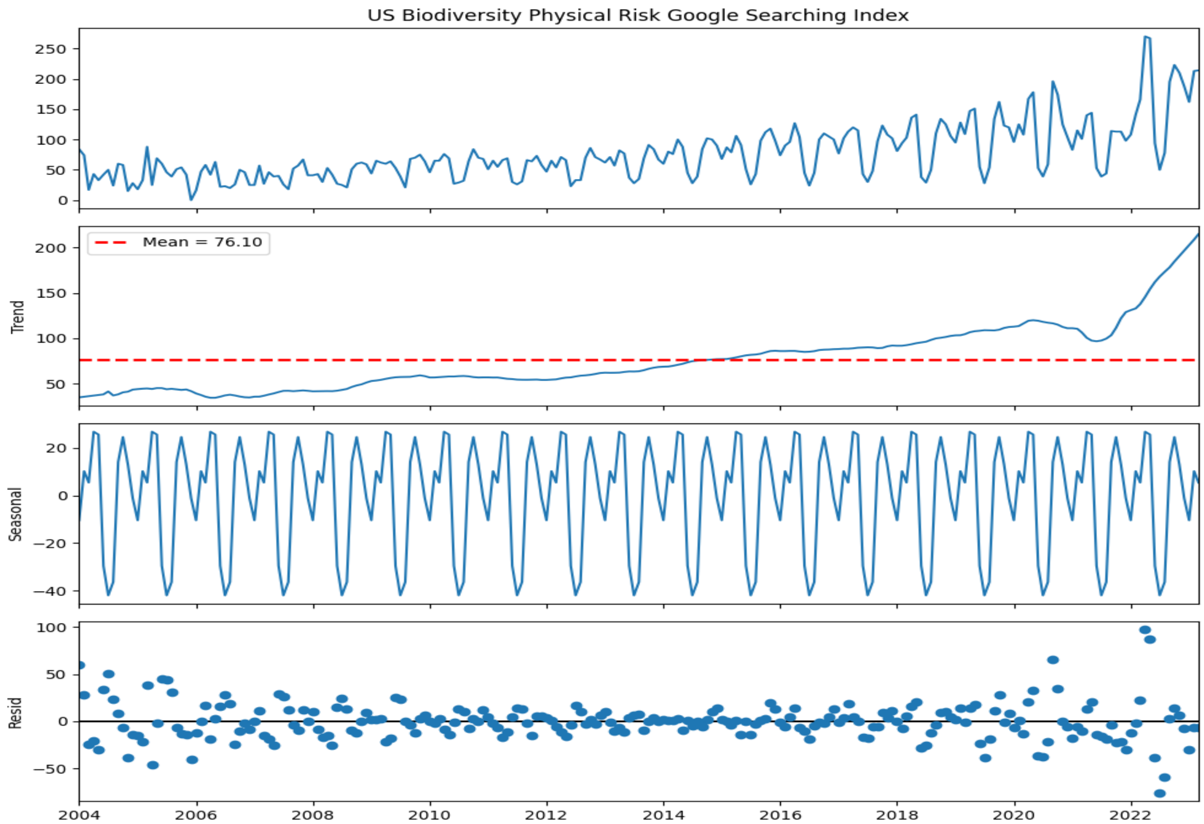


Figure 3: US Biodiversity Physical Risk Google Searching Index Decomposition

This Figure reports the additive decomposition of US Biodiversity Physical Risk Google Searching Index Decomposition. The searching volume index is calculated by the sum of key words 'Biodiversity Loss', 'Species Loss' and 'Ecosystem Services'. The sample period is from 2004 to 2022.



Appendix

For

Biodiversity Physical Risk, Firm Performance, and Market Mispricing

ANNA CRETI, YUJUN HUANG, BINGHAN JIANG, and MARIA-EUGENIA SANIN

A Additional Analyses of Country Characteristics

A.1 Description of Countries

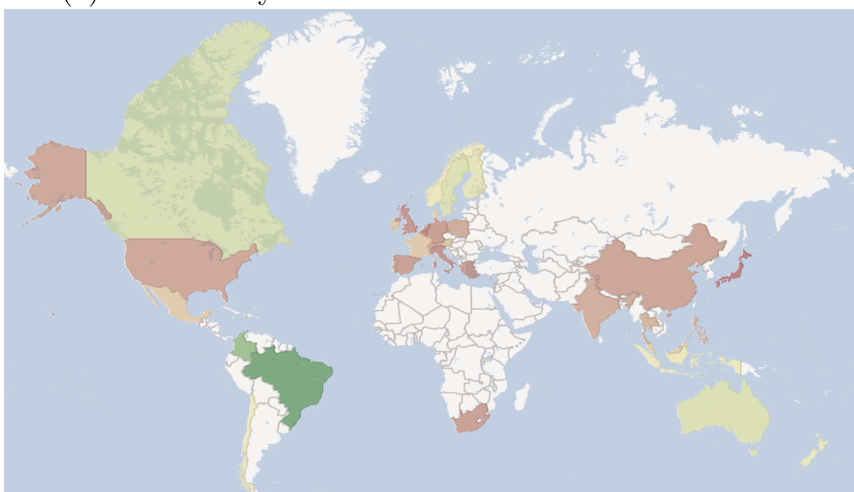
This Appendix reports the average Bio-Footprint and the average Bio-Capacity across countries, between 2000 and 2020. This Appendix also reports the time that countries sign and participate in different conventions and their supplementary. We only investigate the conventions about Biodiversity.

Country	Average Bio-Footprint (Per capita)	Average Bio-Capacity (Per capita)	Convention on Biological Diversity (1992)	Cartagena Protocol (2003)	Nagoya Protocol (2014)
Australia	12.307	13.906	1993/12/29		
Austria	5.108	3.088	1994/11/16	2003/9/11	2018/10/18
Belgium	4.707	1.309	1997/2/20	2004/7/14	2016/11/7
Brazil	3.270	9.260	1994/5/29	2004/2/22	2021/6/2
Canada	12.202	15.853	1993/12/29		
Chile	4.555	3.594	1994/12/8		
China	2.634	0.774	1993/12/29	2005/9/6	2016/9/6
Colombia	1.829	4.102	1995/2/26	2003/9/11	
Denmark	5.634	4.287	1994/3/21	2003/9/11	2014/10/12
Egypt	1.170	0.356	1994/8/31	2004/3/21	2014/10/12
Finland	11.799	12.333	1994/10/25	2004/10/7	2016/9/1
France	4.278	2.764	1994/9/29	2003/9/11	2016/11/29
Germany	4.723	1.693	1994/3/21	2004/2/18	2016/7/20
Greece	4.052	1.668	1994/11/2	2004/8/19	2020/5/14
India	0.875	0.343	1994/5/19	2003/9/11	2014/10/12
Indonesia	1.579	1.265	1994/11/21	2005/3/3	2014/10/12
Ireland	5.588	3.634	1996/6/20	2004/2/12	2023/7/27
Italy	3.106	1.000	1994/7/14	2004/6/22	
Japan	3.796	0.635	1993/12/29	2004/2/19	2017/8/20
Korea, Republic of	4.521	0.698	1995/1/1	2008/1/1	2017/8/17
Malaysia	4.117	2.384	1994/9/22	2003/12/2	2019/2/3
Mexico	2.351	1.404	1993/12/29	2003/9/11	2014/10/12
Netherlands	4.318	1.191	1994/10/10	2003/9/11	2016/11/17
New Zealand	12.445	10.555	1993/12/29	2005/5/25	
Norway	9.429	7.563	1993/12/29	2003/9/11	2014/10/12
Philippines	0.961	0.452	1994/1/6	2007/1/3	2015/12/28
Poland	4.490	1.910	1996/4/17	2004/3/9	
Portugal	3.311	1.425	1994/3/21	2004/12/29	2017/7/10
South Africa	3.791	1.355	1996/1/31	2003/11/12	2014/10/12
Spain	4.064	1.595	1994/3/21	2003/9/21	2014/10/12
Sweden	7.999	9.582	1994/3/16	2003/9/11	2016/12/7
Switzerland	2.828	1.272	1995/2/19	2003/9/11	2014/10/12
Thailand	2.335	1.150	2004/1/29	2006/2/8	
United Kingdom	3.485	1.176	1994/9/1	2004/2/17	2016/5/22
United States of America	8.977	3.898			

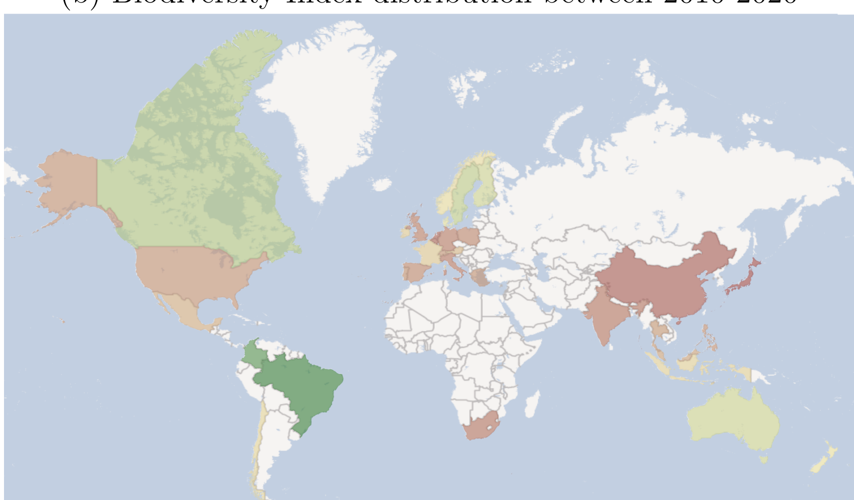
A.2 Spatial Distribution of Biodiversity Index

The heat maps display the average Biodiversity Index for each country over two decades. Figure (a) covers the period from 2000-2010, and Figure (b) covers 2010-2020. Countries with a Biodiversity Index above 1 are shaded in green, with deeper greens indicating higher values. Conversely, countries with an index below 1 are shaded in red, with deeper reds indicating lower values, while yellow represents intermediate value 1.

(a) Biodiversity Index distribution between 2000-2010



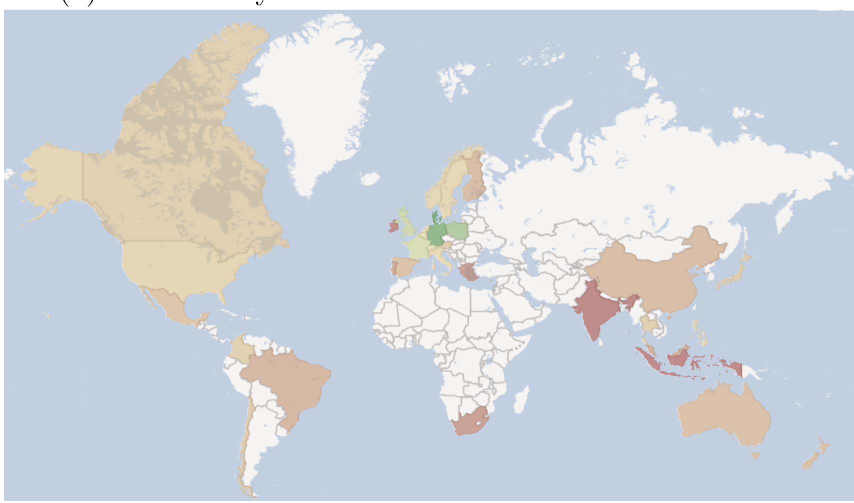
(b) Biodiversity Index distribution between 2010-2020



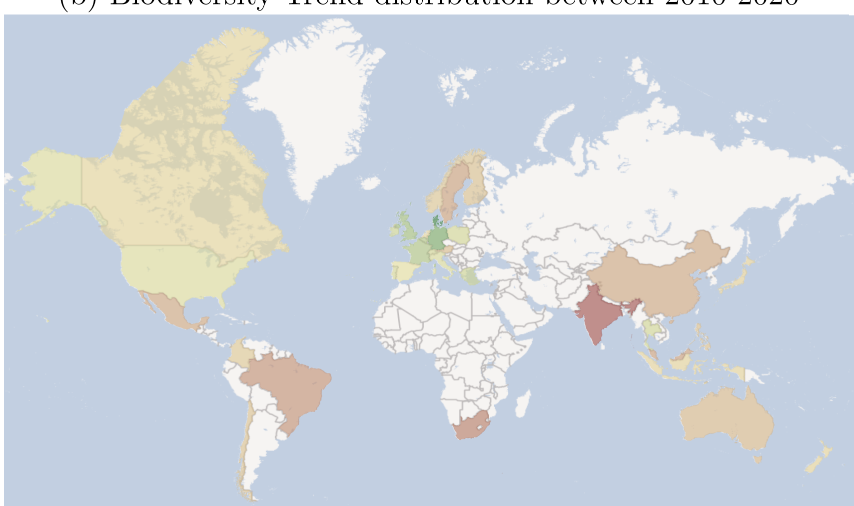
A.3 Spatial Distribution of Biodiversity Trend (Cont')

The heat maps display the 30-year rolling estimated average Biodiversity Trend for each country over two decades. Figure (a) covers the period from 2000-2010, and Figure (b) covers 2010-2020. Countries with a Biodiversity Trend above 0 are shaded in green, with deeper greens indicating higher values. Conversely, countries with Biodiversity Trend below 0 are shaded in red, with deeper reds indicating lower values, while yellow represents intermediate value 0.

(a) Biodiversity Trend distribution between 2000-2010



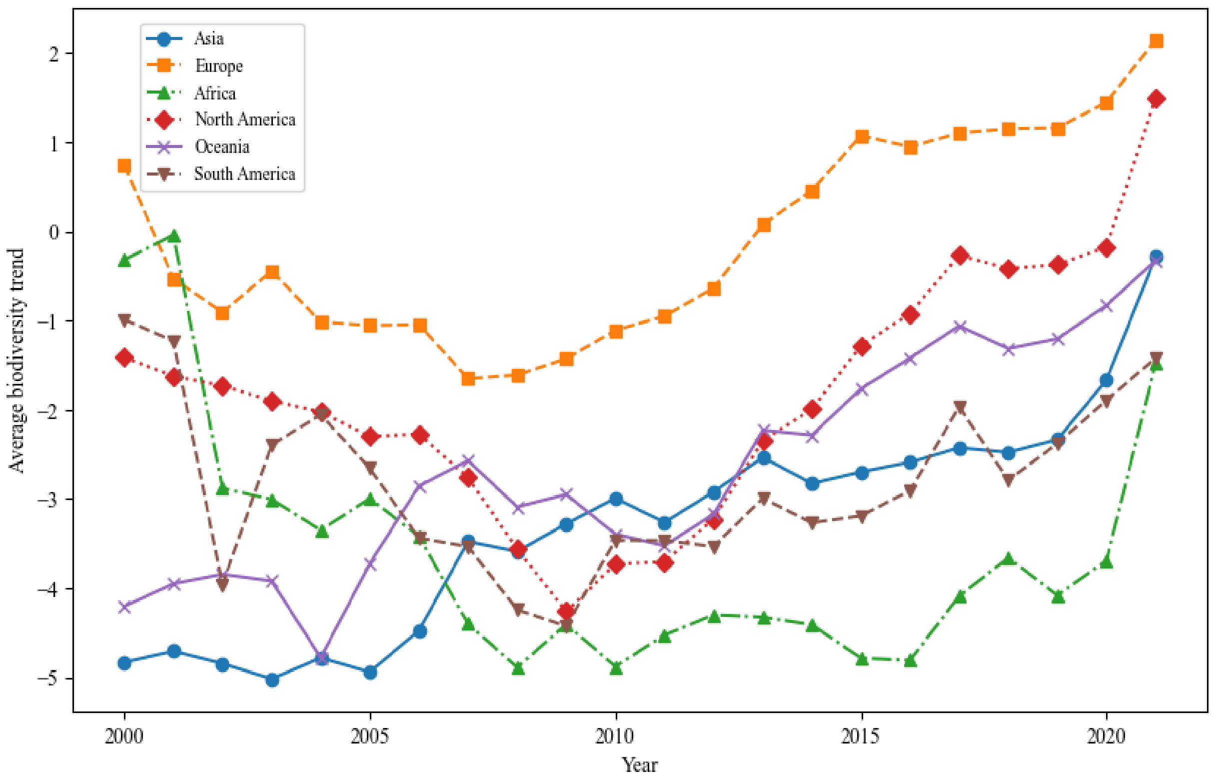
(b) Biodiversity Trend distribution between 2010-2020



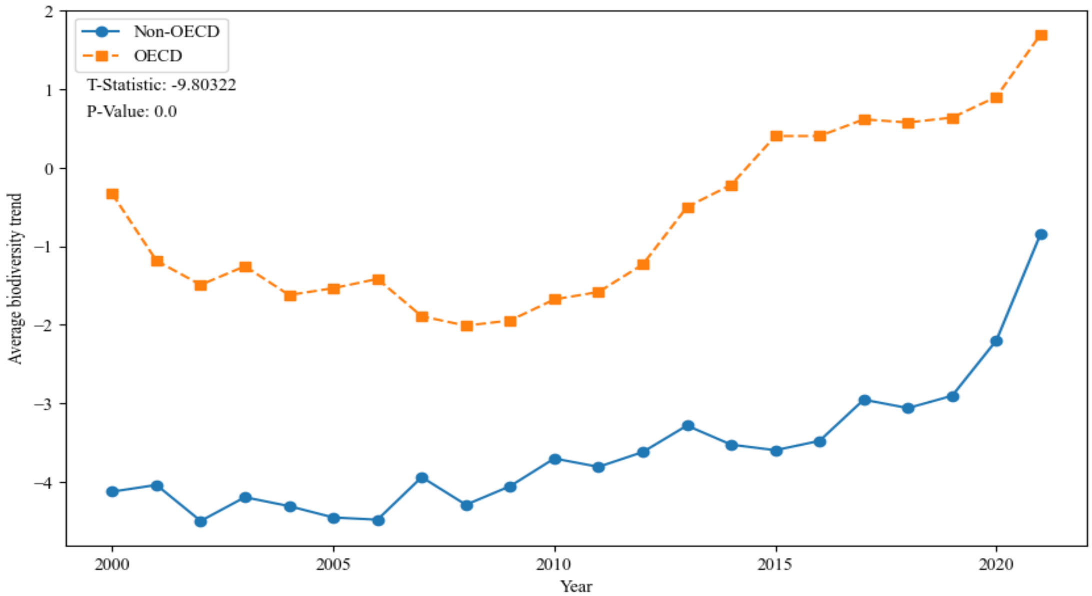
A.4 Biodiversity Trend Comparison

Figures in this section presents a comparison of Biodiversity Trends across different economic groups. All graphs cover a period of 20 years starting from the year 2000. Figure (a) depicts the general average biodiversity trend across six continents. In Figure (b), we classify 35 countries based on OECD membership status. Figure (c) classifies countries into "bio-sufficient" (Biodiversity Index ¿ 1) and "bio-deficit" (Biodiversity Index ¡ 1) categories.

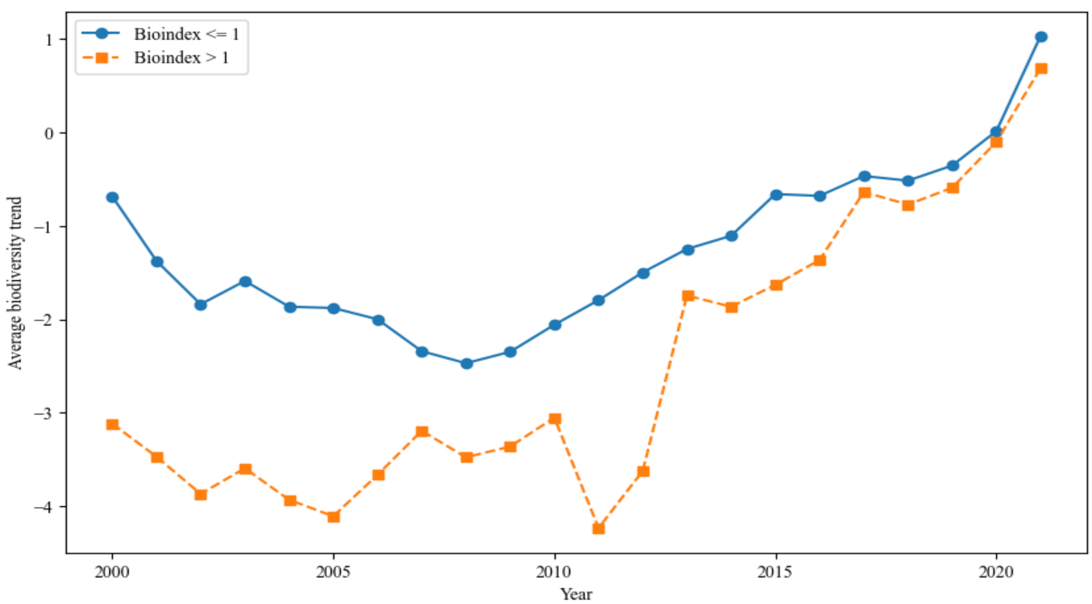
(a) Average Biodiversity Trend between Continents



(b) Average Biodiversity Trend between OECD and Non-OECD Countries



(c) Average Biodiversity Trend between Bio-deficit and Bio-sufficient Countries



B Construction of the Biodiversity Dataset

According to the European Central Bank's Guide on climate-related and environmental risks, it is essential to assess and measure physical climate risks such as chronic environmental changes, as these pose long-term threats to financial stability and economic performance across sectors in Europe[25]. Biodiversity loss is considered a type of physical climate risk because it directly affects ecosystems' resilience to climate change impacts, such as floods, droughts, and other extreme weather events. As noted by the European Environment Agency, "the loss of biodiversity can exacerbate climate-related risks, as ecosystems with reduced biodiversity are less able to provide essential services like carbon sequestration, water filtration, and protection against natural disasters"[26]. Given this context, several studies suggest that biodiversity loss links directly and indirectly to the productivity of the Eco-system services (Cardinale et al., 2012).

To build our index we use data provided by the "Ecological Footprint Initiative". The source data can be found in Dworatzek, Miller, Lo, Howarth, and Kazubowski-Houston (2024) while details on the database construction and measures can be found to a certain extent in Borucke et al. (2013). From such data we extract two measures:

(i) The "bio-capacity" index that traces the biodiversity capacity at the national level, described as follows:

$$\text{Bio-Capacity} = (\mathrm{A}_{c,n} * \mathrm{Y}_{c,n}/\mathrm{Y}_w) * \mathrm{EQF}$$

Where $\mathrm{A}_{c,n}$ is the area in country "c" for this land-use category n, including (1) Fishing Grounds: Area of marine and inland waters used to produce the fish, invertebrates, and aquatic plants that were captured or cultured by humans; (2) Built-up land: Area of land occupied by human-built infrastructure, including housing and other buildings, roads and paved areas, and urban greenspace; (3) Cropland: Area of cropland used to grow food and fibre crops consumed by humans, and for crops that humans fed to animals and cultured fish; (4) Grazing land: Area of grassland needed to feed livestock beyond the feed supplied by crops; (5) Forest Products: Area of forests harvested for timber products and pulpwood; and (6) Forest carbon up-take: Area of forests needed to sequester anthropogenic carbon emissions from the combustion of fuels including for electricity generation and for the production and transportation of globally traded goods, minus the proportion of anthropogenic emissions sequestered in the same year by the world's oceans. $\mathrm{Y}_{c,n}$ is the national average yield for this land-use category in tons per hectare and year.

(ii) The "bio-footprint" index that traces the footprint, namely "Ecological Footprint" (EF) and define as follows:

$$\text{Bio-Footprint} = (\mathrm{P}_c/\mathrm{Y}_w) * \mathrm{EQF}$$

[25]See European Central Bank's Guide on climate-related and environmental risks, https://www.bankingsupervision.europa.eu/

[26]See European Environment Agency, https://www.eea.europa.eu/soer/2020

Where P_c is the production (or harvest) in tons per year in country c estimated in total; Y_w is the world average yield for this land-use category in tons per hectare, per year; and EQF an equivalence factor that we do not document in detail.

Then, we we construct our Biodiversity index as a ratio between bio-capacity and bio-footprint. The resulting measure can then be expressed as follows and traces the total (and potential) yield as compared to the total output, in a certain year t:

$$\text{Biodiversity Index}_{c,t} = \frac{\text{Bio-Capacity}_{c,t}}{\text{Bio-Footprint}_{c,t}} = (\mathrm{A}_{c,n,t} * \mathrm{Y}_{c,n,t})/\mathrm{P}_{c,t}$$

Here, we closely follow Dasgupta (2021), as the author affirms: "ensure that our demands on nature do not exceed its supply and that we increase nature's supply relative to its current level.". And we interpret the values of this ratio as follows: the value of the index superior to one means that global biological resilience outweighs the destruction of biodiversity by production activities, and vice versa.

C Supplementary Analyses and Robustness

C.1 Return Predictability in Short Horizon

Our biodiversity physical risk is considered having macroeconomic phenomena, and the impact that this risk factor may have on company earnings takes multiple quarters to be gradually reflected in share prices. In the short term, noise (e.g., momentum, market sentiment) may mask the factor signals, but noise interferes with the signals to a lesser extent over long time windows. To test the short-term return predictability, we run the regression which is the same as Equation 3. Where the main dependent variable Excess Return$_{i,t}$ is short term cumulative returns, for 1 month, 3 months, and 6 months period. We take the same independent variable and set of controls as previous expressed.

Table 14 reports our estimation. We employ all controls in the regression. For all columns, the coefficients of the biodiversity physical risk are not significant. For example, in Column (1), (3), and (5), a firm which encounters a lower biodiversity physical risk exposure that fall into the upper 20th percentile within the industry peers is not linked to a higher cumulative return compared to firms fall into other quintile groups. We find similar situations for firms that are within the top 5th percentile, as demonstrated other Columns.

These results expose negative returns that are not significant in the short run, which confirm our assumption that biodiversity physical risk may be affected by short-term market volatility, information lags or behavioral biases. This does not undermine the long-term predictive power of the factor, but rather suggests a time-dependent pricing efficiency of the market.

C.2 Horse Race of Other Risk Measurements

To rule out the confounding hypothesis that the definition of biodiversity physical risk is not clear, I run a horse race of a set of biodiversity physical risk variables measured differently. Specifically, (1) we use only the estimated coefficient of the long-term trend in biodiversity capacity as a proxy for risk, replacing the biodiversity index in the main regression. (2) We also use regressions from the start year to year $t-1$ to replace 30-year rolling regressions and obtain alternative risk estimates. (3) We add an AR(2) term to the regression to capture the autocorrelation of the biodiversity series over a longer period of time.

Table 15 reports our estimation. We employ all controls in the regression. In columns with odd-number, our biodiversity physical risk is measured from Biodiversity Index; in columns with even-number, our biodiversity physical risk is measured from natural logarithm of Biodiversity capacity. Specifically, columns (1) and (2) show the regression results of baseline measurements, which means our biodiversity physical risk is estimated by a 30-year rolling regression with an AR(1) term. Columns (3) and (4) show the regression results of biodiversity physical risk estimated by a 30-year rolling regression with both AR(1) and AR(2) terms. Columns (5) and (6) show the regression results of biodiversity physical risk estimated by a full series regression from the first appearance of biodiversity information with an AR(1) term. For all five columns, the coefficients of the biodiversity risk are significantly positive at the 10% level or better, illustrating that the biodiversity physical risk, associated with each measurement that we choose, is associated with stock return predictability.

C.3 Horse Race of Other Profitability Measurements

In this section, we replace our profitability from net income divided by total assets (RoA) to other types of measurements. For example, return on equity is the net income divided by book equity, following Frankel and Lee (1998). EBIDTA is the earnings Before Interest, Taxes, Depreciation, and Amortization divided by total assets, following Nissim and Penman (2001). Net profit margin (NPM) is calculated as operating income before depreciation divided by sales following Novy-Marx (2013).

Table 16 reports our estimation. columns with odd-number report links of firms that fall into the top 20th percentile within its industry to their profitability change. We find our baseline results remain robust in most cases, except for column (3), which shows insignificant results between low biodiversity physical risk and higher future EBIDTA. We then employ the same regression for extreme low risk firms, meaning that they fall into top 5th percentile within its industry, just as what we show in Section 4.1. We find that the estimates for firms that have extreme low biodiversity physical risk benefits from a 2.630% higher RoE yearly change, a 0.425% higher EBITDA yearly change, and a 3.481% higher NPM yearly change, compared to other quintile groups, and significant at 1% level. These evidence are highly consistent with what we find in the baseline regression.

Table 14: Return Predictability in Short Horizon

This table reports estimation results of cross-sectional excess returns in year t on the biodiversity physical risk exposure estimated in year $t-1$. The independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 20th or 5th quintile within its industry at the end of the year $t-1$, and zero otherwise. We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 2003 to 2021.

	1 Month		3 Months		6 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
BioPhyRisk_{20th}	-0.175		-0.190		0.243	
	(0.138)		(0.642)		(0.885)	
BioPhyRisk_{5th}		0.045		-0.631		-0.375
		(0.553)		(1.962)		(1.270)
Obs.	9642	9642	9632	9632	9575	9575
R^2	0.173	0.173	0.158	0.157	0.150	0.149
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Table 15: Horse Race of Other Risk Measurements

This table reports estimation results of cross-sectional excess returns in year t on the biodiversity physical risk exposure estimated in year $t-1$. The independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 20th quintile within its industry at the end of the year $t-1$, and zero otherwise. We use Biodiversity Index to represent BioPhyRisk in columns of odd-number, and Log(Biodiversity Capacity) to represent BioPhyRisk in columns of even-number. We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 2003 to 2021.

BioPhyRisk_{low}	Baseline		Rolling-AR(2)		All-AR(1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Index	2.291**		1.366*		1.838***	
	(0.844)		(0.780)		(0.540)	
Log(Biodiversity Capacity)		2.391**		1.566**		2.208*
		(0.999)		(0.593)		(1.199)
Obs.	9389	9389	9389	9389	9389	9389
R^2	0.172	0.172	0.171	0.172	0.171	0.172
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Table 16: Horse Race of Other Profitability Measurements

This table reports estimation results of cross-sectional change in profitability at time t on the biodiversity physical risk exposure estimated at the previous period. The main independent variable, BioPhyRisk, is a dummy variable that equals one if firm i's biodiversity physical risk exposure fall in the top 20th or 5th quintile within its industry at the end of the year $t-1$, and zero otherwise. The main dependent variable that we use to proxy profitability is RoE for columns (1) and (2), EBITDA for columns (3) and (4), and NPM columns (5) and (6). We include the Fama and French (1997) 48-industry fixed effects. We do not report intercepts for brevity. Standard errors, given in parentheses, are Newey-West corrected. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 2003 to 2021.

	ROE		EBIDTA		NPM	
	(1)	(2)	(3)	(4)	(5)	(6)
BioPhyRisk_{20th}	1.715***		-0.017		0.513*	
	(0.521)		(0.089)		(0.281)	
BioPhyRisk_{5th}		2.630**		0.425***		3.481***
		(1.021)		(0.122)		(0.697)
Obs.	8327	8327	8327	8327	8327	8327
R^2	0.108	0.108	0.118	0.117	0.095	0.097
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES