Biodiversity Risk, Firm Performance, and Market Mispricing*

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Abstract

Combining new data on biodiversity-capacity and biodiversity-footprint with firm fundamentals, we conduct a causal analysis of the impact of biodiversity physical risk on firms' profitability and stock returns. With this purpose, we build a biodiversity index for 35 countries and use a time series model to capture its variation over time. We show that such time trend estimation can be aggregated as risk exposure and can significantly forecast establishment-level profitability. We then show that the market under-prices biodiversity physical risk, which is due to the insufficient analysis of related information and its impact on the firm-level future cash flow. We also document disparities of risk exposure across firms and sectors, and our results are consistent with previous findings in terms of climate physical risk.

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

JEL Classification: G1, G12, G14, Q57

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1 Introduction

Since the last decade, people have been increasingly focusing on solving the problems of climate change and global warming. Indeed, the body of scientific evidence supports the statement that climate change is closely related to biodiversity issues. For instance, Isbell et al. (2015) argue that the degradation of regional biodiversity ecosystems decreases the risk resilience to climate extremes. A crucial outcome of the interaction between human economic activities and the planet is the degradation of global biodiversity. 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. 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%. (WWF, 2022)[1]. Countries worldwide have collaborated actively to develop and participate in the Convention on Biological Diversity in 1992, the Cartagena Protocol in 2003, and the Nagoya Protocol in 2014. In this context, several studies suggest that biodiversity loss may impact economic activity directly or through its impact on the economic resilience to climate change. Specifically, Costanza et al. (1997) estimate that the whole biosphere provides an economic value of between 16 and 54 trillion dollars per year.[2]

Despite the recognition of its importance, biodiversity has not attracted much attention in finance so far, even if investors are trying to measure assets' exposure to biodiversity-related physical and transition risks. (Karolyi & Tobin-de la Puente, 2023). To our limited knowledge of literature, there are only four finance papers discussing biodiversity. Flammer, Giroux, and Heal (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. Giglio, Kuchler, Stroebel, and Zeng (2023) construct a news-based index of biodiversity to show people's attention to such a theme. They also conduct survey-based research and find the exposures to biodiversity risk vary substantially across sectors according to the views of academics and professionals. Empirically, Garel, Romec, Sautner, and Wagner (2023) and Coqueret and Giroux (2023) use firm-level

[1]Biodiversity loss represents 66% in Africa; 55% in Asia-Pacific; 20% in North America, respectively.
[2]This value was estimated for 1997, when the global gross GDP was 18 trillion dollars.

biodiversity footprint collected by the Iceberg Data lab to evaluate the biodiversity transition risk and its premium (referred to as the biodiversity risk premium hypothesis). In brief, most existing literature considers biodiversity transition risk. However, the physical risk of long-run biodiversity loss, and its market pricing remains to be discussed.

Another important question comes from the perception of biodiversity as a climate physical risk. This latter is considered local and limited. For example, Hong, Li, and Xu (2019) construct an analysis of estimating the drought trend of the Palmer Drought Index. They find heterogeneity of vulnerability to drought across regions (e.g. global warming even reduces the severity of drought in countries in the Southern Hemisphere.). Besides, Addoum, Ng, and Ortiz-Bobea (2023) show in their paper that industries with high seasonality have a higher exposure to temperature shocks compared to those with low seasonality. To the extent of understanding such a question, our research spans from a macro assessment of biodiversity loss to a sector and firm-level evaluation of the risks that firms incur when there is biodiversity degradation (or a profitability premium if biodiversity improves). We are going to test (i) whether biodiversity loss is at the same level for all countries or regions (e.g. one would expect regions (countries) whose economic activities depend on agriculture more likely to destroy local biodiversity than those where the services are the main economic activity.); and (ii) whether biodiversity loss affects all kinds of economic sectors (e.g. one would expect biodiversity to be a systematic risk factor if there is a strong and broad network of value chains across all companies and sectors.).

We aim to fill the research gap in several aspects. First, we complement the blank of biodiversity physical risk research and provide empirical evidence on how to measure the biodiversity physical risk and at which level such risk affects the firm-level profitability. Then, we study whether biodiversity physical risk is priced in the market. We also study whether different types of sector and firm characteristics have different risk exposure.

Early studies show that climate change and its consequences can be considered as sources of risks. As pointed out by Giglio, Maggiori, Rao, Stroebel, and Weber (2021), risks can be divided into two categories: acute physical risks and chronic physical risks. In terms of acute physical risk, extreme events like hurricanes or wildfires destroy the value of financial assets, especially house prices (Issler, Stanton, Vergara-Alert, & Wallace, 2020;

Ortega & Taspinar, 2018). Regarding chronic climate physical risk, many measurements are considered as a source of risk already, such as sea level rise (Bernstein, Gustafson, & Lewis, 2019; Murfin & Spiegel, 2020; Goldsmith-Pinkham, Gustafson, Lewis, & Schwert, 2023), abnormal temperature or temperature shocks (Balvers, Du, & Zhao, 2017; Addoum, Ng, & Ortiz-Bobea, 2020; Addoum et al., 2023; Pankratz, Bauer, & Derwall, 2023), pollution (Hsu, Li, & Tsou, 2023), drought (Hong et al., 2019), etc. In particular, Balvers et al. (2017) find that temperature fluctuations systematically affect cash flow, thus increasing the cost of capital for firms (because of higher expected returns). Pankratz et al. (2023) study the link between extremely high temperatures and firms' operational performance. They find that the increase in hot days decreases firms' quarterly revenues. In contrast, Addoum et al. (2020) show that, in the U.S., sales, productivity, and profitability at the firm level are unrelated to temperature shocks and that the result is robust in the commonly classified heat-sensitive sectors. They complement their findings in the following research, showing that extremely high and low temperatures decrease the earnings of specific sectors (e.g. consumer discretionary, industrial, and health care), while warmer fall months usually have a positive impact.

We use the same risk classification or methodology as these papers looking at climate and we extend it to biodiversity. Thus our work primarily contributes to the literature by measuring the impacts of physical climate change risks on firm-level operational revenues. We investigate the causal relationship between physical climate risks on institutional profitability by stressing biodiversity physical risk. We use country-level data on biodiversity capacity and biodiversity footprint to create a novel biodiversity index that measures biodiversity resilience for the last 50 years. Methodologically, We define biodiversity resilience as the biodiversity endowments divided by the biodiversity footprint of human activity for each country, named the biodiversity index. We apply the general context of physical risk to our biodiversity analysis, which means that it has three dimensions: physical hazards (biodiversity loss); exposure to the hazard (different levels of biodiversity loss across countries); and vulnerability (long-term biodiversity loss over time). We define physical hazards as chronic instead of acute.[3] We show heterogeneity in terms of biodiversity degradation

[3] This measure also considers large-scale shocks on biodiversity and later recovery (e.g., nuclear leakage

across countries: some countries are rapidly losing biodiversity while others are recovering it over time. We also show that the bio-ecosystem is worsening from a global point of view since negative trends are more widespread than positive ones.

We then assess globally whether biodiversity loss over time can be considered a source of long-term risk. We combine the biodiversity index with firm-level financial performance and data on market returns to study the impact of biodiversity loss on firms' profitability and returns across countries. To do so, we run a 30-year rolling estimation to explore the effect of the long-term biodiversity degradation trend on firms' profitability between 1970 and 2021. Our results validate the disparity in the profitability level between countries where biodiversity is increasingly degrading and those where biodiversity is replenishing. Both the scalar biodiversity index and its long-term trend have significant impacts on the firm performance. A one-standard-deviation increase in the biodiversity index leads to a 0.613% increase in annual profitability, which raises to 1.750% for those countries that are less resilient. Besides, the discrepancy in annual profitability between the countries whose biodiversity has been most severely degraded and most lightly degraded is 1.024%.

Moreover, we assume that the phenomenon of over-pricing or under-pricing of physical risk is prevalent in the market because investors and financial markets lack sufficient information regarding biodiversity to be able to incorporate it into their cash flow analysis. The cash-flow scenarios used by financial analysts do not incorporate biodiversity and its potential effects on the future. Herein, we refer to this as the "market inefficiency related to physical climate risk due to biodiversity loss". Past literature finds no evidence that the market price of physical risks is sufficient.[4]

We test the market efficiency hypothesis in our paper. We find evidence of underpricing of the long-term biodiversity degradation and this undervaluation is due to inaccurate predictions of future cash flow. We show that the difference in annual return between the countries with the most severe biodiversity degradation and those with the lightest degra-

into the ocean, forest fires, earthquakes, etc.).

[4]For example, Krueger, Sautner, and Starks (2020) show that institutional investors (as part of respondents to the survey) believe on average that physical climate risks are not priced, which is consistent with the findings from Hong et al. (2019). This latter paper documents that drought risk is under-priced for the agriculture sector. Similarly, Alok, Kumar, and Wermers (2020) show that the salience bias may cause the overreaction of the fund managers and they will over-underweight the investments in the disaster zone.

dation is 22.559%, which means that the "market inefficiency" is economically significant as the difference in annual profitability is not priced in the stock markets. The robustness of this conclusion persists when we estimate the trend of biodiversity degradation from the initial year of data availability (1970) instead of using the 30-year rolling estimation. In this alternative check, the difference in biodiversity loss corresponds to a 32.365% difference in stock returns.

Other things equal, given the importance of firm-level and sector-level characteristics, they are regarded as determinants of the magnitude of the climate risk exposure for firms (Engle, Giglio, Kelly, Lee, & Stroebel, 2020; Addoum et al., 2023). To this extent, we expand this assumption to biodiversity. We examine first the heterogeneity across sectors' exposure to biodiversity physical risk by splitting our sample. We follow the exposure classification determined by Giglio et al. (2023) to divide our sample into three: "High (biodiversity) Risk", "Medium Risk", and "Low Risk".[5] We find that sectors lowly exposed to biodiversity risk are efficiently priced compared to the other two groups, which shows a 5.381% annual difference in stock returns due to the trend estimation of biodiversity loss and is insignificant. On the other hand, the "Medium Risk" group presents a 26.775% annual difference in stock returns, and the "High Risk" group exhibits a 23.214% yearly disparity in stock returns, and both are statistically significant. Additionally, we show that the lack of relevance in estimating stock returns for the "Low Risk" group arises from the absence of conclusive findings in the cash flow analysis.

We also add firm characteristics variables to create interaction terms in the regression. Specifically, we assume that the book value, the Property, plant, and equipment (PPE), and the growth rate (Investment) of firms will impact their risk exposure level, and the leverage ratio will not (Titman, Wei, & Xie, 2004; Cooper, Gulen, & Schill, 2008; Li, Shan, Tang, & Yao, 2020; Addoum et al., 2023). To separate the firm-level heterogeneity from the sector-level heterogeneity, we compute firstly the mean value of the mentioned firm

[5]They rank the physical exposure of sectors but do not classify them. We classify manually four sectors with GICS 3020 (Food, Beverage, and Tobacco), 1510 (Materials), 3510 (Health Care Equipment and Service), and 3520 (Pharmacy, Biotech, and Life Science) in our "High Risk" group. The "Low Risk" group comprises industries classified under GICS 5010 (Communication Services), 5020 (Media and Entertainment), 4510 (Software and Services), and 4530 (Semiconductors and Equipment). The rest of the industries are in the "Medium Risk" group.

characteristics in each sector. Then we generate dummy variables to represent whether those characteristics for a specific firm were higher (or lower) than the average value. For example, we compute the mean Property, plant, and equipment (PPE) for the sector ”Consumer service”, and for those with a higher value of PPE compared to the sector's mean, we denote that the dummy (e.g. PPE) of this firm equals one, and zero otherwise. Our main findings in the firm heterogeneity tests are consistent with our hypotheses from the literature.

We show that firms with lower book value, higher PPE, and higher growth rates are more affected by biodiversity risk. Specifically, this impact results in a reduction of firm-level yearly profitability by 0.310%, 0.715%, and 1.398%, respectively. Moreover, we do not find any evidence indicating that the leverage ratio has a substantial effect on the level of risk exposure. Typically, we find that the pricing of the heterogeneity of firms' PPE is efficient, although firms with larger PPE are more exposed to biodiversity physical risk (as mentioned before). The variation in firm characteristics only accounts for a negligible -0.005% difference in stock returns and is not statistically significant.

The remainder of the paper is organized as follows. We describe the data and variables in Section 2. In Section 3, we figure out the impact of biodiversity loss on the real economy. In Section 4, we show that biodiversity is a long-term risk source and negatively destroys the values of the firms. In Section 5, we show the market pricing of such risk is not appropriate. We conclude in Section 6.

2 Data and Variables

We use the country-level dataset named National Ecological Footprint from the Ecological Footprint Initiative[6]. By combining this dataset with the firm-level financial fundamentals and stock return data in the Compustat for all listed companies worldwide from 1999 to 2021, we are allowed to analyze the causal impact of biodiversity loss to the firm-level

[6]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.

profitability and stock returns[7].

2.1 Financial Data

We extract our stock return data from Compustat. For the ”Global” database, We calculate the monthly and yearly stock returns by compounding the daily stock returns in the local currency, and we convert the stock returns to US dollars. Then we follow the recommendation from Ince and Porter (2006) after broad investigations. We remove: firms not domestically incorporated and listed, stocks with prices less than one dollar, stocks with zero return strings occurring for the whole period of our series, and those firms with monthly returns that exceed 300 percent and reversed within 1 month. One single exchange with the largest number of listed stocks is selected for all countries. We also extract the market index which is accessible on Compustat. We include live and dead stocks to make sure that there is no survivorship bias for the firms. We extract the country-level data from the site of the World Bank, including the inflation rate (%), and the GDP per capita (Thousand $).

In terms of the accounting variables, we extract our firm-level variables from the Compustat database (Global and North America). 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. Utilities and financial services bear the brunt of regulations. We aim to distinguish the two different sources of risk in our study and focus specifically on physical risk. We also remove those firms with equity less than 0. Then, we use GICS to classify the industries (sectors) of firms in our sample.

After careful examination of the data quality, we find the financial data coverage in the early years is sparse, especially for emerging countries in the Compustat Global database, which we need to convert to US dollars. Thus, we maintain only the data after the year

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

2000.

2.2 Biodiversity Data

The biodiversity measurement can be divided into two sub-categories: Bio-Capacity and Bio-Footprint. The Bio-Capacity and the Bio-Footprint are measured in terms of global hectare, and computed by multiplying with an appropriate equivalence factor.[8] The Bio-Capacity proxies the richness of the total biodiversity of a country, and the Bio-Footprint measures the damage imposed on such richness. Both cover cropland, grazing land, built-up land, fishing grounds, forest products, and carbon uptake as components. This database is monitored and updated yearly.

We remove countries and regions with very small territories (e.g. Singapore and Hong Kong) and 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 and population. For example, we expect that biodiversity conditions around the tropical forest (e.g. Brazil) are better than those around the desert (e.g. Egypt). Besides, countries with larger territories (e.g. 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 become 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 that countries sign for the international conventions. It reports that most of the 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.

[8]Global hectare measures world average biological productivity for a given year.

We construct the biodiversity index as the variable aggregating at the country level. A higher biodiversity index represents higher resilience and less vulnerability to biodiversity loss. We follow the previous discussion and create the formula to eliminate the population effects. Using this formula, we consider only the natural endowments of a country and at which level the country creates damages on such endowments in their economic activities. The index is then as follows:

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

. The "Bio-Capacity" values the endowments of the ecosystem to produce bio-materials 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.[9]

The index is positive and depends on the different geography and ecology of countries. It can be considered as the biodiversity resilience index since it values the ratio between natural richness and damage. The value of the index superior to 1 means that global biological resilience outweighs the destruction of biodiversity by production activities, and vice versa. We have only five countries in our sample, Brazil, Canada, Colombia, Finland, and Sweden, whose average biodiversity index is above the balanced level.

Figure 1 plots the time series of the yearly biodiversity index for India and Denmark along with the fitted lines. The figure shows that India has been facing a worsening situation in terms of biodiversity over time while the latter has been improving in Denmark after a sharp decrease between the 1960s and the 1970s. The Convention on Biological Diversity (CBD) confirms our findings and shows in its reports that the general trend for natural resources in India is toward biodiversity degradation and loss.[10] In contrast, the general

[9]Appendix B.1 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.

[10]The main threats to biodiversity in India include over-exploitation of resources that leads to habitat fragmentation and loss; invasive alien species; declining forest resource base and desertification; and the impact of pollution. See also https://www.cbd.int/countries/profile/

biodiversity in Denmark has been rebuilt since this century, although it faced a quick decline from the 1960s to the 1980s.[11] To preserve its biosphere, Denmark has taken several actions, such as "National Strategy 2040", in which the government decides to conserve the biodiversity of Danish forests, including genetic resources.

[Insert Figure 1 here]

2.3 Summary Statistics: Biodiversity, Firm and Country Characteristics

Table 1 reports summary statistics of the variables in this paper.[12] Panel A of the summary table shows that the Bio-Capacity per capita, the Bio-Footprint per capita, and the biodiversity index are greater than 0. The mean and median values of the biodiversity index are 0.39 and 0.25, which means that our planet is suffering from biodiversity loss on the average level.

Panel B reports the firm-level variables. Our profitability in percentage is computed as the net income divided by total assets. The mean profitability across the sample is 3.5%. We also include gross income as an alternative to net income. The statistics of gross income are close to the net income but with lower standard errors of 7.45 (which values 7.49 for the net income). We include return on equity (RoE), capital expenditure (Capex), net property and plant (PPE), leverage ratio (LEV), market value (MV), book-to-market ratio (BM), asset growth rate (Atgrowth) in percentage[13], and earnings per share (EPS) as other firm characteristics in our control variables. In some tests, we include lagged stock returns for a 12-month holding period in our controls. All variables in Panel B are winsorized at 1% and 99% level.

Panel C reports the country's characteristics. We get the return of the market index, the inflation rate, and the GDP involved. From the year 1999 to 2020, the average market

[11] As reported by CBD, extensive drainage and forestry intensification for timber production, and delayed negative response to the continued loss of habitat for these species (extinction debt) lead to a significant decrease in biodiversity. See also https://www.cbd.int/countries/profile/

[12] We define and describe all variables and details in Appendix A.2.

[13] Which is also named as the investment ratio

return of selected countries is 8.53% per year. The mean of the inflation rate is 1.42% per year.

[Insert Table 1 here]

3 Biodiversity: Global Impact for the Economy

3.1 Biodiversity and the Economy

Before exploring the impact of biodiversity risk on stock returns, we assess if biodiversity impacts the productivity of the whole economy. We expect that the firms attributed to countries with lower biodiversity index will have lower level profits. Our assumption is based on empirical evidence which indicates the effects of biosphere degradation will spillover to the whole economic system (Cardinale et al., 2012; Hanley & Perrings, 2019). For this reason, we perform our analysis firstly across countries and on broad industries rather than on specific ones.

Note that we do not consider that the biodiversity index is itself a representative of risk. Instead, we assume that it measures the average situation of the biosphere across countries as a macro-indicator. Countries with biodiversity indexes higher than one show good resilience to biodiversity extreme events and biodiversity loss, meaning that the capacity for absorption and recovery is greater than the damage put on.

3.2 Cross-Sectional Regression

Our empirical design relies on cross-sectional regression to build the relationship between the biodiversity index and profitability. We estimate the regression for firm i at year t, with the Biodiversity Index at year $t-1$, as follows.

$$\text{Profitability}_{i,t} = \vartheta_0 + \vartheta_1 \text{Biodiversity Index}_{i,t-1} + \phi^{'} X_{i,t-1} + \gamma_t + \lambda_c + \mu_s + \epsilon_{i,t} \qquad (2)$$

Where the $\text{Profitability}_{i,t}$ is our variable of interest for firm i, attributed to country c in year t. We follow the way that Fama and French (2000) use to compute profitability. The

Profitability$_{i,t}$ is expressed as Net Income$_{i,t}$ divided by Total Asset$_{i,t}$. Our explanatory variable is the Biodiversity Index$_{i,t-1}$. The vector $X_{i,t-1}$ contains various firm characteristics and country characteristics as control variables. Our one-year-lagged dependent variables include return on equity (RoE) in percentage, capital expenditure (Capex), net property and plant (PPE), leverage ratio (LEV), market value (MV), book-to-market ratio (BM), and asset growth rate (Atgrowth) in percentage at the firm level. We also involve the inflation rate in percentage and GDP per capita divided by thousand dollars at the country level.[14] We use γ_t, λ_c, and μ_s to display the year, country, and sector fixed effects respectively.

Table 2 reports the results of Equation (2) with different controls and fixed effects. We firstly regress without any controls to avoid abusing the model (Becker, 2005). Then, we add control variables to explain the firms' profitability. We show that the impact of the biodiversity index on the firm-level profitability (with or without controls) is significant and positive. Column (4) reports that a one-unit standard deviation change of biodiversity index at year $t-1$ leads to an overall profitability change of 0.613% at year t. We also observe a substantial association between the biodiversity index and the profitability in the relatively long-term period in columns (5) and (6), which suggest that our latter result remains statistically significant for years $t+1$ and $t+2$. This finding illustrates that the higher biodiversity index corresponds to the higher profitability of the organizations across countries.

Moreover, in our definition, an index equal to one means the balance of the recovery capacity and the damage created by the footprint. We then split our sample into two subsamples and create different attributions of the firms to the countries with strong resilience (Biodiversity Index > 1) and to those with weak resilience (Biodiversity Index < 1).

Column (1) of Panel B of Table 2 reports that one standard error change in the biodiversity index at time $t-1$ generates a 1.75% change in profitability at time t (rather than 0.613% in Panel A) for countries whose biodiversity index are below to one. This result implies that there is a significant driving force in improving the Biodiversity for most of the

[14]Following deHaan (2021), we do not include firm-level fixed effects in our models because the biodiversity index is estimated at the country level.

countries given that only five countries have sufficient biodiversity endowments. Looking at the results of columns (2) and (3), the conclusion remains significant in our sub-sample regression at time $t+1$ and $t+2$ respectively. However, as shown in columns (4) to (6), for the countries already above the equilibrium level, there is no significant impact if they continue to increase the biodiversity index.

[Insert Table 2 here]

4 Biodiversity: A Source of Long-Term Risk

4.1 Measure of Biodiversity Physical Risk

We explore the long-term impact of biodiversity degradation. We construct a time series regression following the methodology of Hong et al. (2019) to measure the trend over time of the biodiversity index. This ”Trend” term helps us to capture the unexpected evolution of biodiversity across countries and we use this term to represent the long-run biodiversity risk.[15] We use a simple AR(1) model to identify the trends across the countries, with a time trend characteristic t.[16] 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 to capture unexpected biodiversity loss over 30 years, given the consideration of policy adjustments and initial differences in biodiversity index.Thus, for each year t and each country c from 1970 to 2020, to get the trend β_1 from 1999 to 2020.[17]

$$\text{Biodiversity Index}_{c,t} = \beta_{0,c} + \beta_{1,c}t + \beta_{2,c}\text{Biodiversity Index}_{c,t-1} + \epsilon_{c,t} \tag{3}$$

[15] 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.

[16] 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.

[17] We also estimate the trends using data since the first record appears instead of running 30-year rolling regression to perform our robustness check in section 5.

Table 3 reports our average estimations of the draft (β_0) and trend (β_1) as well as 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 increasing trends in terms of their biodiversity, with t-statistics of 2.860, 2.485, and 1.657 respectively.[18]

From Appendix B.3 (a) we find that such positive trends appear mostly in European countries, showing that the European Union is in the most advanced position in the protection and reconstruction of biodiversity.[19] Besides, the North America improves its performance from 2010. Appendix B.3 (b) shows that developed countries have been given more efforts on the protection of biodiversity given that OECD Membership countries have statistical significant higher average Biodiversity Trend. In Figure B.3 (c) we also show the Biodiversity Trend between 'bio-sufficient' (Biodiversity Index >1) and 'bio-deficit' (Biodiversity Index <1) countries and find For the bio-deficit countries, an extremely increase shows since 2011.[20]

[Insert Table 3 here]

[18]See also Appendix B.2, 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.

[19]The EU places several regulations related to biodiversity risk (such as the Taxonomy guidelines).

[20]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.

4.2 Quantile sorting of Biodiversity Trend

The "Trend" represents the unexpected risk exposure of the Biodiversity, captured by t in Equantion (3). We use similar methods that Fama and French (1992, 1993) provide to create a "difference" between groups of "Trend". To do so, we comply with the following steps:

First, we rank the countries for each year $t-1$ by their trend estimates β_1 from 30-year rolling estimation.

Then, we set four breakpoints the 20th, 40th, 60th, and 80th percentiles to sort each country into five different groups (Q1 to Q5), named *Trend Quantile*, based on their ranking at each year. We identify that the first quantile (Q1) contains the countries most affected by biodiversity degradation (i.e. the countries with the lowest time trend coefficients), followed by the second, third, and fourth groups. The fifth quantile (Q5) contains the countries that most benefited from improving the biosphere (i.e. the countries with the highest time trend coefficients).[21]

Finally, to test the significance of differences in β_1 between the quantile groups, we compute, for each year, the average value of β_1 from Q1 to Q5. We get 22 values (from 1999 to 2020) for each quantile. We do not report the values at each year and in each quantile for brevity, because countries are attributed to the different quantiles each year (e.g. in the year 2000, we have the US in Q5 and Canada in Q1, in the year 2008, US in Q1 and Canada in Q5. All depend on the evolution of β_1 in the last 30 years, and such attribution changes over time.) Our key question is to identify whether the average Trend of quantile 1 is lower than that of quantile 5. To do so, we run a one-way t-test. Our null hypothesis is that the average value of "Trend" between the two quantiles is identical ($trend_{Q1} - trend_{Q5} = 0$), and the alternative hypothesis is that the average value of trend between the two quantiles is negative ($trend_{Q1} - trend_{Q5} < 0$). We obtain the t-statistics of -26.22, thus the null hypothesis of the equal trends between two quantiles is rejected. Instead, we take the position of accepting that the difference in trends between the first

[21] We show in Table 4 and Table 5 that the marginal effect of change of "Trend" is vague and it is hard to identify different risk exposure levels according to their "Trend" estimations. By doing so, we show clearly that the risk exposure of countries in the first quantile (Q1) is bigger than those in the fifth quantile (Q5).

quantile and the fifth quantile is statistically meaningful, which implies that biodiversity for countries in the first quantile is worse than that for countries in the fifth quantile over the last 30 years.

4.3 Biodiversity Trend and Firm Performance

We examine in this section whether the biodiversity physical risk over time affects the operating profits of firms. We assume that biodiversity degradation is a long-term process and explores the physical risk exposure in real business, thus destroying the future cash flow of firms. We imply our regression Equation (2) and we change the key explanatory variable to $\text{Trend}_{i,t-1}$, and $\text{Trend Quantile}_{i,t-1}$. We estimate the regressions as follows:

$$\text{Profitability}_{i,t} = \vartheta_0 + \vartheta_1 \text{Trend}_{i,t-1} + \phi' X_{i,t-1} + \gamma_t + \lambda_c + \mu_s + \epsilon_{i,t} \quad (4)$$

$$\text{Profitability}_{i,t} = \vartheta_0 + \vartheta_1 \text{Trend Quantile}_{i,t-1} + \phi' X_{i,t-1} + \gamma_t + \lambda_c + \mu_s + \epsilon_{i,t} \quad (5)$$

Where $\text{Profitability}_{i,t}$ is our variable of interest for firm i, attributed to country c in year t. We compute the profitability as same as previous. We have key independent variables: $\text{Trend}_{i,t-1}$, and $\text{Trend Quantile}_{i,t-1}$. $\text{Trend}_{i,t-1}$ is the yearly average percentage change of the biodiversity index for the country c, from year $t-30$ to year $t-1$. $\text{Trend Quantile}_{i,t-1}$ is a dummy variable equal to 0 if the firms are attributed to the country c in the group of first quantile (Q1), and equal to 1 if the firms are attributed to the country c in the group of fifth quantile (Q5). We include the same set of control variables as in the regression of Equation(2) in the vector $X_{i,t-1}$. We use γ_t, λ_c, and μ_s to display the year, country, and sector fixed effects respectively.

We display our results in Table 4. The table shows that a positive $\text{Trend}_{i,t-1}$ during the last 30 years creates an insignificant and negligible impact on the firm's profitability. For instance, a standard deviation increase in the $\text{Trend}_{i,t-1}$ will decrease the profitability by -0.007% without country controls, and by -0.038% with country controls, which does not provide strong interpretive power.[22] However, when we include only the worst cases (Q1)

[22] Johannesson, Ohlson, and Zhai (2023) suggests that the standardized regression (SR) helps to avoid the effects of large sample size on the t-statistics, and if the coefficient of a variable in SR is less than 0.05,

and the best cases (Q5), measured by the Trend Quantile$_{i,t-1}$ in the regression, we find that the firms attributed in the fifth quantile (Q5) have 1.32% (without country controls) or 1.02% (with country controls) more than the firms attributed in the first quantile (Q1) in terms of the profitability.

Our regression results illustrate a phenomenon wherein the inclusion of each scale of the trend, leading to an average effect, significantly diminishes the explanatory power of biodiversity degradation on corporate profitability. Meanwhile, we show that the spread in performance as driven by the sensitivity to unexpected biodiversity risk is clear-cut, through the estimation of Equation (5). We also show an increase of approximately 1% in terms of annual profitability at time t for the firms attributed to the countries with improving biodiversity and to those with worsening biodiversity situation, at time $t-1$. The results help us to identify that our "Trend" can be considered a representative of the long-run risk.

[Insert Table 4 here]

5 Biodiversity Risk and Stock Returns

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 market efficiency hypothesis proposes that, when the investors correctly and promptly incorporate the information (here the information is expressed in terms of the biodiversity risk), then 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.

then it brings negligible incremental explanation although the t-statistics support the significance.

5.1 Cross-Sectional Regressions

In this section, we explore the effects of biodiversity degradation on stock returns across counties. To do so, we rely on cross-sectional regressions and build the relationship between biodiversity risk and stock returns. We estimate the following regressions for firm i in year t, with the trend estimated from year $t-30$ to year $t-1$. Following the instruction of Petersen (2008), we do not perform regression of Fama and MacBeth (1973), because our sample is relatively constrained on the time horizon (yearly observations). Instead, We follow the method of Bolton and Kacperczyk (2021). We double-cluster our standard errors at firm and year levels. Our regression design is presented as follows:

$$\text{Return}_{i,t} = \vartheta_0 + \vartheta_1 \text{Trend}_{c,t-1} + \phi' X_{i,t-1} + \gamma_t + \lambda_c + \mu_s + \epsilon_{i,t} \tag{6}$$

$$\text{Return}_{i,t} = \vartheta_0 + \vartheta_1 \text{Trend Quantile}_{c,t-1} + \phi' X_{i,t-1} + \gamma_t + \lambda_c + \mu_s + \epsilon_{i,t} \tag{7}$$

Where $\text{Return}_{i,t}$ is our variable of interest for firm i, attributed to country c at year t. Our $\text{Return}_{i,t}$ is the total stock return, calculated with the price, the distribution of cash and its equivalents, and the dividend payment. We suppose that we hold the stock of firm i for a 12-month horizon. Definitions of $\text{Trend}_{c,t-1}$ and $\text{Trend Quantile}_{c,t-1}$ remain the same as previously modeled. The vector $X_{i,t-1}$ contains various firm characteristics and country characteristics as control variables. We use one-year-lagged dependent variables and controls to reduce the endogeneity in the regression. We include the same set of control variables as in the regression of Equation(2) in the vector $X_{i,t-1}$, with the addition of lagged earning per share (EPS) and lagged stock returns. We use γ_t, λ_c, and μ_s to display the year, country, and sector fixed effects respectively.

Panels of Table 5 report our estimation. Panel A confirms the results of Table 4. $\text{Trend}_{c,t-1}$ does not impact firm's profitability or stock returns. However, columns (3) and (4) report significant positive return predictability during the holding horizon (12 months). Such kind of return predictability comes from the different physical risk exposure between the top quantile (Q5) and the bottom quantile (Q1), and displays that the firms in countries with the lowest biodiversity physical risk generate 22.604% (22.559% with additional controls) more in terms of annual stock returns compared to those countries with the highest biodiversity physical risk. This result remains robust after adding one-year-lagged stock returns and earnings per share as controls. For the control variables, we find that a high return on equity/book-to-market ratio/earning per share ratio predicts positively the yearly stock returns. In contrast, a high market value of firms predicts negatively the returns. All other variables cannot predict returns. In panel B, we re-run the regression by sorting our quantiles based on the trend estimated from the beginning (year 1970) to year $t-1$ to illustrate the compatibility of the long-term horizon. We find that Panel B reports similar results to Panel A, which confirms that the Trend Quantile has return predictability, and such predictability remains robust when we sort our Trend Quantile using either rolling or unrolling estimations in the time horizon.

The results of Table 5 do not conform to the hypothesis of market efficiency. The spread on the future performance of firms in quantile 1 (Q1) relative to quantile 5 (Q5), is both significant in terms of profitability and stock returns. In a 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, we assume that the financial market adjusts and adapts quickly once it absorbs such information. In this case, each kind of risk (physical or transition risks of biodiversity) should be priced immediately because it is related to the next year's profitability. Thus, in an efficient market, we can not expect that such a piece of public information (e.g. ranking or quantile for biodiversity index) of countries in terms of biodiversity degradation can predict the stock returns for a long-term horizon. However, Table 5 shows a significant spread in stock returns between quantile 1 (Q1) and quantile 5 (Q5), which means that the difference in the profitability of firms is not correctly priced in the financial markets.

[Insert Table 5 here]

5.2 Digging in Sub-Industry Heterogeneity

From the previous sections, we know that the long-run biodiversity loss will negatively impact the firm's profitability at the average level. However, the heterogeneity of biodiversity risk exposure across industries is not yet clear. For example, Addoum et al. (2020) show that there is no evidence that the temperature exposures have impacts on firm-level profitability, including firms among the heat-sensitive industries. 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 examine in this section whether this conclusion is still validated in the case of biodiversity. To do so, we use the industry classification of Giglio et al. (2023). They analyze firm-level biodiversity risk exposure from US firms' 10-K statements and surveys and rank the biodiversity physical and transition risk exposure for all industries. We follow their sector exposure ranking and display if the industries highly exposed to biodiversity risk suffer from more financial loss. We choose only the ranking in terms of the biodiversity physical risk and remove the transition risk pillar for brevity and to make it consistent with our previous works. We first classify our industries according to the survey, then we gather them into three groups, named separately "Low Risk", "Medium Risk", and "High Risk". The industries in the group "High Risk" are the ones most severely exposed to the physical risk of biodiversity. In contrast, the ones in the group "Low Risk" are the least exposed. We consider that the group "Medium Risk" gathers the industries with neutrality to the physical risk. Similar to the way that we perform to estimate the average impact of biodiversity loss on profitability, we investigate whether we get different results if the same level of pressure on biodiversity is applied to different sectors. This investigation is considered a placebo analysis,[23] that is, we expect that profitability reductions should be significantly stronger in sectors with high exposure to the biodiversity physical risk than in sectors with (virtually) low exposure. To carry out the test for our assumption, we re-estimate the Equation (7) for the three groups. Other arrangements for the estimation remain the same.

Table 6 reports the sub-sample estimation of stock returns of grouped sectors with different levels of risk exposure. We find that the return predictability remains robust for the most exposed sectors and relevant exposed sectors. However, there is no return predictability for the least exposed sectors. The firms grouped in the pillar of "High Risk"

[23]The treatment group includes sectors that are classified as sectors highly exposed to biodiversity loss, and the control group includes sectors that are classified as sectors lowly exposed to biodiversity loss.

and "Medium Risk" in countries that improved the biodiversity in the last 30 years generate 23.444% and 26.775% more in terms of annual stock returns compared to those in countries where the biodiversity has been worsening. The estimations are slightly higher than 22.604%, which is the coefficient estimated in Equation (7) for the whole sample. The results reported confirm the heterogeneity of risk levels in different economic sectors.

[Insert Table 6 here]

This sub-sample estimation shows two pieces of evidence. Columns (3) - (6) of Table 6 show the first evidence is that the biodiversity physical risk exists broadly and systemically across sectors. The impact of biodiversity loss on the market price in the most exposed sectors and moderately exposed sectors is close to the average level. However, we cannot identify which sector has the highest exposure compared to the others. Columns (1) and (2) of Table 6 show that physical risk will not be reflected in sectors with very low exposure levels.

The biodiversity physical risk affects the real business value and makes no impact on the industries out of the value chain (like entertainment and media). To take a close look at this insignificance, we construct an interaction term Trend Quantile × Low Risk and regress the coefficient of this term, as follows.

$$\begin{aligned} \text{Profitability (or Return)}_{i,t} = {} & \vartheta_0 + \vartheta_1 \text{Trend Quantile}_{c,t-1} \times \text{Low Risk}_{c,t-1} \\ & + \vartheta_2 \text{Trend Quantile}_{c,t-1} + \vartheta_3 \text{Low Risk}_{c,t-1} \\ & + \phi^{'} X_{i,t-1} + \gamma_t + \lambda_c + \epsilon_{i,t} \end{aligned} \tag{8}$$

The Table 7 reports our estimation with different controls. The first two columns show the results of estimating the profitability. The last two show the results of estimating the returns. We find that the difference in terms of the profitability for low-risky sectors between the countries with biodiversity improving and biodiversity loss is -0.595% (-0.589%) and statistically significant only at the 10% level. As for the medium and high risky sectors, the difference is 1.364% (1.051%) and statistically significant at the 1% level. We also find that the estimation for these two groups has opposite signs. In the previous sections, we confirm that the profitability will be at a higher level for the firms attributed to the countries that have been increasing their biodiversity, which is not the same case for the sectors with low-risk exposure levels. Columns (3) and (4) confirm the results of the sub-sample regression in Table 6 that the market prices efficiently the low-risk sectors but not the medium and high-risk sectors, which is consistent with the analysis of the profitability.

[Insert Table 7 here]

We also give out the economic sector biodiversity physical risk exposure by re-estimate Equation (7) one-by-one, controlling for specific sectors while retaining the reset fixed effects and controls as before. The profitability discrepancy under specific economic sector are based on the coefficient of ϑ_1. We sort the economic sector by the coefficient and mark out the statistical significant sectors as shown in Figure 2. 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 profitability. That is, whichever industry has a higher estimated coefficient indicates a greater exposure to risk in that industry.

By making comparison our physical risk sector exposure with 10-k based physical risk sector exposure proposed by Giglio et al. (2023) in Figure 3, we find similar yet discrepancy in the sector ranking. Firstly, our sector exposure regarding the past 20 years rather than a specific year. Secondly, we focus on global market rather than a specific economic body. Generally, compared to our 20-year cross-country exposure, the 10-k-based physical risk measurements may either amplify or reduce the impact of biodiversity-related physical risks, depending on the specific economic entities or particular years considered.

Our result shows that, as expected, Pharmaceuticals, Biotechnology & and Life Sciences and Food, Beverage & Tobacco have the largest exposure. However, Software & Services, Consumer Distribution & Retail, and Telecommunication industry suffer more from biodiversity physical risk than they (professionals and academia) expected. On the opposite, we find that Capital Goods, Consumer Durables, Automobiles & Components, Household Products and Commercial & Professional services are exposed to biodiversity physical risk at a very low level, which is not compatible with the survey-based results.

[Insert Figure 2 here]

[Insert Figure 3 here]

5.3 Firm Characteristics and Heterogeneity

Besides the heterogeneity across sectors, we are interested in the heterogeneity in terms of firm characteristics. Li et al. (2020) show in their paper that the PPE value of a firm at time $t-1$ will positively influence the chronic risk exposure level of such firm at time t. Other variables such as firm size, Capex, and leverage, however, have no impacts. Addoum et al. (2023) also shows that firms with higher book values of equity are more resistant to biodiversity loss because they have higher capital adequacy and thus more resilience to potential risks. Moreover, we consider the business life cycle, which is related to the growth rate of total assets. Dickinson (2011) define that firms with a higher growth rate are expanding their business and have a higher investment ratio, and we suppose that they are more likely to be less resistant to biodiversity loss and its impact on operations. In this section, we investigate the impact of biodiversity loss on firms with different characteristics. Given the results of the last section, we select only the firms in the sectors pre-determined as medium or high-risk exposure and remove the firms in the "Low Risk" sectors. Our hypotheses to test are presented as follows.

H_1 : *Firms with higher book values of equity are more resistant to biodiversity loss.*

H_2 : *Firms that have relatively large Property, Plant, and Equipment (PPE) will be more exposed to biodiversity physical risk.*

H_3 : *Firms with different leverage levels are equally exposed to biodiversity physical risk.*

H_4 : *Firms with a higher growth rate are expanding their business and are more likely to be less resistant to biodiversity loss.*

We compute first the average value of the financial fundamentals as mentioned in the hypothesis within each sector and provide our results in Panel A of Table 8. We find that the Automobiles, Materials, and Transportation sectors have the largest average booking value. As for the PPE and Leverage, Transportation also ranks first. However, in terms of asset growth, the Pharmaceuticals, Healthcare, and Software sectors have the highest value. Then we divide the firms in each sector into two groups, naming above or below average, to build the heterogeneity of firm characteristics. We design regressions with an interaction term of firm-level characteristics as follows.

$$
\begin{aligned}
\text{Profitability (or Return)}_{i,t} = {} & \vartheta_0 + \vartheta_1 \text{Trend Quantile}_{c,t-1} \times \text{Firm Characteristics}_{c,t-1} \\
& + \vartheta_2 \text{Trend Quantile}_{c,t-1} + \vartheta_3 \text{Firm Characteristics}_{c,t-1} \\
& + \phi^{'} X_{i,t-1} + \gamma_t + \mu_s + \lambda_c + \epsilon_{i,t}
\end{aligned} \tag{9}
$$

Panel B of Table 8 reports the estimation results. We find that heterogeneity exists across book value and asset growth rate and this heterogeneity has not yet been priced. Our estimations confirm the assumption that firms with higher book values are more resistant to biodiversity degradation, which represents -0.31% less loss in terms of profitability compared to the firms with relatively small book values. We also prove that firms with higher growth rates are affected by biodiversity loss, by 1.398% more. Such an effect generates 8.578% unexpected annual returns. The interesting point is that the results of the PPE on profitability are partially consistent with our assumption, showing that firms with more PPE are more exposed (by 0.715%) to biodiversity loss. However, such kind of impact is priced. The market is trying to price the biodiversity physical risk but only reflected in tangible assets. Besides, we do not find heterogeneity in terms of the leverage ratio of firms compared to the last three aspects.

[Insert Table 8 here]

6 Discussion and concluding remarks

In this paper, we quantify the materiality of biodiversity physical risk and the negative impact of biodiversity degradation on the firm-level future cash flows (measured by profitability). We also study the inefficient market pricing of such impact and find supportive results. Motivated by the scientists' calls, we build a novel set of biodiversity indexes for 35 countries, covering both Bio-Capacity and Bio-Footprint. We find that biodiversity in most countries is degrading due to our 30-year rolling estimation.

We show results at the firm level that biodiversity physical risk exposure is significantly related to profitability and stock returns. To the extent that biodiversity physical risk exists broadly, we find that biodiversity physical risk exposure at the firm level is heterogeneous across the sectors and firms with specific characteristics.

Although we document a consistent set of results for our initial hypothesis, we have to take into account limited knowledge of biodiversity's financial impact in the long term. Thus, we provide a starting point for further examination, especially for testing the market efficiency after several initiatives and international conventions. For example, our sample ends in 2020 (we have firm-level data for 2021), while global biodiversity policies and initiatives (e.g. COP15) occur after that year. A promising avenue for research is to construct an investor sentiment indicator for biodiversity following and use this as a basis for testing whether the market improves gradually its sensitivity to biodiversity risk and its pricing of related information flows along the lines of Engle et al. (2020) and Ardia, Bluteau, Boudt, and Inghelbrecht (2023); Giglio et al. (2023)).

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Table 1: Summary Statistics

This table reports the summary statistics of different classes of variables used in this paper. All variables are measured at the annual frequency. We divide Bio-Capacity per capita by Bio-Footprint per capita to get the Biodiversity Index. Definitions of variables are provided in Appendix A.

Variables	Obs	Mean	SD	Min	Max	Median	P25	P75
				Panel A: Biodiversity Variables				
Bio-Capacity per capita	120681	2.07	3.07	0.33	17.79	0.79	0.63	1.69
Bio-Footprint per capita	120681	4.41	2.20	0.73	15.72	3.88	3.42	4.41
Biodiversity Index	120681	0.39	0.40	0.14	3.43	0.25	0.17	0.42
				Panel B: Firm-level Variables				
Profitability (%)	120681	3.50	7.49	-38.23	25.33	3.51	1.19	6.59
Gross profitability (%)	120681	3.50	7.45	-38.06	25.07	3.51	1.19	6.59
Stock Return (%)	120681	16.36	51.21	-71.55	302.27	7.11	-14.37	35.13
RoE (%)	120681	6.07	19.78	-123.75	57.87	7.45	2.73	13.41
CAPEX	120681	0.04	0.04	0.00	0.26	0.03	0.01	0.06
PPE	120681	0.27	0.19	0.00	0.85	0.24	0.12	0.39
LEV	120681	0.28	0.23	0.00	0.88	0.26	0.07	0.45
Ln(MV)	120681	5.68	1.85	1.66	10.32	5.61	4.30	6.96
Atgrowth (%)	120681	9.28	23.73	-32.39	151.69	5.26	-2.87	14.76
BM	120681	0.96	0.82	0.04	4.19	0.71	0.37	1.29
EPS ($)	120681	1.76	6.84	-6.53	56.44	0.35	0.07	1.12
				Panel C: Country-level Variables				
Market Index (%)	120681	8.53	21.90	-65.47	160.16	10.67	-2.49	20.38
Inflation Rate (%)	120681	1.42	1.89	-4.48	29.51	1.18	0.06	2.30
GDP per capita (Thousand $)	120681	34.25	12.43	2.09	106.57	35.52	28.62	41.68

Table 2: Biodiversity Index and Firm's Profitability

This table reports estimation results of the firm's profitability at time t on the Biodiversity Index at time $t-1$. The profitability is computed as the total net income divided by total assets. We use the Z-score method to standardize our variables. The normalized formula is as follows: $\frac{\text{Variable}-\text{E[Variable]}}{\sigma_{\text{Variable}}}$. In Panel A, columns (1) to (4), we estimate the causal relationship between the profitability at time t and the Biodiversity Index at time $t-1$. We also estimate the profitability at time $t+1$ and $t+2$ in columns (5) and (6) respectively. All the control variables are lagged for one year and defined in Table 1. We rerun the estimation for two sub-samples in Panel B by dividing the whole sample into two, based on whether the Biodiversity Index is higher or lower than one. We do not report intercepts for brevity. Standard errors are clustered at the firm level and reported in parentheses below the estimations. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 1999 to 2021.

Panel A: Whole Sample Regression

Profitability	(1) t	(2) t	(3) t	(4) t	(5) $t+1$	(6) $t+2$
Biodiversity Index	0.614***	0.472**	0.451*	0.613***	0.644***	0.521**
	(0.055)	(0.241)	(0.231)	(0.232)	(0.222)	(0.236)
RoE		0.184***	0.176***	0.176***	0.176***	0.175***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ln(MV)		0.216***	0.220***	0.222***	0.222***	0.213***
		(0.022)	(0.020)	(0.020)	(0.020)	(0.021)
BM		-1.091***	-1.244***	-1.241***	-1.241***	-1.297***
		(0.049)	(0.049)	(0.049)	(0.049)	(0.052)
CAPEX			0.450	0.393	0.387	0.078
			(0.735)	(0.736)	(0.736)	(0.759)
PPE			1.236***	1.246***	1.245***	1.164***
			(0.199)	(0.199)	(0.199)	(0.208)
LEV			-4.168***	-4.154***	-4.152***	-4.345***
			(0.150)	(0.150)	(0.150)	(0.155)
Atgrowth			-0.006***	-0.006***	-0.006***	-0.004**
			(0.001)	(0.001)	(0.001)	(0.001)
Inflation Rate				0.013	0.014	0.033
				(0.019)	(0.019)	(0.020)
GDP per capita				-0.046***	-0.046***	-0.045***
				(0.010)	(0.010)	(0.011)
Market Index				0.007***	0.006***	0.008***
				(0.001)	(0.001)	(0.001)
Observations	120,681	106,601	106,601	106,601	106,601	94,426
Adj. R-squared	0.007	0.309	0.323	0.323	0.323	0.329
Sector FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes

Panel B: Sub-Sample Regression

	Biodiveristy Index < 1			Biodiveristy Index > 1		
Profitability	(1) t	(2) $t+1$	(3) $t+2$	(4) t	(5) $t+1$	(6) $t+2$
Biodiversity Index	1.750***	1.989***	2.008***	0.618	0.656	-0.008
	(0.458)	(0.470)	(0.502)	(0.461)	(0.434)	(0.476)
RoE	0.168***	0.168***	0.167***	0.244***	0.244***	0.233***
	(0.004)	(0.004)	(0.005)	(0.012)	(0.012)	(0.013)
Ln(MV)	0.240***	0.240***	0.234***	0.141*	0.143*	0.082
	(0.021)	(0.021)	(0.021)	(0.080)	(0.080)	(0.088)
BM	-1.213***	-1.215***	-1.257***	-1.478***	-1.479***	-1.701***
	(0.051)	(0.051)	(0.053)	(0.233)	(0.233)	(0.255)
CAPEX	0.452	0.433	0.200	-0.523	-0.553	-1.773
	(0.767)	(0.767)	(0.785)	(2.570)	(2.566)	(2.814)
PPE	1.283***	1.285***	1.186***	1.211*	1.214*	1.134
	(0.208)	(0.208)	(0.215)	(0.733)	(0.732)	(0.804)
LEV	-4.105***	-4.105***	-4.258***	-5.754***	-5.764***	-6.204***
	(0.154)	(0.154)	(0.158)	(0.673)	(0.673)	(0.719)
Atgrowth	-0.003**	-0.003**	-0.001	-0.023***	-0.023***	-0.022***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.005)
Inflation Rate	0.065***	0.068***	0.075***	-0.186***	-0.182***	-0.141*
	(0.020)	(0.020)	(0.022)	(0.067)	(0.067)	(0.075)
GDP per capita	-0.035***	-0.037***	-0.041***	-0.151***	-0.160***	-0.068
	(0.011)	(0.011)	(0.011)	(0.051)	(0.050)	(0.056)
Market Index	0.006***	0.006***	0.007***	0.010	0.009	0.016
	(0.001)	(0.001)	(0.002)	(0.009)	(0.009)	(0.010)
Observations	98,317	98,317	87,248	8,231	8,231	7,125
Adj. R-squared	0.312	0.312	0.318	0.412	0.412	0.404
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Summary Statistics of Biodiversity Index Trend over Time

This table reports the average value of the estimated trend from 1999 to 2020 using the Biodiversity Index from 1970 to 2020. The coefficients reported are the average value of the AR(1) regression from year $t-30$ to year $t-1$. We report only the estimates of constants and Trend with their t-statistics over time. We then rank these countries by their Trend estimations.

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 4: Biodiversity Trend and Firm's Profitability

This table reports estimation results of the firm's profitability at time t on the biodiversity physical risk at time $t-1$. The dependent variable is the profitability of firms, which is computed as the total net income divided by total assets. We use Z-score to standardize the Trend at time $t-1$ for the estimation in columns (1) and (2). In columns (3) and (4), we set a dummy variable named Trend Quantile at time $t-1$, which is equal to 1 for the firms in the fifth quantile (Q5), and 0 for the firms in the first quantile (Q1). All the control variables are lagged for one year and reported in Table 1. We do not report intercepts for brevity. Standard errors are clustered at the firm level and reported in parentheses below the estimations. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 1999 to 2021.

Profitability	(1)	(2)	(3)	(4)
Trend	-0.007	-0.038**		
	(0.018)	(0.018)		
Trend Quantile			1.321***	1.024***
			(0.305)	(0.339)
RoE	0.176***	0.176***	0.197***	0.197***
	(0.004)	(0.004)	(0.006)	(0.006)
Ln(MV)	0.221***	0.224***	0.286***	0.288***
	(0.020)	(0.020)	(0.034)	(0.034)
BM	-1.246***	-1.244***	-1.534***	-1.533***
	(0.049)	(0.049)	(0.114)	(0.114)
CAPEX	0.437	0.374	0.038	0.066
	(0.735)	(0.736)	(1.182)	(1.185)
PPE	1.243***	1.254***	1.736***	1.715***
	(0.199)	(0.199)	(0.324)	(0.324)
LEV	-4.170***	-4.162***	-4.161***	-4.146***
	(0.150)	(0.150)	(0.296)	(0.296)
Atgrowth	-0.006***	-0.006***	-0.011***	-0.011***
	(0.001)	(0.001)	(0.002)	(0.002)
Inflation Rate		0.017		-0.162***
		(0.019)		(0.038)
GDP		-0.045***		0.008
		(0.011)		(0.021)
Market Index		0.007***		-0.001
		(0.001)		(0.003)
Observations	106,601	106,601	36,056	36,056
Adj. R-squared	0.322	0.323	0.355	0.355
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Table 5: Biodiversity Trend and Stock Returns

This table reports estimation results of stock returns at time t on the biodiversity risk estimated at the previous period. We use Z-score to standardize the Trend at time $t-1$ for the estimation in columns (1) and (2). In columns (3) and (4), we set a dummy variable named Trend Quantile at time $t-1$, which is equal to 1 for the firms in the fifth quantile (Q5), and 0 for the firms in the first quantile (Q1). In panel A, the Trend and Trend Quantile at time $t-1$ are estimated from $t-30$ to $t-1$; In panel B, the Trend and Trend Quantile at time $t-1$ are estimated from 1970 to $t-1$. All the control variables are lagged for one year and reported in Table 1. We do not report intercepts for brevity. Standard errors are double clustered at the firm and year level and reported in parentheses below the estimations. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 1999 to 2021.

Panel A: Quantile sort based on the estimated trend from the last 30 years

Stock Returns	(1)	(2)	(3)	(4)
Trend	1.891	1.860		
	(2.689)	(2.670)		
Trend Quantile			22.604**	22.559**
			(8.713)	(8.830)
RoE	0.172***	0.167***	0.173***	0.165***
	(0.029)	(0.033)	(0.034)	(0.035)
Ln(MV)	-1.806***	-1.856***	-2.118***	-2.205***
	(0.300)	(0.301)	(0.532)	(0.539)
BM	5.366***	5.137***	6.161***	5.998***
	(1.108)	(1.066)	(1.267)	(1.232)
CAPEX	19.048	17.548	5.735	5.533
	(15.037)	(14.496)	(10.649)	(10.442)
PPE	-6.847*	-6.597*	-3.906	-4.067
	(3.393)	(3.280)	(3.725)	(3.683)
LEV	3.451	3.528	-0.977	-0.612
	(2.101)	(2.102)	(2.213)	(2.248)
Atgrowth	0.001	0.006	-0.004	-0.003
	(0.035)	(0.032)	(0.021)	(0.019)
Inflation Rate	1.614	1.650	1.245	1.251
	(1.404)	(1.387)	(1.671)	(1.674)
GDP per capita	0.312	0.294	0.629	0.621
	(0.487)	(0.490)	(0.579)	(0.584)
Market Index	0.055	0.071	0.521	0.525
	(0.199)	(0.196)	(0.331)	(0.331)
Stock Returns		-0.018		-0.003
		(0.029)		(0.035)
EPS		0.168**		0.184**
		(0.060)		(0.072)
Observations	106,601	106,601	36,056	36,056
Adj. R-squared	0.172	0.173	0.232	0.232
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Panel B: Quantile sort based on the estimated trend from the 1970

Stock Returns	(1)	(2)	(3)	(4)
Trend	2.559	2.469		
	(5.989)	(6.004)		
Trend Quantile			32.141***	32.365***
			(7.086)	(7.008)
RoE	0.172***	0.167***	0.209***	0.197***
	(0.029)	(0.033)	(0.033)	(0.035)
Ln(MV)	-1.795***	-1.844***	-1.502***	-1.556***
	(0.314)	(0.315)	(0.404)	(0.415)
BM	5.333***	5.102***	7.152***	7.319***
	(1.091)	(1.048)	(1.534)	(1.400)
CAPEX	19.271	17.754	-1.016	-0.862
	(14.820)	(14.273)	(8.328)	(8.192)
PPE	-6.847*	-6.596*	-4.888	-4.979
	(3.407)	(3.291)	(3.588)	(3.566)
LEV	3.381	3.456	0.243	0.701
	(2.058)	(2.064)	(1.774)	(1.897)
Atgrowth	0.002	0.006	0.022	0.017
	(0.034)	(0.031)	(0.022)	(0.022)
Inflation Rate	1.692	1.726	2.339*	2.326*
	(1.412)	(1.395)	(1.248)	(1.256)
GDP per capita	0.228	0.211	-0.248	-0.236
	(0.492)	(0.497)	(0.660)	(0.657)
Market Index	0.060	0.076	-0.074	-0.085
	(0.195)	(0.192)	(0.116)	(0.118)
Stock Returns		-0.018		0.016
		(0.030)		(0.021)
EPS		0.168**		0.129
		(0.059)		(0.088)
Observations	106,601	106,601	27,803	27,803
Adj. R-squared	0.172	0.172	0.255	0.255
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Table 6: Heterogeneity of Sub-Industry and Stock Returns

This table reports sub-sample estimation of stock returns at time t on different ranges of the biodiversity physical risk. We set a dummy variable named Trend Quantile at time $t-1$, which is equal to 1 for the firms in the fifth quantile (Q5), and 0 for the firms in the first quantile (Q1). Our "High Risk" group contains sectors with GICS 3020 (Food, Beverage, and Tobacco), 1510 (Materials), 3510 (Health Care Equipment and Service), and 3520 (Pharmacy, Biotech, and Life Science). Our "Low Risk" group contains sectors with GICS 5010 (Communication Services), 5020 (Media and Entertainment), 4510 (Software and Services), and 4530 (Semiconductors and Equipment). The rest of the industries are in the "Medium Risk" group. This classification draws on the survey-based research of Giglio et al. (2023). All the control variables are lagged for one year and reported in Table 1. We do not report intercepts for brevity. Standard errors are double clustered at the firm and year level and reported in parentheses below the estimations. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 1999 to 2021.

	Low Risk		Medium Risk		High Risk	
Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
Trend Quantile	5.486	5.381	26.773**	26.775**	23.444**	23.214**
	(10.435)	(10.325)	(10.256)	(10.368)	(8.288)	(8.428)
RoE	0.132**	0.106*	0.183***	0.177***	0.188***	0.177***
	(0.051)	(0.052)	(0.042)	(0.045)	(0.034)	(0.032)
Ln(MV)	-2.742***	-2.947***	-1.825***	-1.883***	-2.301***	-2.422***
	(0.860)	(0.885)	(0.580)	(0.587)	(0.721)	(0.728)
BM	6.028	6.021	5.556***	5.459***	7.608***	7.306***
	(3.604)	(3.590)	(1.184)	(1.162)	(1.586)	(1.510)
CAPEX	21.944	21.432	2.823	2.609	5.471	5.785
	(29.685)	(29.562)	(10.815)	(10.558)	(11.700)	(11.167)
PPE	-9.208	-9.611	-2.923	-3.067	-2.662	-2.831
	(10.444)	(10.457)	(3.495)	(3.395)	(4.385)	(4.359)
LEV	-1.453	-1.090	-2.468	-2.242	2.145	2.829
	(3.629)	(3.384)	(2.615)	(2.725)	(2.304)	(2.335)
Atgrowth	-0.021	-0.021	0.004	0.004	0.001	0.004
	(0.034)	(0.035)	(0.029)	(0.028)	(0.019)	(0.019)
Inflation Rate	1.059	1.167	1.322	1.324	1.143	1.150
	(1.459)	(1.495)	(1.804)	(1.808)	(1.702)	(1.694)
GDP	0.642	0.616	0.673	0.672	0.587	0.561
	(1.072)	(1.093)	(0.564)	(0.565)	(0.609)	(0.610)
Market Index	0.681	0.676	0.578	0.579	0.412	0.423
	(0.486)	(0.481)	(0.347)	(0.351)	(0.263)	(0.261)
Stock Returns		0.002		-0.001		-0.013
		(0.052)		(0.038)		(0.029)
EPS		0.835***		0.106		0.274***
		(0.270)		(0.083)		(0.084)
Observations	5,513	5,513	20,210	20,210	10,332	10,332
Adj. R-squared	0.251	0.252	0.250	0.250	0.211	0.212
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Further Analysis of Heterogeneity of Sub-Industry

This table reports estimations of profitability in columns (1) and (2), and stock returns in columns (3) and (4) at time t on the biodiversity risk estimated at the previous period $t-1$. We set a dummy variable named Trend Quantile, which is equal to 1 for the firms in the fifth quantile (Q5), and 0 for the firms in the first quantile (Q1). We also set a dummy variable named Low risk which is equal to 1 for sectors with GICS 5010 (Communication Services), 5020 (Media and Entertainment), 4510 (Software and Services), and 4530 (Semiconductors and Equipment), and equal to 0 otherwise. We do not include sector fixed effects to avoid collinearity. All the control variables are lagged for one year and reported in Table 1. We do not report intercepts for brevity. Standard errors are clustered at the firm level for the profitability estimation and double clustered at the firm and year level for the stock returns estimation, and reported in parentheses below the estimations. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 1999 to 2021.

	Profitability		Stock Returns	
	(1)	(2)	(3)	(4)
Trend Quantile × Low Risk	-0.595*	-0.589*	-3.601	-3.347
	(0.335)	(0.335)	(5.393)	(5.362)
Trend Quantile	1.364***	1.051***	22.935**	22.849**
	(0.301)	(0.332)	(8.485)	(8.612)
Low Risk	0.574**	0.573**	3.857	3.860
	(0.257)	(0.257)	(4.528)	(4.525)
RoE	0.203***	0.203***	0.167***	0.160***
	(0.007)	(0.007)	(0.035)	(0.036)
Ln(MV)	0.237***	0.239***	-2.114***	-2.196***
	(0.033)	(0.033)	(0.523)	(0.530)
BM	-1.444***	-1.445***	6.015***	5.852***
	(0.117)	(0.117)	(1.308)	(1.292)
CAPEX	-0.130	-0.106	6.809	6.709
	(1.195)	(1.198)	(10.781)	(10.604)
PPE	1.356***	1.340***	-5.022	-5.240
	(0.287)	(0.287)	(4.001)	(3.951)
LEV	-3.945***	-3.931***	-1.655	-1.358
	(0.326)	(0.326)	(2.382)	(2.448)
Atgrowth	-0.012***	-0.013***	-0.003	-0.002
	(0.002)	(0.002)	(0.021)	(0.020)
Inflation Rate		-0.166***	1.248	1.253
		(0.038)	(1.675)	(1.679)
GDP		0.006	0.623	0.615
		(0.020)	(0.581)	(0.585)
Market Index		-0.001	0.521	0.524
		(0.003)	(0.330)	(0.331)
Stock Returns				-0.003
				(0.035)
EPS				0.167**
				(0.072)
Observations	36,056	36,056	36,056	36,056
Adj. R-squared	0.346	0.347	0.232	0.232
Sector FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Table 8: Heterogeneity of Firm Characteristics

In this table, panel A reports summary statistics of mean within sectors. The PPE, the Leverage, and the Asset Growth rate are computed as the ratio of total assets. Panel B reports the interaction term of estimation for profitability in columns (1) - (4) and stock returns in columns (5) - (8). All the control variables are lagged for one year and not reported for brevity. Standard errors are clustered at the firm level for the profitability estimation and double clustered at the firm and year level for the stock returns estimation, and reported in parentheses below the estimations. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 1999 to 2021.

Panel A: Summary Statistics Across Sectors

GICS	Sector	Book Value (Million $)	PPE (%)	Leverage (%)	Asset Growth (%)
1510	Materials	6.030	0.384	0.303	8.906
2010	Capital Goods	5.521	0.226	0.284	7.815
2020	Commercial & Professional Services	3.939	0.211	0.276	9.624
2030	Transportation	5.656	0.493	0.437	8.051
2510	Automobiles & Components	6.978	0.354	0.316	7.772
2520	Consumer Durables & Apparel	5.110	0.238	0.263	7.214
2530	Consumer Services	3.601	0.434	0.348	8.737
2540	Consumer & Media	3.452	0.174	0.302	12.243
2550	Consumer Discretionary Distribution	4.785	0.267	0.320	8.849
3010	Consumer Staples Distribution & Retail	5.060	0.350	0.350	7.259
3020	Food, Beverage & Tobacco	4.769	0.358	0.303	7.929
3030	Household & Personal Products	3.244	0.265	0.233	7.410
3510	Health Care Equipment & Services	3.181	0.223	0.258	13.617
3520	Pharmaceuticals, Biotechnology & Life Sciences	2.857	0.201	0.194	14.971
4510	Software & Services	2.798	0.089	0.168	13.085
4520	Technology Hardware & Equipment	4.513	0.194	0.223	8.957
4530	Semiconductors & Semiconductor Equipment	4.248	0.271	0.229	10.862
5010	Telecommunication Services	3.802	0.343	0.402	11.833
5020	Media & Entertainment	3.540	0.150	0.228	11.543

Panel B: Heterogeneity of Firm Characteristics

	Profitability				Stock Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trend Quantile × BV	-0.310**				-3.677**			
	(0.157)				(1.718)			
BV	-0.137***				-8.867***			
	(0.034)				(1.172)			
Trend Quantile × PPE		0.715***				-0.005		
		(0.174)				(1.242)		
PPE		-11.622***				-70.671***		
		(1.085)				(10.782)		
Trend Quantile × LEV			0.225				-0.449	
			(0.168)				(1.299)	
LEV			-19.134***				-38.868***	
			(0.661)				(6.160)	
Trend Quantile × Atgrowth				1.398***				8.578***
				(0.123)				(2.035)
Atgrowth				0.026***				0.353***
				(0.003)				(0.039)
Trend Quantile	0.909***	22.509***	0.460	25.288**	0.674*	25.150**	0.048	19.268**
	(0.350)	(7.747)	(0.357)	(9.274)	(0.348)	(9.146)	(0.345)	(8.909)
Observations	30,542	30,542	30,542	30,542	30,542	30,542	30,542	30,542
Adj. R-squared	0.366	0.328	0.371	0.239	0.414	0.238	0.378	0.269
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: Two Examples of Biodiversity Evolution

Series of the biodiversity index for selected Countries from 1961 to 2020. The red dashed line presents the fitted value over time.

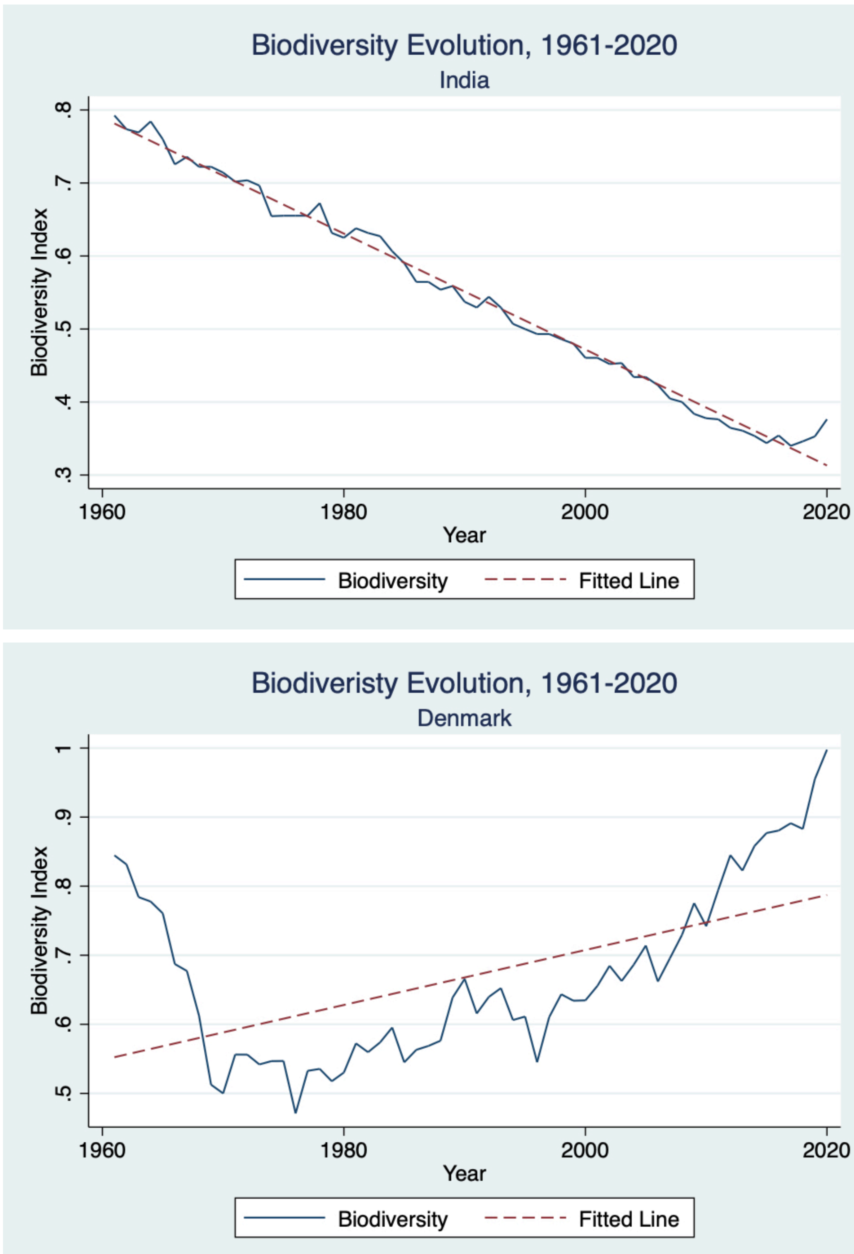


Figure 2: Economic Sector Exposure with Biodiversity Physical Risk

Figure 2 illustrates the ranking of economic sector biodiversity physical risk exposure differences between groups. We refer such exposure to firm-level profitability. We re-estimate Equation (7), controlling for specific sectors while retaining the reset year, country fixed effects, and country- and firm-level controls as before. The profitability discrepancy under specific economic sectors are based on the coefficient of ϑ_1. We sort the economic sector by the coefficient and market out the statistical significant sectors. Note that sectors such as Automobiles & Components, Consumer & Media, and Semiconductors & Semiconductor Equipment are excluded due to limited observations.

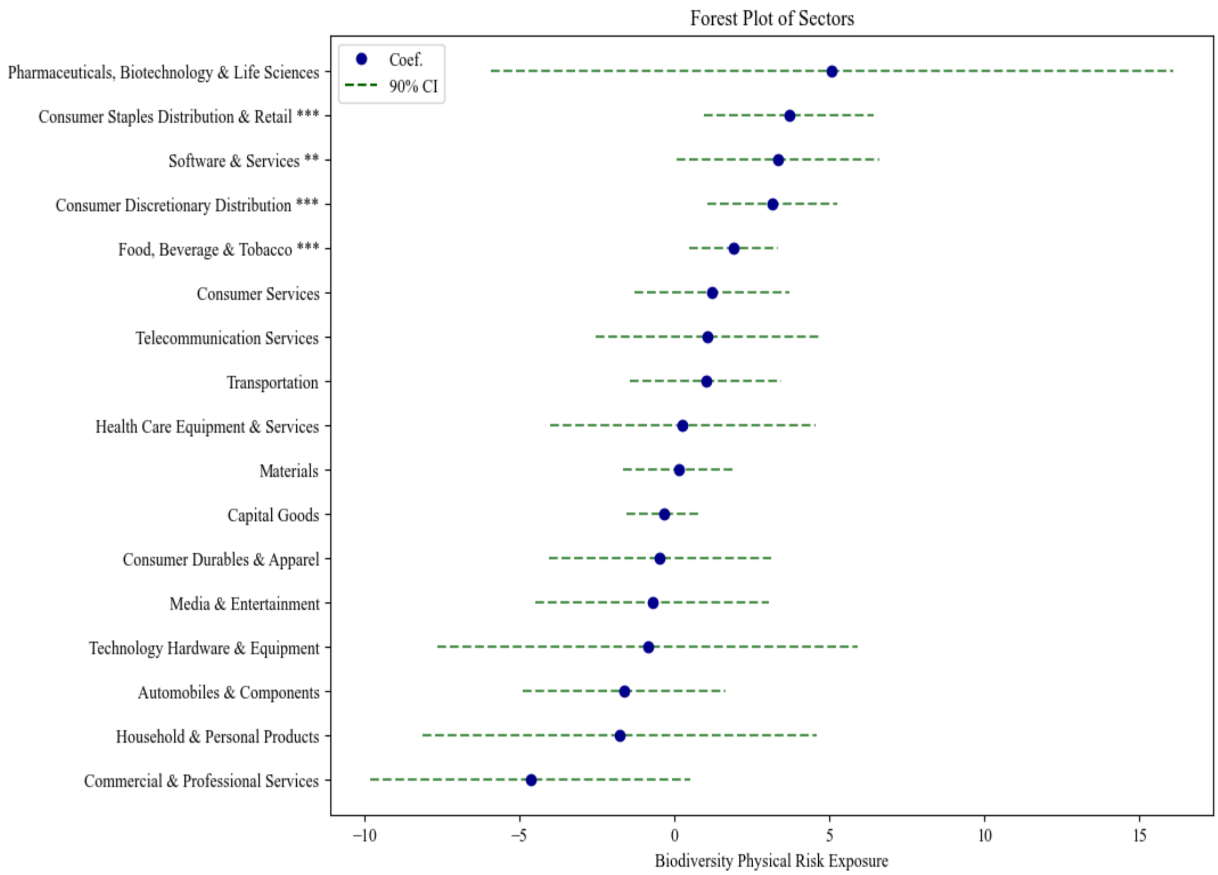
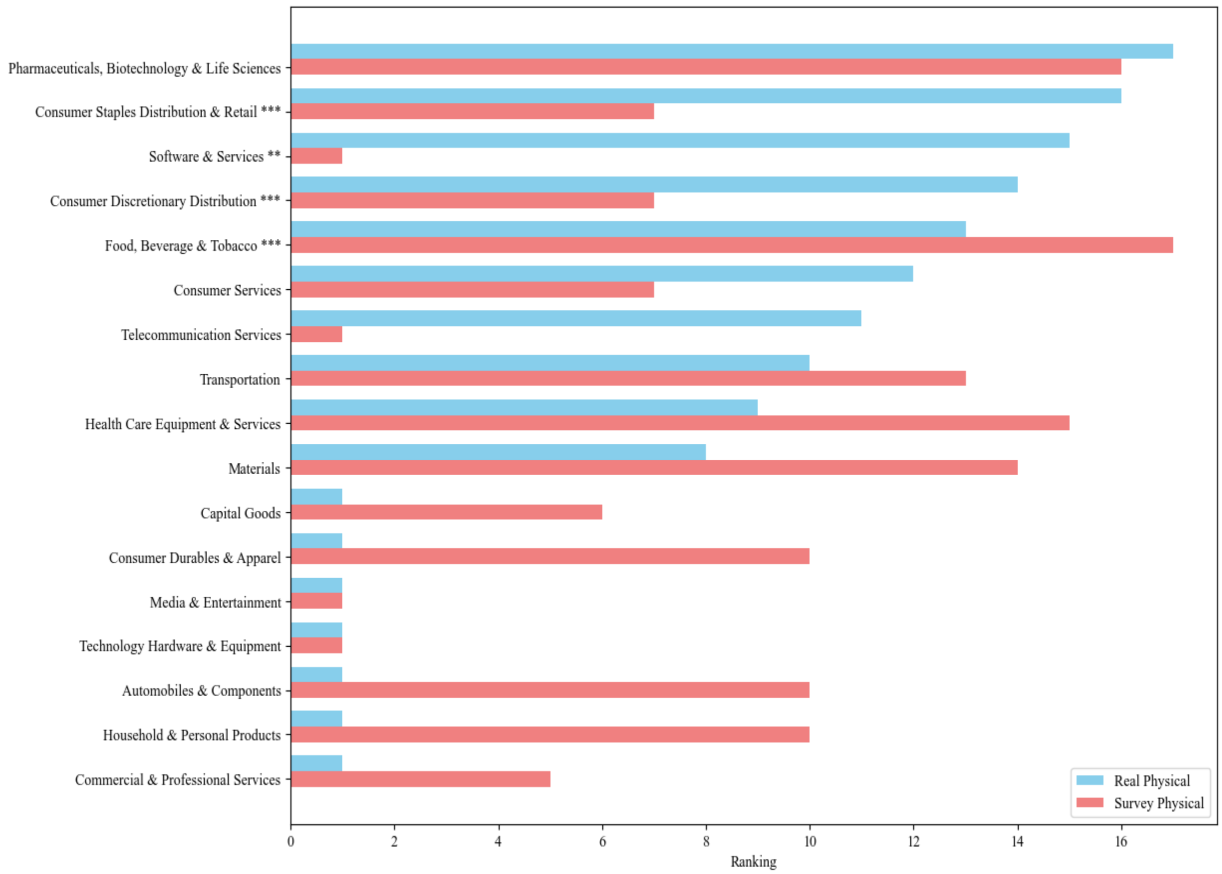


Figure 3: Comparison of Physical Risk Exposure to Giglio et al. (2023)

Figure 3 illustrates



Appendix

A Tables

A.1 Description of Countries

This Appendix reports the average Bio-Footprint and the average Bio-Capacity across countries, between 1999 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	Average Bio-Capacity	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 Description of Variables

Variables	Definitions	Sources
Bio-Capacity per capita	Bio-Capacity (measured in global hectares) divided by the population of the country. Bio-Capacity is the area of biologically productive land and ocean area to provide food, fiber, and timber, accommodate urban infrastructure, and absorb excess CO2. One global hectare is the world's annual amount of biological production for human use and human waste assimilation, per hectare of biologically productive land and fisheries.	Ecological Footprint Initiative
Bio-Footprint per capita	Ecological Footprint (measured in global hectares) divided by the population of the country. The Ecological Footprint measures how much demand human consumption places on the biosphere. One global hectare is the world's annual amount of biological production for human use and human waste assimilation, per hectare of biologically productive land and fisheries.	Ecological Footprint Initiative
Biodiversity Index	Bio-Capacity per capita divided by Ecological Footprint per capita.	Ecological Footprint Initiative
Profitability (%)	Net income divided by total assets, expressed in percentage. Winsorized at the level of 1% and 99%. Annual frequency data.	Compustat
Gross Profitability (%)	Growth profit divided by total assets, expressed in percentage. Winsorized at the level of 1% and 99%. Annual frequency data.	Compustat
Stock Returns (%)	Yearly stock return (12-month holding period). We build daily total return using daily stock prices (prccd), adjustment factors (ajexdi), and total return factors (trfd). We convert our return to USD using the exchange rate (exratd), then we compound daily return to year frequency. Winsorized at the level of 1% and 99%. Annual frequency data.	Compustat and CRSP
RoE (%)	Net Income divided by common equity. Winsorized at the level of 1% and 99%. Annual frequency data.	Compustat
CAPEX	Capital expenditures divided by total assets. Winsorized at the level of 1% and 99%. Annual frequency data.	Compustat

PPE	Net property, plant, and equipment, divided by total assets. Winsorized at the level of 1% and 99%. Annual frequency data.	Compustat
LEV	Total debt divided by the sum of total debt and total equity value. Winsorized at the level of 1% and 99%. Annual frequency data.	Compustat
ln(MV)	Natural logarithm of Market Capitalization. Winsorized at the 1% and 99% levels. Annual frequency data.	Compustat
Atgrowth (%)	Percentage change in total assets. Winsorized at the 1% and 99% levels. Annual frequency data.	Compustat
BM	Ratio of book equity to market capitalization. Winsorized at the 1% and 99% levels. Annual frequency data.	Compustat
Market Index (%)	Total return of equity market index in selected countries. Winsorized at the 1% and 99% levels. Annual frequency data.	Compustat
EPS ($)	Earning per share. Net income divided by total common shares. Winsorized at the 1% and 99% levels. Annual frequency data.	Compustat
Inflation Rate (%)	Inflation rate of consumption. Annual frequency data.	World Bank
GDP (Thousand $)	Gross domestic production per capita. Annual frequency data.	World Bank

A.3 Further Analysis of Stock Returns

This table reports sub-sample estimation of stock returns at time t on different ranges of the biodiversity physical risk exposure. We re-estimate Equation 7, and define the Trend Quantile dummy which is equal to 1 for the firms in the i-th Quantile (Q_i), and 0 for the firms in the rest Quantile ($\cup_{j \neq i} Q_j$) at time $t-1$. *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively. The sample period is from 1999 to 2021.

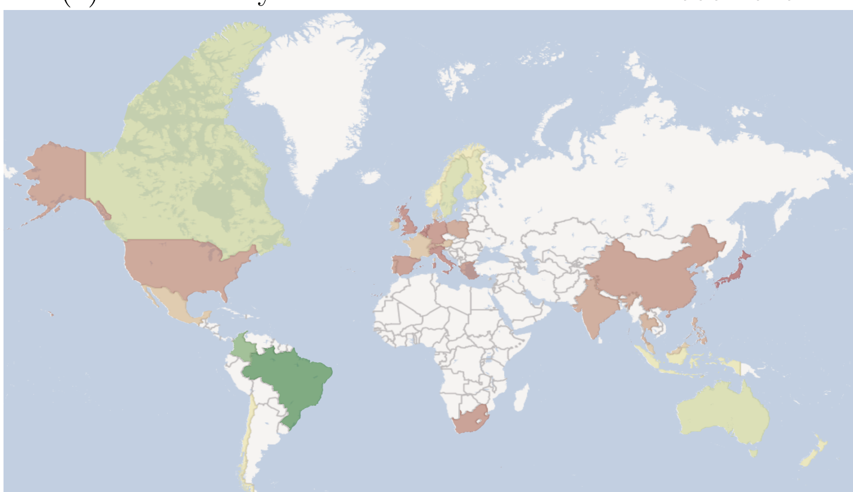
Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
Q_1	-2.282					-2.376
	(3.226)					(3.210)
Q_2		2.437				
		(3.264)				
Q_3			6.780			
			(5.090)			
Q_4				-8.322		
				(5.162)		
Q_5					11.90**	11.92**
					(4.326)	(4.328)
RoE	0.167***	0.167***	0.164***	0.164***	0.167***	0.167***
	(0.0329)	(0.0329)	(0.0312)	(0.0313)	(0.0330)	(0.0330)
Ln(MV)	-1.839***	-1.840***	-1.807***	-1.811***	-1.852***	-1.851***
	(0.314)	(0.314)	(0.320)	(0.316)	(0.313)	(0.313)
BM	5.101***	5.100***	5.034***	5.021***	5.114***	5.113***
	(1.047)	(1.048)	(1.028)	(1.030)	(1.051)	(1.051)
CAPEX	17.57	17.60	17.13	17.12	17.47	17.55
	(14.51)	(14.47)	(14.16)	(14.21)	(14.54)	(14.52)
PPE	-6.628*	-6.631*	-6.698*	-6.820*	-6.740*	-6.761*
	(3.279)	(3.272)	(3.279)	(3.294)	(3.303)	(3.295)
LEV	3.428	3.423	3.511	3.566*	3.505	3.503
	(2.033)	(2.036)	(2.037)	(2.041)	(2.034)	(2.035)
Atgrowth	0.00496	0.00502	0.00239	0.00174	0.00456	0.00454
	(0.0320)	(0.0321)	(0.0325)	(0.0327)	(0.0320)	(0.0320)
Inflation Rate	1.678	1.673	1.313	1.258	1.724	1.740
	(1.388)	(1.388)	(1.309)	(1.329)	(1.410)	(1.409)
GDP	0.201	0.204	0.234	0.308	0.277	0.282
	(0.470)	(0.470)	(0.432)	(0.427)	(0.476)	(0.473)
Market Index	0.0744	0.0742	0.0481	0.0379	0.0695	0.0692
	(0.192)	(0.192)	(0.199)	(0.201)	(0.194)	(0.194)
Stock Returns	-0.0182	-0.0183	-0.0182	-0.0182	-0.0180	-0.0181
	(0.0297)	(0.0296)	(0.0292)	(0.0291)	(0.0297)	(0.0297)
EPS	0.168**	0.168**	0.175***	0.175***	0.167**	0.167**
	(0.0596)	(0.0596)	(0.0570)	(0.0572)	(0.0599)	(0.0598)
Observations	106,601	106,601	106,601	106,601	106,601	106,601
Adj. R-squared	0.173	0.173	0.174	0.175	0.174	0.174
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

B Figure

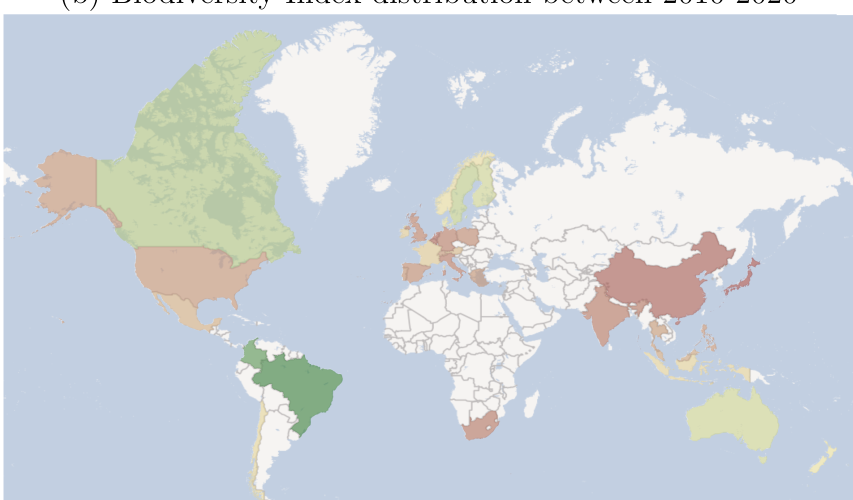
B.1 Spatial Distribution of Biodiversity Index

The heat maps display the 30-year rolling estimated 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



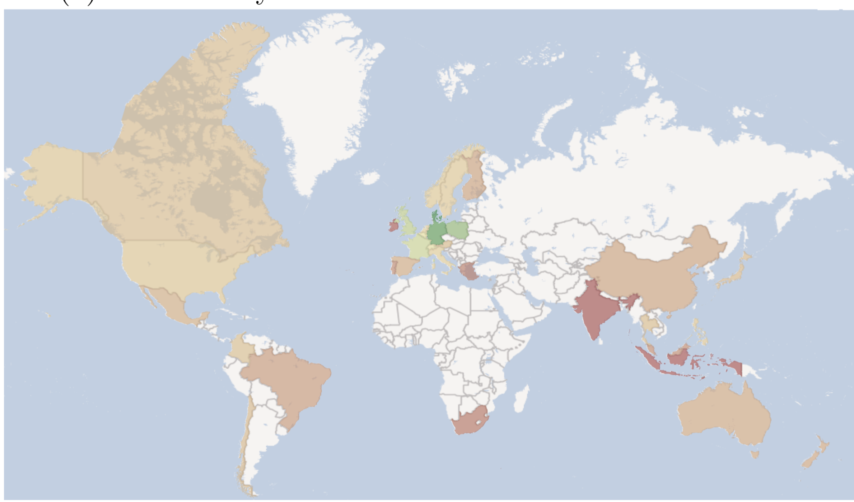
(b) Biodiversity Index distribution between 2010-2020



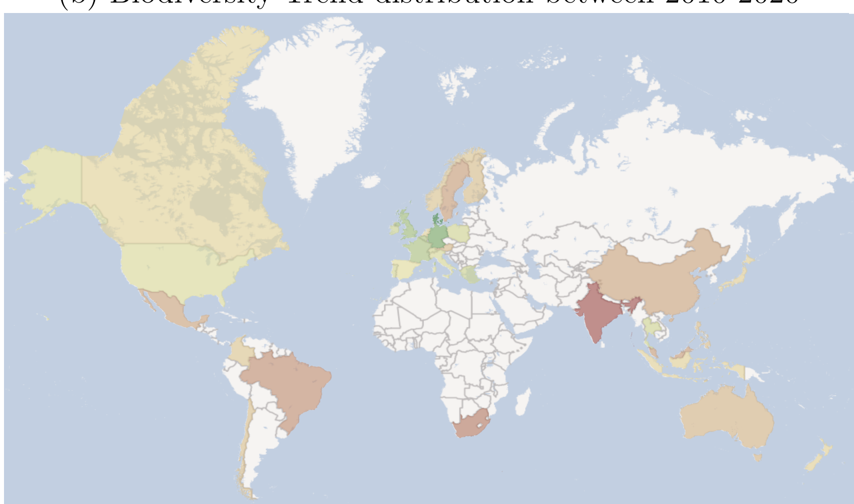
B.2 Spatial Distribution of Biodiversity Trend

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



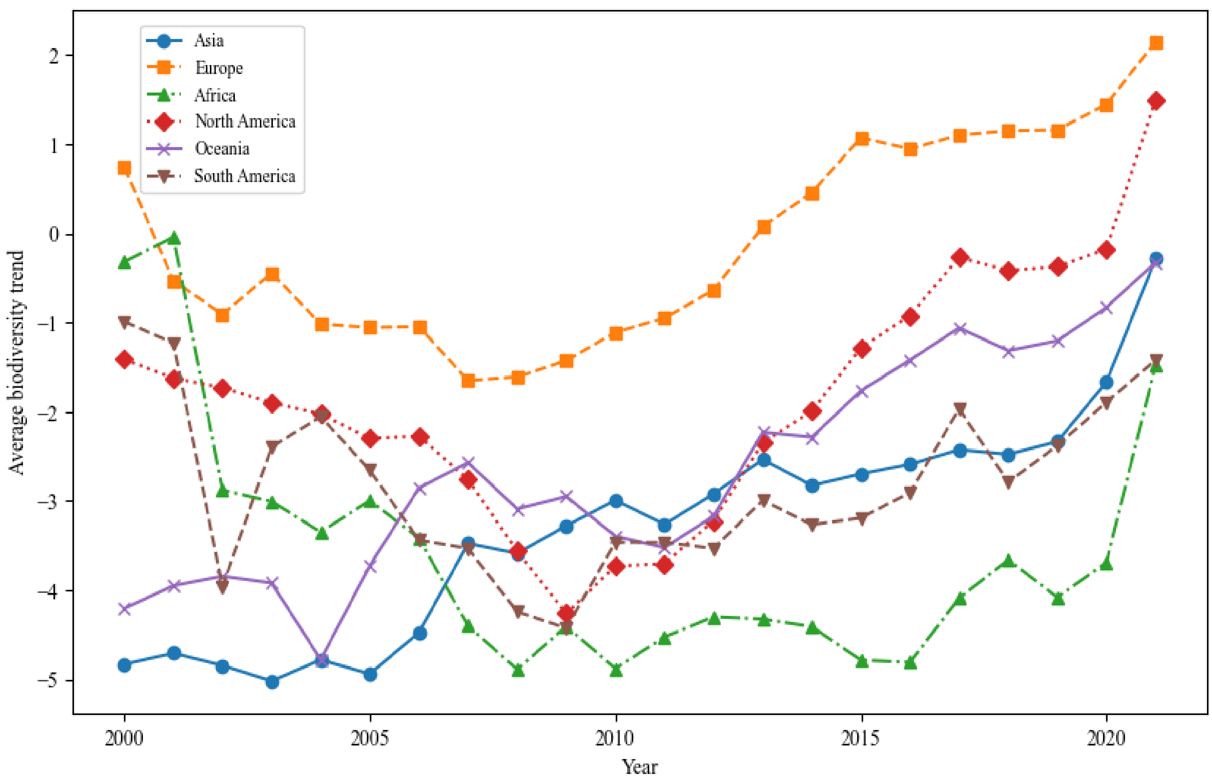
(b) Biodiversity Trend distribution between 2010-2020



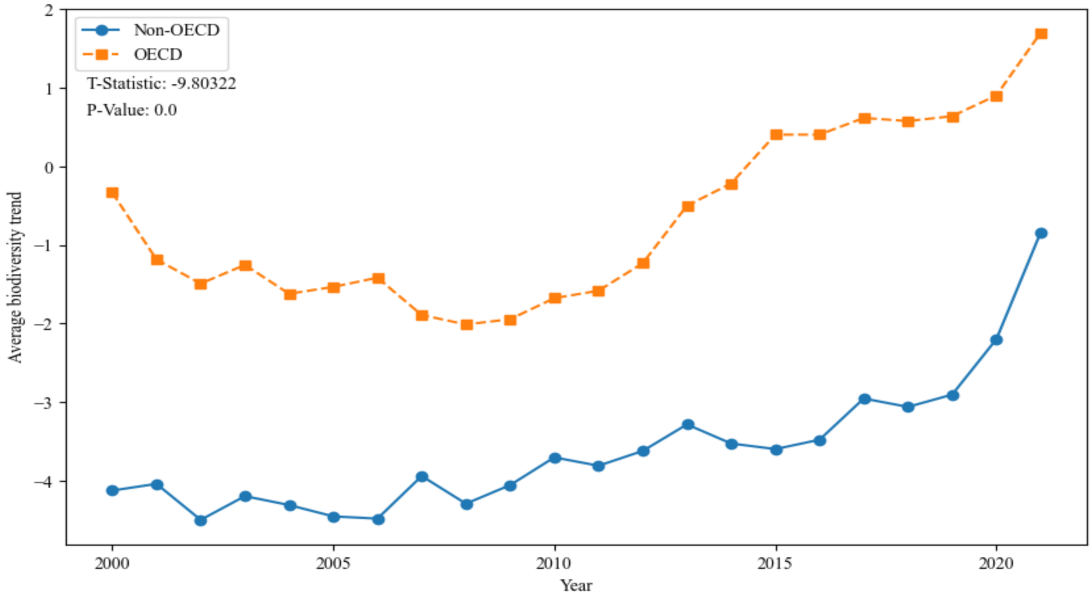
B.3 Biodiversity Trend Comparison

Figure B.3 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, observing statistically significant differences between OECD and non-OECD countries. 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