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Does public attention to biodiversity matter to stock markets?

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Abstract: Biodiversity has become an important issue in recent years, attracting great public attention. Arguably, biodiversity risk can be treated as a risk factor that should be priced in stock markets. To examine this issue, this paper begins by constructing a biodiversity attention index (BAI) based on information provided by the Baidu search engine and then examines its impact on the returns of listed firms in China. Specifically, the BAI is added to a capital asset pricing model as an additional pricing factor, and then the model is used to analyse individual stock returns. By summarising the results from a bottom-up perspective, we find that BAI can affect stock returns to a certain extent and that the impacts are highly heterogeneous across sectors. The pricing power of the BAI increases over time, with a growing number of companies affected. Further investigation shows that younger, larger firms and firms with better financial or environmental performance tend to be less sensitive to the BAI. Overall, this study provides important evidence to understand biodiversity–finance linkages and further highlights the need to incorporate into financial practices public attention towards environmental issues.

Keywords: Biodiversity; Public attention; Risk factors; Stock returns.

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1. **Introduction**

Amid the growing attention on global warming, the need to protect biodiversity is increasingly being discussed. Human activities have had a significant impact on ecological systems across the globe (Fuller et al., 2017). Data from the *Living Planet Report* (Almond et al., 2020) show an average 68% drop in the population in various animal species since 1970, mainly due to habitat destruction and the changing climate. Not only can biodiversity losses have a direct impact on our ecosystem, but they can also lead to greater uncertainty for human society (Cardinale et al., 2012). For example, the Global Risk Perception Survey reported by the World Economic Forum (WEF, 2023) lists loss of biodiversity as the fourth greatest global risk in the long term.

In addition to the growing interest in biodiversity from society in general, investors have started to pay attention to it. Corporate environmental, social and governance (ESG) factors are popular concerns among value investors, and ESG performance is generally believed to affect corporate performance (Guo et al., 2024). While the biodiversity impact or ecological consequences of corporate operations are within the scope of the ESG system, the biodiversity factor has become a separate matter that has attracted greater attention in recent years (Starks, 2023). Based on a survey of the relevant literature, Nedopil (2023) highlights the importance of integrating biodiversity into financial decision-making and lists four principles to guide actual practices.

Academic research has recently highlighted the importance of the relationship between biodiversity and finance. For example, Karolyi and Tobin-de la Puente (2023) call for more attention to be paid to the field of biodiversity finance. They find almost no relevant research in top-tier finance journals and argue that comprehensive biodiversity-related data and measurements are needed. To fill in this gap, Giglio et al. (2023) use textual analysis and surveys to construct biodiversity risk factors. Their empirical research showed that biodiversity risks have already been incorporated into stock prices. Garel et al. (2023) find different results, reporting that the biodiversity footprints of companies do not have significant impacts on stock returns. They show, however, that policy shocks over biodiversity (i.e. the Kunming Declaration and the Montreal Agreement, both part of COP15) have led to investors paying greater attention to biodiversity. Nonetheless, attention to biodiversity has become more evident, and further investigation into its relationship with financial markets is urgently needed.

The relevance of biodiversity to financial markets arises from two main aspects. On the one hand, financial markets value corporate ecological footprints and reward companies with better performance, and evidently, a wave of biodiversity funds has emerged in these markets[1]. On the other hand, uncertainty over biodiversity losses and policies to protect biodiversity have made biodiversity a risk factor in financial markets, affecting stock returns (Bassen et al., 2024). For example, biodiversity losses can affect the supply of raw materials for certain industries, such as agriculture, forestry, animal husbandry and fisheries (WEF, 2020), which can affect the performance of firms in these areas. Stricter policies have also been adopted by national governments to protect natural habitats and ecosystems[2]. Of course, the shocks are not limited to these industries, as the risks can spread across markets. In general, these direct and indirect sources of uncertainty will inevitably be reflected in stock market performance, although great heterogeneity is expected.

Evidence of biodiversity–finance relationships at the international level remains limited, and more efforts are needed to build a clear framework. This paper follows recent research and pays special attention to the issue in China, a country that has greater—or perhaps the greatest—relevance to biodiversity than other countries in the world (Lu et al., 2020; Mi et al., 2021). China has experienced fast economic growth in recent decades, making it the world's second-largest economic power, but this has come at a cost of environmental degradation and significant biodiversity losses (Liang and Zhuang, 2024). The country has prioritised

[1]Biodiversity funds are springing up in the investor market, https://www.ft.com/video/abdb0541-104a-45e9-9551-5e43854c717d
[2] See 'Classification Catalogue for Environmental Impact Assessment of Construction Projects (2021 Version)', https://www.mee.gov.cn/xxgk2018/xxgk/xxgk02/202012/t20201202_811053.html

environmental and ecological protection since 2012. Various measures, regulations and laws have been adopted to protect biodiversity. *Opinions on Further Strengthening Biodiversity Conservation* was published in 2021 to affirm China's commitment to protecting biodiversity. China also hosted the UN Biodiversity Conference (COP15) and played a crucial role in promoting the passage of the Kunming–Montreal Global Biodiversity Framework, a monumental document to establish a roadmap for protecting biodiversity at the global level. With China's increasing efforts to promote ecological conservation and improve biodiversity, the public has started to pay more attention to the health of the ecosystem, raising awareness of biodiversity conservation (Liang and Zhuang, 2024). Consequently, investors may take biodiversity into consideration when making investment decisions, thereby affecting stock market performance.

To test this hypothesis and explore the empirical patterns of the biodiversity–finance relationship in China, this paper adopts a simple research strategy. First, public attention is proxied through internet search volume (see also Da et al., 2015; Choi et al., 2020). This way of measuring public attention has been widely used to quantitatively capture investor sentiment or attention (e.g. Ackert et al., 2016; Fang et al., 2020). Here, the Baidu Search Index is used, since Baidu is the main search engine used in China. Second, a bottom-up approach is used to examine the biodiversity–stock relationship. Individual stock returns are used in a capital asset pricing model (CAPM) model extended by including an index of public attention to biodiversity, the biodiversity attention index (BAI). The benefit of using the bottom-up approach is that it allows great flexibility in summarising results (Broadstock et al., 2016). Third, we explore both static and dynamic relationships between the BAI and individual stock returns. In general, the hypothesis is that the BAI–stock relationship should have become stronger as more investors have started to incorporate environmental and ecological factors into their investment decisions. More stocks are expected to be affected by the BAI.

The empirical study covers a sample period from 2011 to 2023. In general, our empirical results, based on the extended CAPM model, identify 764 companies with significant linkages to biodiversity, representing 15.75% of the entire sample companies. This percentage may seem to be smaller than expected, but in the subsamples separated by the passage of the Paris Agreement in 2015, the proportion of significant companies increased from 5.13% to 17.68% before and after 2015, respectively, indicating the increasing role of the BAI in stock markets. Dynamic analysis using rolling-window regressions further confirms a trend in which the percentage of firms affected by BAI increases over time. By summarising the results across industries, the BAI impacts on stock returns demonstrate clear sectoral heterogeneity, where the agriculture, forestry, animal husbandry and fishery (AFF) sector leads all others in responding to biodiversity shocks.

A series of additional analyses are performed to explore the characteristics of the above-mentioned relationship. For example, to control for possible delayed attention to certain biodiversity-related events, lagged terms of the BAI are included in the basic model. Following Ji et al. (2022), a 10-day lag is included. In general, the percentage of significantly affected firms increases with additional lags included.

Further to the confirmation of the biodiversity–finance relationship above, it is also important to understand what kind of firms are more sensitive to the BAI index. In other words, we would like to further explore which firm-level characteristics are associated with firms' sensitivity to biodiversity attention. Here, we use a Fama–MacBeth (1973)-type strategy to explore this. Estimated coefficients based on time series regressions are used to perform the second-stage regression to examine the explanatory power of a set of firm-level characteristics. Two sets of regressions are used: one on which firms are likely to be sensitive to biodiversity attention and the other to explore which factors affect those sensitive firms more. Whereas the first regressions are binary and on the full sample, the second apply only to firms with a significant relationship with biodiversity attention. As for the variables of interest, we include a set of firm-level characteristics, such as age, size, capital structure, and financial performance. In addition, ESG-related measures are included because they are related to biodiversity in nature. The regression results show that firms with higher ESG scores, especially E-scores, tend to have low sensitivity to biodiversity attention. In other words, firms with better environmental performance are less likely to be affected by biodiversity attention.

This paper contributes to the emerging literature on the biodiversity–finance relationship, providing useful information in support of the existence of such a relationship in China. Biodiversity has attracted widespread attention, and this attention from the public can affect stock market performance, confirming that it can have practical meaning for investors. Another important contribution is the use of the bottom-up approach, which allows us to identify sectors that are more sensitive to biodiversity than others. In addition, the firm-level regression analysis enables us to find what kind of firms are more likely to be affected by the BAI.

The rest of the paper is organised as follows. Section 2 reviews the relevant literature. The research design, data and descriptive statistics are given in Sections 3 and 4. Section 5 reports and discusses the empirical results. The final section concludes.

2. Literature review

According to the traditional wisdom of the efficient market hypothesis (EMH), price can quickly and accurately reflect information, leaving no room for persistent excess returns. However, many investors, especially retail investors, are often unable to acquire information and thus trade on noise (De Long et al., 1990). To explain this, behavioural finance theories have been developed and suggest that investor sentiment matters to stock returns (Barberis et al., 1998; Baker and Wurgler, 2007). These theories have been used to explain the empirical anomalies found in testing the CAPM model or the EMH (Stambaugh et al., 2012). Noise traders do not necessarily seek the fundamentals of a firm when forming strategies; instead, they tend to follow news media, which affects stock returns. For example, Tetlock (2007) shows that the media and stock markets interact. Similarly, Broadstock and Zhang (2019) identify significant relationships between social media and stock returns. Following this line of research, we can argue that investors' attention to certain events (e.g. climate change or biodiversity) can effectively affect their investment decisions, which are then reflected in stock returns.

In the extensive empirical literature linking public attention and stock returns (e.g., Klemola et al., 2016; Yang et al., 2021), some recent studies have begun to pay attention to environmental issues. For example, El Ouadghiri et al. (2021) examine public attention towards climate change and stock returns, finding that attention towards climate change and pollution can have a significant impact on US stock indices; in particular, a positive effect was found on sustainability stock indices, and the opposite was found on conventional stock indices. Schuster et al. (2023) show that stocks with better environmental performance tend to outperform when public attention is high. Regarding issues in China, Chen et al. (2022) find a positive relationship between climate attention and stock market downside risks.

Despite the large volume of work in this line of research, one of the major challenges is how to measure public attention quantitatively. One option is to explore the news media. For example, Broadstock and Zhang (2019) use textual analysis based on Twitter; Engle et al. (2020) use news media data as a proxy for public attention, finding that industry-balanced portfolios perform well in hedging climate news; and Santi (2023) takes social network data as a proxy for investor climate sentiment, finding that higher investor climate sentiment is associated with lower returns for the emission-minus-clean portfolio. Another option is to use search volume information from major search engines, such as Google Trends (Choi et al., 2020) or the Baidu Search Index for China (e.g. Da et al., 2015; Chen, 2017; Chen et al., 2022). Ji et al. (2023) adopt Baidu search volume to form a climate risk perception index in China. They also use a bottom-up approach to show that climate shocks have a significant asymmetric effect on stock returns and that the effect has been increasing over time.

Relative to climate change, which has long been discussed and has attracted greater public attention for some time, attention to biodiversity has risen only in recent years. As discussed earlier, there is a limited number of studies on biodiversity–finance linkages (Karolyi and Tobin-de la Puente, 2023). Flammer et al. (2023) introduce a conceptual framework outlining the potential of private capital and blended capital in promoting biodiversity conservation. They explore the ‘monetization’ of biodiversity, which refers to the extent to which investments in biodiversity can yield financial gains for private investors.

Regarding the pricing power of biodiversity, Giglio et al. (2023) apply textual analysis and questionnaire surveys to assess biodiversity risks at both the corporate and industry levels. They discover that biodiversity risks exhibit sectoral heterogeneity, with the energy, utilities and real estate industries having higher biodiversity risks, while firms in the software and communications sectors have lower biodiversity risks. They further explore the pricing power of biodiversity risks in financial markets and argue that such risks have already been reflected in asset pricing. By constructing portfolios with a long position in low-biodiversity risk assets and short positions in high-biodiversity risk assets, they find a positive correlation between the asset portfolio and the biodiversity risk index. Garel et al. (2023), on the other hand, obtain different results. They calculate the biodiversity losses caused by the activities of each company (measured by mean species abundance) and construct an indicator—the corporate biodiversity footprint—to measure the level of biodiversity exposure for each company. Their study shows that, on average, the biodiversity footprint does not significantly affect stock returns, even after considering differences across countries, regions and industries. Nevertheless, by analysing the impacts of two recent biodiversity policy shocks, the Kunming Declaration and the Montreal Agreement (both part of COP15), they find that investors have started to price biodiversity in stock markets.

Overall, the development of the literature has clearly pointed to the need to explore the biodiversity–finance relationship. This direction of research has distinctive features that are worthy of investigation separate from the literature related to the climate–finance relationship or to ESG-relevant issues. Biodiversity risks can have unique impacts on financial markets, especially in certain sectors, such as agriculture and fisheries. Growing public attention since the Paris Agreements and the Kunming Declaration has further created support for potential linkages between biodiversity and stock prices, making the current research an important addition to the literature.

3 Research design

The main technical approaches used here are similar to those of Ji et al. (2022), who explore the relationship between climate change attention and stock returns. Given the bottom-up approach in our research design, the first step is to construct a time series regression model for each individual stock. Starting from a very simple regression model connecting stock returns and the biodiversity attention measure, the baseline model is set as follows:

$$\text{Model I: } R_{it} = \alpha_i + \beta_i BAI_t + \varepsilon_{it}, \tag{1}$$

where R_{it} represents the stock return of company i in period t and BAI_t is the biodiversity attention index defined above. The coefficient of interest is β_i, and a statistically significant β_i means that the stock investigated is sensitive to biodiversity attention, and the higher the value, the more sensitive this stock is to the BAI. In addition to the baseline model, we also include the market return in the regression, or an extended market model (Equation 3). Equation 4 can be called an extended CAPM model, where R_{Ft} denotes the risk-free rate of return at time t. Finally, as argued by Ji et al. (2022), stock returns may have lagged responses to biodiversity attention, especially considering that daily data are used. To address this concern, we choose a lag period of 10 days in Equation 5. In all regressions, seasonable dummies are included to control for the possible seasonal effect.

$$\text{Model II: } R_{it} = \alpha_i + \beta_i BAI_t + \delta_i R_{Mt} + \varepsilon_{it} \tag{2}$$

$$\text{Model III: } R_{it} - R_{Ft} = \alpha_i + \beta_i BAI_t + \delta_i (R_{Mt} - R_{Ft}) + \varepsilon_{it} \tag{3}$$

$$\text{Model IV: } R_{it} - R_{Ft} = \alpha_i + \sum_{j=0}^{10} \beta_{ij} BAI_{t-j} + \delta_i (R_{Mt} - R_{Ft}) + \varepsilon_{it} \tag{4}$$

From the graphic illustration of the Baidu search volumes, we can easily point out an increasing trend, especially after 2015, when the Paris Agreement was signed. More attention and search volumes can be seen in the later stages of the sample period. To explore the potential changes in public attention and examine the possible time-varying relationship, we take two approaches: the first is to divide the sample into two subsamples (before and after 2015) and the second is to use a rolling-windows approach and allow biodiversity sensitivity to change over time. Here, we set the window size to 22 days, the number of working days in a month.

Finally, we perform a Fama–MacBeth (1973) type of regression analysis, followed by the results found in Equation (4)[3]. The first stage is to run time series regressions of Model III using data from each year. From the regression results, two variables are constructed. One dummy variable captures whether or not a firm is affected by biodiversity attention—denoted as BAD and equal to 1 if a stock return has a significant link (β_{it}) with the BAI and 0 otherwise. The other variable is the absolute value of the estimated $|\beta_{it}|$, representing how sensitive a firm's stock return is to the BAI, and this variable is defined as biodiversity attention sensitivity (BAS). Given that the number of this coefficient is generally small, we multiply β_{it} by 1000 as the BAS used in the second-stage regressions.

As the dependent variable for the first set of regressions is binary, the probit model is used to analyse which firm-level characteristics are more likely to lead firms to have significant links to the BAI. The model is standard and can be written as follows:

$$Prob(BAD_{it} = 1|\boldsymbol{X}_{it}) = F(\alpha_i + \boldsymbol{\Phi}_i\boldsymbol{X}_{it} + \eta_i + \theta_t + \mu_{it}), \tag{5}$$

where $Prob(BAD_{it} = 1|\boldsymbol{X}_{it})$ is the conditional probability of whether firm *i* has a significant coefficient in year *t* after controlling $\boldsymbol{X}_{it}$. $\boldsymbol{X}_{it}$ is a vector of firm-level explanatory variables. η_i represents industry fixed effects, and θ_t represents year fixed effects. F(•) is the cumulative distribution function of the normal distribution.

For the second type of regression, firms with insignificant β_{it} are assigned to BAS = 0, and thus the dependent variable is truncated. We are interested in the question of which types of firms have a stronger link with the BAI; thus, the Tobit model is applied as follows:

[3] The extended CAPM model is used as the benchmark model for all the following analysis. We did check other model specifications, and the results are not reported due to space constraints.

$$BAS_{it} = \alpha_i + \boldsymbol{\Phi}_i \boldsymbol{X}_{it} + \eta_i + \theta_t + \mu_{it}, \tag{6}$$

$$BAS_{it} = |\beta_{it} \times 1000| \times \mathrm{I}(BAD_{it} = 1),$$

where I(•) is the indicator function that equals one when a firm has a significant relationship with the BAI and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of firm-level explanatory variables. η_i represents industry fixed effects, and θ_t represents year fixed effects.

4 Data and descriptive statistics

4.1 Biodiversity attention index

Quantitatively measuring public attention to biodiversity is the first and most important aspect of this research, although achieving a direct measure is difficult. Between the two popular approaches, namely new media and internet search, we follow Da et al. (2015) and Ji et al. (2023) to use the second method to proxy for public attention to biodiversity. Both papers used Baidu search volume as an indicator of public attention. Relative to news media, internet search represents more active attention. In other words, people actively search for biodiversity-related information on the internet. Such active information acquisition is more likely to lead to actual investment behaviour (Loibl and Hira, 2009).

The second task here is to choose the right keywords to obtain the search volume from Baidu. Giglio et al. (2023) construct a biodiversity dictionary, which is used here. In practice, they derived the dictionary through cosine similarity to 'biodiversity' in Google's Word2vec implementation. These keywords are translated into Chinese and then used to construct the biodiversity search index. Keywords that are not included in Baidu or that do not have sufficient search volume are eliminated. Overall, 16 keywords remain, and the associated search volumes are used to construct the BAI. These keywords include biodiversity, ecosystem, ecology, habitat, rainforest, forest, marine, freshwater, wetland, wild animals, coral, aquatic fauna, aquatic flora, desertification, carbon sink and biosphere.

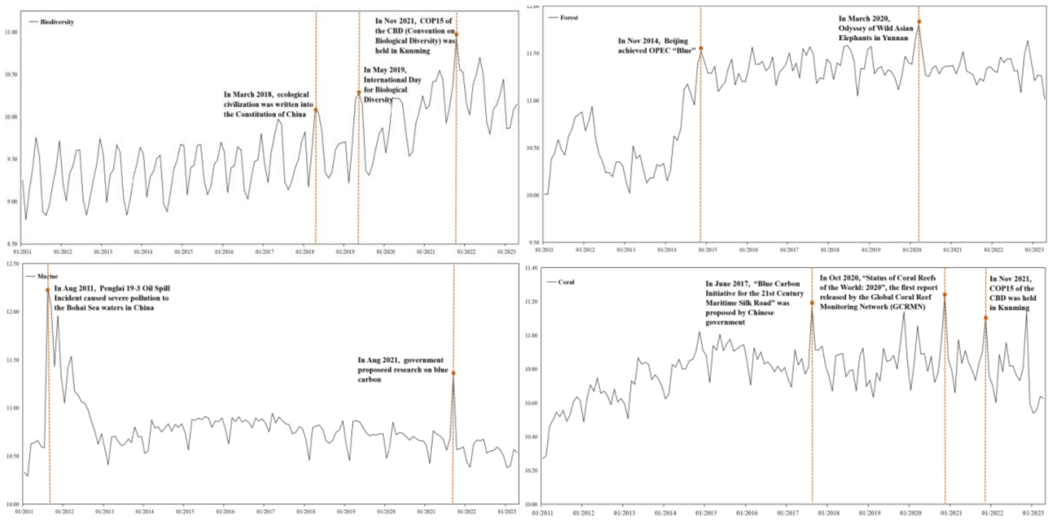


Figure 1. Search volumes (in log-terms) of the top three keywords and 'biodiversity'.

Since the earliest data for the Baidu search index are from January 1, 2011, our sample period starts from January 1, 2011, to April 28, 2023, and is in daily frequency. Among the 16 keywords, marine, forest and coral are the three most searched items. The search volumes of these three keywords, together with the search volume of biodiversity', are plotted in Figure 1. Note that the figures here are based on the logarithm of the monthly aggregation of the search volumes. Doing so makes the trend smooth and thus enables us to gain a clear picture of the time-varying patterns.

A few spikes are marked in the figure, and their timing is associated with several landmark events, such as the biodiversity conference in Kunming (COP15) and the International Day for Biological Diversity. These major events tend to trigger great public interest and lead to higher search volumes. Note that the public interest in 'marine' has been flat, but the spikes are closely related to major events. One obvious pattern is that the search volumes of the other keywords have generally increased over time. Although these keywords are closely related to biodiversity, the public in China have started to raise their interest in 'biodiversity' in recent years.

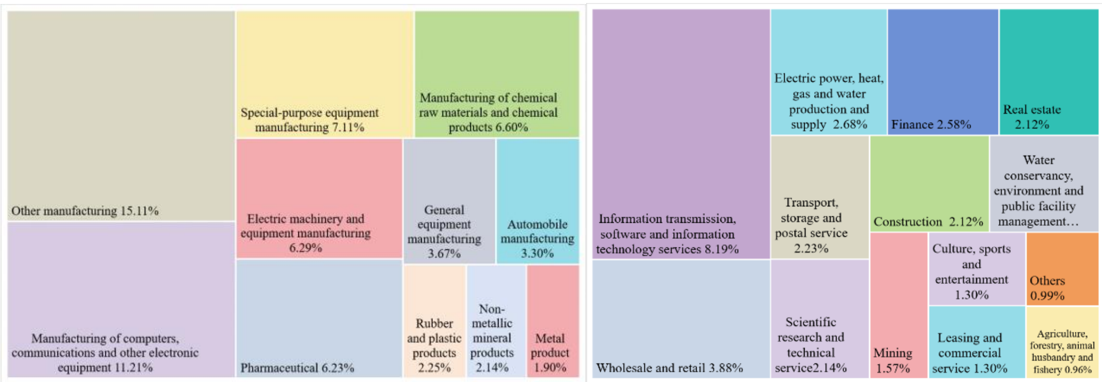
Given that the search volumes are generally non-stationary and contain trends, they are not fit for entering regressions later. Here, we follow Da et al. (2015) to take first-order difference to each $SV_{j,t}$ and then sum the differences to construct the BAI. This can be written as the following equation:

$$BAI_t = \sum_{j=1}^{16}\{ln(SV_{j,t}) - ln(SV_{j,t-1})\}, \tag{7}$$

where $SV_{j,t}$ is the search volume index for keyword j.

4.2 Stock returns data

In line with the BAI samples, daily stock returns also cover the same period, from January 1, 2011, to April 28, 2023, including only trading days. Stocks listed on the China A-share market before 2023 are all considered, resulting in a sample of 4849 listed companies. ST firms are excluded from the sample, as usual. Firms with limited observations during the sample period are also excluded. The data on stock returns and market returns are collected from the China Stock Market and Accounting Research (CSMAR) database, while the risk-free rate was collected from the RESSET financial database.



(a) Manufacturing sectors *(b) Other sectors*

Figure 2. Sample distribution across sectors.

When sectoral heterogeneity is considered, industrial classification is used, which is based on the 'Guidelines for Industry Classification of Listed Companies' (2012 Revision) published by the China Securities Regulatory Commission (CSRC). All listed firms are categorised into sectors classified by CSRC. The sample distribution of firms across different industries is shown in Figure 2. Panel (a) is for the manufacturing sector. Note that manufacturing firms have the largest sample size, accounting for 65.81% of the overall sample firms, which may also feature within-sector differences. To take care of this concern, all manufacturing firms are further disaggregated into sub-categories. Panel (b) is for all other sectors. The leading sector is information transmission, software and information technology services (ISI), with a share of 8.19% of the overall sample. The smallest sector is AFF, with a share of 0.96% of the overall sample, or 47 firms altogether. Together, the number of firms in Panel (b) encompasses 34.19% of the overall sample. The detailed title and associated abbreviations are given in Appendix Table A2.

4.3 Firm-level data

To understand which types of firms are more likely to be affected by public biodiversity attention and which types are more sensitive to biodiversity concerns, we need to explore firm-level information, which will be used in the second-stage regression analysis. In addition to the typical firm characteristics, such as size, age, capital structure and financial performance (e.g. return on assets, or ROA), we would also like to consider firms' environmental performance as an extra source of possible explanatory power to their sensitivity to biodiversity attention. The logic behind this is that recent research has incorporated biodiversity into the ESG framework. For example, Kopnina et al. (2024) explored how this framework can be useful in addressing biodiversity issues. Although the ESG framework, in a broader sense, should contain biodiversity impacts, its relationship with biodiversity attention is not entirely clear. Two possible linkages may exist. First, better ESG performance, especially environmental performance, makes firms less sensitive to biodiversity attention, as it is already incorporated, and second, firms with better ESG performance can benefit from biodiversity attention in financial markets.

The data used to examine the above-mentioned questions were sourced from the Chinese Research Data Services Platform (CNRDS) and the CSMAR. Both the aggregate ESG scores and the scores of each individual pillar are used. The data cover the period from 2011 to 2022 in annual frequency. Two new variables that capture firm-level biodiversity and attention sensitivity, BAD and BAS, are defined in section 3. All variables are winsorised at the 1% and 99% percentiles. The descriptive statistics are given in Table 1.

Table 1. Firm-level descriptive statistics

Variable	N	Mean	Median	SD	P25	P75
BAD	28137	0.082	0.000	0.274	0	0
BAS	28137	0.383	0.000	1.430	0	0
ESG Score	28137	27.132	24.603	10.966	19.408	32.922
E Score	28137	16.09	8.803	17.704	2.87	22.269
S Score	28137	25.198	24.232	11.825	16.704	32.486
G Score	28137	24.501	23.221	10.551	16.817	30.89
Age	28137	1.972	2.079	.948	1.386	2.773
Size	28137	22.383	22.102	1.465	21.344	23.112
Capital structure	28137	0.408	0.397	0.205	0.242	0.554
ROA	28137	0.062	0.055	0.051	0.031	0.087

Note: BAD is the dummy variable equaling to 1 when a firm has significant relationship with BAI and zero otherwise. It is constructed at the annual level to match the firm-level sample frequency. BAS is sensitivity to biodiversity attention, equaling to the absolute value of coefficient β_{it} *when a firm has significant relationship with BAI, and zero otherwise. The number is small, so the original number is multiplied by 1000. Please refer to section 3 for how to construct this variable.*

5 Empirical results

This section reports the empirical results, from the full sample analysis to the sectoral analysis, the subsample and the time-varying analysis, and then we attempt to understand what characteristics affect firms' sensitivity to biodiversity attention. In general, the questions we aim to answer are as follows. Are firms affected by biodiversity attention, and if so, how many? Do we expect to see more firms sensitive to biodiversity attention after the Paris Agreements or in more recent years? What sectors are more likely to be affected by biodiversity attention? What types of firms are more likely to be affected by biodiversity attention, or what type of firm-level characteristics make firms more sensitive to biodiversity attention?

5.1 Are firms affected by biodiversity attention?

For the first question, the returns of each firm in the full sample are examined with Models I – IV. Not all firms are expected to be affected by biodiversity attention, but the bottom-up approach allows us to summarise the number of significant firms or the shares of significant firms, which are then useful for understanding the general status of biodiversity–stock return links in China.

Starting with the simplest model (Model I), which directly links stock returns with the BAI, stocks with significant β_i (at the 5% level) are counted. From the full sample of 4850 stocks, 804 have significant β_i, meaning the returns of these firms are affected by public biodiversity attention. This represents 16.58% of the total sample of firms in the entire market. Of these firms, the majority have a positive coefficient and only 25 have a negative one. The message from this distribution is that biodiversity attention pushes down asset prices and thus raises returns. In other words, biodiversity attention can be considered an additional risk factor in the asset pricing model.

To further confirm this argument, we move to Model II (the extended market model) and Model III (the extended CAPM). The difference between these models is whether to include the risk-free interest rate, which will essentially not affect the estimated coefficient β_i and its level of significance; therefore, in the following discussions, only the results of Model III are given. First, a slightly smaller number of companies with a significant β_i is found. A total of 764 firms, or 15.75%, are significantly linked to biodiversity attention. Similarly, the majority of these firms have positive coefficients (711 out of 764), confirming the argument above that the BAI has certain pricing power after controlling for market risks.

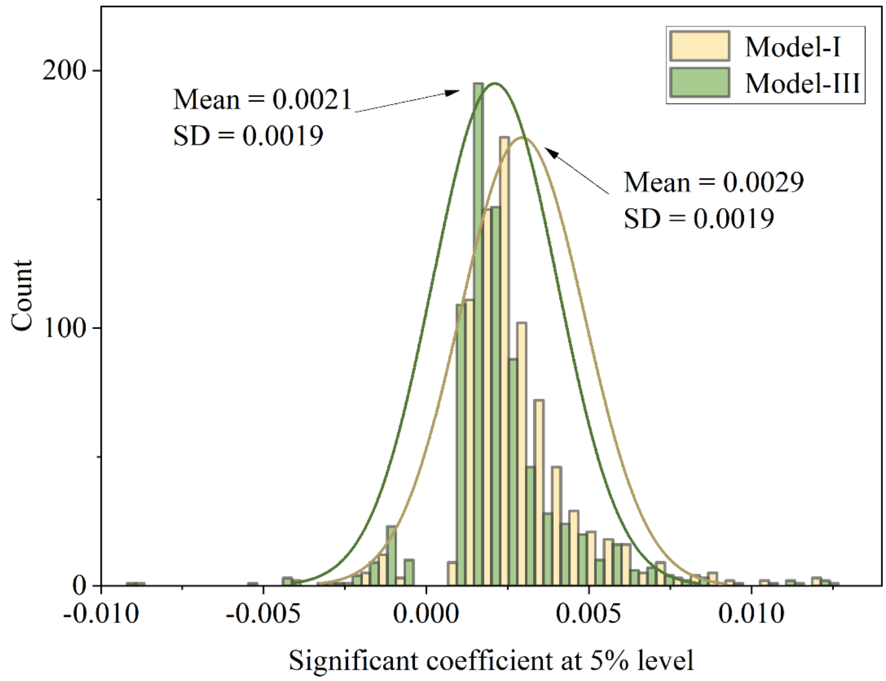


Figure 3. Distribution of significant coefficients in the BAI for Models I and III.

The distributions of significant coefficients for Models I and III are plotted in Figure 3, which provides a visual description of the results discussed above. In general, the distributions of these two model results are generally similar, with marginal differences. Positive significant coefficients dominate in both cases. The mean value is smaller for Model III after controlling for market-level risks. In general, although the number of firms affected is relatively small, we can confirm that the biodiversity–stock return relationship exists.

5.2 Lagged effects and subsample analysis

Because the frequency in our model is in daily frequency, a delayed effect may exist that could underestimate the linkage. This is especially true for the Chinese stock market, which uses a T+1 trading rule (Guo et al., 2012). This refers to how investors cannot sell stocks that they have bought on the same day. Due to this special institutional arrangement, investors' reactions to biodiversity news may not necessarily be reflected instantaneously. To address this concern and following the work by Ji et al. (2023), we estimate Model IV as additional work to the other models. Intuitively, the share of firms with significant relationships should be larger. The results show that there are 2263 companies with at least one significant β_{ij}, increasing the proportion of significant firms to 46.66%. Among them, the coefficients of 1717 companies are positive, while 434 companies are negative. Additionally, 112 companies have both positive and negative coefficients.

Furthermore, the Paris Agreement not only matters for climate actions but was also a critical move for biodiversity conservation (Citroen et al., 2016). The passage of this agreement has triggered a round of public attention to climate change and biodiversity. Although not all the keyword search volumes show major changes, it remains very likely that the biodiversity–stock return relationship became more significant after 2015. Following this concern, the full sample is then divided into two subsamples (2011–2015 and 2016–2024), which are investigated separately. For all models, there is clear evidence that the biodiversity–stock return linkages are stronger in the second subsample.

Table 2. Subsample analysis

	2011-2015			2016-2023		
	No. of firms	No.of firms (β_i>0)	No.of firms (β_i<0）	No. of firms	No.of firms (β_i>0)	No.of firms (β_i<0）
Model I	180	3	177	1395	1390	5
Model III	134	93	41	789	735	54
Model IV	1235	897	271	1884	1331	437

Note: This table shows the number of companies significantly affected by biodiversity attention index. Model II and Model III have the same results, so the conclusions of Model II are not reported. In subsample 2011-2015, there are 2613 firms in total, and in subsample 2016-2023, there are 4462 firms. In Model IV, some companies have both positive and negative lag coefficients. In the sub-sample from 2011 to 2015, there are 67 such companies. From 2016 to 2023, there are 116 companies.

For example, in Model I, in the subsample period of 2011–2015, only 6.89% (180 out of 2613) of companies have significant coefficients. However, in the second subsample, this proportion increases to 31.26% (1395 out of 4462). The results of Model III also share the same distributive patterns; the number of companies with significant companies in the first subsample is 134, or 5.13% over the entire sample, while the number for the second subsample is 789, or 17.68% over the entire sample. The same pattern applies to Model IV, and the results are reported in Table 2. Note also that the share of firms with positive coefficients dominates in all cases. These findings align with our expectations, suggesting that after the Paris Agreement, both market attention to biodiversity and its impact on stock markets increased.

5.3 Investigating sectoral heterogeneity

In theory, certain sectors are more likely to be affected by biodiversity attention than others. For example, the agriculture business has closer links to nature/the ecosystem than the financial sector; therefore, we expect to see that a greater proportion of agricultural firms have significant linkages with the BAI than that of financial firms. With the flexibility of the bottom-up approach, the results can be summarised by sector.

Figure 4 depicts the proportion of companies with significant coefficients and the mean value of the coefficient for each industry. The industry with the largest number of affected firms is AFF, with the proportions being 44.68% for the full sample (2011–2023), 22.22% for the first subsample (2011–2015), and 39.47% for the second subsample (2016–2023). Taking the full sample as an example, the mean value of the BAI coefficient in AFF is 0.0022, indicating that this industry is mainly positively affected by the BAI. The empirical results are generally consistent with our expectations. The AFF industry relies highly and directly on nature, and its firms are dependent on ecosystems and affected by related issues, such as pollination, climate stability and soil and water conservation. Therefore, these firms have the most sensitivity to biodiversity attention.

Interestingly, the ISI industry ranks second in terms of the percentage of affected companies. In the full sample, 23.68% of companies are affected, while in the second subsample period of 2016–2023, 25.89% of companies are affected. The significant impact on this industry may be due to the role of information and communications technology in biodiversity conservation efforts because they facilitate data gathering, analysis and remote monitoring (Wang and Gamon, 2019; Cavender-Bares et al., 2022). For example, in 'Opinions on Further Strengthening Biodiversity Conservation', the Chinese government emphasised the need to enhance biodiversity protection and establish a monitoring information cloud platform.

This involves developing monitoring equipment, accelerating the application of satellite remote sensing and drone aerial remote sensing technology, exploring the application of artificial intelligence and promoting the modernisation of biodiversity monitoring.

Furthermore, over 22.34% of firms in the construction sector are affected by the BAI, making it the third most affected sector in the subsample from 2016–2023. Construction projects are usually required to comply with environmental regulations and policies, which often include measures to preserve biodiversity, such as protecting endangered species and habitats and mitigating impacts on ecosystems. This explains why the BAI has a more significant impact on companies in this industry. In addition, sectors with a greater proportion of firms impacted by the BAI include electric power, heat, gas and water production and supply (EGW) and manufacturing (MAN). These results indicate that industries that are highly reliant on biodiversity in their production processes or supply chains are more sensitive to the BAI.

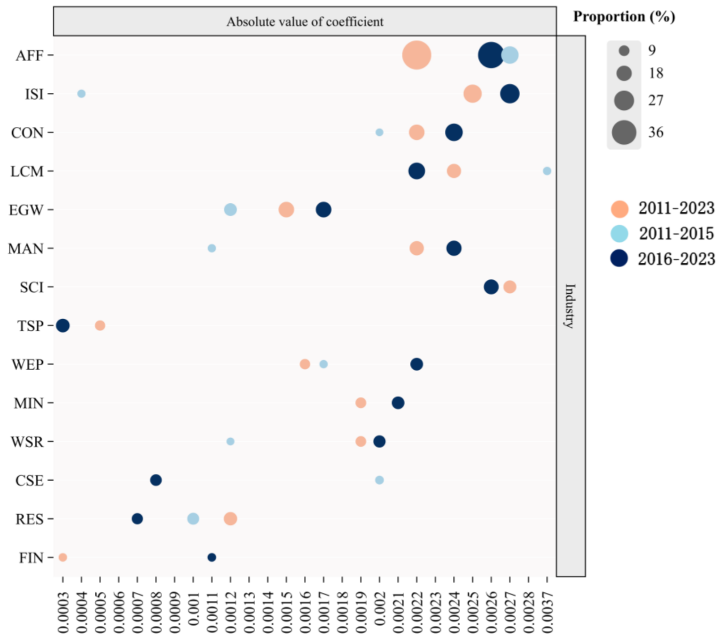


Figure 4. Proportion of significant coefficient on BAI in sectors.[4]

[4] Note that the x-axis represents the mean value of the biodiversity attention coefficient of firms in an industry. Here, we use absolute value, and only a few coefficients are negative. The y-axis represents the classification of industries. Specifically, the industries consist of agriculture, forestry, animal husbandry and fisheries (AFF); information transmission, software and information technology services (ISI); construction (CON); leasing and commercial services (LCM); electric power, heat, gas and water production and supply (EGW); manufacturing

Note that the manufacturing sector has the most sample firms, and it thus warrants looking deeper into how manufacturing firms in the sub-sectors react to biodiversity attention. For detailed results, please refer to Appendix I. For the full sample analysis, petroleum processing, coking and nuclear fuel processing; agricultural and sideline food processing industry; and non-metallic mineral products are the top three of all sub-sectors, with percentages of 37.50%, 25.86% and 22.12% of significant coefficients on BAI, respectively. Energy, mining and agricultural-related manufacturing are more likely to be affected by biodiversity changes, which makes sense that it is more exposed to biodiversity attention.

5.4 Dynamic analysis

Evidence given by the subsample indicates that the biodiversity–stock return relationship can change over time. More firms in the stock market are expected to be affected by the BAI as attention to the value of nature increases. A rolling-windows approach is used to examine the dynamic patterns, allowing flexible changes in the biodiversity–stock return relationship. Here, we only apply the analysis for Model III, the extended CAPM model. A window size of 22 days (the number of working days in a month) is used for the analysis. The percentage of firms with a significant coefficient β_i is calculated for each window, and the results are plotted in Figure 5.

(MAN); scientific research and technical services (SCI); transport, storage and postal services (TSP); water conservancy, environment and public facility management (WEP); mining (MIN); wholesale and retail (WSR); culture, sport and entertainment (CSE); real estate (RES); and finance (FIN). They are ranked by the impact degree in 2016–2023. The size of the bubble represents its proportion (%), indicating the percentage of firms affected in an industry. Each industry is ranked by the largest proportion of firms with a significant BAI coefficient (from top to bottom) in the 2016–2023 subsample.

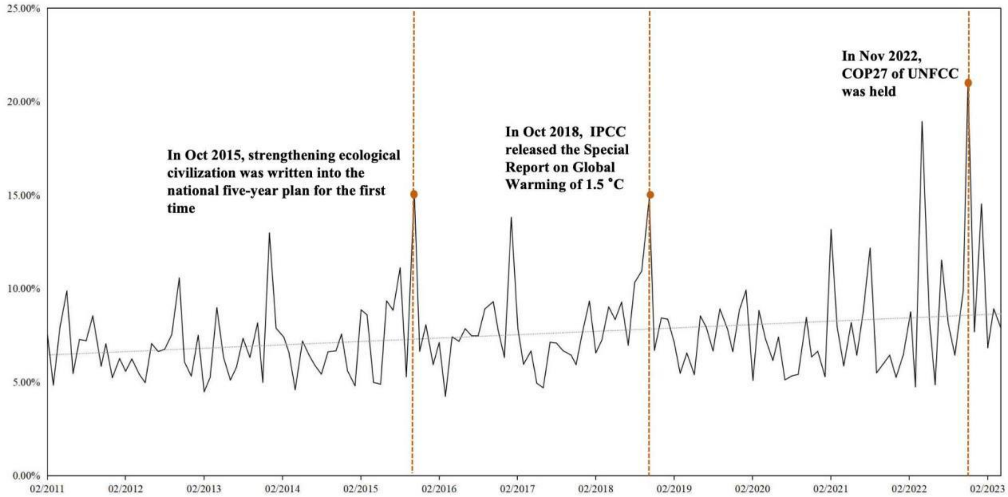


Figure 5. Dynamic analysis of the percentage of firms with a significant relationship with the BAI.[5]

The patterns here are generally consistent with our expectations; a general upward trend can be spotted, although we can see that the reaction of stock market returns to biodiversity attention is not smooth. More firms tend to react to public attention around major biodiversity-related events. For example, in October 2015, the strengthening of ecological civilisation was written into the national five-year plan for the first time. In October 201, the IPCC released the 'Special Report on Global Warming of 1.5°C'. The report points out that when the global temperature rise exceeds 1.5°C and reaches 2°C, it will bring more destructive consequences, such as loss of habitat, the melting of ice caps and a rise in sea levels, which will threaten the survival of all species and harm biodiversity.

Next, the results of the rolling-window analysis are sorted into sectors, as before. The number of significant windows and the percentage of significant firms are plotted in Figure 6, which is split into positive and negative coefficient groups. The percentage of significant windows is over all windows (adding all windows for firms in a particular sector). Sectors are ranked from the lowest percentage to the highest. The top three sectors are real estate (RES), mining (MIN) and AFF, which is roughly consistent with the findings above.

[5] Note that the window size is set to be 22. The figure plots the percentage of firms with a significant β_i based on the regressions of Model III.

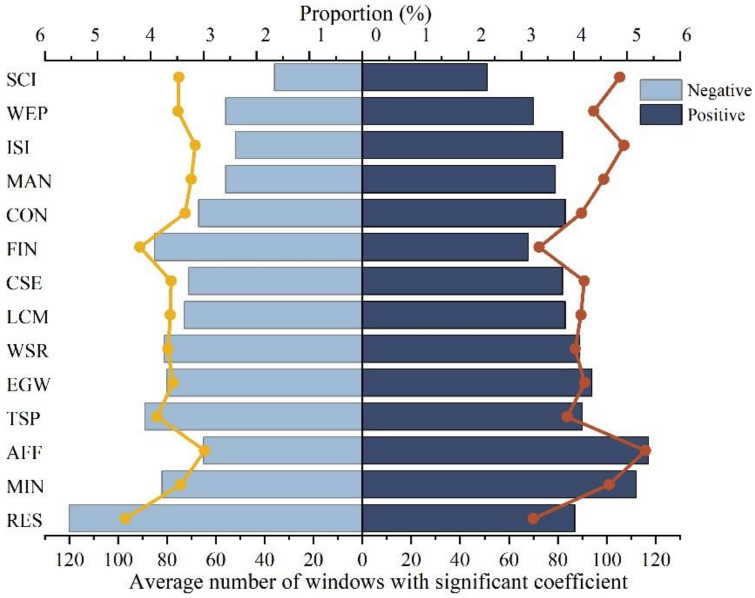


Figure 6. Number of windows with significant coefficients for different sectors.[6]

5.5 Which characteristics matter?

Finding firms with significant relationships to the BAI and summarising these firms into sectors reveal useful information, but more work is needed to find which firm-level characteristics drive these relationships. This question is examined through a probit and a Tobit model. While the probit model examines which factors make a firm's return sensitive to the BAI, the Tobit model explains which factors are associated with stronger sensitivity. The details of these two models are given in Section 3 (Equations 5 and 6).

First, basic firm-level characteristics are considered, and the results of both the probit and Tobit models are reported in Table 3. As expected, the relationship between sensitivity to biodiversity attention and basic firm-level characteristics is mainly driven by the second subsample. This is due to the much smaller number of firms with significant results in the first subsample. Here, the discussions of these results are mainly on the second subsample, as the full sample regressions have almost the same results.

[6] Please refer to Table A2 in the Appendix for the abbreviations and the detailed industrial sectors they represent.

Table 3. Tobit and Probit regression results of the impact of basic firm-level characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	2011-2022		2011-2015		2016-2022	
	BAD	BAS	BAD	BAS	BAD	BAS
Age	0.075***	0.444***	0.019	-0.044	0.092***	0.572***
	(0.014)	(0.123)	(0.036)	(0.338)	(0.016)	(0.134)
Size	-0.040***	-0.398***	0.052**	0.384*	-0.062***	-0.569***
	(0.012)	(0.101)	(0.025)	(0.224)	(0.013)	(0.113)
Capital structure	0.104	1.458**	-0.178	-0.996	0.167*	1.971***
	(0.079)	(0.681)	(0.173)	(1.580)	(0.089)	(0.755)
ROA	-0.936***	-7.168***	-0.404	-3.615	-1.033***	-7.717***
	(0.247)	(2.117)	(0.572)	(5.305)	(0.269)	(2.268)
Constant	-0.864***	-7.028***	-2.647***	-22.773***	-0.506*	-3.695
	(0.259)	(2.216)	(0.537)	(4.869)	(0.293)	(2.477)
Observations	28,098	28,137	7,693	7,735	20,369	20,402
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*Note: This table reports the results of the Probit and Tobit model for the full sample and two sub-samples. The dependent variable BAD equals to 1 if the biodiversity attention sensitivity coefficient is significant, otherwise equals to 0; whereas the dependent variable BAS equals to the absolute value of coefficient *1000 if the biodiversity attention sensitivity coefficient is significant, otherwise equals to 0. Robust standard errors clustered at firm level are in parenthesis. *, ** and *** denote 10%, 5% and 1% level of significance, respectively.*

In general, the four chosen firm-level characteristics are generally significant, except capital structure, which has only marginal significance for the probit model. Age has a positive relationship, with the chance of having a significant relationship with the BAI; it can also increase the level of sensitivity to biodiversity attention. This is consistent with the literature, in that old firms tend to be less likely to engage in climate actions relative to young firms. For example, Engler et al. (2023) find that firms' age is negatively associated with the likelihood of carbon offsetting in the past. In other words, older firms are more likely to be affected by climate risks, especially transition risks (Zhang et al., 2024). The same logic can apply to the case of biodiversity; older firms may be less likely to engage in biodiversity conservation, which makes them more sensitive to biodiversity risks. It might be worth noting that for the first subsample, the coefficients on firms' age take the opposite sign, which makes it somewhat controversial. However, we must note that both the sample size of firms with significant relationships and the number of sample firms are small. Meanwhile, public attention to biodiversity was generally low during that sample period.

Capital structure, measured by the debt-to-asset ratio, has a weak positive relationship with the likelihood of firms having a significant relationship with the BAI but significantly increases the level of sensitivity. A higher debt-to-asset ratio, if it goes beyond a certain level, is related to financial distress, thus causing firms to have higher risk exposures. The other two variables, *size* and *ROA,* are both negatively linked to the likelihood of being affected by BAI and the level of sensitivity. This indicates that large firms and firms with better financial performance are less likely to be subjected to biodiversity risks.

Table 4. Probit regression results of the impact of ESG and basic financial characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BAD	2011-2022				2016-2022			
ESG_Score	-0.001				-0.001			
	(0.001)				(0.001)			
E_Score		-0.001*				-0.001*		
		(0.001)				(0.001)		
S_Score			-0.000				0.000	
			(0.001)				(0.001)	
G_Score				0.000				-0.000
				(0.001)				(0.002)
Age	0.076***	0.076***	0.076***	0.074***	0.093***	0.093***	0.091***	0.092***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)	(0.016)
Size	-0.039***	-0.038***	-0.040***	-0.041***	-0.062***	-0.060***	-0.062***	-0.062***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)
Capital structure	0.103	0.103	0.103	0.103	0.165*	-1.010***	0.168*	0.168*
	(0.079)	(0.079)	(0.079)	(0.079)	(0.089)	(0.269)	(0.089)	(0.089)
ROA	-0.925***	-0.919***	-0.934***	-0.939***	-1.022***	-0.001*	-1.034***	-1.031***
	(0.248)	(0.247)	(0.247)	(0.247)	(0.269)	(0.001)	(0.269)	(0.269)
Constant	-0.870***	-0.906***	-0.856***	-0.858***	-0.507*	-0.556*	-0.518*	-0.507*
	(0.259)	(0.259)	(0.260)	(0.260)	(0.293)	(0.293)	(0.296)	(0.293)
Observations	28,098	28,098	28,098	28,098	20,369	20,369	20,369	20,369
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

*Note: This table reports the results of Probit model for the full sample and the second subsample with ESG factors. The dependent variable BAD equals to 1 if the biodiversity attention sensitivity coefficient is significant, otherwise equals to 0. Robust standard errors clustered at firm level are in parenthesis. *, ** and *** denote 10%, 5% and 1% level of significance, respectively.*

In addition to basic firm-level characteristics, we also consider firm-level ESG performance and see how they may affect the results. The results of the probit and Tobit models are reported in Tables 4 and 5, respectively. Note that only the results for the full sample and the second subsample are reported. Including ESG performance factors does not change the results of those with basic firm-level characteristics (Table 3). In fact, although we expected to see ESG performance matter, the results are not so obvious. For all model specifications, the total ESG scores do not matter for BAD or BAS, although when we turn to individual pillars, environmental scores appear to be relevant. However, the E-score matters only marginally (at a 10% level) to the likelihood of stock returns being related to the BAI. Nonetheless, it matters at the 5% level to sensitivity to the BAI. These results indicate that firms with better environmental performance are less likely to be affected by biodiversity risks, and even if they are affected, the magnitude is relatively smaller. The findings here are consistent with the arguments made above. Firms with better environmental performance are less exposed to biodiversity attention.

Table 5. Tobit regression results of the impact of ESG and basic financial characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BAS	2011-2022				2016-2022			
ESG_Score	-0.008				-0.008			
	(0.010)				(0.010)			
E_Score		-0.012*				-0.014**		
		(0.006)				(0.007)		
S_Score			-0.005				0.003	
			(0.009)				(0.009)	
G_Score				0.003				-0.002
				(0.012)				(0.013)
Age	0.454***	0.451***	0.447***	0.437***	0.583***	0.581***	0.570***	0.576***
	(0.125)	(0.124)	(0.124)	(0.127)	(0.136)	(0.134)	(0.135)	(0.139)
Size	-0.391***	-0.381***	-0.397***	-0.403***	-0.562***	-0.546***	-0.569***	-0.567***
	(0.101)	(0.101)	(0.101)	(0.103)	(0.113)	(0.113)	(0.113)	(0.114)
Capital structure	1.444**	1.447**	1.451**	1.450**	1.954***	1.944***	1.976***	1.977***
	(0.681)	(0.680)	(0.682)	(0.681)	(0.754)	(0.753)	(0.755)	(0.756)
ROA	-7.060***	-7.005***	-7.145***	-7.192***	-7.605***	-7.500***	-7.727***	-7.707***
	(2.123)	(2.115)	(2.118)	(2.119)	(2.271)	(2.264)	(2.268)	(2.270)
Constant	-7.087***	-7.403***	-6.949***	-6.981***	-3.701	-4.155*	-3.768	-3.703
	(2.216)	(2.216)	(2.222)	(2.222)	(2.476)	(2.476)	(2.499)	(2.478)
Observations	28,137	28,137	28,137	28,137	20,402	20,402	20,402	20,402
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

*Note: This table reports the results of Tobit model for the full sample and the second subsample with ESG factors. The dependent variable BAS equals to the absolute value of coefficient *1000 if the biodiversity attention sensitivity coefficient is significant, otherwise equals to 0. Robust standard errors clustered at firm level are in parenthesis. *, ** and *** denote 10%, 5% and 1% level of significance, respectively.*

6. Conclusions

Biodiversity has become a major concern across the world and has been attracting increasing attention from policymakers, academia and the public. While protecting biodiversity has great meaning, the loss of biodiversity and the uncertainties associated with biodiversity conservation can have a significant impact on society. In recent research, among the numerous relationships between biodiversity and broader socioeconomic issues, the biodiversity–finance linkage has emerged as a hot topic. This paper follows this line of frontier literature to examine whether public attention to biodiversity matters for stock returns in China. The results from this paper provide valuable support for the literature, and they can also have important meanings for investors.

This paper began by building a quantitative measure of biodiversity attention, the BAI. Following some existing research, we opted to use Baidu search volume as the foundation for constructing this index. Keywords were extracted from a dictionary provided by Giglio et al. (2013), and the daily search volumes between 2011 and 2023 over 16 selected keywords were used. The time series patterns were generally consistent with major biodiversity-related events, confirming the validity of using this approach.

In the next step, regression analysis, the BAI entered a series of pricing models from the extended market model to the extended CAPM, and these models were then applied to examine the relationship between the BAI and individual stock returns. Not all stocks were sensitive to biodiversity, but the results showed substantial increases in the proportion of firms affected by the BAI over time. We also identified clear sectoral differences, in that some sectors were more sensitive to biodiversity attention, while others were not. Specifically, the top three industries were AFF, ISI and construction. These intuitively made sense because the top three industries had closer links with biodiversity.

Through a rolling-windows analysis, we observed an increasing trend in terms of the number of companies affected by BAI, although the percentage of the affected firms fluctuated.

Given that more attention has been given by the public, together with increasing concerns about sustainability in the financial markets, we would expect to see an even stronger link in the future, calling for attention to both investors and financial practitioners.

Further analysis at the firm level helped identify which factors led to firms' sensitivity to biodiversity attention (BAD and BAS). The regression results showed that firms with a long history, smaller size, higher debt ratio, worse financial performance and worse ESG scores, especially scores in the environmental pillar, were likely to be more sensitive to biodiversity attention and had a stronger link with it. Considering that biodiversity attention represents extra risk in financial markets, these firm-level characteristics are more likely to be affected by biodiversity risks.

While the current research is valuable to the existing literature, there are some shortcomings and issues that should be solved and are worthy of further investigation. First, the BAI index constructed from Baidu search volume reflects only the attention of the public and is not necessarily capable of depicting attention among investors, who are directly linked with the stock market through actual investment decisions. Alternative measures should be constructed to directly capture investors' attention, which may help build a clearer and stronger link between biodiversity and finance. Second, public attention is only one side of the story; policy interventions may have a strong impact on the relationship and thus should be investigated in the future. Finally, more international evidence is needed to confirm the above-found relationship.

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Appendix I Sub-sector results for manufacturing firms

Table A1 Sub-sector results for top-ten manufacturing sectors

Panel A: full sample 2011-2023

Sub-sectors	No. of firms affected	Total No. of firms	Proportion	Beta (mean)
Petroleum processing, coking, and nuclear fuel processing	6	16	37.50%	0.0015
Agricultural and sideline food processing industry	15	58	25.86%	0.0024
Non-metallic mineral products	23	104	22.12%	0.0018
Manufacturing of computers, communications and other electronic equipment	120	544	22.06%	0.0026
Printing and recording media reproduction industry	3	14	21.43%	0.0020
Rubber and plastic products	23	109	21.10%	0.0021
Automobile manufacturing	32	160	20.00%	0.0020
General equipment manufacturing	34	178	19.10%	0.0025
Metal product industry	15	92	16.30%	0.0019
Papermaking and paper product industry	6	37	16.22%	0.0012

Panel B: subsample 2011-2015

Industries name	No. of firms affected	Total No. of firms	Proportion	Beta (mean)
Wood processing and wood, bamboo, rattan, Palm fiber, and straw product industry	1	6	16.67%	0.0020
Furniture manufacturing	1	7	14.29%	0.0024
Ferrous metal smelting and rolling processing	4	29	13.79%	-0.0001
Agricultural and sideline food processing industry	4	35	11.43%	0.0019
Special-purpose equipment manufacturing	12	142	8.45%	0.0018
Instrument and meter manufacturing	2	27	7.41%	0.0094
Papermaking and paper product industry	1	18	5.56%	0.0016
Manufacturing of computers, communications and other electronic equipment	12	217	5.53%	0.0010
Alcohol, beverage and refined tea manufacturing	2	39	5.13%	0.0016
Non-metallic mineral products	3	65	4.62%	0.0040

Panel C: subsample 2016-2023

Industries name	No. of firms affected	Total No. of firms	Proportion	Beta (mean)
Petroleum processing, coking, and nuclear fuel processing	6	14	42.86%	0.0020
Non-metallic mineral products	27	101	26.73%	0.0020
Rubber and plastic products	26	106	24.53%	0.0022
Agricultural and sideline food processing industry	12	52	23.08%	0.0027
Printing and recording media reproduction industry	3	13	23.08%	0.0024
Chemical fiber manufacturing	6	26	23.08%	0.0026
General equipment manufacturing	37	163	22.70%	0.0026
Manufacturing of computers, communications and other electronic equipment	117	518	22.59%	0.0028
Instrument and meter manufacturing	13	69	18.84%	0.0021
Non-ferrous metal smelting and rolling processing	13	72	18.06%	0.0029

Note: There are 3,192 companies in the manufacturing sector in the sample 2011-2023, 1,583 companies in the sub-sample 2011-2015 and 2,974 companies in the sub-sample 2016-2023. All data are based on biodiversity attention coefficients that are significant at the 5% level.

Table A2. Sector names and abbreviations

Sector code	Sector
AFF	Agriculture, forestry, animal husbandry and fishery
CON	Construction
FIN	Finance
CSE	Culture, sports and entertainment
EGW	Electric power, heat, gas and water production and supply
ISI	Information transmission, software and information technology services
LCM	Leasing and commercial service
MAN	Manufacturing
MIN	Mining
RES	Real estate
SCI	Scientific research and technical service
TSP	Transport, storage and postal service
WEP	Water conservancy, environment and public facility management
WSR	Wholesale and retail
Others	Accommodation and catering Diversified Education Health and social work

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