

Do Investors Care About Biodiversity Greenwashing?

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Abstract

We investigate the relation between firms' biodiversity-related disclosures and stock returns and idiosyncratic risk. We use 10-K filings of US listed firms from 2018 to 2024 and text-based measures of biodiversity greenwashing risk. The evaluation is conducted through a customized large language model, with rule-based instructions for assessing the biodiversity disclosures. When considering biodiversity footprints provided by Iceberg Data Lab, we find that companies with high biodiversity impact show lower returns when their disclosure is subject to biodiversity greenwashing risk. We find a similar pattern for the idiosyncratic stock risk. The latter increases when firms with high biodiversity footprint provide disclosure with high biodiversity greenwashing risk. Notably, these results are based on biodiversity footprints adjusted by capital expenditure. The results do not hold when the biodiversity footprint is adjusted by sales. Our interpretation is that investors consider biodiversity risk as a future long-term risk related to long-term investments and not to recent sales. The findings highlight the importance of biodiversity disclosure practices for financial markets, emphasizing the need for standardized reporting frameworks and highlighting potential greenwashing risk faced by investors.

Keywords: Biodiversity disclosure, Greenwashing, ChatGPT, Idiosyncratic volatility

JEL Codes: G11, G12, Q56, D80

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1 Introduction

The growing emphasis on environmental sustainability and nature-related risks has elevated biodiversity loss to a material issue for firms, investors, and regulators. As a result, biodiversity-related disclosures are gaining prominence in corporate reporting frameworks, including the Taskforce on Nature-related Financial Disclosures (TNFD).¹ However, despite growing research on biodiversity reporting practices (Blanco-Zaitegi et al., 2022), little is known about how financial markets perceive and react to such disclosures, particularly within mandatory filings such as annual 10-K reports. Recent advances in text-based finance research have enabled the extraction of environmental and social themes from corporate documents. Dictionary-based methods, such as those employed by Giglio et al. (2023), provide firm-level biodiversity exposure scores by capturing the frequency of biodiversity-related terminology. As biodiversity disclosures become more common, the risk of greenwashing also increases.

The study's objective is to determine if stock returns incorporate risk related to the potential of biodiversity disclosure being perceived as greenwashing. A dictionary-based approach with keywords from Giglio et al. (2023) is applied to extract relevant text from 10-K filings of US firms. The approach applies a large language model (LLM), specifically ChatGPT, to evaluate the credibility and potential greenwashing characteristics of each disclosure.² To complement the textual analysis of biodiversity-related disclosures, this study incorporates biodiversity footprint data from Iceberg Data Lab (Iceberg). Integrating this external measure allows for a more comprehensive analysis of corporate biodiversity reporting. Specifically, the biodiversity footprints serve as an established proxy for a firm's actual biodiversity impact and can be used to benchmark the biodiversity content in financial disclosures. Discrepancies between disclosure scores and actual biodiversity impact are an indicator of potential greenwashing or symbolic disclosure.

Based on the textual analysis, the study investigates how financial markets respond to biodiversity-related disclosures using an event-study framework. Abnormal stock returns are calculated around the 10-K filing dates to assess whether investors react to the presence of biodiversity disclosures. This allows for testing whether biodiversity information embedded in 10-K reports is perceived as value-relevant or merely symbolic. The event window focuses on short-term price adjustments surrounding the filing date, with cumulative abnormal returns

¹ See <https://tnfd.global/wp-content/uploads/2023/08/Recommendations-of-the-Taskforce-on-Nature-related-Financial-Disclosures.pdf?v=1734112245> (accessed September 29, 2025).

² ChatGPT has been shown to provide helpful advice in finance guidance (see e.g., J. H. Kim, 2023; Ko & Lee, 2024; Neuss, 2025; Oehler & Horn, 2024; Osterrieder & GPT, 2023; Romanko et al., 2023; Schneider & Yilmaz, 2025) and performs good in disclosure-related tasks (Bilinski, 2024; Fan et al., 2025; Föhr et al., 2023; A. G. Kim et al., 2023; Shimamura et al., 2025).

(CARs) computed relative to a standard market model. By linking biodiversity-related content to subsequent market reactions, the analysis provides empirical evidence on the informational content of biodiversity-related risk communication.

Our results show an interesting interaction between firms' biodiversity footprint, greenwashing risk, and stock returns. Specifically, stocks of firms with a large biodiversity footprint and disclosure with high greenwashing risk suffer from lower cumulative abnormal returns around 10-K filing dates while firms assessed with smaller biodiversity footprint and lower greenwashing risk exhibit significantly higher cumulative abnormal returns.

By empirically exploring stock market reactions on biodiversity disclosures, this study follows the calls of Hudson (2024) and Blanco-Zaitagi et al. (2022). This research contributes to the growing literature at the intersection of sustainable finance, textual analysis, and AI applications as well as biodiversity, and offers practical implications for corporate managers, investors, and regulators. Specifically, this paper provides evidence that biodiversity disclosure matters to investors and is priced in stock markets. Since stocks of firms with large biodiversity footprint and high greenwashing risk suffer from lower returns, managers should address these issues and introduce credible and effective biodiversity risk management practices. This would match investors' and regulators' interests and expectations. Information asymmetries hamper the effective asset allocation in (financial) markets and biodiversity risk will significantly impact the economies around the globe (Karolyi & Tobin-de La Puente, 2023). Since we found indications of biodiversity greenwashing, regulators should take further steps to ensure high quality biodiversity disclosure and stop greenwashing practices.

This study is organized as follows: In the next section, the literature is reviewed, and the hypotheses are introduced. Section 3 presents the data and methodology, and Section 4 presents the results, robustness checks and a discussion of the results. Section 5 concludes.

2 Literature Review

As comprehensively explained by Garel et al. (2024), a firm's biodiversity footprint, i.e., the biodiversity loss caused by a firm's activities, can correlate with stock returns in three ways. Firms with higher biodiversity footprint can earn higher returns as they face higher transition risks for which investors require a risk premium (Bolton & Kacperczyk, 2021, 2023; Hsu et al., 2023). Second, these firms can earn higher returns due to mispricing caused by unexpected cash flow shocks. Third, firms can earn lower returns as growing concerns about biodiversity cause a shift in investors' preferences and penalize firms with high biodiversity footprint.

Recent empirical studies so far do not provide clear support that one of these three ways is dominant. Garel et al. (2024) find no significant relationship between firms' biodiversity

footprints and stock returns for the 2019-2022 period. In contrast, Hoepner et al. (2023) document that infrastructure firms with stronger biodiversity risk management benefit from more favorable financing conditions, as indicated by lower credit default swap slopes. Coqueret et al. (2024) show that, since 2021, US firms in sectors that strongly depend on or affect biodiversity display higher expected returns, consistent with the idea that biodiversity risk has become increasingly priced.

To the best of our knowledge, a systematic biodiversity risk factor has not been proven to be significant or used by practitioners. Similar to other environmental issues, we assume that investors only consider biodiversity when they come across biodiversity-related information (Pelster et al., 2024). Therefore, we focus on short-term price adjustments following the disclosure of biodiversity-related information. Measuring and disclosing biodiversity impacts is inherently complex and less standardized compared to carbon footprints, which reduces transparency and comparability. This creates a fertile ground for biodiversity-related greenwashing.

Greenwashing misleads investor decision-making by creating an overly positive picture of a firm's environmental performance, practices or products (Lyon & Maxwell, 2011; Lyon & Montgomery, 2015). Specifically in our case, greenwashing refers to creating an overly biodiversity-protective image that, however, lacks the corresponding value and actions. Consistent with disclosure theory (Jensen & Meckling, 1976; Verrecchia, 1983), high-quality reporting is expected to mitigate information asymmetries (see Oehler & Neuss, 2025a for ESG disclosures), reduce firm-specific risk (see e.g., He et al., 2022; Oehler & Neuss, 2025b), and enhance reputation and investment efficiency (e.g., Karwowski & Raulinajtys-Grzybek, 2021).

In contrast, greenwashed disclosure is vague or symbolic (Brown & Tucker, 2011; De Freitas Netto et al., 2020; Forlano et al., 2025; He et al., 2025; Walker & Wan, 2012), similar over years, false or shows misleading information. Reasons for firms to greenwash include pressure from stakeholder groups. Firms with low sustainability performance are more likely to greenwash than firms with high performance (Lee & Raschke, 2023). Firms with higher climate change risks tend to disclose extensive biodiversity information (Orazalin et al., 2024), using disclosures as a legitimizing tool. Moreover, firms adjust their sustainability performance in alignment with topics that are classified as being relevant for investors – including performing worse on irrelevant topics (Göttsche et al., 2025).

Fewer studies focus on the impact of greenwashing on investors' behavior and market reactions. Studies like Akyildirim et al. (2023) or Du (2015) identify negative abnormal returns after greenwashing events, suggesting that investors punish misleading claims. However, biodiversity-specific cases are rare (e.g., Boiral, 2016; He et al., 2025). This motivates a

focused investigation into biodiversity disclosure credibility as a determinant of investor reaction. Biodiversity is particularly prone to greenwashing by the lack of measurable actions, e.g., protection of ecosystems (see e.g., Elliot et al., 2024). He et al. (2025) find that higher level of firms' biodiversity disclosure is associated with a reduced greenwashing tendency. The difficulty, however, is to detect greenwashing.

If biodiversity disclosures are vague or symbolic, investors cannot properly assess firms' exposure and may underreact initially or demand a risk premium. If investors initially fall for the greenwashed information, greenwashing may significantly improve short-term returns while long-term returns may suffer from the wrong initial assessment (Li et al., 2024). However, higher levels of greenwashing can lead to a decrease in investment intentions (Gatti et al., 2021; Pizzetti et al., 2021). We assume that investors can differentiate between vague and convincing, concrete disclosure. Therefore, we expect lower abnormal returns of stocks of firms with low-credibility biodiversity disclosures after the publication of 10-K filings, whereas firms with more credible disclosures should display positive abnormal returns as markets reward substantive commitments.

The effect of greenwashed disclosure might depend on firms' biodiversity footprint. If firms have a small biodiversity footprint, i.e. low biodiversity risk, greenwashing the biodiversity disclosure should have a smaller pricing effect compared to firms with a large biodiversity footprint. To test this hypothesis, we incorporate firm's biodiversity footprint into the analysis.

As credible disclosures typically reduce uncertainty about firm-specific risks (Düsterhöft et al., 2023; Lyle et al., 2023; Oehler & Neuss, 2025b) and information asymmetries, they should also lower idiosyncratic volatility (*IVOL*) in the subsequent period, whereas symbolic or boilerplate disclosure may leave uncertainty unresolved and increase *IVOL* (as a measure for idiosyncratic risk).

We summarize our hypotheses as follows:

H1: After the publication of 10-K filings, stocks of firms with a larger biodiversity footprint show lower returns.

H2: After the publication of 10-K filings, stocks of firms with a larger biodiversity footprint and with a disclosure with higher greenwashing risk show lower returns.

H3: After the publication of 10-K filings, stocks of firms with a larger biodiversity footprint and with a disclosure with higher greenwashing risk show higher idiosyncratic risk.

3 Data and Methodology

The analysis relies on US firms' annual 10-K filings obtained from the US Securities and Exchange Commission's (SEC) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. To ensure a comprehensive coverage of the market, all 10-Ks filed by firms listed on the NASDAQ for the period 2018 to 2024 are extracted. This period incorporates important events like the 2022 United Nations Biodiversity Conference in Montreal, the emergence of TNFD discussions, pandemic supply-chain biodiversity issues, and increased SEC ESG disclosure focus. Therefore, it is not surprising that the word 'biodiversity' is more frequently mentioned in this period than in previous years (Giglio et al., 2023).

The downloading process is automated, and the filings are stored in their original formats. The pre-processing includes the extraction of raw text, i.e., HTML tags are removed, and the text is prepared for keyword search. Therefore, the document is split into paragraphs based on newline breaks.

Biodiversity information is identified using the keyword dictionary of Giglio et al. (2023). This dictionary includes terms related to ecosystems, species loss, deforestation, natural capital, and other biodiversity-related topics.³ For each paragraph, the script searches for the occurrence of any biodiversity term using case-insensitive matching of whole words. If a match is found, the paragraph is marked as biodiversity-related, stored in a csv-file and retained for further analysis.

From 3,329 firms considered from the NASDAQ, 1,063 firms show paragraphs with biodiversity-related keywords. However, as mentioned by Giglio et al. (2023), some terms must be considered within context due to their more general meaning (for example the term 'ecosystem'). This task can be conducted by an LLM such as ChatGPT (see also Fan et al., 2025), however, to have a more efficient analysis, the data is screened in advance. Biodiversity statements that only rely on firm names, addresses or similar information are removed, as the content is clearly not related to biodiversity.⁴ According to Giglio et al. (2023), a firm must have at least two biodiversity-related paragraphs within one 10-K report to be considered for the analysis. A firm's ability to greenwash is strongly limited if it only displays one biodiversity paragraph. This reduces the sample to 671 firms. In the next step, the paragraphs are analyzed using ChatGPT. Therefore, a customized GPT is created. This GPT gets information that is relevant to assess credibility and potential greenwashing indicators. Giving the information in advance, lets the customized GPT consider this information for each task. The results from the

³ The keywords include: 'biodiversity, ecosystem(s), ecology (ecological), habitat(s), species, (rain)forest(s), deforestation, fauna, flora, marine, tropical, freshwater, wetland, wildlife, coral, aquatic, desertification, carbon sink(s), ecosphere, biosphere.' Giglio et al. (2023, pp. 53–54).

⁴ Examples for removed keywords are displayed in Appendix A.

textual analysis (i.e., all paragraphs) are collected for each firm and submitted to ChatGPT (version GPT-5) via the web interface for further assessment.⁵

To evaluate the greenwashing risk of biodiversity disclosure, we use a single, study-specific LLM configuration with a fixed instruction set using OpenAI's GPT. It gets a role and the definition of biodiversity-related content based on the keywords from Giglio et al. (2023), a definition of 'greenwashing' consistent with prior literature, and a specification of paragraph-level scoring rules and a firm-year aggregation procedure. The model first applies a binary relevance filter to exclude non-biodiversity text (e.g., brand names such as 'Natural Habitat'). Relevant paragraphs are then scored on greenwashing risk (Low/Medium/High), with justification and indicators (e.g., lack of metrics, symbolic actions, third-party verification). Based on the model's response, paragraphs are coded into categories representing their greenwashing tendency. For robustness checks, a credibility score (ranging from 1–5) is computed to measure the informativeness of the biodiversity related disclosure.

The greenwashing definition includes typical characteristic such as similar content over the years, false or misleading information, and vague or symbolic disclosures (Brown & Tucker, 2011; De Freitas Netto et al., 2020; He et al., 2025; Walker & Wan, 2012) and is expanded by the information distortions mentioned by de Grefte and de Bruin (2025, p. 3). The LLM outcomes consistently show similar credibility scores. The complete instruction set is provided in **Appendix B**; all runs are performed with the same model, temperature, and prompt version for reproducibility.

The credibility score assesses the quality of the disclosure, i.e., whether it is specific and measurable. The lowest credibility score of one is consistently related to a high greenwashing risk. However, high credibility can be related to low or medium greenwashing risk. We introduce both measures, which might appear similar but differ by the approach. We introduce examples in **Appendix C**.

This procedure reduces the sample to 619 firm-year observations that are relevant regarding biodiversity. This means only 4.5% of firm-year observations in the sample show biodiversity disclosure. This is comparable to existing literature (see Giglio et al. (2023) who find a share of 3.8% of 10-K statements between 2015 and 2020).

The firm-year-disclosure data is then matched with the corporate biodiversity footprint (CBF) developed by Iceberg, which aggregates the biodiversity loss caused by firms' activities per year. The activities relate to land use, greenhouse gas emissions, water pollution, and air pollution. The biodiversity footprint is expressed in loss of km² (Garel et al., 2024). Iceberg also

⁵ The use of the web interface provides more reliable results than uploading documents to ChatGPT (Oehler et al., 2025).

provides the *CBF* adjusted by capital expenditure (*CBF_Capex*) and adjusted by sales (*CBF_Sales*). We focus on the *CBF_Capex*, since we assume that particularly long-term investments are subject to biodiversity risk. We multiply the *CBF* values by -1 so that higher values indicate a negative impact on biodiversity. As the *CBF* values are highly skewed, we use logarithmized *CBF* values (see also Garel et al., 2024). After matching with *CBF* data, the sample consists of 81 firm-year observations.

A further measure provided by Iceberg is the Average High Dependency Score, which offers a comparative measure of vulnerability by assessing the relative exposure to high-dependency ecosystem services. For reasons of simplicity, we refer to this score as ‘dependency score’ in the following. The dependency score is measured in percent, and we keep the measure as provided by Iceberg. We employ the dependency score for a robustness check by replacing the *CBF* values.

Stock prices are obtained from yahoo finance. Excess returns are derived by subtracting the risk-free rate (one-month treasury bill rate from the Kenneth French Data Library, KFDL) from the daily returns.⁶ The short-term market reaction to 10-K filings is evaluated using an event study approach. Abnormal returns are estimated as the residuals from the Fama and French (2015) five-factor model (FF5). The daily factors are obtained from KFDL. For each filing, an estimation window of [-250,-30] trading days relative to the filing date was employed to estimate firm-specific factor loadings. The filing dates are extracted from the 10-K reports. The regression model is (Formula 1):

$$r_{i,t}^{excess} = \alpha_i + \beta_{MKT} \times MKT_RF_t + \beta_{SMB} \times SMB_t + \beta_{HML} \times HML_t + \beta_{RMW} \times RMW_t + \beta_{CMA} \times CMA_t + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}^{excess}$ is the daily excess stock return of firm i on day t . MKT_RF_t is the return of the market portfolio net of the risk-free rate. SMB_t and HML_t reflect the size and book-to-market factors by Fama and French (1993). RMW_t presents the factor capturing profitability and CMA_t is the factor capturing investment (Fama & French, 2015). $\varepsilon_{i,t}$ is the residual in period t .

Predicted normal returns are obtained using the estimated coefficients, and abnormal returns (*ARs*) are computed as the difference between realized and predicted excess returns. Cumulative abnormal returns (*CARs*) are the sum of *ARs* over a symmetric event window around the filing dates (Formula 2). The primary specification uses the three-day window [-1,+1], with [-3,+3] employed as robustness checks.

⁶ http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html; accessed August 22, 2025.

$$CARs_{i,[-1,+1]} = \sum_{t=-1}^{+1} AR_{i,t} \quad (2)$$

We follow standard asset pricing literature (see e.g., Ang et al., 2006; but also Horn, 2023; Horn & Oehler, 2024; Oehler & Neuss, 2025b) and measure firm-level *IVOL* as the standard deviation of residuals from factor model regressions of daily excess returns. To obtain a forward-looking measure of *IVOL*, we implement a rolling regression approach. For each firm i and month m , we estimate the above regression (Formula 1) using daily data starting from the filing date and including the subsequent two months (3-month window). The standard deviation of the residuals within this window represents the firm-level *IVOL*. As robustness, we also compute a 6-month measure of *IVOL* by extending the estimation window to the following five months. This rolling approach ensures that *IVOL* is aligned with the information set available at the time of disclosure.

To conduct the event-study examining the capital market reaction to biodiversity disclosures, the following panel regression model is used (Formula 3):

$$CARs_{i,[-1,1]} = \gamma_0 + \gamma_1 GreenwashingRisk_{i,t} + \gamma_2 CBF_Capex_{i,t} + \gamma_3 GreenwashingRisk_{i,t} * CBF_Capex_{i,t} + \mu_{year} + \mu_{firm} + \varepsilon_{i,t} \quad (3)$$

Where $CARs_{i,[-1,1]}$ is the three-day cumulative abnormal return around the filing date of firm i in year t . $GreenwashingRisk_{i,t}$ is a measure capturing the risk of symbolic or misleading disclosure in the corresponding 10-K report derived by ChatGPT-based assessment. $CBF_Capex_{i,t}$ is the capital expenditure-adjusted biodiversity footprint of firm i in year t . Ruiz-Blanco et al. (2022) demonstrate that firms in environmentally sensitive industries greenwash less than firms in other industries.⁷ To address these effects, we include firm-fixed effects. Moreover, we include year-fixed effects to capture market-wide shocks. Regarding the analysis of *IVOL*, the regression model (Formula 3) is adjusted by replacing *CARs* by *IVOL*. If not mentioned otherwise, we rely on panel regressions with Driscoll-Kraay standard errors that are robust to cross-sectional and temporal dependence (Hoechle, 2007).

4 Results, robustness checks and discussion

Descriptive statistics are presented in **Table 1**, showing 32 firm-year observations with low greenwashing risk, 40 observations with medium greenwashing risk, and 9 observations with high greenwashing risk. According to the dependency scores, all firms rely on ecosystem

⁷ Varying industry effects are shown by He et al. (2025).

services with at least 59 percent of their operations. For some firms, this value is as high as 97 percent. The average dependency score is 70 percent.

The credibility scores from ChatGPT show that 51% of firm-year observations across all industries receive a score of 3 or lower. Only 2% (5%) receive the lowest (highest) score.

The CBF measures show that a few companies have no or only a negligible biodiversity footprint, i.e., no relevant negative impact on biodiversity. However, although we use the logarithmized CBF measures, there is still a slightly skewed distribution which shows that the sample also covers some companies with a very large biodiversity footprint.

Table 1: Statistics

	N	Mean	Standard deviation	Min	Median	Max
<i>Greenwashing risk</i>	81	1.72	.66	1	2	3
<i>Dependency</i>	81	.70	.09	.59	.67	.97
<i>Credibility</i>	81	3.21	.96	1	3	5
<i>CBF</i>	81	3.86	2.95	0	3.61	8.69
<i>CBF_Capex</i>	81	.067	.131	0	.02	.79
<i>CBF_Sales</i>	81	.10	.25	0	.03	2.05
<i>CAR_m1_p1</i>	81	.011	.092	-.329	.005	.375
<i>CAR_m0_p5</i>	81	-.001	.105	-.393	-.001	.339
<i>IVOL3Month</i>	81	2.13	1.27	.74	1.75	7.24
<i>IVOL6Month</i>	81	2.16	1.16	.77	1.75	6.61

Notes: This table shows descriptive statistics of the main variables of the empirical analysis. IVOL measures are winsorized at 1% and 99% levels.

We conduct univariate regressions to examine whether the disclosure and CBF-variables individually are related to *CARs* in the three-day window from the day before the publication of the 10-K to the day after the publication (see **Table 2**). The regression analysis reveals a non-significant coefficient for greenwashing risk, credibility score, and dependency score. However, we find a negative relation between the *CBF_Capex* and stock returns with a statistical significance at the 5%-level. This is support for H1. Surprisingly, we find a positive relation between *CBF_Sales* and stock returns with a statistical significance at the 10%-level. However, regarding H1 we put more weight on the results with *CBF_Capex* as independent variable since it better aligns with the long-term horizon of biodiversity risk.

Table 2: Univariate regressions with CARs as dependent variable

Dependent variable: Cumulative abnormal returns [-1;+1]					
	(1)	(2)	(3)	(4)	(5)
Greenwashing risk	-0.039 (0.035)				
CBF_Capex		-0.147** (0.044)			
CBF_Sales			0.205* (0.101)		
Credibility				0.141 (0.077)	
Dependency					-0.054 (0.237)
Constant	-0.055 (0.037)	-0.090 (0.045)	-0.121** (0.041)	-0.447* (0.210)	-0.064 (0.129)
<i>Time-fixed effects</i>	Yes	Yes	Yes	Yes	Yes
<i>Firm-fixed effects</i>	Yes	Yes	Yes	Yes	No
<i>Industry-fixed effects</i>	No	No	No	No	Yes
<i>R²</i>	0.171	0.163	0.165	0.251	0.194

Notes: The table presents regression results examining the relationship between the GPT-generated biodiversity disclosure measures 'Greenwashing risk', 'credibility', the CBF adjusted by capital expenditure and sales and firms' dependency on biodiversity, and CARs measured over a three-day window, estimated using the FF5 model. The Driscoll-Kraay standard errors are displayed in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

Results of multivariate regressions presented in **Table 3** further highlight that corporate biodiversity footprint adjusted by capital expenditure is more relevant to investors than CBF adjusted by sales. For the analysis of H2, we run regressions with an interaction term of *Greenwashing risk* and *CBF_Capex* or *CBF_Sales*. The model fit measured by R^2 is 40 to 50 percentage points higher for models with the *CBF_Capex* variable. The highest model fit is observed for model (2) including time- and firm-fixed effects. The coefficient of the interaction term *Greenwashing risk*CBF_Capex* is negative with a statistical significance at the 1%-level. Since the coefficients of *Greenwashing risk* and *CBF_Capex* are positive, the magnitude of the coefficients is of particular importance for the correct interpretation of the findings. Consider a company with minimum greenwashing risk (=1) and *CBF_Capex* (=0). The *CARs* according to model (2) would be -0.163. In contrast, a company with maximum greenwashing risk (=3) and *CBF_Capex* (=0.79) would have expected *CARs* of -6.53⁸. The coefficients show that greenwashing risk matters particularly. The expected *CARs* can be positive for firms with a large *CBF_Capex* and low *Greenwashing risk*. In contrast, the expected *CARs* cannot become positive for high greenwashing risk companies. Nevertheless, the results are strong support for H2 that after the publication of 10-K filings, stocks of firms with a larger biodiversity footprint and with a disclosure with higher greenwashing risk show lower returns.

⁸ $0.06*3+16.033*0.79-8.082*3*0.79-0.223=-6.53$.

Table 3: Multivariate regressions with CARs as dependent variable

Dependent variable = Cumulative abnormal returns [-1;+1]				
	(1)	(2)	(3)	(4)
Greenwashing risk	0.074*** (0.018)	0.060*** (0.011)	-0.023 (0.027)	-0.027 (0.027)
CBF_Capex	17.296*** (1.195)	16.033*** (1.168)		
Greenwashing risk # CBF_Capex	-8.626*** (0.584)	-8.082*** (0.563)		
CBF_Sales			0.439 (0.774)	1.595 (0.952)
Greenwashing risk # CBF_Sales			-0.159 (0.462)	-0.975 (0.565)
Constant	-0.190** (0.028)	-0.223** (0.047)	0.029 (0.035)	-0.082 (0.042)
<i>Time-fixed effects</i>	No	Yes	No	Yes
<i>Firm-fixed effects</i>	Yes	Yes	Yes	Yes
<i>R</i> ²	0.51	0.60	0.01	0.21

Notes: The table presents regression results examining the relationship between the GPT-generated biodiversity disclosure measures 'Greenwashing risk', the CBF adjusted by capital expenditure and sales, and CARs measured over a three-day window, estimated using the FF5 model. The Driscoll-Kraay standard errors are displayed in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

We check whether our results stay robust by modifying the time window of the analyzed stock returns. Regression results for cumulative abnormal returns from day 0, i.e., the publication day of the 10-K filings, to day 5 are presented in **Table 4**. The explanatory power of the models decreases to 0.31 and 0.11 for the model covering *CBF_Capex* and *CBF_Sales*, respectively. We interpret this as an indication that stock prices incorporate the new information from the 10-K filings quickly so that a longer time window adds more noise to the model. Nevertheless, the model covering *CBF_Capex* still has good explanatory power and provides further support for H2.

Table 4: Robustness heck: Time Window

Dependent variable = Cumulative abnormal returns [0;+5]		
	(1)	(2)
Greenwashing risk	0.097 (0.049)	0.024 (0.058)
CBF_Capex	13.282*** (1.104)	
Greenwashing risk # CBF_Capex	-6.667*** (0.561)	
Greenwashing risk # CBF_Sales		(1.178) -0.774 (0.709)
Constant	-0.222** (0.067)	-0.119 (0.070)
<i>Time-fixed effects</i>	Yes	Yes
<i>Firm-fixed effects</i>	Yes	Yes
<i>R</i> ²	0.31	0.11

Notes: The table presents regression results examining the relationship between the GPT-generated biodiversity disclosure measures 'Greenwashing risk', the CBF adjusted by capital expenditure and sales, and CARs measured over a six-day window, estimated using the FF5 model. The Driscoll-Kraay standard errors are displayed in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

We introduce a further robustness check that replaces the carbon footprint measures by firms' biodiversity dependency. Results of the respective panel regressions are presented in **Table 5**. The results provide further support for H2 as the interacted variable *Greenwashing risk*Dependency* has a negative coefficient which is significant at the 1%-level and 10%-level for the [-1;+1] and [0;+5] time windows, respectively. The magnitudes of the coefficients show a similar pattern as those of the model covering *CBF_Capex*. Therefore, we state that our results are robust to the biodiversity risk measure.

Table 5: Robustness Check: Biodiversity Dependency

Dependent variable =	Cumulative abnormal returns	
	[-1;+1] (1)	[0;+5] (2)
Greenwashing risk	0.388*** (0.084)	0.533* (0.226)
Dependency	1.013** (0.353)	1.528* (0.683)
Greenwashing risk # Dependency	-0.603*** (0.114)	-0.802* (0.317)
Constant	-0.718** (0.209)	-1.031* (0.412)
<i>Time-fixed effects</i>	Yes	Yes
<i>Industry-fixed effects</i>	Yes	Yes
<i>R</i> ²	0.226	0.201

Notes: The table presents regression results examining the relationship between the GPT-generated biodiversity disclosure measures 'Greenwashing risk', the firm's biodiversity dependency, and CARs measured over a three-day window, estimated using the FF5 model. The Driscoll-Kraay standard errors are displayed in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

Another robustness check concerns the disclosure measure. Instead of the greenwashing risk measures, we use the credibility score provided by ChatGPT to assess the disclosure informativeness. We find further support for a positive relation between disclosure quality and stock returns as the interacted variable *Credibility*CBF_Capex* is positive with a statistical significance at the 5%-level in model (1) of **Table 6**. This is in line with H2. Further support for H1 is provided by the negative coefficient of *CBF_Capex*, which is significant at the 1%-level.

Table 6: Robustness Check: Credibility Score

Dependent variable = Cumulative abnormal returns [-1;+1]		
	(1)	(2)
Credibility	0.061 (0.034)	0.161 (0.107)
CBF_Capex	-5.303*** (1.295)	
Credibility # CBF_Capex	2.637** (0.663)	
CBF_Sales		0.708 (0.768)
Credibility # CBF_Sales		-0.165 (0.283)
Constant	-0.342* (0.133)	-0.517 (0.275)
<i>Time-fixed effects</i>	Yes	Yes
<i>Firm-fixed effects</i>	Yes	Yes
<i>R</i> ²	0.32	0.27

Notes: The table presents regression results examining the relationship between the GPT-generated biodiversity disclosure measures 'Credibility, the CBF adjusted by capital expenditure and sales, and CARs measured over a three-day window, estimated using the FF5 model. The Driscoll-Kraay standard errors are displayed in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

We extend the analysis by replacing the dependent variable with *IVOL*. *IVOL* is measured over a rolling window that covers the three or six months after each filing date. This approach allows us to examine whether firm-specific uncertainty changes in response to biodiversity disclosure following the 10-K filings and serves as a measure of post-disclosure uncertainty. With a statistical significance at the 1%-level, greenwashing risk is positively related to *IVOL* (see **Table 7**). The expected 3-months *IVOL* becomes even higher for stocks with high greenwashing risk and a high *CBF_Capex*, see the positive and significant coefficient of the interaction term *Greenwashing risk*CBF_Capex* in model (1). This is support for H3 that stocks of firms with a larger biodiversity footprint and with a disclosure with higher greenwashing risk show higher idiosyncratic risk. Further mild support for this hypothesis is provided by the results of model (4), showing a positive relation between greenwashing risk and *CBF_sales* and the six-months *IVOL*. These directions are consistent with theoretical expectations: firms with more credible biodiversity reporting exhibit lower *IVOL*, suggesting reduced firm-specific uncertainty and more informative disclosures, whereas firms with higher greenwashing risk experience greater *IVOL*, indicating higher information asymmetry and investor uncertainty.

Table 7: Regression results IVOL

Dependent variable =	IVOL (3-months) (1)	IVOL (6-months) (2)	IVOL (3-months) (3)	IVOL (6-months) (4)
Greenwashing risk	0.721*** (0.138)	0.586** (0.148)	0.859*** (0.153)	0.619*** (0.121)
CBF_Capex	-22.474** (5.741)	-2.759 (4.599)		
Greenwashing risk # CBF_Capex	10.521** (2.984)	0.967 (2.331)		
CBF_Sales			7.248 (5.570)	6.473* (2.986)
Greenwashing risk # CBF_Sales			-1.075 (4.632)	-1.946 (2.380)
Constant	0.070 (0.171)	0.473 (0.248)	-0.857*** (0.159)	-0.000 (0.247)
<i>Time-fixed effects</i>	Yes	Yes	Yes	Yes
<i>Firm-fixed effects</i>	Yes	Yes	Yes	Yes
<i>R</i> ²	0.31	0.30	0.38	0.35

Notes: The table presents regression results examining the relationship between the GPT-generated biodiversity disclosure measures 'Greenwashing risk', the CBF adjusted by capital expenditure and sales, and idiosyncratic stock risk measured over a three- or six-months window, estimated using the FF5 model. The Driscoll-Kraay standard errors are displayed in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

The main findings concerning greenwashing risk are consistent with theoretical expectations. Investors demand higher returns for higher biodiversity-related greenwashing risk. This leads to decreasing stock prices after the publication of 10-K filings of companies with large biodiversity footprint and likely greenwashed filings. In addition, stocks of companies with high biodiversity-related greenwashing risk show higher *IVOL* after the publication of 10-K filings. These results are robust to different disclosure credibility measures, biodiversity measures, and time-horizons.

Although the analysis has some limitations (sample size and length of the sample period), these results have important practical implications. First, we provide evidence that biodiversity risk is priced in financial markets, although we cannot say whether the risk is adequately priced in terms of magnitude. Second, the results underline the importance of biodiversity disclosure and data. However, most investors do not have access to detailed external biodiversity performance assessments. Consequently, they may rely on the structure of corporate disclosures rather than on verified indicators of biodiversity performance. Limited standardization and comparability of disclosures make the quality of biodiversity reporting particularly important. Credible disclosures can improve price discovery by helping investors assess exposure and integrate biodiversity risk into valuation models, whereas low-quality or symbolic disclosures can increase information asymmetries and delay market adjustment. In addition, uncertain regulatory environments allow firms to greenwash and not to be punished

by vague disclosure (Delmas & Burbano, 2011). Studies document that regulatory policies do not (yet) reduce corporate greenwashing (Tan et al., 2024). This makes markets vulnerable to symbolic or misleading communication. The finding therefore underlines the importance of initiatives such as the TNFD and emerging biodiversity accounting frameworks, which aim to standardize biodiversity reporting and make performance metrics more comparable.

5 Conclusion

This study examines the market perception and financial implications of biodiversity-related disclosures in US firms' 10-K reports between 2018 and 2024. By employing a text-based approach using a customized GPT model, we evaluate the greenwashing risk and the credibility of biodiversity statements. We integrate biodiversity footprint data from Iceberg – adjusted by capital expenditure – and relate the measures to abnormal stock returns around the filing date and *IVOL* in the following months.

We find that firms with high biodiversity impact show lower returns when their disclosure is subject to biodiversity greenwashing risk. A similar pattern is found for idiosyncratic stock risk which increases when firms with high biodiversity footprint provide disclosure with high biodiversity greenwashing risk. The results do not hold when the biodiversity footprint is adjusted by sales. Our interpretation is that investors consider biodiversity risk as a future long-term risk related to long-term investments and not to recent sales. Our results are robust to an alternative biodiversity risk measure as well as an alternative disclosure measure.

The analysis bridges the gap between greenwashing research and the emerging field of biodiversity finance, where standardized metrics and market integration remain limited. In line with existing studies (e.g., Giglio et al., 2023), biodiversity disclosure remains sparse across firms and years, confirming that biodiversity considerations are only gradually entering corporate reporting practices. From a policy and research perspective, our results underscore the need for standardized biodiversity reporting frameworks and highlight the potential greenwashing risk faced by investors.

Our study contributes methodologically by demonstrating that large language models can serve as rule-based evaluators of biodiversity disclosure risk, complementing existing assessments. Future research could extend this approach to large samples like in cross-country settings, alternative biodiversity indicators, and further investor-level reactions to biodiversity narratives.

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Appendix A: Examples of removed keywords

Keywords	Reason	Underlying biodiversity term	Number of single paragraphs only related to this word
Lake Forest Bank	Firm name	Forest	115
Coral Reef Shopping Center	Firm name	Coral	48
Forest City	Location	Forest	45
Flora Growth	Firm name	Flora	217
Marine & Casualty Insurance	Product	Marine	112

Appendix B: Customized-GPT instructions

Role

You are a professional ESG and biodiversity analyst specialized in evaluating the credibility of biodiversity disclosures. Your task is to screen and score 10-K biodiversity disclosures with reproducible, rule-based judgments.

Scope (what counts as biodiversity-related)

Use the following biodiversity keywords for identification:

- biodiversity, ecosystem(s), ecology (ecological), habitat(s), species, (rain)forest(s), deforestation, fauna, flora, marine, tropical, freshwater, wetland, wildlife, coral, aquatic, desertification, carbon sink(s), ecosphere, biosphere

Context rules (keywords must occur with relevant context):

- **Ecosystem(s):** climate, coast, forest, natur*, sustaina*, water, public health, micro (when ecological).
- **Marine:** marine biodiversity, marine ecosystem, marine environment, marine life, marine species.
- **Tropical:** tropical biodiversity, tropical ecosystem, tropical environment, tropical forest, tropical species.
- **Species:** aquatic, biodiversity, bird, endangered, environment, fish, habitat, invasive, list, marine, protect, threatened, ESA, EPA.

Not biodiversity-related examples:

- firm names with nature-like terms (e.g., “Natural Habitat,” “Forest Hill”),
 - generic environmental compliance without biodiversity relevance,
 - “ecosystem” in IT/business contexts.
-

Greenwashing definitions

1. **General:** misleading biodiversity impression through vague, unsubstantiated, or promotional claims without concrete actions, metrics, timelines, governance, or operational materiality.
 2. **Distortion:** one or more statements are untrue.
 3. **Omission:** statements are true but omit necessary details to give an accurate understanding.
 4. **Pollution:** statements are true but overloaded/complex such that a reasonable reader cannot interpret them.
-

Evaluation sequence per paragraph row

1. **Relevance filter (Yes/No):** Is this paragraph biodiversity-related given the scope?
 - If **No** → record relevant=false and relevance_reason. Skip scoring.
 - If **Yes** → score:
 - credibility_score (1–5): 1 = boilerplate; 5 = specific, measurable, time-bound, externally verifiable.
 - tone: {promotional, neutral, specific, mixed, vague}.

- greenwashing_risk: {Low, Medium, High}.
- indicators: choose all that apply from {vague_language, no_metrics, symbolic_action, disconnected_from_operations, repetition, credible_plan, third_party_verification, targets_timeline}.
- justification: 1–2 sentences explaining why.

Firm-year aggregation (after scoring all rows)

Return additional fields:

- firm_year_relevant: true/false (at least one relevant paragraph).
 - firm_year_credibility_mean: mean of scores.
 - firm_year_credibility_max: maximum score.
 - pct_paragraphs_high_risk: share of paragraphs scored as High risk.
 - progress_signal: {improving, stagnant/repetitive, deteriorating, unclear}, based on change across years if multiple years are present.
 - *Improving*: disclosures more specific/actionable over time.
 - *Stagnant*: repeated boilerplate year after year.
 - *Deteriorating*: declining specificity, dropping commitments.
 - *Unclear*: insufficient information.
-

Input format example

Input format: You will receive a table in plain text. It covers the ticker, year, and biodiversity statements. Each row includes biodiversity-related disclosure paragraphs in the specific year; paragraphs are splitted by "//".

Output format

Return **valid JSON only**, following this schema:

```
{
  "firm": "LIND",
  "results_by_year": [
    {
      "year": 2018,
      "n_paragraphs": 3,
      "relevance": true,
      "relevance_reason": "Two biodiversity-relevant statements; one excluded as weather-only.",
      "credibility_score_mean": 3.7,
      "credibility_score_max": 4,
      "tone_overall": "mixed",
      "greenwashing_risk_overall": "Medium",
      "indicators_overall": ["no_metrics", "credible_plan"],

```

```

    "justification_overall": "Some concrete actions but limited metrics and timelines.",
    "progress_signal": "unclear"
  },
  {
    "year": 2019,
    "n_paragraphs": 2,
    "relevance": true,
    "relevance_reason": "Both statements are biodiversity-related.",
    "credibility_score_mean": 4.5,
    "credibility_score_max": 5,
    "tone_overall": "specific",
    "greenwashing_risk_overall": "Low",
    "indicators_overall": ["credible_plan", "targets_timeline", "third_party_verification"],
    "justification_overall": "Contains measurable targets with verification.",
    "progress_signal": "improving"
  }
]
}

```

Consistency rule: Use low-temperature behavior. Be consistent across years and firms. Do not infer or assume metrics, targets, or verification if they are not explicitly stated in the text.

Appendix C: Examples for credible and non-credible disclosures

Firm Disclosure	Relevance reason and credibility score	Justification overall and greenwashing risk indicator
“ ... not subject to any pending or, to the knowledge of the Issuer, threatened costs or liability under, any and all applicable Laws (including common law), and applicable and binding judicial or administrative decisions or orders, relating to pollution, the generation, use, handling, transportation, treatment, storage, discharge, disposal or release of Hazardous Substances, the protection or restoration of the environment, human health and safety, noise or the protection of natural resources, including wildlife, migratory birds, eagles or endangered or threatened species or habitats (collectively // ... received his B.S. in Physics from Wake Forest University and his ... // ... and Chief Medical Officer, and also served as President of Forest Research Institute ...”	“One paragraph mentions wildlife, migratory birds, eagles, and endangered or threatened species or habitats; the other three paragraphs are biographical or pharmaceutical and not biodiversity-related.” Score: 1	“The disclosure lists species and habitats only in generic legal/compliance terms with no specific actions, metrics, or governance; appears boilerplate.” Score: high
“This change in the learning ecosystem simplified the user experience for our learners and enabled rich analytics for the team to continuously make the learning experience more engaging, impactful, and easy. // We and our business are subject to extensive domestic and international environmental, health and safety regulations. In addition to environmental, health and safety regulatory compliance obligations, we may face liability arising out of the normal course of business, including alleged personal injury, property damage, and human health risks due to exposure to hazardous substances or processes at our current or former facilities. Additionally, we may be impacted by material changes in environmental, health and safety regulations or subject to substantial liability for environmental impacts caused by our (or our predecessors’) operations. Compliance with environmental laws and regulations and associated expenditures, including but not limited to our capital expenditures for environmental control equipment, are forecasted and may be inconsistent based on multiple variables. Our compliance cost forecasts may be substantially different from actual results, which may be affected by factors such as: changes in law that impose new or increased restrictions on air or other emissions, wastewater management, waste disposal, hydraulic fracturing, or wetland and land use practices // The physical risks of climate change can include extreme variability in weather patterns such as increased frequency and severity of significant weather events (e.g. flooding, hurricanes and tropical storms), natural hazards (e.g., increased wildfire risk), rising mean temperature and sea levels, and long-term changes in precipitation patterns (e.g.	“Continues emphasis on physical climate change risks (storms, wildfires, drought, sea-level rise) and regulatory compliance obligations.” Score: 5	“Acknowledges significant physical and regulatory risks from climate change, but primarily framed as risk without clear proactive strategy.” Score: medium

drought, desertification, or poor water quality). Such effects have the potential to affect business continuity and operating results, particularly at facilities in coastal areas or areas prone to chronic water scarcity, and could disrupt our operations or those of our customers or suppliers, including through direct damage to physical assets and indirect impacts from supply chain disruption and market volatility. While we evaluate and incorporate potential ranges of physical risks, it is difficult to predict with certainty the timing, frequency or severity of such events, any of which could have a material adverse effect on our financial condition, results of operations and cash flows. See also "Seasonal and weather conditions, including severe weather associated with climate change, could adversely affect demand for our services and operations." "		
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