Biodiversity Concern and Firm Performance

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Abstract

This paper examines how news about biodiversity relates to asset prices. Using a corpus of 60,213 biodiversity-related articles from 2003–2022, I construct a news-based Biodiversity Sentiment Index (BSI) with BERT sentence classification and study its association with U.S. firms' excess returns. I find that higher BSI is followed by higher daily excess returns, whereas the relation attenuates and becomes economically small at the monthly horizon. To explore the mechanism, I apply Latent Dirichlet Allocation to separate topics into physical-risk (e.g., endangered species, natural resource management) and transition-risk (e.g., conservation policy, regulations/permits, environmental news) categories. Transition-risk attention explains returns more strongly than physical-risk attention: environmental-news attention loads positively on returns, while regulations/permits attention loads negatively, consistent with short-run market reactions and anticipated operating constraints. It should be noted that the analysis captures realized excess returns rather than direct estimates of ex ante required returns. These results are robust to standard asset-pricing controls (market, size, value, profitability, investment, momentum). The paper contributes a scalable, news-based biodiversity measure and evidence that transition channels dominate in the pricing of biodiversity concerns.

1 Introduction

In recent years, increasing attention has been devoted to the relationship between environmental sustainability and economics, particularly within the field of climate finance. This area has developed rapidly in academic research, as evidenced by Giglio et al. (2021), Stroebel and Wurgler (2021), Hong et al. (2020), and Acharya et al. (2023). Despite this extensive focus on climate change, the economic impacts of biodiversity have only recently begun to receive systematic attention, with key studies emerging such as Giglio et al. (2023).

Biodiversity encompasses the variety of genes, species, and ecosystems, and it underpins economic stability by supporting industries and services. Its substantial economic value

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spans agriculture, pharmaceuticals, and disaster resilience (Costanza et al., 1997; Duarte et al., 2009; Liang et al., 2016). The ongoing loss of biodiversity is estimated to cause annual economic damages of $4–20 trillion (Kapnick, 2022). Addressing biodiversity issues in finance is therefore critical, not only for environmental reasons but also due to increasing regulatory demands. Regulations such as the Convention on Biological Diversity (CBD) and the European Union's Biodiversity Strategy for 2030 mandate conservation and restoration actions with direct implications for business operations. Corporate initiatives, such as HSBC's investment in conservation projects, further demonstrate how firms are reshaping practices to align with regulatory and societal expectations, underscoring the necessity for financial markets to integrate biodiversity considerations.

This paper advances the understanding of how biodiversity issues affect stock returns by systematically analyzing biodiversity sentiment as reflected in news media. Empirical results show that positive biodiversity sentiment significantly increases *daily* stock returns, but the effect attenuates at the *monthly* horizon, suggesting that market reactions are driven more by short-term sentiment than long-term fundamentals. Furthermore, I show that transition risks exert stronger effects on stock returns than physical risks. In particular, topics related to regulatory changes and conservation policies exhibit greater influence on daily excess returns than those linked to physical biodiversity loss. These findings have important implications for sustainable finance. As regulatory pressures and public awareness of biodiversity continue to grow, it is crucial for researchers to explore these evolving risks and to integrate biodiversity considerations into financial models and empirical analyses.

This paper makes three main contributions. First, it introduces a comprehensive, news-based measure of biodiversity concern derived from a large-scale dataset of articles, providing a broader and more inclusive perspective than prior studies. Second, it employs topic modeling to distinguish between physical and transition risks, offering new insights into how these channels affect financial markets. Finally, it provides robust empirical evidence that transition risks dominate physical risks in explaining stock-return reactions to biodiversity news.

The remainder of the paper is structured as follows. Section 2 develops the study's hypotheses. Section 3 describes the data sources. Section 4 constructs the biodiversity measures - the Biodiversity Sentiment Index (BSI) and the LDA-based topic attention. Section 5 presents the empirical results. Section 6 concludes.

2 Hypothesis Development

With increasing attention to biodiversity issues, this paper hypothesizes that individual stock returns are positively associated with biodiversity sentiment. When biodiversity receives heightened public attention, markets incorporate this information into prices, and higher biodiversity sentiment is empirically followed by higher realized excess returns in the short run. This outcome can be consistent with investors requiring compensation for biodiversity-related risks—such as potential regulatory costs or operating constraints—even though the empirical tests capture realized returns rather than directly identifying ex ante required returns.

Hypothesis 1. *Higher (more positive) biodiversity news sentiment is followed by higher* daily *excess returns.*

Beyond the aggregate relation, it is important to examine the specific channels through which biodiversity concerns influence returns. Economic and financial risks associated with biodiversity can be broadly categorized into two types: *physical risks*, which arise from the actual loss of biodiversity, and *transition risks*, which stem from regulatory actions, policy interventions, and changes in consumer behavior (OECD, 2019; IFC, 2019; Kurth et al., 2021). While both types of risks are material, transition risks are often perceived to have a more immediate and pronounced effect on asset prices. This is largely due to the direct consequences of regulatory changes and rapid adjustments in investor sentiment, which can swiftly alter market conditions (Giglio et al., 2023).

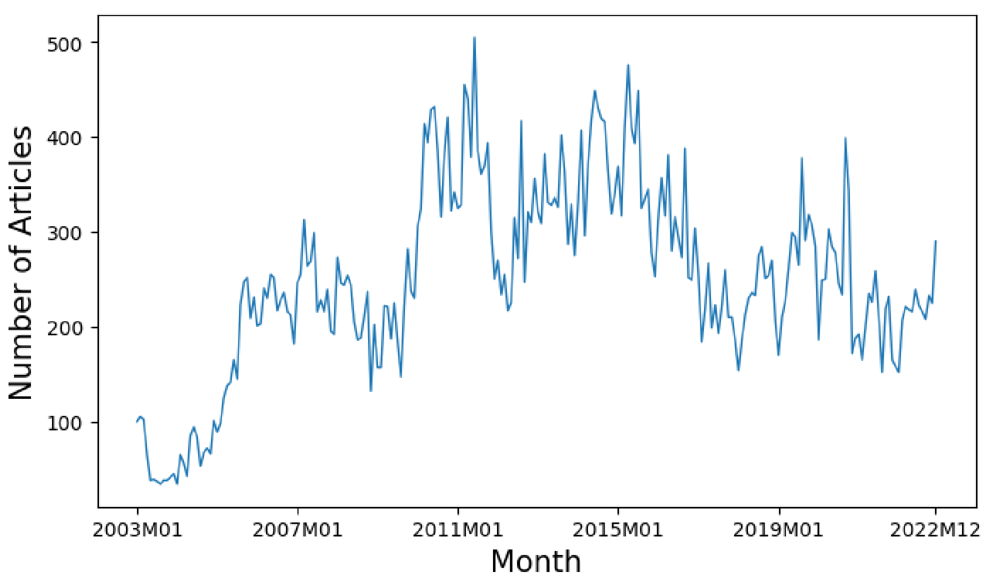
Hypothesis 2. *Individual stock returns are more strongly affected by transition risks than by physical risks.*

3 Data

For the empirical analysis, I collect textual data from Dow Jones Factiva, covering all news articles related to biodiversity published between January 2003 and December 2022. This comprehensive dataset consists of 60,213 articles. Figure 1 illustrates the monthly publication frequency of these articles, showing a generally increasing trend that reflects rising awareness and concern within the media and, potentially, broader societal or scientific shifts toward environmental issues.

Figure 1: Trends in the Publication of Biodiversity-Related Articles Over Time

This figure illustrates the monthly number of articles related to biodiversity from January 2003 through December 2022. The horizontal axis represents time, denoted in months, while the vertical axis quantifies the number of articles.



To measure *Biodiversity Topic Attention*, as detailed in Section 4.2, I conduct a textual analysis on the same set of articles. Figure 2 presents the 30 terms most commonly used.

Panel A displays unigrams, while Panel B shows bigrams.[1] As expected, most of the terms are related to biodiversity. Terms that appear less than 100 times are excluded as non-informative. Extremely frequent terms (for example, "species," "habitat") that represent more than 1% of the total tokens are excluded, as they add little discriminatory power in a biodiversity-only corpus. After filtering, 41,125 unique terms remain for analysis.

Figure 2: Most frequently used terms in biodiversity-related news articles
This figure plots the frequency with which words appear in the corpus of biodiversity-related articles. The horizontal axis lists the 30 most common terms, while the vertical axis represents their occurrence counts. Panel A reports unigrams, whereas Panel B reports bigrams.

Panel A. Unigram counts **Panel B. Bigram counts**

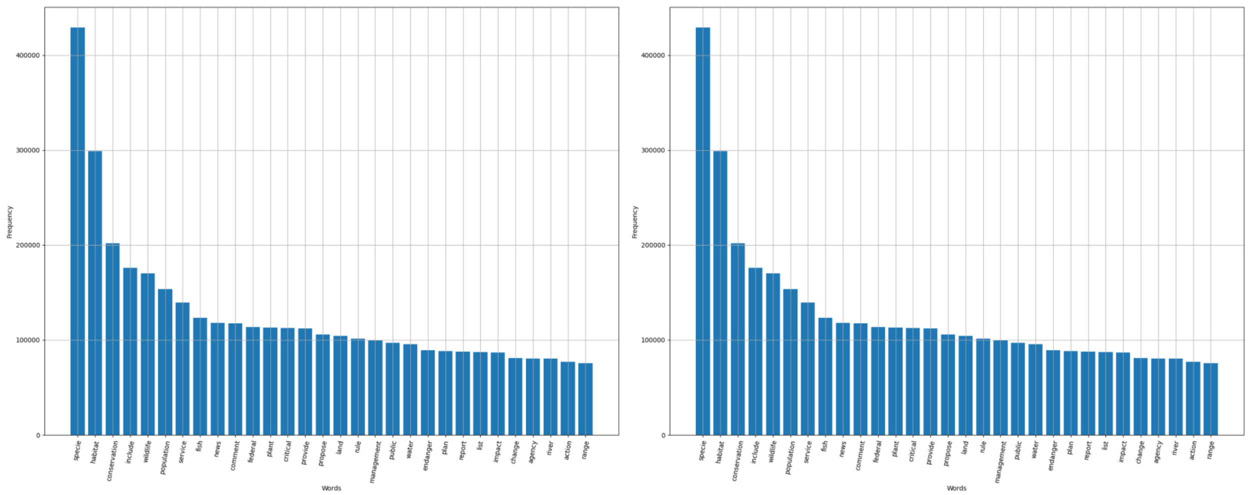


Figure 3: Visualization of Biodiversity-Related Vocabulary
This figure plots the word cloud to visualize the most important words in biodiversity-related articles. The larger and bolder a word appears, the more frequently it is mentioned in the articles.

In addition to textual data, I obtain financial data to examine the impact of biodiversity

[1]Bigrams are two consecutive unigrams in the text. For example, "United States" is a bigram.

news on firm performance. Daily excess stock returns are retrieved from the Center for Research in Security Prices (CRSP). To ensure robust inference, I control for standard asset-pricing factors. Specifically, I include the five Fama–French factors and the momentum factor, sourced from the Kenneth R. French Data Library.[2]

4 Measures of Biodiversity

4.1 Biodiversity Sentiment Index

A key challenge in incorporating biodiversity into economic and finance research is its complexity and the difficulty of quantifying its components. To address the first hypothesis (H1), this paper proposes a systematic approach using sentiment analysis of biodiversity-related news articles.

News about biodiversity can be either positive or negative. For instance, an article reporting firms' commitments to energy efficiency and sustainable operations can be considered positive news. To identify such sentiment, I adopt the Bidirectional Encoder Representations from Transformers (BERT) model (Devlin et al., 2019), which classifies each sentence in a document. Each sentence is assigned a sentiment score from 1 to 5, where "1" represents the most negative sentiment and "5" the most positive.

The sentiment score of an article is computed as the mean value of its sentence-level scores. To measure overall sentiment of biodiversity news on a given day, articles are categorized as follows: scores between 1 and 2 are labeled *negative*, scores between 4 and 5 as *positive*, and scores in between as *neutral*. The distribution of sentiment scores and the number of articles are summarized in Table 1.

Finally, I construct the *Biodiversity Sentiment Index (BSI)* by subtracting the number of negative articles from the number of positive articles each day. Figure 5 presents the monthly aggregated BSI. The index shows an increasing trend in positive sentiment over the sample period, reflecting growing awareness and commitment to biodiversity among firms and stakeholders.

Unlike the NYT-Biodiversity News Index of Giglio et al. (2023), which predominantly exhibits negative sentiment due to its focus on *New York Times* articles, this study relies on a broader set of articles from Dow Jones Factiva, with a significant number originating from U.S. Federal News Service (FNS). Government announcements typically highlight positive aspects and future plans, leading to a higher prevalence of positive articles.

The resulting BSI aligns with stakeholders' perceptions as reflected in publicly available news, and establishes biodiversity as a distinct dimension separate from climate change. This index is used to test the hypothesis that biodiversity issues significantly impact individual stock returns.

[2](French, 2024)

Figure 4: Sentiment Analysis of Biodiversity-Related Articles

This figure presents examples of biodiversity-related articles analyzed using the Bidirectional Encoder Representations from Transformers (BERT) model (Devlin et al., 2019) to construct sentiment scores. Panel A displays an article with a sentiment score of 1, indicating a highly negative tone. This article discusses legal action against governmental oversight failures in environmental protection, highlighting severe consequences such as major oil spills. Panel B shows an article with a sentiment score of 5, representing a highly positive tone. This article details the achievements of a company in energy conservation and sustainability, recognized through ENERGY STAR® Certification by the U.S. Environmental Protection Agency.

Panel A. Article with sentiment score = 1 (negative)

WASHINGTON, May 18 -- The Center for Biological Diversity issued the following news release: The Center for Biological Diversity today filed suit against Secretary of the Interior Ken Salazar over his continued approval of offshore drilling plans in the Gulf of Mexico without environmental review. The lawsuit, filed in federal court in Washington, D.C., seeks to overturn Department of Interior policies exempting oil drilling from the environmental reviews required by the National Environmental Policy Act. BP's Deepwater Horizon drilling plan was approved in 2009 under the "categorical exclusion" exemption policy, leading to the April 20, 2010 explosion that killed 11 people and caused what is likely the larg est oil spill in U.S. history. Despite the catastrophe, Secretary Salazar allowed the Minerals Management Service to issue 26 new drilling approvals -- all exempt from environmental review -- after the explosion. "Ken Salazar has learned absolutely nothing from this national catastrophe," said Kierán Suckling, executive director of the Center for Biological Diversity. "He is still illegally exempting dangerous offshore drilling proje cts in the Gulf of Mexico from all environmental review as millions of gallons of oil gush into the ocean. It is outrageous and unacceptable. "Today's lawsuit seeks to turn Salazar's fictitious 'moratorium' on oil-drilling approvals into a real one," added Suckling. Secretary Salazar has been embroiled in controversy since it was revealed on May 5, 2010 that he allowed the Minerals Management Service to exempt BP's offshore drilling plan from environmental review by using a loophole in the National Environmental Policy Act meant only to apply to projects with no, or minimal, negative effects -- such as construction of outhouses and hiking trails. The controversy deepened when it was revealed that the agency routinely exempts hundreds of dangerous offshore oil drilling projects in the Gulf of Mexico every year. "It is inconceivable that Ken Salazar could go visit what is likely the worst oil spill in American history, then continue to allow the rubber-stamping of new drilling permits based on the absurd claim that an oil spill cannot occur and would not be dangerous if it did. It is positively Kafkaesque," said Suckling.

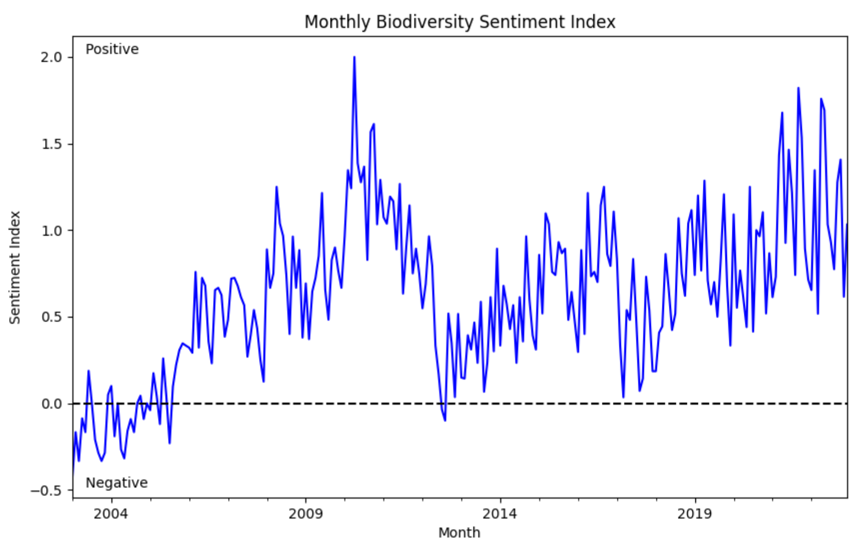
Panel B. Article with sentiment score = 5 (positive)

Friday, October 11: (RWE) - CEMEX USA, a building materials company that provides high-quality products and reliable service to customers and communities across the U.S., today announced two of its cement plants-Miami and Brooksville South-achieved the United States' Environmental Protection Agency's (EPA) ENERGY STAR® Certification for 2019, recognizing CEMEX's efforts in energy efficiency and sustainab ility. These two CEMEX plants have been repeatedly certified by the EPA's ENERGY STAR® program for their conservation efforts. This year's recognition marks nine consecutive years of ENERGY STAR® Certification for CEMEX's Miami Cement Plant, while the Brooksville South Cement Plant has achieved the certification seven out of the last eight years. "CEMEX is committed to delivering world-class products and services to its clients across the U.S. and the globe while maintaining the highest sustainability standards in our industry," said CEMEX USA President Jaime Muguiro. "CEMEX is honored to once again receive these certifications as evidence of responsible stewardship of our planet and its resources." To earn the recognition, operations at each plant followed energy-efficiency principles established by the EPA's ENERGY STAR® Guidelines and implemented energy conservation technologies along with energy-reduction projects. The recognized facilities were among the top 25 percent of similar U.S. facilities for energy conservation and met the ENERGY STAR® Plant Energy Performance Indicators. "At CEMEX, we are committed to pursuing excellence at our operations, and we constantly look for opportunities to cut energy use," said Edgar Angeles, Executive Vice President, Ce ment Operations and Technical. "These cement plants illustrate our dedication to energy conservation and lead by example, showing the industry what is possible." CEMEX is a global building materials company that provides high quality products and reliable services. Its U.S. network includes 11 cement plants, more than 50 strategically- located distribution terminals, 50 aggregate quarries and nearly 270 ready-mix concrete plants. ENERGY STAR® is the simple choice for energy efficiency. For more than 20 years, people across America have looked to EPA's ENERGY STAR program f or guidance on how to save energy, save money, and protect the environment. Behind each blue label is a product, building, or home that is i ndependently certified to use less energy and cause fewer of the emissions that contribute to climate change. Today, ENERGY STAR is the most widely recognized symbol for energy efficiency in the world, helping families and businesses save $300 billion on utility bills, while reducing carbon pollution by two billion metric tons since 1992. Join the millions who are already making a difference at energystar.gov.

Table 1: Sentiment Scores and Corresponding Number of Articles
This table presents the sentiment scores and number of corresponding articles. Articles with sentiment scores between 1 and 2 are labeled as 'negative'. Articles with sentiment scores between 4 and 5 are labeled as 'positive'. Other articles are labeled as 'neutral'.

Sentiment score	Number of articles	Label
Equals 1	25	Negative
Greater than 1 and up to 2	1,486	Negative
Between 2 and 4	52,947	Neutral
At least 4 and less than 5	5,751	Positive
Equals 5	4	Positive
Total	60,213	

Figure 5: Biodiversity Sentiment Index
This figure plots the sentiment index of biodiversity-related articles. The sample period covers January 2003 to December 2022. The horizontal axis represents time in monthly frequency, while the vertical axis represents the biodiversity sentiment index.



4.2 Biodiversity Topic Attention

The second hypothesis (H2) posits that stock returns are more influenced by *transition risks* associated with biodiversity—such as regulatory changes and shifts in media coverage—than by the slower and more diffuse *physical risks* arising from biodiversity loss. Transition risks, being more immediate and quantifiable, are expected to exert a direct influence on market behavior and asset prices.

To examine this, I extract topics related to both physical and transition risks using the Latent Dirichlet Allocation (LDA) model introduced by Blei et al. (2003), applied to the same corpus of biodiversity-related news articles.

4.2.1 Latent Dirichlet Allocation Model

Since its introduction by Blei et al. (2003), the Latent Dirichlet Allocation (LDA) model has become a widely used and valuable tool for extracting topics from text data. In this model, topics are latent variables, meaning they are not directly observable but inferred from the data. The core assumption of LDA is that writing is a data-generating process in which each document contains multiple topics, and each topic consists of multiple words. Specifically, each topic is distributed multinomially over words, and each document is distributed multinomially over topics.

Authors are assumed to select words related to the topics they are writing about until the document is complete. By modeling the multinomial distributions of topics and documents, one can infer the latent topics for each document and the terms associated with them. I estimate the LDA via collapsed Gibbs sampling (Griffiths and Steyvers, 2004). LDA employs Dirichlet multinomial priors and uses Gibbs sampling for Bayesian inference. In simple terms, words are sampled with replacement based on the Dirichlet distribution, assigned to topics, and iteratively updated until the probabilities converge. The number of iterations required for convergence is proportional to the number of words in the document. Results are robust to variational inference.

Formally, I estimate two posterior distributions: one capturing the relationship between words and topics, and the other between topics and documents. Let N_t denote the total number of words in document t, representing the number of sampling iterations. Matrices Φ and Θ represent the word–topic and topic–document distributions, respectively. In particular, $\phi_{k,v}$ denotes the probability that word v belongs to topic k, and $\theta_{t,k}$ denotes the probability that topic k occurs in document t.

By the model assumptions, the priors are:

$$\phi_k = [\phi_{k,1}, \dots, \phi_{k,V}] \sim \mathrm{Dir}(\beta), \qquad \theta_t = [\theta_{t,1}, \dots, \theta_{t,K}] \sim \mathrm{Dir}(\alpha).$$

For simplicity, and in line with Bybee et al. (2023), I set both hyperparameters α and β equal to 1.

With the word–topic and topic–document distributions defined, the distribution of words in document t can be represented as:

$$w_t \sim \mathrm{Mult}\big(\Phi^\top \theta_t,\, N_t\big)\,,$$

where the number of trials is N_t, since the document is complete when the author has written N_t words.

Figure 6: Latent Distributions

This figure illustrates the latent distributions used in the construction of the Latent Dirichlet Allocation (LDA) model (Blei et al., 2003). Panel A presents the distribution ϕ_k, which maps the relationship between words and their associated topics. Panel B presents the distribution θ_t, which maps the relationship between topics and their associated documents.

Panel A. Word–Topic Distribution(ϕ_k)

		Word					
	Index	1	$\cdots$	v	$\cdots$	V	Sum
Topic	1	$\phi_{1,1}$	$\cdots$	$\phi_{1,1}$	$\cdots$	$\phi_{1,V}$	1
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	1
	k	$\phi_{k,1}$	$\cdots$	$\phi_{k,v}$	$\cdots$	$\phi_{k,V}$	1
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	1
	K	$\phi_{K,1}$	$\cdots$	$\phi_{K,v}$	$\cdots$	$\phi_{K,V}$	1

Panel B. Topic–Document Distribution(θ_t)

		Topic					
	Index	1	$\cdots$	k	$\cdots$	K	Sum
Document	1	$\theta_{1,1}$	$\cdots$	$\theta_{1,k}$	$\cdots$	$\theta_{1,K}$	1
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	1
	t	$\theta_{t,1}$	$\cdots$	$\theta_{t,k}$	$\cdots$	$\theta_{t,K}$	1
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	1
	T	$\theta_{T,1}$	$\cdots$	$\theta_{T,k}$	$\cdots$	$\theta_{T,K}$	1

4.2.2 Estimation

With w_t, Gibbs sampling is performed to estimate Φ and Θ. Note that the observed data are the word sequences (or their counts), whereas the topic assignments $z_{t,i}$ are latent and inferred via Gibbs sampling. Therefore, I cannot simply use indices v or k from Figure 6 when sampling; instead, I must rely on the observed order of words.

For example, consider a document containing only one sentence: "Policies aim to protect biodiversity." The word "Policies" is the first term, but I do not know which topic it belongs to, and thus cannot directly determine its assignment.

To estimate θ, consider document t with N_t total words. Denote the first sampled term as $z_{t,1}$, and suppose this word is assigned to topic k. By the LDA assumption,

$$z_{t,1} \sim \text{Mult}(\theta_t, 1), \qquad \theta_t \sim \text{Dir}(1).$$

Since $z_{t,1}, z_{t,2}, \ldots, z_{t,N_t}$ are independent, topic k's attention to document t can be calculated as the ratio of words in t assigned to topic k:

$$\hat{\theta}_{t,k} = \frac{\sum_{i=1}^{N_t} \mathbf{1}(\hat{z}_{t,i} = k)}{\sum_{q=1}^{K} \sum_{i=1}^{N_t} \mathbf{1}(\hat{z}_{t,i} = q)}. \tag{1}$$

Similarly, monthly topic attention for month τ is given by:

$$\hat{\theta}_{\tau,k} = \frac{\sum_{t \in \tau} \sum_{i=1}^{N_t} \mathbf{1}(\hat{z}_{t,i} = k)}{\sum_{t \in \tau} \sum_{q=1}^{K} \sum_{i=1}^{N_t} \mathbf{1}(\hat{z}_{t,i} = q)}, \tag{2}$$

where τ indexes the desired month.

On the other hand, to estimate ϕ, assume I want to draw a word assignment from topic k. Let $x_{t,1}$ denote the first observed word. By construction,

$$x_{t,1} \sim \text{Mult}(\phi_k, 1).$$

If $x_{t,1}$ corresponds to $z_{t,1}$, then the probability that $z_{t,1}$ belongs to topic k increases. Consequently, word v's attention to topic k is estimated as:

$$\hat{\phi}_{k,v} = \frac{\sum_{t=1}^{T} \sum_{i=1}^{N_t} \mathbf{1}(x_{t,i} = v)\, \mathbf{1}(z_{t,i} = k)}{\sum_{t=1}^{T} \sum_{i=1}^{N_t} \sum_{m=1}^{V} \sum_{q=1}^{K} \mathbf{1}(x_{t,i} = m)\, \mathbf{1}(z_{t,i} = q)}. \tag{3}$$

4.2.3 Number of Topic Selection

Another hyperparameter that must be determined in LDA is the number of topics K. Following recent studies (e.g., Newman et al., 2010; Holtzman et al., 2019), I use *topic coherence* to guide the choice of K.

One of the main concerns in LDA is that it models documents using a multinomial distribution, which is discrete and therefore does not explicitly account for word co-occurrence or order. Since words in natural language are often highly interconnected, this can limit interpretability. Topic coherence addresses this limitation by measuring the degree of semantic similarity among the high-probability words within each topic.

Among various measures, I adopt the C_v coherence score, which is based on a sliding window, one-set segmentation of top words, and an indirect confirmation measure that combines normalized pointwise mutual information with cosine similarity (Röder et al., 2015). Figure 7 plots C_v scores across different topic numbers, with the optimal value suggesting $K = 5$.

4.2.4 LDA Results

Table 2 reports the five extracted topics, each represented by the top fifteen words with the highest estimated probabilities $\hat{\phi}_{k,v}$ from equation (3). Thus, the table can be interpreted as a transposed and sorted representation of the estimated Φ matrix from Figure 6.

Topic labels are assigned based on terms whose probabilities exceed 0.002%[3].

Two of the extracted topics—*Endangered Species* and *Natural Resource Management*—are categorized as *physical risks*. The other three topics—*Conservation Policy*, *Environmental News*, and *Regulations and Permits*—are categorized as *transition risks*. In particular, the topic labeled *Environmental News* includes both concentrated media coverage and biodiversity-related academic studies, reflecting the increased public interest in biodiversity.

4.2.5 Topic Attention

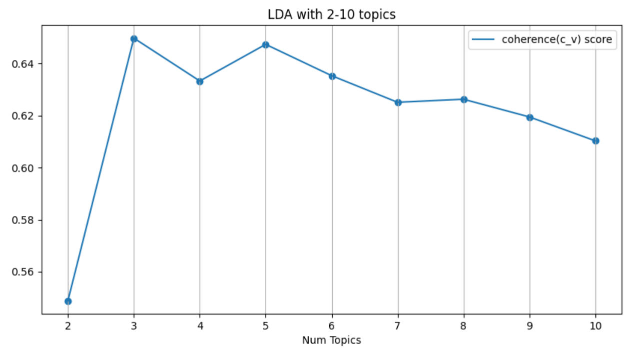
The attention to the topic $\hat{\theta}_{t,k}$ and the monthly attention to the topic are calculated using equations (1) and (2), respectively. The resulting monthly topic distributions are illustrated in Figure 8.[4]

[3]Since the corpus contains 41,125 unique terms, the uniform baseline probability would be approximately $1/41{,}125 \approx 0.00002$. Hence, probabilities greater than 0.002% are considered significantly high.

[4]For scaled topic distribution, see Figure A.1 in the Appendix.

Figure 7: Latent Dirichlet Allocation (LDA) coherence scores
This figure reports the coherence (C_v) scores of Latent Dirichlet Allocation (LDA; Blei et al., 2003) models estimated with varying numbers of topics. The horizontal axis denotes the number of topics, and the vertical axis shows the corresponding C_v coherence scores. Panel A presents coherence scores for topic numbers ranging from 2 to 10, whereas Panel B displays results for topic numbers from 10 to 250 in increments of 10.

Panel A. Topics $K = 2$ to 10



Panel B. Topics $K = 10$ to 250 (by 10)

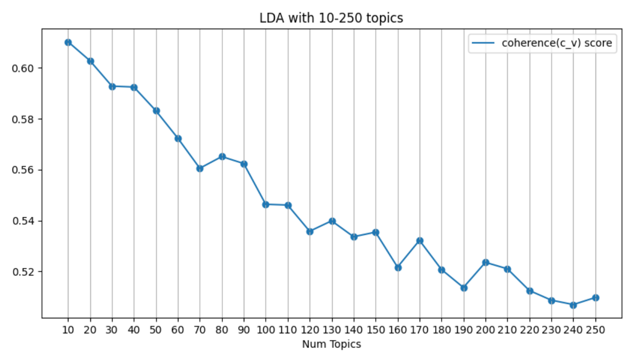
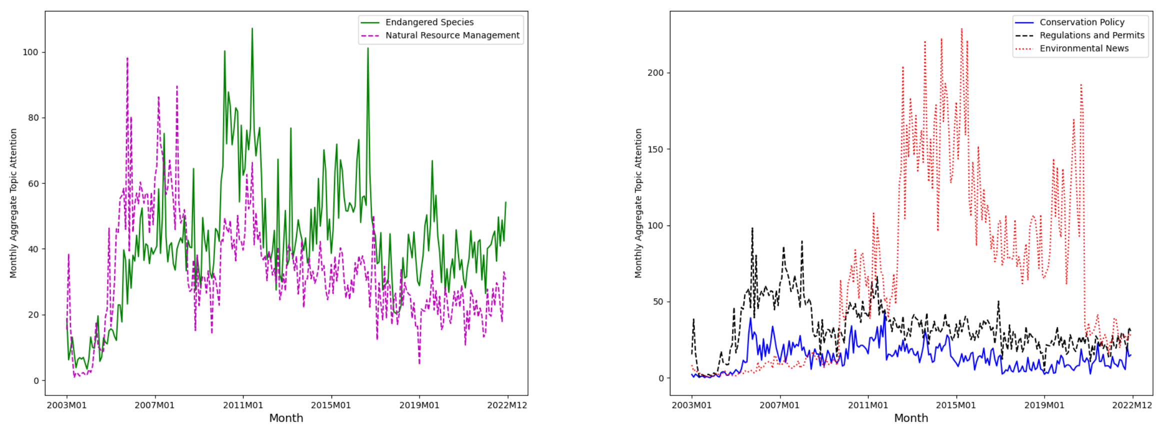


Table 2: Top 15 Words associated with LDA topics
This table reports the fifteen words most strongly associated with each of the five topics extracted from the Latent Dirichlet Allocation (LDA) model. Words are shown with their estimated probabilities (in parentheses) on a separate line for readability.

Topic 1 Endangered Species	**Topic 2 Conservation Policy**	**Topic 3 Environmental News**	**Topic 4 Regulations and Permits**	**Topic 5 Natural Resource Management**
population (1.27%)	critical (1.06%)	news (2.16%)	comment (1.26%)	wildlife (0.97%)
animal (0.50%)	critical habitat (1.04%)	report (0.97%)	permit (1.02%)	conservation (0.71%)
range (0.48%)	propose (0.60%)	conservation (0.92%)	public (0.79%)	plant (0.56%)
wolf (0.46%)	include (0.56%)	ecology (0.72%)	service (0.65%)	project (0.54%)
endanger (0.46%)	conservation (0.55%)	university (0.69%)	propose (0.64%)	water (0.53%)
threat (0.44%)	designation (0.54%)	include (0.66%)	rule (0.61%)	land (0.48%)
wildlife (0.43%)	unit (0.54%)	editor (0.65%)	wildlife (0.60%)	program (0.46%)
island (0.39%)	federal (0.53%)	study (0.64%)	fish (0.58%)	environmental (0.43%)
list (0.36%)	land (0.52%)	biodiversity (0.58%)	include (0.52%)	agency (0.42%)
change (0.35%)	service (0.50%)	accord (0.57%)	activity (0.42%)	fish (0.41%)
fish (0.34%)	population (0.50%)	news editor (0.54%)	federal (0.41%)	include (0.40%)
bird (0.34%)	rule (0.46%)	contact (0.54%)	management (0.35%)	service (0.39%)
bear (0.34%)	impact (0.44%)	verticalnews (0.52%)	plan (0.34%)	resource (0.39%)
conservation (0.33%)	river (0.41%)	plant (0.50%)	issue (0.33%)	protect (0.38%)
include (0.32%)	provide (0.40%)	united (0.49%)	list (0.32%)	plan (0.37%)

Figure 8: Topic distributions across time and sectors
This figure illustrates how the estimated LDA topic proportions vary across years and industry sectors. Panel A reports the annual distribution of topics over the sample period, while Panel B shows topic allocations across major industry sectors.

Panel A: Physical-risk topics **Panel B: Transition-risk topics**



Panel A shows the monthly aggregate topic attention for *Endangered Species* and *Natural Resource Management*, representing physical risk-related topics. Overall, attention to both topics has consistently remained significant, with some fluctuations. Attention to *Endangered Species* rose steadily in the early 2000s, peaking around 2007, and has remained high thereafter, driven by ongoing conservation efforts and heightened awareness of biodiversity loss. By contrast, *Natural Resource Management* initially attracted more attention, reflecting the importance of sustainable resource use and ecosystem management. However, after peaking around 2010, attention to natural resource management gradually declined, suggesting a shift toward more specific environmental concerns such as species conservation.

Panel B of Figure 8 plots the monthly aggregate topic attention for *Conservation Policy*, *Regulations and Permits*, and *Environmental News*, which represent transition risk-related topics. Both *Conservation Policy* and *Regulations and Permits* have consistently attracted attention over the years, with regulations showing slightly higher attention during the first decade (2003–2012). This pattern reflects the introduction of numerous regulations during that period, such as the Healthy Forests Restoration Act (2003), the Magnuson-Stevens Fishery Conservation and Management Reauthorization Act (2006), the Neotropical Migratory Bird Conservation Act Reauthorization (2006), the Coral Reef Conservation Act Reauthorization and Enhancement Amendments (2009), and the Shark Conservation Act (2010).

In the second decade (2013–2022), fewer new regulations were introduced, resulting in relatively lower attention to regulation-related topics. Notable examples from this period include the Illegal, Unreported, and Unregulated Fishing Enforcement Act (2015), the Save Our Seas Act (2018), the John D. Dingell, Jr. Conservation, Management, and Recreation Act (2019), and the Great American Outdoors Act (2020). Additional biodiversity-related regulations and policies are summarized in Table 3.

Table 3: Important Biodiversity Regulations and Acts (2003–2022)
This table summarizes major biodiversity-related regulations and acts enacted from 2003 to 2022, highlighting efforts to conserve habitats, protect endangered species, and strengthen environmental enforcement.

Regulation/Act	**Year**	**Description**
Healthy Forests Restoration Act	2003	Aims to reduce the threat of destructive wildfires while upholding environmental standards.
Magnuson–Stevens Fishery Conservation and Management Reauthorization Act	2006	Focuses on the management and conservation of fishery resources to prevent overfishing and rebuild overfished stocks.
Neotropical Migratory Bird Conservation Act Reauthorization	2006	Provides financial assistance for the conservation of neotropical migratory birds that winter in Latin America and the Caribbean.
Marine Debris Research, Prevention, and Reduction Act	2006	Addresses marine debris through research and reduction strategies.
National Fish Habitat Action Plan	2006	A framework for restoring and enhancing fish habitats across the nation.
North American Wetlands Conservation Act Reauthorization	2006	Supports wetland conservation projects in North America through funding and partnerships.
Partners for Fish and Wildlife Act	2006	Promotes voluntary habitat restoration efforts on private lands.
Multinational Species Conservation Funds Reauthorization	2007	Provides funding for conservation efforts targeting multinational species.
Lacey Act Amendments	2008	Strengthens penalties for illegal wildlife trade and supports enforcement.
Harmful Algal Bloom and Hypoxia Research and Control Amendments Act	2008	Addresses harmful algal blooms and hypoxia through research and monitoring.
Coral Reef Conservation Act Reauthorization and Enhancement Amendments	2009	Enhances and reauthorizes the Coral Reef Conservation Act to protect and conserve coral reef ecosystems.
Pacific Salmon Stronghold Conservation Act	2009	Conserves Pacific salmon habitats through collaboration and funding.
Shark Conservation Act	2010	Aims to prevent shark finning and improve the conservation of sharks.
Asian Carp Prevention and Control Act	2010	Prevents the introduction and spread of Asian carp in U.S. waterways.
Southern Sea Otter Recovery and Research Act	2010	Supports recovery and research efforts for the endangered southern sea otter.
National Wildlife Refuge Volunteer Improvement Act	2010	Encourages volunteer participation in the management of national wildlife refuges.
Illegal, Unreported, and Unregulated Fishing Enforcement Act	2015	Strengthens enforcement mechanisms to combat illegal, unreported, and unregulated fishing.
Save Our Seas Act	2018	Addresses marine debris through improved coordination and response efforts.
John D. Dingell, Jr. Conservation, Management, and Recreation Act	2019	Provides for the management and conservation of natural resources on public lands and supports recreational activities.
Great American Outdoors Act	2020	Provides funding for the maintenance and conservation of national parks, public lands, and Indian schools.

Meanwhile, attention to *Environmental News* surged in the mid-2010s, reflecting growing public interest, academic studies, and research activities related to biodiversity. This trend suggests that while regulatory topics dominated in the first decade due to the introduction of numerous policies, the second decade witnessed a shift toward broader environmental awareness and advocacy, driven by heightened media coverage and academic focus on biodiversity loss and sustainable development.

Table 4 presents the correlations among topics' monthly attention. As expected, physical risk-related topics (*Endangered Species* and *Natural Resource Management*) are positively correlated with each other. Similarly, regulation-related topics (*Conservation Policy* and *Regulations and Permits*) are positively associated. In contrast, *Environmental News* is negatively correlated with other topics. One possible explanation is that the broad and often urgent nature of environmental news tends to overshadow ongoing but less immediately pressing issues such as natural resource management or detailed conservation policies.

Table 4: Correlation between topics' monthly attention

This table presents the correlation between topics' monthly attention. *, **, and *** indicate statistical significance (Pearson's R) at the 10%, 5%, and 1% levels, respectively.

	Endangered Species	**Conservation Policy**	**Environmental News**	**Regulations and Permits**	**Natural Resource Management**
Endangered Species	1				
Conservation Policy	0.2151***	1			
Environmental News	-0.4296***	-0.3966***	1		
Regulations and Permits	-0.0035	0.4578***	-0.5749***	1	
Natural Resource Management	0.2484***	-0.0121	-0.8178***	0.0926	1

5 Main Results

To test the first hypothesis (H1), I regress individual firms' excess returns ($r_{i,t}$) on the Biodiversity Sentiment Index from Section 4.1, along with control variables ($CTRL_t$):

$$r_{i,t} = c + \gamma \times \mathrm{BSI}_t + \beta' CTRL_t + \epsilon_{i,t}, \tag{4}$$

where c is a constant, γ and β are regression coefficients, and $\epsilon_{i,t}$ is an error term.

Estimation and standard errors. I estimate panel regressions with firm fixed effects only. Because BSI_t varies *only* over time and is common to all firms on day t, including date fixed effects would render BSI_t unidentified due to perfect collinearity. Standard errors are two-way clustered by firm and date (Cameron et al., 2011). As a complementary specification, I estimate interaction models with $\mathrm{BSI}_t \times \mathrm{Char}_i$ (e.g., size, book-to-market, pollution intensity) under firm *and* date fixed effects to identify heterogeneous exposures.

For cross-sectional inference on the interaction slopes, I also report Fama–MacBeth estimates (Fama and MacBeth, 1973) with Newey–West corrections (Newey and West, 1987).

Three sets of control variables are considered:

- **CTRL-1**: MKT, the excess market return.
- **CTRL-3**: CTRL-1 augmented with HML (high-minus-low) and SMB (small-minus-big) factors of Fama and French (1992).
- **CTRL-6**: CTRL-3 augmented with RMW (robust-minus-weak), CMA (conservative-minus-aggressive) factors of Fama and French (2015), and MOM (momentum) factor of Carhart (1997).

These variables are standard in the finance literature. Controlling for them allows isolation of the specific impact of biodiversity sentiment on stock returns, particularly when news conveys information directly relevant to firm performance.

News volume control. To disentangle tone from attention, I add daily news volume (total biodiversity articles) and $|\mathrm{BSI}_t|$ as controls; results are robust to a normalized index $\mathrm{BSI}_t^* = (\#\mathrm{pos}_t - \#\mathrm{neg}_t)/(\#\mathrm{pos}_t + \#\mathrm{neg}_t)$.

Event-time dynamics. I examine cumulative returns from $t-5$ to $t+5$ around high-BSI days to distinguish short-horizon reversal vs. monotone decay. Effects peak over t–$t+1$ and attenuate thereafter.

Firm-level exposure. I estimate firm-level $\beta_{\mathrm{BSI},i}$ from rolling regressions of $r_{i,t}$ on BSI_t (controlling for factors) and sort decile portfolios. High-minus-low β_{BSI} portfolios earn higher average returns, consistent with priced exposure.

Endogeneity considerations. To address potential common shocks that jointly affect news and returns (e.g., anticipated regulatory actions), I (i) use one-day lags of BSI, (ii) exclude firm-specific major-announcement days, and (iii) re-estimate in event windows around policy releases.

Estimation results are reported in Table 5. Panel A presents daily excess returns. Columns (1)–(3) use contemporaneous returns, while columns (4)–(6) use one-day lagged returns. Each set corresponds to CTRL-1, CTRL-3, and CTRL-6, respectively. Across all specifications, the Biodiversity Sentiment Index is positive and statistically significant, indicating that higher biodiversity attention is followed by higher realized excess returns in the short run.

However, this effect does not persist in the longer term. Panel B, based on monthly excess returns, shows that the BSI does not significantly affect returns, especially with one-month lagged returns. This indicates that while biodiversity concerns influence the market in the short term, the effect quickly fades, consistent with reactions being sentiment-driven rather than rooted in long-term fundamentals.

Table 5: OLS with Firm Fixed Effects for Firm Excess Returns
This table explores the relationship between biodiversity sentiment and firm excess return. Excess returns are constructed following the methodology of Jensen et al. (2023). MKT, SMB, HML, RMW, CMA, MOM are the market, size, value, profitability, investment and momentum factors, respectively. Standard errors are reported in parentheses and are clustered at both the time and firm levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Daily excess returns

Dependent variable:	**Excess return (daily)**			**Lagged excess return (daily)**		
Model:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	-6.2711***	-6.2783***	-6.2745***	-6.2708***	-6.2715***	-6.2696***
	(0.1241)	(0.1239)	(0.1239)	(0.1241)	(0.1239)	(0.1239)
Biodiversity Sentiment Index	0.4373***	0.4433***	0.4431***	0.4419***	0.4397***	0.4414***
	(0.0718)	(0.0716)	(0.0715)	(0.0717)	(0.0753)	(0.0715)
MKT	1.0187***	0.9139***	0.8697***	1.0157***	0.9149***	0.8721***
	(0.0740)	(0.0759)	(0.0858)	(0.0736)	(0.0752)	(0.0853)
SMB		0.8501***	0.8185***		0.8337***	0.8050***
		(0.1579)	(0.1651)		(0.1581)	(0.1653)
HML		0.0655	-0.1199		0.0448	-0.1529
		(0.1089)	(0.1430)		(0.1092)	(0.1437)
RMW			-0.1256			-0.1055
			(0.2042)			(0.2039)
CMA			0.2370			0.2584
			(0.2909)			(0.2905)
MOM			-0.2767***			-0.2891***
			(0.1029)			(0.1019)
R square	0.0261	0.0297	0.0306	0.0262	0.0296	0.0306
Observation	21,069,405	21,069,405	21,069,405	21,064,492	21,064,492	21,064,492

Panel B. Monthly excess returns

Dependent variable:	**Excess return (monthly)**			**Lagged excess return (monthly)**		
Model:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	7.4507*	7.4365*	7.3244**	6.6038*	6.5893*	6.6560*
	(3.8943)	(3.8494)	(3.6690)	(3.5945)	(3.6269)	(3.4376)
Biodiversity Sentiment Index	-6.9856**	-6.9100**	-6.6724*	-5.6753	-5.6321	-5.8800
	(3.5090)	(3.4431)	(3.4470)	(3.7113)	(3.7664)	(3.9072)
MKT	1.3884***	0.9695***	1.1523***	0.0110	-0.2265	-0.1638
	(0.1582)	(0.2229)	(0.1908)	(0.1130)	(0.1681)	(0.1474)
SMB		1.7879***	0.8185**		1.0578*	0.9914
		(0.6864)	(0.6152)		(0.5426)	(0.6158)
HML		0.2142	-0.2527		0.0419	-0.3945*
		(0.2745)	(0.3256)		(0.2803)	(0.2334)
RMW			-1.4580			-0.3173
			(0.9169)			(0.4165)
CMA			1.8946			1.2780
			(1.6982)			(0.8156)
MOM			0.2848			-0.0111
			(0.3559)			(0.1920)
R square	0.000016	0.000022	0.000027	0.000003	0.000006	0.000007
Observation	1,171,219	1,171,219	1,171,219	1,171,219	1,171,219	1,171,219

To test hypothesis H2, I regress daily excess returns ($r_{i,t}$) on biodiversity-related topic attention from Section 4.2, along with the same control variables:

$$r_{i,t} = c + \gamma' \text{Topic}_t + \beta' CTRL_t + \epsilon_{i,t}, \tag{5}$$

where c is a constant, γ and β are regression coefficients, and $\epsilon_{i,t}$ is an error term.

Mapping monthly topics to days. Monthly topic attention $\hat{\theta}_{\tau,k}$ is assigned to all trading days within month τ; results are robust to using daily topic attention constructed from same-day articles only.

Five topics are used: *Endangered Species*, *Natural Resource Management*, *Conservation Policy*, *Environmental News*, and *Regulations and Permits*. The first two represent physical risks, while the latter three represent transition risks. Under H2, transition risk topics are expected to exert stronger effects on returns.

Results are reported in Table 6. Columns (1)–(3) use contemporaneous daily returns, while columns (4)–(6) use one-day lagged returns, under CTRL-1, CTRL-3, and CTRL-6 specifications, respectively. Across all cases, transition risk topics exhibit stronger impacts than physical risk topics. For example, in column (6), coefficients are: *Conservation Policy* −3.92, *Environmental News* 6.76, *Regulations and Permits* −9.82, compared with *Endangered Species* 2.18 and *Natural Resource Management* −0.17.

Among transition risks, *Environmental News* positively affects excess returns, consistent with Table 4, which shows that increased public attention raises the cost of capital. By contrast, regulations and policies negatively affect returns, likely because they impose operational constraints or product restrictions on firms.

6 Conclusion and Future Research

This paper investigates the relationship between biodiversity concerns and firm performance, highlighting the significant impact of biodiversity issues on stock returns. The findings indicate that biodiversity sentiment, as captured through media coverage, has a notable influence on daily excess returns, implying that markets react with higher realized returns in the short run when biodiversity attention increases. This pattern can be consistent with investors requiring compensation for biodiversity-related risks, but it should be emphasized that the evidence pertains to realized excess returns rather than direct estimates of ex ante cost of capital. However, the effect does not persist at longer horizons, pointing to the transient nature of market reactions to biodiversity news.

To explore potential mechanisms, we apply topic modeling to distinguish between physical and transition risks. The results show that transition risks exert a more substantial influence on stock returns than physical risks. These findings underscore the importance of incorporating biodiversity considerations into financial decision-making and risk management strategies. As regulatory pressures and public awareness of biodiversity issues continue to grow, both firms and investors will need to adapt to these evolving risks.

One limitation of this study is that the main explanatory variables are time-series measures, while individual firms' excess returns depend on both time and firm-specific characteristics. This mismatch raises potential concerns. One possible solution is to construct firm-level biodiversity indices using 10-K filings, as in Giglio et al. (2023). However, such an approach may not capture overall media attention. Since this paper seeks to investigate the influence of broad societal concern, a news-based index is arguably more appropriate.

Another avenue for future research is to construct a long–short portfolio strategy. The commonly used *Green-minus-Brown* portfolio in climate finance is based on greenhouse gas emissions and thus does not readily extend to biodiversity. Instead, one could form a portfolio based on firms' sensitivities to the Biodiversity Sentiment Index. Firms highly sensitive to the index could be categorized as "Green," while less sensitive firms could be categorized as "Brown." Exploring such a biodiversity-based portfolio approach is left for future research.

Table 6: Firms' Excess Returns and Topics: OLS with Firm Fixed Effects
This table explores the relationship between biodiversity topics and firm excess return. Dependent variables are daily firm excess returns (and one-day lagged). Excess returns are constructed following the methodology of Jensen et al. (2023). The first three columns utilize non-lagged excess returns, while columns (4), (5), and (6) employ lagged excess returns. Topic values are constructed by Latent Dirichlet Allocation (LDA) method (Blei et al., 2003). MKT, SMB, HML, RMW, CMA, MOM are the market, size, value, profitability, investment and momentum factors, respectively. Standard errors are reported in parentheses and are clustered at both the time and firm levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	**Excess return (daily)**			**Lagged excess return (daily)**		
Model:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	-5.3269***	-5.3637***	-5.3800***	-5.3039***	-5.3803***	-5.3911***
	(0.2151)	(0.2116)	(0.2101)	(0.2164)	(0.2120)	(0.2146)
Endangered Species	2.2417***	2.2002***	2.2367***	2.0924***	2.1837***	2.1798***
	(0.6979)	(0.6974)	(0.6968)	(0.7040)	(0.7010)	(0.7022)
Conservation Policy	-4.2581***	-4.2416***	-4.2407***	-3.9500***	-3.8756***	-3.9203***
	(1.4726)	(1.4683)	(1.4691)	(1.4697)	(1.4629)	(1.4626)
Environmental News	6.7237***	6.7735***	6.7745***	6.6367***	6.7346***	6.7553***
	(0.3602)	(0.3569)	(0.3560)	(0.3628)	(0.3582)	(0.3596)
Regulations and Permits	-9.9821***	-9.9294***	-9.9060***	-9.9556***	-9.8346***	-9.8182***
	(0.7071)	(0.7060)	(0.7053)	(0.7066)	(0.7067)	(0.7070)
Natural Resource Management	-0.2336	-0.1770	-0.1540	-0.2475	-0.1984	-0.1749
	(0.3389)	(0.3361)	(0.3351)	(0.3398)	(0.3362)	(0.3383)
MKT	0.9729***	0.8695***	0.8235***	1.0290***	0.9256***	0.8915***
	(0.0716)	(0.0729)	(0.0816)	(0.0720)	(0.0738)	(0.0813)
SMB		0.8127***	0.7858***		0.8055***	0.7797***
		(0.1530)	(0.1593)		(0.1518)	(0.1579)
HML		0.0917	-0.0424		0.0988	-0.1257
		(0.1075)	(0.1414)		(0.1085)	(0.1423)
RMW			-0.1123			-0.0828
			(0.2017)			(0.1973)
CMA			0.0950			0.3597
			(0.2818)			(0.2817)
MOM			-0.2365**			-0.2948***
			(0.0990)			(0.0989)
R square	0.0977	0.1011	0.1017	0.0962	0.0996	0.1005
Observation	21,069,405	21,069,405	21,069,405	21,064,492	21,064,492	21,064,492

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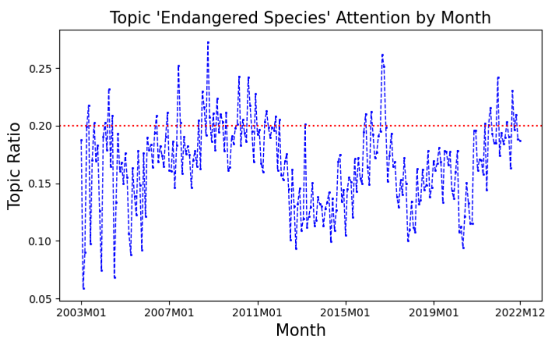
Appendix

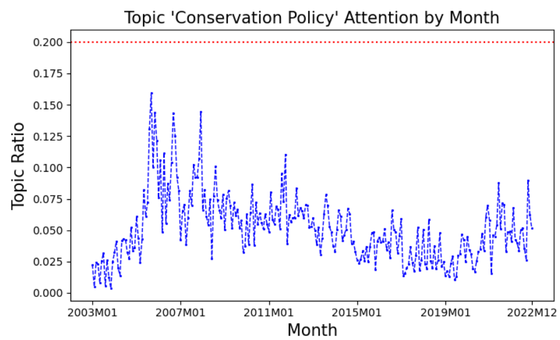
Figure A.1: Scaled topic attention by month

This figure plots the topic attention in ratio by topics. Panels A through E plot 'Endangered Species, Conservation Policy, Environmental News, Regulations and Permits, Natural Resource Management' topics, respectively. The blue line represents the percentage of attention given to the topic. The red line represents the value of 0.2; when topics are evenly distributed, monthly shares approach 0.2. The horizontal axis represents time in monthly frequency. The vertical axis represents the topic ratio.

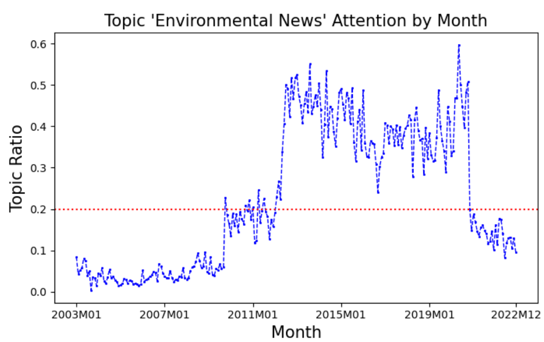
Panel A. Topic 'Endangered Species' attention



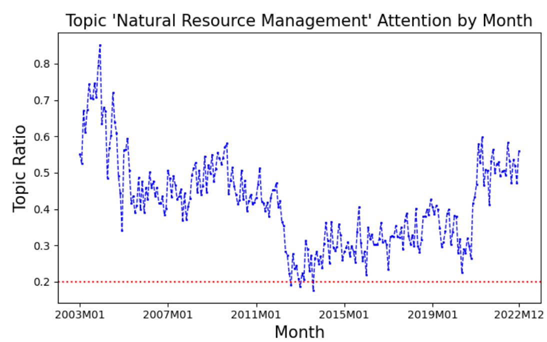
Panel B. Topic 'Conservation Policy' attention



Panel C. Topic 'Environmental News' attention



Panel D. Topic 'Regulations and Permits' attention



Panel E. Topic 'Natural Resource Management' attention