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Fresh evidence on climate and biodiversity risks in asset pricing

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ABSTRACT

The study explores the effects of both climate risk, proxied by the physical risk, and biodiversity risk on stock returns. Using New York Stock Exchange firms, Dow Jones30 firms and SP500 firms, along with an EGARCH-X model, the analysis documents that both types of risk are priced, with the biodeversity risk dominating the climate risk, especially in the case of 'dirty' firms. The findings are highly significant for market participants in forming investment strategies.

KEYWORDS
Climate risks; biodiversity risks; NY stocks; EGARCH-X model

JEL CLASSIFICATION
G12; Q54; Q57

I. Introduction

The theoretical literature on the standard theory of sustainable asset pricing, according to which the price of financial assets largely depends on financial investors' expectations about payoffs and risk exposure, has offered studies on the role of climate risk in asset markets, especially in stock markets (Faccini, Matin, and Skiadopoulos 2021). Bressan and Romagnoli (2021) explore the role of climate and weather derivatives as instruments for hedging climate risks. They also document the presence of bias in capital risk calculation (i.e. mispricing and over/underestimations) in the presence of climate risk, which may provide detrimental effects to financial stability. Nordhaus (2019) provides evidence that financial markets do not adequately price climate risks due to the presence of a discrepancy between market prices and true social costs, a view also fully supported by Campiglio et al. (2023).

Nevertheless, the literature remains inconclusive in relevance to the findings regarding climate risks. Certain studies highlight that physical risks are priced in credit markets (Huynh and Xia 2021), others agree for sovereign debt markets (Mallucci 2022), and corporate debt markets (Lalwani 2024), while others disagree (Faccini, Matin, and Skiadopoulos 2023). This ambiguity in the results has been attributed to the fact that climate risk is characterized by heterogeneity across firms and types of assets, as well as to diverse proxies for climate risks (Krueger, Sautner, and Starks 2019).

The economic risks associated with biodiversity losses, i.e. biodiversity risks, have emerged as another important dimension of the complex interactions between the economy and the environment (Giglio et al. 2023). Our study asks a very important question. Which risk is more prominent in impacting the return and volatility of stock prices? The literature has focused on climate risks and shows that they command a risk premium that increases firms' cost of capital with a large carbon footprint (De Angelis, Tankov, and Zerbib 2023). Our study contributes to the literature of sustainable asset pricing by investigating the proximity of climate and biodiversity risks to stock prices. In this strand of literature, several studies focus solely on investigating the link between physical climate risk and equity returns using metrics like temperature anomaly measures (Bansal, Kiku, and Ochoa 2019). Our work contributes to this literature by investigating whether biodiversity risks is priced, and whether it is more prominent in comparison to climate risk, as this is mostly proxied by physical risk.

II. Methodology

The analysis employs an EGARCH-X model (Nelson 1991), with the X factor being both the biodiversity and climate risks in the mean return

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equation and the conditional variance equation of US stock prices. These equations yield:

$$RET_{it} = \mu + dZ_{it} + \theta_1 X_{1t} + \theta_2 X_{2t} + \delta_t + \zeta_i + \varepsilon_{it} \quad (1)$$

$$h_{it} = \omega_0 + \alpha_0 h_{it-1} + \beta_0 \left(\frac{|\varepsilon_{it-1}|}{\sigma_{it-1}} - \sqrt{\frac{2}{\pi}} \right) + \gamma_0 \frac{\varepsilon_{it-1}}{\sigma_{it-1}} + \psi_1 X_{1t} + \psi_2 X_{2t} \quad (2)$$

where RET is stock returns for firm i, X_1 is the climate risk factor, X_2 is the biodiversity risk factor, Z is a vector of controls, which includes firm-specific variables. δ_t, ζ_i denote time and firm-fixed effects, respectively, ε_{it} is the error term. σ^2_{it}, h_{it} denote, respectively, the unconditional and the conditional variances, $\frac{\varepsilon_{it}}{\sigma_{it}}$ is the standardized shock. The parameter γ_0 captures the leverage effect, which accounts for the model's asymmetry. If $\gamma_0 < 0$, positive shocks generate less volatility than negative shocks, whereas if $\gamma_0 > 0$, negative news is less disruptive. The coefficients of interest in the two equations are θ_1 and θ_2, as well as ψ_1 and ψ_2, respectively.

III. Data

Climate risk is proxied by physical risk, measured as temperature/precipitation data for the US, sourced from the Berkeley Earth database (http://berkeleyearth.lbl.gov/regions/united-states), a compilation of monthly observations from diverse weather monitoring stations. It offers an estimation of temperature/precipitation trends, reported as anomalies relative to the January 1951-December 1989 average. Data is calculated as the variance between the daily temperature/precipitation value and the corresponding reference temperature value, defined as the deviation from the average monthly temperature/precipitation of the preceding years (January 1951–December 1989) for the same month. A positive (negative) anomaly indicates a higher (lower) temperature/precipitation compared to their historical average (Cao and Wei 2005).

Regarding stock prices/returns, the universe of choice for the cross-sectional empirical analysis is the New York Stock Exchange (NYSE) with 2,132 listed firms. Moreover, returns data on DJIA and SP500 was also retrieved from Refinitiv, spanning the period 2010–2024. Controls, as in Bolton and Kacperczyk (2021), are also sourced from Refinitiv over the same period. The model includes as controls certain firm characteristics, common predictors in literature explaining stock returns, such as: firm size measured by the logarithm of total assets, the ratio of book equity to market capitalization, financial leverage measured by the ratio of total debt to total assets, asset tangibility defined as net property, plant, and equipment, divided by total assets, capital expenditures divided by total assets, return on assets measured by net income after tax divided by total assets, asset growth defined as the percentage change in total assets, momentum measured by the cumulative stock return over the 1-year period. Regarding the biodiversity risk factor, the analysis uses the Giglio et al. (2023)'s measure of biodiversity risk. Table 1 reports descriptive statistics.

IV. Empirical analysis

First, we fit an EGARCH-X (1,1) model for stock returns and volatility, with the X factors taken to be the physical climate risk and the biodiversity risk proxies, respectively. Table 2 illustrates the following findings: Panel A shows the negative and significant (at 1%) coefficient on both the climate and biodiversity risk factors. Moreover, the coefficient of the biodiversity risk is higher than its counterpart of climate risk. As for the volatility results in Panel B, we note the positive and significant (at 1%) coefficient on both the climate and biodiversity risk factors in the conditional volatility equation, with that of the biodiversity risk being higher than that of the climate risk. The negative correlation in the mean equation suggests that investors are inclined to accept diminished returns in exchange for insulation against both temperature anomalies and biodiversity risks. The results also point to the prediction of a positive biodiversity risk premium, implying that investors may start considering the risks associated not only with climate, but also with biodiversity footprints.

For robustness, the analysis also uses precipitation anomalies to check the results validation. The

Table 1. Descriptive statistics.

Variables	Mean	SD	Min	Max	Skew	Kurt
Temperature anomalies	0.22	0.20	−0.04	1.55	−2.33	−3.78
Precipitation anomalies	0.17	0.26	−0.10	2.37	−3.16	−4.62
Biodiversity index	0.05	0.37	−4.05	5.16	−1.74	3.91
NY stock firm returns (%)	1.14	10.94	0.71	4.56	−1.15	4.66
Log size	8.54	1.62	5.51	13.71	1.69	2.94
Book-to-market cap ratio	0.56	0.43	0.24	1.46	2.26	3.37
Financial leverage	0.26	0.21	0.17	0.52	1.94	3.08
Asset tangibility	0.06	0.05	0.01	0.19	2.18	3.26
Capital expenditures divided by total assets	0.06	0.07	0.01	0.25	3.11	3.16
Return on assets	9.81 4.59	22.25	1.16	46.35	−4.03	
Asset growth	0.17	0.06	−0.06	10.16	2.71	3.26
Momentum (%)	0.16	0.53	0.04	0.31	−1.73	2.64
Observations:	383,760					
Dow-Jones returns (%)	0.02	0.49	−6.01	1.68	−0.96	22.76
Observations:	5,400					
SP500 returns (%) -	0.02	0.46	−2.34	2.64	0.48	2.50
Observations:	90,000					

SD = standard deviation.

Table 2. EGARCH-X estimates.

Panel A. Estimation results of the mean equation				
Model parameters	$X^{climate/temperature}$	$X^{biodiversity}$	$X^{climate/precipitation}$	$X^{biodiversity}$
θ_1	−0.0375		−0.0316	
	[0.00]		[0.00]	
θ_2		−0.0571		−0.0536
		[0.00]		[0.00]
Panel B. Estimation results of the conditional volatility equation				
Model parameters	$X^{climate/temperature}$	$X^{biodiversity}$	$X^{climate/precipitation}$	$X^{biodiversity}$
ψ_1	0.0429		0.0395	
	[0.00]		[0.00]	
ψ_2		0.0615		0.0569
		[0.00]		[0.00]
Log likelihood	−4, 966.39		−4, 365.32	
α_0	0.764	0.214	0.665	0.199
β_0	[0.00]	[0.00]	[0.00]	[0.00]
γ_0		0. 046		0. 042
		[0.00]		[0.00]

Figures in brackets denote p-values. To save space, only the results pertaining to the asymmetry coefficient and the coefficients on the X factors are reported.

new findings are also reported in Table 2. They clearly validate the baseline results and the role of both risk in the mean and volatility of stock returns. In the online Appendix, further robustness checks are offered which all provide solid support to the baseline findings.

To get more insight into these findings, we repeat the analysis by making use of the firms' ESG ratings (data comes from Refinitiv), while we sort these firms into low- and intensive-carbon firms. Following Berg, Koelbel, and Rigobon (2022) and Serafeim and Yoon (2022), the analysis applies normalized ratings with a mean value of 0 and a standard deviation of 1. The normalized value (z-score) of the ESG rating of stock i is computed as:

$$ESG_{nratingi} = \left[ESG_{ratingi} - ESG_{rating}\right] / \sigma_{ESGrating}$$

where, $\mathrm{ESG}_{\mathrm{nrating}}$ = normalized ESG rating, $\mathrm{ESG}_{\mathrm{rating}}$ = the mean ESG rating, and $\sigma_{\mathrm{ESGrating}}$ = the standard deviation of the ESG ratings assigned. Higher values of $\mathrm{ESG}_{\mathrm{nratingi}}$ indicate better ESG-

Table 3. EGARCH-X estimates: low- vs intensive-carbon firms.

Panel A. Estimation results of the mean equation		
Low-carbon firms		
Model parameters	$X^{climate}$	$X^{biodiversity}$
θ_1	−0.0276	
θ_2		−0.0468
Intensive-carbon firms		
Model parameters	$X^{climate}$	$X^{biodiversity}$
θ_1	−0.0314	
θ_2		−0.0582
Panel B. Estimation results of the conditional volatility equation		
Low-carbon firms		
Model parameters	$X^{climate}$	$X^{biodiversity}$
ψ_1	−0.0353	
ψ_2		−0.0486
Log likelihood: −4,316.35		
Intensive-carbon firms		
Model parameters	$X^{climate}$	$X^{biodiversity}$
ψ_1	−0.0449	
ψ_2		−0.0604
Log likelihood: −4,655.28		

Figures in brackets denote p-values. To save space, only the results pertaining to the coefficients on the X factors are reported.

performance, i.e. lower unmanaged ESG risk, i.e. more sustainable firms. ESG normalized ratings above the median are considered as low-carbon firms, while those below are intensive-carbon firms. The new results are reported in Table 3. They highlight that in terms of both climate and biodiversity risk factors, the impact on mean returns is negative and stronger for intensive-carbon firms, while the impact on the conditional volatility of returns turns out positive and stronger also for intensive-carbon firms. Investors seem sensitive about how to stronger price biodiversity risks, especially in the case of firms with low environmental performance.

Moreover, robust analysis also considers the Dow-Jones and the SP500 indexes as proxies of stock returns. The new findings in Table A1 in the online Appendix provide support to the baseline results. Finally, the analysis provides robust support by including an interaction term between climate and biodiversity risks. The results reported in Table A2 not only provide support to the baseline results, but also highlight the negative coefficient of this interaction term implying that both risk substantially contribute to lower asset prices.

V. Conclusion

This study explored the impact of both climate and biodiversity risks on US stock returns. Both in terms of aggregate stocks and in terms of clean versus dirty firms, the results documented that both types of risks are priced and exerted a negative impact on mean returns and a positive impact on their conditional volatility, while the latter risks dominated this effect. The findings survive certain robustness checks and raise a crucial question: what is the impact that investors can have on firms with a high biodiversity footprint; can these firms reduce their biodiversity footprint?

Author contributions

CRediT: **Nicholas Apergis:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing.

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Data availability statement

Part of the data will be available upon request. The remaining are under contractual agreements that forbid data sharing.

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