Nature and Climate Risk in Asset Prices*

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Abstract

Climate and nature risks are distinct but interrelated. Exposure to physical risk from climate change or loss of natural capital arises from a company's dependency on climate and nature, while exposure to transition risk depends on the impact of company on climate change or nature. Therefore, we consider four categories of risk—nature dependence, climate dependence, nature impact, and climate impact—and study whether financial markets price them. To frame our analysis, we develop a theoretical model distinguishing these dependence and impact channels. To test the pricing implications, we use two complimentary empirical strategies. We compare company-level characteristics from S&P Global with sensitivity of stock returns to shocks about biodiversity and climate news, which we call nature and climate beta, respectively. We also compare returns on characteristic-sorted portfolios with those on nature/climate beta-sorted portfolios. We find greater pricing of nature dependence, but not nature impact, post-2015 (relative to earlier years). We also find that post-2015, markets pay more attention to the interplay between climate impact and nature dependence.

JEL classification: C21, C23, G3, G12, Q25, Q42.

Keywords: Nature and climate risks, risk premia, betas.

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> "Our economies and political systems are unconsciously predicated on the belief that nature will continue to be a benign and regular provider of the conditions we need to thrive."
>
> — Sir David Attenborough

1 Introduction

It is well known that economies are threatened by climate change and that negative feedback effects exist between climate change, economic activities, and the financial flows that enable them. However, while the financial implications of climate change are increasingly studied, much less is understood about the economic impact and market pricing of other critical nature-related threats such as water stress, pollution, deforestation, biodiversity loss, and soil degradation. This gap persists despite growing awareness, leaving the extent to which financial markets distinctly price these complex nature-related risks as a significant open question. While there are some early findings on the negative impact of economic activities on nature (NGFS, 2022, Ceglar et al., 2023, Boldrini et al., 2023), the literature remains relatively sparse.

Furthermore, although climate and nature risks are distinct – climate risk stems from changes in climatic conditions, whereas nature risk arises from ecosystems degradation – they are deeply interconnected. Climate change accelerates nature loss, and the degradation of natural environments contributes to climate change, for instance, by amplifying the impacts of natural disasters (Taylor and Druckenmiller, 2022, Rizzi, 2023). Forward-looking equity prices, which encapsulate expectations about future growth and risks, can offer valuable insights into the economic costs of nature loss.

Quantifying the economic and financial impact of nature loss presents substantial empirical challenges. First, nature involves several dimensions and cannot be reduced to a single

metric such as CO_2 emissions. Second, the consequences of nature loss tend to be local and context-specific, reducing the external validity of empirical findings. Third, as highlighted above, climate change and nature loss are deeply interconnected and mutually reinforcing, which introduces large uncertainty in assessments and can lead to underestimating the risks. Fourth, because the most severe consequences have yet to materialize, nature risks are difficult to detect through historical data.

Recognizing these limitations, this paper addresses the central question: To what extent, and through which channels (dependence vs. impact), do financial markets price nature and climate risks? This question is crucial for at least two reasons. First, suppose investors and financial markets demand higher premia for companies with higher exposure to nature and climate risks. In that case, they can have an impact on the financing costs of firms and could steer resource allocation towards less environmentally harmful activities. This shift not only optimizes resource allocation, but also mitigates the adverse externalities associated with environmental degradation. Second, shedding light on how nature risk is priced - if at all - enables us to identify potential market inefficiencies and could ultimately inform more targeted and effective regulatory measures to protect natural ecosystems.

Mirroring the approach taken with climate risk, we distinguish between physical and transition risks pertaining to nature. This delineation reflects the concept of double materiality, which identifies two primary aspects of nature and climate risk. Physical risks related to nature involve immediate, tangible damage to capital, such as volcanic eruptions, pestilence, earthquakes, or wildfires, as well as the gradual loss of ecosystem services. For example, the productivity of companies may be compromised by a lack of soil fertility or the decrease of groundwater levels below vital thresholds. The extent to which economic activities rely on ecosystem services, which we refer to as *nature dependence*, can be understood as physical risks associated with nature.

Transition risks associated with nature emerge primarily through regulatory actions aimed

at reducing environmental impact, such as regulations for water filtration systems or restrictions on logging. Furthermore, a shift in preferences toward sustainable investment (consumption) highlights another dimension of transition risk, potentially limiting capital (demand) for companies that negatively impact the environment. These transition risks are reflected in the *nature impact* measures, which quantify the effects of companies' economic activities on the natural environment.

To formalize the distinction between dependence and impact and derive testable predictions, we develop a stylized general equilibrium asset pricing model. The model features a representative investor whose utility depends on both consumption and the quality of the environment (represented by aggregate nature and climate states). Firms' production depends on these environmental states (capturing dependence, or physical risk), but firms also affect the evolution of these states through their activities (capturing impact, or transition risk). Crucially, we assume firms are atomistic and generally do not internalize the environmental externality caused by their impact, although the model incorporates an explicit carbon price that levies a charge on climate impacts (emissions), linking this aspect of transition risk directly to firm cash flows.

Environmental conditions and policy (like the carbon price) are subject to uncertainty, and investors learn about them through noisy news signals. In equilibrium, the model yields a factor structure where expected asset returns compensate for exposure (beta) to systematic environmental and policy news shocks. A central prediction is that a firm's risk premium should primarily reflect its dependence on environmental conditions, as this directly affects its cash flows and covaries with the investor's marginal utility. In contrast, a firm's environmental impact is predicted to be priced only to the extent it is internalized via policy mechanisms like the carbon tax; pure nature impact remains unpriced in the baseline. This theoretical framework provides the foundation for the hypotheses tested in our empirical analysis.

Our paper makes three main contributions. First, we develop a stylized general equi-

librium asset pricing model that explicitly distinguishes between firms' dependence on environmental conditions (physical risk) and their impact on those conditions (transition risk), providing a theoretical foundation for why these two dimensions of risk might be priced differently. Second, building on this framework, we provide novel empirical evidence on whether and how financial markets price nature and climate risks, addressing a critical gap given the distinct but interrelated nature of these risks. Third, we explicitly analyze how markets perceive the interaction between climate-related and nature-related risks, deepening our understanding of how these factors jointly influence asset pricing. Our analysis reveals that since 2015, financial markets have rewarded firms with greater dependence on nature, consistent with a premium for nature physical risk, as predicted by our model's dependence channel. In contrast, and also consistent with the model's baseline predictions, we find no evidence of a premium for firms based solely on their negative environmental impacts (transition risk). Moreover, investors appear to perceive companies with substantial climate impacts (i.e., high emitters) as more vulnerable to nature dependence, underscoring the market's recognition of the interconnectedness between climate and nature risks.

To understand whether financial markets price nature risks, we employ a dataset provided by S&P Global that contains information about nature and climate risk exposures of companies. These company-level characteristics are constructed using a combination of climate and environmental models, sector and company-specific information on business activities, geographical location of companies' assets, and corporate disclosures. As these characteristics are based on analysis of companies' operations and do not rely on information derived from financial markets, we refer to them *fundamental* characteristics. We classify these fundamental characteristics into 4 categories - nature dependendency, climate dependence, nature impact, and climate impact. The first two categories correspond to physical risks, while the latter two correspond to transition risks. We want to understand how these risk exposures are priced by financial markets. For this purpose, we estimate sensitivities of comapnies'

stock returns to nature and climate-related news shocks, which we refer to as nature and climate betas, respectively. In contrast to fundamental characteristics, these can be viewed as *market-implied* exposures to nature and climate risks. Our analysis focuses on comparing the fundamental characteristics with betas. We do this in two ways: first, we examine the correlations between the fundamental characteristics and the betas; second, we investigate the co-movement between returns of fundamental characteristics-sorted long-short portfolios and beta-sorted long-short portfolios. These approaches allow us to evaluate whether market perceptions are consistent with measurements of fundamentally derived exposures.

1.1 Relation to the literature

Our paper builds on theoretical contributions related to the performance of green assets (Hong and Kacperczyk, 2009, Pedersen et al., 2021, Pástor et al., 2021, 2022, Hsu et al., 2023) and on the role of news for the evaluation of the current state by agents, which in turn guides their asset pricing and consumption-saving decisions (Bybee et al., 2024, Jeon et al., 2022, Bybee et al., 2023, Serafeim, 2024). For instance, Pástor et al. (2021) highlight the importance of distinguishing between realized and expected returns in the context of green assets. Bybee et al. (2024) use business news narratives in The Wall Street Journal to estimate a narrative factor model and show that this outperforms standard characteristic-based factor models. Our work connects to this by using news shocks to construct market-implied risk factors (betas) for nature and climate. Moreover, it relies on the literature on investors attention (Peng and Xiong, 2006, Kacperczyk et al., 2016, Mankiw and Reis, 2002). Kacperczyk et al. (2016) develop a model where attention constraints affect how investment managers process risk factor information, relevant to our model's assumption about learning from noisy signals.

Other related studies have examined the impact of climate events and global warming on asset pricing. Bansal et al. (2019) reveal the asset pricing implications of rising temperatures using an equilibrium framework with an endogenous temperature process embodied in

a standard long-run risk model. Hong et al. (2023) propose an asset pricing model in which natural disaster mitigation costs are priced in the cross section of firms, while Hong et al. (2019) find that stock markets do not efficiently price the increasing risk of drought caused by climate change. Balvers et al. (2017) shows that the average cost of equity capital is 0.22 percentage points higher on an annual basis due to temperature shocks, while Jagannathan et al. (2025) find limited incremental compensation for climate transition risk. While informative about climate risk pricing, these studies generally do not incorporate the distinct role of nature-related risks or the dependence/impact dichotomy central to our analysis.

The materialized and potential negative consequences of nature risks for the financial system have been highlighted in recent contributions (van Toor et al., 2020, Svartzman et al., 2021, NGFS, 2022, 2023, Ceglar et al., 2023, Boldrini et al., 2023, Arlt et al., 2024). For example, Ceglar et al. (2023) estimate the biodiversity footprints of the economic activities of the euro area (and the bank loans provided to enable them) and find that they resulted in the loss of 582 million hectares of pristine natural areas worldwide. Moreover, Boldrini et al. (2023) find that 75% of all corporate loan exposures in the euro area strongly depend on at least one ecosystem service. Arlt et al. (2024) look at the financial stability implications arising from biodiversity-related transition risk. Moreover, authors have looked at the impact of biodiversity risk on cash holdings (Ahmad and Karpuz, 2024) and firms' performance (Bach et al., 2025).

The papers closest to ours focus on the emerging evidence around a biodiversity premium. Interest in the financial implications of biodiversity and nature-related factors has increased notably, particularly following recent calls for research in this area by Karolyi and Tobin-de la Puente (2023) and Starks (2023). Recent empirical contributions document that financial markets have either historically mispriced biodiversity risks (Huang et al., 2024) or have started to price such risks only in recent years, especially for companies with significant biodiversity impacts (Garel et al., 2023, Coqueret and Giroux, 2023, Xin et al., 2023).

Additionally, markets continue to misprice companies' exposure to water-related risks (Colesanti Senni et al., 2023). Relatedly, firms heavily reliant on ecosystem services have begun to face increased downside risks following nature-related disruptions or regulatory shocks (Garel et al., 2025). At the same time, corporate biodiversity disclosures appear increasingly incorporated into equity valuations (Giglio et al., 2023).

Beyond equities, higher exposure to biodiversity risks is associated with increased yield spreads on long-term bonds (Soylemezgil and Uzmanoglu, 2024). Similarly, municipal bond yields in Chinese regions with national nature reserves significantly increased following the introduction of stricter environmental regulations (Chen et al., 2024). Conversely, proactive management of biodiversity risks has been linked to lower refinancing costs (Hoepner et al., 2023) and positive abnormal returns around biodiversity-related policy announcements (Kalhoro and Kyaw, 2024). Recent studies have also begun integrating biodiversity metrics into portfolio optimization frameworks (Bouyé et al., 2024, Naffa and Czupy, 2024).

Our paper differs from earlier studies in several key ways. First, by explicitly addressing both dimensions of double materiality (impact and dependence), unlike Garel et al. (2023) and Coqueret and Giroux (2023), which exclusively consider the impact component. Second, in contrast to Giglio et al. (2023), we emphasize production-based risk metrics rather than disclosure-based ones. Third, our empirical analysis centers on equity returns rather than sovereign bond portfolios, which distinguishes our approach from that of Bouyé et al. (2024).

In addition, a core focus of our paper is explicitly investigating the interaction between nature and climate risks. Although extensive ecological literature highlights the complex biophysical interconnections among different ecosystems (Foley et al., 2003, Zarnetske et al., 2012, Blois et al., 2013, Lade et al., 2019, Arneth et al., 2020, Bouyé et al., 2024), economic and financial analyses exploring the feedback effects between nature and climate risks remain sparse, with only a few recent studies addressing these aspects (Taylor and Druckenmiller, 2022, Rizzi, 2023). Our analysis contributes direct evidence on how financial markets perceive

this interaction.

Finally, in developing our nature and climate risk factors, we build upon methodologies established in the literature on factor models for asset pricing (Zou and Hastie, 2005, Erichson et al., 2020, Pelger and Xiong, 2022, Giroux et al., 2024).

The remainder of this paper proceeds as follows. Section 2 introduces a stylized model that helps us to formulate and rationalize our hypotheses. Section 3 describes the data and construction of our main dataset. Section 3.2 details our methodological framework for analyzing the pricing of nature and climate risks and presents our empirical findings. Section 4 concludes.

2 Stylized model of nature and climate risk pricing

We develop a parsimonious general-equilibrium model that distinguishes *physical* environmental risk—arising from firms' *dependence* on natural and climatic conditions—from *transition* risk—arising from firms' *impact* on those conditions and on climate policy. Our model features a representative investor and a continuum of firms in a discrete-time, infinite-horizon economy. Two aggregate environmental state variables evolve over time: a *nature state* N_t (capturing the quality or abundance of natural capital, e.g., biodiversity or ecosystem health) and a *climate state* Z_t (capturing the level of climate-related damage or pollution, e.g., atmospheric carbon or climate hazard intensity). The *carbon price* τ_t is an exogenous, per-unit charge on emissions.[1] The environmental states (N_t, Z_t) are latent, i.e., investors observe only noisy public signals and learn about the true states through a Kalman filter whose precision differs across firms and over time. The carbon price τ_t is publicly observed.

In what follows we detail (i) the firms' production technology and environmental impact, (ii) household preferences that link environmental quality to marginal utility, (iii) the information structure—featuring heterogeneous signal precision—that generates *nature, climate,*

[1]The exogeneity of τ_t isolates its asset-pricing role. Endogenizing it—for instance, via an optimal carbon-tax rule that depends on Z_t—does not alter the qualitative results.

and transition news shocks, and (iv) the equilibrium asset-pricing conditions. Throughout, we emphasize that a firm's *dependence* affects directly its cash flows and hence its systematic risk, whereas its environmental *impact* parameters matters only through their aggregate effect on environmental states, unless an explicit policy (the carbon price τ_t) internalizes the climate externality. The interplay of dependence, impact, policy, and information precision yields the empirical predictions we test in Section 3.2.

2.1 Firms: production, dependence, and impact

Firms are indexed by $i \in [0,1]$ and produce a homogeneous consumption good. Firm i's output at time t is given by a Cobb–Douglas technology with productivity that *depends* on the aggregate environmental conditions:

$$Y_{i,t} \;=\; A_{i,t}\, K_{i,t}^{\alpha}\, N_t^{\gamma_i^N}\; Z_t^{\gamma_i^Z}. \tag{1}$$

Here $K_{i,t}$ is firm-specific physical capital, $A_{i,t}$ is an idiosyncratic total factor productivity term, and $\alpha \in (0,1)$ is the output elasticity of capital. The exponents γ_i^N and γ_i^Z capture firm i's *nature dependence* and *climate dependence*, respectively. A larger $\gamma_i^N > 0$ means that firm i's productivity is more sensitive to the health of the natural environment (for example, an agricultural firm or tourism business benefits greatly from a higher biodiversity or cleaner ecosystem). Conversely, $\gamma_i^Z < 0$ indicates that firm i is adversely affected by a worsening climate state Z_t (for instance, higher pollution or more frequent natural disasters reducing output). All else equal, a firm with higher $|\gamma_i^N|$ or $|\gamma_i^Z|$ experiences larger fluctuations in cash flows in response to environmental shocks.

Firms face a standard investment problem. Each period, firm i pays a dividend $D_{i,t}$ to its shareholders. Capital accumulates according to $K_{i,t+1} = (1-\delta_K)\,K_{i,t} + I_{i,t}$, where $I_{i,t}$ represents investment in new capital and δ_K the depreciation rate. A firm also emits $\delta_i^Z Y_{i,t}$ units of carbon, where δ_i^Z is its *climate impact intensity*. Paying the carbon price τ_t yields

net dividends

$$D_{i,t} = (1 - \tau_t \, \delta_i^Z) \, Y_{i,t} - I_{i,t}. \tag{2}$$

In our baseline model, we assume that nature impacts δ_i^N (e.g., habitat loss per unit output) are not priced.[2]

Firm i chooses its investment policy $\{I_{i,t}\}$ to maximize its market value, given by the expected present value of all future dividends discounted at the stochastic discount factor (SDF) $M_{t,t+s}$ of the representative household:

$$\max_{\{I_{i,t}\}_{t\geq 0}} \; E_0 \left[\sum_{t=0}^{\infty} M_{0,t} \, D_{i,t} \right], \tag{3}$$

subject to the capital accumulation constraint and taking the processes $\{N_t, Z_t.\tau_t\}$ taken as exogenous. The firm's optimization yields the standard Euler equation (we omit these standard derivations for brevity). Importantly, in equilibrium, the value and dividend stream of firm i will reflect how its output $Y_{i,t}$ comoves with the aggregate states. Equations (1) and (2) make clear that fluctuations in the state variables translate into fluctuations in dividends via the dependence and impact parameters γ_i^N, γ_i^Z, and δ_i^Z. This is the channel through which *nature* and *climate dependence risk* will enter asset prices.

While producing output, firms also generate externalities that affect the evolution of the environmental states. We denote by δ_i^N the *nature impact* of firm i (the rate at which its production depletes or degrades the natural state) and by δ_i^Z the *climate impact* of firm i (the rate at which its production increases climate-related damage).[3] These impact parameters introduce a *transition risk* aspect: they determine how firms collectively influence future

[2] We remark that we could also introduce a "nature tax". However, we want to keep the baseline model as parsimonious as possible.

[3] The introduced δ_i^Z here is the same emissions coefficient that appears in the carbon–tax term of dividends in (2); a tonne of greenhouse gas emissions simultaneously harms the climate state and triggers the statutory levy. We note that nothing in the ensuing asset-pricing results hinges on this exact identity. Allowing the tax base to capture, e.g., free allowances or gas-specific conversion rates, leaves all cross-sectional slopes unchanged because, in the empirical analysis, it will be absorbed by firm fixed effects.

environmental conditions. The aggregate dynamics of the environmental states are given by:

$$N_{t+1} = F(N_t, Z_t) - \int_0^1 \delta_i^N Y_{i,t}\, di + \varepsilon_{t+1}^N, \tag{4}$$

$$Z_{t+1} = G(Z_t, N_t) + \int_0^1 \delta_i^Z Y_{i,t}\, di + \varepsilon_{t+1}^Z. \tag{5}$$

The functions $F(\cdot)$ and $G(\cdot)$ capture natural growth or decay in the absence of economic activity.[4] The terms ε_{t+1}^N and ε_{t+1}^Z are exogenous shocks (e.g. from weather, natural disasters, or other factors) which are zero-mean with finite variances. The integrals $\int_0^1 \delta_i^N Y_{i,t} di$ and $\int_0^1 \delta_i^Z Y_{i,t} di$ represent the total impact of all firms' production on the nature and climate states, respectively. A higher δ_i^N means firm i contributes more to degrading N_{t+1} (for instance, through resource extraction or habitat destruction), and a higher δ_i^Z means the firm emits more pollution or greenhouse gases, worsening Z_{t+1}.

Because each firm is atomistic, it rationally ignores the infinitesimal effect of its own output on the aggregate stocks N_t and Z_t. The environmental externality is therefore *not* internalized through the state-transition channel. The carbon levy, however, introduces a private cost that is linear in the firm's own emissions, $\tau_t \delta_i^Z Y_{i,t}$, and thus enters cash flows directly. Consequently, a firm's γ (dependence) directly affects its cash flows and thereby its risk premium, and climate impact δ_i^Z is priced to the extent that the policy assigns it a positive and adequate shadow price τ_i. The pure nature impact δ_i^N remains an unpriced externality under the laissez-faire benchmark.

2.2 Household preferences and stochastic discount factor

The representative household has preferences defined over consumption and environmental quality. Let C_t be aggregate consumption at time t (which in equilibrium will equal the aggregate after-tax dividends). We adopt a non-separable utility specification in which environmental conditions scale the felicity of consumption. To this end, we define an augmented

[4]For example, $F(N_t)$ may represent the natural regeneration of ecosystem N, which could be diminishing as N_t approaches a carrying capacity, and $G(Z_t)$ could capture the physical dynamics of the climate/pollution state (e.g. a portion of Z_t dissipates or decays each period).

consumption variable

$$\tilde{C}_t = C_t\,\Phi(N_t, Z_t), \qquad \Phi_N \equiv \frac{\partial \Phi}{\partial N} > 0,\ \Phi_Z \equiv \frac{\partial \Phi}{\partial Z} < 0, \tag{6}$$

where $\Phi(N_t, Z_t)$ is a function capturing the direct contribution of environmental quality to utility. A convenient specification is $\Phi(N_t, Z_t) = N_t^{\chi_N} Z_t^{-\chi_Z}$ with $\chi_N, \chi_Z > 0$. The household's one-period utility is:

$$U(C_t, N_t, Z_t) \;=\; \frac{\tilde{C}_t^{\,1-\sigma}}{1-\sigma}\,, \tag{7}$$

where $\sigma > 0$ is the coefficient of relative risk aversion. This non-separable CRRA form implies that the marginal utility of consumption is directly affected by the environmental state. Intuitively, the household derives more utility from a unit of consumption when N_t is higher or Z_t is lower (since Φ raises the effective consumption). As a result, fluctuations in N_t and Z_t will influence the household's intertemporal marginal rate of substitution, i.e., the pricing kernel.

The representative household maximizes $\mathbb{E}_0\left[\sum_{t=0}^{\infty} \beta^t U(C_t, N_t, Z_t)\right]$, where $0 < \beta < 1$ is the subjective discount factor. Standard arguments yield the stochastic discount factor,

$$M_{t,t+1} = \beta\,\frac{U_C(C_{t+1}, N_{t+1}, Z_{t+1})}{U_C(C_t, N_t, Z_t)} = \beta\left(\frac{\tilde{C}_{t+1}}{\tilde{C}_t}\right)^{-\sigma} = \beta\left(\frac{C_{t+1}\,\Phi(N_{t+1}, Z_{t+1})}{C_t\,\Phi(N_t, Z_t)}\right)^{-\sigma}. \tag{8}$$

Equation (8) makes clear that the pricing kernel responds to two forces: (i) *consumption-growth risk*, $\Delta \ln C_{t+1}$, which now embeds any surprise in τ_{t+1} via after-tax dividends; and (ii) *environmental-quality risk*, $\Delta \ln \Phi(N_{t+1}, Z_{t+1})$, which captures the direct welfare effect of future nature and climate conditions. Both components will therefore command prices of risk in equilibrium.

Intuitively, a negative shock to biodiversity (lower N_{t+1}) or a positive shock to climate damage (higher Z_{t+1}) raises marginal utility twice: directly through a fall in $\Phi(N_{t+1}, Z_{t+1})$ and indirectly via the induced decline in aggregate dividends and consumption. Assets that covary negatively with such shocks must offer a higher expected return, a prediction we test empirically below.

2.3 Information structure and environmental news shocks

A distinctive feature of environmental risk is informational opacity: the true conditions of natural and climatic systems are only imperfectly observed in real time. We therefore treat the environmental stocks *nature* N_t and *climate* Z_t as latent Markov processes that investors must infer from noisy public signals (for example, climate and biodiversity related news, but also scientific reports, satellite observations, or climate model updates). By contrast, the carbon price τ_t is *observable each period when set by the regulator*, but its *future* path is uncertain ex ante and thus generates a separate source of policy news.

Environmental transition signal. In each period t, after the states N_t, Z_t (and firms' outputs $Y_{i,t}$) have realized, investors receive signals about the next period's environmental states.,

$$s_{t+1} = \left(s^N_{t+1}, s^Z_{t+1}\right)^\top,$$

each a noisy linear mixture of log-nature $n_{t+1} \equiv \ln N_{t+1}$ and log-climate $z_{t+1} \equiv \ln Z_{t+1}$:

$$\begin{aligned} s^N_{t+1} &= w_N\, n_{t+1} + (1 - w_N)\, z_{t+1} + \eta^N_{t+1}, \\ s^Z_{t+1} &= (1 - w_Z)\, n_{t+1} + w_Z\, z_{t+1} + \eta^Z_{t+1}, \end{aligned} \qquad 0 \le w_N, w_Z \le 1, \tag{9}$$

where the Gaussian noises $\eta^{\cdot}_{t+1} \sim \mathcal{N}(0, 1/\phi^{\cdot}_t)$ capture time-varying signal precision. A higher ϕ^N_t, for example, makes s^N_{t+1} a more reliable, less noisy indicator of the particular linear combination $w_N n_{t+1} + (1 - w_N) z_{t+1}$. The weights w_N and w_Z capture the empirical fact that most news sources mix nature and climate content. Investors observe both signals and update their beliefs about (n_{t+1}, z_{t+1}) through the Kalman filter. Because the signals load differently on the two states whenever $w_N \neq w_Z$, receiving two independent noisy readings *both* sharpens overall precision *and* provides the cross-signal variation needed to disentangle nature from climate news.

Stacking the log stocks in $\mathbf{x}_t = (n_t, z_t)^\top \equiv (\ln N_t, \ln Z_t)^\top$, log-linearizing the transition laws (4)–(5) around the deterministic steady state, and premultiplying by suitable scaling

matrices, yields the canonical linear Gaussian system

$$\underbrace{\mathbf{x}_{t+1}}_{\text{state}} = A\,\mathbf{x}_t + \mathbf{w}_{t+1}, \qquad \mathbf{w}_{t+1} \sim \mathcal{N}(\mathbf{0}, Q), \tag{10}$$

$$\underbrace{\mathbf{y}_{t+1}}_{\text{measurement}} = C\,\mathbf{x}_{t+1} + \boldsymbol{\varepsilon}_{t+1}, \qquad \boldsymbol{\varepsilon}_{t+1} \sim \mathcal{N}(\mathbf{0}, R), \tag{11}$$

with observation vector $\mathbf{y}_{t+1} = (s^N_{t+1}, s^Z_{t+1})^\top$ and loading matrix $C = \left[\begin{smallmatrix} w_N & 1-w_N \\ 1-w_Z & w_Z \end{smallmatrix}\right]$. The matrices A and Q inherit the physical dynamics of N_t and Z_t; $R = \mathrm{diag}(1/\phi^N_t, 1/\phi^Z_t)$ collects the time-varying signal variances. Given (A, C, Q, R) and the prior $(\hat{\mathbf{x}}_{0|-1}, \Sigma_{0|-1})$, the Kalman recursion delivers optimal beliefs,

$$\hat{\mathbf{x}}_{t+1|t+1} = \hat{\mathbf{x}}_{t+1|t} + K_{t+1}\boldsymbol{\nu}_{t+1}, \qquad \boldsymbol{\nu}_{t+1} = \mathbf{y}_{t+1} - C\hat{\mathbf{x}}_{t+1|t},$$

where K_{t+1} is the usual gain. The innovation $\boldsymbol{\nu}_{t+1} = (\nu^N_{t+1}, \nu^Z_{t+1})^\top$ is mean-zero and orthogonal to all information dated t. The unexpected components of the latent states satisfy[5]

$$\Delta n_{t+1} - \mathbb{E}_t[\Delta n_{t+1}] = a_{NN}\,\nu^N_{t+1} + a_{NZ}\,\nu^Z_{t+1}, \qquad \Delta z_{t+1} - \mathbb{E}_t[\Delta z_{t+1}] = a_{ZN}\,\nu^N_{t+1} + a_{ZZ}\,\nu^Z_{t+1}, \tag{12}$$

with coefficients a_{ij} pinned down by (A, C, Q, R). We refer to the two linear combinations on the right-hand side as the *nature-news* and *climate-news* shocks, respectively. They summarize all information surprises about future environmental conditions.

Firm-level transition signal. We treat our third state variable, the carbon tax, as an exogenous policy instrument determined outside the model's private-sector general equilibrium. Consistent with the empirical evidence that successive rounds of climate legislation adjust existing schemes rather than overhaul them each year, we model the log tax as a mean-reverting first-order autoregression,[6]

$$\ln \tau_{t+1} = \mu_\tau + \rho_\tau \left(\ln \tau_t - \mu_\tau\right) + \varepsilon^\tau_{t+1}, \qquad \varepsilon^\tau_{t+1} \sim \mathcal{N}\big(0, \sigma^2_\tau\big). \tag{13}$$

[5] See Appendix G.

[6] This specification for the tax rate has also been used in other asset pricing literature, see, e.g., Croce et al. (2012).

The persistence parameter $\rho_\tau \in (0,1)$ captures gradual policy tightening of the type observed for the EU ETS and California's cap-and-trade programme,[7] while the drift μ_τ allows for a secular trend in the real price of carbon. At date t investors rationally anticipate the conditional mean $\mathbb{E}_t[\ln \tau_{t+1}] = \mu_\tau + \rho_\tau(\ln \tau_t - \mu_\tau)$. The innovation

$$\upsilon_{t+1} \equiv \varepsilon^{\tau}_{t+1} = \ln \tau_{t+1} - \mathbb{E}_t[\ln \tau_{t+1}] \tag{14}$$

is revealed only when the new policy rate is announced at $t+1$. Because each realization of τ_t is observed without measurement error once in force, υ_{t+1} is a *pure policy-news shock*: it carries no estimation noise, yet it directly alters cash flows through the term $-\tau_{t+1}\delta_i^Z Y_{i,t+1}$.

While the nature and climate state filtering operates at the *aggregate* level, each stock also carries a *private* transition parameter, its log emission intensity $e_i = \ln \delta_i^Z$, that investors must learn in parallel. In practice, they do so from voluntary or mandated disclosure, and they devote only limited analytical resources to firms that generate little aggregate pollution. We model the resulting information frictions in two steps.

In the first step, investors receive a noisy signal

$$s^{\delta}_{i,t+1} = e_i + \eta_{i,t+1}, \qquad \eta_{i,t+1} \sim \mathcal{N}\big(0,\ 1/\varphi_{i,t}\big), \tag{15}$$

where the *precision* $\varphi_{i,t} = q_{i,t}\, a_{i,t}$ is the product of a *disclosure component* $q_{i,t}$ and an *attention component* $a_{i,t}$. Before 2015, reliable emission data existed only for firms whose intensity exceeded a threshold $\bar{\delta}$ (e.g., under EU ETS Phase III protocols): $q_{i,t} = \bar{q}_H$ if $\delta_i^Z \geq \bar{\delta}$ and $q_{i,t} = \bar{q}_L \ll \bar{q}_H$ otherwise. Following the Paris Agreement, disclosure quality for low-emission entities increases to $\bar{q}_H$, driven by initiatives such as CDP questionnaires and TCFD guidelines.

The attention term $a_{i,t}$ captures market participants' focus, which remains low for small emitters due to unfavorable cost-benefit tradeoffs in information processing.[8] For these firms,

[7] See, e.g., Bredin and Muckley (2011), Hintermann (2010).

[8] This aligns with the sticky information framework of Mankiw and Reis (2007).

the Paris Agreement altered disclosure requirements but not the economics of analyst coverage. Consequently, we model three precision regimes:

$$\varphi_{i,t} = \begin{cases} \phi_H \equiv \bar{q}_H\, a_H & \text{if } \delta_{Z,i} \geq \bar{\delta} \quad \text{(high emitters)}, \\ \phi_L \equiv \bar{q}_L\, a_L & \text{if } \delta_{Z,i} < \bar{\delta}, t < 2015 \quad \text{(low emitters, pre-Paris)}, \\ \phi_M \equiv \bar{q}_H\, a_L & \text{if } \delta_{Z,i} < \bar{\delta}, t \geq 2015 \quad \text{(low emitters, post-Paris)}, \end{cases} \qquad \phi_H > \phi_M > \phi_L.$$

This framework captures the evolving emission reporting landscape: high emitters maintain high precision (ϕ_H) throughout, while low emitters transition from low precision (ϕ_L) to an intermediate level (ϕ_M) following the 2015 Paris Agreement's enhanced disclosure mandates.

In the second step, investors perform a Bayesian update. With diffuse prior $e_i \sim \mathcal{N}(e_0, 1/v_0)$, the static Kalman step delivers

$$m_{i,t+1} = \frac{\varphi_{i,t} s^{\delta}_{i,t+1} + v_0 e_0}{v_0 + \varphi_{i,t}}, \qquad v_{i,t+1} = \frac{1}{v_0 + \varphi_{i,t}},$$

so the posterior mean and variance are

$$\widehat{\delta}_{Z,i,t} = e^{m_{i,t} + \frac{1}{2(v_0+\varphi_{i,t})}}, \qquad \mathrm{Var}_t(\delta_{Z,i}) = e^{2m_{i,t}+1/(v_0+\varphi_{i,t})}\big(e^{1/(v_0+\varphi_{i,t})} - 1\big).$$

With a near-zero prior, e_0, an increase in precision, $\varphi_{i,t}$, increases $\widehat{\delta}_{Z,i,t}$. The precision regimes described above imply that low emitters posterior emissions increase after 2015, while those of high emitters stay the same.[9,10]

Summarizing the above discussion, we can collect the complete vector of priced surprises into

$$F_{t+1} = \big(\nu^N_{t+1},\, \nu^Z_{t+1},\, \upsilon_{t+1}\big)^{\top},$$

where ν^N_{t+1} and ν^Z_{t+1} are the Kalman innovations from the two-state environmental filter and υ_{t+1} is the policy innovation in (14). The block-diagonal structure of the joint filter guarantees that learning about e_i does not interfere with the extraction of nature and climate news, yet it delivers, as we will see, richer empirical predictions for the post-Paris period.

[9]The condition for a positive $\widehat{\delta}_{Z,i,t}$ is a 65% level gap ($s^{\delta}_{i,t+1} - e_0 > 1$). We assume low emitters reveal intensities ¿¿70% above near zero prior.

[10]The uncertainty about the firm's emission intensity $\delta_{Z,i}$ is captured by its posterior variance, $\mathrm{Var}_t(\delta_{Z,i})$. Uncertainty is therefore decreasing in the level of precision φ. Hence, it is largest for low emitters pre-2015, falls discretely to an intermediate level at Paris, and is negligible for heavy emitters throughout.

2.4 Equilibrium Asset Prices and Risk Premia

Three shocks drive aggregate uncertainty: (i) nature news $F^N_{t+1} \equiv \nu^N_{t+1}$, (ii) climate news $F^Z_{t+1} \equiv \nu^Z_{t+1}$, and (iii) carbon-policy news $F^\tau_{t+1} \equiv \upsilon_{t+1} = \ln \tau_{t+1} - \mathbb{E}_t[\ln \tau_{t+1}]$, where (ν^N, ν^Z) are the Kalman innovations and υ_{t+1} is revealed when the regulator announces next period's levy.[11] A first-order log-linearization of the SDF in (8) yields

$$\ln M_{t,t+1} = \ln \beta - \sigma\big(\Delta \ln \tilde{C}_{t+1}\big) + \text{const},$$

and unexpected consumption growth decomposes as[12]

$$\Delta \ln \tilde{C}_{t+1} - \mathbb{E}_t[\Delta \ln \tilde{C}_{t+1}] = b^N_t F^N_{t+1} + b^Z_t F^Z_{t+1} + b^\tau_t F^\tau_{t+1} = \sum_{k\in\{N,Z,\tau\}} b^k F^k_{t+1}, \tag{16}$$

with $b^N_t > 0$, $b^Z_t < 0$, and $b^\tau_t < 0$ by inspection of firm cash flows.[13] This gives rise to a linear factor CAPM. For any asset paying gross return $R_{i,t+1}$,

$$1 = \mathbb{E}_t\big[M_{t,t+1} R_{i,t+1}\big] \;\Rightarrow\; \mathbb{E}_t[R_{i,t+1}] - r_{f,t} = \sum_{k\in\{N,Z,\tau\}} \lambda^k_t \beta^k_{i,t}, \tag{17}$$

where

$$\lambda^k_t = \sigma b^k_t \mathrm{Var}_t(F^k_{t+1}), \qquad \beta^k_{i,t} = \frac{\mathrm{Cov}_t(R_{i,t+1}, F^k_{t+1})}{\mathrm{Var}_t(F^k_{t+1})}, \tag{18}$$

are, respectively, the time-varying market prices of risk and the conditional betas for $k \in \{N, Z, \tau\}$.

The structural determinants of betas can be derived as follows. Using the dividend rule $D_{i,t} = (1 - \tau_t \widehat{\delta}_{Z,i,t}) Y_{i,t} - I_{i,t}$ and holding capital fixed over one period (Campbell and Mei, 1993, Campbell and Vuolteenaho, 2004),

$$\partial_{n_{t+1}} \ln D_{i,t+1} = \gamma^N_i, \quad \partial_{z_{t+1}} \ln D_{i,t+1} = \gamma^Z_i, \quad \partial_{\upsilon_{t+1}} \ln D_{i,t+1} \approx -\widehat{\delta}_{Z,i,t},$$

[11] Idiosyncratic firm shocks are diversifiable; other aggregate shocks orthogonal to (ν^N, ν^Z, υ) are omitted for brevity.

[12] The coefficients b^N_t and b^Z_t in (16) absorb *both* channels through which an environmental shock affects the SDF: (i) its impact on real consumption via firm output, and (ii) its direct welfare effect through $\Phi(N_{t+1}, Z_{t+1})$. Writing the elasticities separately, $b^N_t + c^N_t$ and $b^Z_t + c^Z_t$, would leave all subsequent pricing equations unchanged, because the market prices of risk depend only on the combined coefficients.

[13] $b^\tau_t < 0$ because an unanticipated rise in τ_{t+1} is a lump-sum transfer from shareholders to the tax authority.

so that

$$\beta_{i,t}^{N} \propto \gamma_i^{N}, \qquad \beta_{i,t}^{Z} \propto \gamma_i^{Z}, \qquad \beta_{i,t}^{\tau} \approx -\tau_t \, \widehat{\delta}_{Z,i,t}. \tag{19}$$

Two modeling restrictions underlie equations (16)–(19). First, any discount-rate news that reaches investors between t and $t+1$ is either common across all firms or perfectly collinear with the three aggregate innovations (F^N, F^Z, F^τ). In either case the effect is absorbed by the consumption-loadings b_t^k in (16), so cross-sectional betas depend only on dividend news. Second, the three shocks span unexpected consumption growth and their loadings b_t^k already combine each shock's impact on real consumption and its direct welfare effect through $\Phi(N, Z)$; separating those channels would leave all subsequent pricing equations unchanged. Under these two conditions, the dividend sensitivities in (19) are sufficient statistics for conditional betas, and the linear factor pricing relation in (17) holds without further qualification. Log-linearizing the SDF around a deterministic steady state supplies the only additional approximation needed. Extending the analysis beyond this first-order log-linear approximation, e.g., allowing for nonlinear SDF dynamics or a Campbell–Shiller cash-flow/discount-rate decomposition, is an important avenue for future research.

With these restrictions in place, the structural beta expressions in (19) have an intuitive interpretation. Physical dependence parameters (γ^N, γ^Z) *always* map into priced betas; transition exposure enters *only* when a positive levy renders emissions intensity financially material. We remark that, because we assume $\widehat{\delta}_{i,t}^{Z}$ is estimated more precisely for low emitters after 2015, their $|\beta^\tau|$ rises relative to heavy emitters, narrowing the cross-sectional return spread.

Remarks on the theoretical setup. Our stylized equilibrium highlights why *double materiality* (dependence vs. impact) leads to different asset pricing outcomes. Our distinction between dependence and impact parameters aligns directly with the concept of "double materiality," a term increasingly used in sustainability reporting and risk assessment. The

dependence parameters (γ_i^N, γ_i^Z) capture financial materiality: how environmental conditions (the state of N_t and Z_t) affect the firm's financial performance (output $Y_{i,t}$ and cash flows $D_{i,t}$. The impact parameters(δ_i^N, δ_i^Z) capture impact materiality: how the firm's activities affect the environment and society (by contributing to the degradation of N_t or worsening of Z_t. Our theoretical results illustrate that, in a market equilibrium focused solely on financial returns and lacking mechanisms to internalize externalities, only financial materiality (γ_i) is directly priced via its effect on systematic risk exposure (β_i). Impact materiality (δ_i) becomes financially relevant, and thus potentially priced, only if and when it translates into anticipated financial consequences for the firm, for instance through regulation, reputational damage affecting sales, or changes in operating costs.

Our model relies on log-linearization of the environmental dynamics and the stochastic discount factor around a steady state, along with the assumption of Gaussian shocks. While common in macroeconomic modeling, these assumptions necessarily abstract from potentially crucial features of environmental systems, such as strong non-linearities, feedback loops, critical thresholds, or tipping points. Furthermore, environmental risks might exhibit non-Gaussian characteristics like fat tails or jump risk, associated with extreme events or abrupt system shifts (see, e.g., Fernández-Villaverde et al., 2024). Capturing these features is beyond the scope of our current linearized framework.

3 Empirics

3.1 Data and sample construction

We assemble a comprehensive dataset by merging multiple S&P Global data sources on firm-level environmental characteristics with traditional financial data. In particular, we combine three proprietary S&P Global datasets containing nature- and climate-related firm characteristics with stock return data from CRSP and news-based indices of climate and

biodiversity risk.[14]

3.1.1 Description

The firm-level environmental data come from three integrated datasets provided by S&P Global, each covering one of the four risk categories (nature dependence, nature impact, climate physical risk, climate transition risk). We describe these datasets and the fundamental characteristics they include, then outline the financial data and news-based risk indices that complement our analysis.

Fundamental characteristics

Nature risk: Our primary source on nature-related risk is the S&P Global Nature and Biodiversity Risk dataset, which evaluates a firm's exposure to nature-related risks arising from its operations at specific locations.[15] Consistent with the Taskforce on Nature-related Financial Disclosures (TNFD) framework, this dataset focuses on two dimensions: a company's dependence on nature and its impact on nature.[16]

Nature dependence measures how much a company relies on ecosystem services and the vulnerability of those services to degradation. It evaluates the firm's operational reliance on various ecosystem services (e.g., disease control, mass stabilization of soil, groundwater replenishment) in conjunction with the resilience of the ecosystems providing those services. The reliance component reflects the materiality of each service to the firm's production processes and the relevance of that service given the firm's geographic footprint. The resilience component gauges the capacity of the local ecosystem to continue supplying the service. Combining these factors, the dataset provides a granular assessment of nature dependence, with scores across 21 distinct ecosystem services (for example, pollination, water filtration, and climate regulation). In total, there are 82 metrics capturing different aspects of a firm's

[14]See Appendix C and D for a description of the variable selection process and descriptive correlation among the variables.

[15]For methodological details, see the S&P Global report.

[16]See the latest TNFD recommendations.

dependence on nature.

Nature impact captures the degree to which a company's activities adversely affect natural ecosystems. This dimension is driven by the magnitude and spatial extent of the firm's environmental footprint and the ecological importance of the areas impacted. Key determinants include the intensity of the firm's operational pressures on nature (e.g., land use or pollution) and the sensitivity or critical significance of the affected ecosystems (such as biodiversity hotspots or protected areas). Unlike the dependence metrics, which mix firm needs with ecosystem traits, the impact metrics are purely location-specific measures of harm. The Nature and Biodiversity Risk dataset provides 21 metrics of nature impact, including indicators of ecosystem integrity (how closely an ecosystem remains to a pristine state), species extinction risk, and overlap of the firm's operations with critical natural habitats.

Climate risk: Climate risks are captured through two complementary datasets: S&P Global Sustainable1, focusing on physical climate risks, and S&P Global Trucost, concentrating on emissions.

Climate dependence is quantified using exposure scores derived from S&P Global Sustainable1, indicating companies' vulnerability to eight climate-related hazards: water stress, droughts, wildfires, coastal floods, fluvial floods, extreme heat, extreme cold, and tropical cyclones. The dataset includes 544 metrics per company, constructed through advanced climate change models (CMIP6), asset-level information, and proprietary methodologies. Exposure scores, ranging from 1 (least exposed) to 100 (most exposed), measure point-in-time hazard exposure relative to global conditions across eight decadal horizons (2020–2090) under four distinct climate scenarios aligned with IPCC pathways and TCFD guidelines (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5).

Climate impact addresses transition risks via company-level emissions data provided by S&P Global Trucost. This dataset encompasses annual Scope 1, 2, and 3 emissions as well as emission intensities calculated by scaling total emissions relative to company revenues.

Data sources include corporate disclosures and outputs from S&P Global's environmentally-enhanced proprietary Input-Output model.

Return data

Data on stock returns is obtained from CRSP. Returns are defined as the change in closing price between the last trading day of two consecutive months. We compute the excess return as the return above the risk-free rate obtained from Keith French's website, from which we also download the Fama-French five factors. We utilize daily returns obtained from CRSP's daily security file to estimate CAPM-implied market betas and idiosyncratic return volatilities.

News-based risk indices

To capture broad shifts in market concern about climate- and nature-related risks, we use news-based indices developed by Engle et al. (2020) and Giglio et al. (2023). Specifically, we employ the New York Times (NYT) Biodiversity News Index and the NYT Climate News Index. Each index is constructed by scanning daily news articles and counting the number of articles with negative versus positive tone on the respective topic. The index value for a given day is defined as the number of negative news articles minus the number of positive news articles concerning biodiversity (for the Biodiversity News Index) or climate change (for the Climate News Index). Thus, a higher index indicates a day with more bad news (negative coverage) than good news about biodiversity or climate. We interpret increases in these indices as proxies for shocks to perceived nature-related or climate-related risks. Both series span multiple decades and were kindly provided by Giglio et al. (2023). These news indices will be used to derive "nature betas" and "climate betas" for each stock, based on how sensitive a firm's returns are to biodiversity or climate news shocks.

3.1.2 Dataset construction

Our sample consists of U.S. common stocks over the period January 2006 to December 2021. Following standard practice, we include only firms with CRSP share codes 10 or 11 (common equity) and exclude securities that are likely erroneous or illiquid. In particular, we drop any stock-month observations with a share price below $1 at the end of the month or a raw monthly return above 300%. This filter eliminates penny stocks and implausibly large return outliers that could bias the results. To further mitigate the influence of outliers, all continuous characteristics (e.g., emissions intensities or betas) are winsorized at the 5% level. These filtering steps yield a broad panel of firms for which we have both the S&P Global environmental data and the necessary return and news data.

3.2 Empirical analysis

The general equilibrium framework in Section 2 yields specific testable predictions relating firms' exposure to nature and climate risks to their expected returns. Our empirical strategy proceeds in two parts. First, we estimate firm-level nature and climate betas from stock returns and test whether these estimated betas correlate with fundamental risk characteristics as predicted by the theory (the "characteristics comparison"). Second, we form portfolios sorted by estimated betas and underlying characteristics, and we test whether their returns align, particularly in the post-2015 period (the "characteristic-sorted portfolio comparison"). The following subsections describe the beta estimation procedure and the econometric setups for the two comparisons.

3.2.1 Estimating betas

The market-implied nature and climate characteristics, or betas, are computed as the sensitivities of stock returns to aggregated nature and climate risks measures in the form of biodiversity and nature related indices.

News innovation

To compute innovations in the news related to nature and climate, we calculate moving averages for the biodiversity and climate news indices provided by Giglio et al. (2023) using a seven-day window. The biodiversity and climate indices are likely to have some day-to-day fluctuations, which may not be of primary interest for the analysis. To smooth out these short-term variations and focus on the broader trends, we calculate the moving average of each index using the current and the six preceding days. Next, we fit a daily AR(1) model to transform news indices using a four-year rolling window, and use it to generate a one-day-ahead prediction. News innovations, or news shocks, are calculated as the difference between the observed and predicted values. Hence, they capture unexpected changes in biodiversity or climate news.

Betas

Following Huij et al. (2023), we run company-by-company time-series regressions of stock returns on news innovations to estimate the sensitivity of returns to biodiversity and climate shocks, while controlling for other equity risk factors. Specifically, we run rolling window regressions using daily observations using the following specification:

$$\begin{aligned} r_{i,t} = \alpha_i + \beta_{i,t}^{Bio}\text{BioShock}_t + \beta_{i,t}^{Clim}\text{ClimShock}_t + \\ + \beta_{i,t}^{MKT}\text{MKT}_t + \beta_{i,t}^{SMB}\text{SMB}_t + \beta_{i,t}^{HML}\text{HML}_t + \epsilon_{i,t}, \end{aligned} \tag{20}$$

where $r_{i,t}$ is the excess return (above the risk-free rate) of company i's stock at time t. BioShock_t and ClimShock_t are the biodiversity and climate news shocks, respectively.

MKT is the excess return on the market portfolio, SMB represents the return spread between small- and large-cap stocks and HML measures the return spread between high book-to-market and low book-to-market stocks. The coefficient of interests are the monthly sensitivities to biodiversity and climate shocks, $\beta_{i,t}^{Bio}$ and $\beta_{i,t}^{Clim}$.

Each rolling window is defined by an end date corresponding to the last day of each month.

We restrict the width of the window to less than 6 months and only run the regression if the number of observations in the window exceeds 100 days. This gives us estimates for $\beta_{i,t}^{Bio}$ and $\beta_{i,t}^{Clim}$ corresponding to the end of each month. To create a monthly dataset of nature and climate betas, we assign the betas estimated for the window corresponding to the last day of month m to the entire month $m+1$.[17]

3.2.2 Characteristics comparison

The first type of comparison investigates whether betas are correlated with exposures as measured by fundamental characteristics. Since the Paris Agreement in 2015, there has been a significant global increase in awareness regarding environmental sustainability, including biodiversity loss. This heightened awareness has been driven by international agreements, scientific findings, and public discourse around the importance of protecting natural ecosystems. The increased awareness affects investors' behavior and might lead to changes in the perception of climate and nature-related risks (Acharya et al., 2022).[18] Hence, we are interested in the correlation between the change in the betas after the Paris Agreement and the fundamental characteristics. Accordingly, we run the panel regression

$$\hat{\beta}_{i,t}^{\kappa} = \Gamma^{\kappa,Char}\text{Characteristic}_i \times \text{Post}_{2015} + \text{Fixed effects} + \epsilon_{i,t}, \tag{21}$$

where $\hat{\beta}_{i,t}^{\kappa}$ is the monthly sensitivity of stock i to biodiversity ($\kappa = Bio$) or climate news shocks ($\kappa = Clim$), estimated in regression (20), Post_{2015} is a dummy variable taking value 1 after 2015 and Characteristic is a fundamental characteristic. We consider three alternative transformations of fundamental characteristic. We rank companies on each characteristics

[17] This approach enable us to detect the financial markets perception of nature and climate risks. Under the specification adopted we are able to find some evidence of nature risk pricing and of the markets perception of the interaction between nature and climate risks despite the signal being weak. More traditional approaches do not deliver satisfactory results. The intuition is that the estimated sensitivities pick up company and time variation in risk at a higher frequency (daily): stock prices might react to news at short horizons and the effects are not long lived, but the higher frequency helps us pick up how these small effects are correlated with fundamental risk exposure.

[18] Although the Paris Agreement was a climate-related event, we believe that the increased attention in the markets that it generated might had implications also for the pricing of other nature-related risks.

in our full sample (as described in Section 3). The *pooled* rank gives unconditional relative exposures of companies. We also want to decompose this into sectoral and within-sector exposures. For the latter, we rank companies within each sector, which we refer to as the *within-sector* rank. For the former we rank sectors based on the average pooled rank of companies in each sector - and assign the *sectoral* rank to all companies in that sector.

Our theory makes predictions about how the correlation between betas and fundamental characteristics changes from pre-2015 to post-2015 for any given company or sector. Consistent with this, for each transformation, we adopt a fixed effects specification that isolates this variation. With pooled ranks, we use month-year and firm fixed effects. With within sector ranks, in addition to month-year and firms fixed effects, we also use sector fixed effects, to control for any sector-level variation in betas. Finally, with sectoral ranks, we use month-year and sector fixed effects.[19] Standard errors clustered at the company and month-year level to account for potential correlation in the errors within company and within month.[20]

We are interested in the coefficient on the interaction between the fundamental characteristics and the post-2015 dummy, $\Gamma_1^{\kappa,Char}$, that is, how the change in beta after 2015 correlates with the fundamental characteristics.

We use the predictions of the model to investigate whether nature and climate risk are priced by financial markets.

We first present the results from characteristics comparison and the characteristic-sorted portfolio comparison results within nature and climate categories. A positive correlation implies that stocks more exposed to nature and climate risk (both impacts and dependencies) are more sensitive to biodiversity and climate news, that is, to news related to the same type of risk. Hence, financial markets price the risk under investigation.

[19] As a robustness test, we also run regressions without firm fixed effects, which amounts to computing the pooled cross-sectional correlation before and after 2015 and looking at the difference. Results are qualitatively unchanged.

[20] As an additional robustness test, we also run the regression with Driscoll and Kraay standard errors to account for potential autocorrelation in the errors. Results are qualitatively unchanged, but significance is higher, as expected given that clustered standard errors produce more conservative estimates.

Second, we present the results related to the comparison between betas and fundamental characteristics and the corresponding sorted portfolio returns across the nature and climate categories (for instance, climate sensitivity and nature impact). This gives us insights into how markets perceive companies with different nature or climate exposures to be affected by climate and biodiversity news, respectively. Hence, it captures the markets perception of the interaction between nature loss and climate change.[21]

Importantly, the results have to be interpreted as differential effects. Our results show whether companies deemed fundamentally riskier became more sensitive to nature/climate news post 2015, relative to less risky companies (Callaway et al., 2024). In other words, our results capture whether the gap in the premium or discount offered to riskier versus less risky companies is higher or lower compared to before 2015.

An increase in the gap in beta between more and less risky after 2015 results in a higher correlation between betas and the fundamental risk metrics for riskier firms compared to less risky firms. A decrease in the gap in beta between more and less risky after 2015 results in a lower correlation between betas and the fundamental risk metrics for riskier firms compared to less risky firms.

3.2.3 Risk pricing

This section presents the results related to the pricing of nature and climate risks by financial markets, comparing market-implied betas with fundamental characteristics and examining beta- and characteristic-sorted portfolios.

Betas and fundamental characteristics

We study how the nature and climate betas for individual firms have changed after 2015 and whether this change is correlated with the nature and climate fundamental characteristics

[21] In this section, we present the results obtained using the specifications shown in the previous section and the main fundamental characteristics. Additionally, we perform our characteristics comparison with year dummies, to capture the change in effect compared to the base year and including company fixed effects. Moreover, we include additional characteristics in the analysis. Results are available upon request .

(that is, with the firm's fundamental risk exposure), respectively. Recall that our model predicts positive pricing for dependence risks γ^N, γ^Z and pricing for impact risk δ^Z only via policy (the carbon tax), with pure nature impact δ^N unpriced. The post-2015 period potentially involves shifts in attention, disclosure, and policy implementation. A positive interaction coefficient Γ^κ in equation (21) indicates that the pricing of the risk considered has increased for riskier companies compared to less risky companies after 2015. In other words, the gap in the sensitivity to news of stock prices of more versus less risky companies has increased. A negative correlation indicates that the premium differential for riskier versus less risky companies has decreased compared to before 2015 (it does not necessarily mean that companies receive a discount).

We display our results as heatmaps for better visualization. The color of the cell corresponds to the point estimate of the parameter of interest and the statistical significance is indicated by stars.

Nature beta and nature dependence. The correlation between nature betas and nature dependence increases significantly after 2015 across various dependence characteristics (see Figure 1). This implies that stocks fundamentally more exposed to nature dependence become more sensitive to negative biodiversity news after 2015, relative to less dependent firms. Hence, nature dependence risk seems to be priced more strongly after 2015, consistent with the model's prediction that dependence (γ^N) should be priced.

Nature beta and nature impact. In stark contrast, we find no significant correlation between nature beta and the impact of companies on nature post-2015 (Figure 2). This suggests that while markets have started to price nature dependence more after 2015, they have not significantly priced the negative impact on nature. Hence, while investors seem to care about physical risk (dependence), this does not generally apply to transition risk (impact) when it is not directly linked to policy costs, aligning with the model's prediction

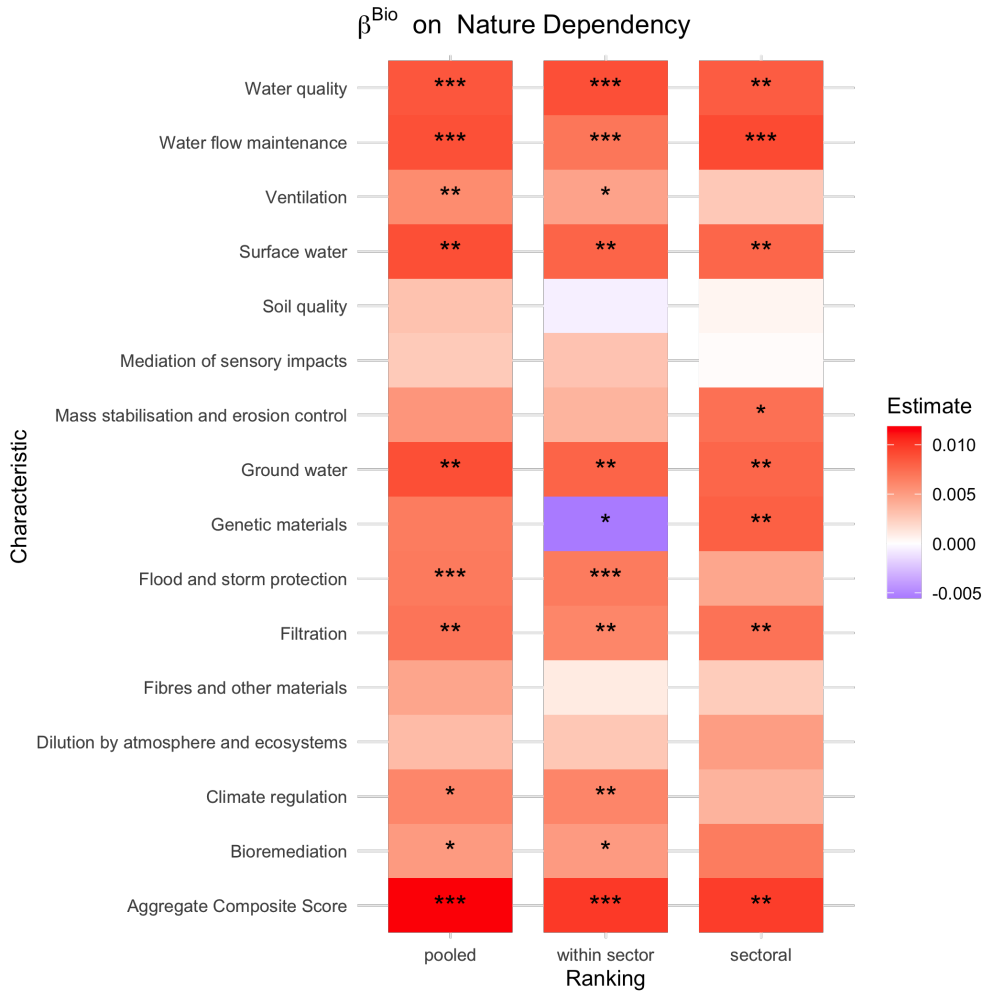


Figure 1: Nature beta and nature dependence.

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

for uninternalized externalities (δ^N). In other words, investors appear more focused on how much a company relies on natural ecosystems rather than the degree to which that company contributes to environmental degradation.

Climate beta and climate dependence. Interestingly, no significant positive pattern arises for climate beta and climate dependence (Figure 18). This suggests that stocks that are more exposed to climate physical risk do not systematically become more responsive to negative climate news after 2015 relative to less exposed firms. Given the predictions of our

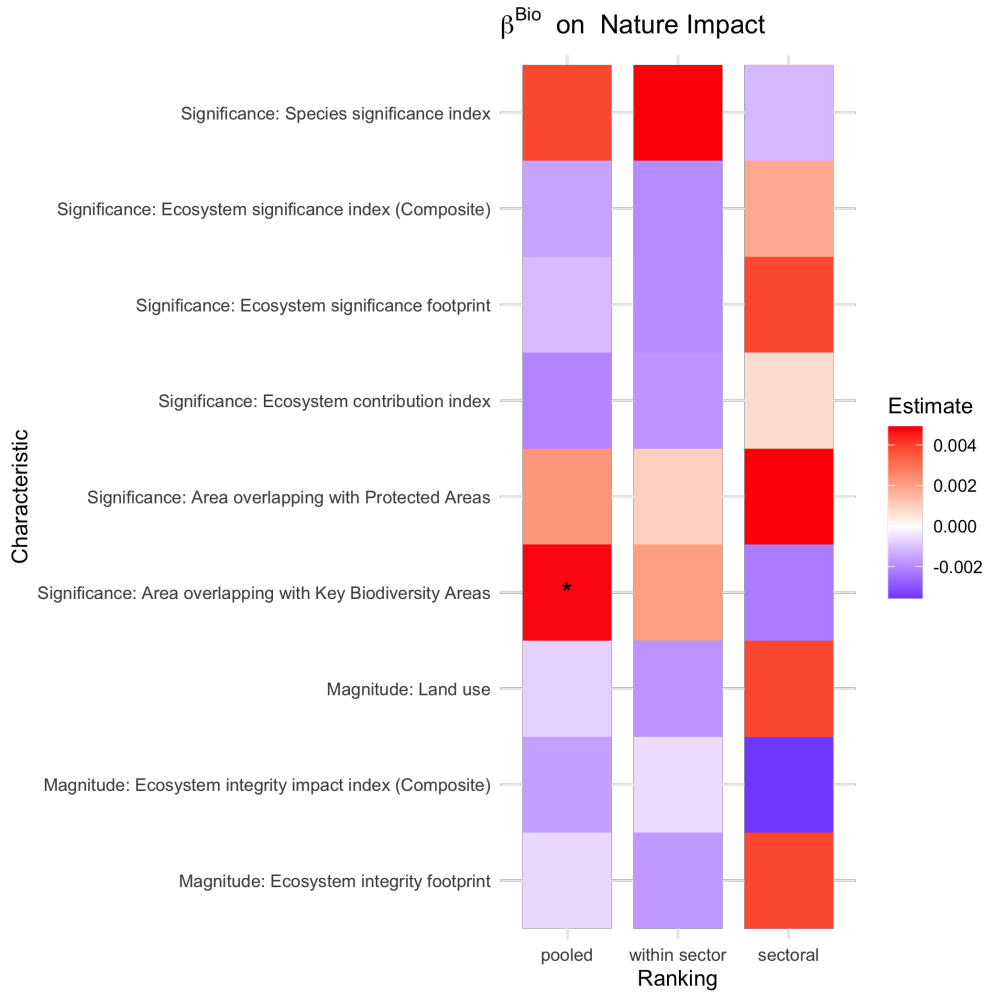


Figure 2: Nature beta and nature impact

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

model, this result might point towards potential mispricing or offsetting factors not captured in our baseline framework related to climate dependence.

Climate beta and climate impact. Companies with higher climate impact (emissions, δ^Z) become relatively less sensitive to climate news after 2015, compared to lower risk companies (i.e., the interaction coefficient is negative, see Figure 25). The intuition offered by our model's information channel is that before 2015, perhaps only very polluting companies (high δ^Z) were closely watched and thus sensitive to climate news and the existing carbon

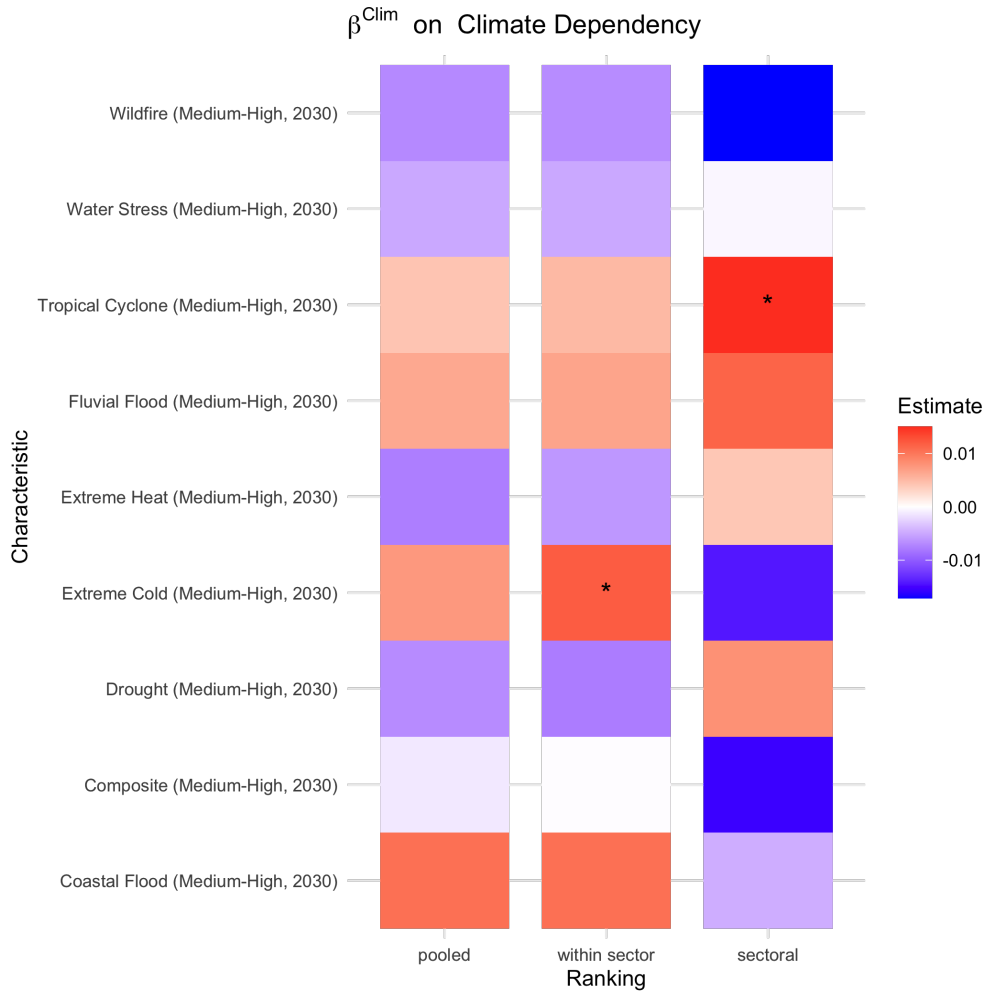


Figure 3: Climate beta and climate dependence

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

price signals. After 2015, driven by enhanced disclosure and attention (e.g., Paris Agreement effects), less polluting companies also become more sensitive as their emissions data becomes more precise ($\phi_{i,t}$ increases for low emitters). This increased scrutiny and potential pricing for lower emitters could narrow the sensitivity gap relative to high emitters. The changing regulatory landscape might also play a role. As more companies adapt to new standards or face anticipated future policies, their perceived marginal risk associated with climate news might adjust, potentially leading to the observed negative differential change in sensitivity. It is important to note that this negative coefficient reflects a change in relative sensitivities

and does not imply that climate impact overall is not priced; indeed, the model predicts pricing via the carbon tax channel. The negative differential effect might also reflect adaptation measures implemented by the highest emitters, mitigating their relative sensitivity to further climate-related news.

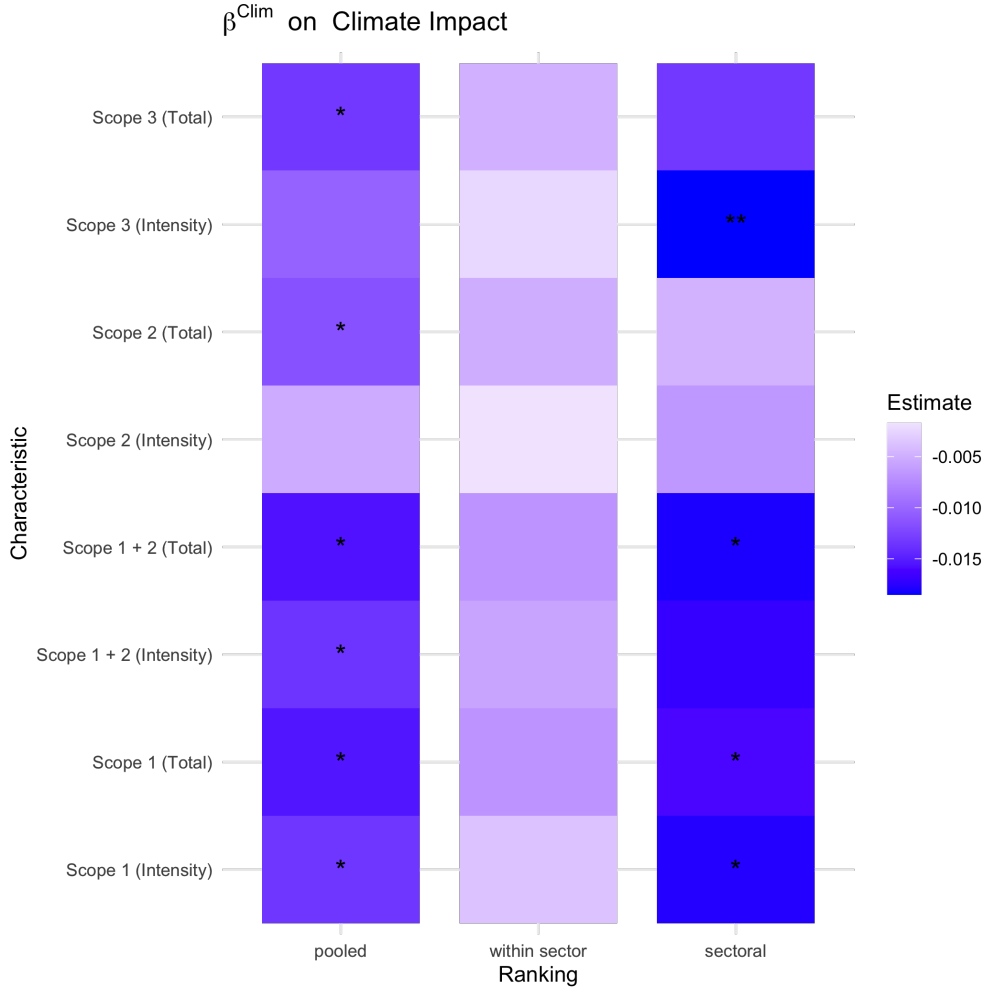


Figure 4: Climate beta and climate impact

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

We also show how beta-sorted portfolio returns correlate with the fundamental characteristic-sorted portfolios after 2015 (See Appendix E). Consistently with the comparison of the characteristics, the clearest effects are a positive correlation between the nature beta- and nature dependence-sorted portfolios and a negative correlation between the climate beta- and cli-

mate impact-sorted portfolios after 2015. However, the effects are less statistically significant when considering portfolio returns.

3.2.4 Nature-climate interaction

In this section, we present results related to the market's perception of the interaction between nature and climate risks. In other words, we answer the question of whether nature and climate risks are treated as correlated in the eyes of financial markets. We start by investigating the correlation between the nature and climate betas themselves and then examine the cross-correlations between betas and characteristics across risk types.

Correlation among betas

A first insight on the relationship between nature and climate risks can be obtained by looking at the correlation between nature and climate betas. Hence, we run the regression

$$\hat{\beta}_{i,t}^{Bio} = \hat{\beta}_{i,t}^{Clim} + \gamma + \varepsilon_{i,t} \tag{22}$$

without fixed effects, with time fixed effects (month-year)to understand the correlation within each cross section, and with company fixed effects to study the correlation for each company over time. Table 1 shows that nature and climate betas are negatively correlated, although the coefficients are not statistically significant. The results also show that most of the variation in cross sectional, supporting our ranking assumption.

We also look at the correlation between nature and climate beta-sorted portfolios under the three different ranking specifications. As in the previous analysis, we look at the change in correlation after 2015 and use HAC standard errors.Results are reported in Table 2 and show that nature beta sorted-portfolios and climate beta-sorted portfolios are negatively correlated. This weak negative correlation might hint at hedging behavior but requires cautious interpretation.

Dependent Variable:		$\hat{\beta}^{Bio}$	
Model:	(1)	(2)	(3)
Variables			
Constant	-0.0001		
	(0.0005)		
$\hat{\beta}^{Clim}$	-0.0101	-0.0109	-0.0084
	(0.0103)	(0.0102)	(0.0101)
Fixed-effects			
month:year		Yes	
permno			Yes
Fit statistics			
Observations	243,326	243,326	243,326
R^2	0.00044	0.01102	0.03648
Within R^2		0.00051	0.00030

*Clustered (permno & month*year) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 1: Correlation between nature and climate characteristic-sorted portfolios

Dependent Variable:		$r^{\hat{\beta},\text{Bio}}$	
Model:	(1)	(2)	(3)
Variables			
$\text{Post}_{2015} \times r^{\hat{\beta},\text{Clim}}$	-0.0949	0.0118	0.0052
	(0.1920)	(0.1571)	(0.2232)
Fit statistics			
Observations	180	180	199
R^2	0.06864	0.06228	0.05892
Adjusted R^2	0.00765	0.00088	0.00356

vcovHAC standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Correlation between nature and climate beta-sorted portfolios

Betas and fundamental characteristics

Our theoretical model provides a framework for understanding potential cross-channel relationships. The model incorporates mechanisms that could lead to such cross-effects, such as investors learning about both nature and climate states from potentially mixed news signals or preferences that depend jointly on both environmental states. Therefore, finding significant cross-correlations empirically would suggest that markets perceive these risks as interconnected, potentially reflecting these underlying model mechanisms, spillovers, or omitted factors not captured in the baseline formulation. We now examine the empirical evidence for such cross-relationships

Nature beta and climate dependence. Our results show that the correlation between exposure to physical climate risk (dependence) and the sensitivity of returns to biodiversity news is generally non-significant post-2015, with the exception of wildfires (Figure 5). Companies that are more exposed to wildfires are relatively more sensitive to biodiversity news after 2015. The negative correlation observed for fluvial floods might potentially be explained through public adaptation; if the latter increases, stocks could become less sensitive as physical capital substitutes for natural capital.

Nature beta and climate impact. Companies that have a higher climate impact are relatively more sensitive to biodiversity news post-2015 compared to lower emitters (Figure 6). This suggests that the market perceives a link where high climate impact signals higher vulnerability to nature-related news or risks.

Climate beta and nature dependence. Stocks that are more exposed to nature dependence are generally relatively less sensitive to climate news after 2015 (Figure 7). This result might be driven by a larger relative increase in sensitivity for less nature-dependent firms (narrowing the gap) or potentially by adaptation measures among the most dependent firms

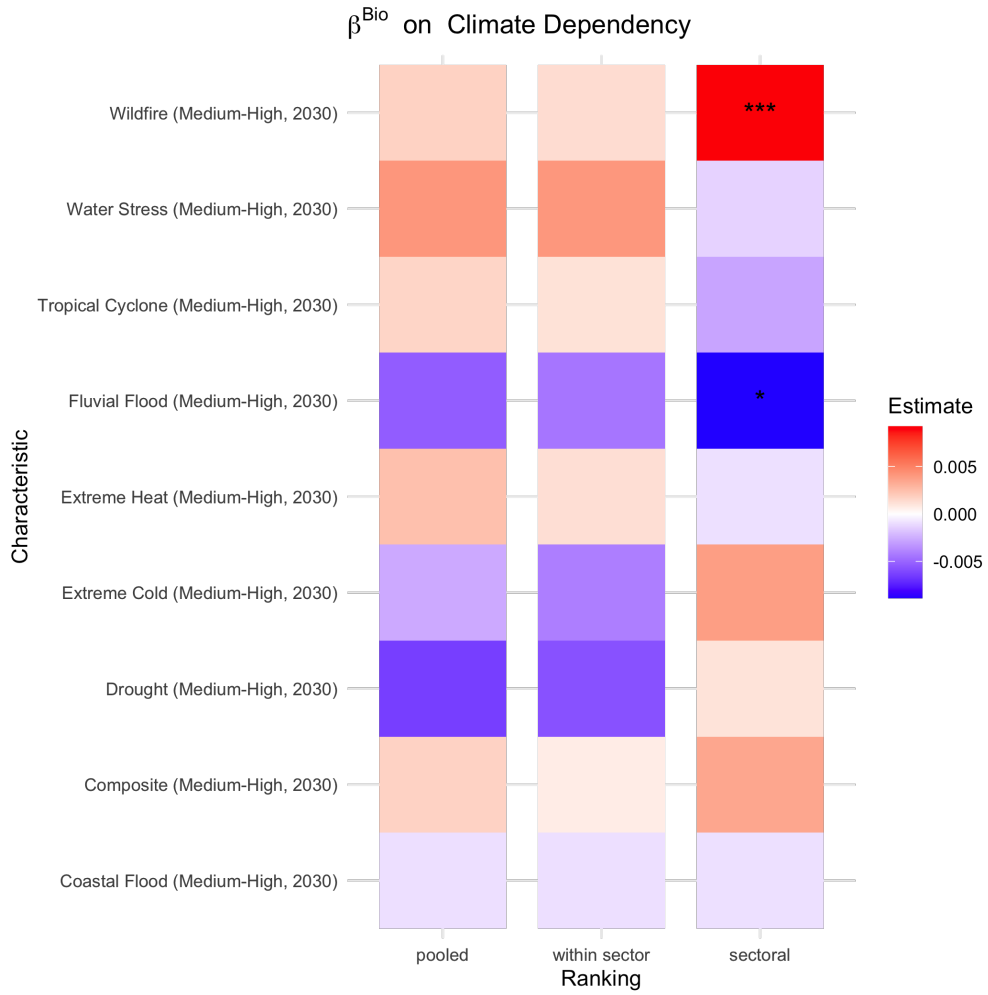


Figure 5: Nature beta and climate dependence

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

reducing their relative sensitivity to climate news.

Climate beta and nature impact. We do not find any significant correlation between nature impact and sensitivity to climate news after 2015 (Figure 8). This aligns with the general finding that pure nature impact seems largely unpriced.

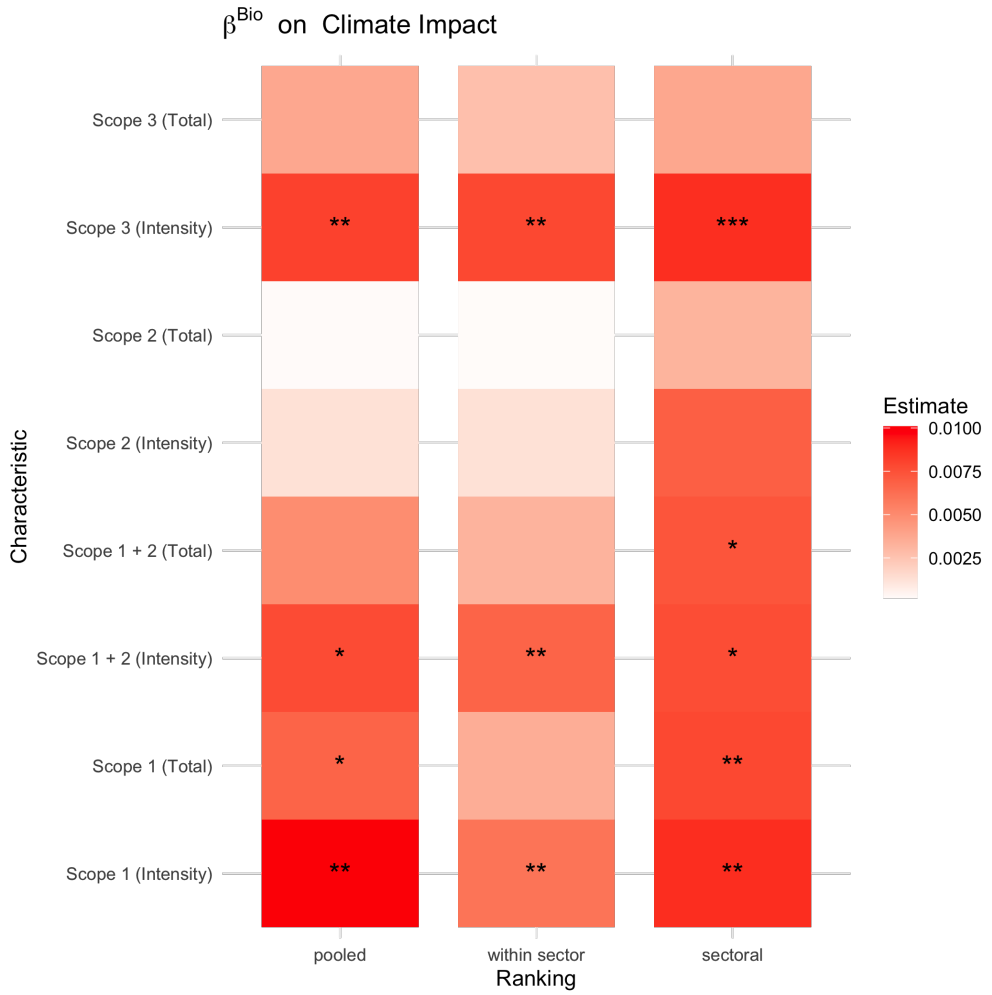


Figure 6: Nature beta and climate impact

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

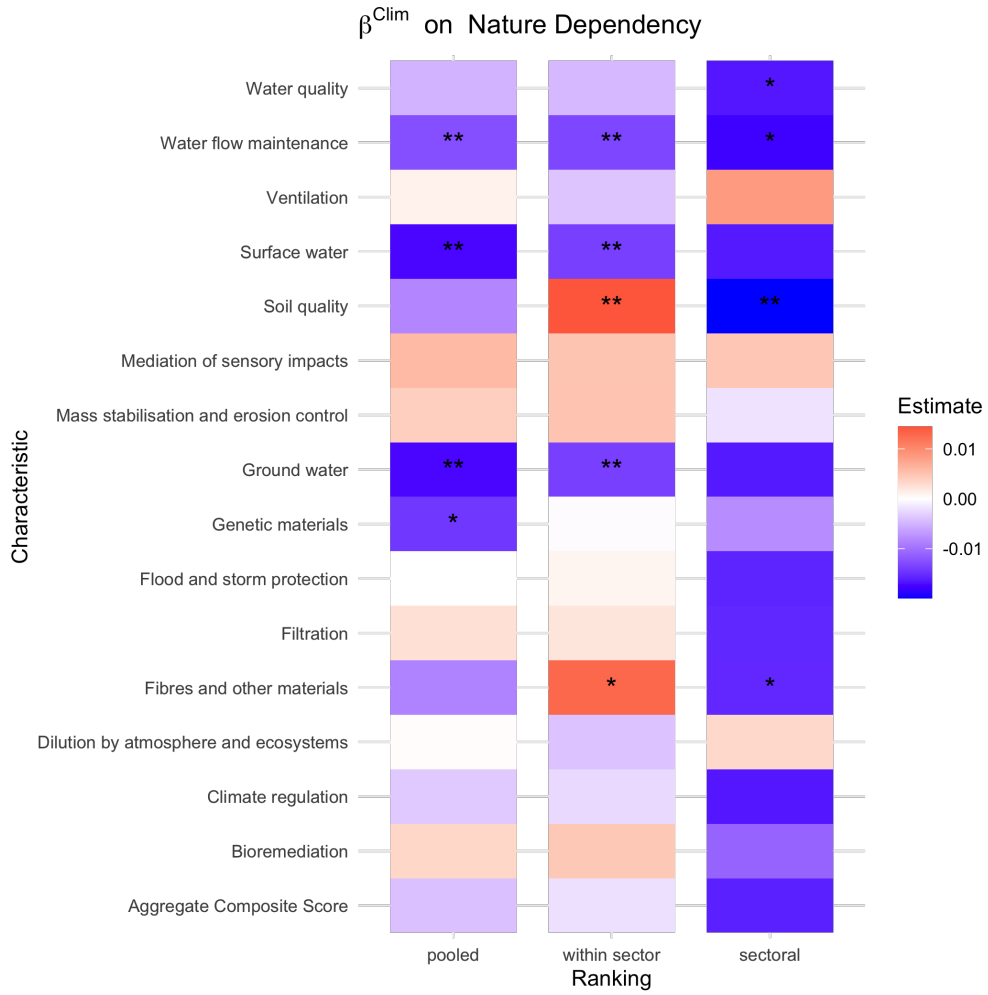


Figure 7: Climate beta and nature dependence

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

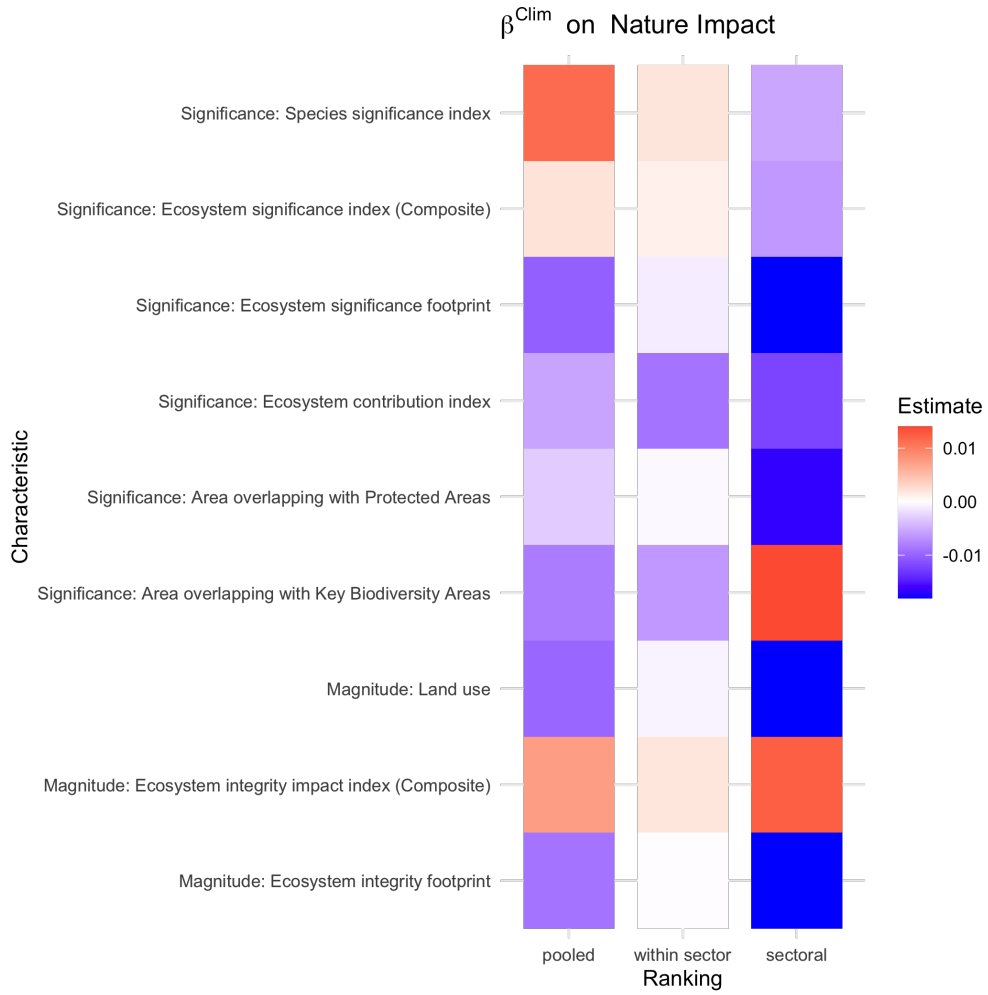


Figure 8: Climate beta and nature impact

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

The results from the beta- and fundamental characteristic-sorted portfolio comparisons (Appendix E) are qualitatively similar for these cross-comparisons but often lack statistical significance. The main findings from the characteristic cross-comparisons are summarized in Table 3.

	Nature dependence	**Nature impact**	**Climate dependence**	**Climate impact**
Nature beta	+	0	+ (wildfires)	+
Climate beta	-	0	0	-

Table 3: Summary results for the characteristics comparison.

4 Conclusion

There is increasing awareness of the risks arising from the complex relationship between the economy and the natural environment, extending beyond climate change. Our study addresses the pricing of these intertwined risks by first developing a stylized general equilibrium asset pricing model. The model features a representative investor sensitive to both consumption and environmental quality (nature and climate states), alongside firms whose production depends on these states (dependence, or physical risk) but whose activities also degrade them (impact, or transition risk). We explicitly incorporate a carbon price that links climate impact to cash flows, while nature impact remains an unpriced externality in the baseline. Investors learn about the latent environmental states and uncertain policy through noisy news signals, facing information frictions that evolve, particularly concerning emissions disclosures post-2015.

The model predicts that dependence should be priced as it directly affects firm cash flows and covaries with marginal utility, while impact should only be priced if internalized by policy like the carbon tax. Empirically, we investigate these predictions by examining four risk categories derived from the model's structure: nature dependence, nature impact, climate dependence, and climate impact. Using company-level data and comparing fundamental characteristics with market-implied betas derived from stock return sensitivities to nature and climate news shocks, our findings offer support for the model's predictions.

Consistent with the pricing of the dependence channel, we find that since 2015, financial markets have begun rewarding firms with greater dependence on nature. This suggests an increasing recognition of physical risks associated with nature loss. However, mirroring the model's baseline prediction for uninternalized externalities, the impact of companies on nature—the transition risk component not subject to a direct tax—remains largely unpriced by investors. This points to potential market inefficiencies in reflecting the full cost of environmental degradation. Furthermore, we find evidence that markets perceive an in-

terconnectedness between climate impact and nature dependence, highlighting the interplay captured theoretically by the joint evolution of environmental states and investor learning.

These findings have implications for sustainable finance. If markets increasingly price nature dependence, it could steer capital towards less environmentally reliant activities. However, the lack of pricing for nature impacts suggests that market mechanisms alone may be insufficient to address ecological degradation comprehensively. Enhanced transparency and potentially regulatory measures, perhaps analogous to the carbon price mechanism for nature impacts, might be needed to ensure corporate environmental footprints are fully reflected in market prices, aligning financial incentives with long-term ecological and economic viability. Our work provides a theoretically grounded framework and empirical evidence contributing to this ongoing exploration.

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A Ecosystem services

Ecosystem service	Description
Animal-based energy	Physical labour provided by domesticated or commercial species, including oxen, horses, donkeys, goats and elephants.
Fibres and other materials	Includes wood, timber, and fibres which are not further processed, as well as material for production, such as cellulose, cotton, and dyes, and plant, animal and algal material for fodder and fertiliser use.
Genetic materials	Genetic material is understood to be deoxyribonucleic acid (DNA) and all biota including plants, animals and algae.
Ground water	Groundwater is water stored underground in aquifers made of permeable rocks, soil and sand. The water that contributes to groundwater sources originates from rainfall, snow melts and water flow from natural freshwater resources.
Surface water	Surface water is provided through freshwater resources from collected precipitation and water flow from natural sources.
Maintain nursery habitats	Nurseries are habitats that make a significantly high contribution to the reproduction of individuals from a particular species, where juveniles occur at higher densities, avoid predation more successfully, or grow faster than in other habitats.
Pollination	Pollination services are provided by three main mechanisms: animals, water and wind. The majority of plants depend to some extent on animals that act as vectors, or pollinators, to perform the transfer of pollen.

Table 4: Ecosytem services

Ecosystem service	Description
Soil quality	Soil quality is provided through weathering processes, which maintain bio-geochemical conditions of soils including fertility and soil structure, and decomposition and fixing processes, which enables nitrogen fixing, nitrification and mineralisation of dead organic material.
Ventilation	Ventilation provided by natural or planted vegetation is vital for good indoor air quality and without it there are long term health implications for building occupants due to the build-up of volatile organic compounds (VOCs), airborne bacteria and moulds.
Water flow maintenance	The hydrological cycle, also called water cycle or hydrologic cycle, is the system that enables circulation of water through the Earth's atmosphere, land, and oceans. The hydrological cycle is responsible for recharge of groundwater sources (i.e. aquifers) and maintenance of surface water flows.
Water quality	Water quality is provided by maintaining the chemical condition of freshwaters, including rivers, streams, lakes, and ground water sources, and salt waters to ensure favourable living conditions for biota.
Bio-remediation	Bio-remediation is a natural process whereby living organisms such as micro-organisms, plants, algae, and some animals degrade, reduce, and/or detoxify contaminants.
Dilution	Water, both fresh and saline, and the atmosphere can dilute the gases, fluids and solid waste produced by human activity.
Filtration	Filtering, sequestering, storing, and accumulating pollutants is carried out by a range of organisms including, algae, animals, microorganisms and vascular and non-vascular plants.
Mediation of sensory impacts	Vegetation is the main (natural) barrier used to reduce noise and light pollution, limiting the impact it can have on human health and the environment.

Table 5: Ecosystem services

Ecosystem service	Description
Buffering and attenuation of mass flows	Buffering and attenuation of mass flows allows the transport and storage of sediment by rivers, lakes and seas.
Climate regulation	Global climate regulation is provided by nature through the long-term storage of carbon dioxide in soils, vegetable biomass, and the oceans. At a regional level, the climate is regulated by ocean currents and winds while, at local and micro-levels, vegetation can modify temperatures, humidity, and wind speeds.
Disease control	Ecosystems play important roles in regulation of diseases for human populations as well as for wild and domesticated flora and fauna.
Flood and storm protection	Flood and storm protection is provided by the sheltering, buffering and attenuating effects of natural and planted vegetation.
Mass stabilisation and erosion control	Mass stabilisation and erosion control is delivered through vegetation cover protected and stabilising terrestrial, coastal and marine ecosystems, coastal wetlands and dunes. Vegetation on slopes also prevents avalanches and landslides, and mangroves, sea grass and macroalgae provide erosion protection of coasts and sediments.
Pest control	Pest control and invasive alien species management is provided through direct introduction and maintenance of populations of the predators of the pest or the invasive species, landscaping areas to encourage habitats for pest reduction, and the manufacture of a family of natural biocides based on natural toxins to pests.

Table 6: Ecosystem services

B Impacts

Impact	Description
Magnitude: Land use	Extent of land used for or affected by an asset or company's business activity.
Magnitude: Ecosystem integrity index (Composition)	Quantifies the relative integrity of the species present in a given location compared to a pristine state. Ecosystem composition refers to the identity and variety of life. A value of 0 indicates a low integrity, a value of 1 means a pristine state.
Magnitude: Ecosystem integrity index (Structure)	Quantifies the relative integrity of the physical characteristics of a given location compared to a pristine state. Ecosystem structure is dependent on habitat area, intactness, and fragmentation. A value of 0 indicates a low integrity, a value of 1 means a pristine state.
Magnitude: Ecosystem integrity index (Function)	Quantifies the relative functioning state of an ecosystem in a given location compared to a pristine state. A value of 0 indicates a low integrity, a value of 1 means a pristine state.
Magnitude: Ecosystem integrity index (Composite)	Quantifies the relative integrity of an ecosystem in a given location compared to a pristine state calculated as the minimum of all three components: ecosystem structure, composition, and function. A value of 0 indicates a low integrity, a value of 1 means a pristine state.
Magnitude: Ecosystem integrity impact (Composition)	Quantifies the impact of all pressures applied in a given location on the species present in an ecosystem compared to a pristine state. A value of 0 indicates no impact, a value of 1 means complete degradation.

Table 7: Impacts

Impact	Description
Magnitude: Ecosystem integrity impact index (Structure)	Quantifies the impact of all pressures applied in a given location on the physical characteristics of an ecosystem compared to a pristine state. A value of 0 indicates no impact, a value of 1 means complete degradation.
Magnitude: Ecosystem integrity impact index (Function)	Quantifies the impact of all pressures applied in a given location on the functioning state of an ecosystem compared to a pristine state. A value of 0 indicates no impact, a value of 1 means complete degradation.
Magnitude: Ecosystem integrity impact index (Composite)	Quantifies the impact of all pressures applied in a given location on the integrity of an ecosystem compared to a pristine state calculated as the maximum of all three components: ecosystem structure, composition, and function. A value of 0 indicates no impact, a value of 1 means complete degradation.
Magnitude: Ecosystem integrity footprint	Provides a condition-adjusted area footprint of an asset or company's operations. The total area of ecosystem occupied by a business activity can be adjusted for the degree to which its integrity is reduced, thereby expressing impact of different business activities on a common scale. This provides a measure of the equivalent area in hectares where integrity is reduced to zero.

Table 8: Impacts

Impact	Description
Significance: Species Threat Abatment and Restoration Metric (STAR)	Allows the quantification of the potential contributions that species threat abatement and restoration activities offer towards reducing extinction risk across the world. It quantifies the relative significance of the area studied for biodiversity conservation.
Significance: Species significance index	A normalised version of STAR (from 0 to 1) to more clearly indicate the relative significance of species impact in an area. The index quantifies the relative significance of the area studied for biodiversity conservation. A value of 0 means no significance, a value of 1 means highest significance.
Significance: Nature Contribution to People (NCP)	Quantifies the critical nature of the ecosystems in which an asset or company operates, defined as the natural and semi-natural terrestrial and aquatic ecosystems required to maintain 12 of nature's 'local' contributions to people (local NCP) on land (green) and in the ocean (blue).
Significance: Ecosystem contribution index	Quantifies the critical nature of the ecosystems in which an asset or company operates, defined as the natural and semi-natural terrestrial and aquatic ecosystems required to maintain 12 of nature's 'local' contributions to people (local NCP) on land (green) and in the ocean (blue). It is a normalised value of the Nature Contribution to People indicator. A value of 0 means no significance, a value of 1 means highest significance.
Significance: Ecosystem significance index (Composite)	Quantifies the relative environmental significance of a specific ecosystem in terms of biodiversity and nature contribution to people in the form of ecosystem services (from 0 to 1). It is a composite index calculated as the maximum of the species significance index and the ecosystem contribution index. A value of 0 means no significance, a value of 1 means highest significance.

Table 9: Impacts

Impact	Description
Significance: Overlap with Protected Area(s)	Indicates the number of WDPAs that an asset or company overlaps with.
Significance: Area overlapping with Protected Area(s)	Indicates the total area of an asset or company overlaping with one or more WDPA.
Significance: Overlap with Key Biodiversity Area(s)	Indicates the number of KBAs that an asset or company overlaps with.
Significance: Area overlapping with Key Biodiversity Area(s)	Indicates the total area of an asset or company overlaping with one or more KBA.
Aggregate: Ecosystem footprint (HSA)	Significance-weighted and condition-adjusted area footprint of an asset or company's operations. The total area of ecosystem occupied by a business activity can be adjusted for the degree to which its integrity is reduced as well as the degree to which it is ecologically significant, thereby expressing impact of different business activities on a common scale. This provides a measure of the equivalent area in hectares of the most pristine and significant ecosystems where integrity is reduced to zero.

Table 10: Impacts

C Selecting characteristics

The combined data initially include a very large set of fundamental environmental characteristics (hundreds of variables across the four categories of nature dependence, nature impact, climate physical, and climate transition risk). Before proceeding to the analysis, we address two key challenges in using these characteristics: time availability and multicollinearity.

(i) Time dimensions and rankings: Most of the S&P environmental metrics (with the exception of the annual emissions data) are only available as a one-time assessment for each firm (or are very low-frequency). This means we effectively have a cross-sectional snapshot of each firm's nature and climate exposures, rather than a time series. To incorporate these into our asset pricing tests, we assume that each firm's relative risk exposure is persistent over the sample period. In practice, we rank companies cross-sectionally on each characteristic and use the rank (scaled between 0 and 1) as the variable of interest. This ranking approach converts each metric into a unit-free measure of relative exposure (with 0 indicating the lowest exposure in the universe and 1 the highest). It also puts all characteristics on a comparable scale. For the climate impact (emissions) variables that do vary over time, we take each firm's historical average emissions (over the sample period) and then assign a rank based on those averages, to make them conceptually consistent with the mostly cross-sectional nature of the other categories. While using long-run averages and ranks sacrifices some time variation, it is aligned with the notion that a firm's risk profile (in terms of, say, highest emitters vs. lowest emitters, or most nature-dependent vs. least) remains fairly stable over the sample. This assumption – that the cross-sectional ranking of risk exposures is roughly constant – is similar to the approach in Acharya et al. (2022) and is reasonable given the relatively slow-moving nature of these fundamental exposures.

(ii) Redundancy and multicollinearity: Many of the raw characteristics are highly correlated or even explicitly constructed from others (for example, an ecosystem service de-

pendence score might be the product of two underlying factors, materiality and resilience). Including numerous collinear variables would add noise and complexity to the analysis without improving insight. We therefore impose a variable selection procedure to distill a smaller set of informative, low-redundancy characteristics. First, within each of the four risk categories, we identify and retain a subset of "core" metrics that are relatively broad or important, avoiding mechanically derived sub-components. (In the example above, we might keep the composite dependence score but drop its two multiplicative components, or vice versa, to prevent double-counting the same effect.) Next, we examine the correlations among the retained characteristics. We sequentially eliminate variables until no pair of remaining variables has an absolute pairwise correlation above a high threshold (we use 0.98).[22] Hence, we retain the largest set of features, ensuring that each pair is sufficiently distinct in what it measures. This data-driven filtering significantly reduces the dimensionality of the characteristics while preserving the vast majority of unique information. The result is a final set of firm-level metrics that capture nature and climate exposure, serving as the independent variables in our empirical tests.

D Correlation among fundamental characteristics

As an initial check, we examine the correlations among the selected environmental characteristics to understand their relationships. Figures 9 to 12 in Appendix D present heatmaps of the correlation matrices for these variables, both within each category and across categories.[23] These visual summaries confirm that the remaining characteristics, while not perfectly orthogonal, capture distinct aspects of nature and climate risk. A few noteworthy patterns emerge from the correlation analysis:

Within nature-related measures: Firms with a larger ecosystem footprint or greater

[22] See Appendix D.2 for the full correlation matrices before screening.

[23] For completeness, Appendix D.2 reports the corresponding heat-maps for all underlying S&P Global metrics (Figures 15 to 13), which confirm that the broad correlation patterns hold once the full variable universe is considered.

resource use tend to exhibit higher dependence on ecosystem services. In other words, companies that extensively use land and natural resources are usually more reliant on the services provided by those ecosystems (such as clean air, water filtration, pollination, and climate regulation). This is an intuitive result – resource-intensive operations require more ecosystem services to sustain them. An exception is that dependence on certain specialized services (e.g., bioremediation or the mediation of sensory impacts) is not strongly correlated with broader footprint measures, perhaps because those services are context-specific. Conversely, firms operating in environments with high ecosystem integrity (ecosystems closer to pristine condition) tend to show lower dependence on ecosystem services. Companies that heavily depend on ecosystem services often degrade those very ecosystems, resulting in a negative correlation between a high dependence score and the ecosystem's integrity index. Overall, the nature dependence and nature impact variables are meaningfully but not perfectly correlated, indicating that they capture related yet distinct facets of a firm's interaction with nature.

Within climate-related measures: The various physical climate hazard exposure scores are generally positively correlated with one another and with the emissions-based measures. Firms that are highly exposed to one type of climate hazard (say, drought) often tend to be exposed to others (like heat or wildfire), and these firms also often have larger carbon footprints. Notably, in our data most hazard exposure scores have a positive correlation with the firm's emission levels (climate impact), with a couple of outliers: extreme heat exposure and fluvial flood exposure show little correlation with total emissions. This suggests that high emitters (typically large industrial firms) also face multiple physical climate risks, though certain risks like heatwaves may threaten a different set of firms (e.g., utilities in specific regions) irrespective of their emissions.

Across nature and climate categories: We also observe interesting interactions between climate risk and nature risk at the firm level. Firms with high overall exposure to physi-

cal climate hazards tend to also rank highly in nature dependence. In particular, exposure to hazards such as extreme cold and wildfires (and, to a lesser extent, coastal flooding) is positively correlated with a firm's dependence on ecosystem services. Likewise, companies with large carbon emissions (high climate impact) overwhelmingly also have high nature dependence scores – intuitively, businesses that emit more (e.g., heavy manufacturers) often rely more on natural resources and ecosystem services, with one minor exception being the above-mentioned sensory impacts service. The correlation between climate dependence (physical hazard exposure) and nature impact is more mixed: some hazard exposures (notably coastal flood, extreme cold, and wildfire risk) are positively correlated with metrics of nature impact (such as land use or ecosystem degradation footprints), while others are weakly related. Finally, looking at climate impact vs. nature impact, we find that certain impact metrics go hand-in-hand – for example, firms with extensive land use (a nature impact) also tend to have high greenhouse gas emissions, and those that degrade ecosystem integrity or affect ecologically significant areas likewise tend to be high emitters. These cross-category correlations highlight that climate and nature risks are often intertwined: companies that contribute heavily to climate change or are exposed to climate hazards also exert significant pressure on natural capital. Importantly, however, none of these correlations is so extreme as to indicate perfect collinearity, underscoring the value of examining each risk dimension separately.

In summary, our final dataset provides a rich cross-sectional profile of each firm's nature and climate risk exposures, with relatively limited redundancy among the variables. These patterns in the data serve as a backdrop for our asset pricing analysis. With the key characteristics defined and understood, we now turn to testing whether these nature- and climate-risk exposures are reflected in stock returns. In the next section, we use news-based shocks to estimate firms' nature betas and climate betas, and examine whether those betas – and the underlying characteristics themselves – carry significant risk premia as suggested

by our theoretical framework.

D.1 Correlation heatmaps for the main mharacteristics

In this Section, we show the correlation between the metrics used in the analysis.

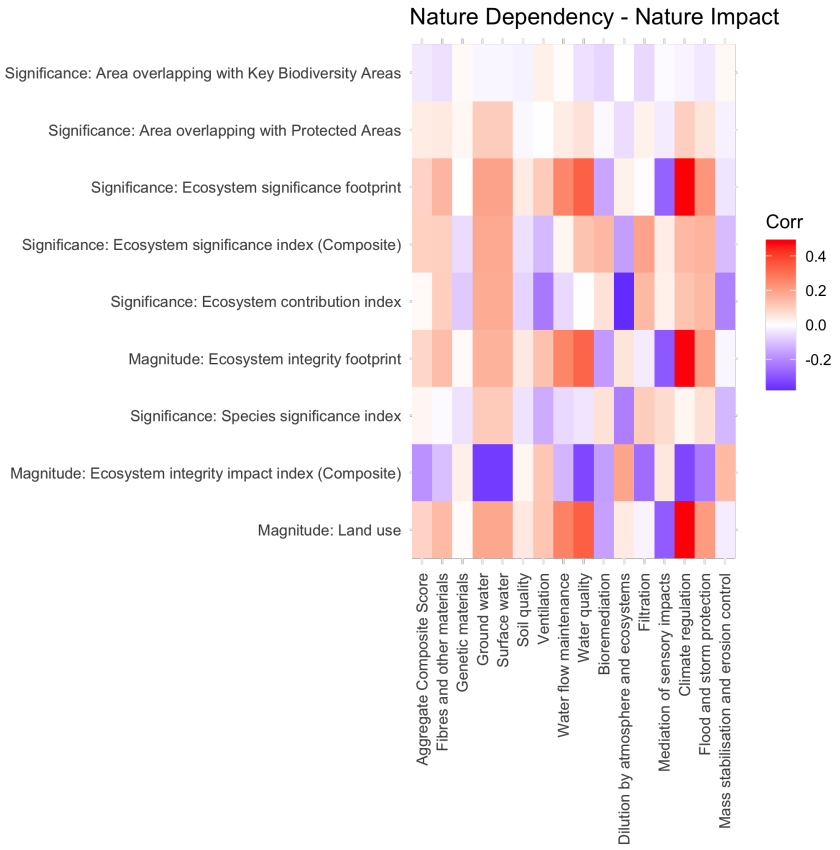


Figure 9: Correlation between nature impact and nature dependence fundamental characteristics

Figure 9 indicates that firms with larger environmental footprints (high *nature impact*) generally also rely more heavily on ecosystem services (high *nature dependence*). The resulting correlations are therefore predominantly positive and often strong. Nonetheless, several specialised dependence metrics exhibit only weak co-movement with broad footprint measures, and operations located in pristine ecosystems display a modest negative link—underscoring that impact and dependence capture related but distinct facets of corporate interaction with nature.

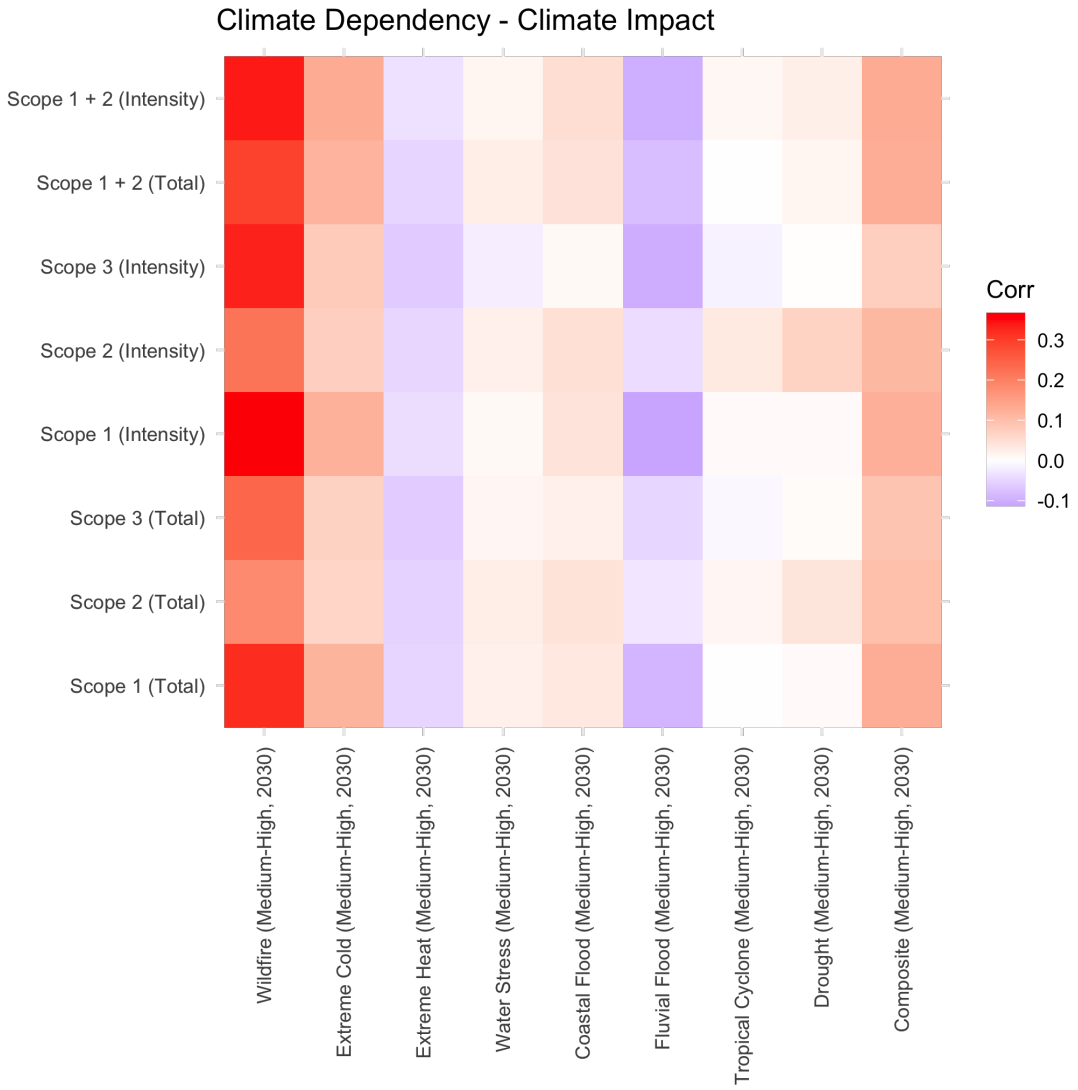


Figure 10: Correlation between climate impact and climate dependence fundamental characteristics

In Figure 10, most pairwise correlations are positive: firms with sizeable greenhouse-gas emissions (*climate impact*) tend also to face multiple physical climate hazards (*climate dependence*). The alignment is particularly pronounced for combined drought–heat–wildfire risks, whereas exposures such as extreme heat or fluvial floods show weaker links with emissions. Thus, high emitters frequently shoulder several climate risks, but no single hazard perfectly tracks a firm's emission profile.

Interpretation. Figure 11 reveals a clear positive relationship between *climate dependence* and

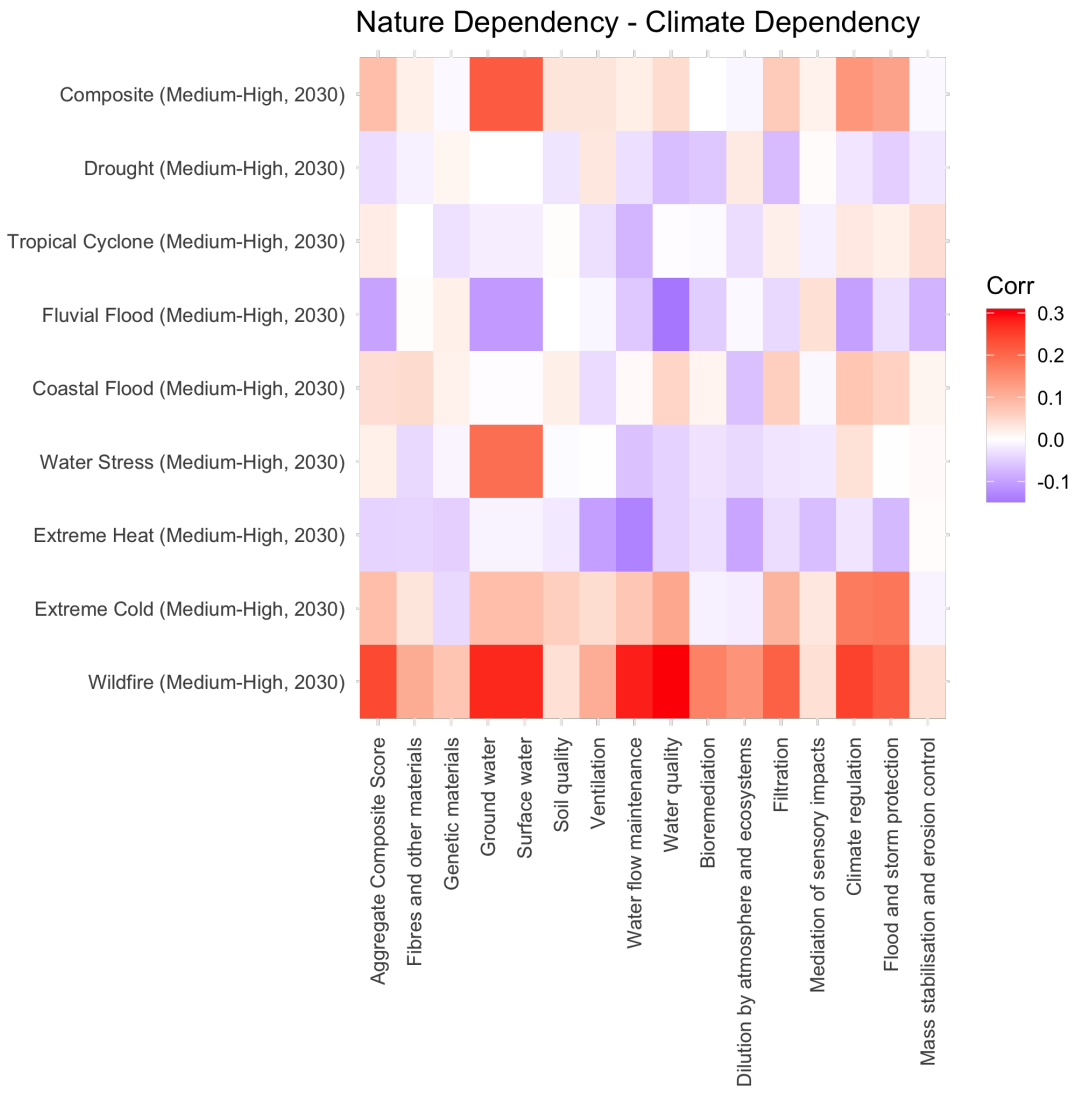


Figure 11: Correlation between climate and nature dependence

nature dependence: firms vulnerable to physical climate hazards also tend to rely more on ecosystem services. Exposures to wildfires, extreme cold, and coastal flooding map especially strongly into higher nature dependence, highlighting an interconnected risk profile whereby climate-vulnerable businesses are simultaneously reliant on natural capital.

Figure 12 shows that heavy emitters (*climate impact*) almost invariably register high *nature dependence*. Virtually every emissions measure is strongly and positively associated with aggregate dependence scores, suggesting that businesses contributing most to climate

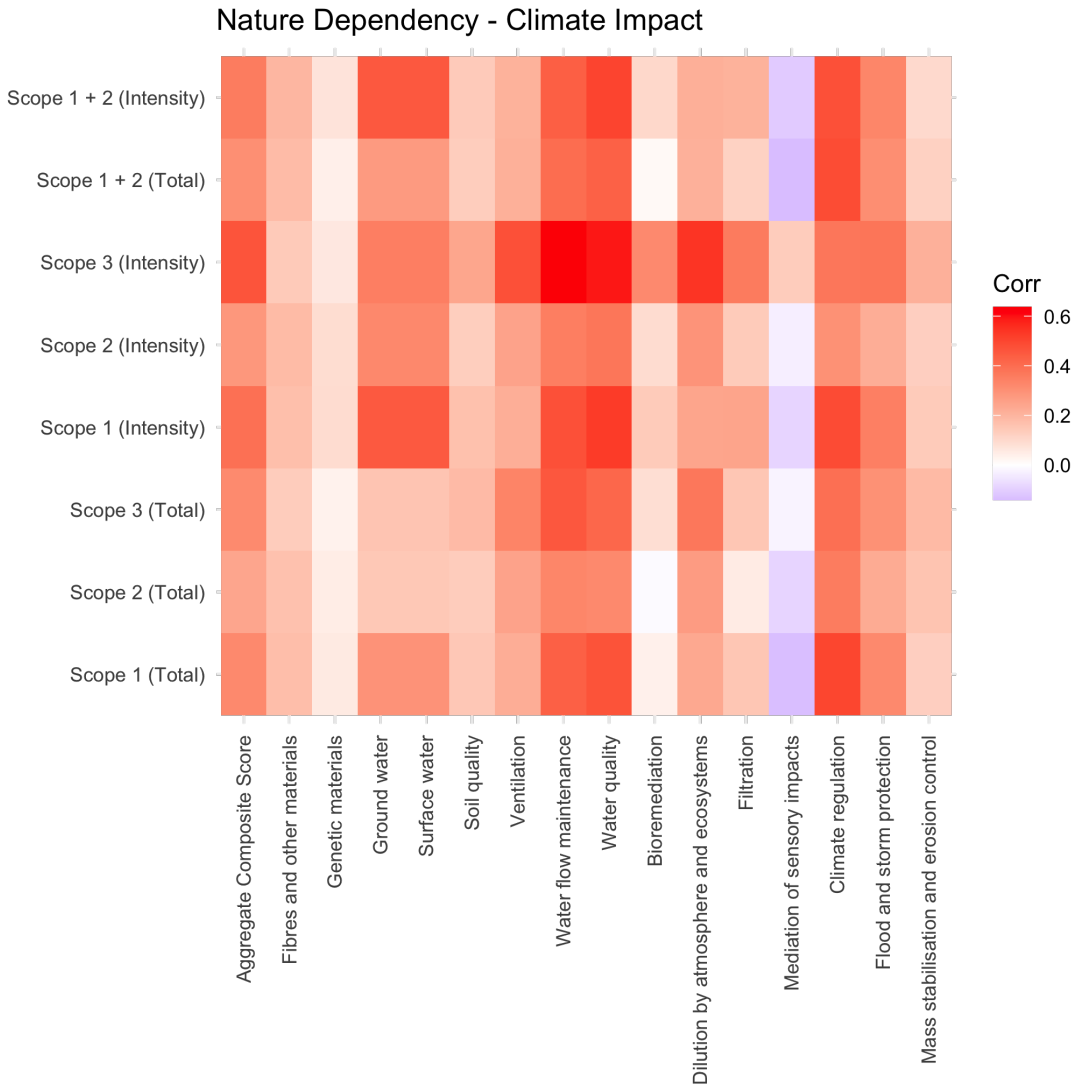


Figure 12: Correlation between climate impact and nature dependence

change are also those most reliant on ecosystem services. The lone exception—one narrow dependence metric—confirms the rule by demonstrating that, while highly aligned, the two constructs remain conceptually distinct.

Correlations in Figure 13 are heterogeneous. Certain hazards—coastal flood, extreme cold, wildfire—display moderate positive links with *nature impact* metrics such as land-use or ecosystem-integrity loss, whereas other hazards show little association. These mixed results imply that physical climate risk and environmental footprint sometimes coincide but can just

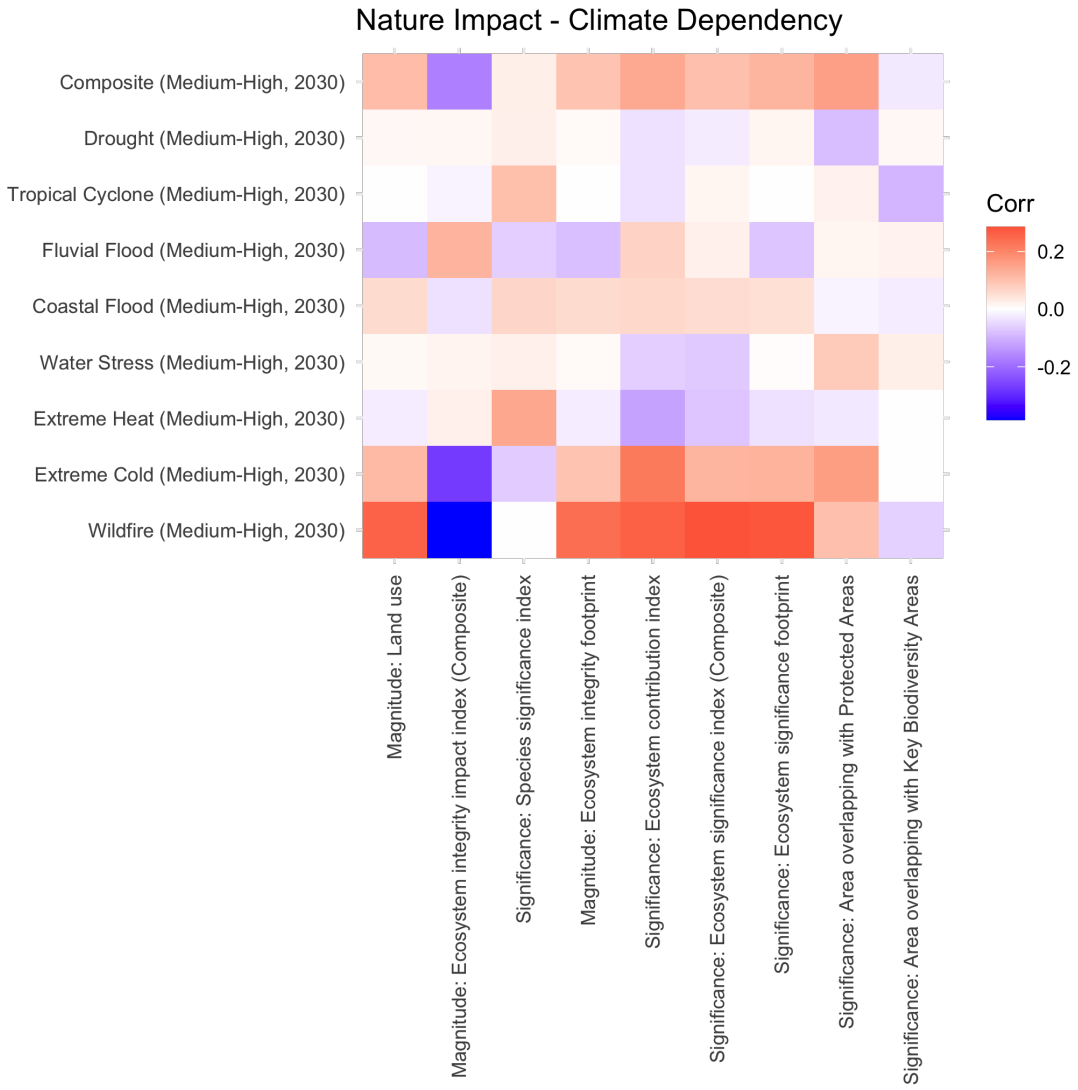


Figure 13: Correlation between climate dependence and nature impact

as easily diverge across firms.

Figure 14 confirms that firms with high *climate impact* also tend to register sizeable *nature impact*. Large land-use footprints, ecosystem-integrity degradation, and overlap with ecologically significant areas are all strongly correlated with emissions. Yet none of the coefficients approach unity, indicating that each impact metric captures a separate environmental dimension even when they frequently co-occur.

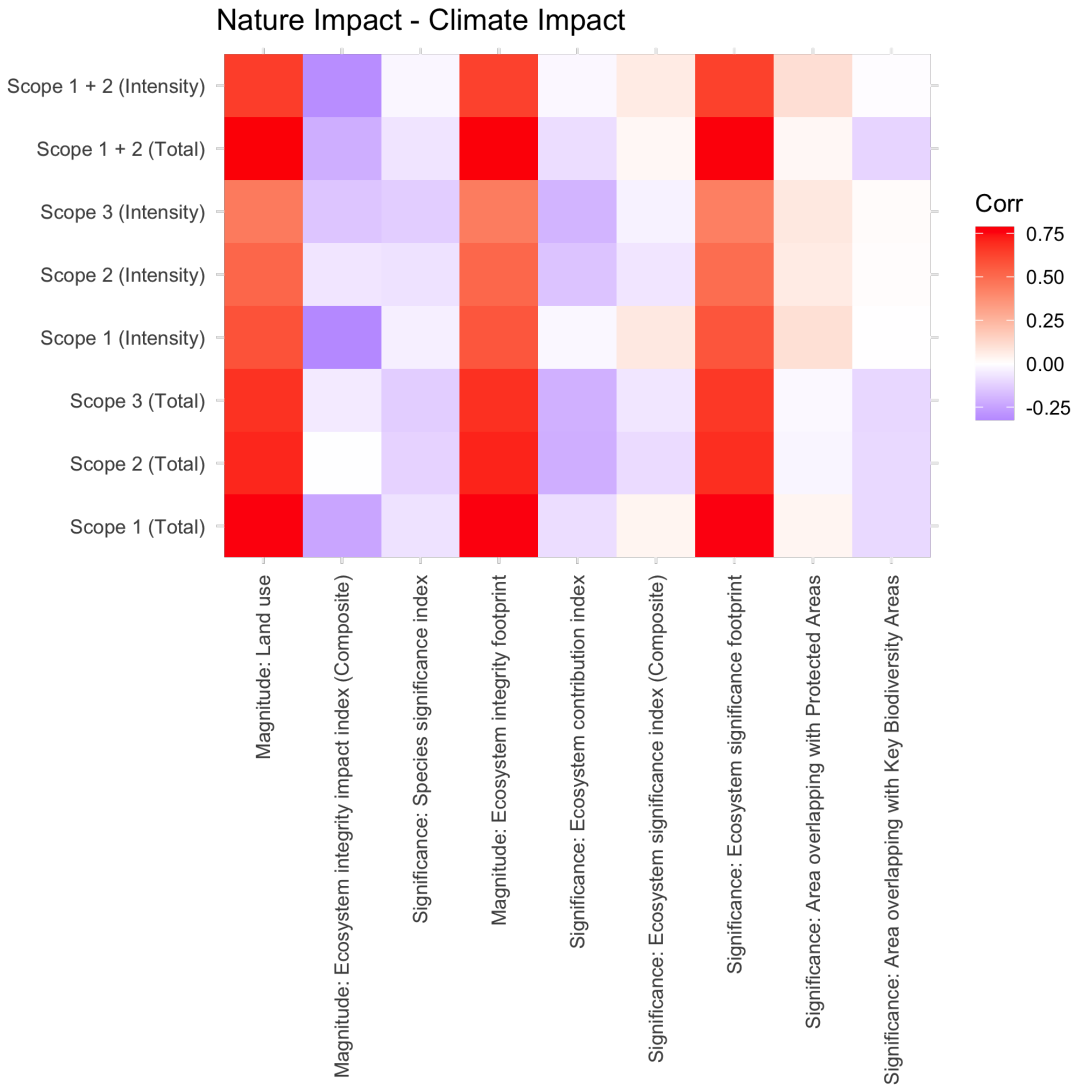


Figure 14: Correlation between climate impact and nature impact

D.2 Correlation heatmaps for all the characteristics

In this appendix we show correlation heat-maps for *all* underlying S&P Global metrics—well beyond the streamlined set analyzed in the main paper. These figures let readers verify that the broad patterns reported in Section 3 and Appendix D persist when the entire variable universe is considered.

Figure 15 confirms that a broad, positive association runs through the nature panel: firms with large ecosystem footprints (high impact) also rely more on ecosystem services

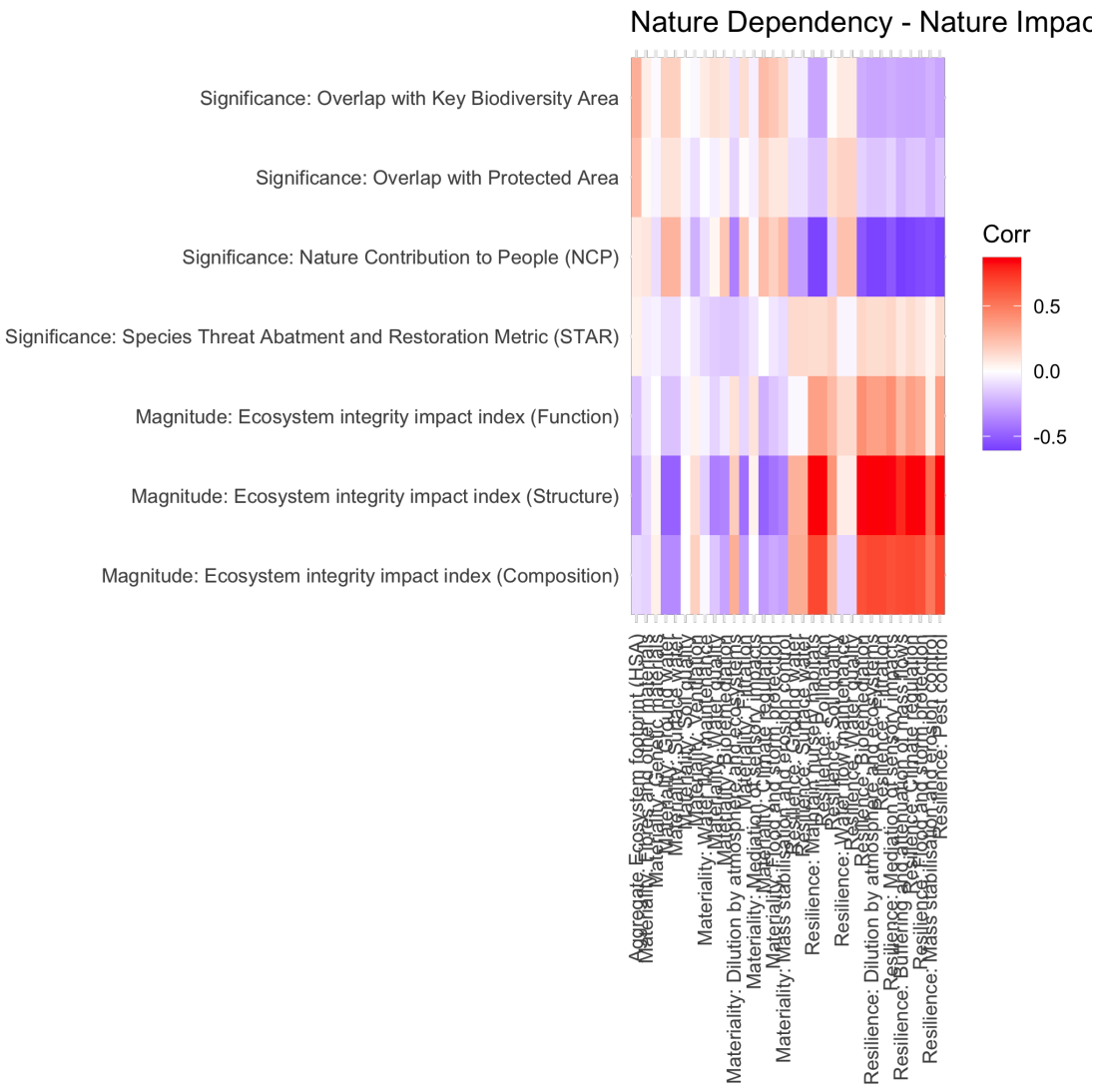


Figure 15: Correlation between **all** nature-dependence and nature-impact metrics

(high dependence). The warm diagonal blocks highlight especially strong links (e.g., land-use versus water-flow maintenance), yet cool cells along the right edge show that some dependence measures, such as those tied to pristine ecosystem integrity, move inversely with impact, underscoring that the two constructs are related but not redundant.

Figure 16 illustrates that the dozen-plus nature-impact variables do *not* collapse to a single dimension. While many pairs cluster positively (e.g. land-use with ecosystem integrity loss), others show only modest correlation, and a few— notably STAR versus certain footprint

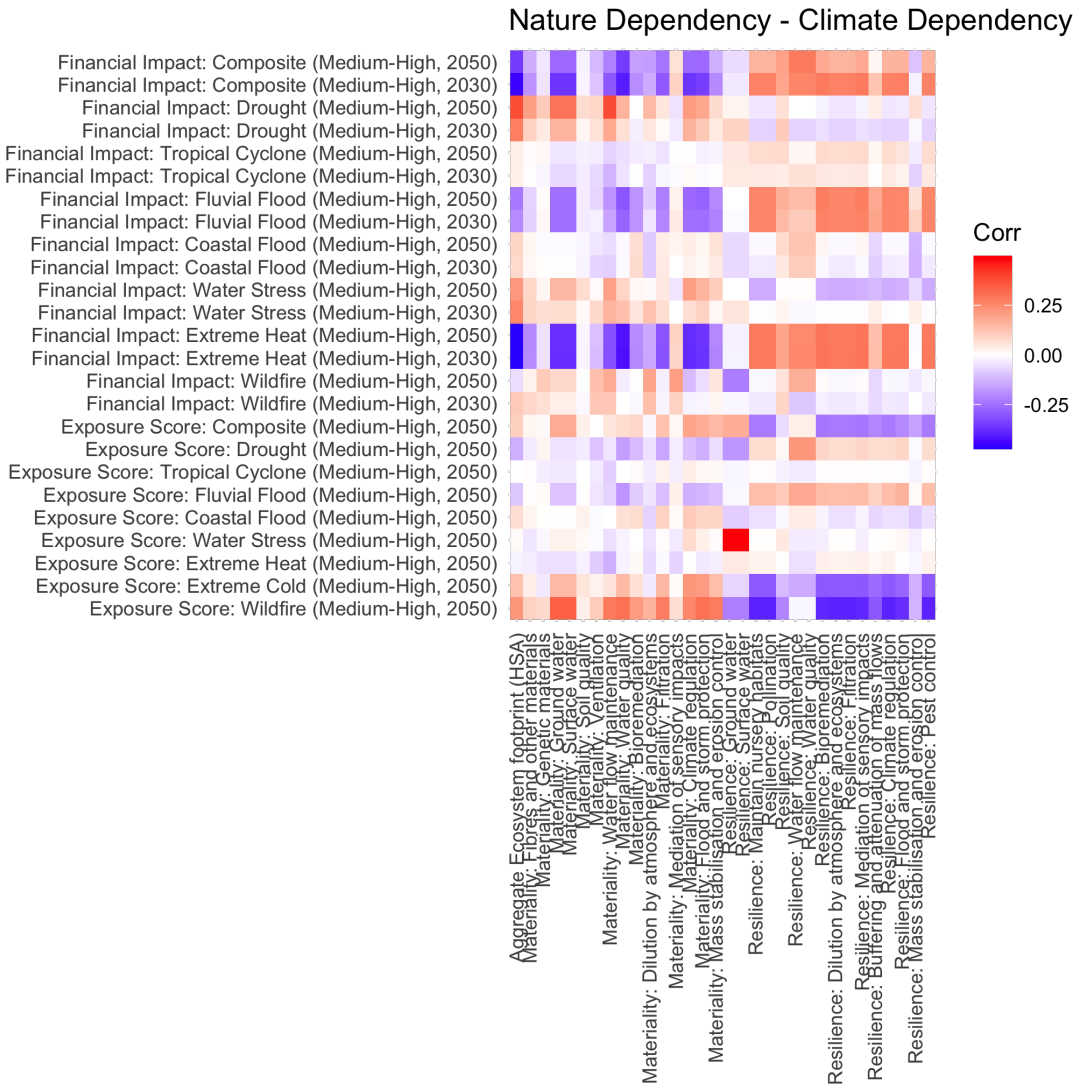


Figure 16: Correlation *within* nature-impact metrics (full sample)

measures—are virtually orthogonal. The dispersion justifies keeping multiple impact metrics in robustness tests and rules out multicollinearity concerns.

Figure 17 shows that firms exposed to physical climate hazards frequently also score high on nature-dependence. The strongest links appear for wildfire, extreme cold and coastal-flood risks, all of which align with elevated demand for key ecosystem services such as water filtration and pollination. Some hazards (e.g. extreme heat) exhibit weaker ties, indicating that climate–nature interdependence is pronounced but not universal across risk dimensions.

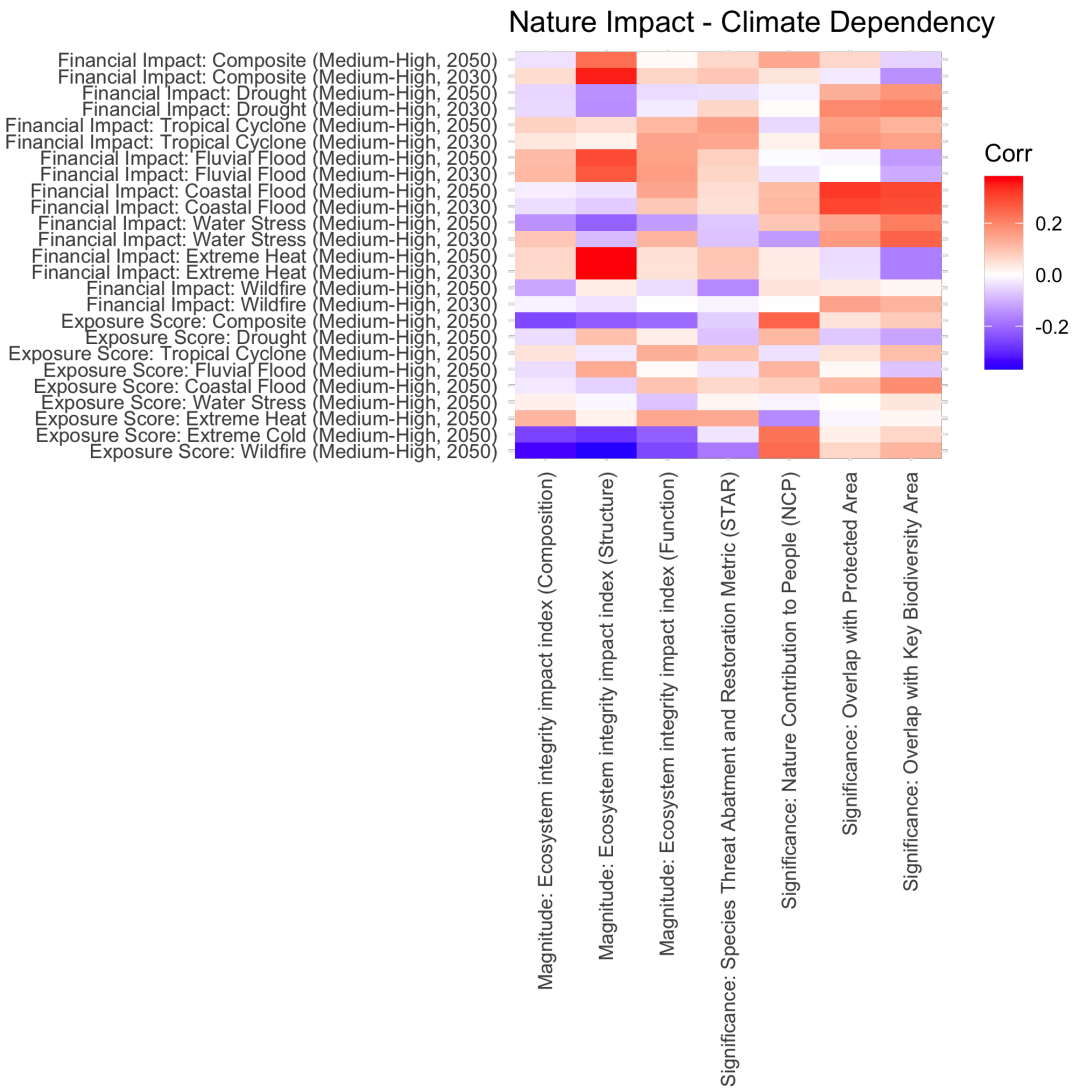


Figure 17: Correlation between climate-dependence and nature-dependence metrics

E Sorted-portfolios results

E.1 Characteristic-sorted portfolios comparison

The second type of comparison involves the returns of long-short portfolios sorted on betas with those sorted on fundamental characteristics.

We construct equal-weighted portfolios sorted on our characteristics and betas. For the betas, we rank companies based on the sorting characteristic within each time period, whereas for the fundamental characteristics the ranks are computed in 2021. In both cases, we assign

the companies to 2 quantiles based on ranks. We rank companies following three different approaches, namely pooled ranks, within sector ranks and sectoral ranks.We then calculate the monthly average excess return for each quantile and compute the return differential between the two quantiles, representing returns on a long-short portfolio.

We investigate whether the returns on betas- and fundamental characteristics-sorted portfolios comove more after 2015. The intuition is that markets should care more about the exposure to nature and climate risks (as captured by the fundamental characteristic-sorted portfolios) after 2015 and this should be reflected in the returns on the beta-sorted portfolios. Hence, we run the time series regression

$$\begin{aligned} r_t^{\hat{\beta},\kappa} = \Omega_0^{\kappa,Char} r_t^{Char} + \Omega_0^{\kappa,MKT} \text{MKT}_t + \Omega_0^{\kappa,SMB} \text{SMB}_t + \Omega_0^{\kappa,HML} \text{HML}_t + \\ + \left(\Omega_1^{\kappa,Char} r_t^{Char} + \Omega_1^{\kappa,MKT} \text{MKT}_t + \Omega_1^{\kappa,SMB} \text{SMB}_t + \Omega_1^{\kappa,HML} \text{HML}_t \right) \times \text{Post}_{2015} + \epsilon_t, \end{aligned} \tag{23}$$

where $r_t^{\hat{\beta},\kappa}$ (r_t^{Char}) are the returns on beta- (fundamental characteristics-) sorted portfolios. We use heteroskedasticity and autocorrelation-consistent standard errors. We run regression (23) for returns obtained using pooled portfolios, within-sector portfolios and sectoral portfolios. We are interested in the coefficient on the interaction between the returns on the beta-sorted portfolios and the Post_{2015} dummy, $\Omega_1^{\kappa,Char}$.

E.1.1 Beta- and fundamental characteristic-sorted portfolios

We also show how beta-sorted portfolios returns are correlated with the fundamental characteristic-sorted portfolios after 2015. Consistently with the comparison of the characteristics, the most evident effects are a positive (negative) correlation between the nature (climate) beta- and nature dependence- (climate impact-) sorted portfolios after 2015. However, the effects are less significant when considering portfolio returns.

Results depends on the type of nature impact and climate hazard when we look at the biodiversity sensitivity and climate impact and climate sensitivity and climate dependence.

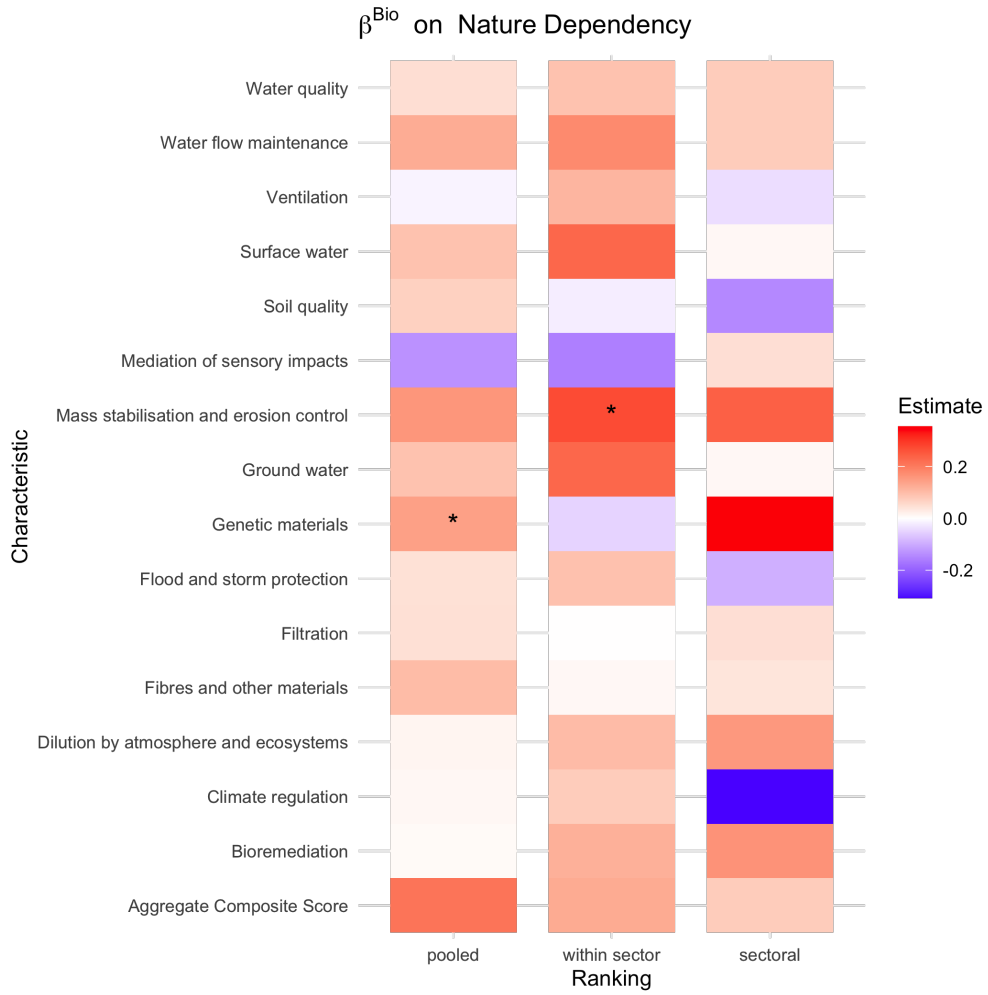


Figure 18: Nature beta-sorted portfolios and nature dependence-sorted portfolios

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

E.2 Beta- and fundamental characteristic-sorted portfolios

The results from the beta- and fundamental characteristic-sorted portfolios comparison are qualitatively similar to the ones obtained when looking at betas and characteristics, but they are not precisely estimated.

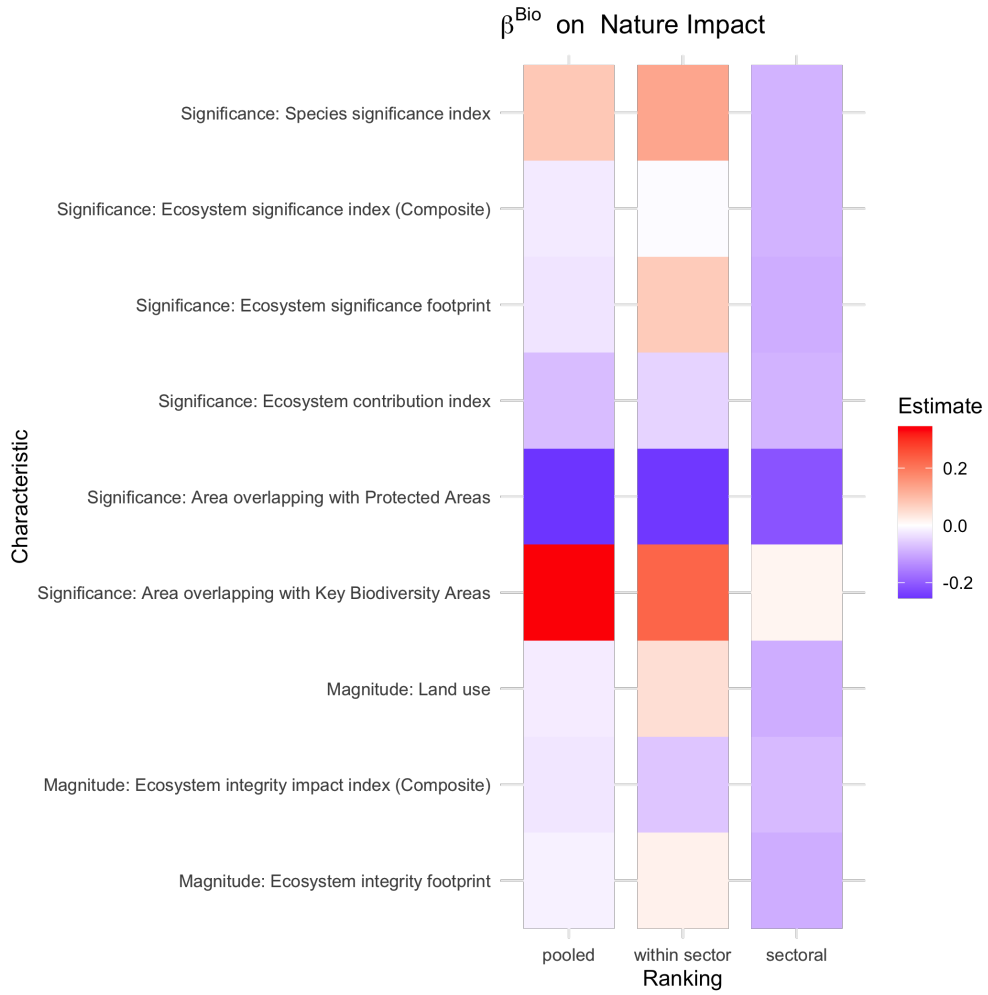


Figure 19: Nature beta-sorted portfolios and nature impact-sorted portfolios

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

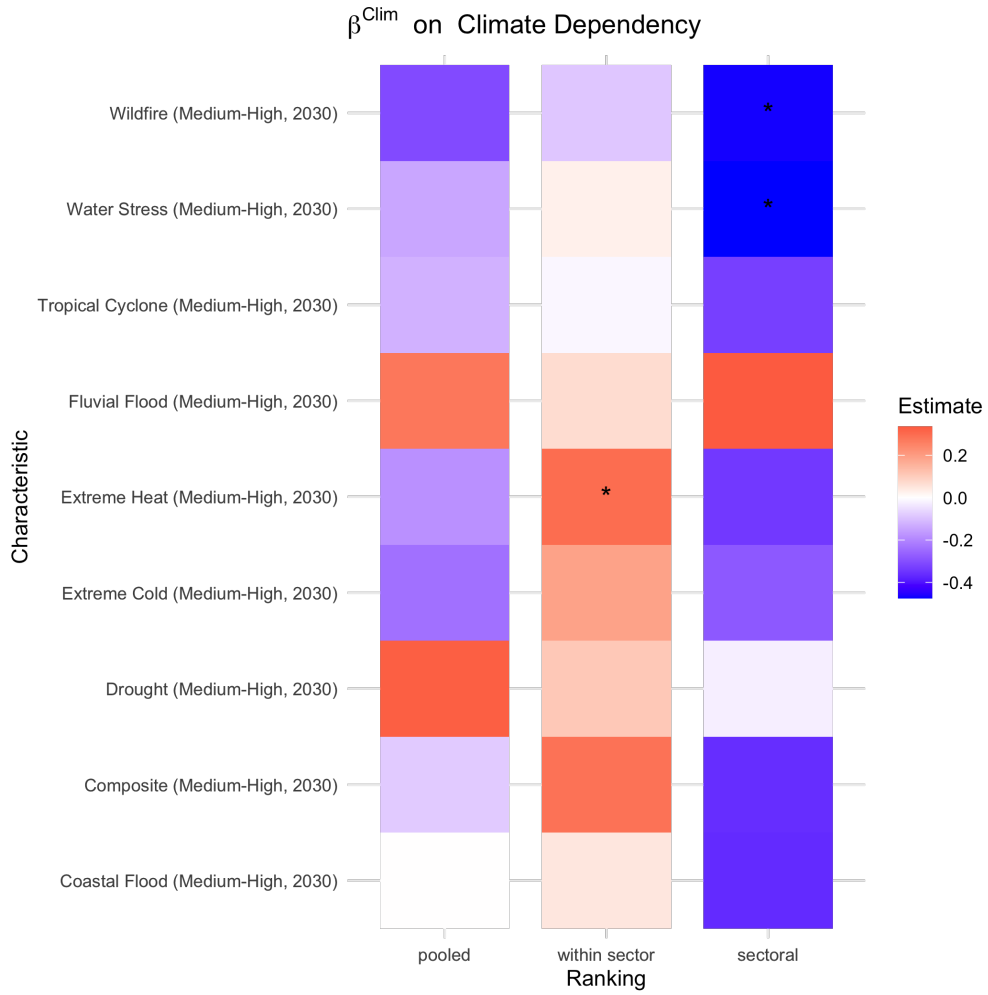


Figure 20: Climate beta-sorted portfolios and climate dependence-sorted portfolios

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

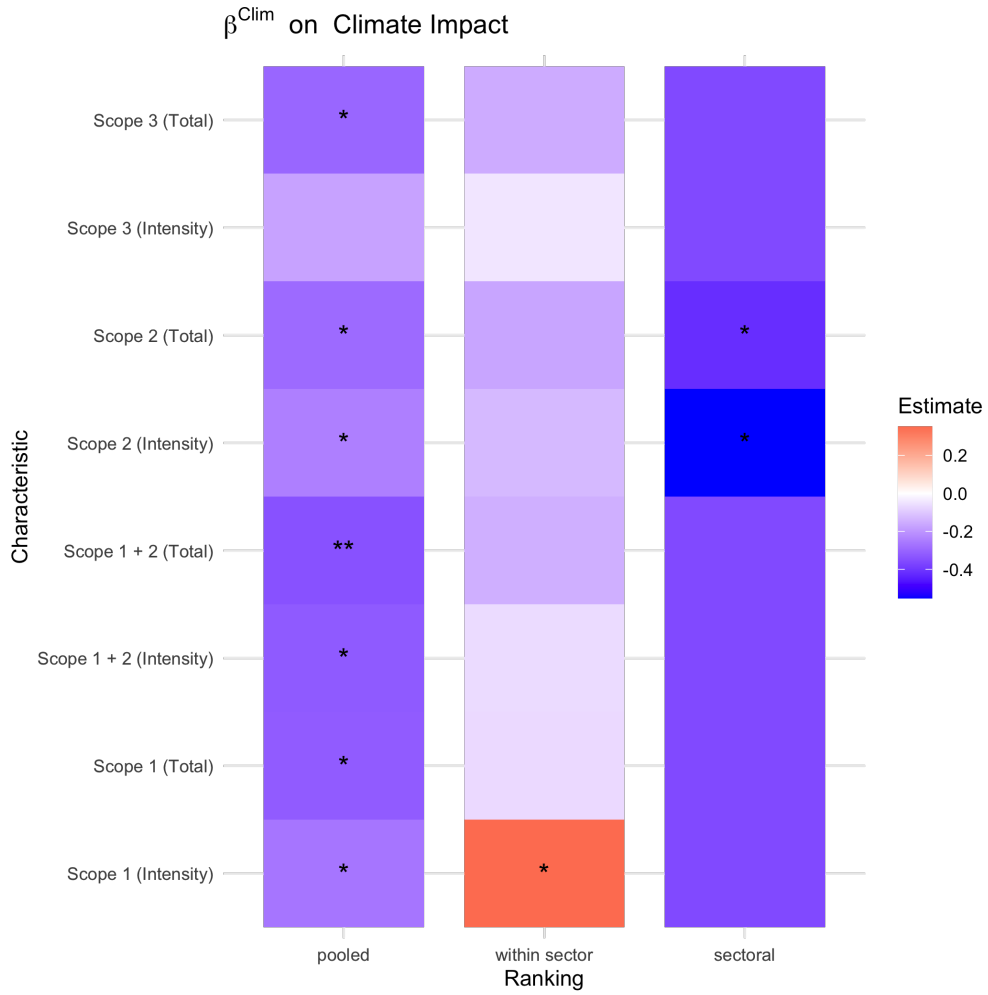


Figure 21: Climate beta-sorted portfolios and climate impact-sorted portfolios

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

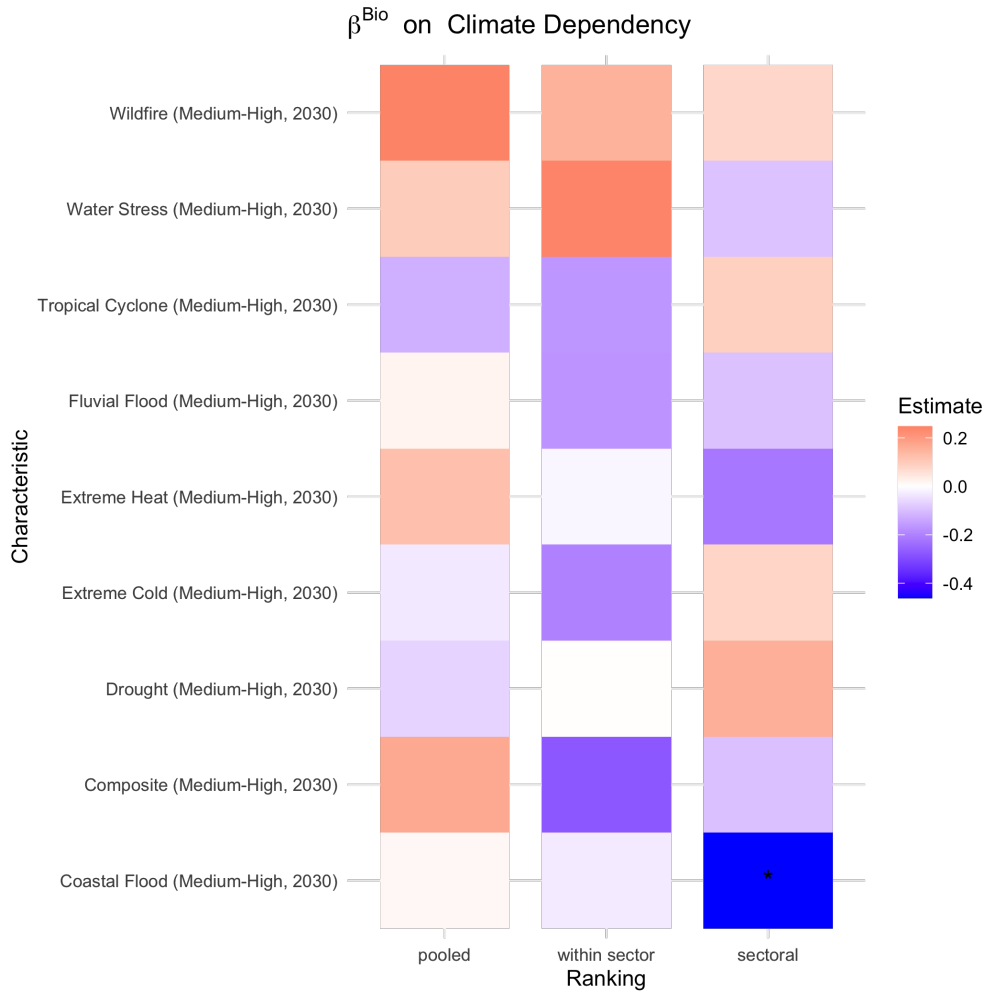


Figure 22: Nature beta sorted portfolios and climate dependence sorted portfolios

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

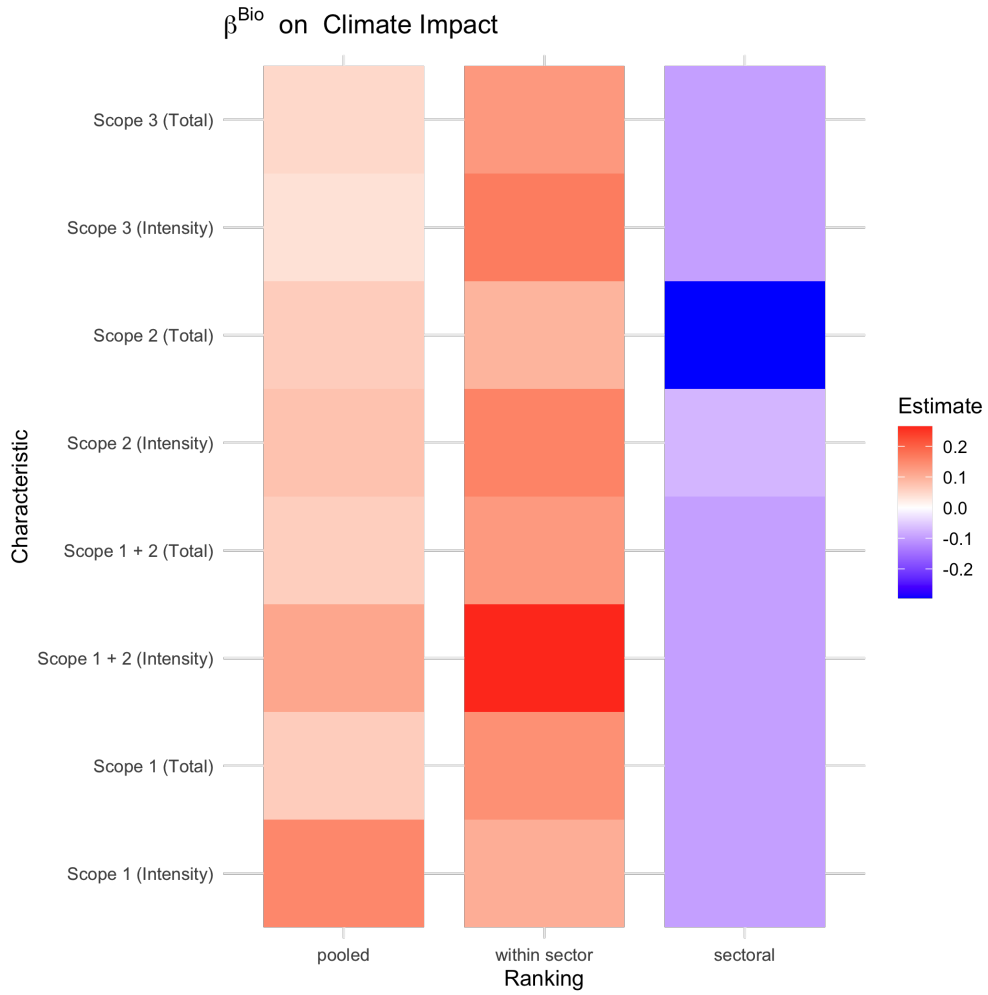


Figure 23: Nature beta-sorted portfolios and climate impact sorted portfolios

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

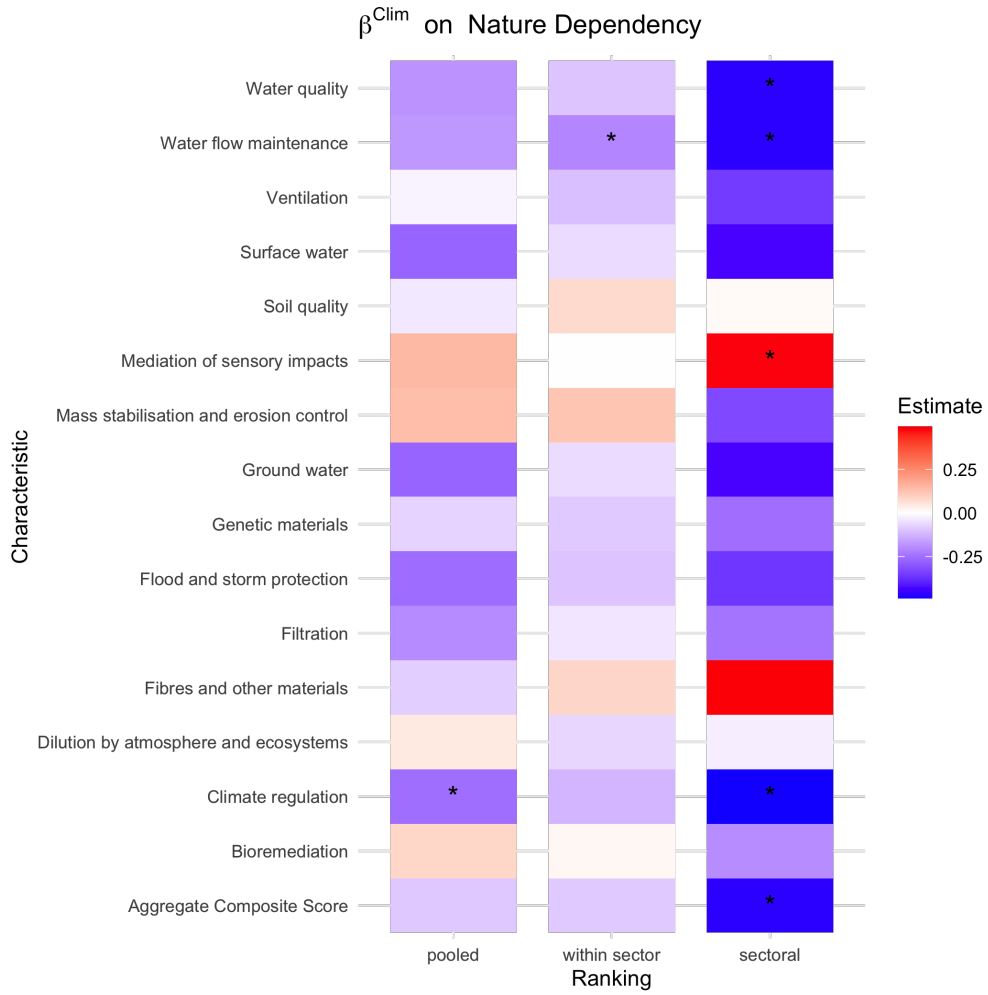


Figure 24: Climate beta sorted portfolios and nature dependence sorted portfolios

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

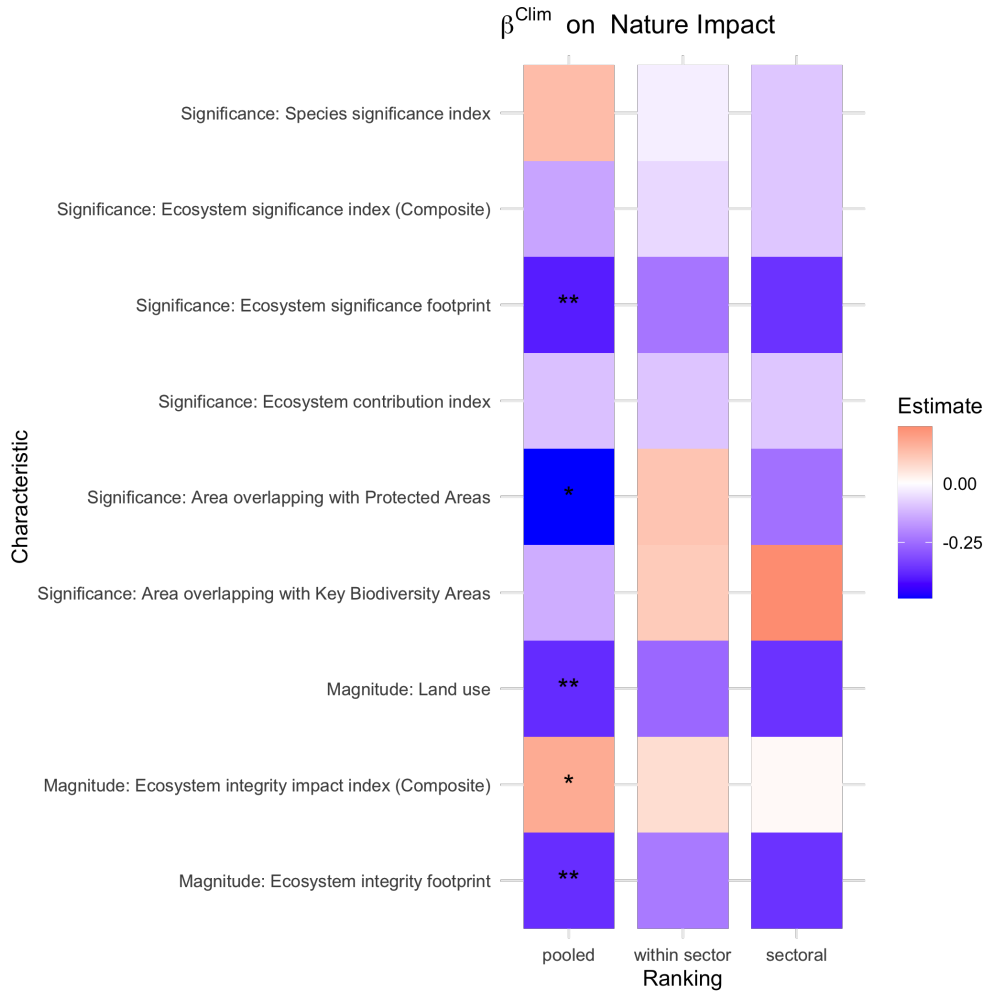


Figure 25: Climate beta sorted portfolios and nature impact sorted portfolios

Notes: The stars refers to the three significant thresholds for the t-value used in the analysis. *Significance codes: ***: 3, **: 2.5, *: 2.*

F Variables construction

In this section, we describe how each firm-level variable is constructed. Data are retrieved from Compustat, and we apply standard filters to restrict the sample to industrial firms ('indfmt = INDL'), standardized data format ('datafmt = STD'), U.S. domestic companies ('popsrc = D'), and consolidated records ('consol = C'). These filters ensure that each unique gvkey–datadate pair corresponds to a single observation.

Annualized returns. Daily stock returns are compounded to obtain realized returns at a monthly frequency. Specifically, we compute

$$(1 + r_1)(1 + r_2) \cdots (1 + r_T) - 1,$$

where $r_1, \ldots, r_T$ are the daily returns in the period. This expression yields the realized return over the period, expressed at a monthly frequency.

Book-to-market ratio. Following Bali et al. (2016), the book-to-market ratio (BM) is defined as the book value of common equity (BE) divided by the market value of equity (ME), i.e. $BM = BE/ME$, where $BE = SEQ + TXDB + ITCB - BVPS$. Here, SEQ denotes stockholders' equity (book value) in Compustat notation. We adjust this book equity for deferred taxes (TXDB) and investment tax credits (ITCB), and subtract the book value of preferred stock (BVPS). The book value of preferred stock is taken as the redemption value (PSTKRV), or if that is unavailable, the liquidating value (PSTKL), and if still unavailable, the par value (PSTK). If either SEQ or $TXDB$ is missing in Compustat, we cannot compute BE (and thus BM). If $ITCB$ is missing, we set it to zero. Similarly, if all preferred stock fields are missing, we set the preferred stock value to zero. For each year, we use the latest reported book equity value, and we obtain the firm's market capitalization from CapitalIQ Pro (using the December market cap of that year).

Timing assumption. To ensure that our BM measure uses only information available at the time of portfolio formation, we adopt a standard timing convention. Specifically, the BM computed using year-y accounting data is assumed to become public only at the end of June of year $y+1$. Thus, from June of year y through May of year $y+1$, we use the BM value based on year $y-1$ data. This approach follows Fama and French (1992), who assume a six-month gap after the fiscal year-end to account for reporting lags (firms have up to three months after year-end to report data, and many fail to meet this deadline).

Momentum. Momentum at time t is defined as the cumulative (geometric) stock return from month $t-11$ to month $t-1$. Formally,

$$Mom_{i,t} = 100\left(\prod_{m=t-11}^{t-1}(1+R_{i,m})-1\right),$$

where $R_{i,m}$ is the return of firm i in month m.

Volatility. Volatility at time t is the annualized standard deviation of monthly returns from $t-11$ to $t-1$. Formally,

$$Vol_{i,t} = 100\sqrt{12\cdot\frac{\sum_{m=t-11}^{t-1}R_{i,m}^2}{n}},$$

where n is the number of monthly return observations in the 12-month window (typically $n=12$).

Profitability. We consider two definitions of profitability. The first is gross profit ('gp') divided by book equity (BE), following Ball et al. (2015). The second, following Fama and French (2015), is operating profit ('opprft') divided by book equity. Here, operating profit is calculated as total revenues ('revt') minus cost of goods sold ('cogs'), interest expense ('xint'), and selling, general, and administrative expenses ('xsga'). We apply the same timing convention here as described above for BM.

Investment. We use the Fama and French (2015) definition of investment:

$$inv_t = \frac{at_{t-1} - at_{t-2}}{at_{t-2}},$$

where 'at' denotes total assets. Additionally, following Bolton and Kacperczyk (2023), we include the logarithm of net property, plant, and equipment ('ppent') as a control variable (since 'ppent' measures fixed assets). The same BM timing convention is applied here as well.

Market leverage. Market leverage is defined as the ratio of debt to total assets. We compute total debt as total assets minus book equity (BE). Thus, market leverage (see, for instance, Ozdagli (2012)) is

$$\text{MktLeverage} = 1 - \frac{BE}{at}\,.$$

Size. Size is measured as the natural logarithm of the firm's market capitalization.

Market beta. Market beta is measured as the correlation between the firm's stock returns and the corresponding market returns.

G Deriving the Nature- and Climate-News Shocks

This appendix shows in detail why the unexpected components of the latent states can be expressed as linear combinations of the signal innovations, as stated in the main text. Throughout, we work with the linear–Gaussian state–space system:

$$\mathbf{x}_{t+1} = A\,\mathbf{x}_t + \mathbf{w}_{t+1}, \qquad \mathbf{w}_{t+1} \sim \mathcal{N}(\mathbf{0}, Q),$$

$$\mathbf{y}_{t+1} = C\,\mathbf{x}_{t+1} + \boldsymbol{\varepsilon}_{t+1}, \quad \boldsymbol{\varepsilon}_{t+1} \sim \mathcal{N}(\mathbf{0}, R),$$

with state vector $\mathbf{x}_t = (n_t, z_t)^\top$ and observation vector $\mathbf{y}_{t+1} = (s^N_{t+1}, s^Z_{t+1})^\top$. The measurement matrix is $C = \left[\begin{smallmatrix} w_N & 1-w_N \\ 1-w_Z & w_Z \end{smallmatrix}\right]$ and the noise processes $\mathbf{w}_{t+1}$ and $\boldsymbol{\varepsilon}_{t+1}$ are mutually independent as well as independent of information dated t.

Innovation representation. Define the one-step *prediction* and its error

$$\hat{\mathbf{x}}_{t+1|t} \;=\; A\,\hat{\mathbf{x}}_{t|t}, \qquad \boldsymbol{\nu}_{t+1} \;\equiv\; \mathbf{y}_{t+1} - C\,\hat{\mathbf{x}}_{t+1|t}.$$

Because the model is linear and Gaussian, the joint distribution of $(\mathbf{w}_{t+1}, \boldsymbol{\varepsilon}_{t+1})$ conditional on history is normal with mean zero and block-diagonal covariance $\mathrm{diag}(Q, R)$. Furthermore,

$$\boldsymbol{\nu}_{t+1} = C\,\mathbf{w}_{t+1} + \boldsymbol{\varepsilon}_{t+1}.$$

Best linear predictor of the state surprise. The *unexpected change* in the state vector is

$$\mathbf{u}_{t+1} \equiv \mathbf{x}_{t+1} - \mathbb{E}_t[\mathbf{x}_{t+1}] = \mathbf{w}_{t+1},$$

since $\mathbb{E}_t[\mathbf{x}_{t+1}] = A\,\mathbf{x}_t$. We want the conditional expectation of $\mathbf{u}_{t+1}$ given the signal innovation $\boldsymbol{\nu}_{t+1}$:

$$\mathbf{m}_{t+1} \;\equiv\; \mathbb{E}_t[\mathbf{u}_{t+1} \mid \boldsymbol{\nu}_{t+1}].$$

By the properties of the multivariate normal distribution, the *minimum-mean-square-error* linear predictor is

$$\mathbf{m}_{t+1} = \underbrace{Q\,C^\top \big(C\,Q\,C^\top + R\big)^{-1}}_{K_{t+1}} \boldsymbol{\nu}_{t+1}.$$

The matrix pre-multiplier is exactly the Kalman gain K_{t+1}. Substituting back, the first element of $\mathbf{m}_{t+1}$ is the expected surprise in nature, the second in climate:

$$\begin{bmatrix} \Delta n_{t+1} - \mathbb{E}_t[\Delta n_{t+1}] \\ \Delta z_{t+1} - \mathbb{E}_t[\Delta z_{t+1}] \end{bmatrix} = K_{t+1} \begin{bmatrix} \nu^N_{t+1} \\ \nu^Z_{t+1} \end{bmatrix}.$$

Writing the two rows of K_{t+1} as (a_{NN}, a_{NZ}) and (a_{ZN}, a_{ZZ}) yields the main equation in the main text:

$$\Delta n_{t+1} - \mathbb{E}_t[\Delta n_{t+1}] = a_{NN}\,\nu^N_{t+1} + a_{NZ}\,\nu^Z_{t+1},$$

$$\Delta z_{t+1} - \mathbb{E}_t[\Delta z_{t+1}] = a_{ZN}\,\nu^N_{t+1} + a_{ZZ}\,\nu^Z_{t+1}.$$

Closed-form expression for the coefficients For the two-dimensional case, the Kalman gain is

$$K_{t+1} = Q\,C^\top \big(C\,Q\,C^\top + R\big)^{-1}, \qquad Q = \begin{bmatrix} \sigma_n^2 & 0 \\ 0 & \sigma_z^2 \end{bmatrix}, \quad R = \begin{bmatrix} 1/\phi_t^N & 0 \\ 0 & 1/\phi_t^Z \end{bmatrix}. \tag{24}$$

Plugging C, Q, and R into (24) and inverting the 2×2 matrix $CQC^\top + R$ produces the explicit formulas

$$\begin{aligned} a_{NN} &= \frac{\sigma_n^2 w_N \phi_t^N + \sigma_n^2 (1 - w_Z)\phi_t^Z}{\Delta}, & a_{NZ} &= \frac{\sigma_n^2 (1 - w_N)\phi_t^N + \sigma_n^2 w_Z \phi_t^Z}{\Delta}, \\ a_{ZN} &= \frac{\sigma_z^2 (1 - w_N)\phi_t^N + \sigma_z^2 w_Z \phi_t^Z}{\Delta}, & a_{ZZ} &= \frac{\sigma_z^2 w_N \phi_t^N + \sigma_z^2 (1 - w_Z)\phi_t^Z}{\Delta}, \end{aligned} \tag{25}$$

where $\Delta = \big(w_N^2\sigma_n^2 + (1 - w_N)^2\sigma_z^2\big)\phi_t^N + \big((1 - w_Z)^2\sigma_n^2 + w_Z^2\sigma_z^2\big)\phi_t^Z$. Equation (25) confirms that the mapping from signal innovations to state surprises depends only on *observable* objects $(w_N, w_Z, \sigma_n^2, \sigma_z^2, \phi_t^N, \phi_t^Z)$; all structural parameters of the production side drop out. In particular, when $w_N = w_Z = \frac{1}{2}$ and $\phi_t^N = \phi_t^Z$, the rows of K_{t+1} are identical, reproducing the well-known result that equally noisy, perfectly collinear signals cannot disentangle the two latent states.