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 ecosystem services arises from a company's dependency on climate and nature, while exposure to transition risk depends on the impact of a company on climate or nature. 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 that distinguishes dependence and impact channels. Our model guides an empirical analysis that compares sensitivities of stock returns to news about biodiversity and climate, which we call nature and climate beta, with company-level characteristics from S&P Global. Our model predicts that with better information, firms' nature and climate betas should more accurately reflect their fundamental risk exposures. We examine whether, after the 2015 structural shift in information availability and investor attention, changes in these betas correlate with firm-level environmental risk characteristics. We find that climate betas increasingly reflect corporate climate impact, with higher-impact firms showing greater sensitivity. Furthermore, climate betas became more aligned with firms' nature dependence. However, nature betas for companies more dependent on nature decrease relative to less dependent companies, suggesting inconsistencies in the financial market's perception and pricing of nature-specific news and risks.

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

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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 ecosystem 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.

This paper addresses the central question: To what extent, and through which channels (dependence versus 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 premiums 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. Nature-related physical risks to a company include, among other things, loss of ecosystem services on which a company depends for its operations. For example, the productivity of companies may be compromised by a lack of soil fertility or a decrease in groundwater levels below vital thresholds. We refer to physical risk as *nature dependence*. 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. 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, 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). Firms are atomistic and 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 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 beta 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. The model also suggests the critical role of information in the pricing of environmental risk. As firm-level information on environmental dependence and impacts becomes more precise, betas should become more aligned with firm-level dependence. In other words, there should be greater consonance between fundamental and market-implied risk exposures.

Guided by this model, our empirical analysis is based on evaluating the fundamental and market-implied risk exposures. We employ a dataset provided by S&P Global that contains information about companies' nature and climate risk exposures. 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 (in some cases) 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 observe fundamental characteristics corresponding to all four categories - nature dependence, climate dependence, nature impact, and climate impact.

Also in line with the theoretical model, we estimate sensitivities of companies' stock returns to nature and climate-related news shocks - firm-level nature and climate betas, respectively. In contrast to fundamental characteristics, these can be viewed as *market-implied* exposures to nature and climate risks, as suggested by the factor structure in the model.

As discussed above, the model predicts that with better information, firms' nature and climate betas should more accurately reflect their fundamental risk exposures. Hence, our main analysis studies whether the change in betas around the year 2015, which represented a structural shift in information availability and investor attention to environmental issues, is correlated with the fundamental characteristics. If markets optimally process information about environmental risks, the availability of better firm-level datasets (and increased attention to environmental risks) should align market perceptions of firm-level climate and nature risks with fundamentally determined exposures. We evaluate whether this happened around 2015, indicating whether nature and climate risks are priced by markets.

Our analysis reveals three key findings. First, climate betas increasingly reflect corporate climate impact after 2015, with higher-impact firms showing greater sensitivity to climate news, relative to earlier years. Second, we find that post-2015, markets' perception of firm-level climate change risk exposures becomes more aligned with firms' nature dependence (in particular on water-related ecosystem services). Specifically, changes in climate betas in 2015 are positively correlated with fundamental measures of firm-level climate impact and nature dependency. In contrast, we do not find a positive correlation between nature betas and firm-level nature or climate dependence. In fact, companies that depend more on nature saw a decrease in nature betas relative to less nature-dependent companies. This puzzling finding suggests inconsistencies in the financial market's perception and pricing of nature-specific news and risks.

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) proposes an asset pricing model in which natural disaster mitigation costs are priced in the cross-section of firms, while Hong et al. (2019) finds 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 either misprice biodiversity risks (Huang et al., 2024, Dey, 2025) 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 captures nature and climate physical and transition risks and guides our analysis. Section 3 describes the data, details our methodological approach and presents our empirical findings on the pricing of nature and climate risk. 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 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 ecosystem services, such as biodiversity or soil quality) and a *climate state* Z_t (capturing the level of climate quality, such as 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. 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, 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.

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

[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.

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). $\gamma_i^Z > 0$ indicates that firm i is positively affected by a better climate state Z_t (for instance, lower pollution or less frequent natural disasters). All else equal, a firm with higher γ_i^N or γ_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*. Under the carbon price τ_t net dividends are

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

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:

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

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

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, as well as climate impact, 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 environmental conditions. The aggregate dynamics of the environmental states are given by:

$$
\begin{aligned}
N_{t+1} &= F(N_t, Z_t) \; - \int_0^1 \delta_i^N \, Y_{i,t} \, di \; + \; \varepsilon_{t+1}^N, \qquad (4) \\
Z_{t+1} &= G(Z_t, N_t) \; + \int_0^1 \delta_i^Z \, Y_{i,t} \, di \; + \; \varepsilon_{t+1}^Z. \qquad (5)
\end{aligned}
$$

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

[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.

[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).

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.

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 consumption. To this end, we define an augmented 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 states. 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, that is, 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 nature quality (lower N_{t+1}) or to the climate conditions (lower Z_{t+1}) raises marginal utility directly through a fall in $\Phi(N_{t+1}, Z_{t+1})$ and indirectly via the induced decline in aggregate dividends and consumption.

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

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

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; $R = \operatorname{diag}(1/\phi^N_t, 1/\phi^Z_t)$ 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 Kalman 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.

We treat our third state variable, the carbon tax, as an exogenous policy instrument determined outside the model. At date t investors rationally anticipate the conditional mean $\mathbb{E}_t[\ln \tau_{t+1}]$. The innovation

$$v_{t+1} \equiv \varepsilon^{\tau}_{t+1} = \ln \tau_{t+1} - \mathbb{E}_t[\ln \tau_{t+1}] \tag{13}$$

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, v_{t+1} is a pure policy-news shock: it carries no estimation noise, yet it directly alters cash flows through the term $-\tau_{t+1}\delta^Z_i Y_{i,t+1}$.

Firm-level signals. Investors form expectations based on noisy public signals regarding environmental states, firm characteristics, and potential future policy or cost scenarios. A key element of this model is a structural shift post-2015 in information availability. Investors may learn about latent firm-specific parameters, such as a firm's true underlying exposure $\theta_i \in \{\gamma^N_i, \gamma^Z_i, \delta^Z_i\}$ to an emerging risk factor. Let $e_i = \ln \theta_i$ be the parameter of interest. Investors receive a noisy signal $s^{\theta}_{i,t+1}$ about e_i:

$$s^{\theta}_{i,t+1} = e_i + \eta^{\theta}_{i,t+1}, \quad \eta^{\theta}_{i,t+1} \sim \mathcal{N}(0, 1/\varphi_t) \tag{14}$$

where φ_t is the signal precision. Post-2015, φ_t increased due to improved corporate disclosures and improved datasets. Hence, investors receive more precise signals about the dependence or impact of companies.

[5] See Appendix H for a derivation of the results.

After receiving the signal, investors perform a Bayesian update. With diffuse prior[6] $e_i^\theta \sim \mathcal{N}(e_0, 1/v_0)$, the static Kalman step delivers

$$m_{i,t+1} = \frac{\varphi_t s^\theta_{i,t+1} + v_0 e_0}{v_0 + \varphi_t}, \qquad v_{i,t+1} = \frac{1}{v_0 + \varphi_t},$$

so the posterior mean and variance are

$$\widehat{\theta}_{i,t} = e^{m_{i,t} + \frac{1}{2(v_0+\varphi_{i,t})}}, \qquad Var_t(\theta_i) = e^{2m_{i,t}+1/(v_0+\varphi_t)}\big(e^{1/(v_0+\varphi_{i,t})} - 1\big).$$

An increase in precision, φ_t, increases $\widehat{\theta}_{i,t}$.[7]

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.

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 $F^\tau_{t+1} \equiv \upsilon_{t+1} = \ln \tau_{t+1} - \mathbb{E}_t[\ln \tau_{t+1}]$. 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[8]

$$\Delta \ln \tilde{C}_{t+1} - \mathbb{E}_t[\Delta \ln \tilde{C}_{t+1}] = b^N_t F^N_{t+1} + b^Z_t F^Z_{t+1} + b^\tau_t F^\tau_{t+1}, \tag{15}$$

[6] Generally, the prior and signal parameters depend on θ. For example, φ_t should be indexed by θ and should be referred to as φ^θ_t. Similarly, e_0 and v_0 should also be thought of as being indexed by θ. However, we avoid writing this for notational clarity.

[7] The uncertainty about the firm's dependence and impact θ_i is captured by its posterior variance, $\text{Var}_t(\theta_i)$. Uncertainty is therefore decreasing in the level of precision φ.

[8] The coefficients b^N_t and b^Z_t in (15) 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.

with $b_t^N > 0$, $b_t^Z < 0$, and $b_t^\tau < 0$ by inspection of firm cash flows.[9] This gives rise to a linear factor CAPM. For any asset paying gross return $R_{i,t+1}$,

$$1 = \mathbb{E}_t\big[M_{t,t+1}R_{i,t+1}\big] \;\Rightarrow\; \mathbb{E}_t[R_{i,t+1}] - r_{f,t} = \sum_{k\in\{N,Z,\tau\}} \lambda_t^k \beta_{i,t}^k, \tag{16}$$

where

$$\lambda_t^k = \sigma b_t^k \mathrm{Var}_t(F_{t+1}^k), \qquad \beta_{i,t}^k = \frac{\mathrm{Cov}_t(R_{i,t+1}, F_{t+1}^k)}{\mathrm{Var}_t(F_{t+1}^k)}, \tag{17}$$

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),

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

so that

$$\beta_{i,t}^N \propto \widehat{\gamma}_{i,t}^N, \qquad \beta_{i,t}^Z \propto \widehat{\gamma}_{i,t}^Z, \qquad \beta_{i,t}^\tau \approx -\tau_t\,\widehat{\delta}_{i,t}^Z. \tag{18}$$

Two modeling restrictions underlie equations (15)–(18). 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 Equation (15), 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 (18) are sufficient statistics for conditional betas, and the linear factor pricing relation in (16) holds without further qualification. Log-linearizing the SDF around a deterministic steady

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

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.

Remarks on the theoretical setup. Our stylized equilibrium highlights why *double materiality* (dependence vs. impact) leads to different asset pricing outcomes. 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.

Our theoretical model, while stylized, provides sharp predictions regarding the differential pricing of environmental risks in financial markets. The central distinction between *dependence* on environmental states (γ_i^N, γ_i^Z) and *impact* on those states (δ_i^N, δ_i^Z) generates clear implications for the cross-section of expected returns. Specifically, the model posits that financial materiality, captured by dependence parameters that directly influence firm cash flows, should be systematically priced as it covaries with the representative agent's marginal utility. In contrast, impact materiality is predicted to remain largely unpriced unless explicitly internalized through policy mechanisms, such as the carbon tax τ_t for climate impact in our setup.

Our theoretical framework leads to several core hypotheses that can guide to empirical investigation. First, if environmental risks are priced, we should expect firm-level climate betas (β_i^{Clim}), reflecting sensitivities to climate news, to be positively associated with fundamental measures of both climate dependence (γ_i^Z) and climate impact (δ_i^Z), particularly where impact translates into direct costs via mechanisms like carbon pricing. Second, nature betas (β_i^{Bio}) should primarily reflect nature dependence (γ_i^N). A significant link between nature betas and nature impact (δ_i^N) would be less expected under the model's baseline assumptions, potentially emerging only if markets anticipate future regulation or if investor preferences incorporate non-pecuniary aversion to nature degradation beyond our model's scope. Third, the model highlights the critical role of information. The predicted relationships between market-implied betas and fundamental characteristics should strengthen following improvements in information precision (φ_t) and salience, such as the period after the 2015 Paris Agreement.

Our empirical analysis will be guided by these predictions. By estimating firm-specific sensitivities (betas) to systematic nature and climate news shocks and comparing these market-implied risk exposures to the fundamental dependence and impact characteristics sourced from S&P Global, we can assess the extent to which markets price these distinct risk dimensions. The 2015 structural shift in information availability and investor attention provides a powerful setting to operationalize the model's implications regarding the role of information and evolving market perceptions.

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.[10]

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.[11] 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.[12]

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

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

[12] See the latest TNFD recommendations.

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 dependence on nature.[13] For our main analysis, we choose 16 of these.[14]

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 18 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. [15] We choose 9 of these for our main analysis.

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

[13]See Appendix A for a description of the different ecosystem services considered.
[14]Refer to Appendix C for an explanation of how these were chosen.
[15]See Appendix A for a description of the different impacts considered.

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). We use 9 of these in our main analysis - these correspond to exposure to 8 different hazards, and one composite exposure metric, under the SSP3-7.0 scenario in the year 2030.

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.

News-based risk indices

To capture broad shifts in market concern about climate- and nature-related risks, we use news-based indices developed in Giglio et al. (2023). Specifically, we employ the New York Times (NYT) Biodiversity News Index and the NYT Climate News Index.[16] 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 positive news articles minus the number of negative news articles concerning biodiversity (for the Biodiversity News Index) or climate change (for the Climate News

[16] These are available for download on https://www.biodiversityrisk.org.

Index). Thus, a higher index indicates a day with more good news (positive coverage) than bad 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.

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.

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

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 ("characteristics comparison").

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 risk measures in the form of biodiversity and nature-related indices.

News innovations. 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. 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:

$$\begin{aligned} r_{i,t} = \alpha_i + \beta_{i,t}^{Bio}\text{BioShock}_t + \beta_{i,t}^{Clim}\text{ClimShock}_t + \\ + \beta_{i,t}^{MKT}\text{MKT}_t + \beta_{i,t}^{SMB}\text{SMB}_t + \beta_{i,t}^{HML}\text{HML}_t + \epsilon_{i,t}, \end{aligned} \tag{19}$$

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.[17]

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 $m+1$.[18]

3.2.2 Characteristics comparison

Since the Paris Agreement in 2015, there has been a significant global increase in information 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. Increased awareness affects investors' behavior and might lead to changes in the perception of climate and nature-related

[17] In our specification, climate news includes both physical and transition risk-related news, hence we cannot disentangle the effect of a carbon tax, as described in the theoretical model. In other words, our estimated climate beta is a combination of the climate dependence and impact betas in the model, and we do not explicitly capture the news related to a carbon tax. This can introduce a bias in our estimates. In particular, since β^{τ} is negatively correlated with $\widehat{\delta^Z}$, if the correlation between climate impact and dependence is positive, our estimates are biased downward. If the correlation is negative, our estimates would be biased upward. From the correlation analysis (see Figure D.2 in the Appendix), we see that the correlation is generally positive, with the exception of extreme heat and fluvial floods.

[18] This approach enables 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 market's 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.

risks (Acharya et al., 2022).[19] Therefore, guided by our model, we are interested in the correlation between the change in betas after the Paris Agreement and the fundamental characteristics. Accordingly, we run the panel regression

$$\hat{\beta}^{\kappa}_{i,t} = \Gamma^{\kappa,Char}\text{Characteristic}_i \times \text{Post}_{2015} + \text{Fixed effects} + \epsilon_{i,t}, \tag{20}$$

where $\hat{\beta}^{\kappa}_{i,t}$ is the monthly sensitivity of stock i to biodiversity ($\kappa = Bio$) or climate news shocks ($\kappa = Clim$), estimated in regression (19), Post_{2015} is a dummy variable taking value 1 after 2015 and Characteristic is a fundamental characteristic. The fundamental characteristics in our dataset do not vary over time, and the validity of our empirical strategy relies on the ranking of firms remaining unchanged over time. Consistent with this approach, we consider three alternative transformations of the fundamental characteristics. We rank companies on each characteristic 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. Using within-sector ranks, in addition to month-year, 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.[20]

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

[20] 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.

In all cases, standard errors are clustered at the company and month-year level.[21]

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. 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.

Additionally, we form portfolios sorted by estimated betas and fundamental characteristics, and we test whether their returns align, particularly in the post-2015 period ("characteristic-sorted portfolio comparison"). Our results are qualitatively similar to the characteristics comparison results discussed below.[22]

3.3 Results

This section presents our main results for the characteristics comparison. For better visualization, we display our results as heatmaps. The color of the cell corresponds to the point estimate of the parameter of interest, and the statistical significance is indicated by stars.[23]

Climate beta and climate impact. Companies with higher climate impact (emissions, δ^Z) become relatively more sensitive to climate news after 2015, compared to lower risk companies (that is, the interaction coefficient $\Gamma_1^{\kappa,Char}$ is positive, see Figure 1). Based on our model, the interpretation of this finding is that an increase in information precision led to a larger gap between the emissions assigned to high and low polluters, thus resulting in a positive correlation with the actual emission level and intensity at the company level.

[21] 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.

[22] See Appendix F.

[23] In this section, we only present results that provide statistically significant evidence. See Appendix E for additional results based on the characteristics comparison.

While coefficients on all fundamental characteristics for each ranking type - pooled, within-sector, and sectoral - are positive, they are bigger[24] and more statistically significant for pooled and sectoral rankings, indicating that markets perceive these risks to predominantly operate at the sectoral level, rather than within sectors.[25]

Climate beta and nature dependence. Post-2015, market perceptions of firm-level climate change risk exposures became more aligned with firms' nature dependence (in particular on water-related ecosystem services). Specifically, changes in climate betas after 2015 are positively correlated with fundamental measures of nature dependency (see Figure 2). In other words, stocks that are more exposed to nature dependence are relatively more sensitive to climate news after 2015.

A company's climate beta is tied to market perceptions of how its cash flows are linked to its dependence on climate. Our results suggest that markets consider dependence on water-related ecosystem services a relevant aspect of climate risk. Consistent with this, we find a positive (but not statistically significant) correlation between changes in climate beta and firm-level water stress exposure (See Figure E.2 in the Appendix).[26]

Nature beta and nature dependence. The model predicts that for higher signal precision (after 2015), the gap between the posterior mean nature dependence for high and low nature-dependent firms increases. This should result in a higher gap among the nature beta for high and low dependent firms, with nature beta increasing for high dependent firms. Hence, the correlation with the fundamental metric should be positive after 2015. In contrast,

[24] To interpret magnitudes, one approach is to scale the coefficients by the standard deviation of β^{Clim} residualized by firm and month-year fixed effects. Our rankings range from 0 to 1. The (statistically significant) scaled coefficients for pooled rankings range from 0.096 to 0.130. The corresponding scaled coefficients for within sector regressions are between 0.03 and 0.05 and not significant.

[25] An alternative explanation is that our fundamental climate impact characteristics contain less measurement error when averaged over companies within each sector.

[26] Chronic climate dependence characteristics, such as water stress exposure, are based on locations of firms' assets. Unlike nature dependency characteristics, which include the materiality of an ecosystem service to the firm's operations, they do not explicitly take operational dependence into account. This could potentially explain this result.

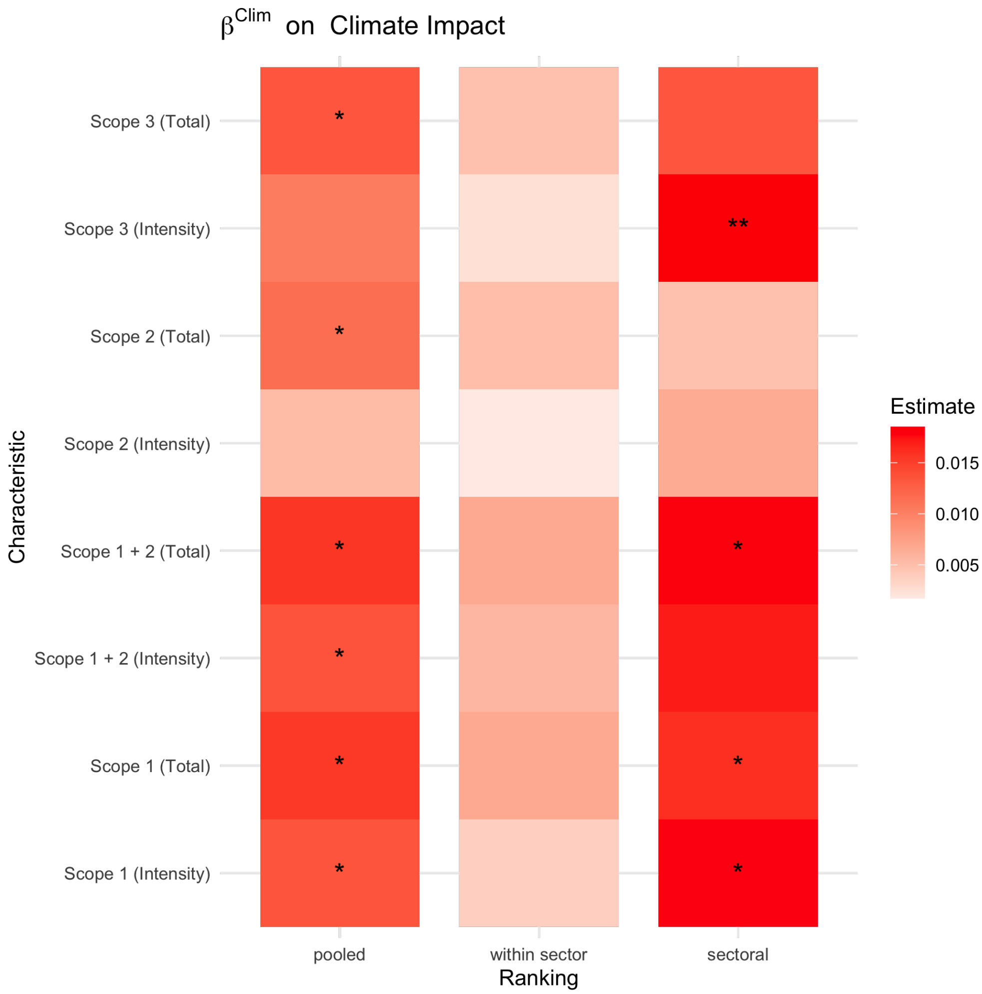

Figure 1: Post-2015 Change in Climate Beta vs. Climate Impact Characteristics. This figure displays the estimated coefficient $\Gamma_1^{Clim,Char}$ from the panel regression in Equation (20). It shows the correlation between the change in firm-level climate beta (β^{Clim}) after 2015 and various fundamental measures of climate impact. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

we do not find a positive correlation between nature betas and firm-level (nature or climate) dependence (see Figure 3). In fact, companies that depend more on nature saw a decrease in nature betas relative to less nature-dependent companies. Through the lens of our model, this suggests that markets are not correctly processing nature-related news, which could be

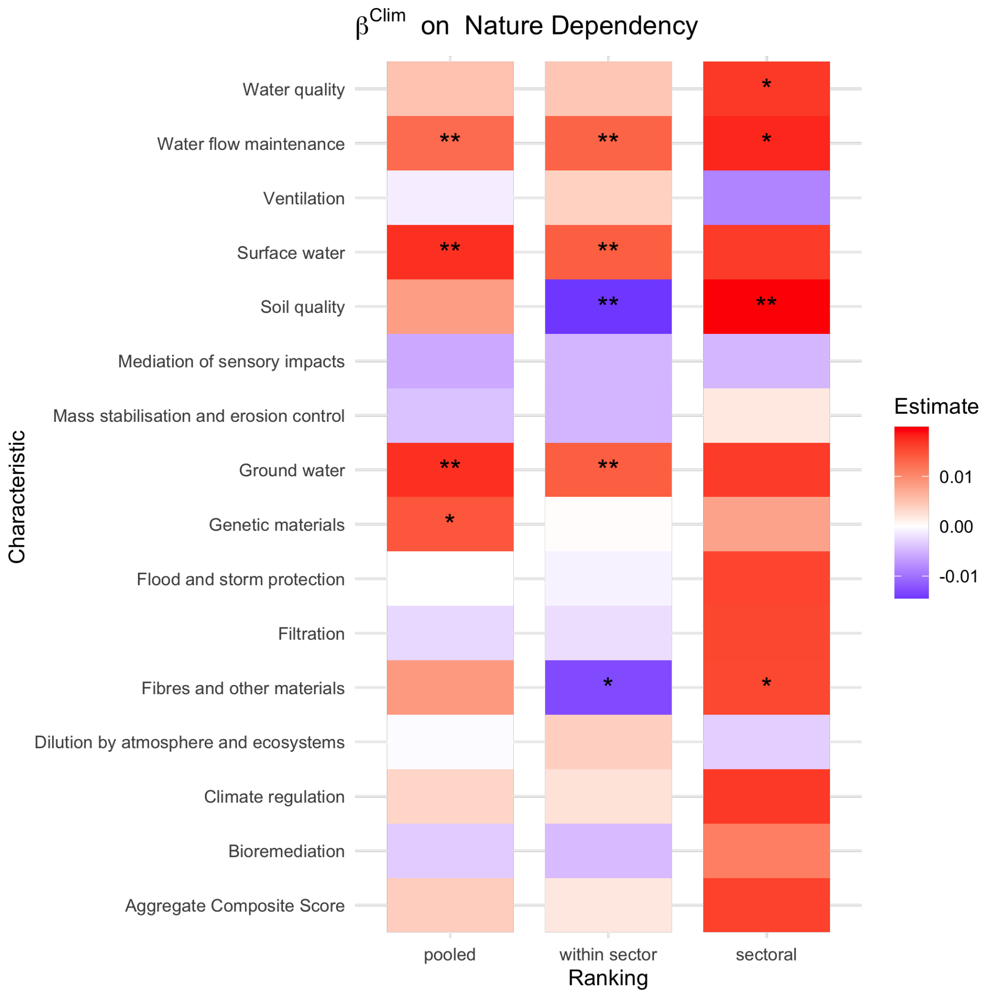

Figure 2: Post-2015 Change in Climate Beta vs. Nature Dependence Characteristics. This figure displays the estimated coefficient $\Gamma_1^{Clim,Char}$ from Equation (20), showing the correlation between the post-2015 change in climate beta (β^{Clim}) and fundamental measures of nature dependence across various ecosystem services. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

due to low precision of nature-related news, less attention to the firm-level dependence or a combination of these. Nonetheless, the fact that we detect statistically significant *negative* correlations for several ecosystem services is a puzzle.

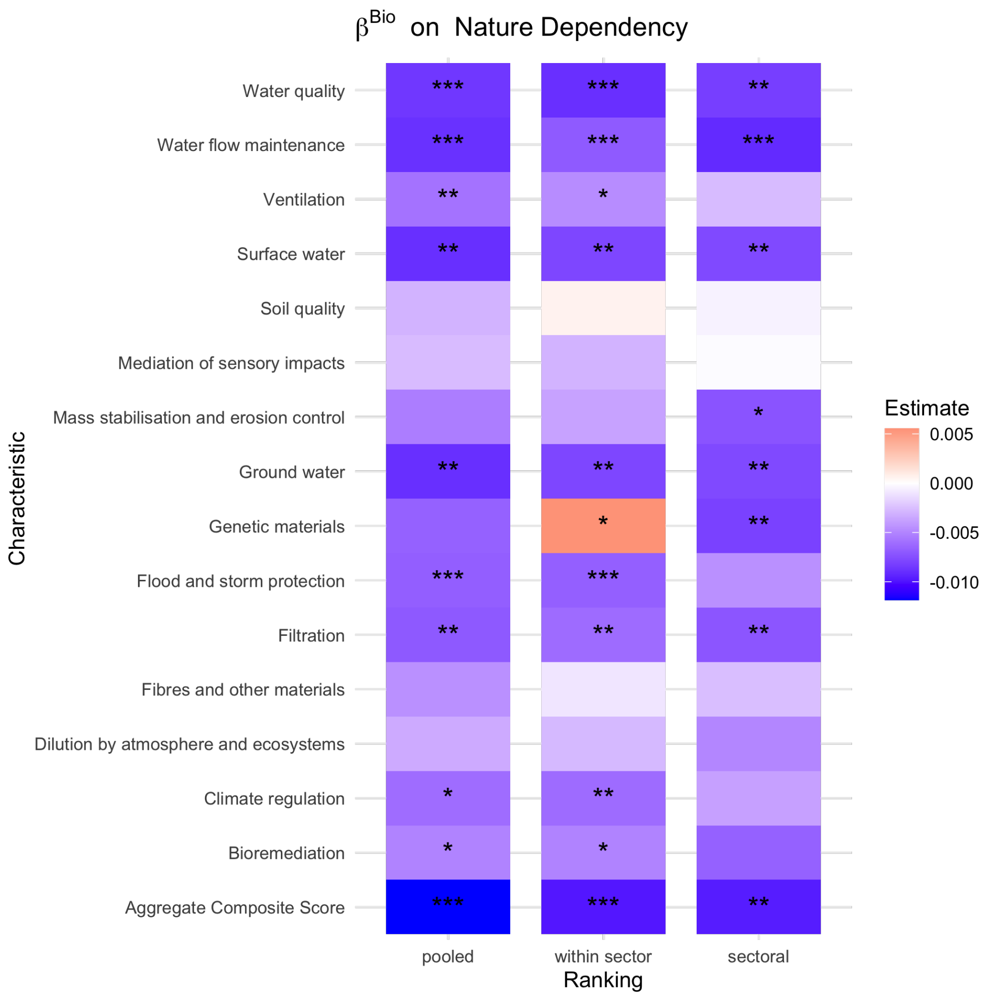

Figure 3: Post-2015 Change in Nature Beta vs. Nature Dependence Characteristics. This figure displays the estimated coefficient $\Gamma_1^{Bio,Char}$ from Equation (20), showing the correlation between the post-2015 change in nature beta (β^{Bio}) and fundamental measures of nature dependence. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

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.

Our analysis reveals three key findings regarding the market's treatment of environmental risks after the 2015 structural shift in information availability and investor attention. First, there's evidence that corporate climate impact is being priced, with climate betas of higher-impact firms showing greater sensitivity after 2015. Second, the market's perception of climate change risk, reflected through climate betas, has become more aligned with firms' nature dependence, particularly on water-related ecosystem services, since changes in climate betas correlate positively with these fundamental risk measures. In contrast, our findings reveal no such positive alignment for nature-specific risks. Instead, companies more dependent on nature experienced a relative decrease in their nature betas, indicating significant inconsistencies in how financial markets perceive and price these distinct environmental risks.

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 melt, 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 A.1: 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 A.2: 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 A.3: 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, and 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, and 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 B.1: 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 B.2: 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 normalized 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 normalized 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 B.3: 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 overlapping 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 overlapping 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 the 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 B.4: Impacts

C Selecting characteristics

The combined data initially include a very large set of fundamental environmental characteristics (123 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 dependence 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).[27] 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 D.1 to D.4 in Appendix D present heatmaps of the correlation matrices for these variables, both within each category and across categories.[28] 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 resource use tend to exhibit higher dependence on ecosystem services. In other words, com-

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

[28] For completeness, Appendix D.2 reports the corresponding heat-maps for all underlying S&P Global metrics (Figures D.7 to D.5), which confirm that the broad correlation patterns hold once the full variable universe is considered.

panies 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 physical 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 ecosystem services. 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.

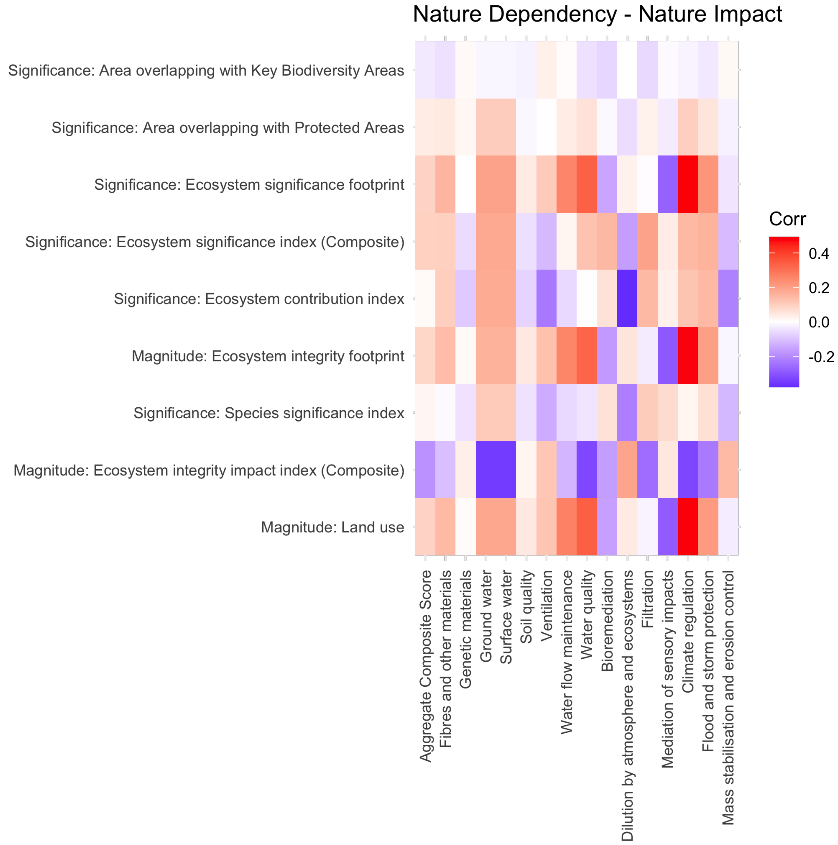

Figure D.1: Correlation Between Selected Nature Impact and Nature Dependence Characteristics. This heatmap shows the pairwise correlations between fundamental characteristics measuring nature impact (y-axis) and nature dependence (x-axis). It generally reveals a positive association, indicating that firms with larger environmental footprints often rely more heavily on ecosystem services.

Figure D.1 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.

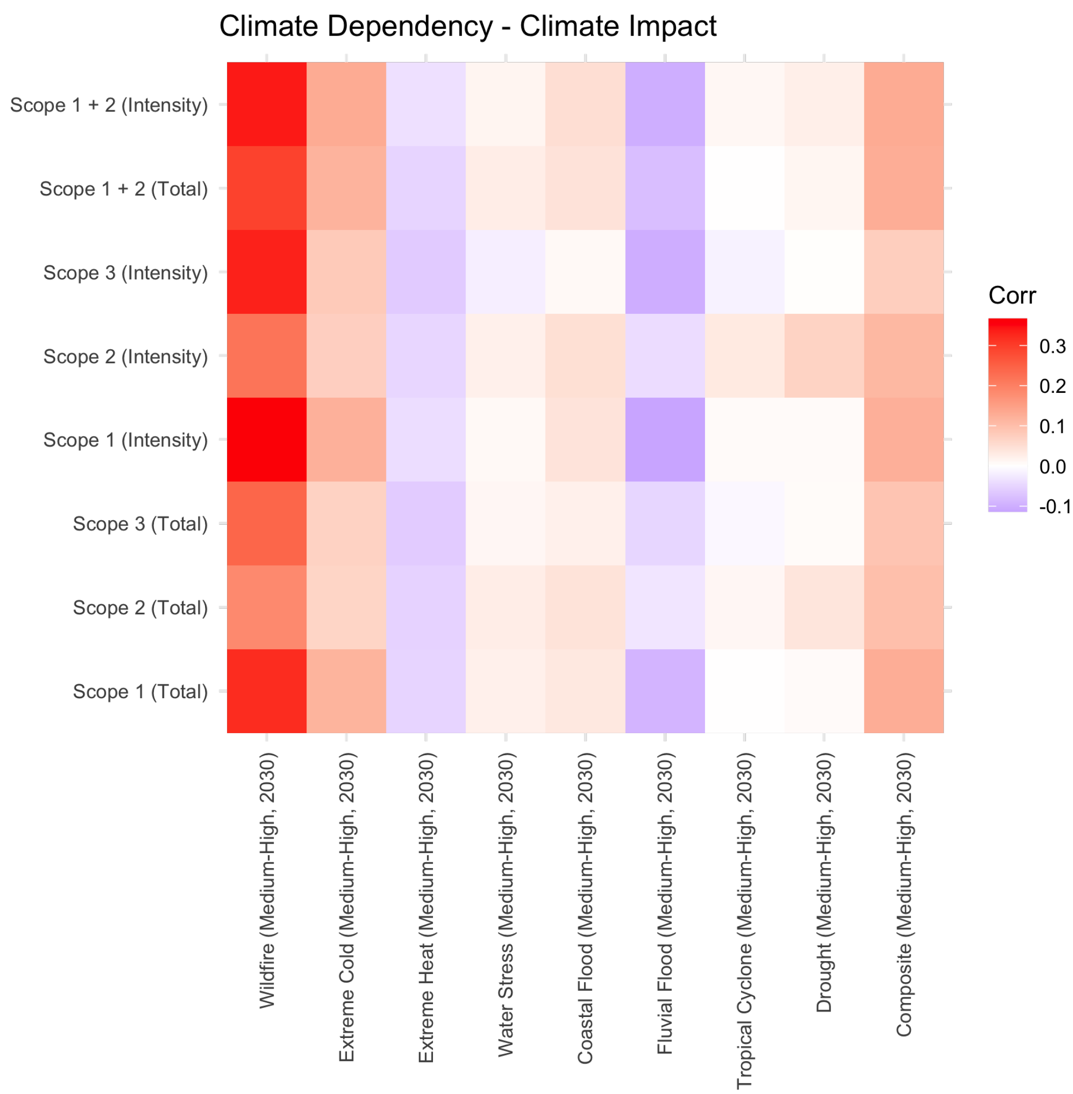

Figure D.2: Correlation Between Selected Climate Impact and Climate Dependence Characteristics. This heatmap displays pairwise correlations between fundamental climate impact (emissions, y-axis) and climate dependence (physical hazard exposure, x-axis) characteristics. Most correlations are positive, suggesting high emitters tend to face multiple physical climate risks, though exposure to specific hazards like extreme heat shows weaker links.

In Figure D.2, 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.

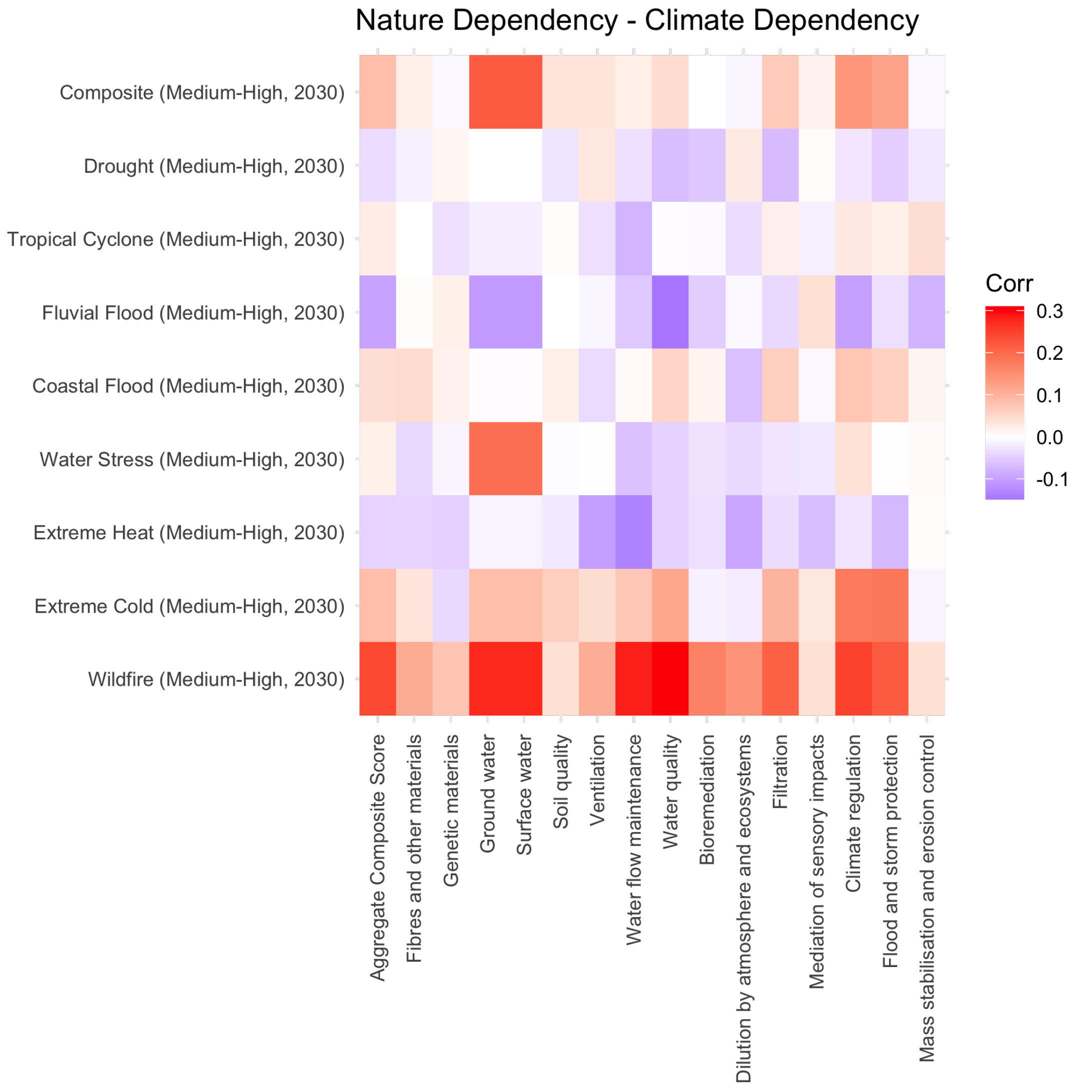

Figure D.3: Correlation Between Selected Climate Dependence and Nature Dependence Characteristics. This heatmap shows pairwise correlations between climate dependence (physical hazard exposure, y-axis) and nature dependence (ecosystem service reliance, x-axis). The predominantly positive correlations highlight that firms vulnerable to physical climate hazards, especially wildfire, extreme cold, and coastal floods, tend to also rely more on ecosystem services.

Interpretation. Figure D.3 reveals a clear positive relationship between *climate dependence* and *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 ecosystem services.

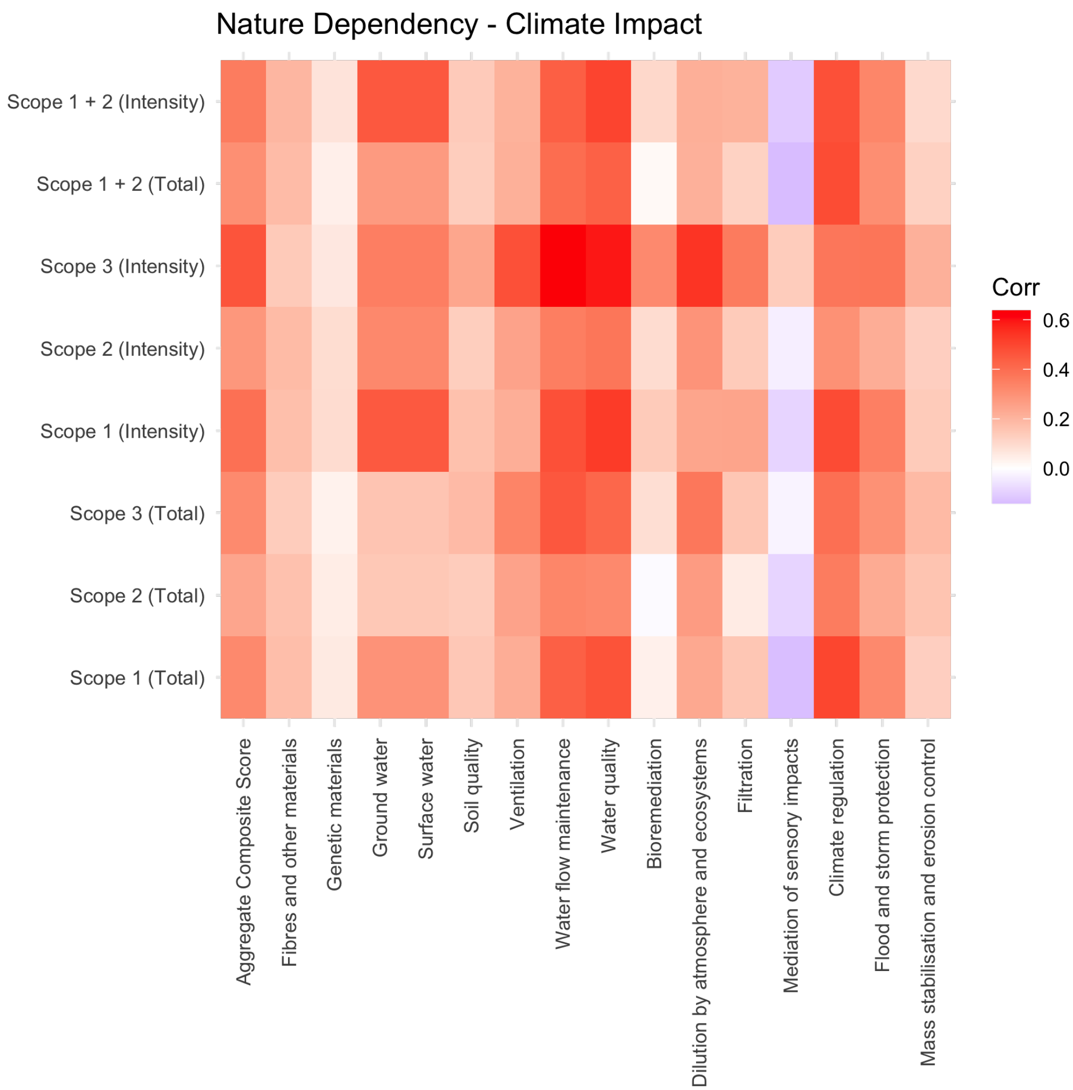

Figure D.4: Correlation Between Selected Climate Impact and Nature Dependence Characteristics. This heatmap displays pairwise correlations between climate impact (emissions, y-axis) and nature dependence (ecosystem service reliance, x-axis). A strong positive relationship is evident, indicating that firms contributing most to climate change (high emitters) are also typically those most reliant on ecosystem services.

Figure D.4 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 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.

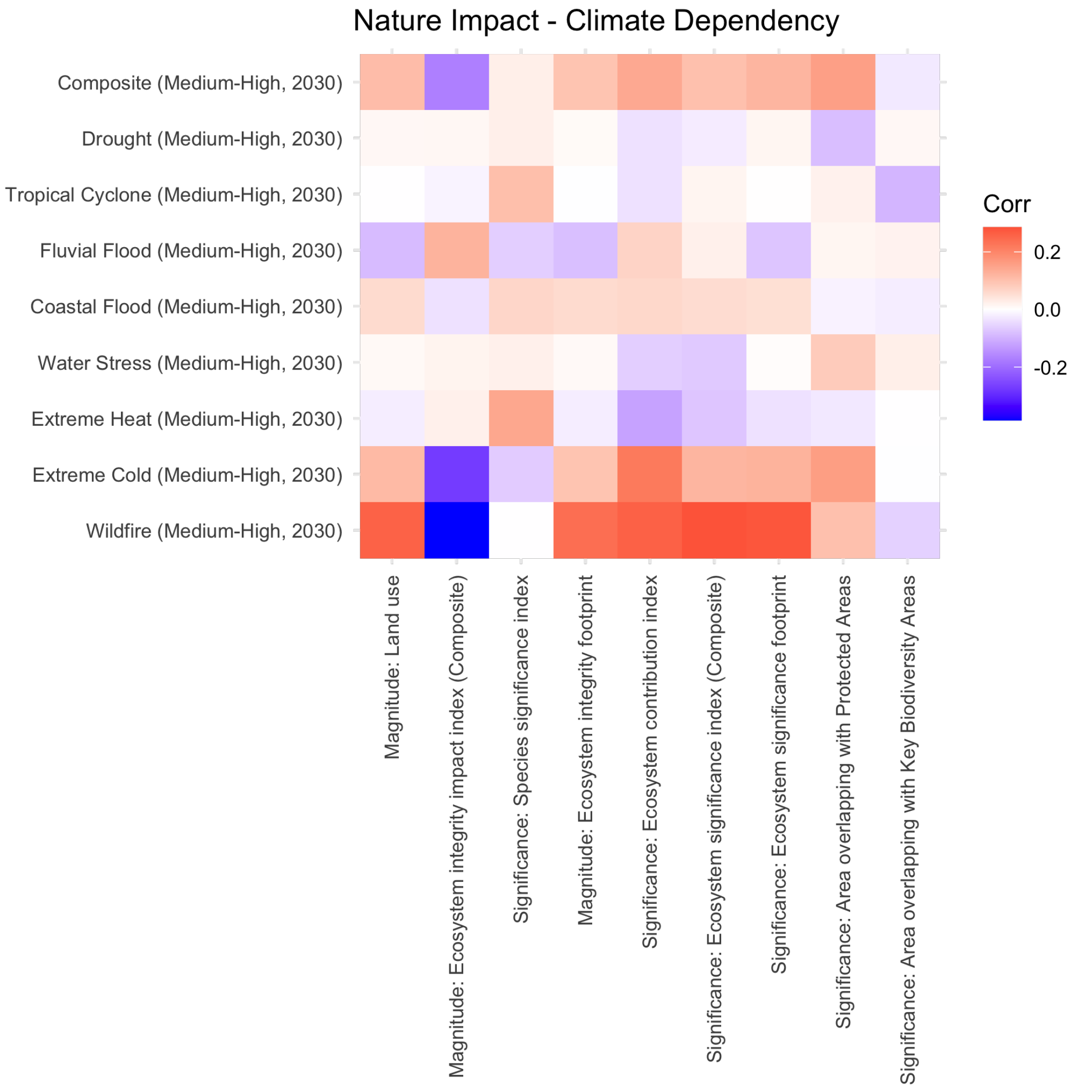

Figure D.5: Correlation Between Selected Climate Dependence and Nature Impact Characteristics. This heatmap shows pairwise correlations between climate dependence (physical hazard exposure, y-axis) and nature impact (environmental footprint, x-axis). The relationships are heterogeneous: exposures to coastal floods, extreme cold, and wildfires show moderate positive links with nature impact metrics, while other hazard exposures show weaker associations.

Correlations in Figure D.5 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 as easily diverge across firms.

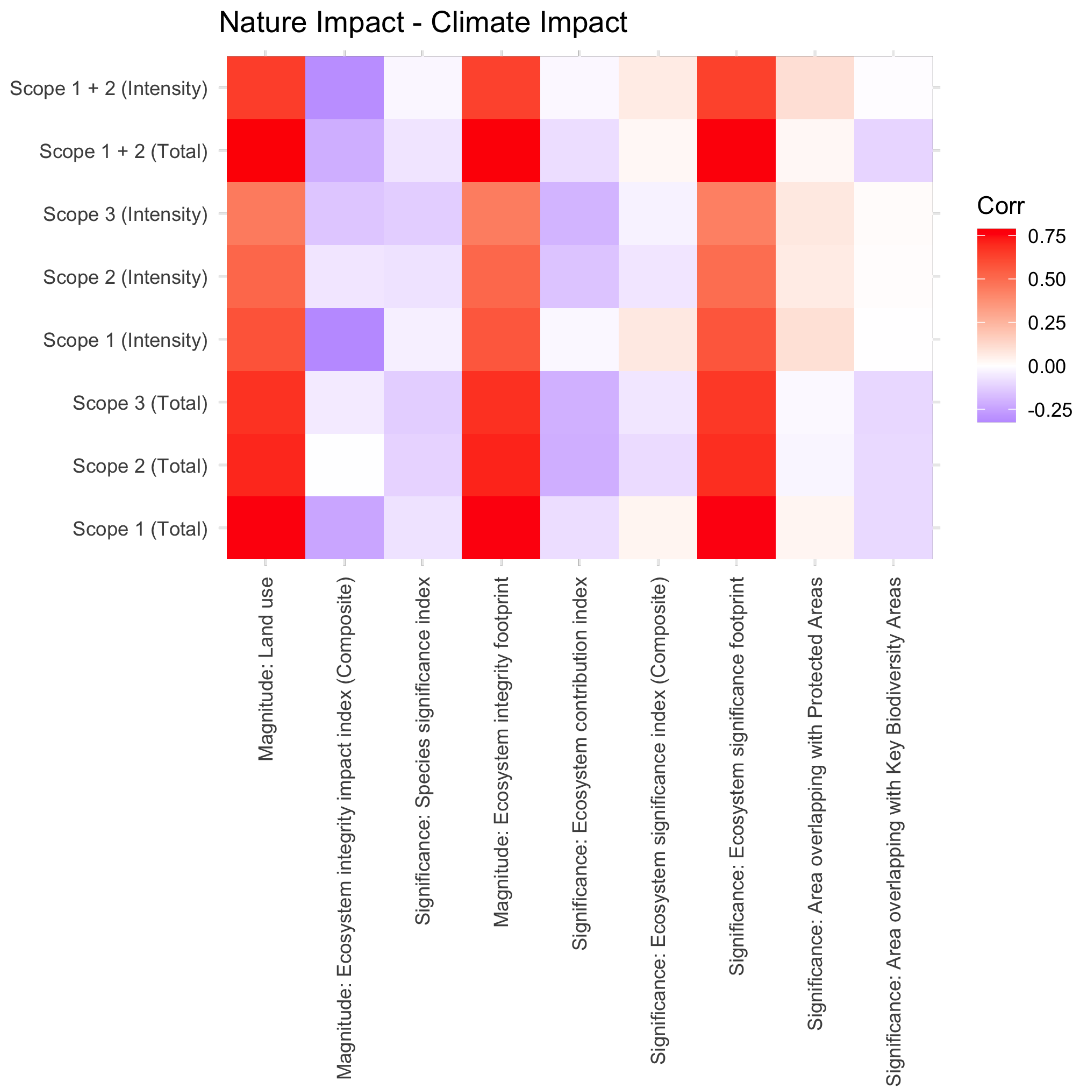

Figure D.6: Correlation Between Selected Climate Impact and Nature Impact Characteristics. This heatmap displays pairwise correlations between climate impact (emissions, y-axis) and nature impact (environmental footprint, x-axis). Strong positive correlations indicate that high emitters tend to have significant nature impacts (e.g., land use, ecosystem integrity loss), though the metrics capture distinct environmental dimensions.

Figure D.6 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.

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 D.7 confirms that a broad, positive association runs through the nature panel: firms with large ecosystem footprints (high impact) also rely more on ecosystem services (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 D.8 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 measures—are virtually orthogonal. The dispersion justifies keeping multiple impact metrics in robustness tests and rules out multicollinearity concerns.

Figure D.9 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.

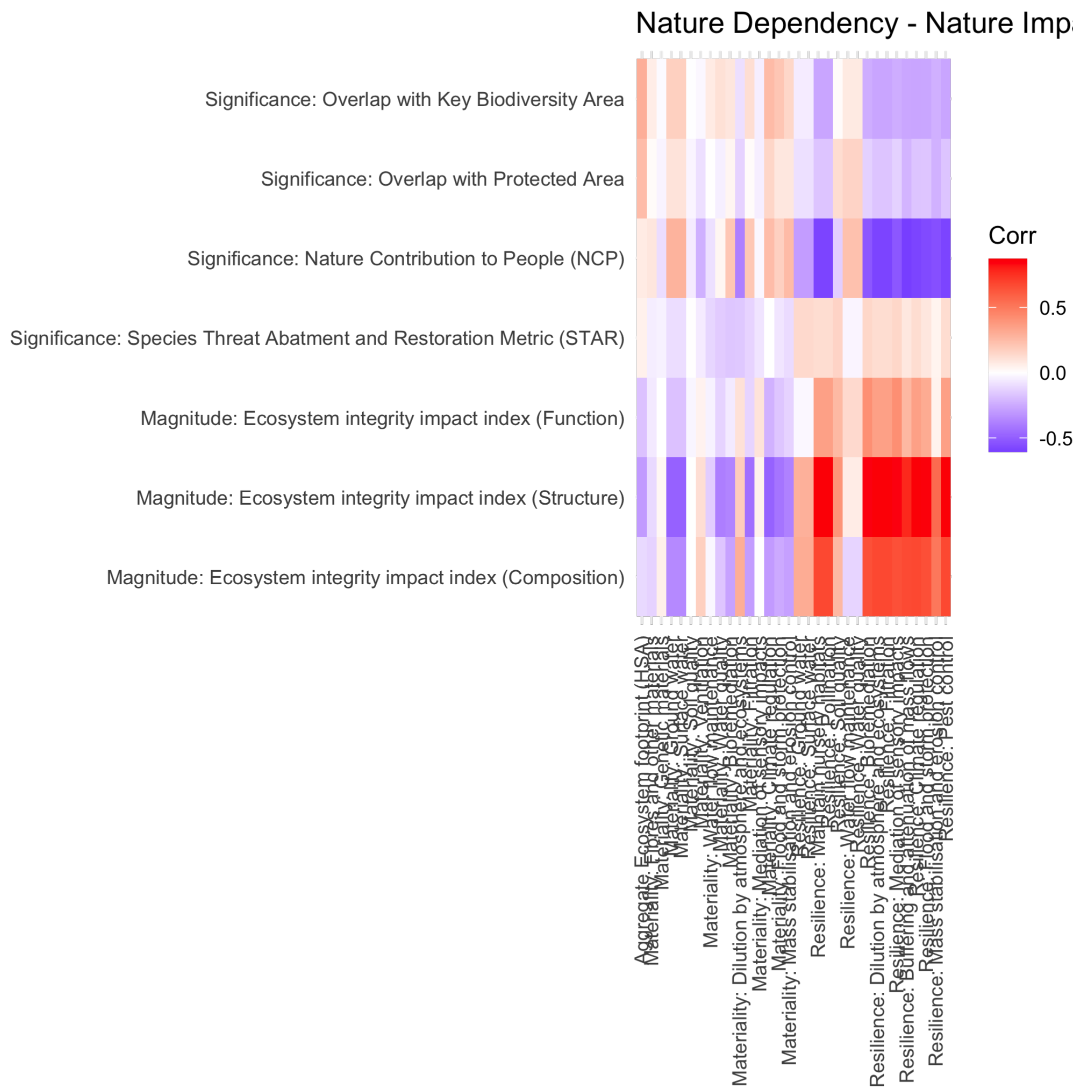

Figure D.7: Correlation Between All Nature Dependence and Nature Impact Metrics. This heatmap shows pairwise correlations across the full set of nature dependence (x-axis) and nature impact (y-axis) metrics available in the data. It confirms a broad positive association, though weaker or inverse correlations for some pairs highlight that the two constructs are related but distinct.

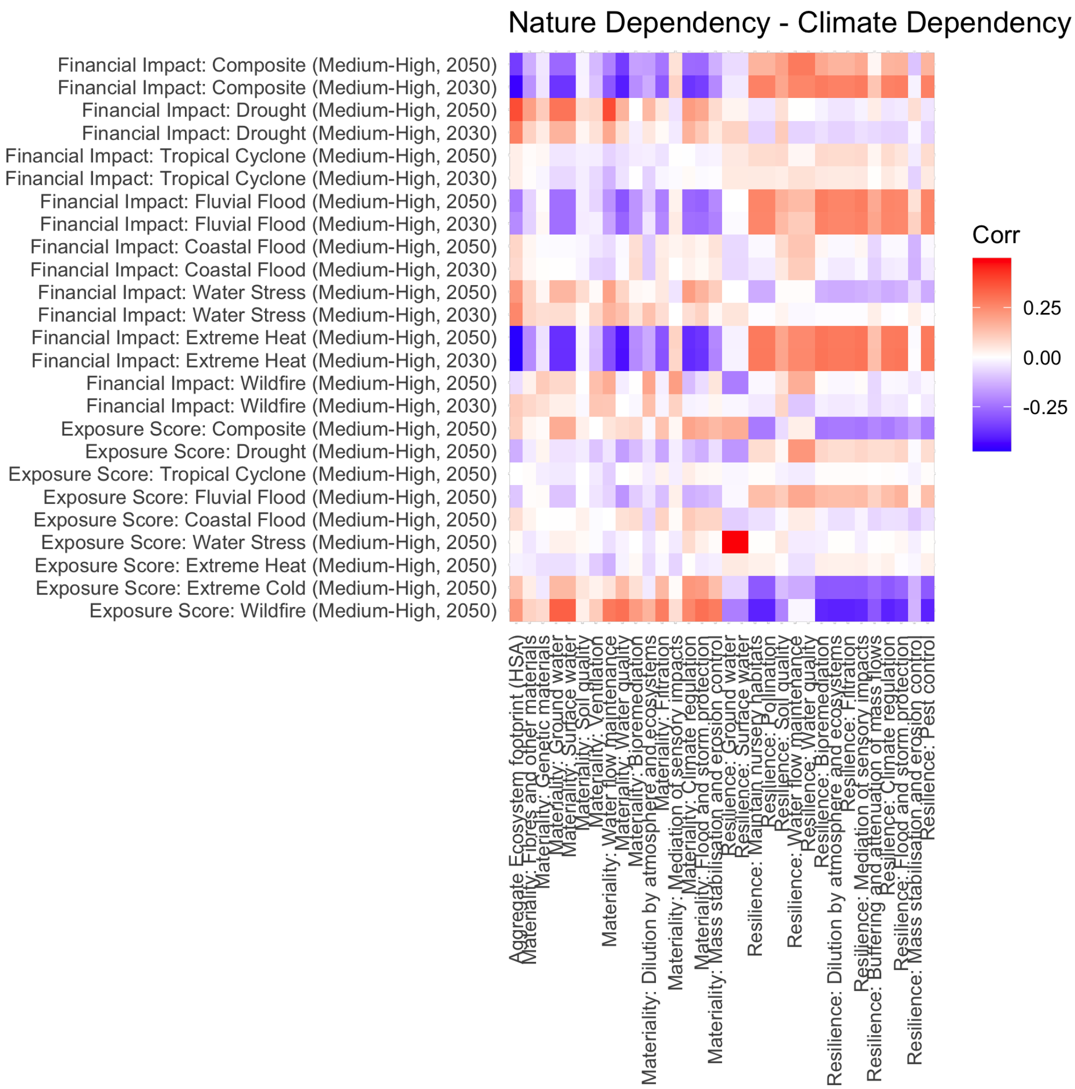

Figure D.8: Correlation Within All Nature Impact Metrics. This heatmap displays pairwise correlations among the full set of nature impact metrics. While some positive clusters exist (e.g., related to land use or integrity loss), the presence of weakly correlated or orthogonal pairs indicates that these metrics do not collapse to a single dimension.

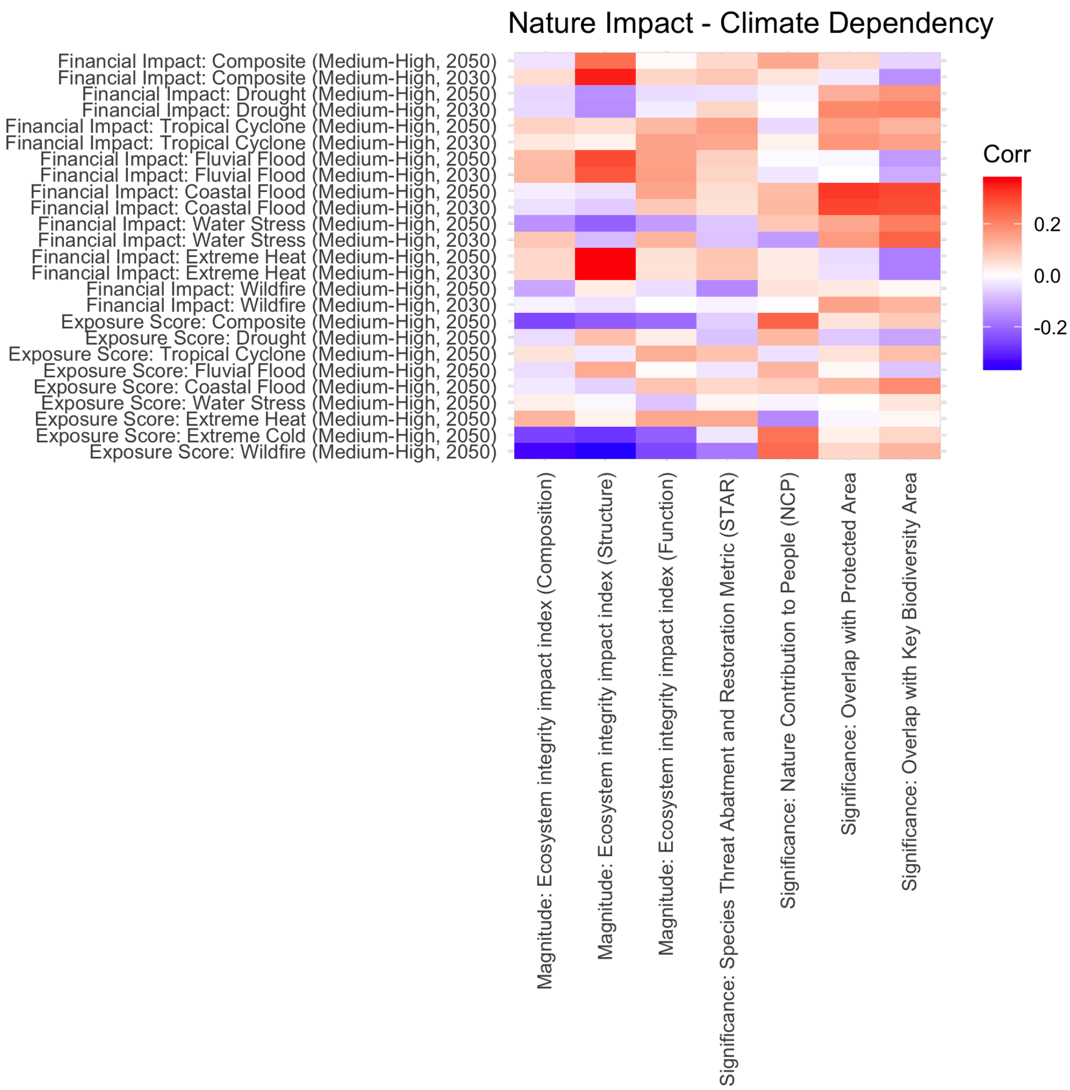

Figure D.9: Correlation Between All Climate Dependence and Nature Dependence Metrics. This heatmap shows pairwise correlations between the full set of climate dependence (physical hazard exposure, y-axis) and nature dependence (ecosystem service reliance, x-axis) metrics. It confirms the positive relationship seen in Figure D.3, with risks like wildfire, extreme cold, and coastal floods showing stronger alignment with nature dependence.

E Additional characteristic comparison results

E.1 Risk pricing

The correlation for nature beta and nature impact and climate beta and climate dependence is not significant in our sample.

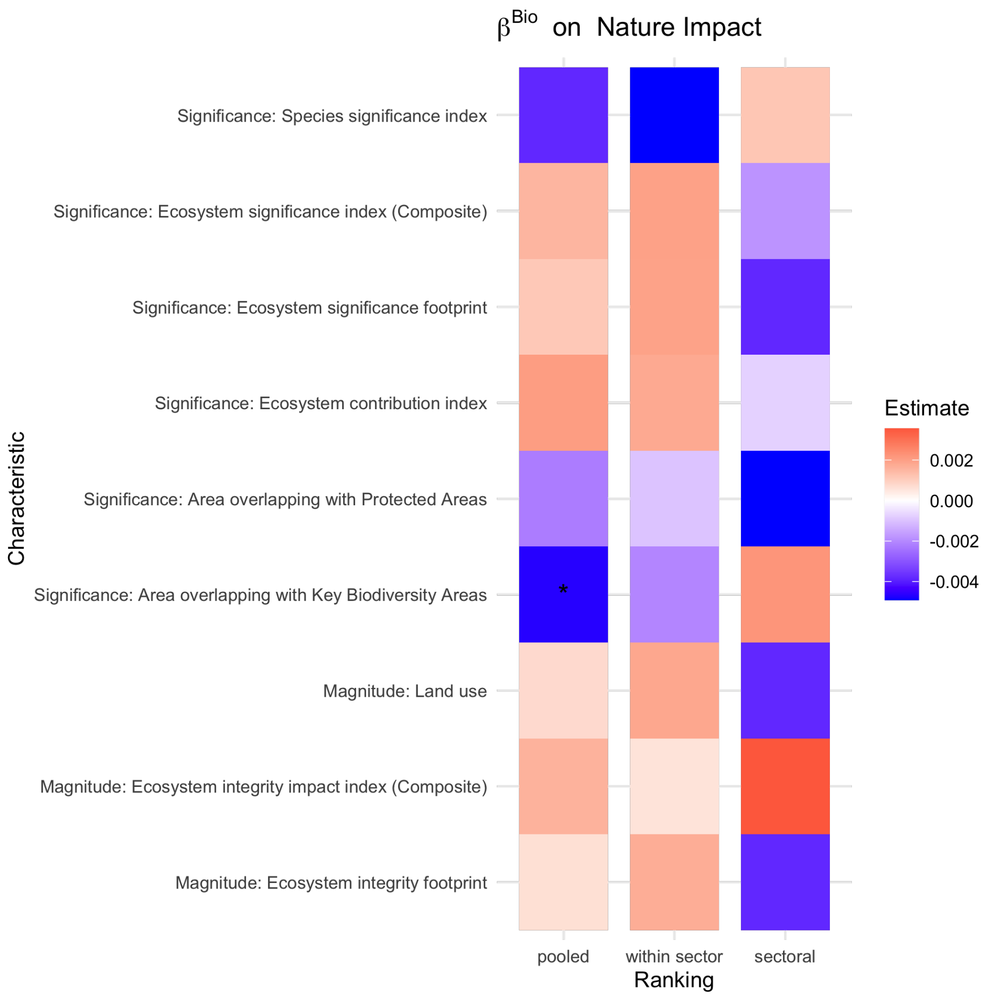

Figure E.1: Post-2015 Change in Nature Beta vs. Nature Impact Characteristics. This heatmap shows the correlation between the change in β^{Bio} after 2015 and fundamental measures of nature impact; no statistically significant correlation is found. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

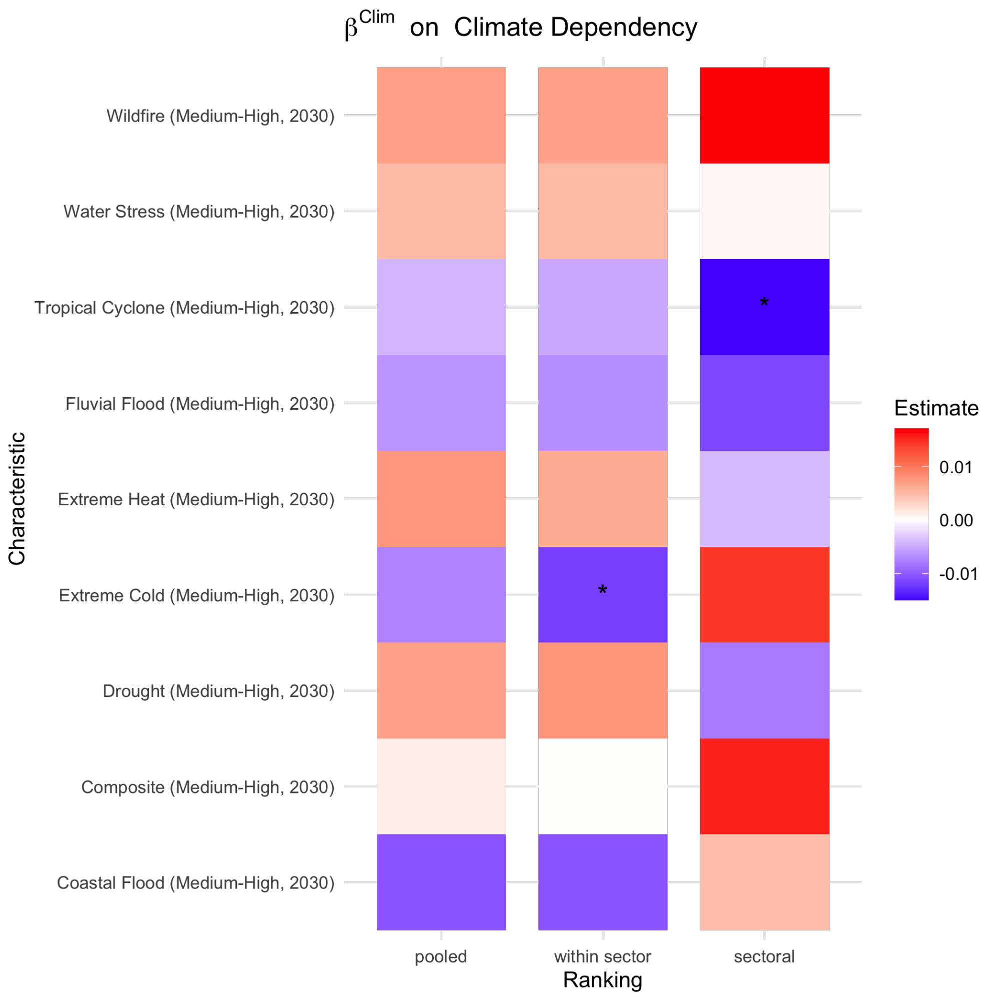

Figure E.2: Post-2015 Change in Climate Beta vs. Climate Dependence Characteristics. This heatmap shows the correlation between the change in β^{Clim} after 2015 and fundamental measures of climate dependence. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value $<$ 0.1, **: p-value $<$ 0.01, ***: p-value $<$ 0.001).

Dependent Variable:		$\hat{\beta}^{Bio}$	
Model:	(1)	(2)	(3)
Variables			
Constant	-0.0003		
	(0.0005)		
$\hat{\beta}^{Clim}$	-0.0111	-0.0116	-0.0092
	(0.0105)	(0.0104)	(0.0103)
Fixed-effects			
month:year		Yes	
permno			Yes
Fit statistics			
Observations	223,057	223,057	223,057
R^2	0.00055	0.01042	0.03918
Within R^2		0.00061	0.00038

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

Table E.1: Correlation between climate and nature betas.

E.2 Nature-climate interaction

E.2.1 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

$$\hat{\beta}_{i,t}^{Bio} = \hat{\beta}_{i,t}^{Clim} + \gamma + \varepsilon_{i,t} \tag{21}$$

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 E.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.

E.2.2 Beta- and fundamental characteristics

We find no significant correlation for nature beta and climate dependence, nature beta and climate impact and cliamte beta and nature impact.

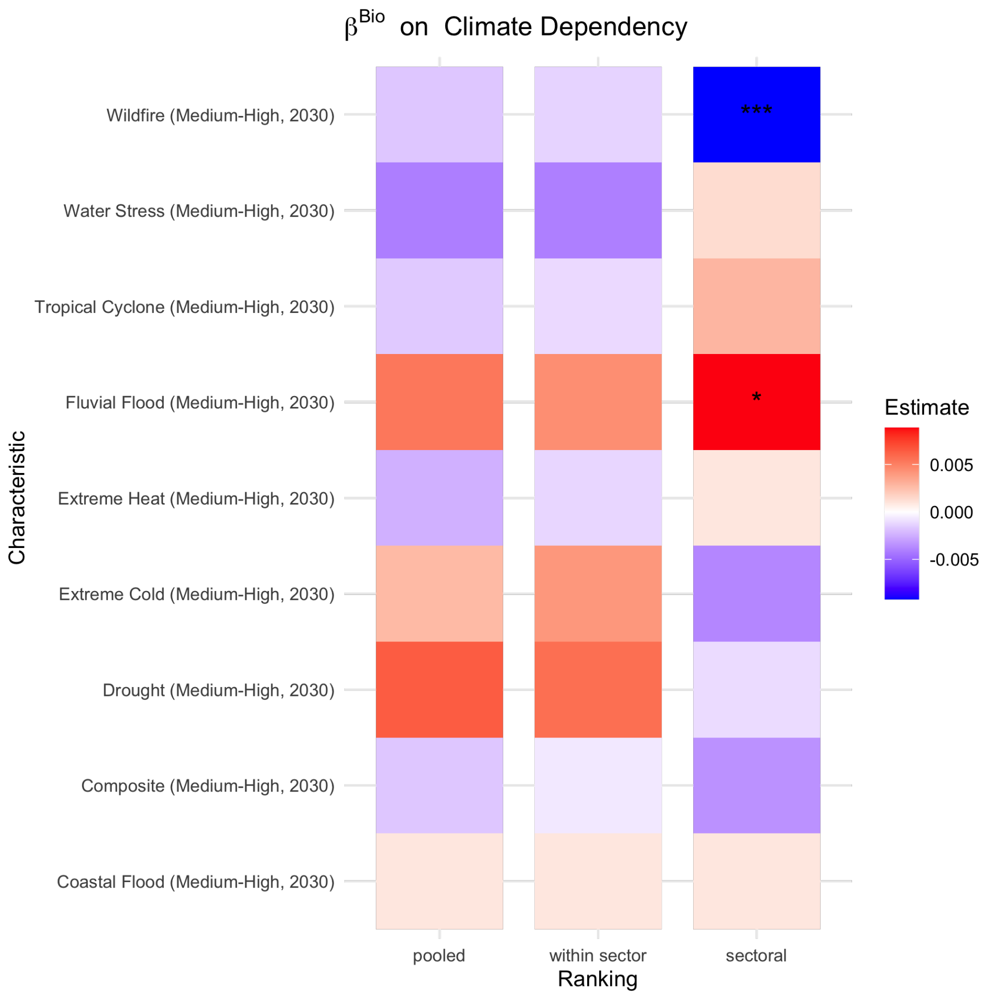

Figure E.3: Post-2015 Change in Nature Beta vs. Climate Dependence Characteristics. This heatmap shows the correlation between the change in β^{Bio} after 2015 and fundamental measures of climate dependence. Significance levels are indicated by stars (*: t-value > 2, **: t-value > 2.5, ***: t-value > 3) using robust standard errors clustered by firm and month-year.

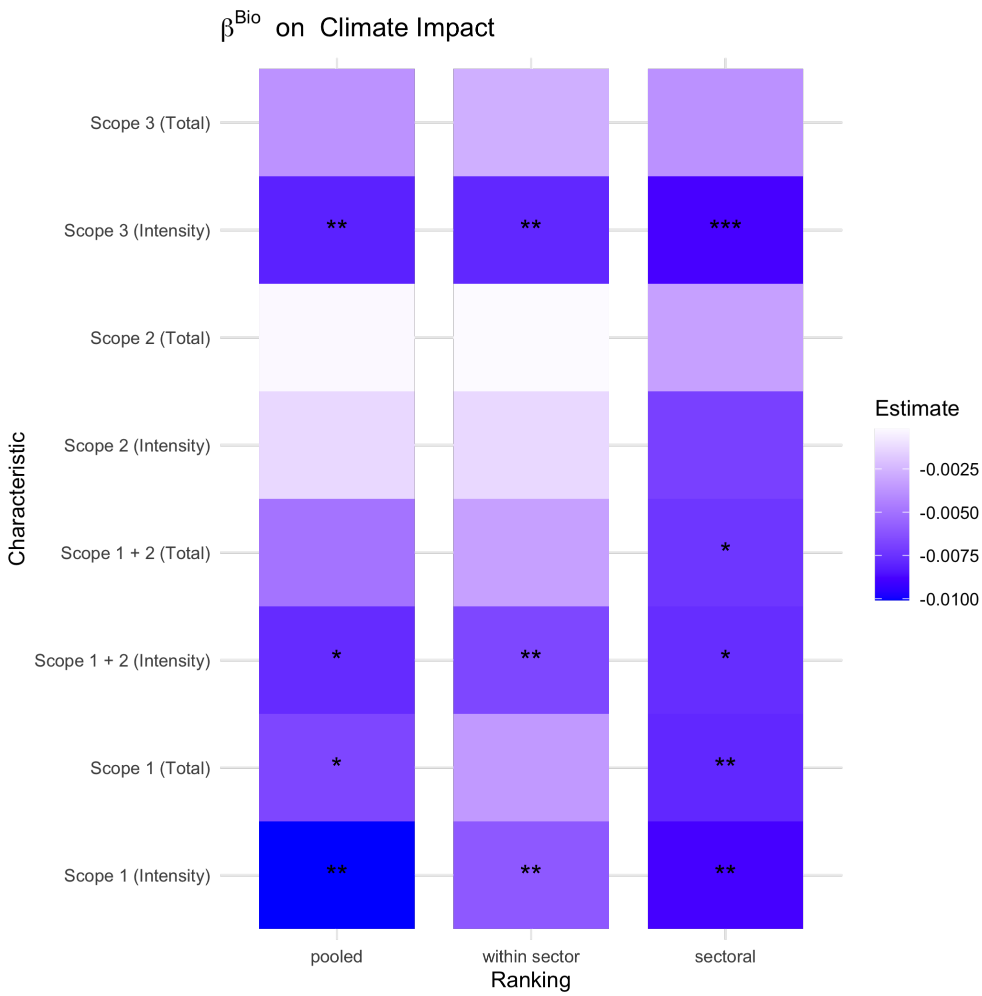

Figure E.4: Post-2015 Change in Nature Beta vs. Climate Impact Characteristics. This heatmap shows the correlation between the change in β^{Bio} after 2015 and fundamental measures of climate impact. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

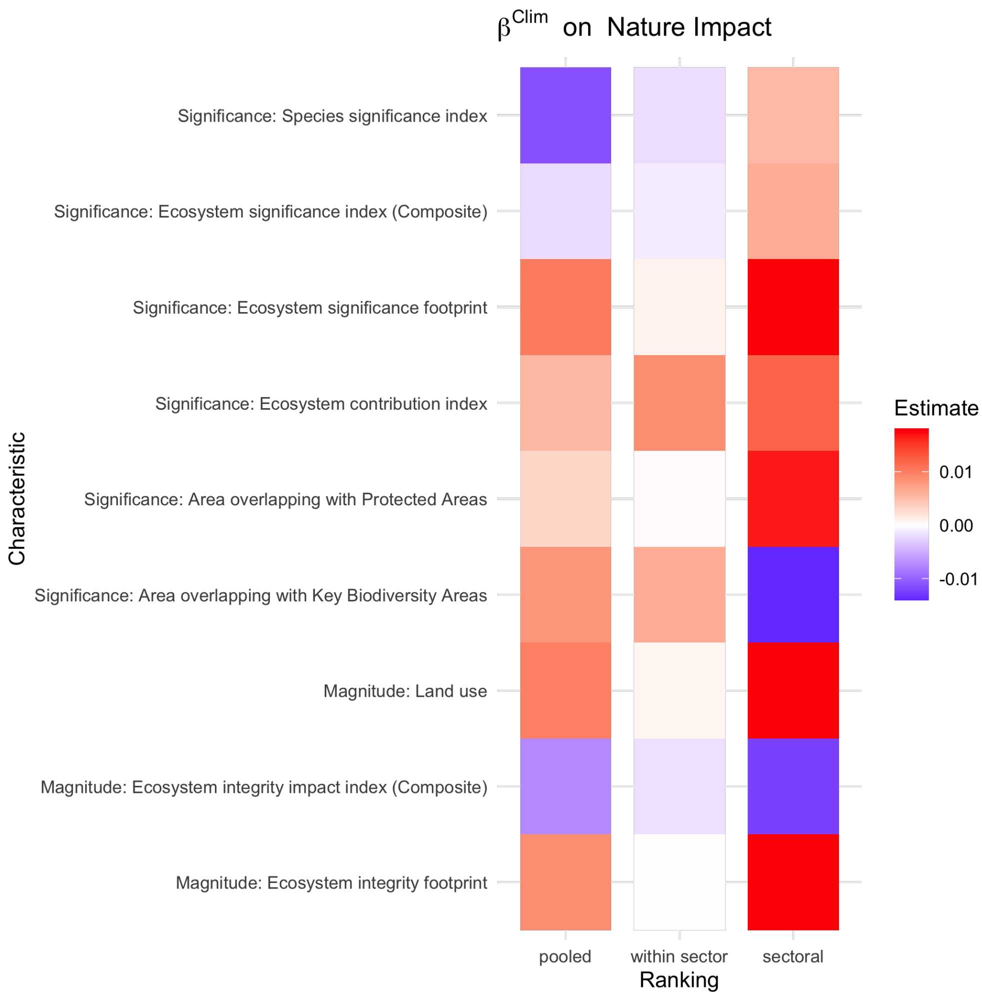

Figure E.5: Post-2015 Change in Climate Beta vs. Nature Impact Characteristics. This heatmap shows the correlation between the change in β^{Clim} after 2015 and fundamental measures of nature impact; no statistically significant correlation is found. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

F Sorted-portfolios results

F.1 Characteristic-sorted portfolios comparison

We also compare 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 two 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 co-move 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

$$\begin{aligned} r_t^{\hat{\beta},\kappa} = {} & \Omega_0^{\kappa,Char} r_t^{Char} + \Omega_0^{\kappa,MKT}\mathrm{MKT}_t + \Omega_0^{\kappa,SMB}\mathrm{SMB}_t + \Omega_0^{\kappa,HML}\mathrm{HML}_t + \\ & + \left(\Omega_1^{\kappa,Char} r_t^{Char} + \Omega_1^{\kappa,MKT}\mathrm{MKT}_t + \Omega_1^{\kappa,SMB}\mathrm{SMB}_t + \Omega_1^{\kappa,HML}\mathrm{HML}_t\right) \times \mathrm{Post}_{2015} + \epsilon_t, \end{aligned} \tag{22}$$

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 (22) 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, $\Omega_1^{\kappa,Char}$.

F.1.1 Correlation among betas

We first 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 F.1 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:		$r^{\hat{\beta},\text{Bio}}$	
Model:	(1)	(2)	(3)
Variables			
$\text{Post}_{2015} \times r^{\hat{\beta},\text{Clim}}$	-0.0963	0.0171	-0.1727
	(0.1978)	(0.1559)	(0.2711)
Fit statistics			
Observations	180	180	180
R^2	0.06957	0.06634	0.12732
Adjusted R^2	0.00865	0.00521	0.07018

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

Table F.1: Testing for Portfolio-Level Synergy: Nature vs. Climate Beta-Sorted Returns. This table examines the time-series correlation between returns of portfolios sorted on nature betas ($r_{\hat{\beta},Bio}$) and climate betas ($r_{\hat{\beta},Clim}$), specifically testing for a shift post-2015 (coefficient on $Post_{2015} \times r_{\hat{\beta},Clim}$). The consistently negative, though statistically insignificant, point estimates across sorting methods hint at a potential diversification or hedging effect between the two risks at the portfolio level, warranting further investigation.

F.1.2 Beta- and fundamental characteristic-sorted portfolios

We 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 negative (positive) correlation between the nature (climate) beta- and nature dependence- (climate impact-) sorted portfolios after 2015. As well as a positive correlation between climate beta-sorted portfolios and nature dependence. However, the effects are less significant when considering portfolio returns.

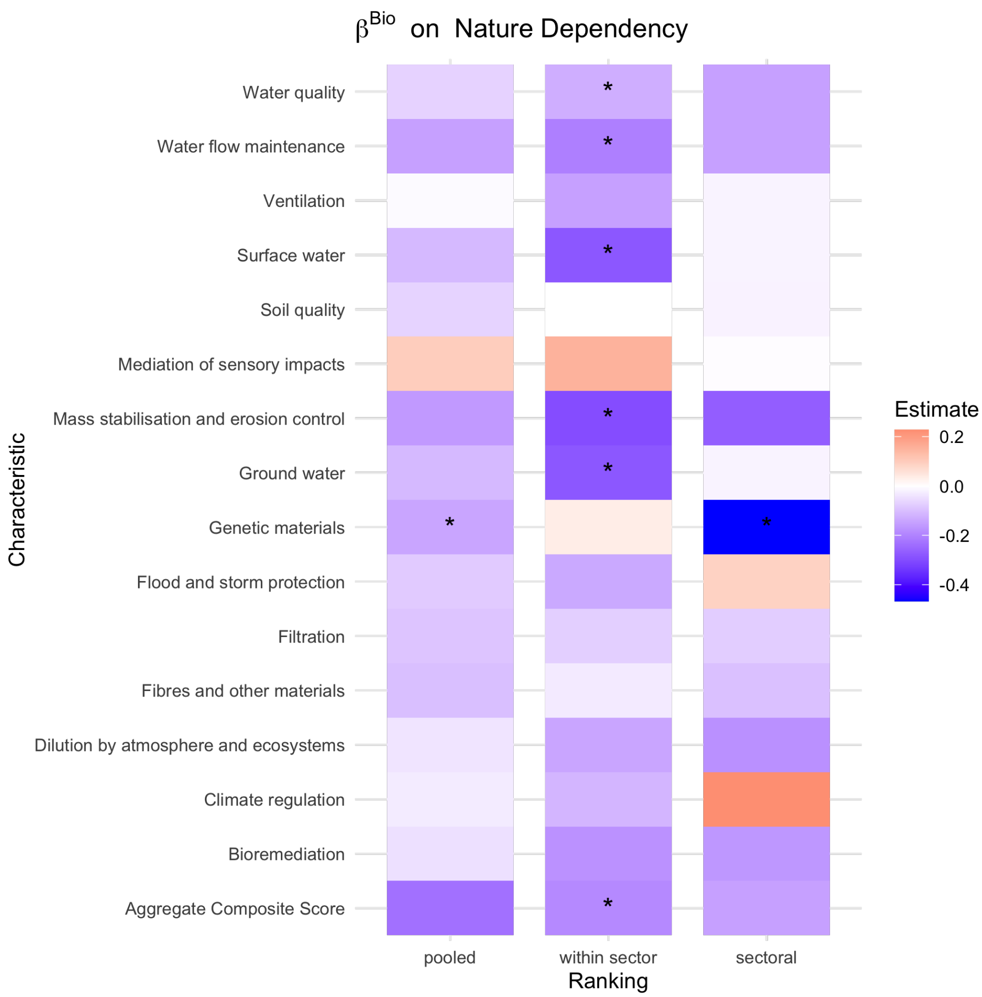

Figure F.1: Nature Beta-Sorted vs. Nature Dependence-Sorted Portfolio Return Correlation (Post-2015). This heatmap displays the coefficient $\Omega_1^{Bio,Char}$ relating post-2015 returns of β^{Bio}-sorted portfolios to nature dependence-sorted portfolios, showing a generally negative but less significant relationship. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

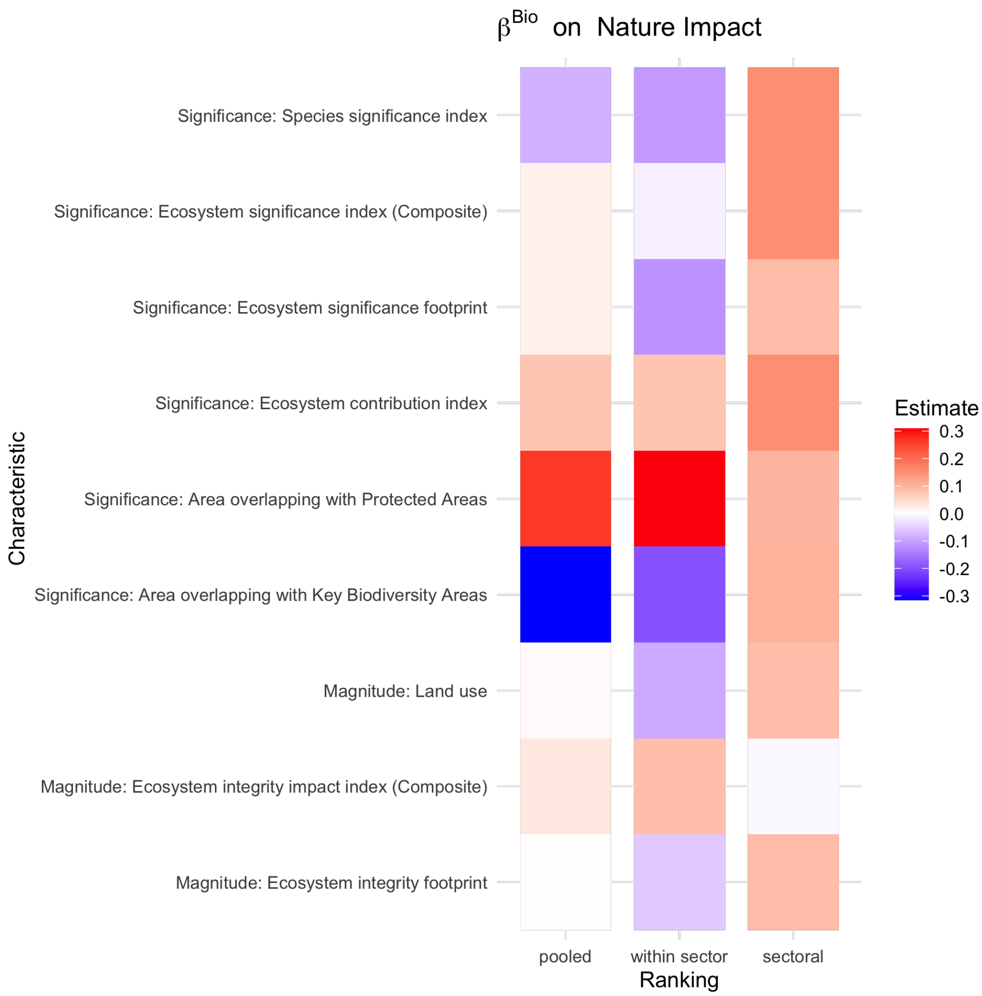

Figure F.2: Nature Beta-Sorted vs. Nature Impact-Sorted Portfolio Return Correlation (Post-2015). This heatmap displays the coefficient $\Omega_1^{Bio,Char}$ relating post-2015 returns of β^{Bio}-sorted portfolios to nature impact-sorted portfolios; results are largely insignificant. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value $<$ 0.1, **: p-value $<$ 0.01, ***: p-value $<$ 0.001).

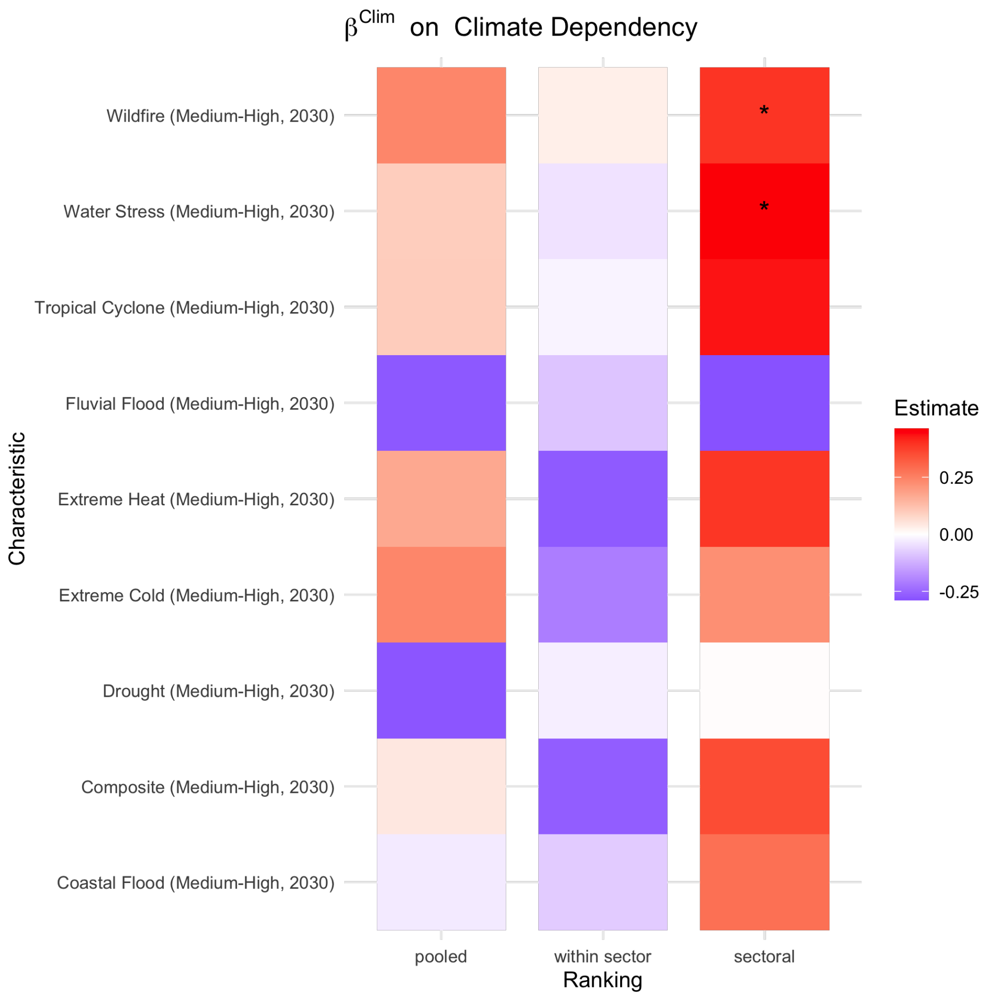

Figure F.3: Climate Beta-Sorted vs. Climate Dependence-Sorted Portfolio Return Correlation (Post-2015). This heatmap displays the coefficient $\Omega_1^{Clim,Char}$ relating post-2015 returns of β^{Clim}-sorted portfolios to climate dependence-sorted portfolios; results are largely insignificant. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

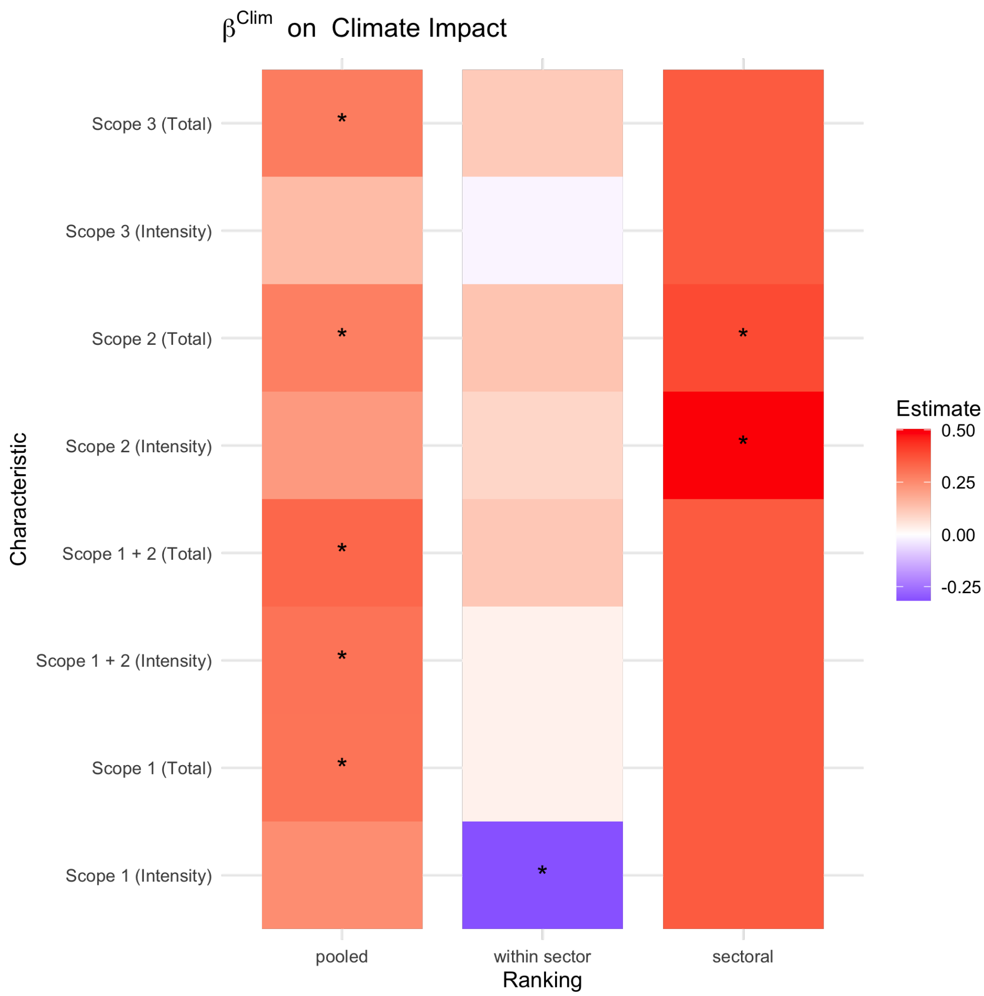

Figure F.4: Climate Beta-Sorted vs. Climate Impact-Sorted Portfolio Return Correlation (Post-2015). This heatmap displays the coefficient $\Omega_1^{Clim,Char}$ relating post-2015 returns of β^{Clim}-sorted portfolios to climate impact-sorted portfolios, showing a generally positive but less significant relationship. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value $<$ 0.1, **: p-value $<$ 0.01, ***: p-value $<$ 0.001).

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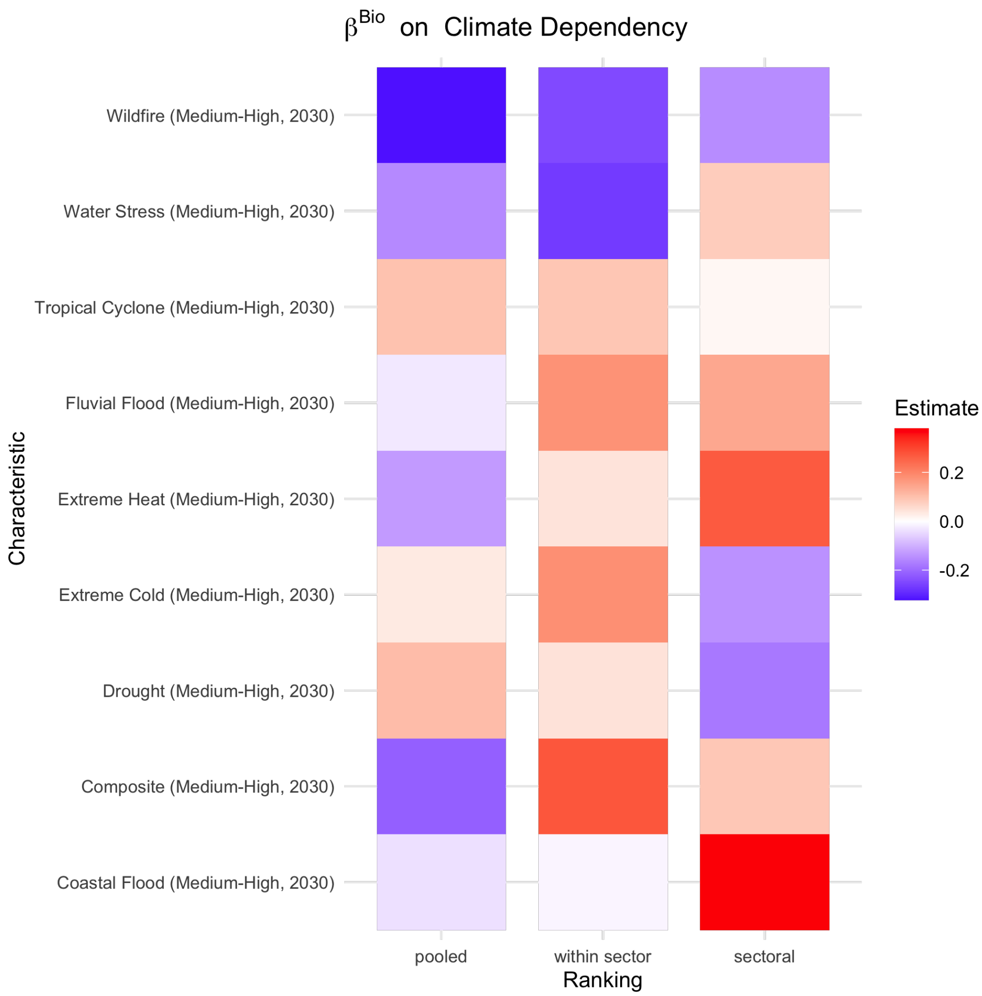

Figure F.5: Nature Beta-Sorted vs. Climate Dependence-Sorted Portfolio Return Correlation (Post-2015). This heatmap displays the coefficient $\Omega_1^{Bio,Char}$ relating post-2015 returns of β^{Bio}-sorted portfolios to climate dependence-sorted portfolios; results are insignificant. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value $<$ 0.1, **: p-value $<$ 0.01, ***: p-value $<$ 0.001).

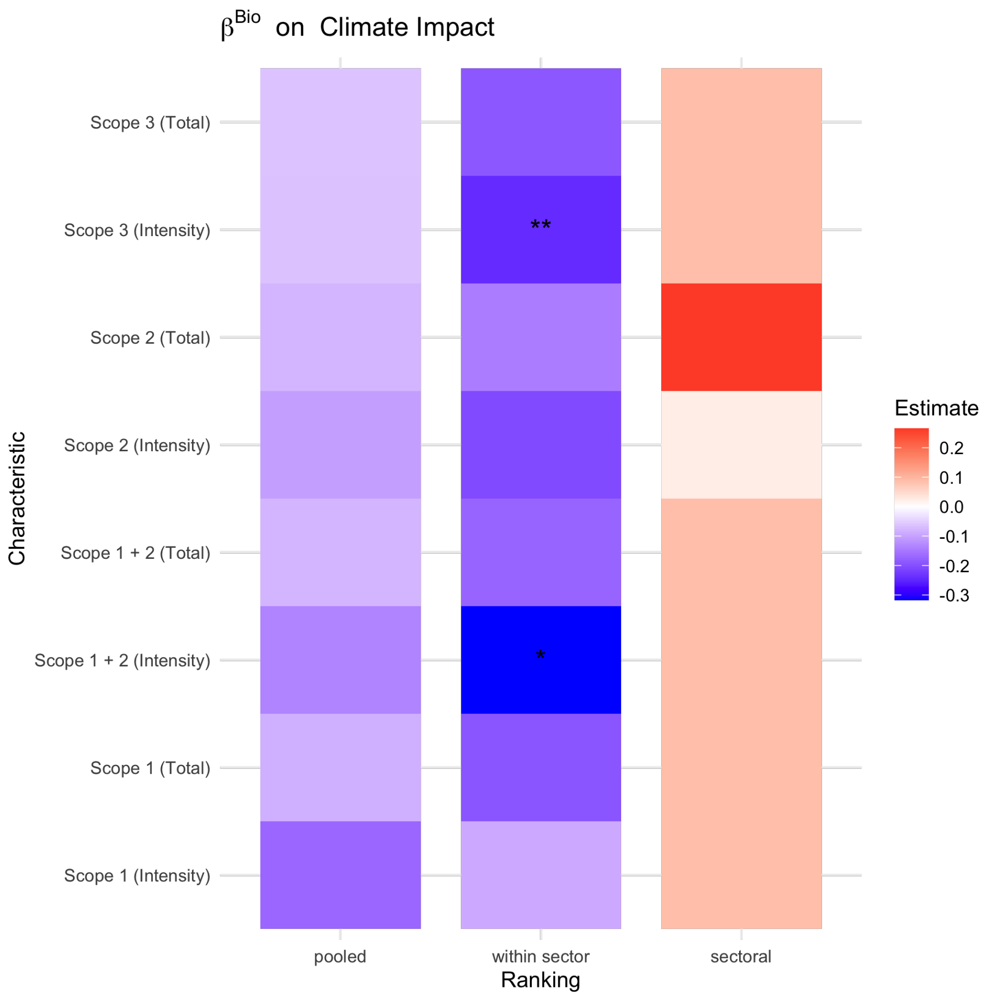

Figure F.6: Nature Beta-Sorted vs. Climate Impact-Sorted Portfolio Return Correlation (Post-2015). This heatmap displays the coefficient $\Omega_1^{Bio,Char}$ relating post-2015 returns of β^{Bio}-sorted portfolios to climate impact-sorted portfolios; results are largely insignificant. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value $<$ 0.1, **: p-value $<$ 0.01, ***: p-value $<$ 0.001).

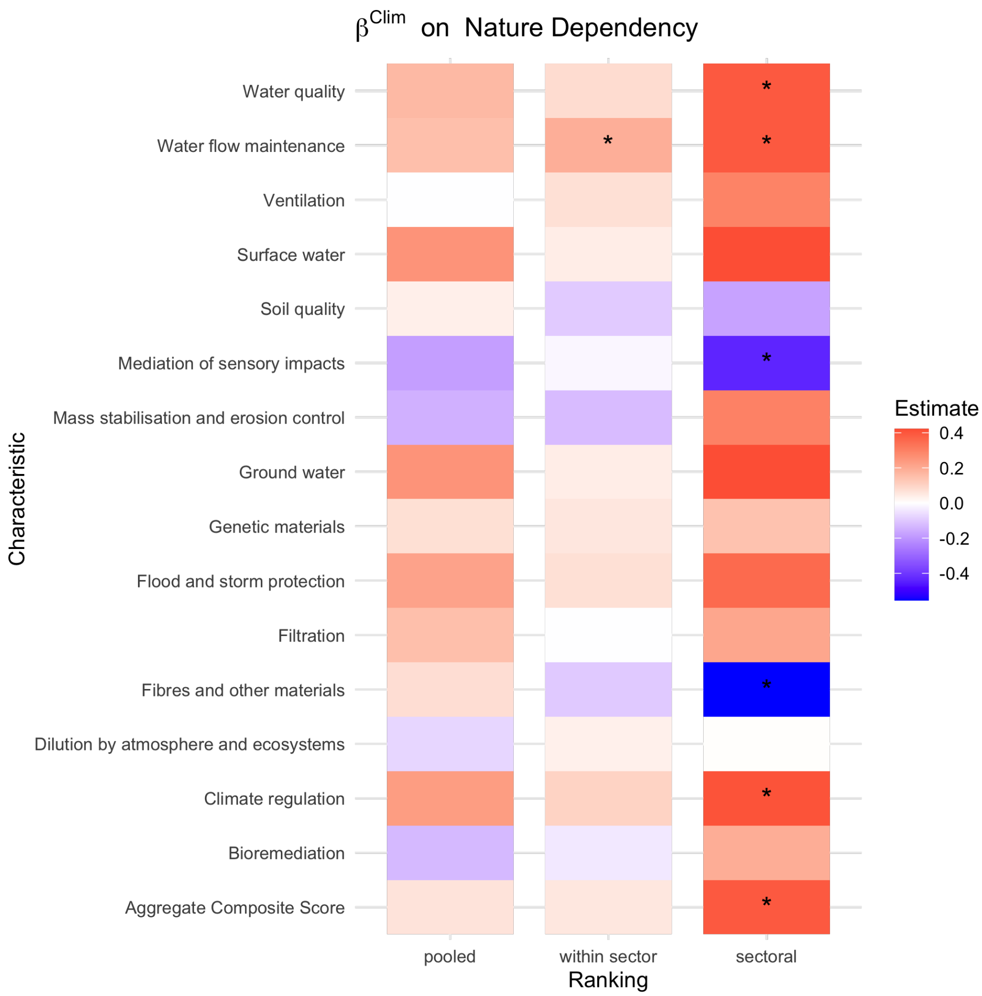

Figure F.7: Climate Beta-Sorted vs. Nature Dependence-Sorted Portfolio Return Correlation (Post-2015). This heatmap displays the coefficient $\Omega_1^{Clim,Char}$ relating post-2015 returns of β^{Clim}-sorted portfolios to nature dependence-sorted portfolios, showing a positive relationship for water-related dependencies but with less significance. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

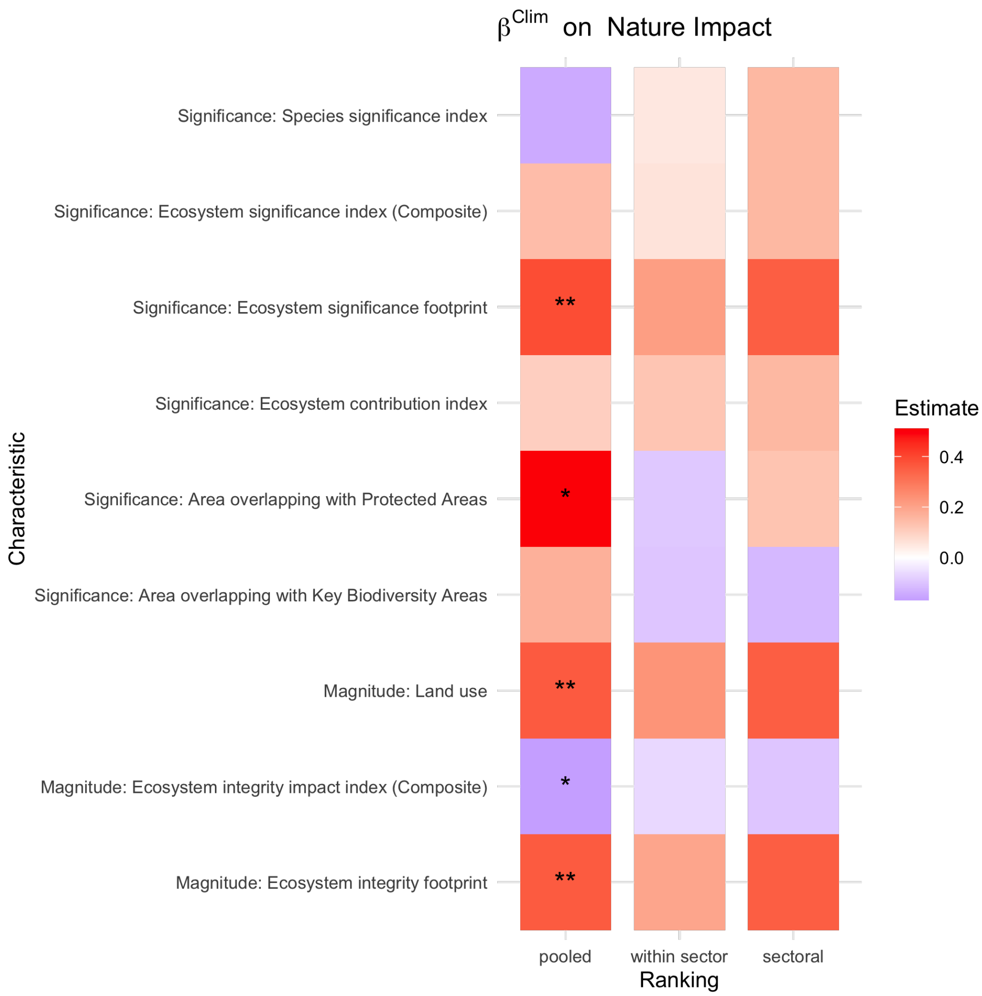

Figure F.8: Climate Beta-Sorted vs. Nature Impact-Sorted Portfolio Return Correlation (Post-2015). This heatmap displays the coefficient $\Omega_1^{Clim,Char}$ relating post-2015 returns of β^{Clim}-sorted portfolios to nature impact-sorted portfolios. The coefficients in column "pooled" correspond to pooled rankings and are estimated with firm and time fixed effects. The coefficients in column "within sector" correspond to within-sector rankings and are estimated with firm and time fixed effects. The coefficients in column "sectoral" correspond to sector rankings and are estimated with sector and time fixed effects. All standard errors are clustered by firm and month-year. Significance levels are indicated by stars (*: p-value < 0.1, **: p-value < 0.01, ***: p-value < 0.001).

G 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.

H 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

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

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

$$K_{t+1} = Q\,C^\top \big(C\,Q\,C^\top + R\big)^{-1}, \qquad Q = \begin{bmatrix} \sigma_n^2 & 0 \\ 0 & \sigma_z^2 \end{bmatrix}, \quad R = \begin{bmatrix} 1/\phi^N_t & 0 \\ 0 & 1/\phi^Z_t \end{bmatrix}. \tag{23}$$

Plugging C, Q, and R into (23) and inverting the 2×2 matrix $CQC^\top + R$ produces the explicit formulas

$$\begin{aligned} a_{NN} &= \frac{\sigma_n^2 w_N \phi^N_t + \sigma_n^2 (1 - w_Z)\phi^Z_t}{\Delta}, \qquad & a_{NZ} &= \frac{\sigma_n^2 (1 - w_N)\phi^N_t + \sigma_n^2 w_Z \phi^Z_t}{\Delta}, \\ a_{ZN} &= \frac{\sigma_z^2 (1 - w_N)\phi^N_t + \sigma_z^2 w_Z \phi^Z_t}{\Delta}, \qquad & a_{ZZ} &= \frac{\sigma_z^2 w_N \phi^N_t + \sigma_z^2 (1 - w_Z)\phi^Z_t}{\Delta}, \end{aligned} \tag{24}$$

where $\Delta = \big(w_N^2 \sigma_n^2 + (1 - w_N)^2 \sigma_z^2\big)\phi^N_t + \big((1 - w_Z)^2 \sigma_n^2 + w_Z^2 \sigma_z^2\big)\phi^Z_t$. Equation (24) confirms that the mapping from signal innovations to state surprises depends only on *observable* objects $(w_N, w_Z, \sigma_n^2, \sigma_z^2, \phi^N_t, \phi^Z_t)$; all structural parameters of the production side drop out. In particular, when $w_N = w_Z = \frac{1}{2}$ and $\phi^N_t = \phi^Z_t$, 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.