Maladaptation Traps: Portfolio Choice Across Engineered and Nature-Based Climate Adaptation

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Firms adapt to extreme heat through engineered cooling or nature-based solutions, yet these technologies fail differently: grey capital fails systemically when collective demand overwhelms the grid, while green capital fails permanently when ecological thresholds are crossed. Existing theory examines technologies in isolation. We model portfolio choice under smooth ambiguity, where a grid externality operates through capital stock composition: each firm's installed cooling capacity raises blackout probability for all firms. The Nash equilibrium features overinvestment in grey; strategic complementarity can generate multiple equilibria. In an illustrative calibration to UK commercial property, welfare losses are in the range of 8 to 12 percent, decomposing into the unpriced externality, ambiguity-driven under-diversification, and coordination failure. Diversified portfolios reduce catastrophic failure probability from over 25 percent for corner allocations to near zero, yielding an adaptation value gap of about 2.6 percent relative to the best single technology allocation. In that calibration, a peak-demand charge shifts composition from 65 to 52 percent grey and captures about 60 percent of the welfare gains. The framework predicts differential portfolio responses to blackout events versus ecological mortality. (*JEL* D62, D81, G11, H23, Q54)

1. Introduction

Extreme heat poses material physical risks to firms. Adaptation is fundamentally a portfolio problem: firms may invest in engineered solutions such as air conditioning (which we term grey capital) or in nature-based solutions such as urban trees (green capital). These two classes of technology fail in quite different ways. Grey capital depends on grid reliability; when temperatures spike, aggregate cooling demand can overwhelm the grid, causing systemic failure across all firms simultaneously. Green capital is vulnerable to ecological thresholds; sustained heat can kill vegetation irreversibly. Existing analyses of adaptation investment examine optimal timing and design for individual

adaptation measures, such as coastal defence (Linquiti and Vonortas, 2012) or flood protection infrastructure (Eijgenraam et al., 2017). We extend this framework to portfolio choice across technologies with heterogeneous failure profiles.

The stakes are considerable. Extreme heat costs European economies between 0.3 and 0.5 percent of GDP in severe heatwave years and caused over 61,000 excess deaths in summer 2022 (García-León et al. 2021; Ballester et al. 2023). During the July 2022 UK heatwave, the National Grid's Loss of Load Probability reached 69.5 percent (Cornwall Insight, 2022). That same summer, widespread urban tree damage across Europe, with up to 80 percent of street trees exhibiting leaf scorch, premature defoliation, or branch dieback, demonstrated that nature-based solutions carry their own vulnerabilities (Haase and Hellwig, 2022). The question before us is not whether to adapt, but how to compose adaptation portfolios that remain robust when hazards materialise.

This paper develops a portfolio framework for adaptation investment under ambiguity about climate trajectories and the resilience of infrastructure and ecological systems. We characterise optimal portfolios, identify the externality that drives a wedge between private and social investment choices, and derive implications for firm value through what we call the adaptation value gap, defined as the diversification premium relative to the best single technology allocation.

Our central finding is that diversification substantially reduces the probability of catastrophic adaptation failure, yet decentralised investment leads to systematic over-reliance on grey capital. In our illustrative calibration, diversified portfolios sharply lower maladaptation-trap risk relative to green-heavy or grey-heavy allocations (Table 3). The Nash equilibrium generates welfare losses of 8 to 12 percent, and the adaptation value gap averages about 2.6 percent of firm value (95 percent confidence interval: 2.1 to 2.9 percent) relative to the best single technology allocation. A suitably designed peak-demand charge shifts portfolio composition from 65 to 52 percent grey, capturing about 60 percent of available welfare gains.

The framework illuminates what we call the *adaptation paradox*: private adaptation can increase aggregate climate risk by stressing shared infrastructure precisely when protection is most needed. We identify two distinct maladaptation traps. In a *green irreversibility trap*, firms that invest heavily in nature-based solutions face permanent capital loss when ecological thresholds are crossed. In a *grey coordination trap*, collective reliance on mechanical cooling triggers systemic grid failure during extreme heat. The grey trap constitutes a coordination failure: each firm's investment is privately optimal given others' choices, yet a Pareto-superior equilibrium with lower aggregate grey capital exists.

The model features firms investing in grey and green capital to reduce heat-related damages, with temperature following a jump-diffusion process. Grey effectiveness depends on both temperature (through thermodynamic efficiency losses) and grid status (blackouts eliminate protection entirely). Green effectiveness depends on temperature (heat stress reduces cooling capacity) and survival status (mortality above ecological thresholds is permanent). The central innovation is that grid failure probability depends on aggregate grey capital across all firms: each firm's cooling demand increases blackout risk for everyone. Firms hold smooth ambiguity preferences (Klibanoff, Marinacci, and Mukerji, 2005) over climate trajectories and infrastructure-ecology resilience, allowing us to isolate how deep uncertainty shapes portfolio choice.

The model's mechanisms are grounded in documented physical and economic relationships. Peak electricity demand for cooling increases by 2 to 4 percent per degree Celsius above threshold temperatures (Santamouris et al. 2015; Akbari, Pomerantz, and Taha 2001). Electricity demand increases by approximately 3 percent per degree Celsius above 21°C under moderate warming scenarios (Auffhammer, Baylis, and Hausman, 2017). Thermal power plants derate by 0.5 to 1 percent per degree Celsius above design temperatures (Mideksa and Kallbekken, 2010). The welfare decomposition identifies three sources of inefficiency: the unpriced grid externality (45 percent of the welfare gap), suboptimal diversification under ambiguity (30 percent), and elevated trap risk from coordination failure (25 percent); Section 5 details the methodology. Each component maps to a distinct policy instrument.

Our contribution may be summarised in four points. First, we model portfolio choice across adaptation technologies with heterogeneous failure mechanisms, introducing diversification motives that arise from differential failure timing and permanence rather than return covariance. Diversification benefits stem from the asymmetric tail risks of systemic temporary failure (grid blackouts) versus idiosyncratic permanent failure (ecological mortality), creating path dependence absent in standard portfolio models. Second, we formalise the grid externality in adaptation investment: coordinated grey capital demand creates negative spillovers through capacity constraints, distinct from standard peak pricing because the externality operates through capital stock composition rather than usage timing. Third, we extend smooth ambiguity preferences to climate, infrastructure reliability, and ecological resilience jointly, generating comparative statics on ambiguity aversion that robust optimisation cannot produce. Fourth, we demonstrate that adaptation strategy, not merely exposure, affects firm valuation and implies a cross-sectional expected return premium for grey-heavy portfolios. The adaptation paradox we identify parallels mechanisms in financial systemic risk (Brunnermeier and Pedersen,

2009): individually rational hedges can amplify tail risk by concentrating demand on scarce capacity.

It is useful to be explicit about what is new relative to known building blocks. A model that simply combines portfolio diversification with a congestion externality would predict overuse of the congested technology and a general motive to diversify. Our framework yields a sharper, event conditional prediction: heatwave blackouts shift portfolios toward green, while ecological mortality events shift them toward grey. This asymmetry does not arise without irreversible ecological loss, time-to-build delays, and ambiguity about thresholds. These elements create path dependence in portfolio adjustment and the two distinct trap mechanisms that our model highlights.

Section 1.1 reviews the related literature. Section 2 develops the model. Section 3 characterises equilibrium. Section 4 presents the main results. Section 5 provides calibrated numerical illustrations. Section 6 concludes.

1.1 Relation to the Literature

This paper engages with several strands of the literature. We adopt the treatment of irreversibility and option value developed by Arrow and Fisher (1974) and Dixit and Pindyck (1994), and draw on their application to climate problems by Pindyck (2000, 2002), Lemoine and Traeger (2014, 2016), and Dietz and Stern (2015). Within the adaptation literature, Linquiti and Vonortas (2012), Eijgenraam et al. (2017), and Nassopoulos, Dumas, and Hallegatte (2012) analyse optimal timing and design for individual adaptation measures under uncertainty. We extend this single-measure approach to portfolio choice across technologies with heterogeneous failure profiles. We also draw on the empirical literature on climate impacts and adaptation, reviewed comprehensively by Carleton and Hsiang (2016) and Heal and Park (2016), with important empirical contributions from Deschenes and Greenstone (2011), Barreca et al. (2016), and Carleton et al. (2022). Our framework complements this evidence by linking heat exposure to infrastructure fragility and ecological thresholds, yielding testable predictions about how firms respond differently to heatwave blackouts than to green mortality events.

Our approach differs from spatial allocation models that optimise predetermined intervention bundles across locations. We address adaptation as an economic choice problem in which individual decisions create collective vulnerabilities through strategic externalities. The grid externality we model differs from standard peak demand pricing because the spillover operates through capital stock composition rather than usage timing, creating a coordination problem in portfolio selection. Whilst robust optimisation methods address parametric uncertainty

in infrastructure planning, smooth ambiguity preferences permit us to separate attitudes toward risk and ambiguity, generating comparative statics on ambiguity aversion not available under maximin or minimax regret criteria. The joint treatment of climate uncertainty, infrastructure reliability uncertainty, and ecological threshold uncertainty within a portfolio framework requiring coordination across these dimensions constitutes our methodological contribution.

We extend work on ambiguity and investment decisions (Gilboa and Schmeidler 1989; Klibanoff, Marinacci, and Mukerji 2005, 2009) to systems that couple climate, infrastructure, and ecology, generating novel comparative statics including non-monotonic relationships between grid ambiguity and green investment. We connect the literature on infrastructure reliability (Joskow 2006; Borenstein 2002) to corporate adaptation decisions, showing how decentralised portfolio choices create collective vulnerability through congestion externalities in grid capacity. Finally, we provide theoretical foundations for ongoing policy debates on nature-based solutions (Seddon et al. 2020; Dasgupta 2021), characterising conditions under which green adaptation is attractive, fragile, or both.

Adjacent literatures provide important building blocks. Ecological insurance and response diversity emphasize diversification benefits from asynchronous responses to environmental fluctuations, and recent work on natural climate solution portfolios formalizes the role of uncorrelated failure risks (Cerasoli and Porporato, 2025; Elmqvist et al., 2003; Loreau et al., 2021; Yachi and Loreau, 1999). That work focuses on mitigation portfolios, whereas our focus is corporate adaptation with a grid externality and pricing implications. Urban climatology documents feedbacks from cooling capacity to heat stress and grid vulnerability (Salamanca et al., 2014; Stone et al., 2021). The maladaptation and lock-in literature highlights path dependence in long-lived infrastructure (Barnett and O'Neill, 2010; Unruh, 2000). We draw on these insights but integrate them in a corporate investment model that couples portfolio choice, a grid externality, and ambiguity, and that delivers a distinct set of equilibrium and pricing implications.

2. Model Setup

2.1 Risk versus ambiguity

Firms facing extreme heat choose total adaptation spending and its split across technologies. Uncertainty concerns both temperature paths and whether the grid and local ecology remain reliable in extreme states. This calls for a framework that separates risk within a model from ambiguity across models.

Following Knight (1921), Gilboa and Schmeidler (1989), and Klibanoff, Marinacci, and Mukerji (2005), outcomes are risky conditional on a model, while the model itself is ambiguous. Smooth ambiguity preferences let us distinguish attitudes toward risk from attitudes toward ambiguity, which matters for portfolio choice. The Online Appendix provides formal definitions and extends the ambiguity set to allow correlation across domains.

2.2 Environment

Time is continuous, $t \in [0,\infty)$. A representative firm produces output using labor and capital, with production subject to heat-related damage. The firm can invest in grey adaptation capital K_G and green adaptation capital K_N to reduce damages.

Climate state: Let T_t denote the local temperature anomaly in °C relative to a baseline $\bar{T}$. Absolute temperature is $\tilde{T}_t = T_t + \bar{T}$. For readability, we write T_t for absolute temperature throughout, implicitly adding the baseline (approximately 15°C for the UK) to all threshold comparisons. Temperature follows a jump diffusion process:

$$dT_t = \mu_T dt + \sigma_T dW_t + dJ_t \tag{1}$$

where μ_T is the drift (trend warming), σ_T is diffusion volatility (interannual variability), W_t is a standard Brownian motion, and J_t is a compound Poisson process capturing extreme heat events with intensity λ_J and jump size distribution F_J.

Production and damages: Absent adaptation, instantaneous profit is:

$$\pi_0(T_t) = \bar{\pi} - D(T_t) \tag{2}$$

where $\bar{\pi}$ is baseline profit and $D(T)$ is the damage function. Consistent with the nonlinear temperature-productivity relationships documented by Burke, Hsiang, and Miguel (2015) and Somanathan et al. (2021), we adopt a threshold-based specification:

$$D(T) = \begin{cases} 0 & \text{if } T < T^* \\ \delta \cdot (T - T^*)^\gamma & \text{if } T \geq T^* \end{cases} \tag{3}$$

where T^* is the damage threshold, $\delta > 0$ scales damage magnitude, and $\gamma \geq 1$ captures damage convexity. Following UK building standards and thermal comfort research, we set $T^* \approx 25$°C (CIBSE 2015; Seppänen et al. 2006).

We use $x^+ = \max\{x, 0\}$ throughout.

2.3 Grey adaptation capital

Grey capital K_G represents conventional engineered adaptation. Examples include air conditioning, mechanical ventilation, building retrofits, and cool roofs.

Costs: The investment cost is C_G per unit and the operating cost is m_G per unit per period. Grey capital depreciates at rate δ_G. It can be resold at price $(1-\kappa_G)C_G$, so $\kappa_G \in [0,1]$ captures reversibility.

State-dependent effectiveness: Grey capital effectiveness depends on temperature and grid status:

$$\theta_G(T_t, G_t) = \bar{\theta}_G \cdot \eta(T_t) \cdot G_t \tag{4}$$

where $\bar{\theta}_G \in (0,1)$ is maximum effectiveness. The function $\eta(T_t) = \max\{1 - \alpha_G(T_t - T^{eff})^+, \underline{\eta}\}$ captures efficiency losses. The threshold T^{eff} is approximately 30°C. The slope α_G is about 2 to 4 percent per °C. The term $\underline{\eta} > 0$ is a minimum efficiency. Grid status is $G_t \in \{0,1\}$, with one for normal operation and zero for blackout.

Grid failure: The central mechanism is that grid status depends on aggregate conditions. Let R_t denote the grid reserve margin:

$$R_t = S(T_t) - D^{agg}(T_t, K_G^{agg}) \tag{5}$$

Here $S(T_t) = \bar{S} \cdot (1 - \beta_S(T_t - T^S)^+)$ is temperature-dependent supply capacity, where $\bar{S}$ is baseline capacity and β_S is the derating rate. Aggregate electricity demand is $D^{agg}(T_t, K_G^{agg}) = D_0(T_t) + \psi \cdot K_G^{agg}$, where ψ is the marginal demand effect of grey capital and $K_G^{agg} = \int K_{G,i} di$ is aggregate grey capital across firms. We take $D_0(T_t) = \xi(T_t - T^D)^+$ as baseline temperature-sensitive demand, where ξ is the baseline demand sensitivity and T^D is the demand threshold, and we take T^S as the supply derating threshold.

Grid status is stochastic, with blackout probability increasing as reserves fall:

$$\mathbb{P}(G_t = 0 | T_t, K_G^{agg}) = \Phi\left(\frac{-R_t}{\sigma_R}\right) \tag{6}$$

where Φ is the standard normal CDF and σ_R captures grid operational uncertainty.

The systemic-risk externality: Each firm's grey capital $K_{G,i}$ increases aggregate demand D^{agg}, reduces reserve margin R_t, and raises blackout probability for all firms. This externality is central to the analysis. We treat grid capacity $\bar{S}$ as exogenous; Section 6 discusses implications of endogenous capacity investment.

2.4 Green adaptation capital

Green capital K_N represents nature-based solutions. Examples include urban trees, green roofs, constructed wetlands, and biodiversity corridors.

Costs: The investment cost is $C_N < C_G$ per unit and the operating cost is $m_N < m_G$ per unit per period. Green capital depreciates at rate δ_N. Full effectiveness is reached after a maturation lag τ_N that reflects

the time for trees to mature. We denote irreversibility by κ_N and take κ_N close to one, so planted trees cannot be sold. We treat K_N as the effective mature stock and let new investment enter after the time-to-build lag.

Co-benefits: Green capital provides additional value B_N per unit per period from carbon sequestration, biodiversity support, amenity value, and stormwater management.

State-dependent effectiveness: Green capital effectiveness depends on temperature:

$$\theta_N(T_t) = \bar{\theta}_N \cdot h(T_t) \tag{7}$$

where $\bar{\theta}_N \in (0,1)$ is maximum effectiveness and $h(T_t)$ captures heat stress effects:

$$h(T_t) = \begin{cases} 1 & \text{if } T_t < T^{**} \\ e^{-\lambda_h (T_t - T^{**})} & \text{if } T_t \geq T^{**} \end{cases} \tag{8}$$

where T^{**} is the stress threshold of about 32°C above which effectiveness degrades, and λ_h controls the degradation rate.

Mortality risk: Green capital faces permanent mortality above a threshold $\hat{T}$:

$$\mathbb{P}(K_N^i \text{ dies at } t | T_t, K_N^i \text{ alive}) = \begin{cases} 0 & \text{if } T_t < \hat{T} \\ q \cdot (T_t - \hat{T}) \cdot dt & \text{if } T_t \geq \hat{T} \end{cases} \tag{9}$$

where $\hat{T}$ is the mortality threshold of about 38°C for common urban trees and q controls mortality intensity. Mortality is irreversible for the existing stock. Dead green capital provides no protection. Firms can replant, but new investment becomes effective only after the maturation lag τ_N. For example, effectiveness scales with $\min\{1, (s-t)/\tau_N\}$ for plantings at time t.

Partial idiosyncrasy: Unlike grey capital's systemic grid failure, green capital mortality has an idiosyncratic component. Microclimate variation, species differences, and local soil and water conditions mean that green capital survival is imperfectly correlated across firms:

$$\text{Corr}(\mathbf{1}_{\{K_N^i > 0\}}, \mathbf{1}_{\{K_N^j > 0\}}) = \rho_N < 1 \tag{10}$$

2.5 Adapted profit function

With both capital types in place, instantaneous profit is:

$$\pi(T_t, K_G, K_N, G_t) = \bar{\pi} - D(T_t) \cdot [1 - \theta_G(T_t, G_t) \cdot K_G - \theta_N(T_t) \cdot K_N]^+ + B_N \cdot K_N - m_G \cdot K_G - m_N \cdot K_N \tag{11}$$

Adaptation reduces damages multiplicatively, with a floor at zero. Figure 1 summarizes the model's causal structure.

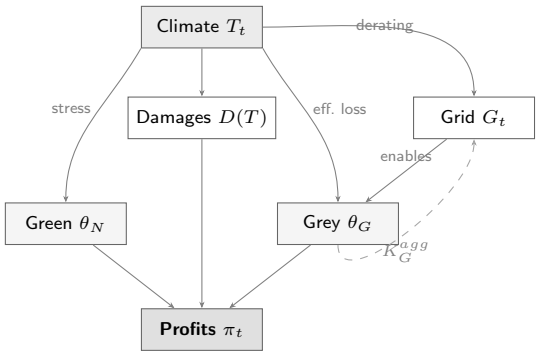


Figure 1
Model architecture. Climate affects damages directly and capital effectiveness through heat stress (green) and efficiency losses (grey). Grey capital requires grid availability; aggregate grey investment stresses the grid (dashed feedback loop), creating a negative externality.

2.6 Information structure and core ambiguity

To keep the main text focused, we work with two core sources of ambiguity and defer richer dependence structures to the Online Appendix.

Level 1: Climate trajectory ambiguity. The drift parameter μ_T is unknown. The firm has a set of priors $\mathcal{P}_1$ corresponding to different climate scenarios such as IPCC SSP1 to 2.6 through SSP5 to 8.5. Let $p \in \mathcal{P}_1$ index specific climate priors.

Level 2: Infrastructure and ecology ambiguity. The joint resilience of ecological and infrastructure systems is uncertain. We summarize this with a set of priors $\mathcal{P}_2$ over a composite state s that captures ecological thresholds $\hat{T}$ and grid resilience parameters $(\bar{S}, \sigma_R)$, treating them as draws from a joint distribution without specifying microfoundations for their covariation. Let $s \in \mathcal{P}_2$ index these priors.

Core ambiguity set:

$$\mathcal{P} = \{(p,s) : p \in \mathcal{P}_1, s \in \mathcal{P}_2\} \tag{12}$$

The Online Appendix splits s into separate ecological and grid priors and adds correlation ambiguity across domains. The qualitative mechanisms in the main text are unchanged.

2.7 Preferences

The firm has smooth ambiguity preferences (Klibanoff, Marinacci, and Mukerji, 2009) over the core ambiguity set. Let P_m denote the probability measure over outcomes induced by model $m = (p,s) \in \mathcal{P}$. The lifetime value is:

$$V = \int_{\mathcal{P}} \phi\left(\mathbb{E}_{P_m}\left[\int_0^\infty e^{-\rho t} u(\pi_t)\, dt\right]\right) d\nu(m) \tag{13}$$

where $u(\cdot)$ is instantaneous utility and is increasing. We take $u(\pi)=\pi$ to focus on ambiguity. The discount rate is $\rho>0$. The measure ν is the second-order belief over the ambiguity set $\mathcal{P}$. The function ϕ is increasing and its concavity captures *ambiguity aversion*. For comparative statics, we index ambiguity aversion by a scalar α so that larger α corresponds to a more concave ϕ. Expectations are taken under the probability measure induced by model m.

This separation between u and ϕ allows us to distinguish risk aversion from ambiguity aversion. If ϕ is linear, the criterion reduces to subjective expected utility. As ϕ becomes more concave, ambiguity aversion increases, and in the limit it approaches maxmin expected utility (Gilboa and Schmeidler, 1989). We focus on ambiguity aversion, and the results extend to concave u.

Learning dynamics and sequencing implications are described in the Online Appendix (Section 3).

With the economic environment and information structure in place, we now turn to equilibrium. We begin with a stylized benchmark that delivers closed-form portfolio shares and explicit thresholds, then analyze the full dynamic model.

3. Equilibrium Analysis

3.1 A stylized static benchmark

To sharpen the equilibrium characterization, we first consider a static benchmark in which a firm allocates a unit of adaptation capital between grey and green. Let $\alpha_G \in [0,1]$ denote the grey share (so $\alpha_N = 1-\alpha_G$). Grey capital delivers effectiveness θ_G when the grid is available; green capital delivers effectiveness θ_N when ecological thresholds are not breached. We capture grid stress with a local linearization of blackout probability around a baseline reserve margin:

$$p_B \approx \bar{p}_B + \psi n \alpha_G, \tag{14}$$

where $\bar{p}_B$ summarizes baseline grid stress (lower $\bar{S}$ implies higher $\bar{p}_B$), ψ is the marginal demand effect of grey capital, and n is the number of firms. Ecological ambiguity enters through the effective green failure probability p_E, defined as the probability that the ecological threshold is crossed in a given period under the relevant climate model. Firms face convex adjustment costs with curvature $c_G, c_N > 0$.

The firm's static objective is:

$$U(\alpha_G) = \theta_G(1-p_B)\alpha_G + \theta_N(1-p_E)(1-\alpha_G) - \frac{c_G}{2}\alpha_G^2 - \frac{c_N}{2}(1-\alpha_G)^2. \tag{15}$$

Proposition 1 (Closed-form grey share). In the static benchmark (15) with linearized blackout probability (14), the optimal grey share is

$$\alpha_G^* = \frac{\theta_G(1-\bar{p}_B) - \theta_N(1-p_E) + c_N}{c_G + c_N + 2\theta_G \psi n}. \tag{16}$$

Comparative statics follow directly: $\partial \alpha_G^* / \partial \bar{p}_B < 0$, $\partial \alpha_G^* / \partial p_E > 0$, and $\partial \alpha_G^* / \partial(\psi n) < 0$.

The mechanism is simple. Higher grid stress or a stronger externality reduces the reliability of grey capital and shifts the portfolio toward green. Greater ecological ambiguity makes green riskier and shifts the portfolio toward grey.

Proposition 2 (Multiplicity threshold in static coordination). Suppose blackout probability is S-shaped in aggregate grey, for example

$$p_B = \Phi\left(\frac{\psi n \alpha_G - \bar{S}}{\sigma_R}\right), \tag{17}$$

and the firm's objective is locally quadratic with curvature κ around an interior solution. A sufficient condition for multiple equilibria is

$$n > n^* \equiv \frac{\kappa \sigma_R}{\psi \varphi(0) \mathbb{E}[L^{blackout}]}, \tag{18}$$

where φ is the standard normal density and $L^{blackout}$ is the per firm loss in blackout states, defined as the damage flow when $G_t = 0$ and protection is unavailable. Equivalently, for fixed n, multiplicity arises when effective grid capacity $\bar{S}$ is low enough that the economy operates near the reserve margin kink.

Multiplicity requires a strong feedback from aggregate grey investment to blackout risk. Large n, high ψ, and large blackout losses steepen the best response sufficiently to generate both low grey and high grey fixed points.

The dynamic model adds path dependence through time-to-build and irreversible ecological loss, which governs trap entry and portfolio sequencing and is absent from the static benchmark.

3.2 Individual firm optimization

Given aggregate grey capital K_G^{agg}, each firm solves:

$$V(T, K_G, K_N; K_G^{agg}) = \max_{i_G, i_N} \int_{\mathcal{P}} \phi\Big(\mathbb{E}_{P_m}\Big[\int_0^\infty e^{-\rho t} \times u(\pi(T_t, K_{G,t}, K_{N,t}, G_t) - C_G i_{G,t} - C_N i_{N,t})\, dt\Big]\Big) d\nu(m) \tag{19}$$

subject to capital dynamics:

$$dK_G = (i_G - \delta_G K_G)dt \tag{20}$$

$$dK_N = (\tilde{i}_N - \delta_N K_N)dt - K_N \cdot dM_t \tag{21}$$

where M_t is the mortality process for green capital and $\tilde{i}_N$ denotes the investment flow chosen at time t that becomes effective at $t+\tau_N$.

3.3 Dynamic programming representation

For each model $m \in \mathcal{P}$, define the value function $V^m(T, K_G, K_N)$ and expected flow profit

$$\bar{\pi}^m(T, K_G, K_N; K_G^{agg}) = (1 - p_B^m)\pi(T, K_G, K_N, G=1) + p_B^m \pi(T, K_G, K_N, G=0), \tag{22}$$

where $p_B^m = \Phi(-R_t/\sigma_R^m)$ is the blackout probability implied by model m. Parameters with superscript m denote model-specific values of μ_T^m, σ_R^m, and λ_J^m within the ambiguity set. With the green time-to-build lag, the control is a delayed investment flow $i_N(t-\tau_N)$. Let $\tilde{i}_N$ denote the decision at time t that becomes effective at $t+\tau_N$.[1] The HJB can be written as:

$$\begin{aligned} \rho V^m = \max_{i_G, \tilde{i}_N} \Big\{ & u\big(\bar{\pi}^m - C_G i_G - C_N \tilde{i}_N\big) + V_T^m \mu_T^m + \tfrac{1}{2}\sigma_T^2 V_{TT}^m \\ & + V_{K_G}^m (i_G - \delta_G K_G) + V_{K_N}^m (\tilde{i}_N - \delta_N K_N) \\ & + \lambda_J^m \mathbb{E}[V^m(T+J, K_G, K_N) - V^m(T, K_G, K_N)] \\ & + \lambda_M^m(T)[V^m(T, K_G, 0) - V^m(T, K_G, K_N)] \Big\}, \end{aligned} \tag{23}$$

where $\lambda_M^m(T) = q_m(T - \hat{T}_m)^+$ is mortality intensity and q_m is the model-specific mortality slope.

The smooth ambiguity aggregator is $V = \int_{\mathcal{P}} \phi(V^m) d\nu(m)$.

With linear u, interior optimality yields $V_{K_G}^m = C_G$ and $V_{K_N}^m = C_N$.

Lemma 1 (Regularity of the HJB). Under the regularity and concavity conditions listed in Appendix B and standard growth bounds on π, the HJB admits a unique viscosity solution that is concave in (K_G, K_N); see, for example, Fleming and Soner (2006) and Yong and Zhou (1999). The first order conditions are sufficient for optimality.

[1] Formally, the state can be augmented with a pipeline of committed green investment over $[t, t+\tau_N]$, or the delayed control can be treated as predetermined on that interval. The reduced-form notation here is standard in models with time-to-build.

3.4 Nash equilibrium

In symmetric equilibrium, all firms choose the same portfolio, so $K_G^{agg} = n \cdot K_G$ where n is the number of firms.

A **symmetric Nash equilibrium** is a portfolio (K_G^*, K_N^*) such that no firm can increase its value by unilaterally deviating, given that all other firms choose (K_G^*, K_N^*).

The equilibrium condition requires:

$$\left.\frac{\partial V}{\partial K_G}\right|_{K_G^{agg} = n \cdot K_G^*} = C_G \tag{24}$$

$$\frac{\partial V}{\partial K_N} = C_N \tag{25}$$

3.5 Existence and uniqueness

We establish conditions under which equilibria exist and characterize their properties.

Proposition 3 (Existence of equilibrium). Under the regularity and concavity conditions in Appendix B, a symmetric Nash equilibrium exists. Specifically:

- The strategy space $\mathcal{K} = [0, \bar{K}_G] \times [0, \bar{K}_N]$ is compact and convex.
- The value function $V(K_G, K_N; K_G^{agg})$ is continuous in all arguments.
- The best response correspondence $BR: \mathcal{K}^{n-1} \rightrightarrows \mathcal{K}$ is upper hemicontinuous with nonempty, convex values.

By Kakutani's fixed point theorem, a symmetric equilibrium (K_G^*, K_N^*) exists.

Proof. See Appendix A. ■

Compact strategy sets and concave payoffs make best responses continuous and guarantee a fixed point.

The presence of the grid externality creates strategic complementarity in grey capital choice, potentially generating multiple equilibria.

Grey capital choices exhibit strategic complementarity if $\frac{\partial^2 V}{\partial K_G \partial K_G^{agg}} > 0$: a firm's marginal value of grey capital increases when other firms invest more in grey.

Proposition 4 (Conditions for multiplicity). Multiple symmetric equilibria exist when strategic complementarity is sufficiently strong:

$$\frac{\partial^2 V}{\partial K_G \partial K_G^{agg}} > -\frac{\partial^2 V}{\partial K_G^2} \tag{26}$$

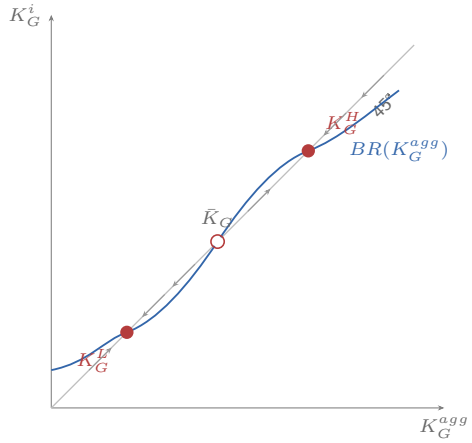


Figure 2
Best response and multiple equilibria. The best response function $BR(K_G^{agg})$ shows how a firm's optimal grey capital depends on aggregate grey investment. Strategic complementarity creates an S-shaped curve that crosses the 45° line at three points: a stable low grey equilibrium K_G^L, an unstable threshold $\bar{K}_G$, and a stable high grey equilibrium K_G^H. Arrows indicate adjustment dynamics.

In this case, there exist at least two stable equilibria:

- A **low grey equilibrium** (K_G^L, K_N^L) with low blackout risk and high green share.
- A **high grey equilibrium** (K_G^H, K_N^H) with elevated blackout risk and low green share.

The high grey equilibrium is Pareto inferior, yet it may be the stable outcome under some initial conditions.

Proof. See Appendix A. ■

This multiplicity is the core coordination problem. When aggregate grey investment is high, blackout risk rises and green becomes less effective in the most stressful states, so each firm finds additional grey privately optimal even though the collective outcome is fragile. When aggregate grey is low, the grid remains reliable and green remains valuable, making a low grey equilibrium self sustaining.

A sufficiently steep best response curve yields both low and high grey fixed points.

Figure 2 illustrates the equilibrium structure when strategic complementarity generates multiplicity.

We refer to the unstable fixed point in Figure 2 as $\bar{K}_G$.

Proposition 5 (Uniqueness conditions). The Nash equilibrium is unique when any of the following conditions hold:

- **Weak grid stress**: Grid capacity $\bar{S}$ is sufficiently large that $\partial\pi/\partial K_G^{agg} \approx 0$ for all feasible aggregate grey capital levels.
- **Strong green effectiveness**: $\bar{\theta}_N$ is sufficiently high that green capital dominates grey at the margin for all temperature realizations below the mortality threshold.
- **Dominant ambiguity about ecological thresholds**: Ambiguity aversion α is high and the variance of $\hat{T}$ dominates the variance of grid capacity, making green capital sufficiently risky that grey dominates.
- **Small number of firms**: $n < n^*$ where n^* is characterized by the condition that individual firm contribution to aggregate demand is large enough to internalize the externality.

Proof. See Appendix A. ■

Any condition that weakens strategic complementarity makes the best response a contraction. In the calibration, the binding constraint is typically the number of firms: with many small firms, each internalises little of the externality, and multiplicity arises.

3.6 Equilibrium selection and transitions

When multiple equilibria exist, which outcome prevails depends on initial conditions and policy coordination.

Proposition 6 (History dependent selection). Under a standard best response adjustment process with adjustment costs, there exists a threshold $\bar{K}_G^{init}$ such that if initial aggregate grey capital $K_G^{agg}(0) > \bar{K}_G^{init}$, the economy converges to the high grey equilibrium; if $K_G^{agg}(0) < \bar{K}_G^{init}$, it converges to the low grey equilibrium.

Proof. See the Online Appendix. ■

Adjustment costs make history matter, so initial conditions determine which basin of attraction the economy enters.

Proposition 7 (Policy induced transition). There exists a temporary policy intervention (e.g., a subsidy $s_N > 0$ or a peak demand tax $\tau_G > 0$ for duration τ) that shifts the economy from the high grey equilibrium to the low grey equilibrium, after which the low grey equilibrium remains self-enforcing when the intervention is removed.

Proof. See the Online Appendix. ■

A temporary subsidy or tax can move the system across the unstable threshold into the low grey basin.

3.7 Comparative statics

Proposition 8 (Equilibrium comparative statics). In the unique equilibrium, or at the low grey equilibrium when multiple exist:

- $\frac{\partial K_G^*}{\partial \mu_T} > 0$: Faster warming increases grey investment.
- $\frac{\partial K_G^*}{\partial S} > 0$: Higher grid capacity increases grey investment (reduces externality).
- $\frac{\partial K_G^*}{\partial \alpha} > 0$: Higher ambiguity aversion increases grey investment.
- $\frac{\partial K_G^*}{\partial \sigma_{\hat{T}}} > 0$: Greater ecological threshold uncertainty increases grey investment, where $\sigma_{\hat{T}}$ is the standard deviation of $\hat{T}$ in the ambiguity set.
- $\frac{\partial K_N^*}{\partial B_N} > 0$: Higher co-benefits increase green investment.
- $\frac{\partial K_G^*}{\partial n} > 0$: More firms increases grey investment (externality less internalized).

Proof. See Appendix A. ■

Parameters that raise expected heat damages or reduce green reliability tilt optimal portfolios toward grey. The positive sign on ambiguity aversion reflects conditions in which ecological threshold uncertainty dominates grid uncertainty; when grid ambiguity is large, the relationship can be non-monotonic (Online Appendix, Proposition 11).

Proposition 9 (Externality wedge). In Nash equilibrium, the private marginal value of grey capital exceeds the social marginal value:

$$\frac{\partial V^{private}}{\partial K_G} > \frac{\partial V^{social}}{\partial K_G} \tag{27}$$

because firms ignore their contribution to aggregate blackout risk. The wedge is:

$$\text{Wedge} = \mathbb{E}\left[\frac{\partial \mathbb{P}(G=0)}{\partial K_G^{agg}} \cdot \text{Blackout Cost}\right] \cdot n \tag{28}$$

Proof. The private first order condition includes only the direct benefit of grey capital. The social planner additionally accounts for the marginal increase in blackout probability times the expected cost across all n firms. ■

Each firm ignores the congestion it imposes on the grid, so private incentives exceed social ones.

3.8 Social optimum

The social planner maximizes aggregate welfare:

$$W = \max_{K_G, K_N} n \cdot V(T, K_G, K_N; n \cdot K_G) \tag{29}$$

internalizing the grid externality.

Proposition 10 (Inefficiency of decentralized equilibrium). The Nash equilibrium features:

- Overinvestment in grey capital: $K_G^{Nash} > K_G^{Social}$.
- Underinvestment in green capital: $K_N^{Nash} < K_N^{Social}$.

relative to the social optimum.

Firms do not internalise the grid externality from grey capital, leading to excessive grey investment. Since grey and green are partial substitutes, this crowds out green investment. Green capital, which does not stress the grid, is underprovided from a social perspective.

With existence, multiplicity, and inefficiency established, we now turn to the core economic mechanisms: why diversification is optimal, how ambiguity shifts portfolios, and how traps emerge.

4. Implications of the Model

4.1 Portfolio diversification under ambiguity

Grey and green capital differ along four dimensions that matter for portfolio choice:

- **Failure triggers:** Grey fails when peak demand triggers grid collapse. Green fails when sustained heat crosses ecological thresholds.
- **Failure correlation:** Grey failure is systemic across firms during blackout. Green failure is only partially correlated across firms.
- **Failure duration:** Grey failure is temporary, typically hours to days. Green failure is permanent and recovery takes years.
- **Failure predictability:** Grid stress is forecastable. Ecological thresholds are uncertain and harder to predict.

Proposition 11 (Diversification rationale). Under ambiguity aversion, the optimal portfolio includes positive quantities of both grey and green capital even if one dominates in expected return, provided:

- Grey and green have different failure triggers (peak vs. sustained heat).
- Grey failure is systemic while green failure is partially idiosyncratic.
- The firm is sufficiently ambiguity averse.

The optimal grey share $\alpha_G^* = K_G/(K_G + K_N)$ satisfies:

$$\alpha_G^* \in (0,1) \text{ for all } \phi'' < \bar{\phi}'' \tag{30}$$

where $\bar{\phi}''$ depends on failure profile parameters. In the static benchmark, $\bar{\phi}''$ is higher when the expected return advantage of concentration is larger and lower when failure loss variances differ more; see Online Appendix Section 4.

Diversification here comes from **differential failure timing and mechanisms**, not from return correlation as in standard portfolio theory. Grey protects against brief spikes when green may be stressed but alive. Green protects against grid failures when grey becomes useless. Ambiguity aversion amplifies diversification motives because both failure modes involve deep uncertainty.

4.2 Temporal complementarity

Proposition 12 (Temporal complementarity). Grey and green capital provide protection on different time scales:

- Grey capital: High-frequency protection against temperature spikes (hours to days), but vulnerable to tail events that cause grid collapse.
- Green capital: Low-frequency protection against sustained moderate heat (seasonal), but vulnerable to threshold crossing during extremes.

The optimal portfolio weights depend on the **spectral composition of climate hazards**, that is, the relative frequency of short-duration spikes versus sustained heat episodes:

- If hazards are predominantly high-frequency spikes: higher grey share.
- If hazards are predominantly sustained heat: higher green share.
- If the hazard distribution has both components: diversification is optimal.

Grey is a high-frequency hedge against spikes, while green is a low-frequency hedge against sustained heat. The optimal mix tracks the hazard spectrum.

Climate change alters optimal portfolios not only by increasing hazard intensity but by shifting the spectral composition. Models projecting more sustained heatwaves favor green; models projecting more intense peaks favor grey.

4.3 Effects of ambiguity on portfolio choice

Proposition 13 (Ambiguity and grey share). Increased ambiguity aversion has nonmonotonic effects, and the sign depends on the source of ambiguity:

- Higher **climate trajectory ambiguity** increases the grey share because grey is more robust to trajectory uncertainty.
- Higher **ecological threshold ambiguity** increases the grey share because green becomes riskier.
- Higher **grid resilience ambiguity** reduces the grey share because grey becomes riskier.

Ambiguity shifts portfolios toward the technology that remains more reliable in the worst case models.

Correlation ambiguity effects and the U-shaped response to grid ambiguity are reported in the Online Appendix (Proposition 11).

Corollary 1 (Dominant ambiguity source). In the stylized benchmark, grid ambiguity dominates ecological ambiguity in determining α_G^* when $\theta_G \Delta p_B > \theta_N \Delta p_E$, where Δp_B and Δp_E denote the changes in blackout and ecological failure probabilities induced by a one standard deviation increase in the respective uncertainty. Ecological ambiguity dominates in the opposite case. In the calibration, grid capacity uncertainty is the most powerful driver when reserve margins are tight, while ecological ambiguity dominates when threshold uncertainty is large.

The dominant ambiguity source is simply the one that perturbs effective protection the most at the margin.

4.4 Necessity of core assumptions

Proposition 14 (Necessity of a portfolio approach). If both blackout risk and ecological threshold risk are strictly positive and failure modes are not perfectly correlated, any single asset portfolio leaves a strictly positive probability of maladaptation. A diversified portfolio strictly reduces trap probability relative to either corner portfolio.

Table 1
Key drivers of the main results

Result	Primary drivers
Multiplicity / coordination trap	$n, \psi, \bar{S}, \sigma_R, \mathbb{E}[L^{blackout}]$
Diversification motive	p_B, p_E, failure asymmetry, irreversibility
Ambiguity shifts	$\mathrm{Var}(\hat{T}), \mathrm{Var}(\bar{S}), \phi''$
Value gap	trap probability, unprotected losses, persistence

When grey and green fail for different reasons, exposure to only one technology leaves an unhedged failure mode.

Proposition 15 (Risk only benchmark). If ϕ is linear (expected utility), the externality wedge and multiplicity conditions remain, but ambiguity-driven effects disappear. The grid ambiguity response that is nonmonotonic (Online Appendix) vanishes and portfolio shares depend only on expected failure probabilities.

Without ambiguity aversion, agents price only expected losses within a model, so ambiguity-induced hedging motives are absent.

Corollary 2 (Externality necessity). If $\psi = 0$ (no grid externality), decentralized and social optima coincide and the grey coordination trap cannot arise.

4.5 Core drivers of the main results

To clarify which parameters matter for each mechanism, Table 1 lists the core drivers of the main results and distinguishes them from calibration details.

It is also useful to state which assumptions are essential for each result. Multiplicity and the grey coordination trap require the grid externality and strategic complementarity in grey investment. The diversification result requires heterogeneous failure modes, and the trap asymmetry requires irreversibility and time-to-build for green capital. Ambiguity effects require a concave ϕ in the smooth ambiguity aggregator. The asset pricing results require that blackout risk is systemic while green mortality risk is idiosyncratic, so grey exposure covaries with the SDF.

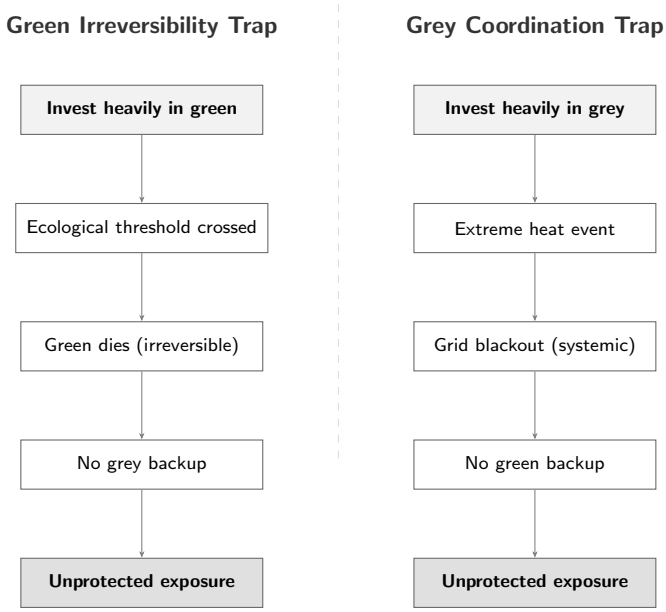


Figure 3
Maladaptation trap mechanisms. *Left*: Green irreversibility trap occurs when ecological thresholds are crossed and nature-based capital dies permanently. *Right*: Grey coordination trap occurs when collective cooling demand triggers systemic grid failure. Both pathways lead to unprotected exposure during extreme heat.

4.6 Maladaptation traps

A **maladaptation trap** is a path-dependent state where a firm's historical portfolio choice leaves it unable to respond effectively when a vulnerability is revealed. We use "trap" as an umbrella term: the green case is an irreversibility problem under uncertainty, while the grey case is a coordination failure.

We identify two distinct trap types:

Type 1: Green irreversibility trap. Occurs when: (i) firm invested heavily in green capital ($K_N \gg K_G$); (ii) the ecological threshold is crossed ($T > \hat{T}$); (iii) green capital dies (permanent loss); (iv) firm cannot afford emergency grey investment due to wealth depletion; (v) firm faces unprotected exposure to ongoing heat damages.

Type 2: Grey coordination trap. Occurs when: (i) all firms invested heavily in grey capital (K_G^{agg} high); (ii) extreme heat event occurs ($T \gg T^*$); (iii) aggregate cooling demand exceeds grid capacity; (iv) **systemic blackout**: all firms' grey capital fails simultaneously; (v) no firm has sufficient green backup (collectively underprovided); (vi) all firms face simultaneous unprotected exposure.

Figure 3 summarizes the two trap mechanisms.

Proposition 16 (Maladaptation traps). *Green irreversibility trap* exists when:

- $C_N \ll C_G$ so green is attractive on cost.
- Ecological ambiguity is moderate (not so high that experimentation dominates).
- Credit constraints bind during crisis, limiting grey replacement.
- The gap between T^* and $\hat{T}$ is large.

Grey coordination trap exists when:

- Many firms (n large) each internalize little of the externality.
- Grid supply is less elastic than demand at high temperature.
- Green backup is insufficient at the portfolio level.
- Heat events exceed grid design capacity.

Traps arise when a dominant portfolio choice becomes locally optimal yet leaves the firm exposed to a distinct failure mode. The essential distinction is that the green trap requires irreversibility and binding credit constraints, while the grey trap requires many firms and grid congestion.

Proposition 17 (Grey coordination trap). The grey coordination trap is a coordination failure: each firm's grey investment is privately rational but collectively creates systemic fragility. An alternative equilibrium with lower grey and higher green investment Pareto dominates the high grey equilibrium when extreme heat is sufficiently likely.

Proof. If all firms could coordinate to reduce grey and increase green, aggregate blackout probability falls. For sufficiently high extreme heat probability, the expected benefit from reduced blackout risk exceeds the expected cost from lower grey effectiveness in states without blackouts. ■

Individual best responses reinforce a fragile grid, even though collective restraint would make everyone better off.

4.7 Welfare implications

Proposition 18 (Welfare decomposition). Social welfare loss from decentralized equilibrium relative to social optimum decomposes as:

$$W^{Social} - W^{Nash} = \underbrace{\text{Externality Loss}}_{\text{Grid overuse}} + \underbrace{\text{Ambiguity Costs}}_{\text{Suboptimal diversification}} + \underbrace{\text{Trap Risk}}_{\text{Coordination failure risk}} \tag{31}$$

where Externality Loss captures the cost of unpriced grid stress; Ambiguity Costs capture welfare loss from ambiguity averse agents facing unnecessary uncertainty; Trap Risk captures expected loss from reaching maladaptation traps.

The welfare gap is the sum of a congestion externality, an ambiguity-driven diversification shortfall, and the expected cost of falling into maladaptation traps.

Learning dynamics that can attenuate ambiguity costs over time are described in the Online Appendix (Section 3).

In the illustrative calibration, this decomposition implies an 8 to 12% welfare loss relative to the social optimum (Section 5), with the grid externality accounting for the largest share.

Corollary (Decentralization with a Pigouvian charge). A time-varying charge on peak grey demand decentralizes the optimum (with φ the standard normal density):

$$\begin{aligned} \tau_G(T_t) &= (n-1)\mathbb{E}\left[\frac{\partial \mathbb{P}(G_t = 0)}{\partial K_G^{agg}} \cdot L_t^{blackout} \,|\, T_t\right] \\ &= (n-1)\frac{\psi}{\sigma_R}\varphi\left(\frac{-R_t}{\sigma_R}\right)\mathbb{E}[L_t^{blackout} \,|\, T_t], \end{aligned} \tag{32}$$

where R_t is the reserve margin (observable from system operator forecasts), ψ the marginal load effect of grey capital, and $L_t^{blackout}$ is the loss in blackout states and can be proxied by value of lost load times peak cooling demand.

Grid age and capacity inform σ_R and $\bar{S}$; climate zone and green cover shift expected blackout losses and ecological exposure. A simple rule of thumb scales τ_G with forecast peak load risk (LOLP/LOLE) and reserve margins.

Detailed instrument design and robustness across ambiguity regimes are reported in the Online Appendix (Section 9.2).

4.8 Firm value implications

The welfare results imply differences in firm value between diversified and concentrated portfolios.

Proposition 19 (Adaptation value gap). Let $V^*(K_G^*, K_N^*)$ denote firm value under the optimal portfolio, and let V^G and V^N denote values under grey only and green only portfolios. Define $V^{conc} \equiv \max\{V^G, V^N\}$. The adaptation value gap is:

$$\Delta V \equiv V^* - V^{conc}, \tag{33}$$

the valuation premium of diversification relative to the best single technology allocation. The gap is larger when failure risks are more asymmetric and less correlated.

The value gap measures how much firm value is gained by combining technologies whose failure modes differ in timing and permanence.

Corollary 3 (Cross-sectional valuation premium). In a cross-section of firms with comparable climate exposure, firms with diversified adaptation portfolios (interior α_G^*) should trade at a premium relative to concentrated portfolios, controlling for current profitability. The premium is increasing in the difference between concentrated and diversified failure risks and in expected unprotected losses.

Diversification reduces exposure to single technology failure, which is capitalised into firm value.

This valuation channel links the model to the climate finance literature on pricing physical risk: it predicts that *adaptation strategy*, not just exposure, should be priced. Section 4.9 presents the asset pricing implications, and the Online Appendix (Appendix 12) provides proofs and empirical implementation details.

4.9 Asset pricing implications

The differential failure profiles of grey and green capital imply a priced risk factor. Let M_t denote the stochastic discount factor and let γ_A denote the coefficient of relative risk aversion. Systemic blackout states are high marginal utility states, so portfolios concentrated in grey capital load on priced risk.

Proposition 20 (Systemic risk premium). The systemic component of grey capital risk commands a premium that cannot be diversified away:

$$\lambda_{systemic} = \gamma_A \cdot \mathrm{Cov}(M_t, \mathbf{1}_{\{blackout\}}) > 0. \tag{34}$$

In contrast, the idiosyncratic component of green capital risk has zero market price:

$$\lambda_{idio} = \gamma_A \cdot \mathrm{Cov}(M_t, \varepsilon_{i,t}^{green}) = 0, \tag{35}$$

where $\varepsilon_{i,t}^{green}$ is firm i's idiosyncratic green mortality shock.

Corollary 4 (Cross-sectional return prediction). Let firms i and j face similar climate exposure but hold different grey shares $\alpha_{G,i} > \alpha_{G,j}$. Expected returns satisfy

$$\mathbb{E}[R_i] - \mathbb{E}[R_j] \approx (\alpha_{G,i} - \alpha_{G,j}) \cdot \lambda_{systemic}, \tag{36}$$

so grey-heavy portfolios earn higher expected returns when blackout states are high marginal utility states.

Intuition. Grey exposure loads on the systemic blackout factor, which is priced. More grey capital increases covariance with the SDF, raising required returns even when current profitability and climate exposure are held fixed. The Online Appendix details the factor structure and outlines a feasible empirical implementation.

These implications align with evidence that physical climate risk is capitalised into asset values (Bernstein, Gustafson, and Lewis, 2019), that disaster states command risk premia (Barro, 2006), and that electricity shortages reduce firm revenues and surplus (Allcott, Collard-Wexler, and O'Connell, 2016). They also complement evidence that physical climate risk affects firms' cost of capital (Ginglinger and Moreau, 2023), providing a direct channel through which adaptation choices can influence valuation.

An empirical test is feasible with available data. Grey exposure can be proxied using cooling electricity intensity, HVAC capex disclosures, or building energy certificate data. Green exposure can be proxied using green roof coverage or urban tree canopy measures drawn from municipal inventories or satellite NDVI. A blackout factor can be constructed from system operator outage reports or reserve margin stress indices. A cross-sectional pricing test then relates firm returns to blackout exposure interacted with these portfolio proxies, controlling for standard risk factors and climate exposure. The Online Appendix provides further details.

4.10 Generality of the framework

While we calibrate to UK commercial property heat risk, the core structure applies whenever one adaptation technology fails systemically and temporarily while another fails idiosyncratically and permanently, and choices load on a shared capacity externality. Table 2 illustrates representative mappings.

Table 2
Mapping the framework to other adaptation domains

Domain	Grey (systemic, temp.)	Green (idiosync., perm.)	Externality
Urban heat	AC, mechanical cooling	Urban trees, green roofs	Grid congestion
Coastal flood	Seawalls, pumping	Mangroves, wetlands	Drainage capacity
Agric. drought	Irrigation from aquifer	Drought-resistant cultivars	Aquifer depletion
Supply chains	Inventory buffers	Supplier diversification	Logistics bottleneck

4.11 Empirical implications and identification

The model yields empirical predictions that distinguish it from single asset adaptation frameworks:

- **Differential event responses**: Heatwave blackouts should trigger shifts toward green infrastructure; green mortality events should trigger shifts toward grey; heatwaves without blackouts should produce modest grey increases. The interaction between event type and portfolio response is unique to our framework.
- **Grid ambiguity effects are not monotonic (Online Appendix, Proposition 11)**: Green adoption should be highest in regions with intermediate grid reliability and uncertainty, unlike standard precautionary models.
- **Correlation dependent diversification**: Firms in regions where heat, drought, and grid stress are more correlated should hold more balanced grey and green portfolios.
- **Return premium**: Holding exposure fixed, grey-heavy firms should earn higher expected returns because they load on systemic blackout risk (Section 4.9).

Feasible tests use existing data. A difference-in-differences design compares cities experiencing heatwaves with blackouts (DOE Form OE-417 or EIA Form 861) to matched heatwaves without blackouts (NOAA GHCN or ERA5), with outcomes measured by green infrastructure investment in the subsequent 1 to 3 years (municipal tree inventories, green roof permits, or NDVI from Landsat and Sentinel). Candidate events include California's 2020 rolling blackouts, the 2021 Texas freeze, and the 2022 UK heatwave. A complementary cross-sectional test examines whether regions with tighter reserve margins (NERC or ENTSO-E assessments) hold more diversified adaptation portfolios, proxied by green cover and cooling penetration.

An analogous event study can use documented urban tree mortality episodes to test the reverse prediction, namely whether mortality shocks lead to subsequent shifts toward grey investment. The Online Appendix (Appendix 12) provides a concrete identification design for the asset pricing tests.

Dynamic sequencing, tipping, and path dependence results are reported in the Online Appendix (Section 10).

5. Numerical Illustrations

The theoretical analysis establishes that diversification reduces trap risk, that the grid externality leads to overinvestment in grey, and that welfare losses decompose into three components. This section translates these qualitative insights into quantitative magnitudes using a calibration to UK commercial property facing heat risk. The exercise is illustrative: the precise numbers depend on parameter choices, but the patterns illuminate the mechanisms and provide a sense of scale for policy discussions.

5.1 Calibration

We calibrate to UK commercial property facing heat risk using ambient temperature as the primary heat indicator, consistent with UKCP18 projections.[2] Motivating evidence for the parameter choices is documented in the Online Appendix (Section 11).

Climate parameters: We set the damage threshold at $T^* = 25$°C following UK building overheating standards (CIBSE, 2015) and thermal comfort research showing productivity decline above 23 to 24°C (Seppänen et al., 2006). We set the damage rate at $\delta = 2\%$ per °C from Somanathan et al. (2021). We set damage convexity at $\gamma = 1.5$, a conservative specification for moderate warming consistent with convex damage relationships in Burke, Hsiang, and Miguel (2015).[3] Climate drift is $\mu_T = 0.03$°C/year from the UKCP18 central estimate. Climate volatility is $\sigma_T = 0.5$°C from historical UK variability. Extreme event intensity is $\lambda_J = 0.1$/year.

Grey capital parameters: Investment cost $C_G =$ £50/m^2 from engineering estimates. Operating cost $m_G =$ £5/m^2/year. Maximum effectiveness $\bar{\theta}_G = 80\%$. Efficiency threshold $T^{eff} = 30$°C based on typical

[2] We use ambient temperature as our primary heat indicator following UKCP18 projections. Alternative metrics such as wet bulb temperature (relevant for labor productivity) or cooling degree days (energy demand) would preserve the threshold-based portfolio dynamics because the damage function only requires a nonlinear heat indicator.

[3] Burke et al. estimate quadratic temperature-productivity relationships. Our power-function specification with $\gamma = 1.5$ represents sub-quadratic convexity, appropriate for the moderate temperature range relevant to UK commercial property. See Weitzman (2010) on functional form flexibility in damage specifications.

HVAC design conditions. Efficiency degradation $\alpha_G = 3\%/°\text{C}$ consistent with peak demand sensitivity estimates in Santamouris et al. (2015). Reversibility $\kappa_G = 0.4$.

Green capital parameters: Investment cost $C_N = £20/\text{m}^2$ from urban forestry data. Operating cost $m_N = £1/\text{m}^2/\text{year}$. Maximum effectiveness $\bar{\theta}_N = 50\%$ from Jamei et al. (2023). Stress threshold $T^{**} = 32°\text{C}$ from Teskey et al. (2015). Mortality threshold $\hat{T} = 38 \pm 5°\text{C}$ (ambiguous). Reversibility $\kappa_N \approx 1$. Co-benefits $B_N = £2/\text{m}^2/\text{year}$.

Grid parameters: Base capacity $\bar{S}$ is normalized to 1. Supply derating is $\beta_S = 1\%/°\text{C}$, consistent with average capacity reductions of 1–3% under climate scenarios (Bartos and Chester, 2015). Demand sensitivity is $3\%/°\text{C}$ above 21°C from Auffhammer, Baylis, and Hausman (2017). The blackout threshold is a reserve margin below 5%. Operational uncertainty is $\sigma_R = 0.02$. We set the grey demand coefficient at $\psi = 0.0044$ to align the marginal demand effect of grey capital with cooling-driven peak load sensitivity in Auffhammer, Baylis, and Hausman (2017) under our normalization. This is a calibration anchor rather than an estimated parameter. We convert simulated temperature anomalies to absolute temperature by adding a 25°C baseline before applying the damage threshold.

Appendix Table 3 reports a targeted sensitivity analysis for the core mechanism parameters. A ±10% perturbation in the grey demand coefficient ψ shifts the optimal grey share from 26% under lower ψ to 19% under higher ψ, while a ±10% perturbation in the mortality threshold $\hat{T}$ shifts it from 24% under higher $\hat{T}$ to 12% under lower $\hat{T}$. These patterns highlight the central roles of the grid externality and ecological thresholds in driving portfolio composition.

5.2 Optimal portfolio results

With the calibration in place, we examine how optimal portfolios respond to ambiguity aversion and grid reliability. The patterns that emerge confirm the theoretical predictions in Section 4 and reveal the quantitative importance of each mechanism.

At low ambiguity aversion, close to risk-neutral, green dominates at approximately 70 percent of the portfolio because of lower cost and co-benefits. At moderate ambiguity aversion, the portfolio shifts toward an even split as both failure modes become salient. At high ambiguity aversion, the grey share rises to approximately 60 percent as ecological threshold ambiguity dominates grid ambiguity. Ecological failure is permanent, while grid failure is temporary.

When grid reliability is high, grey dominates at approximately 75 percent because blackout risk is low. At moderate reliability, a balanced portfolio is optimal. When reliability is low, green dominates

Table 3
Maladaptation trap probabilities by initial portfolio composition at $t = 0$

Portfolio	Green trap	Grey trap	Either trap
100% Green	26.7% (25.2–28.3)	0.0% (0.0–0.1)	26.7% (25.2–28.5)
75% Green	25.7% (24.2–27.4)	0.0% (0.0–0.1)	25.7% (24.2–27.2)
Half and half	0.0% (0.0–0.1)	0.0% (0.0–0.1)	0.0% (0.0–0.1)
75% Grey	0.0% (0.0–0.1)	32.4% (30.6–34.0)	32.4% (31.0–33.8)
100% Grey	0.0% (0.0–0.1)	49.3% (47.7–51.0)	49.3% (47.6–51.2)

Notes: All values show trap probabilities with 95% bootstrap confidence intervals from 3,000 simulated paths. Traps are recorded when the portfolio weight in the relevant technology exceeds 60%. For zero event cells, we report the exact binomial upper bound, which is 0.1% at this sample size.

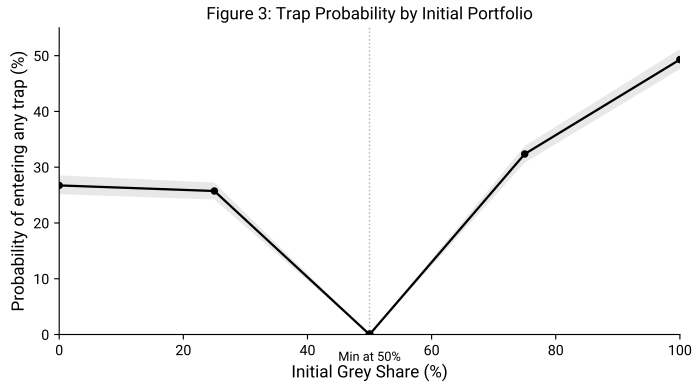


Figure 4
Probability of entering any maladaptation trap by initial grey share. The dotted line marks the 50% portfolio, where trap risk is minimized. The shaded band is the 95% bootstrap interval.

at approximately 70 percent because grey capital becomes unreliable. The relationship is monotonic, while the ambiguity effect is not.

5.3 Maladaptation trap probabilities

We define a green trap as cumulative green capital loss exceeding 30%, and a grey trap as maximum rolling blackout frequency exceeding 20% in any 30-step window. We simulate 3,000 climate paths over 30 years across different initial portfolios:

Figure 4 plots the probability of entering any trap across initial portfolios, with a 95% bootstrap band.

These results bear emphasis. Corner portfolios, whether entirely green or entirely grey, face substantial trap risk: between one quarter and one half of simulated paths end in maladaptation. Balanced portfolios, by contrast, are robust: the probability of either trap falls close to zero. This pattern reflects the diversification logic of Proposition 11: when

Table 4
Welfare decomposition under baseline calibration

Component	Share of gap	Policy response
Grid externality	45%	Peak demand pricing
Ambiguity under diversification	30%	Diversification standards, information
Trap risk	25%	Green subsidies, backup requirements
Total welfare loss	8 to 12% of adaptation benefits	

grey and green fail for different reasons, holding both provides insurance that neither alone can offer. The practical implication is that firms concentrating adaptation investment in a single technology are exposed to tail risks that diversification can largely eliminate.

5.4 Welfare analysis

Table 4 reports the baseline welfare decomposition implied by the calibration. The decomposition reveals where policy effort is best directed. The grid externality accounts for nearly half of the welfare gap, suggesting that peak demand pricing addresses the largest source of inefficiency. Ambiguity costs, at 30 percent, point to the value of information provision and diversification standards. Trap risk, at 25 percent, motivates coordination mechanisms and backup requirements. Each component corresponds to a distinct policy lever, and the calibration provides a rough sense of their relative importance.

A Pigouvian tax on peak electricity demand equal to the estimated externality (£15 to 25/kW during peak hours) shifts equilibrium portfolio from 65% grey to 52% grey, capturing approximately 60% of available welfare gains.

The adaptation value gap averages 2.6% of firm value under the baseline calibration (95% CI: 2.1 to 2.9%), with 2.5% under low climate drift and 0.3% under high drift with tight grid margins. The premium shrinks when grid constraints push the optimal portfolio toward a corner, reducing diversification gains.

To summarise, the calibration delivers three quantitative benchmarks. Diversified portfolios are worth approximately 2.6 percent more than concentrated allocations, reflecting the value of hedging against both systemic and idiosyncratic failure modes. Balanced portfolios reduce trap probability from 25 to 49 percent to close to zero. And the welfare gap of 8 to 12 percent can be substantially closed by a peak demand

charge that shifts portfolios toward a more balanced composition. These magnitudes are illustrative, but they demonstrate that the theoretical mechanisms identified in earlier sections are quantitatively meaningful in a realistic setting.

6. Conclusion

We have examined how firms facing extreme heat allocate adaptation spending between engineered cooling and nature-based solutions when these technologies fail in fundamentally different ways. Grey capital depends on grid reliability and fails systemically when collective demand overwhelms capacity. Green capital is vulnerable to ecological mortality and fails idiosyncratically when sustained heat crosses biological thresholds. The central insight is that this difference in failure mechanisms generates portfolio diversification benefits that conventional models cannot capture. Moreover, the optimal mix depends on the spectral composition of climate hazards: short-duration spikes favour grey capital, while sustained heat episodes favour green.

The illustrative calibration produces three quantitative benchmarks. First, diversified portfolios are worth approximately 2.6 percent more than concentrated allocations, reflecting the value of hedging against both systemic and idiosyncratic failure modes. Second, balanced portfolios sharply reduce catastrophic failure risk: our simulations show a probability of maladaptation traps close to zero for balanced allocations with a 50 percent grey share, compared with 26 to 49 percent for corner portfolios. Third, because each firm's cooling demand raises blackout risk for all firms, decentralised investment generates welfare losses of 8 to 12 percent relative to the social optimum. A peak-demand charge on grey capital captures approximately 60 percent of these potential gains by shifting portfolio composition from 65 to 52 percent grey. These magnitudes are illustrative and depend on the UK commercial property parameterisation; other settings will shift the levels while preserving the qualitative patterns.

These results rest on a mechanism absent from earlier adaptation frameworks. Previous work has examined optimal timing and design for individual adaptation measures such as coastal defences or flood infrastructure. We extend this approach to portfolio choice across technologies with heterogeneous failure profiles. The grid externality we identify differs from standard peak pricing because the spillover operates through capital stock composition rather than usage timing, creating a coordination problem in portfolio selection. This structure yields empirical predictions that distinguish our framework from single technology models: heatwave blackouts should trigger shifts toward green infrastructure, while green mortality events should induce

substitution toward grey. The interaction between event type and portfolio response provides a testable implication.

While related insights appear in ecological insurance and infrastructure resilience, our contribution is the corporate adaptation portfolio and pricing channel under a grid externality. Two immediate tests follow: the event-conditional portfolio response and the blackout-factor pricing relation.

The analysis yields two insights relevant for understanding adaptation inefficiencies. First, the welfare loss we document arises from capital allocation decisions, not merely operational choices. This suggests that policies targeting electricity consumption at peak times may be insufficient if they leave the underlying capital stock composition unchanged. Second, the welfare decomposition identifies three distinct sources of inefficiency: the grid externality accounts for 45 percent, ambiguity-driven under-diversification for 30 percent, and coordination-induced trap risk for 25 percent. These proportions indicate which frictions matter most and suggest that policies addressing only one source will leave substantial inefficiency unresolved.

The framework abstracts from several features that merit further study. We treat firms as symmetric, yet heterogeneity in climate exposure, grid access, and land availability likely affects portfolio composition. We model grid capacity as exogenous, even though operators invest and prices can respond to demand. Endogenous capacity could dampen the externality and alter the size of the coordination trap, so our results are best read as a short-run or institutional constraint benchmark. In particular, when grid operators can expand capacity in response to anticipated demand, the congestion externality shrinks, equilibrium grey share falls, and the welfare gap narrows. We focus on heat adaptation, yet the structure applies wherever one technology fails systemically and temporarily while another fails idiosyncratically and permanently. Future work can relax these assumptions and extend the empirical implications.

More broadly, this analysis suggests that climate adaptation cannot be understood in isolation from infrastructure reliability and ecological resilience. The coupling among these systems becomes most acute during extreme events, precisely when adaptation is most needed. As temperature distributions shift and tail risks intensify, the interdependencies we have modelled will become more pronounced. Understanding how these systems interact, and designing policies that account for strategic externalities in portfolio choice, represents an important research frontier for climate economics and corporate finance.

Appendix A. Proofs of Main Results

Complete proofs for all propositions, including supporting lemmas and formal assumptions, are provided in the Online Appendix.

Appendix B. Formal Assumptions

The proofs rely on the following formal assumptions, stated precisely in the Online Appendix. Notation follows Section 2.

A.1 (Climate Process Regularity): Temperature follows a jump-diffusion with bounded coefficients satisfying standard regularity conditions for strong solutions.

A.2 (Damage Function Properties): The damage function $D(T)$ is continuously differentiable, convex, and satisfies boundary conditions ensuring finite expected damages.

A.3 (Capital Effectiveness): Effectiveness functions $\theta_G(\cdot)$ and $\theta_N(\cdot)$ are bounded, Lipschitz continuous, and monotone in their respective degradation arguments.

A.4 (Grid Structure): Blackout probability $p_B(\cdot)$ is twice continuously differentiable, strictly increasing in both temperature and aggregate grey capital, with bounded derivatives.

A.5 (Firm Preferences): Firms have smooth ambiguity preferences with increasing instantaneous utility $u(\cdot)$ (linear in the baseline case) and a strictly increasing, strictly concave ambiguity function $\phi(\cdot)$.

A.6 (Symmetry and Continuity): Firms are ex ante identical and strategy spaces are compact and convex, ensuring equilibrium existence.

Appendix C. Calibration Details

Climate Parameters: Temperature dynamics calibrated to UK Met Office projections (UKCP18) for the Thames Valley region under RCP 4.5 and RCP 8.5 scenarios. Damage threshold $T^* = 25°\text{C}$ based on productivity studies; damage rate $\delta = 0.02$ from Somanathan et al. (2021). Parameter definitions follow Section 2.

Capital Parameters: Grey capital costs from commercial HVAC industry data; demand sensitivity from Santamouris et al. (2015) and Akbari, Pomerantz, and Taha (2001). Green capital parameters from urban forestry studies; growth reductions up to 50 percent and mortality thresholds from Rötzer et al. (2021) and Teskey et al. (2015).

Grid Parameters: Blackout probability calibrated to Loss of Load Probability data from the July 2022 UK heatwave (Cornwall Insight, 2022). Supply derating rates from generation fleet thermal efficiency specifications.

Ambiguity Parameters: Prior distributions over climate drift span RCP 2.6–RCP 8.5 equivalents. Ecological threshold uncertainty range [33°C, 43°C] reflects species-specific variation in thermal tolerance documented in urban ecology literature.

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