SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

Executive Summary of the Thesis

Temperature Anomalies and Climate Physical Risk in Portfolio Construction

Laurea Magistrale in Mathematical Engineering - Ingegneria Matematica

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1. Introduction

Physical climate risk has emerged as a critical financial threat, comprising both acute hazards like heatwaves and wildfires and chronic shifts such as rising sea levels. Despite global mitigation efforts, the increasing frequency of these threats, poses severe consequences for firms ill-prepared for the resulting economic losses. While asset managers increasingly seek to incorporate these climate-related risks into investment decisions, a significant gap remains in effective quantitative metrics capable of capturing how extreme climate events impact corporate economic value. In this work, we address the lack of precise valuation tools by developing a dynamic framework for firm-specific climate risk assessment. By utilizing extreme temperature anomalies as a quantitative proxy, we move beyond the limitations of broad, qualitative indicators to capture the direct climate impact on individual firms. We first confirm the materiality of physical risk by empirically testing the impact of temperature anomalies on sector returns (similarly to the methodology proposed in [2]), then we model the time-varying probabilities of temperature extreme events to define two novel metrics: *Climate Risk Exposure* and *Climate Exposure Volatility*, mimicking the risk exposure variance decomposition proposed in [3]. By integrating these metrics into a multi-objective optimization problem, we extend the standard mean-variance framework to explicitly account for physical climate risk. To the best of our knowledge, this represents the first attempt to offer a flexible, data-accessible approach for constructing optimal portfolios that are resilient to climate shocks and capable of effective risk diversification.

2. Temperature Anomalies and Their Effects on Returns

We utilize monthly mean temperature data for the period spanning from January 1, 1940, to April 30, 2025. The analysis covers the six major continents: North America, South America, Europe, Africa, Asia, and Oceania. To identify extreme events, we define a reference period (baseline) from 1960 to 1990. For each continent k and each month $m \in \{1, \dots, 12\}$, we calculate the historical mean $\mu_{k,m}$ and the standard deviation $\sigma_{k,m}$. We define an indicator variable $B_{k,t}$ that identifies the occurrence of a positive temperature anomaly at time t for continent k. The raw temperature $T_{k,t}$ is standardized using the mean and standard deviation corresponding to its specific month and continent. An anomaly is recorded if the standardized value exceeds the threshold of 2:

$$B_{k,t} = \begin{cases} 1 & \text{if } \dfrac{T_{k,t} - \mu_{k,m}}{\sigma_{k,m}} > 2 \\ 0 & \text{otherwise} \end{cases}.$$

This threshold ensures that we identify "extreme" events, specifically targeting values more than two standard deviations from the historical norm.
To capture the evolution of climate risk over time, we estimate the probability $p_{k,t}$ that an anomaly occurs in continent k at time t. Given the binary nature of $B_{k,t}$, we employ a Logistic Regression model.
The model incorporates a quadratic trend to account for potential non-linearities in global warming patterns. For each continent, the log-odds of the probability are modeled as

$$\text{logit}(p_{k,t}) = \ln\left(\frac{p_{k,t}}{1 - p_{k,t}}\right) = \beta_{0,k} + \beta_{1,k}t + \beta_{2,k}t^2.$$

The fitted probabilities $\hat{p}_{k,t}$ reveal a consistent trend across all analyzed continents. As illustrated in Figure 1, the probability of encountering an extreme temperature anomaly exhibits a significant increase over time.

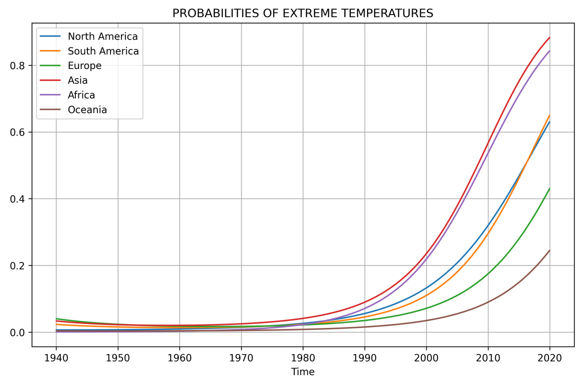

Figure 1: Probabilities of extreme temperatures over time in the period 1940-2020.

Moreover, we aim to understand if temperature anomalies affect stock returns. To do so we perform a panel analysis regressing sectoral total returns $R_{s,k,t}$ of sector s and continent k on the market return and on $B_{k,t}$. To enhance the robustness of our estimates in the regression, we incorporate month fixed effects (δ_m) and continent fixed effects (μ_k) to absorb systematic variations independent of temperature extremes

$$\begin{aligned} R_{s,k,t} - R_{f,t} = &\alpha_s + \beta_{MKT,s}(R_{MKT,t} - R_{f,t}) \\ &+ \gamma_s B_{k,t} + \mu_k + \delta_m + \epsilon_{s,k,t}, \end{aligned}$$

where γ_s is the parameter of interest, representing the *Climate Beta* or the sensitivity of the sector to extreme temperature events.
In Table 1, we report all the sectors with a statistically significant γ_s. We observe that, with the exception of the IT sector (which has historically maintained minimal physical exposure prior to the recent data center expansion), all other sectors are negatively affected by temperature anomalies.

Sector	**Climate Beta (γ)**
Chemicals	-0.0062
Energy - Fossil Fuels	-0.0089
Food & Beverages	-0.0050
Real Estate	-0.0055
Retailers	-0.0026
Software & IT Services	0.0026
Telecommunications Services	-0.0042
Transportation	-0.0032

Table 1: The table reports the estimated *Climate Beta* (γ_s), displaying only the coefficients that are statistically significant.

As a final test, we estimate a single Global Climate Beta (Γ) by pooling all sectors and all continents into a single panel regression

$$\begin{aligned} R_{s,k,t} - R_{f,t} = &\alpha + \beta_{\text{MKT}}(R_{\text{MKT},t} - R_{f,t}) + \Gamma B_{k,t} \\ &+ \text{FE}_{\text{month}} + \text{FE}_{\text{continent}} + \epsilon_{s,k,t}. \end{aligned}$$

The results of this panel regression yield a coefficient Γ that is negative and highly statistically significant, with an estimated value of -0.003 and a p-value of 0.0096. The findings in this section are pivotal, as they provide the empirical foundation for the development of metrics designed to quantify the climate risk of a portfolio.

3. Quantifying Portfolio Risk to Extreme Climate Events

The sensitivity of a firm to physical climate risk depends on its geographical location and the vulnerability of its physical assets and supply chain

in that area. Consequently, an industrial company with significant physical infrastructure is more vulnerable to a local climate disaster than a service-based firm.
We define asset intensity of firm i as in [1]

$$AI_i = \frac{\text{Tangible Assets}_i}{\text{Revenue}_i} \quad .$$

We also define $S_{i,k}$ as the revenues produced in continent k by firm i. We utilize this two metrics to determine the relevance of continent k for company i in term of physical risk. Furthermore, we define the *climate normalized* portfolio weight for continent k

$$\alpha_k(w) = \frac{\sum_{i=1}^{N} w_i \cdot AI_i \cdot S_{i,k}}{\sum_{k=1}^{K} \sum_{i=1}^{N} w_i \cdot AI_i \cdot S_{i,k}} \quad ,$$

where w_i is the portfolio weight of firm i. By using these climate normalized weights we are able to capture the physical risk exposure of the portfolio to a given continent. Using the Bernoulli variables $B_{k,t}$, which indicate the occurrence of extreme events across continents, we can define our two new physical risk metrics.
The first metric, *Climate Risk Exposure*, quantifies the expected average exposure of the portfolio to extreme climate events at a given time t. It represents the "baseline" physical risk, calculated as the expected value of the weighted sum of the time-varying Bernoulli variables $B_{k,t}$, using the climate normalized weights $\alpha_k(\boldsymbol{w})$. Unlike static indicators, this measure accounts for the non-stationarity of climate trends by utilizing the time-dependent probabilities $p_{k,t}$. It is defined as

$$\text{CRE}(w,t) = \mathbb{E}\left[\sum_{k=1}^{K} \alpha_k(w) B_{k,t}\right] = \sum_{k=1}^{K} \alpha_k(w) \cdot p_{k,t},$$

where $p_{k,t}$ is the probability of an extreme temperature event in continent k at time t. A higher $\text{CRE}(\boldsymbol{w},t)$ indicates that the portfolio is potentially highly affected by regions currently experiencing an upward trend in the frequency of climate anomalies.
While the CRE provides a mean expectation of physical risk, it inherently lacks the capacity to account for the uncertainty or the potential for simultaneous disasters across different geographic areas. To address this limitation, we introduce the *Climate Exposure Volatility*, denoted as $\text{CEV}(\boldsymbol{w},t)$. This metric quantifies the variance of the portfolio's climate exposure at time t, offering a rigorous measure of the stability of its risk profile. A high volatility suggests that the portfolio's risk is poorly diversified across climate zones. In such cases, the portfolio becomes highly susceptible to sudden, large-scale shocks where multiple geographic areas might be damaged concurrently. Formally, the function $\text{CEV}(w,t)$ is defined as the variance of the weighted sum of the Bernoulli variables $B_{k,t}$, utilizing the climate normalized weights $\alpha_k(\boldsymbol{w})$ previously derived

$$\begin{aligned}\text{CEV}(w,t) = &\sum_{k=1}^{K} \alpha_k^2 \text{Var}(B_{k,t}) \\ &+ 2\sum_{k<j} \alpha_k \alpha_j \text{Cov}(B_{k,t}, B_{j,t}).\end{aligned}$$

This formulation allows for a decomposition of climate risk into two primary sources: the idiosyncratic and the systematic components [3]. The first term, $\sum_{k=1}^{K} \alpha_k^2 p_{k,t}(1-p_{k,t})$, is akin to a Herfindahl Index and measures the geographic concentration of risk. Under the assumption of uniform probabilities, this idiosyncratic component is minimized when the portfolio's climate exposure is equally distributed across all K regions (i.e., $\alpha_k = 1/K$ for all k), effectively rewarding geographic diversification against localized shocks. The second term, $2\sum_{k<j} \alpha_k \alpha_j \text{Cov}(B_{k,t}, B_{j,t})$, accounts for the systemic component of climate risk, reflecting how the correlation of extreme events across different geographic areas amplifies the overall portfolio volatility, in other words it captures the systemic risk that arises when climate extreme events are geographically correlated: if extreme events in two continents (e.g., North America and Europe) are highly correlated, a portfolio with significant exposure to both will exhibit higher volatility. This metric effectively penalizes a lack of geographic diversification against synchronized climate shocks, providing a more comprehensive view of potential portfolio losses than a simple average exposure metric.

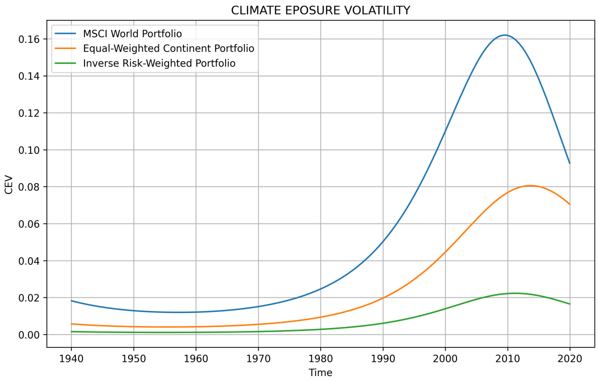

Figure 2: Evolution of Climate Exposure Volatility across three portfolio strategies.

The provided Figure 2 illustrates the evolution of CEV over time, comparing three distinct portfolio strategies to highlight different approaches to managing physical climate risk. Specifically, the analysis considers: i) the MSCI World Portfolio; ii) the Equal-Weighted Continent Portfolio, where the climate normalized weights are distributed equally across all continents; iii) the Inverse Risk-Weighted Portfolio, where geographic weights are assigned inversely proportional to the probability of extreme temperature events in each continent, thereby tilting the portfolio away from high-risk regions.
As clearly shown in the chart, *Climate Exposure Volatility* evolves over time, reflecting fluctuations in the frequency and severity of extreme events. Notably, CEV trends downward after 2010. This trend stems from the properties of the Bernoulli variables $B_{k,t}$: since the variance $p_{k,t}(1-p_{k,t})$ peaks at $p_{k,t} = 0.5$, the increasing probability of extreme events ($p > 0.5$) in several regions since 2010 has paradoxically reduced statistical volatility. This shift reflects a higher degree of "certainty" regarding the occurrence of such events. Furthermore, the comparison reveals a clear hierarchy in risk mitigation. The Equal-Weighted Climate Portfolio consistently exhibits a lower CEV compared to the MSCI World baseline, demonstrating that simply diversifying exposure away from market-cap concentrations can stabilize the climate risk profile. Even more effective is the Optimal Risk-Weighted Portfolio, which achieves the lowest volatility among the three strategies. By tilting the weights away from the most vulnerable regions, this approach significantly curtails the portfolio's susceptibility to climatic shocks, proving that active geographic optimization is the most efficient tool for minimizing physical risk exposure.

4. Climate-Aware Portfolio Optimization

We can employ these two metrics to construct a climate-resilient portfolio. The investment universe is composed of N=120 stocks selected from the MSCI World Index. To ensure the portfolio remains representative of global equity markets, the selection follows a sampling approach based on market capitalization.
The 120 assets are distributed across geographic macro-regions to reflect their relative importance in the global financial landscape. The selection is partitioned according to the following criteria:

- Americas: 45% (54 assets);
- Europe: 25% (30 assets);
- Asia: 25% (30 assets);
- Oceania: 5% (6 assets).

We look for the portfolio $\boldsymbol{w} \in \mathbb{R}^{120}$ that solves the following optimization problem

$$\begin{cases} \min_{\boldsymbol{w}} & \mathbf{F}(\boldsymbol{w}) = [f_1(\boldsymbol{w}), f_2(\boldsymbol{w}), f_3(\boldsymbol{w})]^\top \\ \text{s.t.} & \sum_{i=1}^{120} w_i = 1 \\ & w_i \geq 0, \quad \forall i = 1, \ldots, 120 \end{cases}$$

where the three objective functions to be minimized are:

1. Minus the Expected Return: $f_1(w) = -w^\top r$;
2. Market Variance: $f_2(w) = w^\top \Sigma w$;
3. *Climate Exposure Volatility* (CEV): $f_3(w)$, as defined in Section 3.

To solve this multi-objective optimization problem we employ a Multi-Objective Particle Swarm Optimization (MOPSO) algorithm (see [4]). Unlike single-objective optimization, which seeks a unique global minimum, MOPSO aims to identify the Pareto Front. This front represents the set of all non-dominated solutions, that are portfolios for which it is impossible to improve one objective (e.g., increasing returns) without simultaneously worsening another (e.g., increasing risk or CEV). The MOPSO is an iterative population-based algorithm where a set of candidate solutions, called particles, "fly" through the search space. Each particle represents a potential weight vector w and adjusts its trajectory based on its own historical best position and the best positions found by its neighbors. In Figure 3, we present the resulting three-dimensional Pareto frontier computed as of January 1, 2020. The visualization maps the complex interactions between the three conflicting objectives: the x-axis represents the Portfolio Variance, the y-axis shows the *Climate Exposure Volatility*, and the z-axis denotes the Expected Returns.

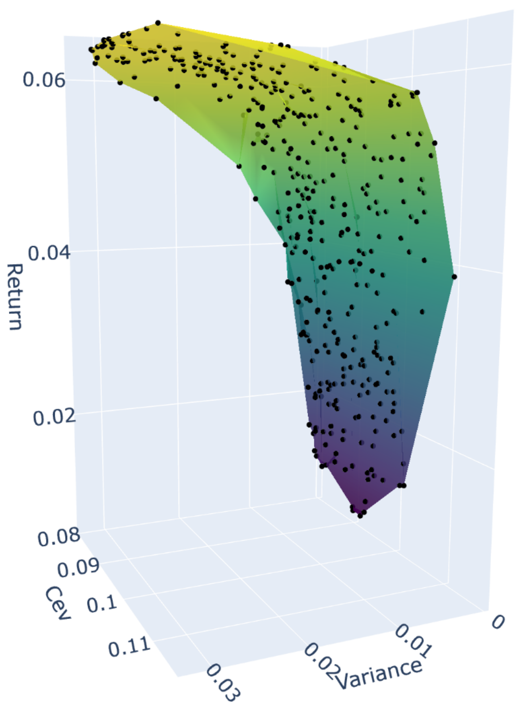

Figure 3: Pareto Frontier for the 3-objective optimization problem.

The visualization clearly illustrates that the classic mean-variance trade-off remains fundamental, even with the integration of *Climate Exposure Volatility*. It is evident that to achieve a higher target for expected returns, one must necessarily accept an increase in portfolio risk, specifically in its variance.
In order to further investigate the relationship between *Climate Exposure Volatility* and the portfolio's Expected Return, we perform a sensitivity analysis by slicing the 3D Pareto frontier into distinct variance intervals. Specifically, the total range of traditional financial variance is divided into several sub-intervals. For each interval, we select the particles (portfolios) falling within that specific range and project them onto a 2D scatter plot.
In these visualizations, the x-axis represents the CEV, while the y-axis represents the Expected Return. To provide a clearer trend analysis, we also plot an interpolated parabolic curve calculated at the mean variance value of the interval.

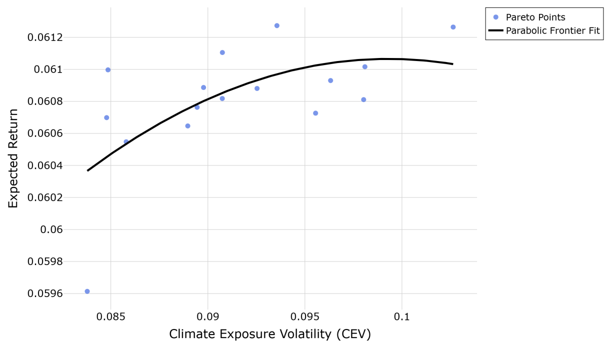

Figure 4: Expected Return vs. *Climate Exposure Volatility*: 2D Cross-Sectional Pareto Projections.

The results, as shown in Figure 4, reveal a clear and consistent pattern: an increase in Expected Return is systematically associated with an increase in CEV. This analysis demonstrates that CEV behaves much like traditional variance in relation to expected return. Investors seeking higher performance must be prepared to accept not only greater market volatility but also higher climate variance, highlighting the conflicting nature of green financial optimization.

5. Backtesting Analysis of Climate-Aware Efficient Frontiers

Finally, we evaluate the potential benefits of selecting portfolios from the Pareto Frontier derived in Section 4, which explicitly incorporates climate risk. Specifically, the backtesting analysis covers the period from January 1, 2020, to April 30, 2025.
On the first business day of each month within this window, the Pareto Frontier is re-optimized

using a 5-year rolling-window approach. The Expected Returns are calculated as the mean of the monthly returns over the preceding five years, and the Covariance Matrix is estimated using daily returns from the same five-year look-back period. Furthermore, the temperature anomaly probabilities for each continent are updated using the data recorded in the month immediately preceding the rebalancing date. To provide a comprehensive benchmark, our analysis includes Market-Cap and Equally-Weighted portfolios, alongside specific points on the Pareto Frontier, such as the minimum market variance and the maximum expected return portfolios.

Moreover, to explore further balance allocations across our three competing objectives, i.e. Expected Return, Variance, and CEV, we apply a Min-Max normalization. This maps each objective into the $(0, 1)$ range while preserving their relative ordering. We then identify optimal portfolios by minimizing convex combinations of these normalized metrics, governed by weights (a, b, c) such that $a + b + c = 1$. By varying these parameters, we can systematically explore different strategic tilts along the frontier.

Table 2: Performance Metrics Comparison (January 2020 – April 2025)

Strategy	**CAGR**	**MDD**	**CEV**
Market-Cap Weights	15.8%	14.8%	0.070
Equally-Weighted	17.5%	16.7%	0.067
Min Market Var.	14.2%	**11.5%**	0.066
Max Exp. Return	3.3%	69.4%	0.103
(1/3, 1/3, 1/3)	**33.5%**	31.5%	0.061
(0, 1/2, 1/2)	14.7%	17.4%	**0.060**
(1/2, 1/4, 1/4)	28.4%	46.1%	0.062
(1/4, 1/2, 1/4)	30.6%	20.8%	0.061
(1/4, 1/4, 1/2)	28.5%	30.6%	0.061
(1/2, 1/2, 0)	33.4%	32.8%	0.076

The results presented in Table 2 measure these portfolios according to three financial metrics: the Compound Annual Growth Rate (CAGR), the Maximum Drawdown (MDD), and the average *Climate Exposure Volatility* (CEV). The Maximum Expected Return portfolio exhibits the worst performance across all evaluated metrics. This shows that selecting a portfolio solely based on expected returns, without incorporating any risk measure, leads to extreme risk exposure. In contrast, the Minimum Market Variance portfolio, while achieving a low CAGR, turns out to be the most effective in controlling market volatility. When considering portfolios on the frontier that properly combine the three objective functions, we observe the best performance. The $(1/3, 1/3, 1/3)$ strategy, which weights all three objectives equally, achieves the highest overall CAGR (33.54%) and a very low average CEV (0.061). The $(1/2, 1/2, 0)$ portfolio attains a similar CAGR of 33.4%; although it does not explicitly weight the *Climate Exposure Volatility* in the convex combination (achieving indeed the second worst CEV), it still benefits from being selected from a Pareto Frontier that was originally constructed including this climate risk metric.

6. Conclusions

This study establishes a robust quantitative foundation for climate-resilient portfolio construction by introducing two dynamic metrics: *Climate Risk Exposure* (CRE) and *Climate Exposure Volatility* (CEV). Unlike static indices, these measures capture time-varying extreme event probabilities and systemic risks arising from spatial correlations.

By integrating these metrics into a Multi-Objective Particle Swarm Optimization (MOPSO) framework, we demonstrate that climate resilience can be embedded within the mean-variance paradigm without sacrificing performance. Specifically, our results show that accounting for CEV enhances risk management, identifying efficient portfolios on the Pareto Frontier that reduce both overall volatility and maximum drawdown while maintaining high expected returns.

References

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