Asia Pacific Science Press

Asia Pacific Economic and Management Review
ISSN(O):3005-9275
ISSN(P):3005-9267
Vol. 2 No.6 (2025)

Climate Big Data and Green Financial Asset Pricing ——A Carbon-Sensitive Valuation Model Based on Multi-Source Environmental Data

Haorong Ma*

JT Academy, Beijing, 100000, China

Corresponding author: Haorong Ma, m186_11817169@163.com

Abstract: Accelerating global efforts toward carbon neutrality are intensifying climate risks within financial markets. Traditional asset pricing models inadequately incorporate climate-related factors, resulting in systemic undervaluation of green assets. This study develops a Carbon-Sensitive Asset Pricing Model (CS-APM) integrating physical and transition risk factors. We conduct empirical analyses using data from six major economies spanning 2015-2024. Results indicate that singular climate risk factors exhibit positive sensitivity to asset returns. However, simultaneous exposure to dual risks triggers defensive capital reallocation and accelerates impairment of high-carbon assets. Emerging market assets demonstrate consistently positive sensitivity, while developed markets show greater climate risk resilience. Regulatory policy intensity maintains a nonlinear relationship with returns, where technological maturity and policy implementation jointly drive sustainable performance trends in industries. This modeling approach provides a new paradigm for quantifying climate risk premiums and redirecting capital toward climate-resilient sectors.

Keywords: Climate Risk; Asset Pricing; Carbon-Sensitive Asset Pricing Models; Green Asset Excess Returns; Machine Learning Optimization

Published: Dec 2, 2025

DOI: https://doi.org/10.62177/apemr.v2i6.939

1.Introduction

1.1 Research Background and Importance

Driven by the objectives of the Paris Agreement, the global transition toward carbon neutrality is accelerating. Climate risks increasingly impact financial markets, where frequent extreme weather events and specific policy shifts—such as the EU Carbon Border Adjustment Mechanism (CBAM) and Nationally Determined Contributions (NDCs)—persistently cause abnormal asset price volatility. [1]Traditional asset pricing models, rooted in the Capital Asset Pricing Model (CAPM), focus on a singular market systemic risk mechanism for asset returns. They inadequately integrate emerging systemic transition risk factors, resulting in systemic undervaluation of green and low-carbon assets—especially those in high-carbon industries. [2] Such mispricing reduces resource allocation efficiency and may hinder global climate governance objectives.

Advances in environmental big data offer new solutions. Satellite monitoring, corporate carbon footprint tracking, and extreme weather alerts enable real-time climate risk quantification for assets in financial markets.[3] Machine learning's capabilities in handling unstructured data further reveal nonlinear relationships between carbon emissions and asset returns. [4] By integrating these technologies with financial data, this research develops key analytical tools to precisely map climate risk's nonlinear impacts on asset pricing.

1.2 Research Objectives

Based on the performance of green assets in the world's six largest economies (2015-2024), this study develops the Carbon-Sensitive Asset Pricing Model (CS-APM). The model integrates multi-source environmental data with financial time-series data, using machine learning to optimize factor weight calculations. This constructs a dual-factor analysis framework for physical and transition risk transmission mechanisms. It reveals nonlinear climate effects on green assets and provides accurate climate risk premium quantification. Consequently, the framework supports investor asset allocation and promotes orderly financial capital flows toward climate-resilient sectors.

1.3 Data Source Description

This study integrates monthly observational data (2015–2024) on climate and financial markets from six major economies, including China and the United States. For climate dimensions, the dataset includes key indicators: atmospheric CO_2 concentration, temperature anomalies, extreme weather frequency, and carbon pricing. Where observational gaps exist, we simulate time-series climate data using historical patterns and current trends to match observed characteristics. For financial dimensions, we analyze three asset classes: green indices, carbon-intensive indices, and risk-free rates. All raw and simulated data underwent rigorous time alignment and standardization, forming a multi-regional, multi-industry panel dataset for robust subsequent modeling.

2.Model Construction Approach

2.1 Factor Design of the Model

This study expands the traditional three-factor asset pricing model by incorporating Physical Risk Factor (PRF) and Transition Risk Factor (TRF), forming a five-factor system. The PRF quantifies direct natural environmental impacts via temperature anomalies and extreme weather frequency. [5]The TRF reflects policy-driven market structural adjustments by analyzing interactions between carbon price fluctuations and emission levels.[6] Subsequently, these factors undergo orthogonal processing to derive an integrated climate risk. Based on this integrated climate risk, the ratio between asset excess returns and standardized climate risk factors is further derived as the "climate beta," serving to measure the sensitivity of individual assets or portfolios to systemic climate risks. [7]Additionally, the model employs generalized method of moments (GMM) estimation to uncover potential nonlinear relationships between climate risk and asset returns.

The Carbon-Sensitive Asset Pricing Model integrates the Physical Risk Factor, Transition Risk Factor, and traditional asset pricing factors—Market Benchmark, Size, and Book-to-Market Ratio. Its core equation is:

$$E[R_i] - R_f = \beta_{i,MKT}MKT + \beta_{i,SMB}SMB + \beta_{i,HML}HML + \beta_{i,PRF}PRF + \beta_{i,TRF}TRF + \alpha_i$$

2.2 Dynamic Adjustment Framework of the Model

Current fixed-parameter models fail to adapt to rapidly evolving climate policies and markets. [8]To address this, our model incorporates a dynamic response mechanism. When major disruptive events occur—such as carbon market rule adjustments or carbon tax introductions—structural discontinuities automatically trigger parameter re-estimation. This enables timely risk premium updates, enhancing model adaptability.

Environmental data complexity also challenges traditional integration methods. [9]We therefore apply machine learning to optimize Physical and Transition Risk Factor weightings through time-series cross-validation, achieving more interpretable composite climate risk indicators.[10]

To maintain predictive validity in dynamic conditions, the model employs seasonal autoregressive moving average (SARMA) for rolling historical forecasts. Regular backtesting evaluates prediction performance. Collectively, these features ensure effective capture of climate risk-pricing relationships and robust forecasting adaptability.[11]

3.Factor Loadings Analysis

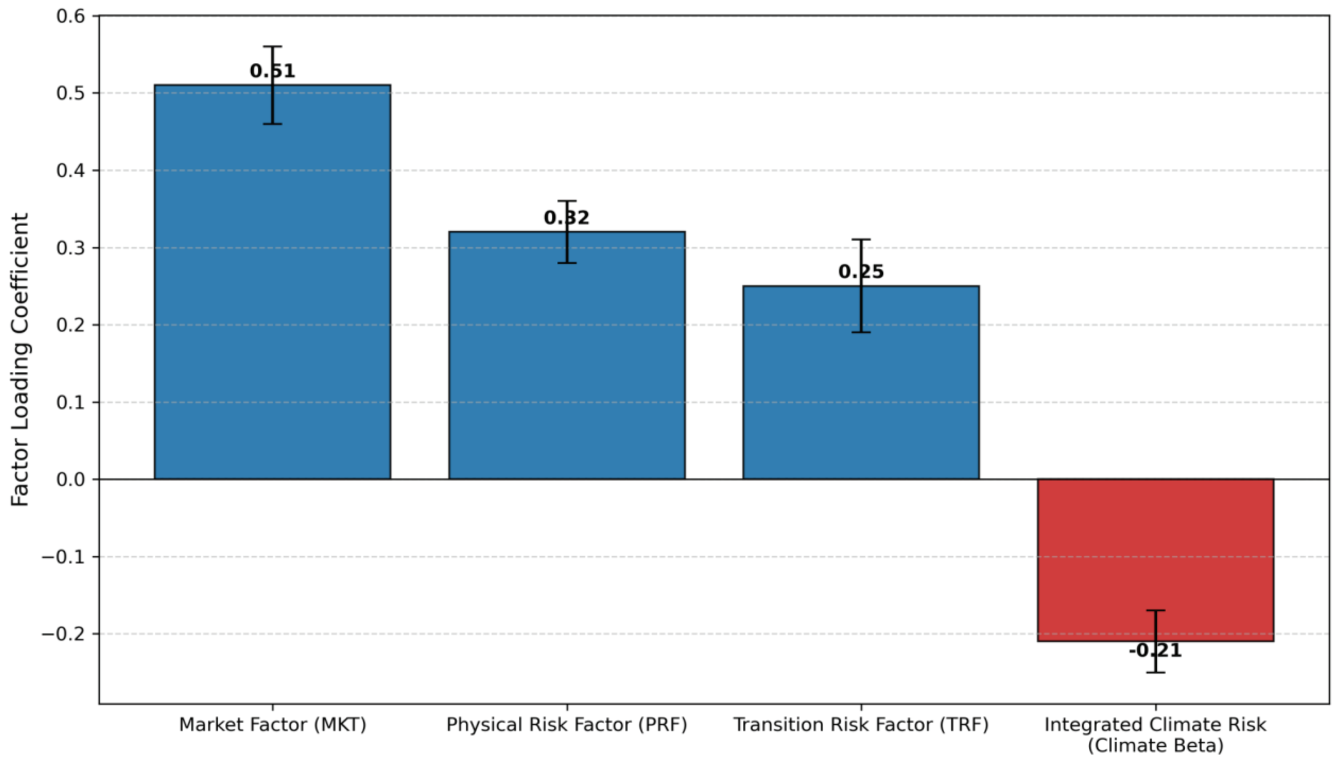
3.1 Significant Climate Risk Premium

Factor loading estimation reveals significant positive values for both the Physical Risk Factor (PRF=0.32) and Transition Risk Factor (TRF=0.25). This demonstrates that asset risk premiums increase when exposed to isolated physical shocks or policy transition pressures. [2]Both factors represent distinct systematic risks: direct physical damage from extreme weather and structural transformation costs from policy changes. These increase corporate operational costs and uncertainty, prompting markets to demand higher compensation through elevated risk premiums. This confirms the pricing role of climate risk factors.

3.2 Dual-Channel Transmission in Factor Loadings

When physical and transition risks compound in markets, their combined impact often exceeds the tolerance thresholds of high-carbon, low-resilience assets. This forces accelerated defensive asset reallocation by investors: capital rapidly shifts from highly vulnerable high-carbon assets to green, low-carbon alternatives supported by policies and technological advantages.[12] Thus, while individual risk factors increase compensation demands, their combined elevation triggers structural market shifts. These manifest through interactive risk effects that accelerate discounting of vulnerable assets.

Figure1: Factor Loading Estimates for CS-APM Model



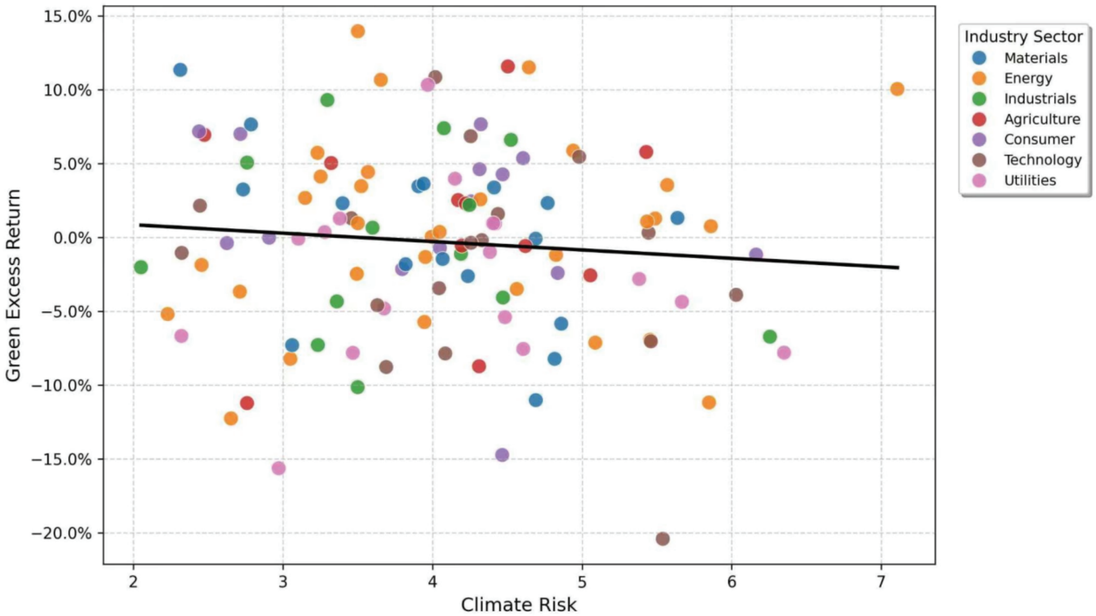
4.Heterogeneity in Carbon Excess Returns

4.1 Limited Sectoral Correlation with Climate Risk

Industry analysis reveals dispersed data points between climate risk exposure and green asset excess returns, indicating weak linear correlation (Figure 2). Technology sector assets generally yield higher returns across risk levels, while utilities show consistently lower returns. Significant cross-industry data overlap suggests sector attributes are not primary drivers of climate risk pricing.[13]

Two factors may explain this dispersion. First, companies facing similar climate risks differ substantially in risk-mitigation capabilities through technological innovation, supply chain resilience, or business model adaptation. [14]Second, climate risks' long-term valuation impacts are masked short-term by market volatility, investor sentiment shifts, and non-climate factor noise.[15] These effects dilute observable correlations at the industry level, producing non-clustered data distributions.

Figure2: Climate Risk Exposure vs. Green Asset Performance



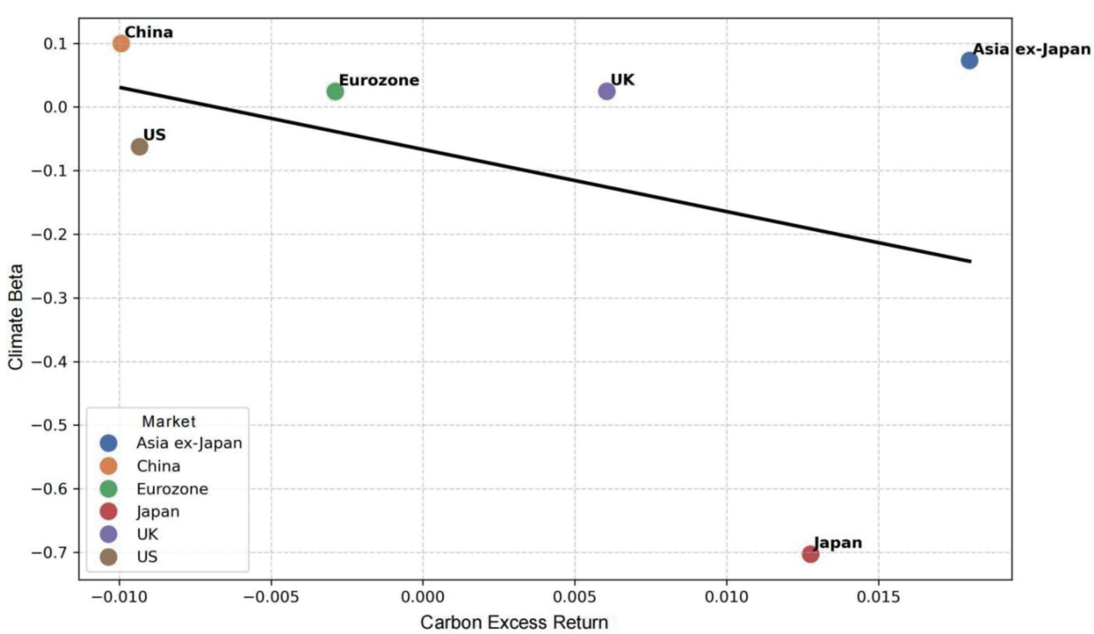
4.2 Regional Disparities in Climate Risk Exposure

Global markets show significant divergence in climate risk response, revealed through a gradient in climate beta distributions. Emerging markets demonstrate positive climate betas, led by China (β=0.1). Developed markets display predominantly negative betas, with Japan lowest (β=-0.7). Asia's newly industrialized economies present an intermediate case: they maintain a positive β=0.08 climate beta yet generate positive carbon excess returns.

Structural disparities likely drive this regional differentiation. Emerging economies face heightened physical climate risks combined with immature risk-hedging mechanisms. [16]These conditions elevate asset climate sensitivity (positive β) but do not translate to excess returns due to technological/policy limitations; instead, climate pressure constrains returns.

Developed markets absorb risk through advanced infrastructure, mature low-carbon technologies, and robust climate adaptation policies.[17] This produces greater resilience (negative β) alongside stable returns supported by sophisticated markets. Asia ex-Japan's industrializing economies achieve balance via superior technology assimilation and supply-chain modernization. These efficiency gains enable moderate climate sensitivity while sustaining positive returns through enhanced competitiveness.

Figure3: Climate Beta Estimate Rollups across Markets



5.Climate Policy-Investment Returns Nexus

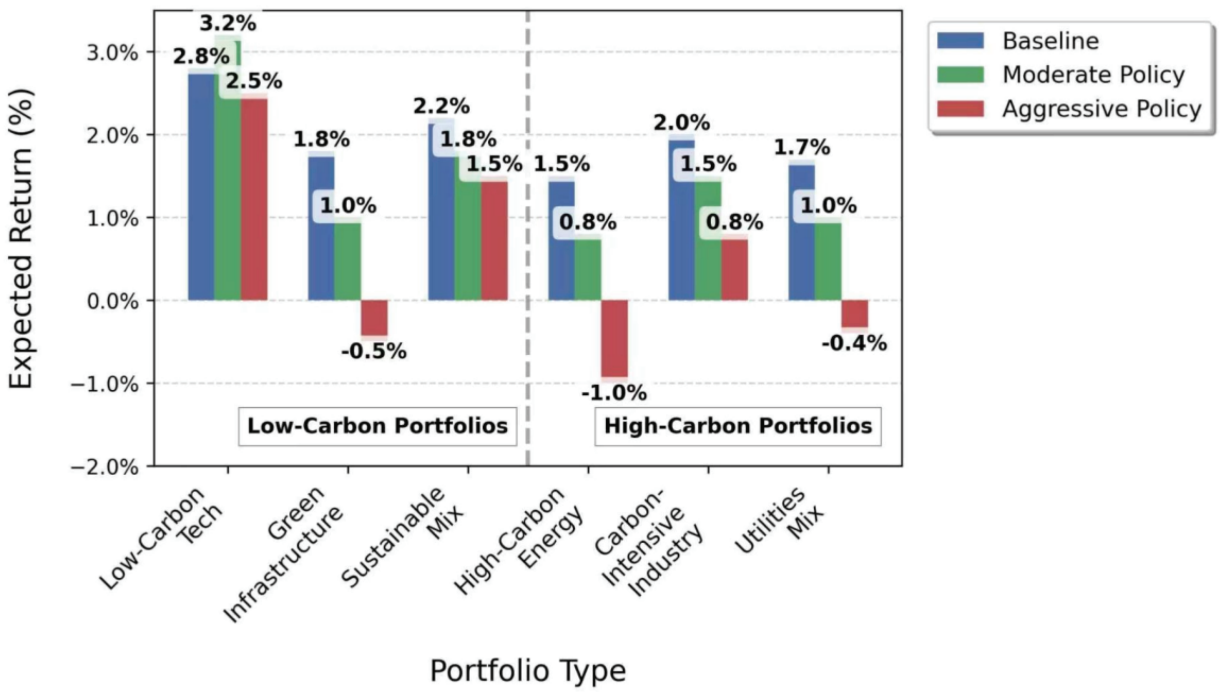
5.1 Policy Intensity as Return Driver

This study continue to investigates diversified portfolio returns under varying carbon policy intensities, revealing dynamic policy-market interactions. Figure 4 shows expected return patterns across six portfolios under three policy scenarios: lenient, moderate, and aggressive.

Under baseline conditions, the low-carbon technology portfolio delivers the strongest returns (2.8%). High-carbon energy (1.5%) and utilities (1.7%) portfolios lag. Moderate policy tightening triggers divergence: low-carbon portfolios retain advantage while high-carbon options decline significantly. Aggressive policies widen disparities dramatically—the low-carbon portfolio outperforms, whereas high-carbon energy plummets to -1.0% and utilities to -0.4%.Crucially, policy-inflicted losses on high-carbon assets accelerate nonlinearly beyond specific intensity thresholds. This accelerating decline contrasts with low-carbon assets' linear policy benefits.

This divergence originates in carbon cost transfer efficiency variations. Low-carbon portfolios leverage technological advantages to hedge policy shocks, enhancing returns. [18]High-carbon assets conversely face mandatory carbon cost internalization. Their diminishing ability to pass costs downstream vanishes entirely under aggressive policies.[19]

Figure4: Impact of Carbon Policy Scenarios on Diversified Portfolios

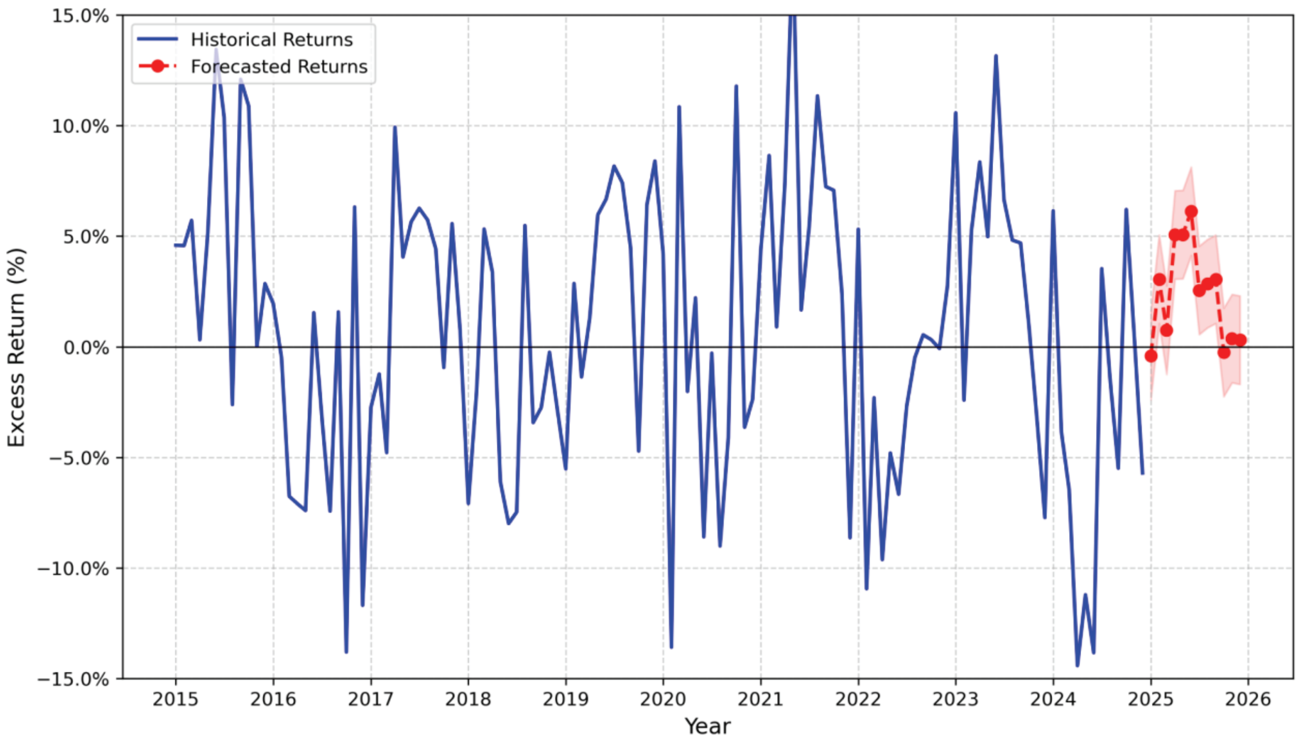


5.2 Policy Orientation Effects on Projections

Figure 5 tracks the dynamic evolution of green asset excess returns through historical fluctuations and model projections. Historical data identifies sharp negative dips reaching -0.14% during 2017 and 2020. The projection however indicates a pivotal shift: from 2024 onward, green asset returns will enter sustained growth, surpassing recent peaks to reach approximately 0.05% by 2025.

This transition from volatility to growth stems from strengthened policy guidance and accumulated market learning. [20] Historical volatility episodes reflect transient market mispricing during policy signal adjustments or external shocks—exemplified by the pandemic-driven 2020 downturn.[21] This demonstrates how major international climate initiatives steadied market expectations. Concurrently, ongoing green technology maturation generates significant scale economies and cost reductions, dampening policy disruption impacts and establishing a clear upward return trajectory.[22]

Figure5: Green Asset Excess Returns Forecast(2015-2025)



Conclusion

Overall, Physical and transition climate risks now systematically influence asset pricing. Their positive loadings confirm that markets incorporate climate shocks into valuations.[23] This necessitates updates to financial theories and investment practices. First, investors must integrate climate risk into asset allocation frameworks by establishing dynamic climate beta monitoring. [24]Jennifer</author><author>Bridges, Todd Arthur</author><author>Shah, Kushal</author></authors></contributors><titles><title>Reinventing climate investing: building equity portfolios for climate risk mitigation and adaptation</title><secondary-title>Journal of Sustainable Finance & Investment</secondary-title></titles><periodical><full-title>Journal of Sustainable Finance & Investment</full-title></periodical><pages>191-213</pages><volume>9</volume><number>3</number><dates><year>2019</year></dates><isbn>2043-0795</isbn><urls></urls></record></Cite></EndNote>Assets with high climate beta require explicit risk premium compensation. Second, dynamic portfolio rebalancing should respond to policy shifts. When carbon prices breach critical thresholds or policies change structurally, carbon-intensive holdings must be adjusted. [25]Financial institutions should develop climate resilience indices integrating Physical Risk Factors (PRF) and Transition Risk Factors (TRF). These instruments will enable more efficient capital allocation toward low-carbon technologies and climate-resilient sectors.[26]

While the Climate Stress-Asset Pricing Model (CS-APM) effectively captures climate risk transmission channels through its dual-factor design, limited corporate carbon footprint data reduces its micro-level precision. Future research could enhance accuracy through granular carbon tracking technologies. The model also omits geopolitical factors despite their moderating effect on climate risk transmission. Future studies should therefore incorporate geopolitical risk indices to support climate-smart investment strategies.

Funding

No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

[1] Erdogdu, E. (2025). The carbon border adjustment mechanism: Opportunities and challenges for non-EU countries. Wiley Interdisciplinary Reviews: Energy and Environment, 14(1), e70000.

[2] Semieniuk, G., Campiglio, E., Mercure, J. F., Volz, U., & Edwards, N. R. (2021). Low-carbon transition risks for finance. Wiley Interdisciplinary Reviews: Climate Change, 12(1), e678.

[3] Miglionico, A. (2022). The use of technology in corporate management and reporting of climate-related risks. European Business Organization Law Review, 23(1), 125-141.

[4] Jiang, M., Che, J., Li, S., Hu, K., & Xu, Y. (2025). Incorporating key features from structured and unstructured data for enhanced carbon trading price forecasting with interpretability analysis. Applied Energy, 382, 125301.

[5] Liu, Y., Yu, D., Su, Y., & Hao, R. (2014). Quantifying the effect of trend, fluctuation, and extreme event of climate change on ecosystem productivity. Environmental monitoring and assessment, 186(12), 8473-8486.

[6] Wang, W., & Zhang, Z. (2025). Dynamic linkages between crude oil, climate policy uncertainty, and agricultural commodities in China: perspective from structural SBTVAR and VIRF analysis. Journal of Accounting Literature.

[7] Wang, R. R., Hertwich, E. G., Fishman, T., Deetman, S., Behrens, P., Chen, W. Q., de Koning, A., Xu, M., Matus, K., Ward, H., Tukker, A., & Zimmerman, J. B. (2023). The legacy environmental footprints of manufactured capital. PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA, 120(24), Article e2218828120.

[8] Lim, K. P., & Brooks, R. (2011). The evolution of stock market efficiency over time: A survey of the empirical literature. Journal of economic surveys, 25(1), 69-108.

[9] Helbig, C., Dransch, D., Böttinger, M., Devey, C., Haas, A., Hlawitschka, M., Kuenzer, C., Rink, K., Schäfer-Neth, C., & Scheuermann, G. (2017). Challenges and strategies for the visual exploration of complex environmental data. International Journal of Digital Earth, 10(10), 1070-1076.

[10] Awijen, H., Ben Jabeur, S., & Pillot, J. (2024). Interpretable machine learning models for ESG stock prices under transition and physical climate risk. Annals of Operations Research, 1-31.

[11] Giannelos, S. (2025). Reinforcement Learning in Energy Finance: A Comprehensive Review. Energies (19961073), 18(11).

[12] Anupindi, R., & Jiang, L. (2008). Capacity investment under postponement strategies, market competition, and demand uncertainty. Management Science, 54(11), 1876-1890.

[13] Li, Y., Wang, X., Niu, T., & Wang, J. (2024). Industry return volatility and spillover effects in stock market under climate risk perception. APPLIED ECONOMICS, 1-18.

[14] Tenggren, S., Olsson, O., Vulturius, G., Carlsen, H., & Benzie, M. (2020). Climate risk in a globalized world: empirical findings from supply chains in the Swedish manufacturing sector. Journal of environmental planning and management, 63(7), 1266-1282.

[15] Kunreuther, H., Gupta, S., Bosetti, V., Cooke, R., Dutt, V., Ha-Duong, M., Held, H., Llanes-Regueiro, J., Patt, A., & Shittu, E. (2014). Integrated risk and uncertainty assessment of climate change response policies. In Climate Change 2014: Mitigation of Climate Change: Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (pp. 151-206). Cambridge University Press.

[16] Xu, Z., Fang, H., & Wang, W. (2025). The Impact of Climate Risk on Insurers' Sustainable Operational Efficiency: Empirical Evidence from China. Sustainability, 17(8), 3423.

[17] Haselip, J., Hansen, U. E., Puig, D., Trærup, S., & Dhar, S. (2015). Governance, enabling frameworks and policies for the transfer and diffusion of low carbon and climate adaptation technologies in developing countries. CLIMATIC CHANGE, 131(3), 363-370.

[18] Kim, Y. J., Cho, S.-H., & Sharma, B. P. (2021). Constructing efficient portfolios of low-carbon technologies. Renewable and Sustainable Energy Reviews, 150, 111515.

[19] Sun, H., Zhang, X., & Luo, C. (2025). A Review of Carbon Pricing Mechanisms and Risk Management for Raw Materials in Low-Carbon Energy Systems. Energies, 18(13), 3401.

[20] Adam, K., Marcet, A., & Nicolini, J. P. (2016). Stock market volatility and learning. The Journal of finance, 71(1), 33-82.

[21] Caprio, G., & Honohan, P. (2001). Finance for growth: policy choices in a volatile world (Vol. 1). World Bank Publications.

[22] Maghyereh, A., Boulanouar, Z., & Essid, L. (2025). The dynamics of green innovation and environmental policy stringency in energy transition investments. JOURNAL OF CLEANER PRODUCTION, 487, 144649.

[23] Campiglio, E., Daumas, L., Monnin, P., & von Jagow, A. (2023). Climate-related risks in financial assets. Journal of economic surveys, 37(3), 950-992.

[24] Bender, J., Bridges, T. A., & Shah, K. (2019). Reinventing climate investing: building equity portfolios for climate risk mitigation and adaptation. Journal of Sustainable Finance & Investment, 9(3), 191-213.

[25] Golub, A. A., Lubowski, R. N., & Piris-Cabezas, P. (2020). Business responses to climate policy uncertainty: Theoretical analysis of a twin deferral strategy and the risk-adjusted price of carbon. Energy, 205, 117996.

[26] Ali, M. A., & Kamraju, M. (2025). Financial Imperatives and Innovations for Climate Resilience. In Global Climate Governance: Strategies for Effective Management (pp. 89-122). Springer.