Strategic Asset Allocation Under Global Warming *

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Abstract

This paper investigates strategic asset allocation that explicitly conditions on global warming formalized through the IPCC's Shared Socioeconomic Pathways (SSPs). We construct a MIDAS-Bayesian-VAR model that incorporates long-run projections of temperature trajectories, along with economic indicators, into monthly asset return-volatility dynamics. Estimating the model across six climate scenarios, we document pronounced heterogeneity in optimal portfolio allocations: sustainability pathways favor substantial green asset weights due to reduced transition risk and policy tailwinds, while high-emissions scenarios generate allocations tilted toward conventional assets, driven by robust fossil fuel demand. We also complement strategic allocations with short-term tactics such as Black-Litterman optimization and sentiment-driven green-brown rebalancing. We show that climate-aware portfolio optimization requires explicit scenario conditioning rather than reliance on unconditional historical moments, with implications for institutional investors and climate-related product design.

Keywords: Strategic Asset Allocation, Climate Change, MIDAS-Bayesian-VAR, Shared Socioeconomic Pathways, Tactical Rebalancing

JEL Classification: G11, G23, Q54, C32, C11

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1 Introduction

Climate change has been emerging as a defining macroeconomic force that alters the foundations of long-term investment decisions. Rising temperatures disrupt agricultural output and increase extreme weather frequency, imposing direct costs on productive capital and undermining traditional growth models. Simultaneously, financial markets undergo structural transformation. Capital markets have witnessed the rapid proliferation of environmental, social, and governance (ESG) investment vehicles, with assets under management in sustainable strategies exceeding $124 trillion globally as of 2024.[1] This reallocation reflects not merely shifting investor preferences but deeper recognition that climate risks are financially material, systematically repricing assets and altering the term structure of expected returns.

Incorporating climate variables into asset pricing models is a recent but rapidly growing area of research. Early theoretical contributions established that environmental risks, when priced by rational investors, should command risk premia distinct from traditional factors (Heinkel, Kraus, & Zechner, 2001). However, empirical validation of these predictions proved challenging due to data limitations and the long-horizon nature of climate impacts. A breakthrough came with Bansal, Kiku, and Ochoa (2016), who document that temperature shocks significantly affect equity valuations through their impact on long-run consumption growth. Their findings suggest that a 1°C increase in global temperature is associated with approximately a 2% decline in equity valuations, operating through reduced productivity and heightened uncertainty about future economic conditions. Barnett, Brock, and Hansen (2020) extend this foundation by developing a formal asset pricing model incorporating climate risks as a systematic factor, demonstrating that climate-sensitive industries exhibit distinct exposure patterns unexplained by traditional factor models such as Fama-French specifications.

Despite these equity market findings, the micro-foundations of climate risk pricing remain contested. Engle, Giglio, Kelly, Lee, and Stroebel (2020) propose that climate risk manifests through corporate cash flow volatility, documenting that firms with higher cli-

[1] https://www.gsi-alliance.org/wp-content/uploads/2025/11/GSIR-2024-Main-Report.pdf

mate exposure exhibit greater earnings unpredictability. Their ”Climate Risk Factor” predicts returns for climate-sensitive portfolios, supporting the view that climate represents a systematic source of risk. Alternatively, Pástor, Stambaugh, and Taylor (2021, 2022) emphasize demand-side mechanisms, arguing that shifting investor preferences toward green assets drive price wedges between otherwise identical securities. In their model, unanticipated increases in ESG concerns raise green asset valuations, generating positive abnormal returns that persist until prices fully adjust to the new preference regime.

Empirical evidence on the pricing of green bonds yields mixed conclusions. Zerbib (2019) analyzes a matched sample of green and conventional bonds issued by the same entities and finds that green bonds trade at a premium, with yields approximately 2 basis points lower than equivalent conventional bonds. This ”greenium” suggests that investors accept lower returns in exchange for environmental attributes, consistent with preference-based pricing. However, the premium varies substantially across issuers and market segments, raising questions about the stability and universality of green pricing effects.

It is worth highlighting that the hedging properties of green assets constitute a particularly important dimension for portfolio construction. Reboredo and Ugolini (2020) find evidence of safe-haven properties of green bonds comparable to government bonds, which means green bonds provide downside protection during equity market stress. Similarly, Albuquerque, Koskinen, Yang, and Zhang (2020) and Huang (2024) document that firms with higher ESG scores exhibited greater resilience during the COVID-19 crisis. They attribute this defensive characteristic to stronger stakeholder relations and operational resilience, which buffer cash flows during economic disruptions.

Despite these substantial advances, several critical gaps remain. First, existing climate-asset pricing studies predominantly focus on cross-sectional return spreads. However, evidence on green premia does not immediately imply that investors should overweight green assets. Unlike transient business cycle fluctuations, climate pathways represent persistent structural shifts in the macroeconomic environment, potentially inducing regime changes in risk premia that standard historical analyses fail to capture. Understanding these long-horizon dynamics is essential for institutional investors whose aims extend decades into the future.

Second, what remains unclear is the optimal strategic allocation between green and non-green assets under different climate scenarios and how the efficient frontier shifts when sustainability-linked instruments are introduced into the investment opportunity set. Whether green assets provide diversification benefits or serve as hedges against climate-related risks, and whether these properties vary systematically across different Shared Socioeconomic Pathways, demands systematic investigation.

Third, Financial markets increasingly exhibit episodic attention to climate risks, driven by extreme weather events, policy announcements, or shifts in social consciousness. Specifically, how investors should respond to short-term climate sentiment fluctuations or discrete policy announcements lacks a coherent framework linking behavioral finance insights to optimal rebalancing rules.

In this paper, we develop an integrated framework for strategic asset allocation under climate uncertainty. This framework jointly models climate scenarios, long-horizon asset dynamics, and short-term tactics. Specifically, we introduce Shared Socioeconomic Pathways (SSP) developed by the Intergovernmental Panel on Climate Change[2] into a MIDAS-Bayesian-VAR framework to capture the joint dynamics of macroeconomic fundamentals and asset returns. This approach preserves the forward-looking nature of climate projections while respecting the econometric requirements of frequency alignment and missing data imputation. The resulting framework yields optimal strategic allocations that explicitly account for climate hedging demands and enables tactical adjustments responsive to high-frequency sentiment indicators.

Our empirical analysis document four main findings. First, we document that climate scenarios systematically differentiate the term structure of expected returns across asset classes. Green assets exhibit superior long-run performance relative to their traditional counterparts under sustainability-oriented pathways (e.g., SSP1, SSP2, SSP6) with stringent emissions controls and credible policy commitment. This outperformance reflects both fundamental channels where aggressive climate policy reduces the cost of capital for low-carbon firms through subsidy mechanisms and regulatory tailwinds, and hedging channels,

[2]It provide internally consistent projections of GDP growth, demographic evolution, and temperature trajectories conditional on policy regimes ranging from aggressive decarbonization to fossil-fueled development.

as institutional investors increasingly demand green exposures to mitigate transition risk. Conversely, in high-emissions scenarios (e.g., SSP3, SSP4, SSP5) marked by weak international coordination and persistent fossil fuel reliance, non-green assets dominate over the long run. Under these projections, robust population and economic growth in carbon-intensive development paths elevate commodity prices, support real estate valuations, and sustain demand for traditional energy infrastructure and inflation-linked instruments.

Second, we document that optimal strategic allocations exhibit sharp regime dependence across SSP scenarios. Under sustainability pathways, optimal portfolios allocate substantial weights to green assets, which reflect both their superior expected returns and hedging value where climate mitigation policies are stringent and consistently implemented. These allocations capitalize on reduced risk premia for green technologies, favorable policy environments, and rising capital inflows driven by institutional mandates to decarbonize portfolios. In stark contrast, high-emissions scenarios generate optimal allocations that favor traditional assets. Non-green equities, commodities, real estate, and inflation-linked instruments receive larger portfolio weights, driven by expectations of sustained fossil fuel demand, robust population growth, and rising inflation risks inherent in carbon-intensive development paths.

The divergence in optimal allocations across scenarios illustrates the critical role of climate narratives in shaping risk-adjusted returns. In fragmented policy environments such as SSP3, where regional rivalries impede global coordination, optimal portfolios exhibit shorter duration and higher liquidity to navigate elevated geopolitical and policy uncertainty. In inequality-driven scenarios like SSP4, allocations display bimodal patterns depending on investment horizon: short-term positioning favors liquid traditional assets, while long-term allocations tilt toward green assets to hedge against eventual regulatory convergence. Climate-aware portfolio optimization requires explicit conditioning on forward-looking climate trajectories rather than unconditional historical moments.

Third, we find that incorporating green assets substantially expands the efficient frontier across all climate scenarios. The inclusion of green equities, green bonds, and other sustainability-linked instruments shifts the mean-variance frontier outward, providing investors with superior risk-return combinations at all levels of portfolio risk. This improvement stems from two mechanisms: asymmetric exposure to climate policy shocks where green assets appreciate following regulatory tightening while brown assets depreciate, and downside protection during climate-related stress episodes.

The magnitude of frontier expansion varies across SSP scenarios but remains economically meaningful even in pathways where green assets underperform on an absolute return basis. In high-emissions scenarios such as SSP5, where non-green assets deliver higher expected returns due to continued fossil-fuel demand and commodity price appreciation, the efficient frontier still expands when green assets are included. This paradoxical result reflects the hedging properties of green assets against tail risks—specifically, the possibility of abrupt policy reversals or physical climate tipping points that would devastate brown-heavy portfolios. The option-like payoff structure of green assets, which appreciate disproportionately following unexpected policy interventions, justifies positive allocations even under baseline scenarios unfavorable to green performance on a stand-alone basis.

Fourth, we develop a hierarchical tactical asset allocation framework that addresses short-term deviations from strategic equilibrium through two complementary mechanisms. At the macro level, we employ Black-Litterman optimization where views are derived not from subjective judgment but from regime-matching procedures that map current conditions to historical regimes, then extract conditional views from these historical analogs. we conduct a case study using the COVID-19 market crash. Our similarity analysis identifies the Oil Crisis period as the nearest historical neighbor in terms of covariance structure and return drawdown patterns. Employing this match to inform Black-Litterman views, we document meaningful improvements in risk-adjusted performance: the optimized portfolio achieves an annual return of 8.64% with volatility of 6.15%, compared to return of 11.38% and volatility of 8.33% for the unadjusted portfolio. While the optimized portfolio sacrifices some raw return, it substantially reduces downside risk during the crisis period, demonstrating that the regime-matching framework successfully identifies defensive positioning when historical parallels signal elevated tail risk.

At the micro level, we operationalize climate sentiment as a tactical signal based on Google Search Volume Index. These high-frequency proxies capture shifts in aggregate market attention to climate risks and opportunities, and drive short-term price pressure in green assets (Pástor et al., 2021; Da, Engelberg, & Gao, 2011). We calibrate a logistic rebalancing function that adjusts green-brown weights based on both the level and momentum of sentiment indicators, with hyperparameters optimized through rolling 60-month windows to maximize Sharpe ratios. Empirical implementation reveals that green exposure responds dynamically to sentiment fluctuations. During periods of heightened climate attention, the model systematically increases green allocations, while waning sentiment triggers reversion toward strategic baselines or temporary underweighting. Between 2022 and 2025, the sentiment-adjusted portfolio maintains an average green weight of approximately 75%, but exhibits smooth adaptive reallocation in response to shifting market narratives. This tactical overlay complements the strategic framework by exploiting predictable patterns in investor attention without abandoning the long-horizon structural positioning dictated by SSP scenarios.

This paper contributes to several strands of literature and practice. First, we contribute to the climate risk and asset pricing literature by providing a comprehensive analysis of how alternative climate scenarios systematically influence the term structure of expected returns across traditional and green asset classes. While prior work documents robust carbon risk premia in cross-sectional returns (Bolton & Kacperczyk, 2021, 2023) or estimates the aggregate temperature sensitivity of equity valuations via long-run risk channels (Bansal et al., 2016; Bansal, Kiku, & Ochoa, 2021), these studies often abstract from non-linear scenario dependence or focus predominantly on short-to-medium horizons. Our scenario-conditional approach reveals that the sign and magnitude of green-brown return differentials reverse across Shared Socioeconomic Pathways (SSPs), challenging the notion of a universal ”green premium.” This finding helps reconcile conflicting empirical results in the literature—such as the tension between the theoretical ”greenium” (lower expected returns) posited by Pástor et al. (2021, 2022) and the realized outperformance of green assets driven by demand shocks—by demonstrating that inconsistencies arise from implicit conditioning on divergent climate trajectories. Furthermore, by dissecting these risks across term structures, we complement Faccini, Matin, and Skiadopoulos (2023), who differentiate between imminent policy risks and long-term physical risks, and Giglio, Maggiori, Rao, Stroebel, and Weber (2021), who emphasize the necessity of horizon-specific discount rates for climate-exposed assets.

We also advance the strategic asset allocation (SAA) literature by integrating forward-looking climate scenarios into the Vector Autoregression (VAR) framework pioneered by Campbell and Viceira (2002) and extended to asset-liability management by Hoevenaars, Molenaar, Schotman, and Steenkamp (2008). Existing VAR-based allocation models typically treat historical return distributions as informative about future opportunity sets. Our augmented VAR approach addresses the ”epistemological crisis” of using backward-looking data for unprecedented climate shifts, a limitation highlighted by Cosemans, Hut, and Van Dijk (2025), who advocate for incorporating climate priors into long-horizon portfolio choice. By extending the assumption to include structural shifts in the climate system, we offer a dynamic alternative to the static ”decarbonized index” hedging strategies proposed by Andersson, Bolton, and Samama (2016), and further necessitate a structural reallocation toward real assets.

Additionally, our research contributes to the growing body that incorporating alternative asset classes like commodities and real estate, which is critical for optimal climate-aware allocations, as traditional equity-bond frameworks fail to capture the non-linear exposure patterns inherent in physical and transition risks. Specifically, real estate is affected by pronounced geographic heterogeneity in climate sensitivity. Consistent with Bernstein, Gustafson, and Lewis (2019), who document that coastal properties exposed to sea-level rise trade at a significant discount, we argue that physical risks generate highly location-specific valuation channels that broad market indices obscure. Simultaneously, we depart from traditional portfolio theory that treats commodities solely as inflation hedges, instead characterizing them as physical inputs vulnerable to distinct climate-induced supply shocks. As Pankratz and Schiller (2024) highlight in their paper, physical climate risks propagate through global supply chains, causing flow-on financial disruptions that traditional diversification cannot fully mitigate. This aligns with Hong, Li, and Xu (2019), who provide evidence that markets often under-react to long-term physical risks like drought trends in food commodities, creating predictable inefficiencies. By recognizing these dynamics, our framework leverages commodities not just for diversification, but as structural hedges against ”greenflation” and supply-side shocks, responding to Engle et al. (2020).

Finally, this paper contributes to the policy and supervisory perspective regarding financial stability. Our findings carry significant implications for central bank climate stress testing and regulatory frameworks governing pension fund asset allocation. Central banks and supervisors, such as those in the Network for Greening the Financial System (NGFS), increasingly conduct climate scenario analyses to assess financial system resilience; however, recent critiques by Acharya, Johnson, Sundaresan, and Tomunen (2022) argue that these exercises often impose arbitrary return shocks or underestimate physical damages rather than deriving them from structural models linking scenarios to asset prices. Our SSP-conditional term structures provide a theoretically grounded alternative, capturing the "endogeneity of risk" highlighted by Battiston, Mandel, Monasterolo, Schütze, and Visentin (2017). Similarly, as argued by Broccardo, Hart, and Zingales (2022) and further supported by the systemic risk measures (CRISK) of Jung, Engle, and Berner (2023), optimal portfolios must shift across SSPs.

The paper proceeds as follows. Section 2 describes the data and asset classifications. Section 3 develops the MIDAS-Bayesian-VAR methodology. Section 4 presents estimates of variables and term structure. Section 5 derives optimal strategic allocations in different scenarios. Section 6 introduces the tactical rebalancing framework. Section 7 concludes.

2 Data and Asset Class

In this section, we introduce the definition and database that we use in this paper. Specifically, we relate exogenous variables to different classes of assets with a primarily focus on US data. This choice is backed by two arguments. First, the US market offers the longest data series for almost all asset classes and is always the largest market in the world. For instance, the high yield bond market has long been solely a US capital market phenomenon. Secondly, using US data avoids geographical mismatch in global data. For example, the global indexes for the relatively new asset class of inflation linked bonds are biased towards the US, French, and UK markets, while global stock indexes are decently spread over numerous countries.

2.1 Shared Socioeconomic Pathways (SSP)

Aggregate economic output, conventionally proxied by Gross Domestic Product (GDP), serves as a fundamental anchor for long-term asset return expectations (Bansal & Yaron, 2004). While short-term output fluctuations are inextricably linked to business cycle dynamics—expanding during booms and contracting in recessions—these transient volatilities tend to mean-revert over extended horizons of two to five decades. Consequently, the analytical focus for long-horizon asset allocation must shift from cyclical noise to the structural determinants of sustained economic growth.

Classical macroeconomic models provide the theoretical foundation. Frameworks ranging from the neoclassical growth model (Solow, 1956) and intertemporal optimization approaches (Ramsey, 1928) to endogenous growth theories and Dynamic Stochastic General Equilibrium (DSGE) models identify technological innovation, capital accumulation, and labor productivity as the primitive forces governing output.

Parallel to economic growth, inflation dynamics represent a pivotal yet elusive macroeconomic variable. A prevailing consensus attributes long-term inflation primarily to monetary phenomena, governed by central bank reaction functions and the quantity theory of money. To anchor expectations and foster price stability, monetary authorities typically adhere to explicit medium-term targets (Bernanke, Laubach, Mishkin, & Posen, 1999; Woodford, 2003). Although point estimates of long-run inflation are inherently uncertain, equilibrium theory posits that output and unemployment eventually converge to their potential levels, or the Non-Accelerating Inflation Rate of Unemployment (NAIRU) (Blanchard & Katz, 1997), which implies that inflationary pressures should arguably stabilize consistent with fundamental economic conditions (Bruno & Easterly, 1998). In this context, demographic trends, particularly population growth, are frequently employed as instrumental proxies to gauge secular shifts in inflationary environments.

However, recent research recognizes environmental externalities as critical constraints on growth. A bunch of literature now highlights the non-linear impact of climate change and rising global temperatures on long-run economic performance (Nordhaus, 2019; Stern, 2007). Accordingly, modern macroeconomic specifications are evolving to incorporate biophysical constraints, acknowledging that climate risks materially affect factor productivity, resource endowment, and the broader sustainability of the economic system.

To include these projections, we utilize the Shared Socioeconomic Pathways (SSP) framework. The SSPs provide forward-looking scenarios encompassing GDP growth, demographic shifts, and climate trajectories under heterogeneous policy assumptions. Notably, the Intergovernmental Panel on Climate Change (IPCC) delineates global temperature pathways based on five distinct SSP scenarios, classified by their radiative forcing levels in the year 2100 (measured in W/m^2). For instance, the SSP1-1.9 pathway delineates a sustainability-focused trajectory characterized by minimal greenhouse gas emissions and a radiative forcing limit of 1.9 W/m^2. We simulate a "SSP6" pathway to represent a global cooling scenario for sensitivity analysis. In this scenario, humans achieve broad collaboration and gives the most attention to global warming thus they sacrifice economic growth to attend the objective of slowing global warming down.

Data regarding these macroeconomic and climatic trajectories are sourced from the International Institute for Applied Systems Analysis (IIASA) database. By treating these projected variables—GDP, population dynamics, and temperature anomalies—as exogenous state variables, we establish a robust framework to identify the determinants of long-run asset returns.

2.2 Short- and Long-term Rates

Central banks predominantly utilize short-term interest rates as the primary instrument to navigate the trade-off between price stability and sustainable output growth. The calibration of these rates is formalized through policy reaction functions, most notably the Taylor Rule (Taylor, 1993), which prescribes rate adjustments strictly contingent on the inflation gap and the output gap. Theoretically, the long-run trajectory of the real short-term rate is anchored to the economy's steady-state growth path. Consistent with the Golden Rule of capital accumulation (Phelps, 1961), this equilibrium converges with the long-term growth rate of potential output. Consequently, in a Fisherian framework, the nominal equilibrium short rate is modeled as the aggregate of long-run inflation expectations and real potential output growth. These structural inter-dependencies highlight how macroeconomic fundamentals dictate the term structure of interest rates, thereby exerting a primal influence on

asset pricing and risk premia.

For empirical estimation, we rely on yield data on 3-month Treasury bills and 10-year zero-coupon government bonds, sourced from the Federal Reserve Economic Data (FRED). Yields are transformed into logarithmic returns. Thus, the yield on the 10-year zero-coupon bond is denoted as $y_{10,t} = ln(1 + Y_{10,t})$, where $Y_{10,t}$ represents the annualized percentage yield. Similarly, the logarithmic risk-free rate, proxied by the 3-month Treasury bill, is expressed as $r_t = ln(1 + R_t)$.

2.3 Equity

In contrast to fixed-income instruments, the no-arbitrage condition dictates that equity prices must equal the present value of expected future cash flows, discounted by a stochastic discount factor. This discount rate functionally equates to the firm's cost of equity capital and, by extension, the theoretical required rate of return demanded by investors. From a corporate finance perspective, the cost of capital is a pivotal determinant of valuation. Analytical frameworks typically posit an inverse relationship between discount rates and asset prices: holding cash flow expectations constant, a reduction in the cost of capital elevates equity valuations, whereas an increase exerts downward pressure. This mechanism underscores the sensitivity of asset prices to shifts in the aggregate discount rate, a dynamic rigorously explored in the variance decomposition literature (Campbell & Shiller, 1988a, 1988b).

To model these long-run valuation dynamics, Gordon's (1962) Growth Model assumes a stable required return and constant dividend growth in steady state, decomposing the expected equity return into the risk-free rate, the equity risk premium, and the dividend yield. Consequently, the dividend-price ratio serves as a primary state variable for assessing valuation levels relative to fundamentals.

While early empirical work (Campbell & Shiller, 1998) treated dividend yields as mean-reverting over long horizons, recent scholarship suggests that the mean of the dividend-price ratio may itself be time-varying. Notably, Favero, Gozluklu, and Tamoni (2011) provide evidence that low-frequency variations in dividend yields are structurally linked to demographic shifts, specifically the ratio of middle-aged to young cohorts (MY ratio). This implies that a sustainable long-term dividend yield is not a static constant but rather a function of evolving demographic structures.[3] In this context, we assume that equity returns are linked to a non-stable dynamics of a bunch of exogenous factors.

To do so empirically, we employ equity return data sourced from MSCI, with a specific focus on climate-adjusted performance. MSCI delineates "Climate Equity Indexes" into two primary methodologies: (1) Positive Screening, which overweights constituents in environmentally sustainable sectors (e.g., clean energy); and (2) Negative Screening, which systematically underweights or excludes issuers with high carbon intensity. Given the increasing mandate for institutional investors to manage "transition risk"—the financial risk associated with the shift to a low-carbon economy—this study utilizes the Negative Screen indexes. This selection criterion allows for a precise examination of how climate risk mitigation strategies impact the cost of equity and long-term asset returns, while controlling for the exclusion of carbon-intensive assets.

[3]This perspective challenges the assumption of a time-invariant long-term dividend growth rate. While dividends historically track earnings, structural breaks in the payout ratio—such as those observed during the 1990s—suggest that payout policies adapt to broader economic and demographic regimes.

2.4 Sovereign Bonds

In the long run, the bond risk premium—the compensation investors demand for bearing duration risk relative to short-term instruments—is theorized to anchor to structural macroeconomic stability. While cyclical volatility dissipates over extended horizons, a positive term premium persists, driven fundamentally by monetary and fiscal credibility. From a monetary perspective, uncertainty regarding central bank inflation targeting introduces inflation risk premiums, eroding real returns at maturity. Consequently, the equilibrium long-term yield is modeled as the aggregation of the short-term equilibrium rate and a time-varying risk premium, which varies positively with long-run inflation volatility.

Our sovereign bond data is sourced from broad market indices provided by MSCI and FTSE. A significant empirical challenge in constructing a dedicated "Green Sovereign" benchmark is the absence of sovereign green bond issuance by the United States, the world's largest fixed-income market. This issuance gap necessitates the use of a global proxy. We employ the FTSE Climate Government Bond Index, which utilizes a negative screening methodology to reweight sovereign exposures based on climate risk resilience and transition preparedness.[4]

2.5 Corporate Bonds

Corporate debt instruments share the duration risk of sovereign bonds but entail an additional layer of default risk. In the structural framework of Merton (1974) and Jones, Mason, and Rosenfeld (1984), corporate equity is viewed as a call option on firm value, implying that bond yields must incorporate a credit spread to compensate for the probability of asset values falling below debt obligations. Over long horizons, these credit spreads are expected to mean-revert to a level consistent with the firm's steady-state default probability and the economy's long-term growth path.

For empirical analysis, corporate bond data is sourced from MSCI, covering two primary

[4]The suitability of this global proxy is supported by the composition of the FTSE World Government Bond Index (WGBI), where the US commands a 42% weight. In the Climate variant, the US remains the dominant constituent, being underweighted by only 5% relative to the WGBI, thus preserving the representative nature of the benchmark.

categories: Investment Grade (IG) bonds and High Yield (HY) bonds. Each category includes both traditional corporate bonds and green bonds. Specifically, we consider the MSCI USD IG Core ESG Universal Corporate Bond Index and the MSCI USD IG Core ESG Leaders Corporate Bond Index. Both indices employ ESG integration methodologies but differ in their selection criteria. The former follows a best-in-class approach, including only companies with the highest MSCI ESG Ratings, whereas the latter adjusts market-capitalization weights based on specific ESG metrics. To make our selection compatible with equities and sovereign bonds, we utilize the former index in this paper.

2.6 Alternative Investments products

The existence of a structural risk premium in commodity markets remains a subject of theoretical debate. Historically, backwardation theories suggest that price appreciation is driven by inventory hedging pressures during periods of excess demand (Keynes, 1930). However, empirical evidence regarding a persistent long-run premium is mixed. Gorton and Rouwenhorst (2006) argue that over extended horizons, commodity returns often converge to the risk-free rate, challenging the notion of a distinct asset class premium. Conversely, structural arguments rooted in resource economics—specifically Hotelling's rule of scarcity rents—suggest that intergenerational conservation needs could underpin sustained price increases. Furthermore, the "financialization" of commodities, driven by secular demand growth from emerging markets, may exert persistent upward pressure on prices (Tang & Xiong, 2012). These factors collectively suggest the possibility of a structurally embedded risk premium in the long run.

For empirical analysis, commodity exposure is proxied by the UBS CMCI Sustainability Index. Unlike traditional benchmarks, the CMCI framework evaluates the social and ecological impact of commodities across their entire lifecycle—from production to utilization. Each constituent is assigned a sustainability score (ranging from C- to A+) based on a granular assessment of labor practices, governance standards, and environmental externalities.[5]

[5]The rating methodology rigorously accounts for geographic origin, production technologies, and operational conditions. It explicitly considers the diverse utility of commodities, ranging from industrial

Real estate investments can be gained through both listed and non-listed indices. However, non-listed indices, which rely on appraisal-based valuations, tend to exhibit a smoothing effect that underestimates the asset class's true risk. This bias arises due to infrequent appraisals and the interpolation of returns, which may fail to capture short-term price fluctuations. Furthermore, market price adjustments are reflected in appraisal values only when sufficient evidence of price shifts accumulates. While statistical techniques exist to mitigate these distortions, they do not fully eliminate the challenge of accurately measuring holding-period returns (Geltner, 1993). Given these concerns, this study focuses on listed real estate indices, which are based on transaction prices and provide more reliable return data. Ibbotson (2006) notes that while some debate remains regarding the comparability of direct and indirect commercial real estate investments, an increasing body of research suggests that their return characteristics are largely similar. Consequently, listed indices are assumed to offer higher-quality return data.

Our real estate data is sourced from the FTSE Nareit Green Target Index, widely recognized as the preeminent global benchmark for Real Estate Investment Trusts (REITs) (Bekkers, Doeswijk, & Lam, 2009). To capture the "green" factor, this index employs a dual-layered methodology: first, it applies negative screening to exclude firms involved in controversial sectors (e.g., weapons, thermal coal); second, it reweights the remaining constituents to maximize green building certifications and energy efficiency metrics. This ensures that the portfolio's carbon intensity is strictly superior to that of the parent index.

It is important to note that this study excludes Private Equity (PE) and Hedge Funds due to significant data opacity and the absence of standardized green benchmarks. Unlike equities and bonds, green investment frameworks for private equity and hedge funds remain underdeveloped, with no widely accepted benchmarks. Measuring environmental impact in these asset classes is particularly challenging due to fragmented and inconsistent methodologies. Private equity investments often involve companies that are not subject to standardized environmental, social, and governance (ESG) disclosure requirements. Similarly, hedge funds, which employ diverse trading strategies, lack transparency regarding their sustainability impact.

applications to medical technologies and renewable energy infrastructure.

Another significant obstacle is the heterogeneous nature of private equity and hedge fund investments. Private equity portfolios often span multiple industries with varying carbon footprints, making it difficult to aggregate ESG data into a single green index. Hedge funds, on the other hand, engage in strategies such as short selling, derivatives trading, and high-frequency trading—none of which lend themselves easily to environmental impact assessments.

Furthermore, the evolving regulatory landscape adds to the uncertainty. Green investment classification systems, such as the EU Taxonomy for Sustainable Activities, continue to develop, leaving asset managers without clear guidelines for defining and measuring sustainability in private markets. The absence of standardized benchmarks complicates efforts to construct reliable green indices for these asset classes, further limiting the availability of robust ESG investment solutions in private equity and hedge funds.

3 Methodology

To empirically characterize the joint dynamics of macroeconomic underlines, climate variables, and asset returns, we develop an integrated econometric framework, which synthesizes a Vector Autoregressive (VAR) process with Mixed Data Sampling (MIDAS) to bridge frequency mismatches, and employs Bayesian imputation to address the truncation bias inherent in the short histories of green assets.

3.1 The VAR Framework

We employ a Vector Autoregressive (VAR) model to capture time-varying risk-return dynamics (Campbell, Chan, & Viceira, 2003; Ghysels, 2016). Unlike structural models that impose rigid identification schemes, the VAR framework allows for the endogenous determination of asset returns and state variables, providing a flexible environment to analyze impulse responses and variance decompositions. The reduced-form model is defined as follows:

$$r_t = c + \sum_{i=1}^{p} A_i r_{t-i} + u_t \tag{1}$$

Where r_t is a vector containing multiple endogenous variables; A_i is the Matrix of lag coefficients; and u_t is the noise term, with assumption that follows standard normal distribution.

This specification serves three functions. First, the vector r_t represents the comprehensive investment opportunity set, treating dynamics of traditional and green asset classes as jointly determined. This endogenous structure allows the model to capture complex spillover effects. Second, the lag matrix A_i embodies the time-varying nature of risk premia. Unlike static models that assume independent and identically distributed (i.i.d.) returns, our VAR framework explicitly models the persistence and mean-reversion properties of asset returns, which are fundamental for determining optimal weights in long-horizon strategic allocation. Third, by refraining from imposing rigid structural restrictions on A_i, the model lets the data reveal the latent transmission mechanisms of climate-related financial risks, which is particularly appropriate given the theoretical ambiguity regarding how climate transition channels interact with market fundamentals.

3.2 Frequency Mismatch and MIDAS Specification

A persistent challenge in integrating macroeconomic variables into asset pricing models arises from frequency mismatches. While financial returns are observed daily or monthly, many climate and demographic variables—such as temperature anomalies, GDP growth, and population dynamics—are measured annually. Naive interpolation of low-frequency data to match high-frequency observations introduces spurious correlations and biases coefficient estimates (Rossana & Seater, 1995). The Mixed Data Sampling (MIDAS) approach, pioneered by Ghysels, Santa-Clara, and Valkanov (2004, 2006), provides a rigorous solution by directly modeling the relationship between variables observed at different frequencies. Rather than transforming low-frequency data, MIDAS employs parametric weighting functions that aggregate high-frequency information into low-frequency forecasts or, conversely, distribute low-frequency shocks across high-frequency observations.

To assimilate annual state variables into our high-frequency estimation without resorting to interpolation or aggregation—which can induce spurious correlations—we adopt the Mixed Data Sampling (MIDAS) approach.

$$r_t = c + \sum_{i=1}^{p} A_i r_{t-i} + \sum_{j=1}^{q} B_j X_{t-j/f} \cdot W_j(\theta) + u_t \tag{2}$$

Where r_t is a vector containing multiple endogenous variables; A_i and B_i are the Matrix of lag coefficients; $X_{t-j/f}$ is Low-frequency exogenous variable with sampling frequency f (annual); $W_j(\theta)$ is a MIDAS weighting function for mapping low frequency variables to high frequencies; and u_t is the noise term, with assumption that follows standard normal distribution.

To parameterize the lag structure, we employ the Beta weighting function. As noted by Ghysels, Sinko, and Valkanov (2007) and Andreou, Ghysels, and Kourtellos (2010), the Beta function is particularly adept at capturing diverse lag decay patterns—ranging from monotonic decay to hump-shaped responses—which is essential given the theoretically ambiguous temporal impact of temperature shocks on asset prices. The weighting function takes the form:

$$W_j(\theta) = \frac{(j+1)^{\theta_1}(q-j+1)^{\theta_2}}{\sum_{k=0}^{q}(k+1)^{\theta_1}(q-k+1)^{\theta_2}} \tag{3}$$

Where j is a lag index for high frequency data, whereas q is a lag index for low frequency data. θ_1 and θ_2 control the rate of growth or decay of weights for high frequency data and low frequency data, respectively.

3.3 Bayesian Data Imputation Model Setting

Complementing the frequency mismatch problem, the nascent history of green assets creates missing data challenges. As expected, time-series for primary assets, such as stocks and bonds, extend over a significantly long historical period. In contrast, data for green assets are considerably shorter, often with time-series horizons averaging less than 10 years. Truncating these return histories is undesirable, as it may result in the loss of potentially valuable information.

To effectively utilize the available data and accurately estimate the dynamics of green and alternative assets, we adopt the methodologies proposed by Stambaugh (1997) and Kadiyala and Karlsson (1997) to address the issue of uneven time-series lengths. Bayesian imputation methods offer a principled approach to extend short return series. By leveraging cross-sectional correlations with established assets, Bayesian techniques generate posterior distributions for missing observations that reflect both sample information and prior beliefs. Kadiyala and Karlsson (1997) develop Minnesota priors specifically for VAR models, which impose shrinkage toward random walk specifications and mitigate overfitting when data are limited.

Specifically, we employ Bayesian inference to estimate missing values by integrating prior information with the observed data. Let r_t denote the observed asset returns at time t, and let $\tilde{r}_t$ be the missing return values that need to be imputed. Our objective is to estimate the posterior distribution of $\tilde{r}_t$ given the observed data r_t:

$$p(\tilde{r}_t|r) \propto p(r|\tilde{r}_t)p(\tilde{r}_t). \tag{4}$$

We assume that asset returns follow a normal distribution with mean μ and variance σ^2, which we estimate from the available data:

$$r_t|\mu, \sigma^2 \sim \mathcal{N}(\mu, \sigma^2). \tag{5}$$

To incorporate prior knowledge, we impose conjugate priors:

$$\mu \sim \mathcal{N}(\mu_0, V_0) \quad and \quad \sigma^2 \sim \mathcal{IG}(\alpha_0, \beta_0), \tag{6}$$

where $\mathcal{IG}(\alpha_0, \beta_0)$ represents the inverse gamma prior on the variance. The missing values $\tilde{r}_t$ are then estimated via Gibbs sampling, iteratively drawing from the conditional posteriors:

$$\mu|\sigma^2, r \sim \mathcal{N}\left(\frac{n\bar{r} + V_0^{-1}\mu_0}{n + V_0^{-1}}, \frac{\sigma^2}{n + V_0^{-1}}\right) \tag{7}$$

$$\sigma^2|r \sim \mathcal{IG}\left(\alpha_0 + \frac{n}{2}, \beta_0 + \frac{1}{2}\sum_{t=1}^{n}(r_t - \bar{r})^2\right) \tag{8}$$

Using these posterior distributions, we iteratively generate samples for $\tilde{r}_t$, ensuring that the imputed values remain statistically consistent with the observed data. This Bayesian imputation method allows us to extend short asset return series without introducing excessive bias.

3.4 MIDAS-Bayesian-VAR

By integrating all previous methods to conquer the difficulties, we estimate our sample within a new MIDAS-Bayesian-VAR framework. Specifically, we follow a standard procedure to introduce step-by-step our model setting into the estimation. First, We use the MIDAS method to smoothly map low-frequency variables to high-frequency time via the Beta weighting function. Here we choose to select appropriate shape parameters for the MIDAS-Beta function, where we fit each exogenous variable individually and determine the initial parameters using the AIC information criterion. Considering the literature description (Ghysels et al., 2006; Andreou et al., 2010; Dietz, Bowen, Dixon, & Gradwell, 2016), we can determine a priori: GDP ($\theta_1 = \theta_2 > 0$), Population ($\theta_1 > \theta_2 = 0$), Temperature ($\theta_1 > \theta_2 > 0$). Then, we estimate the lagged coefficient matrix and covariance matrix for asset returns. The low-frequency exogenous variables are known states and can be modeled and parameters estimated using classical least squares (OLS). For endogenous variables, especially green assets, the problem that short series may lead to unstable estimation needs to be considered. Therefore, we use a Bayesian imputation to complement the data set.

We simplify our model setting for VAR(1) following Campbell et al. (2003) together with MIDAS and Bayesian settings. Then, we get the simplifying formulas with combination. We can describe our variable matrix as follows:

$$\mathbf{X}_t \equiv (GDP_t, Pop_t, Temp_t)^{\mathsf{T}}$$

$$\mathbf{r}_{1,t} \equiv (r_{s,t}, r_{l,t})^{\mathsf{T}}$$

$$\mathbf{r}_{2,t} \equiv (r_{stock,t}, r_{govb,t}, r_{inf,t}, r_{igb,t}, r_{hyb,t}, r_{pe,t}, r_{re,t}, r_{commo,t})^{\mathsf{T}}$$

$$\mathbf{r}_{3,t} \equiv (r_{green})^{\mathsf{T}} \equiv (r_{stock,t}, r_{govb,t}, r_{inf,t}, r_{igb,t}, r_{hyb,t}, r_{re,t}, r_{commo,t})^{\mathsf{T}}$$

In addition, we impose two restrictions on our model setting except of considering GDP, Population, and Temperature as completely exogenous, in response to the large dimension of the VAR model and real economic dynamics (Bernanke & Blinder, 1992). First, primary and alternative asset classes provide no dynamic feedback to short- and Long-term rate. Second, we assume that Green assets provide no explanatory power for the dynamics of other variables. The reason is simple, the green assets we choose are constructed based on the existed financial instruments. Therefore, the performance of green assets should be partially driven by those longer existed asset classes. Thus, we employ the restrictions to describe our VAR(1) model:

$$\mathbf{r}_{1,t} = A_0 + A_1\mathbf{r}_{1,t-1} + \sum_{j=1}^{q} w_{1,j}\mathbf{X}_{t-j/f} \cdot W_j(\theta) + u_{1,t} \tag{9}$$

$$\mathbf{r}_{2,t} = B_0 + B_1\mathbf{r}_{2,t-1} + B_2\mathbf{r}_{1,t-1} + B_3\mathbf{r}_{1,t} + \sum_{j=1}^{q} w_{2,j}X_{t-j/f} \cdot W_j(\theta) + u_{2,t} \tag{10}$$

$$\mathbf{r}_{3,t} = C_0 + C_1\mathbf{r}_{3,t-1} + C_2\mathbf{r}_{2,t-1} + C_3\mathbf{r}_{2,t} + C_4\mathbf{r}_{1,t-1} + C_5\mathbf{r}_{1,t} + \sum_{j=1}^{q} w_{3,j}X_{t-j/f} \cdot W_j(\theta) + u_{3,t} \tag{11}$$

Putting (5), (6), (7) together, we can get the complete VAR(1) as follows by simplification. The two restrictions implicitly set the covariance of $\Sigma_{u1,u2}$, $\Sigma_{u1,u3}$, and $\Sigma_{u2,u3}$ equal to zero.

$$\mathbf{z}_t = \Phi_0 + \Phi_1\mathbf{z}_{t-1} + \Phi_2\sum_{j=1}^{q}\mathbf{X}_{t-j/f}W_j(\theta) + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(0, \Sigma) \tag{12}$$

Where

$$\mathbf{z}_t = (\mathbf{r}_{1,t}, \mathbf{r}_{2,t}, \mathbf{r}_{3,t})$$

$$\Phi_0 = \begin{pmatrix} A_0 \\ B_0 + B_3A_0 \\ C_0 + C_3(B_0 + B_3A_0) + C_5A_0 \end{pmatrix}$$

$$\Phi_1 = \begin{pmatrix} A_1 & 0 & 0 \\ B_2 + B_3 A_1 & B_1 & 0 \\ (C_5 + B_3 C_3) A_1 + B_2 C_3 + C_4 & C_2 + C_3 B_1 & C_1 \end{pmatrix}$$

$$\Phi_2 = \begin{pmatrix} w_{1,j} \\ w_{2,j} + B_3 w_{1,j} \\ w_{3,j} + B_3 C_3 w_{2,j} + C_5 w_{1,j} \end{pmatrix}$$

$$\Sigma = \begin{pmatrix} \Sigma_{u1,u1} & B_3 \Sigma_{u1,u1} & (C_5 + B_3 C_3) \Sigma_{u1,u1} \\ B_3 \Sigma_{u1,u1} & (B_3)^2 \Sigma_{u1,u1} + \Sigma_{u2,u2} & C_3 \Sigma_{u2,u2} \\ (C_5 + B_3 C_3) \Sigma_{u1,u1} & C_3 \Sigma_{u2,u2} & (B_3 C_3 + C_5)^2 \Sigma_{u1,u1} + (C_3)^2 \Sigma_{u2,u2} + \Sigma_{u3,u3} \end{pmatrix}$$

4 Empirical Results

This section presents the empirical findings derived from the integrated framework established in Section 3. The analysis proceeds in two stages. First, we report the coefficient estimates for the block-recursive system, detailing the dynamic transmission mechanisms between macroeconomic state variables and asset returns. Second, we project the term structures of equilibrium returns conditional on the Shared Socioeconomic Pathways (SSPs). The central insight from our analysis is that sustained growth in long-term asset returns is structurally contingent on scenarios where global warming is effectively mitigated.

4.1 Estimation Results

Table 1 reports coefficient estimates across SSP scenarios. Our simulation procedure follows a sequential approach: first, we simulate the potential growth paths of GDP, population, and temperature, incorporating their covariance structure; second, we employ Equation 12 to estimate the dynamic coefficients. Specifically, we estimate return relationships for three components: the term structure, fundamental asset classes, and green assets. The empirical results reveal several critical dynamics.

First, interest rates significantly affect stock and bond returns. This confirms the standard discount rate channel: rising interest rates suppress equity valuations while simultaneously exerting upward pressure on bond yields.

Second, most asset classes demonstrate significant autoregressive coefficients, indicating a high degree of persistence in returns. We also observe substantial spillover and substitution effects among risk assets; for instance, investment-grade bond returns (r_{igb}) positively influence several asset classes, whereas high-yield bond returns (r_{hyb}) exhibit significant negative coefficients in specific equations, reflecting flight-to-quality dynamics.

Third, regarding macroeconomic drivers, GDP growth exhibits a significant negative impact on government bond yields (r_{govb}) in several specifications, suggesting that expectations of declining current output tend to suppress yields (or conversely, strong growth drives yields up). Meanwhile, population changes show positive and significant effects on r_{govb} and inflation (r_{inf}), implying that demographic expansion drives aggregate demand and inflationary pressures, thereby influencing the yield curve.

Crucially, our results highlight the sensitivity of asset markets to climate variables. Both short-term and long-term interest rates, along with several fixed-income instruments, demonstrate significant negative reactions to temperature shocks. For example, the coefficient for the short rate (r_s) is -0.042, implying that a 0.01°C increase in temperature is associated with a 4.2 basis point decrease in short-term rates. Furthermore, green assets exhibit an exceptionally strong negative temperature beta. This suggests that financial markets utilize these assets to hedge against climate-related shocks.

In general, temperature shocks elicit heterogeneous responses across asset classes through three distinct channels: (1) real-economy shocks (impacts on output and demand), (2) risk pricing channels (revaluation of future cash flows and discount rates), and (3) market liquidity channels. Specifically, rising temperatures impair real output—particularly in agriculture, construction, and energy demand—reducing the base for future cash flows and depressing returns. This transmission is rapid and significant in bond markets, especially for issuers with high regional or sectoral exposure. As market recognition of long-term climate risks intensifies, risk premia expand and valuations contract, disproportionately affecting highly exposed sectors such as energy and infrastructure. Additionally, extreme temperature events can trigger acute risk aversion and liquidity tightening, amplifying volatility

(Burke, Hsiang, & Miguel, 2015). This aligns with the ”Green Swan” framework (Bolton, Després, Pereira Da Silva, Samama, & Svartzman, 2020), positing that while individual climate shocks may seem contained, they can trigger systemic financial reassessments through non-linear accumulation.

[Insert Table 1 Here]

4.2 Variables Term Structure

In this section, we present the term structure of various asset classes to compare their long-run returns under differing Shared Socioeconomic Pathways (SSPs). Notably, we show that green assets outperform in sustainable scenarios (SSP1, SSP2, SSP6) over the long term. However, despite the expectation that green assets may attract substantial investment flows and generate higher returns over shorter horizons, non-green assets tend to outperform over the long run in ”high emission” scenarios (SSP3, SSP4, SSP5). These estimations are broadly consistent with established literature. There are several potential explanations.

In high-warming scenarios, physical risks affect non-green assets most severely. These assets are prone to heightened physical hazards, such as more frequent extreme weather events and supply chain disruptions, which theoretically depress expected returns. This aligns with literature documenting that severe climate impacts negatively affect assets heavily exposed to physical risks (e.g., (Bolton & Kacperczyk, 2021)).

Concurrently, however, the projected long-term appreciation in non-green real estate, commodities, and inflation rates is attributable primarily to the robust population and economic growth inherent in high-carbon emission scenarios. In particular, continued demographic expansion and economic development in emerging markets drive aggregate demand for commodities, with urbanization trends supporting housing markets (Roncalli, Le Guenedal, Lepetit, Roncalli, & Sekine, 2016). Similarly, the returns on inflation-linked bonds are fundamentally driven by these underlying economic growth trends.

In the context of extreme warming, the market may perceive green investments as still nascent or insufficient to offset broader economic damages. Under such conditions, green sectors may suffer from transitional uncertainties, including technological immaturity or delays in policy implementation. Furthermore, green infrastructure (e.g., solar farms, wind turbines) faces direct exposure to physical risks—such as floods and storms—that compromise output and erode investor confidence. Allan et al. (2023) suggest renewable energy projects in climate-vulnerable regions face higher physical risks and lower returns in high-warming scenarios. This heightened uncertainty likely compels investors to demand a higher risk premium, effectively compressing the expected returns on green assets.

Conversely, in scenarios characterized by net-zero emissions or long-term cooling, the policy environment becomes markedly more aggressive and supportive of sustainable technologies. Under stringent climate policies, green assets benefit from a reduction in the cost of capital by approximately 1.5%–2.0% (Ehlers, Gao, Packer, & de Greiff, 2022). Moreover, firms aligned with the EU Taxonomy experienced valuation premiums of roughly 9% following the 2021 regulations (Sautner, Van Lent, Vilkov, & Zhang, 2023a, 2023b). Consequently, green assets benefit from enhanced profitability driven by economies of scale and technological innovation. The improved outlook under such scenarios translates to higher expected returns for green assets relative to their non-green counterparts.

Meanwhile, non-green assets face the dual burden of stranded asset risk and increasingly stringent environmental regulations in a net-zero trajectory. Companies reliant on carbon-intensive operations may incur significant write-downs or face competitive disadvantages as the market transitions toward sustainability. Semieniuk et al. (2022) estimate that Overall, listed companies hold \$1.27 trillion in stranded assets in net-zero scenarios, creating a structural drag on non-green returns. Indeed, coal assets lost \$1.3 trillion in value during 2015–2020 (Carbon Tracker Initiative, 2021). This dynamic contributes to a widening divergence between green and non-green asset returns, with the latter penalized by elevated transition risks and diminished growth prospects.

Beyond the fundamental valuation mechanisms discussed above, another crucial factor influencing the relative performance of green and non-green assets under varying climate scenarios is their utility in hedging climate risks. The demand for hedging instruments shifts dynamically: it reinforces green asset price appreciation during periods of aggressive climate action while limiting their performance under weak action scenarios.

Specifically, green assets serve as a hedge against transition risk. In scenarios where governments commit to aggressive decarbonization (i.e., net-zero scenarios), investors anticipate that carbon-intensive assets will decline in value due to regulatory burdens, carbon pricing, and stranded asset risks. Under these conditions, green assets offer an effective hedge, as they are positioned to benefit from the low-carbon transition. As highlighted by Engle et al. (2020), climate risk-hedging portfolios have gained traction among institutional investors, with environmentally robust assets commanding a premium due to their perceived hedging properties. Similarly, Pástor et al. (2022) argue that as investors increasingly incorporate ESG considerations, green assets experience positive capital inflows, reinforcing their outperformance during the transition economy. Furthermore, Andersson et al. (2016) show that ”decarbonization portfolios” effectively hedge transition risks and tend to outperform as climate policies strengthen. Krueger, Sautner, and Starks (2020) also document that institutional investors increasingly demand green assets as part of long-term hedging strategies, bolstering their performance in sustainable policy environments.

Paradoxically, non-green assets may act as a hedge against physical climate risks in high-warming scenarios. In an extreme climate stress scenario, supply disruptions could drive up energy prices, temporarily boosting revenues for traditional energy producers. While physical climate risks (e.g., extreme weather, rising sea levels, economic disruptions) negatively affect the broad economy—including green assets—under high-warming scenarios, investors seeking immediate hedging opportunities may pivot toward traditional assets perceived as more resilient or essential under these specific conditions.

Conversely, green infrastructure, renewable energy, and technology investments require long-term capital commitments, the value of which may be discounted in an environment of heightened uncertainty. For instance, Bansal et al. (2021) show that higher climate risk is associated with greater economic uncertainty, which can temporarily elevate the returns of non-green sectors that remain central to economic activity.

[Insert Table 2 Here]

5 Strategic Portfolio Allocation

We then focus on investment strategies for institutional investors, such as defined contribution pension plans, which typically face fewer or no liability constraints. As a result, these investors can adopt an asset-only approach when constructing their optimal portfolio. This approach, based on the mean-variance framework introduced by Markowitz (1959), aims to maximize the attainable risk-return trade-off without accounting for the risk associated with liabilities.

5.1 Optimal Return-Risk Portfolios

In this section, we present the optimal mean-variance portfolio choice for a buy-and-hold investor. We build the optimal holdings of an "asset-only" investor who is only concerned about the Sharpe Ratio maximization of his investment as follows:

$$\max_{\alpha_t'(\tau)} \quad E_t\left[r_{P,t+\tau}^{(\tau)}\right] - \frac{\gamma}{2} Var_t\left[r_{P,t+\tau}^{(\tau)}\right] \tag{13}$$

Where $r_{P,t+\tau}^{(\tau)} = \sum_{j=1}^{\tau} r_{P,t+j}$ is the cumulative logarithmic return of the portfolio P for the period τ; $\alpha_t'(\tau)$ is the matrix of weights assigned for a set of assets; and γ is the risk aversion parameter. We follow Campbell and Viceira (2002) to determine the formula of return and variance. Specifically, we argue that benchmark and green investments have different sensitivities and exposures to long-term temperature changes. The impact of climate change on green asset returns ($\tilde{x}_{t+\tau}^{(\tau)}$) is coming from a "Temperature Beta", rather than benchmarks ($x_{t+\tau}^{(\tau)}$). Where $x_{t+\tau}^{(\tau)}$ and $\tilde{x}_{t+\tau}^{(\tau)}$ are the vectors of asset returns; $\Sigma_{xx}(\tau) = \text{Var}(x_{t+\tau}^{(\tau)})$; and $\sigma_x^2(\tau) = \text{diag}(\Sigma_{xx}(\tau))$. Thus we get,

$$E_t\left[r_{P,t+\tau}^{(\tau)}\right] = \alpha_t'(\tau)(\mu_x(\tau)) + \frac{1}{2}\alpha_t'(\tau)\sigma_x^2(\tau) \tag{14}$$

$$Var(r_{P,t+\tau}^{(\tau)}) = \alpha_t'(\tau)\Sigma_{xx}(\tau)\alpha_t(\tau) \tag{15}$$

Substituting (14) and (15) in the mean-variance problem (10) leads to a quadratic optimization problem with solution:

$$\alpha_t(\tau) = \frac{1}{\gamma}\Sigma_{xx}^{-1}(\tau)\left(\mu_t(\tau) + \frac{1}{2}\sigma_x^2(\tau)\right) \tag{16}$$

5.2 Short-Selling Restrictions

We introduce then the short selling restriction that helps us to identify the long-only strategy. To do so, we simply add restrictions for holding weights as follows:

$$\max_{\alpha_t'(\tau)} \quad E_t\left[r_{P,t+\tau}^{(\tau)}\right] - \frac{\gamma}{2}Var_t\left[r_{P,t+\tau}^{(\tau)}\right], \quad s.t. \quad \alpha_t'(\tau)e = 1; \alpha_t'(\tau) > 0 \tag{17}$$

To optimize this equation, we apply the Lagrange multipliers to constrains, we can get the function of Lagrange optimization as $\mathcal{L} = \alpha_t'(\tau)\mu_x(\tau) + \frac{1}{2}\alpha_t'(\tau)\sigma_x^2(\tau) - \frac{\gamma}{2}\alpha_t'(\tau)\Sigma_{xx}(\tau)\alpha_t(\tau) + \lambda(\alpha_t'(\tau)e - 1) - \mu\alpha_t'(\tau)$. Thus we get the first order condition (FOC) and the optimal weights as follows:

$$\alpha_t(\tau) = \frac{1}{\gamma}\Sigma_{xx}^{-1}(\tau)\left(\mu_x(\tau) + \frac{1}{2}\sigma_x^2(\tau) + \lambda e - \mu\right) \tag{18}$$

Where e is a vector of ones, with e' being the transpose of e; $\lambda = \frac{\gamma - e'\Sigma_{xx}^{-1}(\tau)\left(\mu_x(\tau) + \frac{1}{2}\sigma_x^2(\tau)\right)}{e'\Sigma_{xx}^{-1}(\tau)e}$ is a Lagrange multiplier with a total weight of 1; μ is a Lagrange multiplier with an asset weight greater than 0, meaning that if some asset weights $\alpha_t'(\tau) < 0$, we need to put them as 0 and re-distribute weights for other assets.

5.3 Empirical Evidence

In light of the return term structures across climate scenarios, we now explore the implications for optimal portfolio allocation. Figure 2a to Figure 2f report optimal strategic asset allocation from 2030 to 2050 through SSP1 to SSP6, in respective. [6]

The optimal asset allocation varies significantly across the six SSP scenarios. In sustainable pathways such as SSP1 ("Sustainability"), SSP2 ("Middle of the Road"), and SSP6 ("Global colling"), portfolios tilt heavily toward green assets. These include renewable energy equity, green bonds, and low-carbon infrastructure funds. The higher weight reflects not only superior long-term return expectations but also the hedging value of green

[6] While long-term expected returns provide a valuable signal, investors must also account for unpriced or partially priced risks—particularly those stemming from climate uncertainty, transition policies, and regime shifts. The point worth mentioning is that the term structure of returns captures time-varying expectations under each scenario, but it does not fully reflect intertemporal hedging demands, investor sentiment shifts, or real-option values under transition ambiguity.

exposures in a world where climate mitigation policies are stringent and consistently implemented. In these scenarios, investors internalize the reduced risk premium on green technologies, favorable policy environments, and rising capital inflows, resulting in allocation that reward green-heavy allocations.

Conversely, in high-emissions scenarios—SSP3 ("Regional Rivalry"), SSP4 ("Inequality"), and SSP5 ("Fossil-fueled Development")—the efficient allocations display a larger share of non-green assets. These include traditional energy equities, commodities, and inflation-linked instruments. Notably, in SSP5, non-green allocations peak, driven by the expectation of sustained fossil-fuel demand and rising inflation risks.

More interestingly, we find that in early transition phases, investors may hedge against rising regulatory risks by increasing allocations to green assets, boosting their prices and returns. Policy arbitrage (e.g., CBAM expansion) and climate disaster impulses (e.g., subsidy hikes after extreme weather) are the core drivers, but technology iteration and policy rollback risks in the long-term dimension need to be taken care.

Importantly, the divergence in optimal allocations across scenarios illustrates the role of climate narratives in shaping risk-adjusted returns. In SSP3, for instance, regional fragmentation leads to reduced global coordination on climate action, elevating geopolitical and policy uncertainty. Portfolio weights shift accordingly toward assets with shorter duration, higher liquidity, or perceived robustness under institutional fragility. Similarly, in SSP4, the unequal distribution of vulnerability (i.e., concentrated physical risk exposure among lower-income regions) creates a complex allocation environment, where green exposure offers only limited protection due to global policy inertia.

By visualizing optimal portfolio weights across asset classes and climate scenarios, we observe that green allocations are not monotonically increasing with global warming. Instead, they are sensitive to both transition intensity and climate policy credibility. These findings suggest that Investors should evaluate each scenario's implied macro-financial environment, policy consistency, and timing of climate action.

In conclusion, asset allocation under different SSP narratives requires a careful balancing of return expectations, hedging value, and scenario realism. Portfolios optimized in a climate-aware framework must not only reflect term structure characteristics, but also integrate forward-looking judgments about climate trajectories, policy credibility, and capital market adjustments. The resulting strategies are inherently path-dependent—what is optimal under SSP1 may become suboptimal under SSP5—emphasizing the value of adaptive, scenario-conditional investing.

5.4 Efficient Frontiers

Figure 3a to Figure 3f report the efficient frontier with or without green assets. We see very clear that adding green assets largely expand the frontier in all SSPs. This expansion of the efficient frontier can be traced to several interrelated mechanisms documented in finance research.

First, green securities exhibit lower correlations with traditional "brown" assets—such as energy equities, commodities, and real estate—thereby delivering meaningful diversification benefits and shifting the mean–variance frontier outward (Pedersen, Fitzgibbons, & Pomorski, 2021). Second, green asset returns embed a distinct climate-transition factor: they capture upside potential from regulatory support, technological innovation, and shifting investor preferences that is orthogonal to conventional risk factors (Pástor et al., 2022). Third, during periods of market stress—such as the COVID-19 sell-off—ESG-focused strategies have been shown empirically to provide downside protection, cushioning portfolios against extreme drawdowns (Huang, 2024). Finally, under stringent climate-policy regimes (e.g. SSP1 and SSP2), the cost of capital for green firms falls and their expected cash flows become more resilient, creating an asymmetric return profile that is unattainable through non-green exposures alone (Ehlers et al., 2022). Together, these channels explain why incorporating green assets consistently enlarges the attainable set of risk–return combinations across all SSP scenarios.

6 Tactical Asset Allocation and Short-Term Rebalancing

Having established the long-term Strategic Asset Allocation (SAA) based on structural pathways, we now turn to Tactical Asset Allocation (TAA). This phase addresses short-term market frictions and deviations from the equilibrium path. Our rebalancing framework operates on two hierarchical levels: (1) macro-adjustments across broad asset classes driven by structural breaks or regime shifts, and (2) micro-adjustments within green and non-green counterparts driven by high-frequency investor sentiment.

For the macro-level adjustment, we employ the Black-Litterman (B-L) framework. However, rather than relying on purely subjective inputs, we derive conditional views by mapping current market anomalies to historical regimes using distance-based similarity measures (e.g., Euclidean Distance). This allows us to calibrate the portfolio weights based on empirically observed responses to similar historical shocks (e.g., recessions, pandemics).

For the micro-level adjustment, particularly the relative weighting between green and non-green assets, we leverage unstructured data to proxy for "green sentiment." By extracting signals from the Media Climate Change Concerns Index and search engine volume, we capture shifts in investor attention, which allows for dynamic rebalancing between green and brown peers independent of broader macro trends.

6.1 Black-Litterman Optimization

Recent contributions recognize that investment opportunity sets shift across regimes. Guidolin and Timmermann (2007, 2008) model asset returns as switching between discrete regimes characterized by different means, volatilities, and correlations. They demonstrate that failure to account for regime dependence leads to substantial welfare losses, as investors either take excessive risk during high-volatility regimes or forgo return opportunities during stable periods. In the context of climate risks, regime-switching models naturally capture the possibility of discontinuous jumps in the economic environment triggered by policy interventions or physical tipping points.

The Black-Litterman methodology serves as a robust Bayesian framework for portfolio construction, designed to synthesize equilibrium market priors with specific investor views (He & Litterman, 2002). Fundamentally, the model mitigates the estimation error inherent in mean-variance optimization—specifically the sensitivity to input parameters—by assuming the market is initially in equilibrium. It then updates these priors with new information (views) to generate a posterior distribution of expected returns.

In our specification, the ”views” are not generated arbitrarily but are state-dependent. We assume that asset return distributions are regime-specific (Ang & Bekaert, 2002). We premise our approach on the evidence that asset return distributions are not static but exhibit regime-switching behavior (Guidolin & Timmermann, 2007). Consequently, relying on a single, unconditional covariance matrix fails to capture the risk dynamics during market anomalies. Specifically, we use the returns (μ) and covariance matrix (Σ) from the long-term SAA as the neutral starting point. When a specific anomaly is detected, we match the current covariance and return characteristics to a historical training period using similarity metrics. The resulting posterior estimates are derived as follows:

$$\mu_{BL} = \left[(\tau\Sigma)^{-1} + P^{\top}\Omega^{-1}P\right]^{-1}\left[(\tau\Sigma)^{-1}\mu + P^{\top}\Omega^{-1}Q\right] \tag{19}$$

$$\Sigma_{BL} = \Sigma + \left[(\tau\Sigma)^{-1} + P^{\top}\Omega^{-1}P\right]^{-1} \tag{20}$$

Where views are based on the matching between the current state to historical states. Vector of expected returns for views (Q) for relevant assets is from the 12-months historical data. The views are incorporated via a view matrix (P) with associated confidence levels represented by an uncertainty matrix (Ω), and the adjustment scaling factor (τ) we set in this paper is 0.025.

To validate this regime-matching approach, We test this approach using the Covid-19 crash. Our similarity analysis identifies the ”Oil Crisis” period as the nearest historical neighbor in terms of covariance structure and return drawdown. This period was characterized by elevated volatility and a breakdown in diversification benefits across asset classes. Table [xx] and Figure [xx] present the empirical results, confirming the efficacy of the B-L adjustment. **As evidenced in Table [xx], the unadjusted portfolio exhibits an annual return of 0.1138 with a volatility of 0.0833. In contrast, the B-L optimized portfolio achieves a risk-adjusted profile with a return of 0.0864 and a significantly reduced volatility of 0.0615. Figure [xx] further illustrates that the B-L model dynamically down-weights high-beta assets during the crash, thereby preserving capital and smoothing the equity curve during extreme volatility.**

[Insert table xx here] [Insert Figure xx here]

6.2 Sentiment-Driven Green Rebalancing

While long-term green asset returns are anchored by fundamental climate pathways, short-term price dynamics are heavily influenced by investor sentiment and attention shocks. Literature suggests that investor attention, often measured by search volume, predicts asset returns and liquidity (Da et al., 2011). Furthermore, Baker and Wurgler (2006) demonstrate that sentiment has a pronounced effect on stocks that are difficult to value or arbitrage, a characteristic shared by many emerging green technologies and ESG-linked assets. Pástor et al. (2021) theoretically demonstrate that shifts in investors' ESG preferences are a primary driver of green asset returns. When climate concerns spike, aggregate demand for green assets increases, creating short-term price pressure that deviates from long-term fundamentals.

To capture this high-frequency component, we utilize two sentiment proxies: the Media Climate Change Concerns Index (MCCC) from Ardia, Bluteau, Boudt, and Inghelbrecht (2023) and the Google Search Volume Index (SVI). These indices serve as barometers for the aggregate market attention dedicated to climate risks and opportunities. Taking the SVI as a primary example, we track the normalized query volume for the term "climate change." To operationalize this into a trading signal, we construct a dynamic adjustment factor based on both the level and the momentum of attention. We calibrate the hyperparameters using a 60-month training window to maximize the portfolio's Sharpe ratio. The tactical weight adjustment is governed by the following logistic function:

$$\text{Sentiment Score}_t = v_{1,t} S_t + v_{2,t} \Delta S_t \tag{21}$$

$$w_t^{\text{new}} = \frac{1}{1 + e^{-\left[\ln\left(\frac{w_t}{1-w_t}\right) + \lambda_t \cdot \text{Score}_t\right]}} \tag{22}$$

Where S_t is a normalized Google search index that measures the absolute market interest in an asset; ΔS_t is the absolute change of the search index; $v_1 \in [0,1]$ and $v_2 \in [0,1]$ represent hyper-parameters that determine the relative importance of the sentiment versus the change of sentiment in investment decisions. We also set $v_1 + v_2 = 1$ to control the absolute value of the sentiment score. $\lambda \in [0,1]$ is an optimal adjustment factor. All of these factors are time-varying.

The primary objective of this overlay is to enhance the risk-adjusted return (Sharpe ratio) by timing the entry and exit into green assets based on public attention cycles. It is crucial to note that this sentiment signal is applied strictly to rebalance the proportion between green assets and their non-green peers, rather than shifting capital across broader asset classes. This isolation ensures that the tactical signals capture the "greenium" component specifically, rather than general market noise. The optimization of these weights simulates the dynamic decision-making process of active management, leveraging historical data to refine the signal-to-noise ratio.

Figure [xx] plots the trajectory of the sentiment-adjusted weights against the strategic baseline. We observe that "green" exposure is highly responsive to sentiment spikes. Notably, periods of negative or waning climate attention correlate with a reversion to the baseline or an underweighting of green assets. Between 2022 and 2025, the model maintains an average green weight of approximately 0.75, but exhibits smooth, adaptive reallocation in response to shifting market narratives.

[Insert Figure xx here]

7 Conclusion

This paper addresses a fundamental challenge confronting institutional investors: constructing optimal portfolios when global warming introduces structural changes in the stationarity assumptions embedded in standard allocation models. By conditioning long-horizon strategies on the IPCC's Shared Socioeconomic Pathways and mapping these scenarios into asset-return dynamics through a MIDAS–Bayesian–VAR framework, we develop an empirically grounded approach for navigating climate uncertainty over multi-decade horizons. The framework preserves the discipline of scenario analysis while exploiting the informational asymmetry between low-frequency climate indicators and higher-frequency market signals.

The empirical results yield several findings with immediate relevance for portfolio construction. Optimal allocations diverge markedly across SSP scenarios. Green assets gain prominence in sustainability-oriented pathways, whereas traditional assets dominate in high-emissions trajectories. This pattern indicates that "green versus brown" is not a static preference; rather, these positions represent explicit exposure to climate risk whose attractiveness hinges critically on which climate future materializes.

Additionally, the consistent expansion of efficient frontiers across all SSP scenarios challenges simplistic narratives that green investing requires sacrificing returns for values. Instead, we show that green assets provide economically meaningful diversification benefits and tail-risk protection, which is meaningful in asset management practice.

The proposed framework also applies to climate-aware target-date funds and dynamic allocation products. By integrating long-run structural indicators—such as demographic trends, output growth, and policy credibility—with shorter-horizon tactical signals related to sentiment and attention, the methodology supports systematic, rules-based rebalancing. This design is particularly relevant for defined-contribution pension systems and sovereign wealth funds, where long investment horizons heighten the relevance of climate trajectories and institutional governance favors transparent, repeatable allocation rules.

Several limitations merit consideration and suggest future research directions. First, while our framework conditions on SSP scenarios, we treat these pathways as exogenous. In reality, financial market dynamics may influence climate policy through feedback loops—for example, stranded asset concerns potentially accelerating decarbonization commitments. Incorporating such endogeneity would require integrating political economy models with asset pricing frameworks, a promising but challenging extension.

Second, our analysis focuses on US markets due to data availability and market depth, potentially limiting generalizability to regions with different policy regimes or sectoral compositions. Multi-country extensions incorporating carbon border adjustments and cross-border spillovers would enhance applicability for global institutional investors.

Third, our tactical framework exploits attention-driven predictability in green asset returns, implicitly assuming these patterns persist as markets mature. As climate investing becomes more sophisticated and information diffusion accelerates, the magnitude of sentiment-driven mispricings may diminish. Future work should test the persistence of these signals and evaluate whether alternative high-frequency indicators such as policysurprise measures or physical-disaster shocks offer more stable tactical guidance.

Fourth, we abstract from investor-specific characteristics such as liability structures, regulatory constraints, and tax considerations that materially affect optimal portfolios in practice. Extending our framework to accommodate asset-liability management and regulatory balance sheet constraints would enhance practical applicability for pension funds and insurance companies.

Finally, our focus on public markets reflects data availability and transparency. Yet private markets—private equity, infrastructure, and direct real assets—represent an expanding share of institutional portfolios and carry distinct climate exposures. As disclosure standards improve and private-market datasets become more reliable, incorporating these asset classes will allow for a more comprehensive assessment of climate-aware allocation.

Table 1: MIDAS-VAR Estimation

	$t-1$ Variables																		
	ΔT_t	ΔGDP_t	ΔP_t	r_s	r_l	r_{stock}	r_{govb}	r_{inf}	r_{igb}	r_{hyb}	r_{re}	r_{commo}	$r_{\text{stock}(green)}$	$r_{\text{gov}(green)}$	$r_{\text{inf}(green)}$	$r_{\text{igb}(green)}$	$r_{\text{hyb}(green)}$	$r_{\text{re}(green)}$	$r_{\text{commo}(green)}$
$r_{s,t}$	-0.042	-0.003	-0.092	1.002	0.009														
	(-2.504)	(-0.552)	(-3.331)	(99.049)	(0.466)														
$r_{l,t}$	-0.031	0.006	-0.038	0.003	0.977														
	(-2.386)	(1.469)	(-1.796)	(0.327)	(67.259)														
$r_{\text{stock},t}$	-0.003	-0.002	0.012	-0.099***	-0.096**	-0.089	0.164	-0.329	0.241	0.143	0.020	-0.048							
	(-0.270)	(-0.723)	(0.687)	(-2.933)	(-2.191)	(-1.107)	(0.460)	(-1.634)	(0.835)	(0.710)	(0.261)	(-0.747)							
$r_{\text{govb},t}$	-0.003	-0.002**	0.010***	0.028***	0.078***	0.014	-0.125	0.009	0.203***	-0.220***	-0.006	0.008							
	(-1.305)	(-2.588)	(2.753)	(3.769)	(7.996)	(0.760)	(-1.573)	(0.196)	(3.158)	(-4.899)	(-0.344)	(0.572)							
$r_{\text{inf},t}$	0.002	-0.002	0.019***	-0.002	0.085***	-0.013	-0.397***	-0.007	0.513***	-0.262***	0.004	0.045**							
	(0.482)	(-1.642)	(3.172)	(-0.197)	(5.606)	(-0.472)	(-3.216)	(-0.098)	(5.134)	(-3.760)	(0.165)	(2.024)							
$r_{\text{igb},t}$	0.000	-0.002	0.009	-0.014	0.065***	0.007	-0.145	0.003	0.331***	-0.240***	0.024	-0.031							
	(-0.059)	(-1.860)	(1.620)	(-1.231)	(4.406)	(0.275)	(-1.209)	(0.050)	(3.417)	(-3.562)	(0.961)	(-1.460)							
$r_{\text{hyb},t}$	0.003	-0.003	0.007	-0.056***	-0.038*	-0.037	-0.294*	0.123	0.472***	-0.000	0.039	-0.051							
	(0.665)	(-1.648)	(0.845)	(-3.371)	(-1.755)	(-0.953)	(-1.682)	(1.246)	(3.342)	(-0.002)	(1.061)	(-1.642)							
$r_{\text{re},t}$	0.005	-0.002	0.027	-0.148***	0.004	0.072	0.129	-0.216	0.466	-0.142	0.020	0.080							
	(0.442)	(-0.458)	(1.320)	(-3.677)	(0.067)	(0.749)	(0.301)	(-0.895)	(1.346)	(-0.590)	(0.217)	(1.049)							
$r_{\text{commo},t}$	0.008	-0.003	0.025	-0.048	-0.113***	-0.094	-0.893**	0.031	0.668**	0.234	-0.026	0.035							
	(0.782)	(-0.787)	(1.488)	(-1.460)	(-2.646)	(-1.201)	(-2.571)	(0.160)	(2.376)	(1.197)	(-0.350)	(0.570)							
$r_{\text{stock(green)},t}$	0.001	-0.000	0.004	-0.016	0.022	0.103*	0.061	0.034	-0.069	0.080	-0.050	0.013	-0.057	-0.003	-0.080	0.091	-0.021	-0.038	-0.024
	(0.200)	(-0.009)	(0.514)	(-0.929)	(0.941)	(1.808)	(0.321)	(0.350)	(-0.478)	(0.778)	(-1.402)	(0.396)	(-1.093)	(-0.048)	(-1.245)	(1.020)	(-0.410)	(-1.200)	(-1.306)
$r_{\text{govb(green)},t}$	-0.016***	0.001	0.007	-0.018	0.017	0.004	0.130	-0.089	-0.224**	0.008	0.039	0.004	-0.035	-0.025	0.016	0.054	0.066*	0.002	-0.038***
	(-4.485)	(0.597)	(1.188)	(-1.550)	(1.000)	(0.107)	(0.965)	(-1.270)	(-2.167)	(0.105)	(1.522)	(0.177)	(-0.949)	(-0.496)	(0.342)	(0.856)	(1.855)	(0.071)	(-2.928)
$r_{\text{inf(green)},t}$	-0.004	-0.000	0.001	0.019	0.011	0.024	-0.061	-0.112	0.107	-0.013	-0.039	0.043*	-0.017	0.017	0.014	-0.006	0.043	-0.010	-0.014
	(-1.035)	(-0.270)	(0.128)	(1.362)	(0.579)	(0.519)	(-0.393)	(-1.401)	(0.912)	(-0.152)	(-1.327)	(1.651)	(-0.394)	(0.294)	(0.259)	(-0.087)	(1.055)	(-0.386)	(-0.942)
$r_{\text{igb(green)},t}$	-0.010***	0.001	0.004	-0.004	-0.003	0.010	0.021	0.071	-0.291***	0.090	-0.015	-0.015	-0.009	0.066	0.018	0.050	-0.009	-0.002	-0.009
	(-3.459)	(0.694)	(0.895)	(-0.436)	(-0.233)	(0.292)	(0.187)	(1.207)	(-3.363)	(1.455)	(-0.684)	(-0.769)	(-0.277)	(1.543)	(0.458)	(0.933)	(-0.298)	(-0.121)	(-0.788)
$r_{\text{hyb(green)},t}$	-0.006	-0.002	0.002	0.009	-0.046*	0.085	-0.133	-0.026	-0.302*	-0.249**	0.025	0.014	-0.026	0.070	0.039	0.146	0.040	-0.000	0.001
	(-1.043)	(-0.906)	(0.177)	(0.483)	(-1.811)	(1.389)	(-0.657)	(-0.243)	(-1.948)	(-2.245)	(0.661)	(0.404)	(-0.464)	(0.915)	(0.563)	(1.531)	(0.750)	(-0.008)	(0.028)
$r_{\text{re(green)},t}$	-0.016*	0.000	-0.013	0.007	-0.032	-0.074	-0.326	-0.005	-0.458*	-0.096	0.107*	-0.055	-0.023	-0.096	0.162	0.225	0.062	-0.007	0.039
	(-1.835)	(0.134)	(-0.881)	(0.234)	(-0.781)	(-0.749)	(-0.987)	(-0.029)	(-1.813)	(-0.532)	(1.704)	(-0.986)	(-0.259)	(-0.768)	(1.446)	(1.453)	(0.710)	(-0.130)	(1.216)
$r_{\text{commo(green)},t}$	-0.005	0.003	-0.027	0.043	-0.076	-0.021	-0.295	0.376	-0.139	-0.314	0.014	-0.119	0.020	-0.513	0.252	0.591	-0.534*	-0.003	0.163*
	(-0.347)	(0.617)	(-1.165)	(0.925)	(-1.151)	(-0.129)	(-0.559)	(1.371)	(-0.344)	(-1.089)	(0.142)	(-1.331)	(0.179)	(-1.082)	(0.919)	(1.478)	(-1.770)	(-0.027)	(1.894)

Notes: This table reports the time series estimation of MIDAS-VAR model coefficients with one month lag. We use Equation (9) to estimate the first block; Equation (10) to estimate the second block, and Equation (11) to estimate the third block. We present only interesting terms and we do not report intercepts for brevity. T-statistics are given in parentheses. The sample period is from 1986 to 2023.

Table 2: Performance Comparison: Original vs. Black–Litterman

Portfolio Performance	**Original**	**Black–Litterman Rebalance**
Return (Monthly)	0.0095	0.0072
Volatility (Monthly)	0.0240	0.0178
Return (Annualized)	**0.1138**	0.0864
Volatility (Annualized)	0.0833	**0.0615**
Sharpe ($r_f = 0$)	1.3671	**1.4042**

Notes: This table reports the performance comparison between the original portfolio and the Black–Litterman optimized portfolio over the period February 2020 to January 2021. Volatility is computed as standard deviation of variance of returns. We assume a zero risk-free rate.

Figure 1: Term Structure of Asset Returns. This figure presents projected trajectories of asset returns (”brown” versus ”green”) under each Shared Socioeconomic Pathway. Subfigure 1(a) to 1(f) shows the dynamic from SSP1 to SSP6, respectively. It is worth noting that SSP1 corresponds to the ”Sustainability” pathway; SSP2 corresponds to the ”Business As Usual” pathway; SSP3 corresponds to the ”Regional Rivalry” pathway; SSP4 corresponds to the ”Inequality” pathway; SSP5 corresponds to the ”Fossil-Fuel Development” pathway. Specifically, we include SSP6, which corresponds to the ”Global Cooling” pathway. The Section 2 explains the meaning of each pathway.

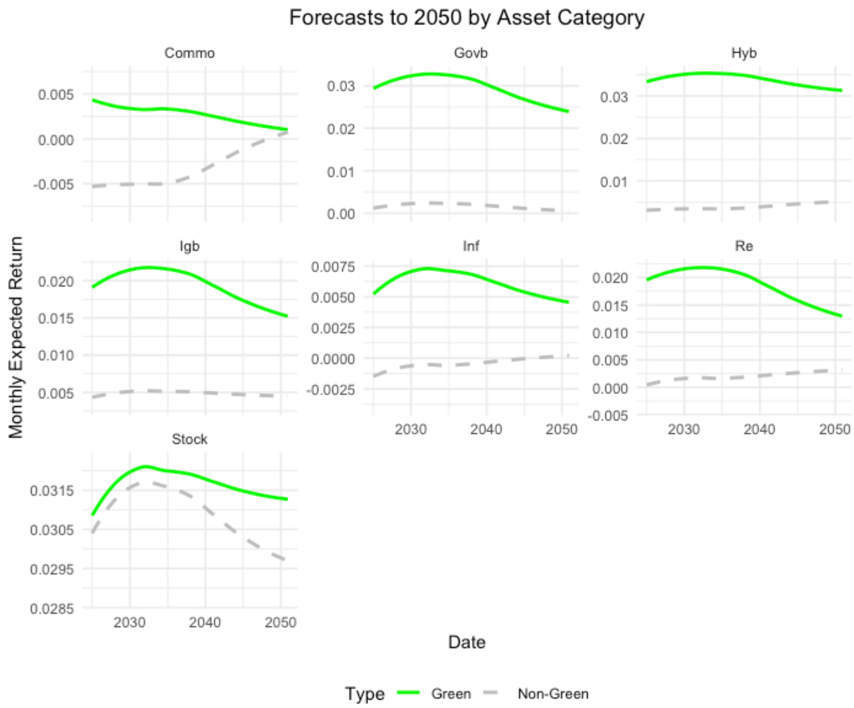


Figure 1(a) SSP1

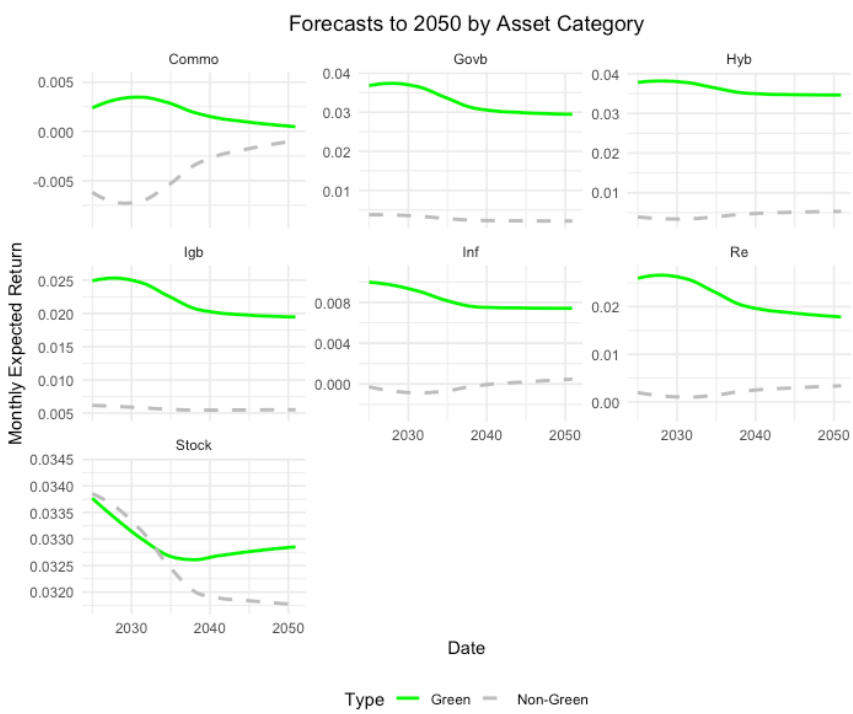


Figure 1(b) SSP2

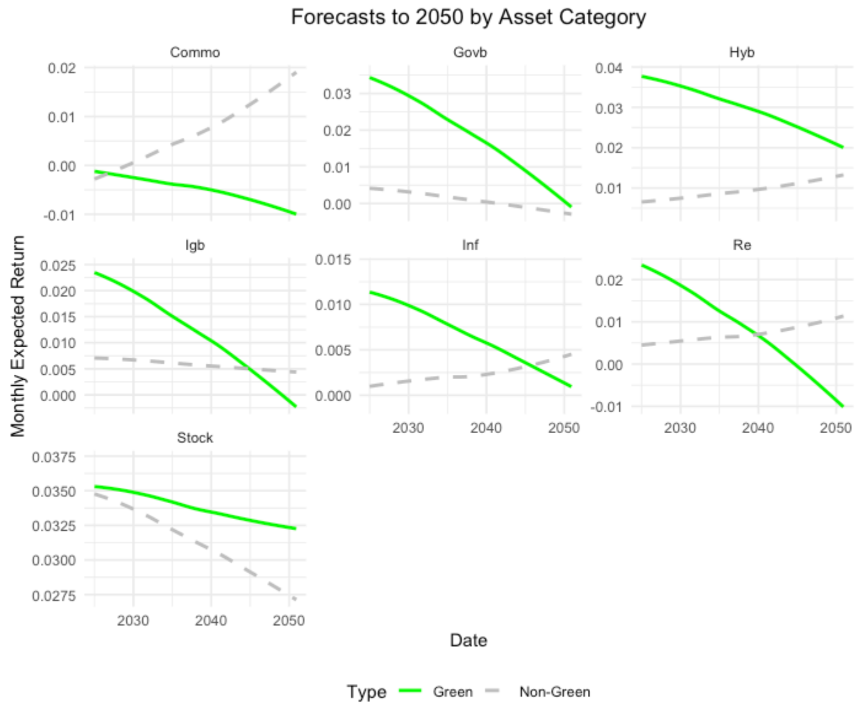


Figure 1(c) SSP3

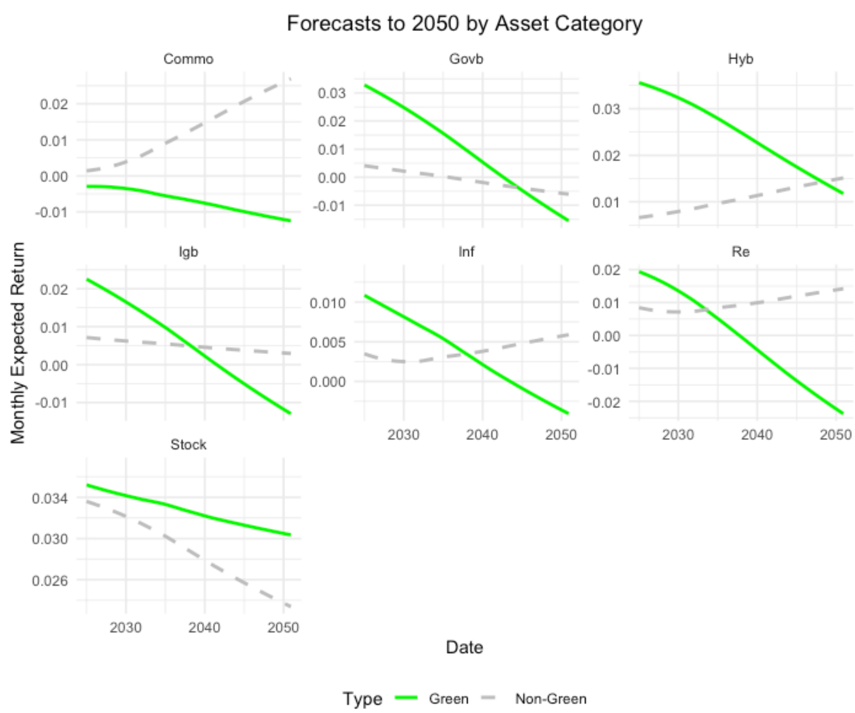


Figure 1(d) SSP4

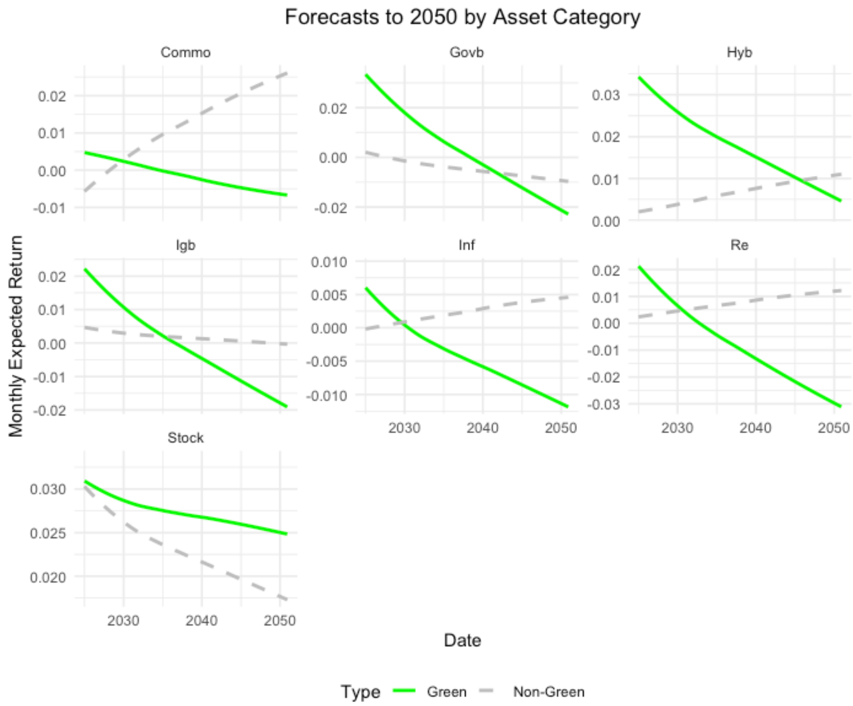


Figure 1(e) SSP5

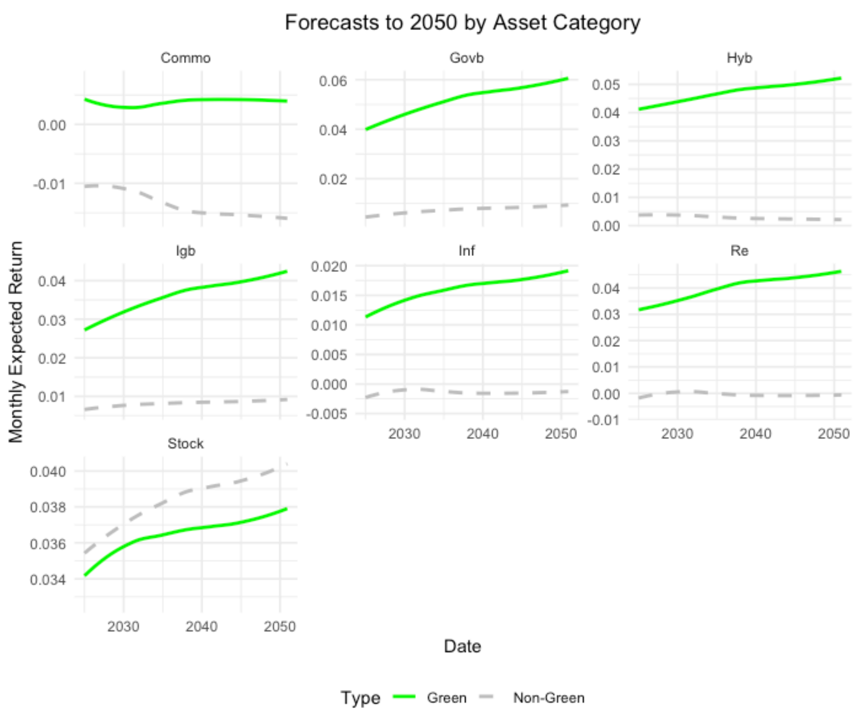


Figure 1(f) SSP6

Figure 2: Optimal Portfolio Allocation. This figure presents the optimal asset allocation structure under each Shared Socioeconomic Pathway. We hold only long position for each asset. Subfigure 2(a) to 2(f) shows the dynamic from SSP1 to SSP6, respectively. It is worth noting that SSP1 corresponds to the "Sustainability" pathway; SSP2 corresponds to the "Business As Usual" pathway; SSP3 corresponds to the "Regional Rivalry" pathway; SSP4 corresponds to the "Inequality" pathway; SSP5 corresponds to the "Fossil-Fuel Development" pathway. Specifically, we include SSP6, which corresponds to the "Global Cooling" pathway. The Section 2 explains the meaning of each pathway.

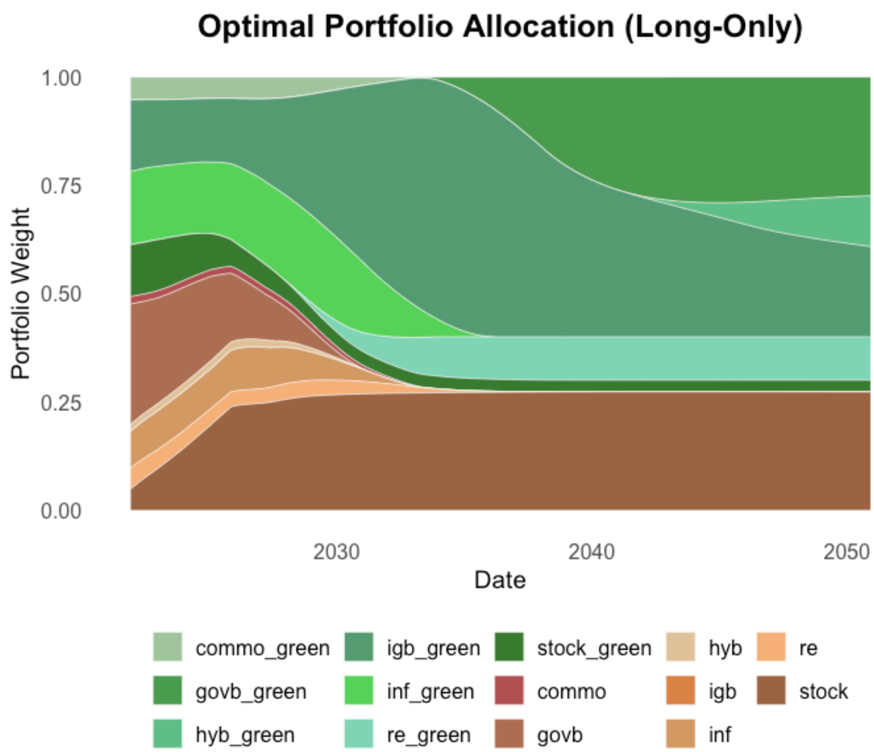


Figure 2(a) SSP1

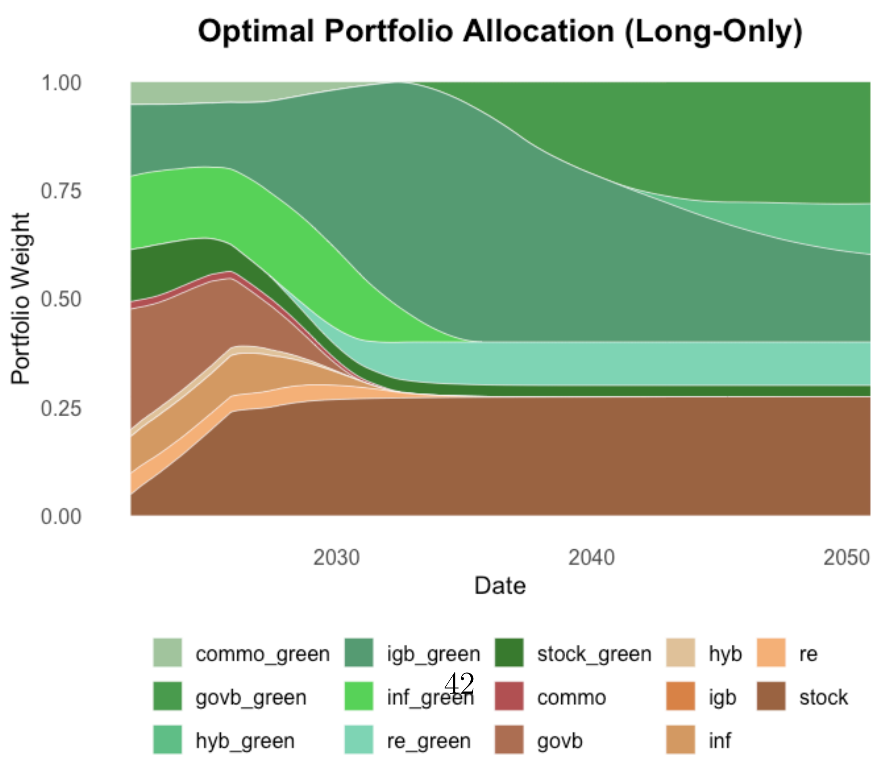


Figure 2(b) SSP2

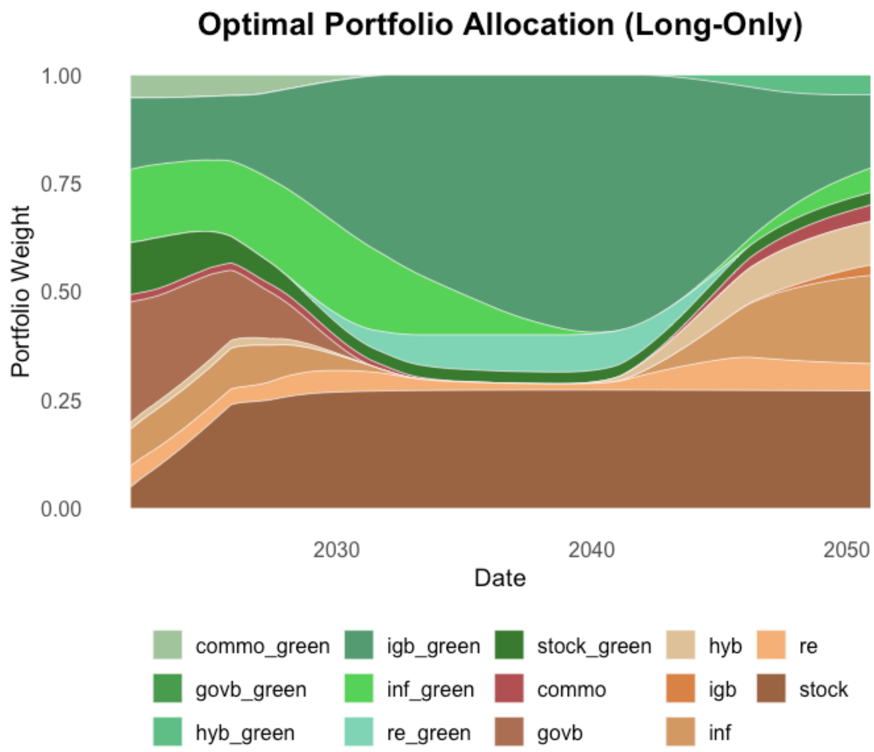


Figure 2(c) SSP3

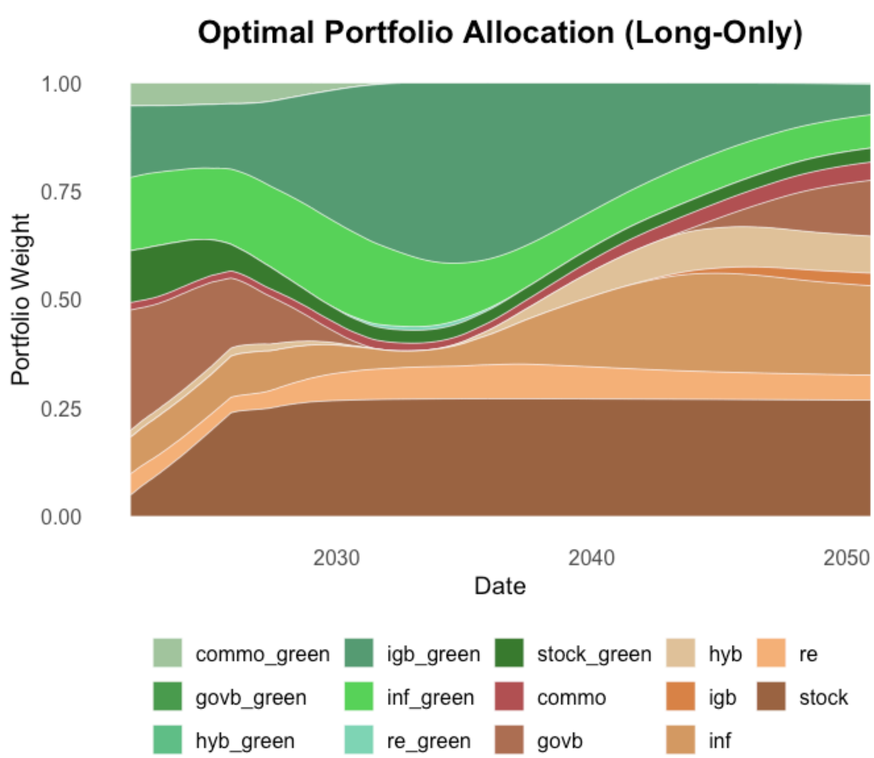


Figure 2(d) SSP4

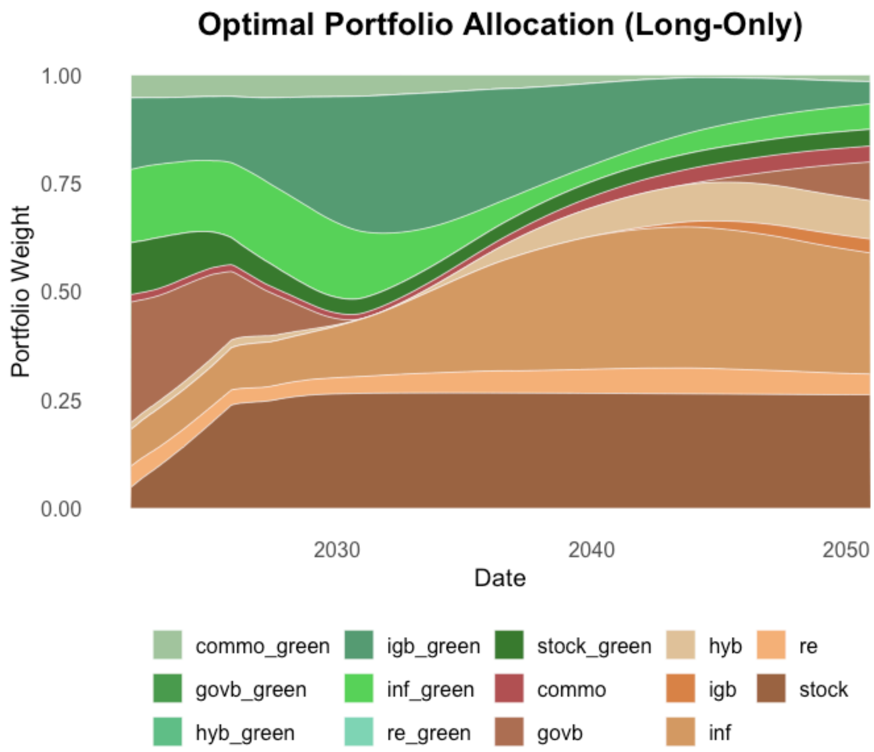


Figure 2(e) SSP5

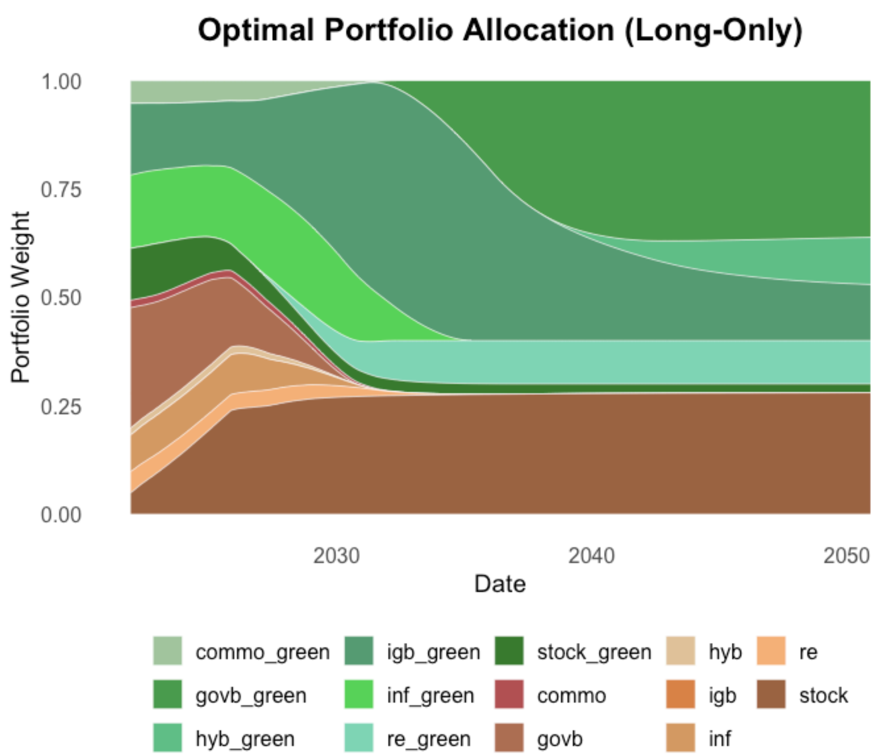


Figure 2(f) SSP6

Figure 3: Efficient Frontier of Strategic Asset Allocation. This figure presents the efficient frontier of allocation with inclusion of "green" assets, under each Shared Socioeconomic Pathway. Subfigure 3(a) to 3(f) shows the dynamic from SSP1 to SSP6, respectively. It is worth noting that SSP1 corresponds to the "Sustainability" pathway; SSP2 corresponds to the "Business As Usual" pathway; SSP3 corresponds to the "Regional Rivalry" pathway; SSP4 corresponds to the "Inequality" pathway; SSP5 corresponds to the "Fossil-Fuel Development" pathway. Specifically, we include SSP6, which corresponds to the "Global Cooling" pathway. The Section 2 explains the meaning of each pathway.

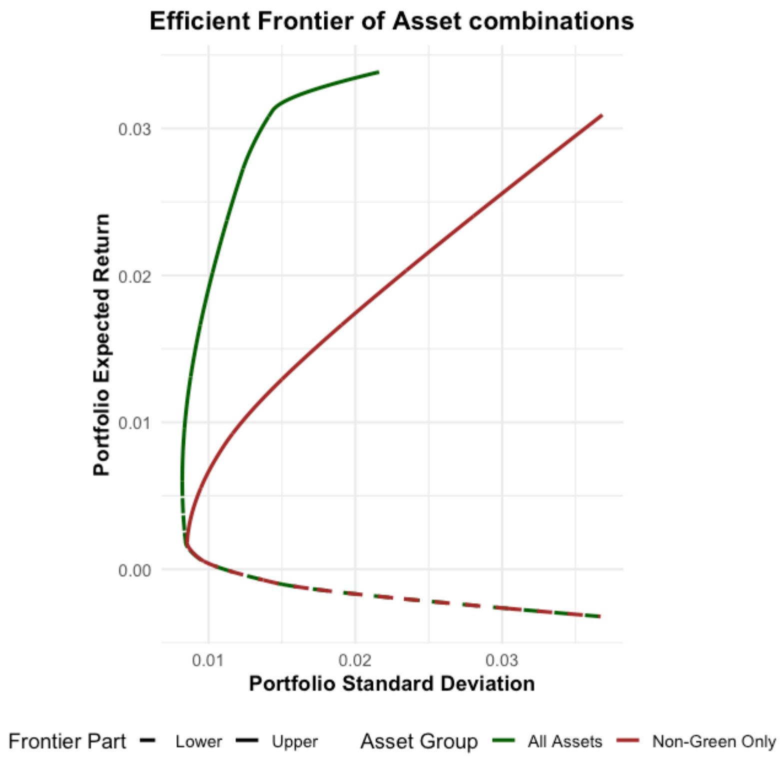


Figure 3(a) SSP1

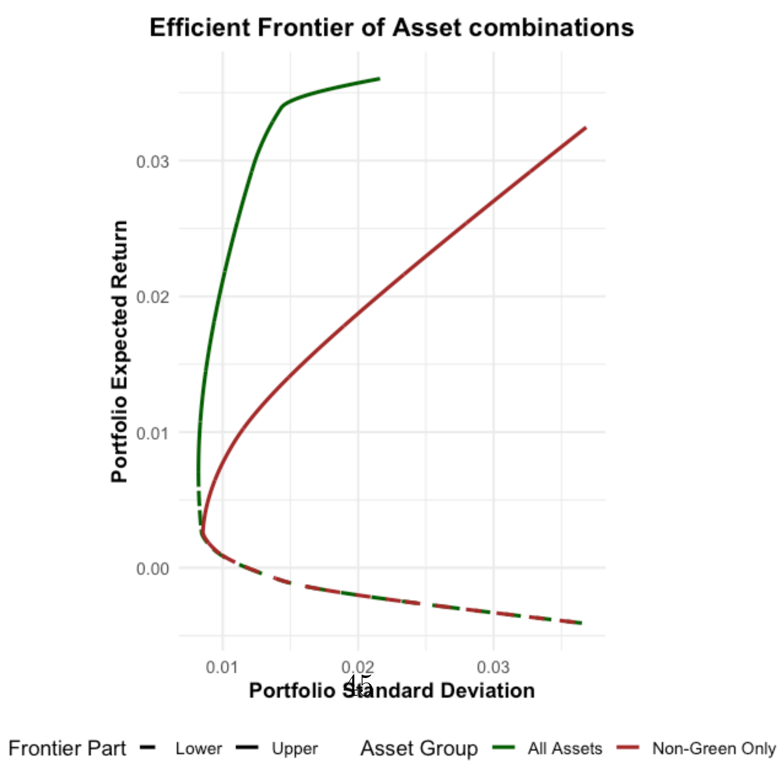


Figure 3(b) SSP2

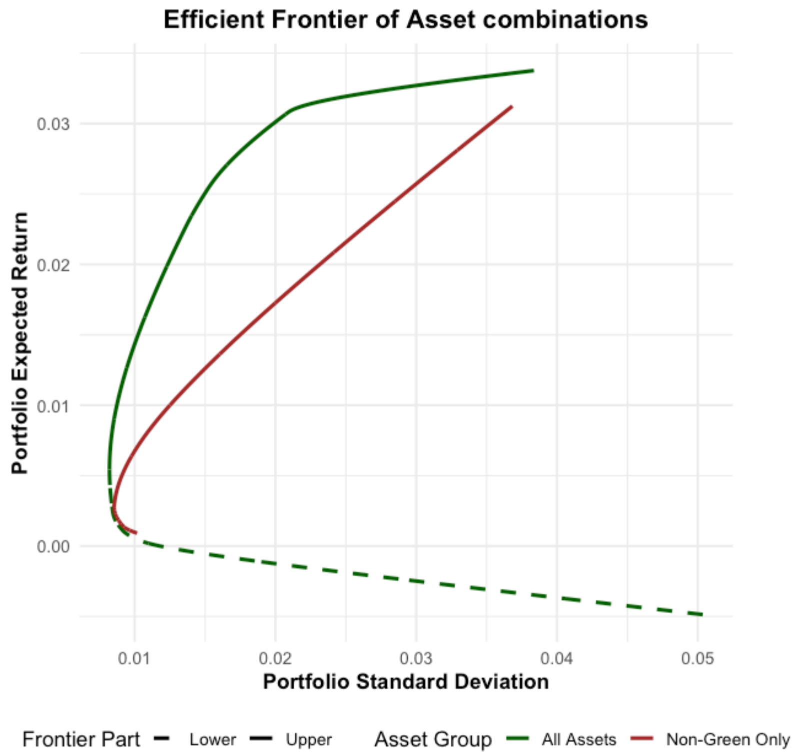


Figure 3(c) SSP3

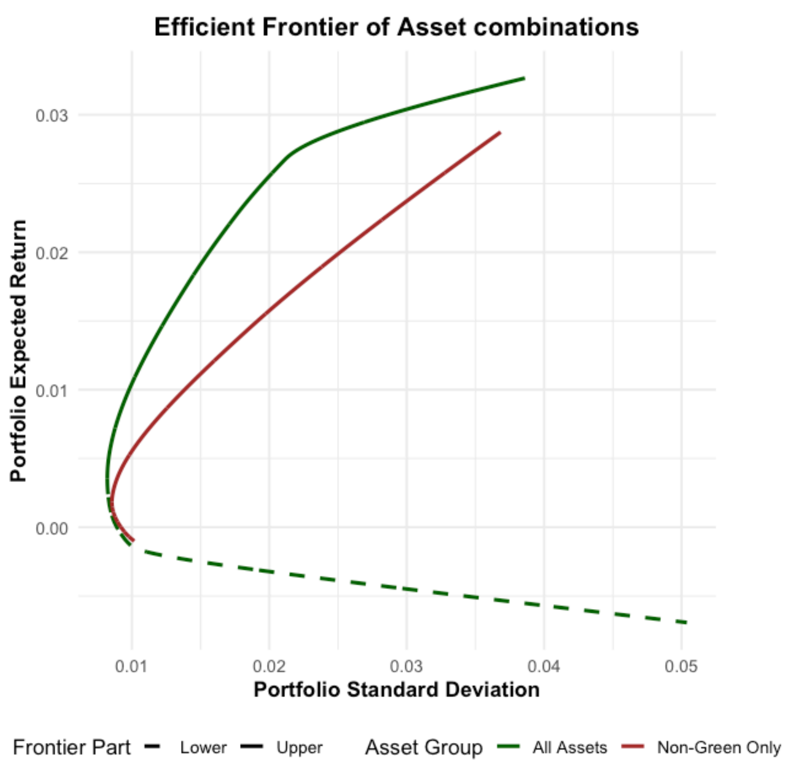


Figure 3(d) SSP4

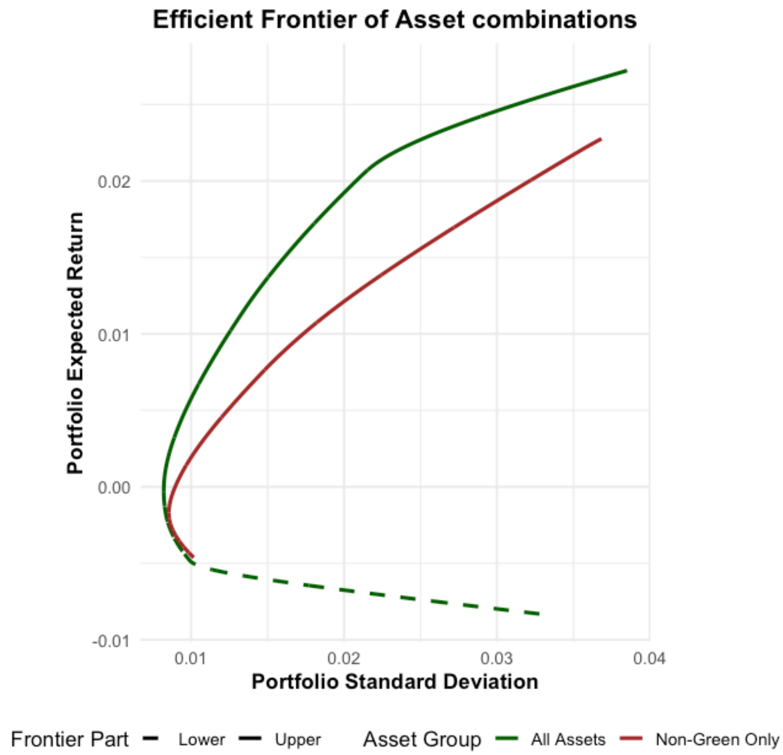


Figure 3(e) SSP5

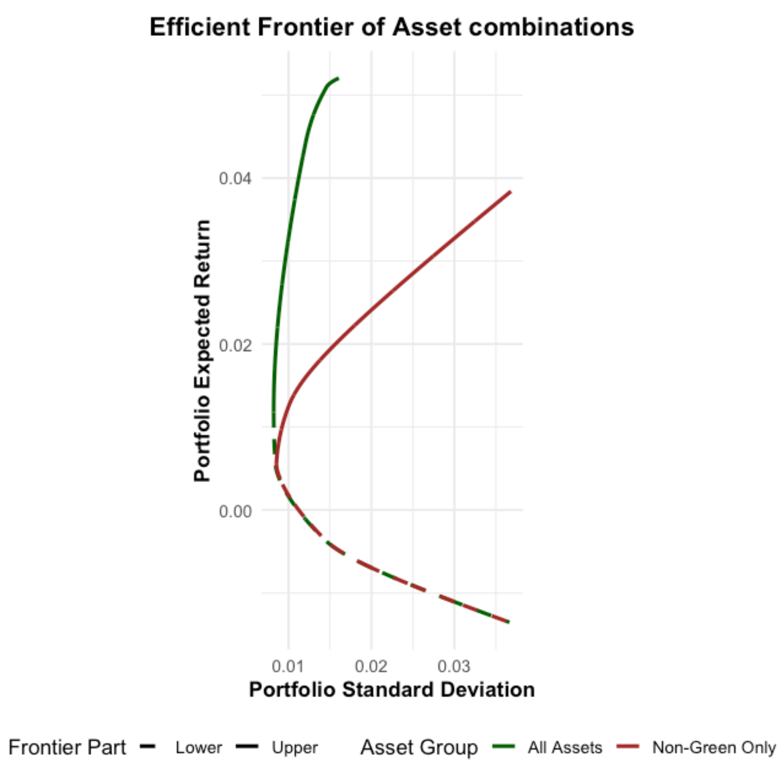


Figure 3(f) SSP6

Figure 4: Cumulative Return Comparison. This figure compares the cumulative returns of the baseline portfolio (Original) and the Black–Litterman optimized portfolio (B–L Rebalance) during the period from February 2020 to January 2021, at a monthly frequency. The cumulative return is normalized to 1 at the start of the sample.

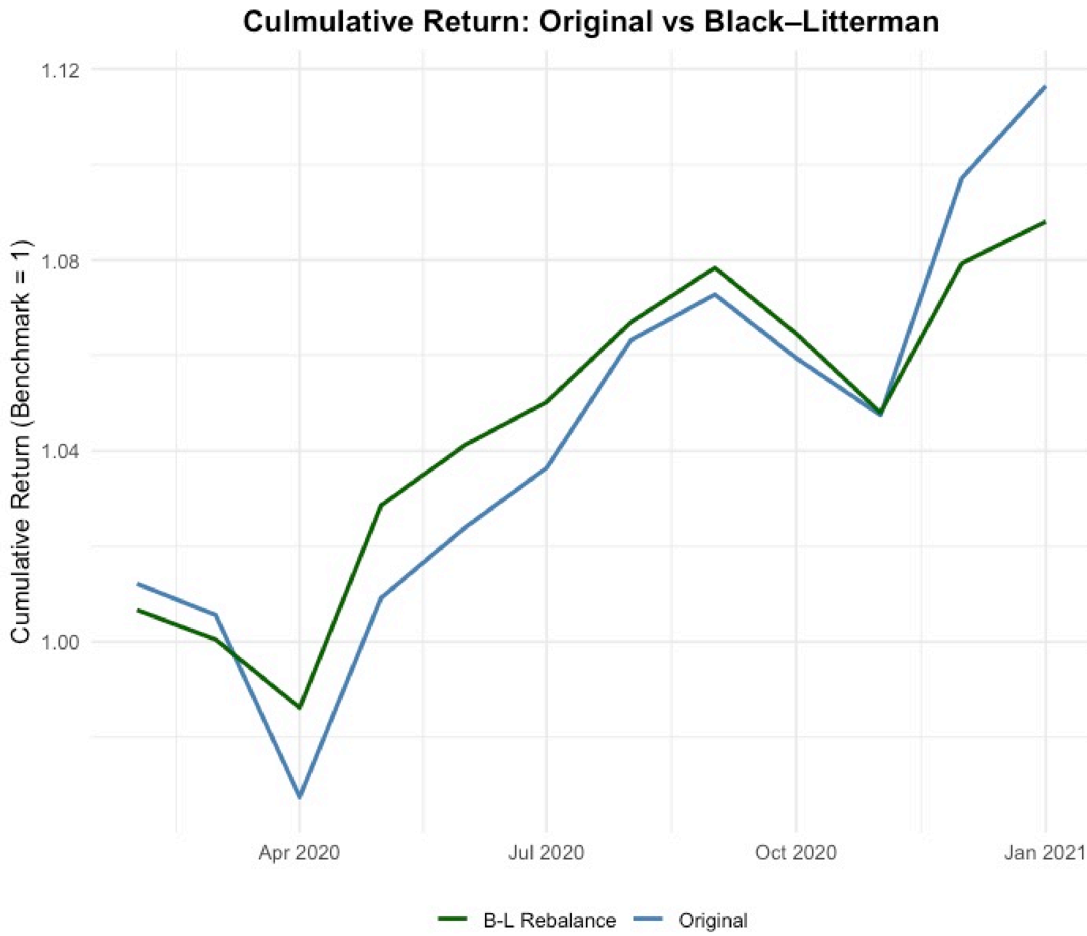
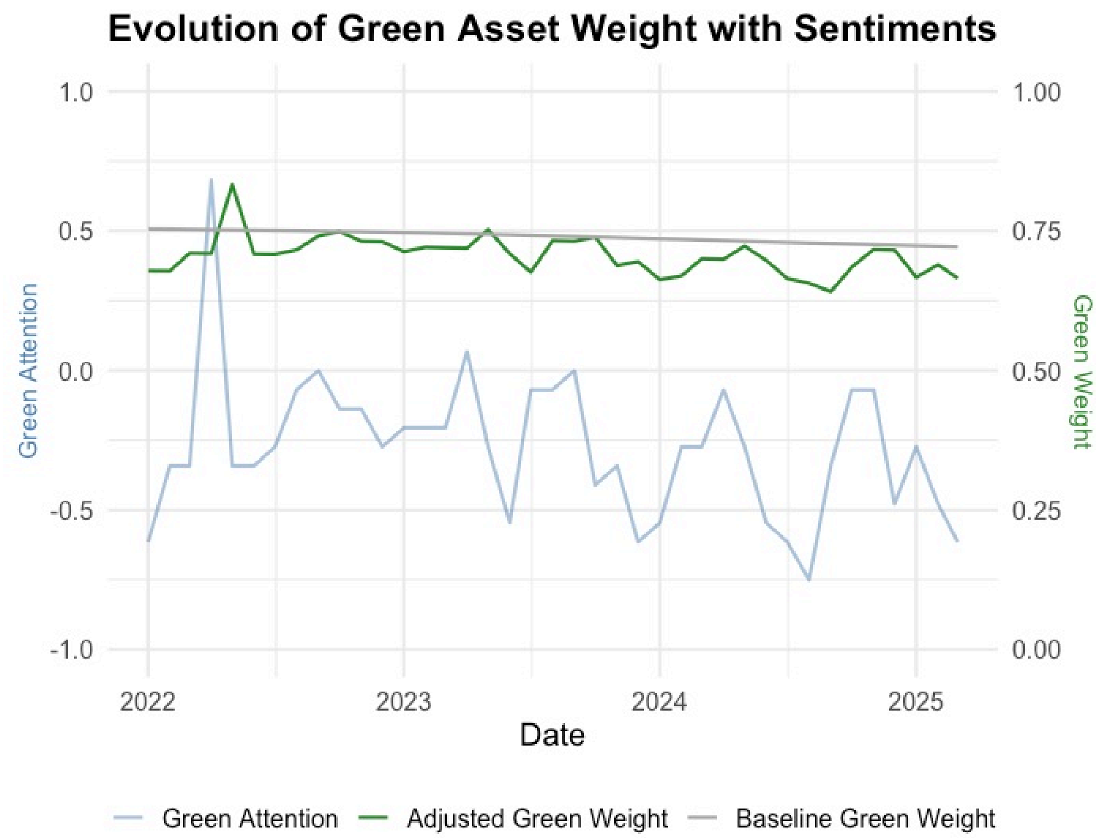


Figure 5: Sentiment-Based Adjustment For Green Assets. This figure compares optimal weights for green assets of the baseline portfolio and the sentiment-adjusted portfolio during the period from 2022 to 2025, at a monthly frequency.



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