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Green Versus Brown Assets Under Stress: Who Hedges Energy and Market Risk?

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Abstract

Sustainable finance increasingly treats green assets as instruments for climate-risk hedging; however, it remains unclear whether they protect investors during energy-market shocks and financial-market stress or merely transmit different transition, equity-market, and growth risks. This study asks whether green assets hedge better than brown assets, or whether the two asset classes hedge different risks across market states. Using daily data from 2010 to 2025 on exchange-traded clean-energy, fossil-fuel, green-bond, ESG, and market-risk instruments, we construct green and brown portfolios and analyze the green–brown return spread across normal conditions, high-volatility regimes, market-stress days, positive and negative oil-price shocks, the COVID-19 crisis, and the recent energy-crisis period. The empirical design combines performance and downside-risk metrics, rolling correlations and betas, Newey–West regressions, stress-state comparisons, quantile regressions, portfolio allocation tests, and supplementary machine-learning classification. The results reveal strong oil-shock asymmetry: brown assets outperform during positive oil-price shocks, while green assets perform relatively better when oil prices fall sharply. However, green assets do not function as broad safe havens during financial-market stress, reflecting persistent equity-market downside exposure and growth-factor repricing. Quantile regressions confirm nonlinear and state-dependent risk transmission, while portfolio tests show weak full-sample return-risk performance for clean-energy equity exposure alone. Shorter-sample suggests that green bonds and ESG assets display more defensive characteristics, whereas machine-learning models show limited short-horizon predictive power. Green assets are therefore not universal hedges but conditional transition-risk assets whose value depends on the shock source, market regime, and sustainable instrument.

Keywords: green assets; brown assets; sustainable finance; climate risk; energy shocks; market stress; green bonds; portfolio allocation

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1. Introduction

The low-carbon transition has transformed green investing from a values-based allocation into a central question in asset pricing and risk management. Institutional investors increasingly treat green assets as instruments for managing climate-related financial exposure, while brown assets remain deeply embedded in portfolios because of their links to fossil-fuel demand, commodity cycles, inflation risk, and energy security. The unresolved question is therefore not whether green assets are environmentally desirable, but whether they provide protection when markets are under stress. If green assets fail during market-wide selloffs, their role is closer to transition-risk exposure than to safe-haven protection. If brown assets outperform during oil-price surges, then conventional energy exposure may still hedge specific energy shocks despite its carbon-transition risk (Agarwal & Padhi, 2025; Bajra et al., 2025).

This paper studies that tension by asking who hedges energy and market risk: green assets or brown assets? The question is theoretically ambiguous. Theory on climate finance predicts that green assets could potentially benefit from the two key trends of decarbonization policies and the repricing of transition risk (Bartolini et al., 2025a; Chen et al., 2025). Sustainable portfolio models also suggest that investors can be willing to trade off the risk and return of their portfolios when incorporating environmental goals into portfolio choice (Jiao & Liu, 2025). But green assets are not necessarily defensive assets. Clean energy stocks are broadly similar to growth-focused, technology-heavy, high-duration stocks, and are subject to discount-rate shock, liquidity stress, and general equity-market declines (Qin et al., 2026; T. Wang et al., 2026). Thus, the climate-aligned label may conceal rather than eliminate conventional market risk.

On the contrary, brown assets present a different problem. Fossil-fuel and conventional energy securities are exposed to carbon regulation, stranded-asset risk, and long-run transition pressure, but they may perform strongly when oil prices rise or when energy scarcity becomes a macro-financial shock. This distinction is important because carbon-transition risk and energy-price hedging are different economic objects. Positive oil shocks may favor brown assets even when the long-run climate transition penalizes carbon-intensive exposure. Prior studies report that oil prices, ESG indices, green bonds, renewable-energy assets, and energy exchange-traded funds transmit shocks asymmetrically across regimes and horizons (Al-Fayoumi et al., 2025; Chang et al., 2025; Rehman et al., 2026). Green and brown assets should therefore be viewed not as simple substitutes but as state-contingent exposures to different risk factors.

The paper addresses two research questions. *First*, when energy-market shocks and financial-market stress materialize, do green and brown assets provide distinct hedging functions, or do they transmit different forms of market, energy, and transition risk? *Second*, are the hedging and portfolio-allocation benefits of green assets conditional on market state, oil-shock direction, and the position of returns in the downside, median, or upside distribution? These questions connect sustainable finance to a central empirical asset-pricing issue: whether risk-management benefits are unconditional or emerge only in particular states of the world. Recent evidence on green bonds, clean energy, carbon markets, and ESG assets suggests that connectedness and spillovers are time-varying, nonlinear, and crisis-dependent (Deng et al., 2025; Jovovic & Popovic, 2025; Konstantakis et al., 2025; J. Wang & Qiao, 2025).

Empirically, the study uses daily data from 2010 to 2025 on exchange-traded clean-energy, fossil-fuel, green-bond, ESG, and market-risk instruments. The green portfolio is constructed from clean-energy exchange-traded funds, while the brown portfolio is constructed from fossil-fuel and conventional energy instruments. The main object of analysis is the green–brown return spread, which directly measures relative performance between green and brown exposures. The analysis examines normal conditions, high-volatility regimes, market-stress days, positive and negative oil-price shocks, the COVID-19 crisis, and the recent energy-crisis period. Spread-based and connectedness approaches are particularly useful when assets are jointly exposed to oil shocks, climate uncertainty, and financial stress (Abdelmalek & Khemakhem, 2026; Albanese et al., 2026; Bouteska et al., 2025).

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The empirical strategy combines performance and downside-risk metrics, rolling correlations, rolling market betas, Newey–West regressions, stress-state comparison tests, quantile regressions, portfolio allocation tests, and supplementary machine-learning classification. This design is necessary because mean regressions alone cannot identify tail-risk hedging, time-varying dependence, asymmetric oil-shock effects, or crisis-state behavior. The transmission of sustainable-finance risk also has asymmetric characteristics, as demonstrated by quantile studies, time-frequency studies, and stress studies, respectively (J. Li & Han, 2025; Maneejuk et al., 2025; J. Wang & Qiao, 2025). Portfolio tests are also crucial since investors are interested not just in the average returns, but also in the downside risk (drawdowns), value-at-risk, return-to-volatility ratios, and diversification benefits (Arouri et al., 2025; Zhang et al., 2025).

The results show that green and brown assets hedge different risks. Brown assets outperform during positive oil-price shocks, consistent with their direct exposure to fossil-fuel markets. Green assets perform relatively better when oil prices fall sharply, indicating relative protection against negative energy-price shocks. However, green assets do not behave as broad safe havens during financial-market stress; instead, they remain exposed to equity-market downside risk. Quantile regressions confirm that the green–brown spread is nonlinear and state-dependent, while portfolio tests show that clean-energy equity exposure alone delivers weak full-sample return-risk performance. Green bonds and ESG-related assets appear more defensive, consistent with evidence that sustainable instruments differ materially in their hedging and safe-haven properties (Meo et al., 2026; Tanos et al., 2026; T. Wang et al., 2026).

Relative to prior green-finance and energy-risk studies, this paper advances the literature by integrating three research streams that are often examined separately: sustainable asset pricing, energy-shock hedging, and market-stress protection. Existing studies have shown that green bonds, ESG assets, clean-energy markets, oil prices, carbon markets, and conventional energy assets are connected through time-varying spillovers, hedging relationships, and crisis-dependent risk transmission (Saeed et al., 2020; Arif et al., 2022; Raheem et al., 2023; Arouri et al., 2025; Deng et al., 2025; Jovovic & Popovic, 2025; Konstantakis et al., 2025). However, much of this evidence does not clearly separate whether green assets hedge energy-specific shocks, protect against broad market stress, or simply transmit a different combination of transition, equity-market, and growth-related risks. This study addresses that gap by treating the green–brown return spread as a relative asset-pricing object and examining its behavior across oil-up shocks, oil-down shocks, high-volatility periods, market-stress days, the COVID-19 crisis, and the energy-crisis period.

The paper contributes to the literature in four ways. *First*, it shows that green assets are not universal hedges but state-dependent transition-risk assets. *Second*, it documents asymmetric oil-shock effects on relative green and brown performance. *Third*, it separates energy-risk hedging from market-stress protection, a distinction often blurred in green-finance research. *Fourth*, it shows that green exposure changes portfolio risk characteristics but does not necessarily improve full-sample return-risk performance unless combined with more defensive sustainable instruments (Arouri et al., 2025; Zhang et al., 2025). The remainder of the paper is organized as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the data, variables, and empirical strategy. Section 4 presents the empirical results. Section 5 discusses the economic interpretation of the findings. Section 6 outlines the theoretical, portfolio, and policy implications. Section 7 concludes with limitations and directions for future research.

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2. Literature Review and Hypothesis Development

2.1. Theoretical Foundation and Hypothesis Logic

This study is grounded in an integrated theoretical framework that combines sustainable asset pricing, carbon-transition risk, and hedging/safe-haven theory. These perspectives jointly explain why green and brown assets may differ in expected returns, risk transmission, and portfolio behavior across energy-market shocks and financial-market stress. Rather than assuming that green assets are inherently superior or that brown assets are uniformly undesirable, the framework treats green and brown assets as distinct exposures to investor preferences, transition expectations, fossil-fuel cash-flow shocks, market stress, and downside risk.

Sustainable asset-pricing theory provides the first foundation. In equilibrium, green assets may be priced differently because investors derive nonpecuniary benefits from holding sustainable securities, institutional ESG mandates create demand for climate-aligned assets, and transition expectations affect discount rates and expected returns (Pástor et al., 2021; Pedersen et al., 2021). This view supports the expectation that green assets may provide distinct risk exposures relative to brown assets. However, sustainable asset-pricing theory does not imply that green assets should always outperform or behave defensively. Clean-energy equities may benefit from decarbonization expectations, but they may also carry equity beta, growth exposure, technology-sector sensitivity, and discount-rate risk. Therefore, green assets can represent transition-risk exposure without necessarily functioning as safe havens during broad financial-market stress.

Carbon-transition risk theory provides the second foundation. Brown assets are exposed to regulation, carbon pricing, technological substitution, stranded-asset risk, and changes in investor demand for low-carbon securities (Bolton & Kacperczyk, 2021, 2023; Giglio et al., 2021). These forces may require compensation through carbon-risk premia and can reduce the long-run attractiveness of fossil-fuel assets. At the same time, brown assets remain directly connected to fossil-fuel cash flows and conventional energy markets. When oil prices rise sharply, brown assets may benefit from improved cash-flow expectations and energy-scarcity effects. This distinction explains why carbon-transition risk and oil-price hedging are not the same economic object: a brown asset can be exposed to long-run transition risk while still hedging positive oil-price shocks in the short run.

Hedging and safe-haven theory provides the third foundation. A diversifier reduces portfolio risk through imperfect correlation, a hedge reduces exposure to a specific risk factor on average, and a safe haven preserves value during extreme market stress (Baur & Lucey, 2010; Baur & McDermott, 2010). This distinction is central to the study because green assets may hedge selected energy or transition risks without protecting investors during systemic selloffs. Similarly, brown assets may hedge positive oil shocks without serving as climate-resilient assets. Climate-finance research further suggests that climate-related risks can be hedged through assets that load on climate-news or transition-risk factors, but these hedging benefits do not necessarily imply general safe-haven behavior during financial crises (Engle et al., 2020; Stroebel & Wurgler, 2021).

Together, these theoretical perspectives provide the logic for the hypotheses. Sustainable asset-pricing theory suggests that green and brown assets should differ because investor preferences and transition expectations affect their valuation. Carbon-transition risk theory suggests that brown assets should respond more strongly to oil-price increases because of their fossil-fuel cash-flow exposure. Hedging theory suggests that green assets may provide conditional diversification benefits but may fail as safe havens when market-wide stress dominates. This framework supports the following predictions: that oil shocks, volatility, and market stress affect the green–brown return spread; that diversification benefits from green exposure are conditional rather than universal; that the relationship may differ across downside, median, and upside return states; and that short-horizon predictive ability should be evaluated separately from economic risk transmission.

2.2. Climate Risk, Carbon Risk, and Sustainable Asset Pricing

There are several pathways for climate risk to be embedded in asset prices—both through the expected cash flows and through the discount rates. Physical risk may have consequences on the operating costs, asset value, and future profitability of firms, while transition risk may impact expected returns of companies due to regulation, carbon pricing, and technological replacement and investor demand. Other factors can affect discount rates, such as climate-policy uncertainty and energy-transition expectations, which can influence investors' risk premia, funding conditions, and the time horizon they consider when pricing decarbonization (Bartolini et al., 2025b; Xu et al., 2025). Such exposures to climate regulation, technological innovation, energy-market shocks, and investor preferences can differ across the green and brown assets in this context, and they do not need to be just on their environmental labels (Chen et al., 2025; Jiao & Liu, 2025).

Brown assets are of special concern when it comes to carbon risk. Fossil-fuel and conventional energy securities are directly exposed to oil-price cycles, carbon regulation, stranded-asset risk, and transition-related repricing. Investors may therefore require compensation for holding carbon-intensive assets, implying a potential carbon-risk premium. However, this long-run transition-risk channel can coexist with short-run energy-hedging benefits. Brown assets may perform well during positive oil-price shocks because higher energy prices can raise expected fossil-fuel cash flows and improve conventional energy valuations (Al-Fayoumi et al., 2025; H. Li et al., 2025). This distinction between carbon-transition risk and energy-price hedging is central to understanding why brown assets may be risky in climate terms but valuable in some stress states.

Green assets generate the opposite prediction. They may benefit from decarbonization policies, clean-technology adoption, sustainability-oriented investor demand, and climate-transition expectations (Qin et al., 2026). However, green assets are not necessarily defensive assets. Clean-energy equities often carry growth, technology, duration, and broad equity-market exposures, making them vulnerable to market selloffs and discount-rate shocks (T. Wang et al., 2026; Zhang et al., 2025). Thus, green assets may hedge selected transition or fossil-fuel risks without serving as safe havens during financial-market stress.

This theoretical ambiguity motivates the study's focus on the green–brown return spread. The spread captures whether green assets outperform brown assets after accounting for oil shocks, market stress, volatility, credit stress, and growth-market conditions. It therefore provides a relative asset-pricing object for testing whether green and brown assets hedge different risks rather than acting as simple substitutes (Agarwal & Padhi, 2025; Albanese et al., 2026). Taken together, sustainable asset-pricing theory and carbon-transition risk theory imply that green and brown assets should respond differently to energy-market and financial-market shocks. Green assets may reflect investor preferences and transition expectations, while brown assets remain more directly exposed to fossil-fuel cash-flow shocks and carbon-risk premia (Pástor et al., 2021; Pedersen et al., 2021; Bolton & Kacperczyk, 2021, 2023). Based on this literature, the study proposes the following hypotheses:

H1. *Green and brown assets respond differently to oil-market shocks.*

H2. *Market stress and volatility shocks significantly affect the green–brown return spread.*

2.3. Green Bonds, ESG Assets, and Sustainable Finance Instruments

Sustainable finance instruments are heterogeneous, and treating them as a single "green" asset class can obscure important differences in pricing, risk transmission, and hedging behavior. Clean-energy equities provide direct exposure to renewable energy, electrification, and low-carbon technologies, but they also carry equity beta, growth exposure, technology-sector sensitivity, policy uncertainty, and valuation risk. In contrast, green bonds are fixed-income securities with defensive characteristics that go beyond the greenness of the projects into which they are invested, partly because of cash-flow structure, duration exposure, issuer quality, and investor clientele. While green bonds' defensive properties may stem in part from their cash-flow structure, duration exposure, issuer quality, and investor clientele, it is not from greenness alone (Meo et al., 2026; Tanos et al., 2026). Assets that fall in a third category are more diverse sustainability-screened portfolios, which can perform more like diversified equity portfolios as well as being more closely aligned with the sustainable economy rather than clean-energy or climate-transition plays (Arouri et al., 2025; T. Wang et al., 2026).

The fact that this is a heterogeneous array of firms is important for the pricing of their assets. The impact of these factors on expected returns and risk premiums varies by instrument (Chen et al., 2025; Jiao & Liu, 2025). Environmental preferences can be priced in green bonds via yield spreads and investor preferences, and there can be a sector exclusion, quality tilt, and diversification effect in ESG portfolios. However, the cash-flow uncertainty, policy credibility, technological competition, and discount-rate repricing of clean-energy equities are more pronounced (Konstantakis et al., 2025; Xu et al., 2025). Thus, a sustainable asset could be a high-scoring asset on its climate index but could have a very different type of cash-flow or discount-rate exposure, as well as a different investor base, liquidity, and crisis state.

These differences are crucial for hedging and safe havens analysis. A green bond could be defensive if it is a bond; an ESG portfolio could perform well because it is diversified; and a clean energy fund could be underperforming as a high-beta growth asset (Jovovic & Popovic, 2025; Deng et al., 2025). For this reason, this study concentrates its primary analysis on the portfolios of clean energy and fossil fuels that have the longest daily time series of available data from 2010 to 2025, with green-bond and ESG instruments used as complementary evidence as their daily time series are shorter. This design ensures that the samples are comparable, while acknowledging that they represent a range of sustainability assets.

The question from a portfolio perspective is not, one could argue, whether green assets are ethically preferred, but rather whether they yield better return-to-volatility ratios, Sortino ratios, drawdowns, value-at-risk, expected shortfall, and stress-state performance when compared with the performance of brown assets and conventional market exposure (Zhang et al., 2025; Arouri et al., 2025). The heterogeneity of sustainable finance instruments suggests that portfolio benefits from green exposure should not be assumed to be unconditional. Clean-energy equities, green bonds, and ESG assets differ in cash-flow structure, duration exposure, investor clientele, diversification potential, and downside-risk behavior (Zerbib, 2019; Flammer, 2021; Arif et al., 2022; Meo et al., 2026; Tanos et al., 2026).

H3. *Green assets provide diversification benefits relative to brown assets during high-volatility periods.*

H5. *Adding green exposure to conventional portfolios changes return-risk performance.*

2.4. Green–Brown Assets, Energy Shocks, and Hedging Behavior

The green–brown distinction is central to sustainable portfolio allocation because it captures competing exposures to energy cycles, transition risk, technological change, and market-wide stress. Brown assets are directly associated with fossil-fuel demand, oil-price variation, energy-security shocks, and commodity inflation, while green assets are related to expectations of clean-technology growth, electrification, credibility of the energy policy, and capital flow towards sustainability (Al-Fayoumi et al., 2025; Albanese et al., 2026; Agarwal & Padhi, 2025). This means that green and brown assets are not synonymous. While brown assets may provide a temporary buffer against positive oil-price shocks, green assets may do better when fossil-fuel prices decline, or when the transition expectations are high (J. Li et al., 2025; Rehman et al., 2026). By contrast, the climate-friendly orientation of clean-energy stocks is not necessarily defensive, since this sector tends to be growth-oriented and equity-market-sensitive. This means that such stocks' defensive characteristics may not be evident during broad market selloffs. (Qin et al., 2026; T. Wang et al., 2026).

This distinction matters for the interpretation of hedging behavior. A hedge reduces exposure to a particular source of risk on average; a diversifier reduces portfolio volatility through imperfect correlation; and a safe haven preserves value during extreme market stress. These concepts are often conflated in green-finance research, although they imply different empirical predictions. Green assets may hedge transition or fossil-fuel-related risk without protecting investors against broad equity-market stress. Conversely, brown assets may hedge positive oil-price shocks while remaining exposed to carbon-transition repricing and regulatory risk. Recent empirical evidence on the effectiveness of hedging of green bonds, ESG indices, clean energy, carbon markets and conventional energy assets considers a conditional, time-varying and regime-sensitive effectiveness of the hedging (Arouri et al., 2025; Bajra et al., 2025; Deng et al., 2025; Jovovic & Popovic, 2025; Konstantakis et al., 2025).

As mentioned, a green–brown return spread is likely to be state-dependent and nonlinear. Positive oil prices should lead to a higher cash flow expectation of brown assets, and a lower spread; negative oil prices should lead to a lower cash flow expectation of brown assets, and a higher spread (Al-Fayoumi et al., 2025; Chang et al., 2025). Yet during broad financial stress, the spread may deteriorate if clean-energy equity beta, liquidity risk, growth-stock repricing, and discount-rate sensitivity dominate sustainability characteristics (J. Li & Han, 2025; J. Wang & Qiao, 2025). This creates a sharp distinction between energy-risk hedging and market-stress protection: the former concerns exposure to oil-market states, whereas the latter concerns resilience during systemic selloffs.

This logic motivates a state-contingent empirical strategy. Rolling correlations and rolling betas identify whether green–brown dependence and market exposure evolve over time. Newey–West regressions estimate average risk transmission while controlling for market, growth, oil, volatility, term-spread, and credit-stress channels. Stress-state comparisons isolate behavior during high-VIX periods, market-stress days, oil-up shocks, oil-down shocks, COVID-19, and the energy-crisis period. Quantile regressions are especially important because hedging value may emerge in the tails rather than at the conditional mean, consistent with evidence that green and carbon-related markets exhibit tail-dependent and time-frequency spillovers (Bouteska et al., 2025; Maneejuk et al., 2025; J. Wang & Qiao, 2025). Supplementary machine-learning classification can assess whether market, oil, volatility, and stress indicators contain short-horizon predictive information, but the main contribution remains the explanation of state-dependent risk transmission rather than trading-rule construction. Hedging theory further implies that the value of green exposure may be nonlinear and state-dependent, because assets can hedge one source of risk while failing to protect against another. If green and brown assets respond differently across oil-shock, volatility, and crisis regimes, then the green–brown spread should vary across downside, median, and upside return states rather than remain stable at the conditional mean (Baur & Lucey, 2010; Baur & McDermott, 2010; Engle et al., 2020; J. Wang & Qiao, 2025).

H4. *The relationship between green–brown performance and energy-market stress is nonlinear and differs across quantiles.*

H6. *Market, oil, volatility, interest-rate, credit, and stress indicators can predict whether green assets outperform brown assets on the next trading day.*

2.5. Conceptual Framework

Figure 1 presents the conceptual framework guiding the study. The framework is developed from three theoretical foundations: sustainable asset pricing, carbon-transition risk, and hedging/safe-haven theory. Sustainable asset-pricing theory explains why green assets may be valued differently because of investor preferences, ESG demand, and climate-related discount-rate repricing (Pástor et al., 2021; Pedersen et al., 2021). Carbon-transition risk theory explains why brown assets may face long-run regulatory, technological, and stranded-asset risks, while still benefiting from short-run fossil-fuel cash-flow shocks when oil prices rise (Bolton & Kacperczyk, 2021, 2023; Giglio et al., 2021). Hedging and safe-haven theory clarifies that an asset may hedge a specific source of risk without preserving value during systemic financial stress (Baur & Lucey, 2010; Baur & McDermott, 2010; Engle et al., 2020).

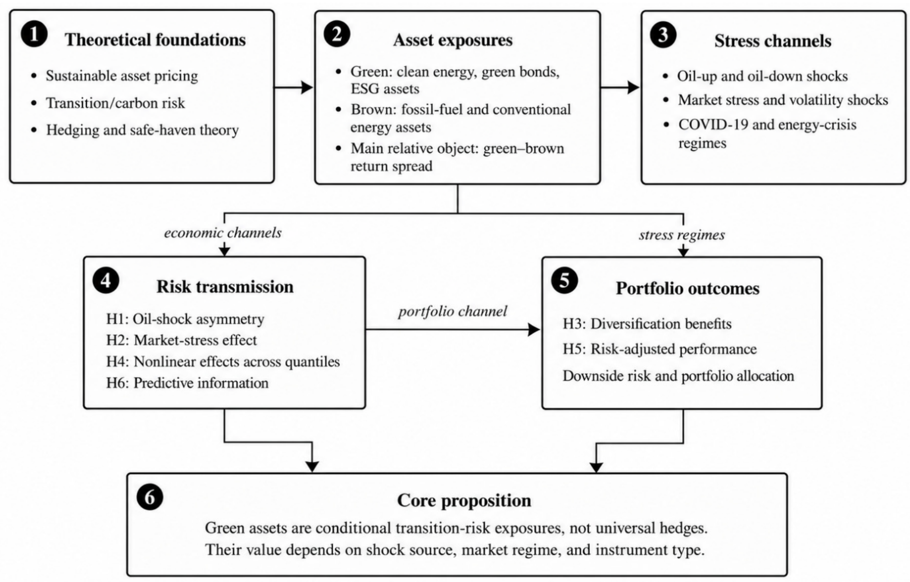

Figure 1. Conceptual framework. Source: Author's own compilation.

The framework links these theoretical foundations to the empirical structure of the study. Green assets, including clean-energy equities, green bonds, and ESG assets, are expected to reflect transition expectations, investor preferences, and sustainability-related demand. Brown assets, including fossil-fuel and conventional energy instruments, are expected to reflect oil-price exposure, commodity-cycle effects, and carbon-transition risk. The green–brown return spread is therefore treated as the main relative asset-pricing object, allowing the study to examine whether green and brown assets hedge different risks rather than acting as simple substitutes.

The framework further identifies the main stress channels through which green and brown assets are expected to respond differently. Oil-up and oil-down shocks capture energy-market risk; market stress and volatility shocks capture broad financial-market pressure; and the COVID-19 and energy-crisis periods capture major stress regimes. These channels affect risk-transmission mechanisms and portfolio-allocation outcomes. H1 and H2 examine oil-shock asymmetry and the effect of market stress on the green–brown return spread. H4 tests whether these effects are nonlinear across return quantiles, while H6 examines whether market, oil, volatility, interest-rate, credit, and stress indicators contain short-horizon predictive information. H3 and H5 focus on portfolio outcomes by testing whether green assets provide diversification benefits and whether adding green exposure changes return-risk performance.

3. Methodology

3.1. Data and Sample Construction

This study examines whether green assets hedge energy-market shocks and financial-market stress better than brown assets. The empirical analysis uses daily adjusted closing prices for exchange-traded clean-energy, fossil-fuel, green-bond, ESG, and market-risk instruments over the period 2010–2025. Exchange-traded instruments are used because they represent investable market exposures and allow the analysis to focus on portfolio-relevant risk transmission.

The empirical setting is based on U.S.-listed exchange-traded instruments and global market-risk proxies traded in U.S. financial markets. The analysis should therefore be interpreted as an investable market-based study rather than a country-level comparison. The raw price series are aligned by common trading days, converted into simple daily returns, and restricted to observations with complete data for all core variables. This cleaning procedure produces a final main sample of 4018 complete daily observations from 6 January 2010 to 30 December 2025. Green-bond and ESG instruments are analyzed separately as Supplementary Materials because their available histories begin later and would otherwise shorten the main sample. Detailed asset availability and data validation are reported in Supplementary Table S1.

The green portfolio is constructed as an equal-weighted portfolio of clean-energy exchange-traded funds: ICLN, QCLN, TAN, and PBW. The brown portfolio is constructed as an equal-weighted portfolio of fossil-fuel and conventional energy instruments: XLE, VDE, XOP, and USO. The main dependent variable is the green–brown return spread, defined as the return on the green portfolio minus the return on the brown portfolio. A positive spread indicates that green assets outperform brown assets, while a negative spread indicates that brown assets outperform green assets.

The portfolios are constructed using equal weights to maintain a transparent and comparable representation of selected green and brown investable exposures. Equal weighting avoids allowing a small number of larger funds to dominate the portfolio return series and ensures that each selected instrument contributes proportionately to the green or brown portfolio. Although value-weighted or liquidity-weighted portfolios may represent alternative investor perspectives, the equal-weighted approach is appropriate because the objective is to compare representative green and brown exposures rather than replicate a capitalization-weighted market index.

USO is included in the brown portfolio to capture direct crude-oil exposure alongside fossil-fuel equity exposure. This inclusion is consistent with the study's focus on energy-market shocks, because brown-asset performance may reflect both energy-sector equity returns and direct oil-price movements. To address the possibility that USO introduces a structural difference between commodity-linked and equity-based risk premia, the study also examines the brown portfolio after excluding USO as a robustness check.

The study also includes market and stress controls. Broad equity-market exposure is proxied by SPY, growth-market exposure by QQQ, oil-market exposure by crude oil futures, market stress by the VIX, bond-market exposure by long-term bond and investment-grade credit instruments, and interest-rate conditions by yield-based market proxies. These variables allow the study to separate green–brown performance from general market movements, oil-market shocks, volatility shocks, and credit-market conditions. The oil-market proxy is the Yahoo Finance CL=F adjusted closing price series, which represents a continuous WTI crude-oil futures series. Daily oil returns are calculated from this series to capture energy-price shocks. No separate roll strategy is constructed by the authors; the analysis relies on the vendor-provided continuous futures series. The April 2020 extreme oil return is retained in the main analysis because it reflects the exceptional negative WTI futures price episode and forms part of the observed energy-market stress environment.

The selected proxies are used because they are liquid, transparent, investable, and widely followed market instruments or indicators that match the portfolio-based design of the study. SPY is used as the broad equity-market proxy because it tracks the S&P 500 and represents diversified U.S. market exposure. QQQ is used to capture growth-oriented and technology-heavy market conditions, which are particularly relevant because clean-energy assets often behave like high-beta growth assets. Crude oil futures are used to capture direct energy-price shocks, while the VIX is used as the market-stress proxy because it reflects option-implied equity-market uncertainty. Long-bond and investment-grade credit instruments are included to capture defensive fixed-income and credit-market conditions, while yield-based variables are used to capture interest-rate conditions. These proxies are preferred over purely macroeconomic or non-investable alternatives because the study focuses on investable green and brown asset exposures rather than macroeconomic aggregates or country-level risk indicators.

3.2. Variable Construction

Daily simple returns are calculated from adjusted closing prices as follows:

$$R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1$$

where $R_{i,t}$ is the daily return of asset i on day t, $P_{i,t}$ is the adjusted closing price of asset i on day t, and $P_{i,t-1}$ is the adjusted closing price of asset i on the previous trading day.

The green portfolio return is calculated as the equal-weighted average return of the clean-energy assets:

$$R_t^G = \frac{1}{N_G} \sum_{i=1}^{N_G} R_{i,t}^G$$

where R_t^G is the green portfolio return on day t, $R_{i,t}^G$ is the return of green asset i on day t, and N_G is the number of assets included in the green portfolio.

Similarly, the brown portfolio return is calculated as the equal-weighted average return of the fossil-fuel and conventional energy assets:

$$R_t^B = \frac{1}{N_B} \sum_{i=1}^{N_B} R_{i,t}^B$$

where R_t^B is the brown portfolio return on day t, $R_{i,t}^B$ is the return of brown asset i on day t, and N_B is the number of assets included in the brown portfolio.

The main dependent variable is the green–brown return spread:

$$GBS_t = R_t^G - R_t^B$$

where GBS_t is the green–brown spread on day t. A positive value of GBS_t indicates that green assets outperform brown assets, while a negative value indicates that brown assets outperform green assets.

Several stress-state variables are constructed to examine whether green and brown assets behave differently under adverse or unusual market conditions. A high-volatility dummy equals one when the VIX is in the top 20% of its sample distribution and zero otherwise. A market-stress dummy equals one when the market return is in the bottom 10% of its sample distribution and zero otherwise. Positive oil shocks are identified when oil returns are in the top 10% of their sample distribution, while negative oil shocks are identified when oil returns are in the bottom 10%. The COVID-19 crisis period and the energy-crisis period are also included as crisis-state indicators. The COVID-19 crisis dummies equal one for trading days from 18 February 2020 to 30 June 2020 and zero otherwise. The energy-crisis dummy equals one for trading days from 4 January 2021 to 30 December 2022 and zero otherwise. These researcher-defined windows are used to capture the acute COVID-19 financial-market shock and the energy-market stress period reflected in the empirical dataset. Credit stress is measured using the negative return on an investment-grade credit-market proxy. These variables allow the analysis to distinguish between normal conditions, energy-market shocks, broad market stress, high-volatility regimes, and crisis periods.

3.3. Empirical Strategy

The empirical strategy proceeds in five stages. *First*, the study reports descriptive statistics, correlations, and risk–return measures for the green portfolio, brown portfolio, green–brown spread, and market-risk controls. Portfolio performance is evaluated using annualized return, annualized volatility, return-to-volatility ratio, Sortino ratio, maximum drawdown, value-at-risk, and expected shortfall. Annualized returns are computed using geometric compounding from daily returns. Specifically, the cumulative return over the sample is converted into an annualized return using a 252-trading-day convention. Therefore, annualized returns may differ from the simple arithmetic daily mean multiplied by 252, particularly for volatile series such as the green–brown spread. *Second*, rolling correlations and rolling market betas are estimated using a 126-day rolling window. This analysis captures time variation in the relationship between green and brown assets, the sensitivity of the green–brown spread to oil-market movements, and the changing market-risk exposure of green and brown portfolios. *Third*, the study estimates Newey–West regressions to account for potential serial correlation and heteroskedasticity in daily return regressions (Newey & West, 1987). The dependent variables are the green return, brown return, and green–brown spread. The baseline regression model is specified as follows:

$$Y_t = \alpha + \beta_1 MKT_t + \beta_2 GROWTH_t + \beta_3 OIL_t + \beta_4 \Delta VIX_t + \beta_5 \Delta TERM_t + \beta_6 CREDIT_t + \varepsilon_t$$

where Y_t represents the dependent variable, measured alternatively as the green portfolio return, brown portfolio return, or green–brown return spread. MKT_t is the market return, $GROWTH_t$ is the growth-market return, OIL_t is the oil return, ΔVIX_t is the change in market volatility, $\Delta TERM_t$ is the change in the term spread, $CREDIT_\mathrm{t}$ is the credit-stress proxy, and ε_t is the error term.

The stress-augmented model adds high-VIX, market-stress, oil-up-shock, oil-down-shock, COVID-crisis, and energy-crisis indicators as follows:

$$Y_t = \alpha + X_t'\beta + S_t'\gamma + \varepsilon_t$$

where X_t is the vector of baseline control variables, including market return, growth-market return, oil return, VIX change, term-spread change, and credit stress. S_t is the vector of stress-state indicators, including high-VIX, market-stress, oil-up-shock, oil-down-shock, COVID-crisis, and energy-crisis dummies. Because the market-stress and oil-shock indicators are constructed from the same market-return and oil-return series that also enter the regressions as continuous variables, the dummy variables should be interpreted as threshold or tail-state effects rather than as independent sources of market or oil stress. The continuous variables capture average linear exposure, while the stress indicators capture whether the relationship changes during extreme market-return or oil-return states.

The interaction model further includes interactions between oil returns and high-volatility or energy-crisis conditions, as well as market returns and high-volatility conditions. This structure tests whether green and brown assets respond differently to energy and market stress:

$$Y_t = \alpha + X_t'\beta + S_t'\gamma + Z_t'\delta + \varepsilon_t$$

where Z_t is the vector of interaction terms used to examine whether the effects of oil returns and market returns differ across stress regimes. These interactions include oil return with high-volatility conditions, market return with high-volatility conditions, and oil return with the energy-crisis period. Variance inflation factors are examined for the interaction specification to assess whether the inclusion of stress dummies and interaction terms creates multicollinearity concerns. The VIF diagnostics are reported in Supplementary Materials Table S8. The diagnostics show that most stress indicators and control variables have low VIF values. Higher VIF values are observed mainly for market return, growth return, oil return, and the oil-return interaction with high-volatility conditions. This pattern is expected because SPY and QQQ capture related equity-market conditions, and interaction terms mechanically share information with their underlying variables. Therefore, the interpretation of the interaction model is based on the consistency of coefficient signs and significance across the baseline, stress-dummy, and interaction specifications rather than on the interaction model alone. *Fourth*, stress-state comparison tests compare average green returns, brown returns, and green–brown spreads during stress and non-stress states. These tests directly evaluate whether green assets hedge or diversify risk during high volatility, market selloffs, and oil shocks. *Fifth*, quantile regressions are estimated for the green–brown spread at the 10th, 25th, 50th, 75th, and 90th percentiles. Quantile regressions are used to examine whether the determinants of the green–brown spread differ across downside, median, and upside states, following the regression-quantile framework of Koenker and Bassett (1978). The quantile-regression specification is more parsimonious than the full Newey–West interaction specification. It retains the baseline continuous controls, including market return, growth-market return, oil return, VIX change, term-spread change, and credit stress, together with selected stress-state indicators. Oil-up and oil-down shock dummies and the COVID-crisis dummy are not included in the main quantile specification to avoid over-parameterization and redundancy with the continuous oil-return variable and other stress-state controls. The oil-shock dummies are threshold indicators constructed from the oil-return distribution, while the continuous oil-return variable already captures oil-price exposure across quantiles. Standard errors for the quantile regressions are computed using heteroskedasticity-robust asymptotic standard errors. The estimated conditional quantiles were inspected for crossing. Limited crossings were observed in a very small number of fitted observations, but these do not materially affect the interpretation because the quantile regressions are used to compare coefficient patterns across distributional states rather than to produce individual conditional-quantile forecasts. The model is specified as follows:

$$Q_\tau(GBS_t|X_t) = \alpha_\tau + X_t'\beta_\tau$$

where $Q\tau(GBS_t \mid X_t)$ represents the conditional quantile of the green–brown return spread at quantile τ. The quantile regressions are estimated at $\tau = 0.10, 0.25, 0.50, 0.75$, and 0.90 to examine whether the determinants of green–brown performance differ across downside, median, and upside market states. Quantile regressions are important because the hedging value of green assets may be strongest or weakest during extreme market conditions rather than at the conditional mean.

3.4. Robustness and Supplementary Analyses

The study further examines downside-risk and hedge characteristics by comparing correlations with market returns, oil returns, and VIX changes across full-sample and stress-state periods. Portfolio allocation tests compare market-only, green-only, brown-only, green–brown, and mixed market–green–brown portfolios to assess whether green exposure improves return-risk and downside-risk performance. Optional green-bond and ESG instruments are examined as supplementary sustainable-finance assets because their shorter data histories make them more suitable for robustness analysis than for the main complete-sample tests.

Finally, supplementary machine-learning classification models are used to examine whether market, oil, volatility, interest-rate, credit, and stress indicators can predict whether green assets outperform brown assets on the next trading day. The target variable equals one when the next-day green–brown spread is positive and zero otherwise. The feature set includes market return, growth return, oil return, VIX change, term-spread change, credit stress, and stress-state indicators. The models include logistic regression, random forest, and histogram gradient boosting classifiers. The models are evaluated using out-of-sample accuracy, precision, recall, and ROC-AUC. This analysis is treated as Supplementary Materials because the main objective of the study is to assess risk transmission, hedging behavior, and portfolio performance rather than to develop a short-term trading model.

4. Results and Discussion

4.1. Descriptive Evidence and Portfolio Performance

Table 1 reports summary statistics and selected correlations for the main variables. The green portfolio has a slightly higher average daily return than the brown portfolio, but it also has higher volatility. This indicates that green assets do not dominate brown assets on a simple risk–return basis. Instead, green assets behave as risky equity-like instruments whose performance varies substantially over time. The green–brown spread is close to zero on average but highly volatile, suggesting that relative green and brown performance is strongly state-dependent. The key correlations reinforce this interpretation. Green returns are strongly correlated with market returns, indicating substantial exposure to broad equity-market risk. Brown returns are more strongly related to oil returns, consistent with their conventional energy exposure. The green–brown spread is negatively correlated with oil returns, suggesting that oil-market strength tends to favor brown assets relative to green assets. The full correlation matrix is reported in Supplementary Table S2.

Table 2 reports portfolio performance and downside-risk metrics. The broad market portfolio delivers the strongest full-sample return-risk performance, while green-only and brown-only portfolios show weak return-to-volatility ratios and large drawdowns. This result is important because it shows that clean-energy assets should not be described as universally safe assets. This finding is consistent with sustainable asset-pricing theory, which suggests that green assets may reflect investor preferences and climate-risk hedging motives but need not dominate conventional assets in realized return-risk performance (Pástor et al., 2021; Pedersen et al., 2021). Their contribution is not that they always outperform, but that they offer different risk exposures from brown assets.

Table 1. Summary statistics and key correlations.

Panel A. Summary Statistics							
Variable	**Obs.**	**Mean (%)**	**Std. Dev. (%)**	**Min. (%)**	**Max. (%)**	**Skewness**	**Kurtosis**
Green return	4018	0.025	1.996	−13.85	13.49	−0.026	3.520
Brown return	4018	0.022	1.852	−25.54	12.66	−0.710	13.367
Green–brown spread	4018	0.002	1.909	−12.80	13.64	0.113	3.668
Market return	4018	0.058	1.085	−10.94	10.50	−0.335	12.111
Growth return	4018	0.076	1.301	−11.98	12.00	−0.209	7.312
Oil return	4018	−0.069	5.817	−305.97	37.66	−38.677	1960.427
VIX change	4018	−0.001	1.874	−18.71	24.86	1.909	29.188
Credit stress	4018	−0.017	0.483	−7.39	5.00	−0.393	30.603

Panel B. Key Correlations		
Relationship	**Correlation**	**Interpretation**
Green return and brown return	0.510	Green and brown assets move together, but not perfectly.
Green return and market return	0.710	Green assets are strongly equity-market-sensitive.
Brown return and market return	0.621	Brown assets also carry market exposure.
Brown return and oil return	0.362	Brown assets are more oil-sensitive.
Green–brown spread and oil return	−0.213	Oil increases favor brown assets relative to green assets.
Green–brown spread and growth return	0.266	Green assets benefit from growth-market conditions.
Green–brown spread and credit stress	−0.166	Credit stress weakens relative green performance.

Notes: Table 1 reports selected daily summary statistics and economically relevant correlations. Returns and volatility are shown in percentage terms. The mean values in Panel A are arithmetic daily means and are not annualized. The full correlation matrix is provided in Supplementary Table S2. Source: Author's calculations.

Table 2. Portfolio performance and downside risk.

Portfolio/Asset	**Ann. Return (%)**	**Ann. Vol. (%)**	**Return-to-Volatility Ratio**	**Sortino**	**Max Drawdown (%)**	**VaR 5% (%)**	**ES 5% (%)**
Green return	1.18	31.68	0.037	0.054	−77.21	−3.17	−4.44
Brown return	1.24	29.40	0.042	0.055	−81.91	−2.88	−4.26
Green–brown spread	−3.91	30.30	−0.129	−0.191	−91.40	−3.00	−4.26
Market return	13.98	17.22	0.812	0.998	−33.72	−1.65	−2.63

Notes: Annualized returns are computed using geometric compounding from daily returns with a 252-trading-day convention. Return-to-volatility ratio is calculated as annualized return divided by annualized volatility and does not subtract the risk-free rate. VaR and ES are historical 5% daily downside-risk measures. The green–brown spread represents a long-green/short-brown relative performance series. Source: Author's calculations.

Figure 2 provides visual evidence on long-run performance and short-run relative performance. Panel A shows that the market portfolio strongly outperforms over the full sample. Green assets experience a sharp boom during the clean-energy rally around 2020–2021, followed by a correction. Brown assets follow a different path linked more closely to energy-market cycles. Panel B shows that the daily green–brown spread fluctuates around zero but exhibits large positive and negative spikes during stress periods. Together, these patterns support the use of stress-state analysis and quantile regressions, because average effects alone cannot capture the instability of green–brown relative performance.

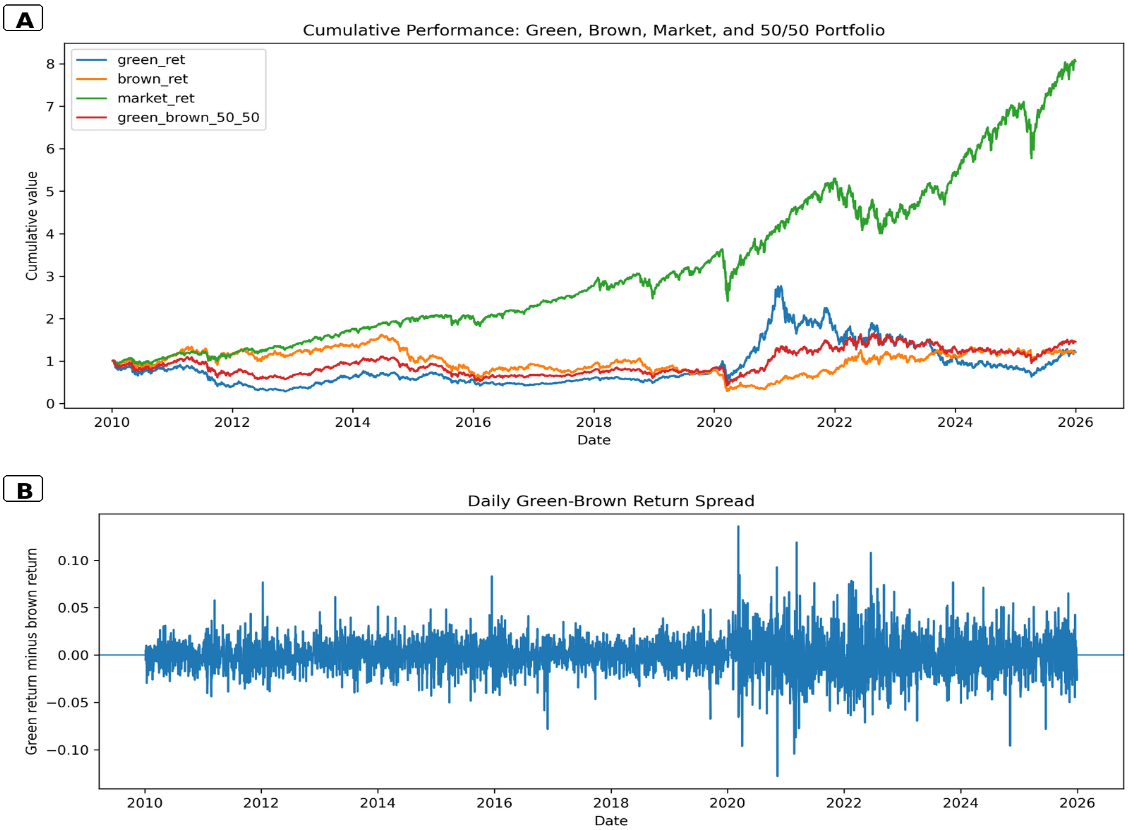

Figure 2. Green–brown performance and spread dynamics. Panel (**A**) plots cumulative performance of the green portfolio, brown portfolio, market benchmark, and the 50/50 green–brown portfolio. Panel (**B**) reports the daily green–brown return spread. Source: Author's calculations.

4.2. Market and Energy Stress Proxies

Figure 3 reports the main stress proxies used in the empirical analysis. Panel A plots the VIX, which captures broad market uncertainty and financial-market stress. The series shows several volatility episodes, with the largest spike occurring during the COVID-19 crisis period. Panel B plots daily oil returns, which are used to identify positive and negative oil-price shocks. The oil-return series shows extreme energy-market movements, including the unusually large oil-price disruption in 2020. This focus is consistent with climate-finance research emphasizing transition risk, energy-market exposure, and the need to understand how climate-related risks are transmitted into financial markets (Giglio et al., 2021; Bolton & Kacperczyk, 2023). The Figure provides visual context for the stress-state variables used in the comparison tests, Newey–West regressions, and quantile regressions.

4.3. Time-Varying Risk Exposure

Figure 4 reports time-varying dependence and market exposure. Panel A presents rolling correlations. The green–brown correlation is positive but clearly time-varying, which means green and brown assets sometimes move together but not consistently. The rolling correlation between the green–brown spread and oil returns is mostly negative, indicating that stronger oil-market performance generally favors brown assets and reduces the relative performance of green assets. Panel B reports rolling market betas. Green assets often have higher market beta than brown assets, especially during transition-growth and post-COVID periods. This confirms that clean-energy assets are not defensive assets in a broad equity-market sense. They often behave like high-beta growth assets. Brown assets, in contrast, show more energy-cycle-specific market exposure. The rolling evidence therefore supports the paper's central argument that green and brown assets represent different and time-varying sources of risk. This time-varying interpretation is consistent with prior evidence that hedging relationships between green and dirty energy assets are unstable across market conditions (Saeed et al., 2020; Raheem et al., 2023).

4.4. Stress-State Comparison Results

Table 3 reports stress-state comparison tests. The strongest evidence appears during oil shocks. During positive oil shocks, brown assets significantly outperform green assets, producing a negative green–brown spread. During negative oil shocks, green assets perform relatively better than brown assets, producing a positive green–brown spread. This directly supports the hypothesis that green and brown assets respond differently to energy-market shocks.

During broad market-stress days, green assets underperform brown assets. This result is important because it shows that green assets do not behave as safe havens during equity-market selloffs. High-VIX periods also hurt both green and brown assets, and the green–brown spread does not show clear safe-haven behavior. Therefore, green assets may diversify some energy risks, but they do not protect investors from broad market stress. This distinction is important because prior research shows that climate-aligned or green assets may offer hedging benefits in some settings, but their safe-haven properties are conditional rather than universal (Engle et al., 2020; Arif et al., 2022; Abuzayed & Al-Fayoumi, 2023).

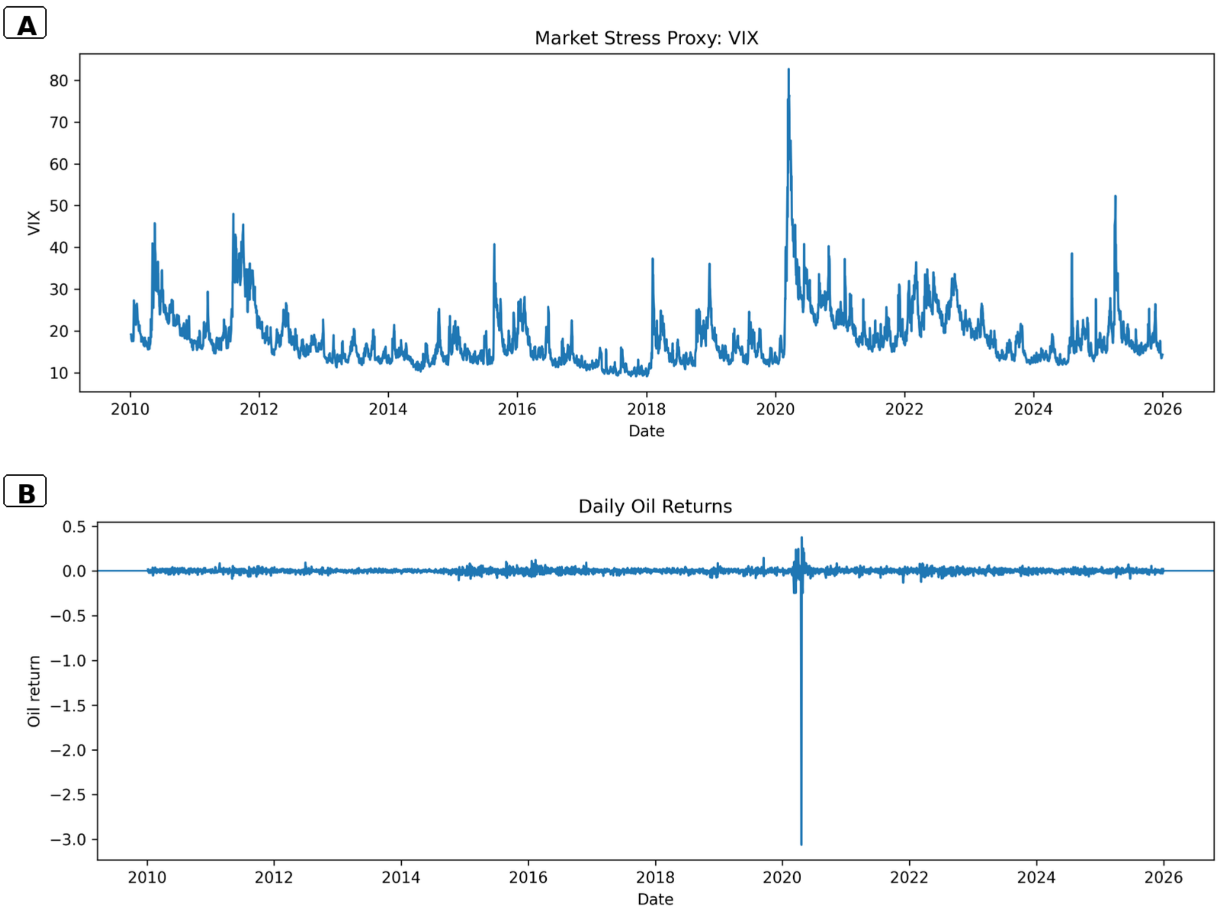

Figure 3. Market and energy stress proxies. Panel (**A**) plots the VIX as the proxy for market stress. Panel (**B**) plots daily oil returns as the proxy for energy-market shocks. Source: Author's calculations.

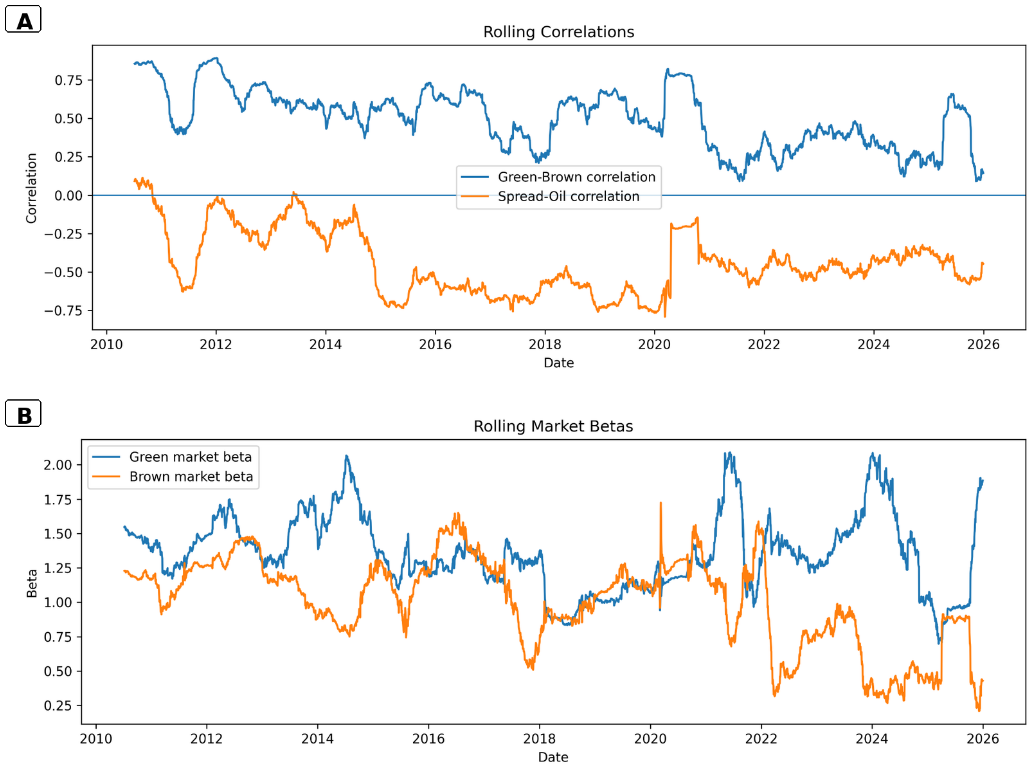

Figure 4. Rolling dependence and market exposure. Panel (**A**) reports rolling correlations. Panel (**B**) reports rolling market betas for the green and brown portfolios. Source: Author's calculations.

Table 3. Stress-state comparison tests.

Stress State	Variable	Stress Mean (%)	Normal Mean (%)	Difference (%)	t-Stat.	Significance
High VIX	Green return	−0.228	0.088	−0.316	−2.86	***
High VIX	Brown return	−0.183	0.074	−0.257	−2.39	**
High VIX	Green–brown spread	−0.045	0.014	−0.059	−0.62	n.s.
Market stress	Green return	−2.774	0.336	−3.110	−31.53	***
Market stress	Brown return	−2.132	0.262	−2.394	−19.08	***
Market stress	Green–brown spread	−0.641	0.074	−0.715	−6.33	***
Oil-up shock	Green return	0.813	−0.063	0.876	7.30	***
Oil-up shock	Brown return	2.391	−0.241	2.632	26.33	***
Oil-up shock	Green–brown spread	−1.578	0.178	−1.756	−15.40	***
Oil-down shock	Green return	−1.049	0.144	−1.193	−9.14	***
Oil-down shock	Brown return	−2.616	0.316	−2.932	−25.12	***
Oil-down shock	Green–brown spread	1.567	−0.172	1.739	16.46	***
COVID crisis	Green return	0.074	0.023	0.050	0.11	n.s.
COVID crisis	Brown return	−0.375	0.032	−0.407	−0.73	n.s.
COVID crisis	Green–brown spread	0.449	−0.008	0.457	1.38	n.s.
Energy crisis	Green return	−0.061	0.037	−0.098	−0.79	n.s.
Energy crisis	Brown return	0.201	−0.003	0.205	2.04	**
Energy crisis	Green–brown spread	−0.262	0.040	−0.303	−2.28	**

Notes: Stress-state differences are computed as stress-period mean minus normal-period mean. Returns are in percentage terms. *** and **, indicate significance at the 1% and 5% levels; n.s. denotes not significant. Source: Author's calculations.

4.5. Newey–West Regression Results

Table 4 reports the main Newey–West regression results for the green–brown spread. The spread regressions provide the central econometric evidence because the study's main question concerns relative green versus brown performance. Full green-return and brown-return regressions are reported in Supplementary Table S4. In the baseline model, the green–brown spread is negatively related to market returns and positively related to growth-market returns. This means green assets outperform brown assets when growth-oriented assets perform well, but underperform when broad market shocks dominate. Credit stress is negative and statistically significant, suggesting that credit-market stress reduces the relative performance of green assets.

In the stress-dummy model, positive oil shocks have a negative and significant effect on the green–brown spread, while negative oil shocks have a positive and significant effect. This confirms that brown assets outperform during oil-price surges, while green assets perform relatively better during oil-price declines. Market stress also has a negative and significant effect on the spread, supporting the conclusion that green assets are not safe havens during broad selloffs. The interaction model improves explanatory power and shows that green–brown risk transmission is state-dependent. Oil returns, oil-shock indicators, market-stress indicators, and interaction terms are statistically significant. These results support the view that the green–brown spread is shaped not only by average oil and market exposure but also by the market regime in which shocks occur.

Table 4. Newey–West regression results for the green–brown spread.

Variable	Baseline	Stress Dummies	Interactions
Market return	−1.247 *** (0.144)	−1.058 *** (0.122)	−0.821 *** (0.126)
Growth return	1.415 *** (0.101)	1.281 *** (0.088)	1.217 *** (0.091)
Oil return	−0.069 (0.049)	−0.032 (0.026)	−0.295 *** (0.023)
VIX change	0.034 (0.036)	0.036 (0.032)	0.038 (0.034)
Term-spread change	−1.275 (1.006)	−0.100 (0.945)	0.076 (0.910)
Credit stress	−0.410 *** (0.139)	−0.445 *** (0.127)	−0.424 *** (0.124)
High VIX	-	0.001 (0.001)	0.001 (0.001)
Market stress	-	−0.003 ** (0.001)	−0.003 ** (0.001)
Oil-up shock	-	−0.015 *** (0.001)	−0.007 *** (0.001)
Oil-down shock	-	0.014 *** (0.001)	0.006 *** (0.001)
COVID crisis	-	0.001 (0.003)	0.002 (0.003)
Energy crisis	-	−0.001 (0.001)	−0.001 (0.001)
Oil return × High VIX	-	-	0.272 *** (0.025)

Table 4. *Cont.*

Variable	Baseline	Stress Dummies	Interactions
Market return × High VIX	-	-	−0.267 *** (0.077)
Oil return × Energy crisis	-	-	−0.273 *** (0.041)
Constant	−0.000 * (0.000)	−0.000 (0.000)	−0.000 (0.000)
Observations	4018	4018	4018
Adjusted R^2	0.218	0.315	0.363

Notes: The dependent variable is the green–brown return spread. All return variables in the regression are measured in decimal units, whereas descriptive and stress-state tables report returns in percentage terms. Newey–West heteroskedasticity- and autocorrelation-consistent standard errors are reported in parentheses. Variance inflation factors were examined for the interaction specification to assess multicollinearity among the main regressors, stress dummies, and interaction terms. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Source: Author's calculations.

4.6. Quantile Regression Results

Table 5 reports quantile regression results for the green–brown spread. The results show that the determinants of green–brown performance differ across downside, median, and upside states. Oil returns remain negative and statistically significant across the distribution, confirming that energy-market movements are central to the green–brown relationship. Market and growth factors also vary in strength across quantiles.

Table 5. Quantile regression results for the green–brown spread.

Variable	Q10	Q25	Q50	Q75	Q90
Market return	−1.077 *** (0.143)	−0.750 *** (0.079)	−0.611 *** (0.069)	−0.845 *** (0.083)	−0.993 *** (0.127)
Growth return	1.188 *** (0.103)	1.070 *** (0.056)	1.001 *** (0.049)	1.188 *** (0.062)	1.272 *** (0.101)
Oil return	−0.219 *** (0.020)	−0.307 *** (0.007)	−0.339 *** (0.004)	−0.338 *** (0.003)	−0.315 *** (0.005)
Credit stress	−0.329 *** (0.125)	−0.506 *** (0.070)	−0.463 *** (0.068)	−0.528 *** (0.090)	−0.379 ** (0.176)
High VIX	−0.004 *** (0.001)	−0.001 * (0.001)	0.002 *** (0.001)	0.004 *** (0.001)	0.007 *** (0.001)
Market stress	−0.007 *** (0.002)	−0.004 *** (0.001)	−0.002 ** (0.001)	−0.002 * (0.001)	−0.003 (0.002)
Energy crisis	−0.011 *** (0.001)	−0.008 *** (0.001)	−0.003 *** (0.001)	0.002 ** (0.001)	0.006 *** (0.001)
Constant	−0.016 *** (0.001)	−0.007 *** (0.000)	−0.000 (0.000)	0.007 *** (0.000)	0.015 *** (0.000)

Notes: The dependent variable is the green–brown return spread. Standard errors are reported in parentheses. Standard errors are heteroskedasticity-robust asymptotic standard errors. The quantile-regression specification is parsimonious and focuses on the main continuous market, growth, oil, credit, and selected stress-state variables. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Source: Author's calculations.

The quantile results support the hypothesis that green–brown performance is nonlinear and state-dependent. This is important because the hedging value of green assets cannot be understood only from average regressions. The behavior of green assets during downside and upside states differs from their behavior under normal market conditions. In particular, market stress is most damaging in the lower tail, while the energy-crisis effect changes sign across quantiles, indicating asymmetric behavior across poor and strong green–brown performance states.

4.7. Portfolio Allocation Results

Table 6 reports portfolio allocation performance. The market-only portfolio dominates in full-sample return-risk performance, while green-only and brown-only portfolios experience large drawdowns and weak return-to-volatility ratios. A mixed green–brown portfolio reduces some sector-specific exposure but does not dominate the broad market. These results imply that green assets should not be used as standalone defensive substitutes for diversified market exposure. The market–green–long-bond portfolio has a lower maximum drawdown than the market-only portfolio, suggesting that defensive fixed-income exposure can improve downside characteristics. However, this portfolio should be interpreted as a mixed allocation with conventional long-bond exposure, not as a green-bond allocation. Therefore, the lower maximum drawdown reflects the role of conventional long-bond exposure in portfolio diversification rather than evidence that green bonds improve full-sample allocation performance. Overall, the portfolio evidence supports a cautious risk-management interpretation: green assets may contribute to thematic transition-risk exposure, but they do not automatically improve return-risk performance when added to diversified portfolios.

Table 6. Portfolio allocation performance.

Portfolio	Ann. Return (%)	Ann. Vol. (%)	Return-to-Volatility	Sortino	Max Drawdown (%)	VaR 5% (%)
Market only	13.98	17.22	0.812	0.998	−33.72	−1.65
Green only	1.18	31.68	0.037	0.054	−77.21	−3.17
Brown only	1.24	29.40	0.042	0.055	−81.91	−2.88
Green–brown 50/50	2.38	26.54	0.090	0.120	−61.17	−2.62
Market–green 80/20	11.77	18.81	0.625	0.792	−35.91	−1.89
Market–brown 80/20	11.79	18.02	0.654	0.803	−39.11	−1.70
Market–green–brown 60/20/20	9.59	19.69	0.487	0.614	−40.92	−1.93
Market–green–long-bond 70/20/10	10.97	16.79	0.654	0.837	−31.95	−1.67

Notes: Portfolio performance is calculated from daily returns over the full sample. Annualized returns are computed using geometric compounding with a 252-trading-day convention. The return-to-volatility ratio is the annualized return divided by annualized volatility and does not subtract the risk-free rate. The market–green–long-bond 70/20/10 portfolio uses conventional long-bond exposure as the defensive fixed-income component and should not be interpreted as a green-bond allocation. Source: Author's calculations.

Figure 5 plots cumulative performance for alternative portfolio allocations. The Figure confirms that the market-only portfolio dominates over the full sample, while green-only and brown-only portfolios remain substantially weaker. The mixed market–green–brown allocation performs better than green-only or brown-only exposure but does not outperform the broad market. This visual evidence supports the conclusion that green exposure should be used selectively within diversified portfolios rather than treated as a standalone hedge. This interpretation aligns with the ESG-efficient frontier framework, in which sustainability preferences and financial risk–return trade-offs jointly shape optimal portfolio allocation (Pedersen et al., 2021).

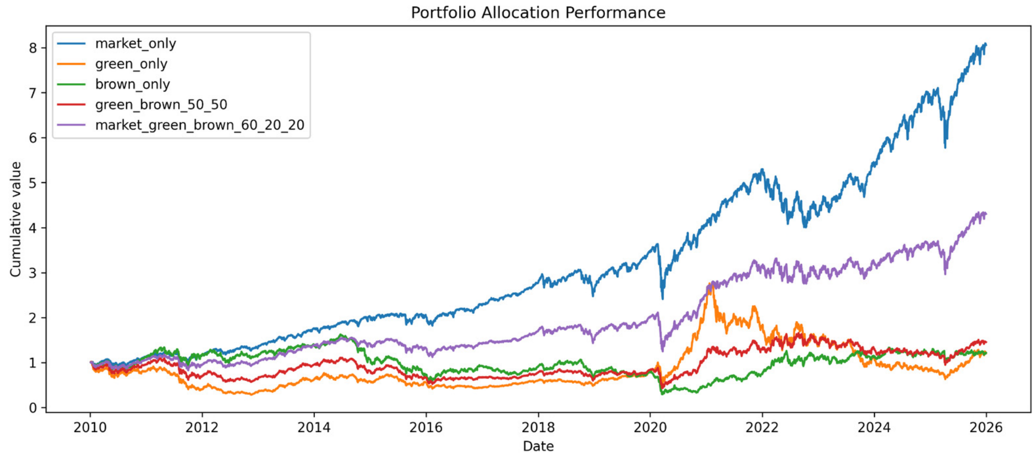

Figure 5. Portfolio allocation performance. This Figure compares cumulative performance across alternative portfolio allocation strategies. Source: Author's calculations.

4.8. Supplementary and Appendix Evidence

The Supplementary Materials provide additional evidence on data coverage, full correlations, full regression outputs, downside-risk tests, green-bond and ESG performance, and machine-learning classification. Supplementary Table S1 confirms the data availability and verifies that the main variables contain no missing values. Supplementary Table S2 reports the full correlation matrix. Supplementary Table S3 reports the full set of portfolio and risk metrics. Supplementary Table S4 presents the full Newey–West regressions for green returns, brown returns, and the green–brown spread. Supplementary Table S5 reports downside-risk and hedge tests across stress states. Supplementary Table S6 shows supplementary green-bond and ESG performance; Supplementary Table S7 reports machine-learning classification results, and Supplementary Table S8 reports VIF diagnostics.

Additional robustness evidence addresses the construction of the brown portfolio. The brown portfolio is reconstructed after excluding USO, leaving XLE, VDE, and XOP as equity-based fossil-fuel instruments. The results remain consistent with the main interpretation. The brown portfolio beta relative to SPY increases from 1.061 in the baseline brown portfolio to 1.174 when USO is excluded, indicating that USO does not inflate the brown portfolio's equity-market beta. The correlation with oil returns declines from 0.362 to 0.270, confirming that USO mainly contributes direct oil-price exposure. The main conclusion that positive oil shocks favor brown assets, while negative oil shocks improve relative green performance, is therefore not driven solely by USO.

The evidence in the appendix supports the main findings. Green returns are strongly exposed to market risk, brown returns are more oil-sensitive, and the green–brown spread behaves differently across stress states. Green bonds and ESG-related assets appear more defensive than clean-energy equity exposure, but these results are treated as shorter-sample supplementary evidence because their data histories begin later than the core green and brown portfolio sample. The machine-learning results show limited predictive power, with accuracy and ROC-AUC close to random classification, so they should not be interpreted as a main contribution.

5. Discussion

The results provide a more nuanced interpretation of green and brown assets than the common view that green assets are natural hedges and brown assets are simply transition-risk exposures. The evidence indicates that green and brown assets hedge different risks, and that their relative performance depends on the source of the shock, the state of the market, and the asset class through which sustainability exposure is obtained. This is consistent with the extensive literature on climate-finance and sustainable asset pricing, which implies that climate-related assets can be a conditional hedge versus climate change rather than the unconditional hedge (Engle et al., 2020; Pástor et al., 2021; Pedersen et al., 2021; Bolton & Kacperczyk, 2021, 2023).

The strongest evidence concerns the first hypothesis. H1 proposed that green and brown assets respond differently to oil-market shocks. The stress-state comparisons and Newey–West regressions support this hypothesis, but the economic interpretation is more important than the statistical confirmation. Brown assets outperform during positive oil-price shocks because fossil-fuel and conventional energy instruments are directly linked to oil-market cash flows, energy demand, and commodity-cycle valuation effects. Green assets, on the contrary, perform better during a sharp drop in oil prices, indicating that they offer some shelter from the effects of negative energy shocks but not from all risks. This reinforces the notion that green and brown assets are state-contingent exposures to energy and transition channels, which are not interchangeable (Saeed et al., 2020; Raheem et al., 2023; Al-Fayoumi et al., 2025; Albanese et al., 2026). The economic magnitude of these effects is meaningful. During oil-up shock days, brown assets outperform green assets by about 1.58 percentage points on average, while during oil-down shock days, green assets outperform brown assets by about 1.57 percentage points. These are large daily spread effects relative to the average daily green–brown spread of 0.002% and the daily spread volatility of 1.909%. The result implies that energy-price shocks are not merely statistically significant; they generate economically important short-horizon reallocations between green and brown exposures. For investors, this means that brown assets may provide short-run protection during positive oil-price shocks, whereas green exposure may offer relative protection when oil prices fall sharply.

The results also support H2, which predicted that market stress and volatility shocks affect the green–brown spread. However, the evidence shows that the market-stress channel operates differently from the energy-shock channel. Green assets do not behave as broad safe havens during financial-market stress. Instead, clean-energy equities remain exposed to equity beta, growth-factor risk, liquidity pressure, and downside market movements. This means that sustainability alignment does not eliminate conventional financial risk. The discovery sharpened the argument for protecting investors against climate risk, as green assets may provide investors with some exposure to transition risks, but not necessarily to systemic selloffs. This is relevant as hedge, diversifier, and safe haven are distinct concepts, and the evidence presented here indicates that clean-energy assets are more likely to be considered conditional transition-risk assets than assets used during a crisis period as safe havens (Engle et al., 2020; Arif et al., 2022; Abuzayed & Al-Fayoumi, 2023; Qin et al., 2026; T. Wang et al., 2026). The market-stress effect is also economically important. During market-stress days, the average green–brown spread is about −0.64 percentage points, indicating that green assets underperform brown assets when broad equity markets sell off. This is not a small effect in daily return terms and shows that clean-energy equity exposure can amplify downside risk during market-wide stress. For portfolio managers, the implication is that green equity exposure should not be used as a substitute for defensive assets during broad market drawdowns.

H3 receives conditional rather than unconditional support. Green assets provide diversification benefits relative to brown assets in selected energy-shock states, especially when oil prices fall sharply, but they do not provide reliable diversification during broad market-stress or high-volatility periods. This conditional result is theoretically meaningful because it shows that diversification benefits depend on the type of shock being hedged. Green exposure may diversify fossil-fuel price declines, but it may fail to diversify market-wide equity drawdowns. This interpretation is consistent with evidence that green bonds, ESG assets, clean-energy equities, and conventional energy assets have time-varying connectedness and stress-dependent hedging properties (Arouri et al., 2025; Deng et al., 2025; Jovovic & Popovic, 2025; Konstantakis et al., 2025).

The quantile regression evidence supports H4 and provides one of the study's key contributions. The determinants of the green–brown spread differ across downside, median, and upside states, showing that the relationship is nonlinear and state-dependent. Average regressions identify the central direction of risk transmission, but they cannot fully capture how oil shocks, market stress, growth exposure, and credit stress affect relative performance in the tails. The lower-tail results are particularly important because investors care most about hedging when losses are severe. The evidence therefore supports a distributional interpretation of sustainable asset pricing: the value of green exposure cannot be evaluated only at the mean; it must be evaluated across downside and crisis states (Koenker & Bassett, 1978; Bouteska et al., 2025; Maneejuk et al., 2025; J. Wang & Qiao, 2025).

H5 is also supported, but only in a conditional portfolio-allocation sense. Adding green exposure changes portfolio risk–return characteristics, yet clean-energy equity exposure alone does not improve full-sample return-risk performance. The portfolio results show weak return-to-volatility and Sortino ratios and large drawdowns for clean-energy exposure, while supplementary green-bond and ESG evidence appear more defensive. This does not mean that green assets lack portfolio value; rather, it means that the value depends on instrument choice. Clean-energy equities, green bonds, and ESG assets differ in cash-flow structure, duration exposure, investor clientele, diversification, and crisis behavior. Therefore, the defensive characteristics of green bonds and ESG assets should be interpreted as sustainable-asset heterogeneity, not as evidence that all green instruments are safe havens (Zerbib, 2019; Flammer, 2021; Pedersen et al., 2021; Arif et al., 2022; Meo et al., 2026; Tanos et al., 2026). The portfolio magnitudes reinforce this interpretation. The green-only portfolio has an annualized volatility of 31.68% and a maximum drawdown of −77.21%, while the brown-only portfolio has an annualized volatility of 29.40% and a maximum drawdown of −81.91%. These drawdowns are economically large and show that both standalone green and brown exposures carry substantial downside risk. By contrast, the market–green–long-bond allocation reduces the maximum drawdown to −31.95%, but this improvement reflects conventional long-bond diversification rather than green-bond exposure. The practical implication is that green allocation decisions should be made within diversified portfolio structures rather than treated as standalone downside-risk protection.

H6 is not supported in a strong predictive sense. The supplementary machine-learning models show limited ability to predict next-day green outperformance, with accuracy and ROC-AUC close to random classification. This result should not be interpreted as a weakness of the study; rather, it is consistent with the broader empirical asset-pricing literature, which shows that short-horizon return prediction is difficult, unstable, and highly sensitive to out-of-sample validation. Goyal and Welch (2008) show that many variables proposed for equity-premium prediction perform poorly out of sample, while McLean and Pontiff (2016) document that return predictability declines substantially outside the original sample and after publication. More recent machine-learning studies show that nonlinear methods can improve risk-premium estimation when large cross-sectional information sets and complex interactions are available, but they also emphasize that successful prediction depends on signal strength, model design, sample structure, and validation discipline (Gu et al., 2020; Kelly et al., 2024; Lo & Singh, 2023). In this paper, the target is particularly demanding because the model predicts next-day relative green-versus-brown outperformance rather than longer-horizon risk premia or cross-sectional returns. The weak classification results therefore reinforce the paper's main contribution: the evidence is stronger for explaining state-dependent risk transmission than for producing a short-horizon trading rule.

Overall, the findings refine the role of sustainable assets in portfolio construction and climate-risk management. Brown assets hedge positive oil-price shocks; green assets provide relative protection during negative oil shocks; clean-energy equities do not provide broad market-stress protection; and green bonds and ESG assets offer more defensive characteristics because they represent different asset structures.

6. Implications

6.1. Theoretical Implications

The findings contribute to climate finance by shifting the theoretical interpretation from unconditional green-asset superiority to conditional risk exposure. Clean-energy equities behave more like state-dependent transition-risk assets than universal safe havens. This is consistent with sustainable asset-pricing theory, which suggests that green asset values may reflect investor preferences, climate-hedging motives, technological expectations, and transition-risk repricing, but need not generate superior realized return-risk performance in all market states (Engle et al., 2020; Pástor et al., 2021; Pedersen et al., 2021). The study also builds on the literature by differentiating clean-energy equities from green bonds and green ESG assets. The equity beta, growth risk, and repricing risk of the technology sector and market-wide downside risk all apply to clean energy stocks. ESG assets and green bonds might also exhibit more defensive traits due to the fixed-income structure, diversification, institutional demand, and investor base (Zerbib, 2019; Flammer, 2021; Arif et al., 2022; Meo et al., 2026). Sustainable-asset pricing therefore depends on asset-class structure, cash-flow exposure, and discount-rate sensitivity, not only environmental classification.

The study further contributes to carbon-risk and green–brown asset-pricing theory. Brown assets may carry long-run carbon-transition risk, but they can still provide short-run hedging benefits during positive oil-price shocks. Green assets may benefit during negative oil shocks or transition-friendly states, but they can fail during broad market stress. This green–brown spread is thus an asset-pricing subject that is regime-dependent, due to oil shocks, market stress, growth exposure, volatility, and credit conditions (Bolton & Kacperczyk, 2021, 2023; Saeed et al., 2020; Raheem et al., 2023). Lastly, the quantile evidence adds to the study of nonlinear asset-pricing theory by demonstrating that the factors driving the spread vary across states in the downside quantiles and those in the upside quantiles rather than remaining stable around the conditional mean (Koenker & Bassett, 1978; Bouteska et al., 2025; J. Wang & Qiao, 2025).

6.2. Portfolio and Investment Implications

The portfolio results caution against treating clean-energy equity exposure as a standalone defensive allocation. Clean-energy assets experience high volatility, large drawdowns, and weak full-sample return-risk performance. Green equity exposure should therefore be interpreted as thematic transition-risk exposure rather than a substitute for diversified market exposure or safe-haven assets. This distinction is important for institutional investors, risk committees, and sustainable portfolio managers because climate alignment does not automatically imply downside protection (Arouri et al., 2025; Zhang et al., 2025).

The role of brown assets is also more nuanced than a simple exclusionary view implies. Brown assets are undesirable from a long-run carbon-transition perspective, yet they may hedge positive oil-price shocks because they are exposed to conventional energy markets. Brown exposure thus might be seen as a 'short-term' energy-price-inflation hedge or oil-supply risk protection by investors worried about energy-price inflation or about commodity-cycle risk, whereas investors worried about fossil-fuel downside or about the acceleration of the transition could prefer green exposure (Al-Fayoumi et al., 2025; Albanese et al., 2026).

The results support state-contingent portfolio allocation. Green assets perform relatively better during negative oil-price shocks but underperform during broad market-stress days. Investors should therefore avoid asking whether green assets hedge risk in general and instead ask which risk, under which state, and relative to which benchmark. Portfolio managers should consider the use of return-to-volatility ratios, Sortino ratios, drawdowns, value-at-risk, expected shortfall, rolling betas, stress-state correlations, and tail-risk behavior when evaluating green exposure. In particular, the improved downside performance of the market–green–long-bond allocation should be interpreted as evidence of conventional long-bond diversification, not as evidence of green-bond performance in the full-sample portfolio test. The supplementary evidence suggests that green bonds and ESG-related assets have more defensive properties than clean-energy stocks, but this evidence is based on shorter available histories and should not be interpreted as proof that all green instruments have safe-haven attributes (Zerbib, 2019; Flammer, 2021; Arif et al., 2022; Tanos et al., 2026).

6.3. Policy and Risk-Management Implications

The findings have direct implications for climate-related financial-risk monitoring. Sustainable assets are heterogeneous: clean-energy equities, green bonds, ESG assets, and fossil-fuel assets respond differently to energy shocks, market stress, volatility regimes, and crisis conditions. Regulators, central banks, and climate-risk supervisors should therefore avoid treating all green assets as a single low-risk category. An asset can be green in purpose but still exposed to equity-market and growth-factor risk, while a brown asset can carry long-run carbon-transition risk but provide short-run protection during positive oil-price shocks. Climate-risk classification should therefore be separated from financial-risk classification (Giglio et al., 2021; Stroebel & Wurgler, 2021; Bolton & Kacperczyk, 2023). For financial-risk managers, the main implication is that climate-aligned portfolios require stress testing. Green portfolios can be vulnerable during broad financial-market downturns because clean-energy equities retain equity beta, growth exposure, liquidity risk, and discount-rate sensitivity. Climate-risk stress tests should therefore include market-stress scenarios, high-volatility regimes, positive and negative oil-price shocks, credit-stress conditions, and energy-crisis periods. This is consistent with the view that climate-related financial risk should be quantified, monetized, and controlled on transition-risk pathways as well as market-risk pathways (Engle et al., 2020; Giglio et al., 2021).

A policy implication is that sustainable financial markets should be deep and diversified. Because many climate-aligned investments are concentrated in clean energy, investors may assume that environmental alignment necessarily implies financial resilience. However, this assumption does not always hold. Developing higher-quality markets for green bonds, sustainability-linked bonds, climate-aligned fixed-income products and multifaceted ESG products would facilitate a clearer separation between environmental objectives and downside risk-management considerations. It is therefore important to distinguish environmental classifications from financial-risk characteristics, including oil-price exposure, market sensitivity, downside risk, duration, liquidity and performance across stress regimes (Flammer, 2021; Zerbib, 2019; Arif et al., 2022).

7. Conclusions, Limitations, and Future Research

7.1. Conclusions

This research compares the ability of green vs. brown assets to protect against energy market shocks and financial market stress. Using daily data from 2010 to 2025, the analysis constructs investable green and brown portfolios from exchange-traded clean-energy and fossil-fuel instruments and evaluates their performance across normal, volatile, and crisis states. The green–brown spread is used as the main relative-performance measure to assess whether green assets outperform brown assets during oil shocks, high-volatility periods, market-stress days, the COVID-19 crisis, and the energy-crisis period.

The findings show that green and brown assets hedge different risks. Brown assets outperform during positive oil-price shocks, while green assets perform relatively better when oil prices fall sharply. However, green assets do not behave as broad safe havens during market stress; they remain exposed to equity-market downside risk and often resemble high-beta growth assets. Quantile regressions show that the determinants of the green–brown spread differ across downside, median, and upside states, confirming nonlinear and state-dependent risk transmission. Portfolio tests show that clean-energy equity exposure alone has weak full-sample return-risk performance. The market–green–long-bond allocation indicates that conventional long-bond exposure can improve downside characteristics, but this should not be interpreted as green-bond evidence. Shorter-sample supplementary evidence suggests that green bonds and ESG-related assets appear more defensive. The supplementary machine-learning evidence provides limited predictive power and should be interpreted as auxiliary evidence rather than as a trading model.

Overall, the study shows that sustainable assets should not be treated as homogeneous hedges or universal safe havens. The practical value of green exposure depends on the source of risk, the market state, and the specific sustainable-finance instrument. For investors and policymakers, the main implication is that climate alignment and financial resilience are related but distinct dimensions of asset performance.

7.2. Limitations

This study has several limitations that should be interpreted as deliberate empirical choices rather than weaknesses. *First*, the analysis uses exchange-traded instruments rather than firm-level securities, emissions-based portfolios, or country-level green and brown indices. Although the selected proxies are liquid and widely used market indicators, future research can test alternative market, volatility, interest-rate, and credit-risk measures to examine whether the results are sensitive to proxy choice. *Second*, the main sample is restricted to complete daily observations for core assets from 2010 to 2025, while green-bond and ESG instruments have shorter histories and are therefore treated as supplementary evidence. *Third*, oil-market returns include extreme events, especially the 2020 oil-price disruption, which may influence oil-shock estimates. These observations are part of the stress environment analyzed in this paper, but they should not be interpreted as normal oil-price movements. *Fourth*, the study uses researcher-defined stress windows and quantile thresholds. These definitions are transparent and economically motivated, but future work may complement them with alternative regime-classification methods. *Fifth*, the machine-learning analysis is short-horizon and Supplementary Materials. Its limited predictive performance means that the paper should not be interpreted as offering a trading model; instead, it separates risk-transmission analysis from short-term prediction.

7.3. Future Research

Future research can extend the analysis beyond exchange-traded instruments by constructing firm-level green and brown portfolios using emissions intensity, carbon-transition scores, climate-policy exposure, taxonomy alignment, green revenue shares, or disclosed decarbonization targets. Such data would help distinguish whether green–brown performance is driven by sector exposure, firm-level transition credibility, or broader market factors. International extensions are also important. Green–brown hedging behavior can vary by region depending on energy mixes, climate policies, carbon markets, disclosure regimes, and investor bases among various regions, including Europe, China, and emerging markets or fossil-fuel exporting economies.

Additional climate-risk inputs can also be included in future studies, such as carbon price, climate-risk policy uncertainty, climate-risk news shocks, emissions data, physical-risk exposure, transition-risk measures, green patent, renewable-energy policy indicators, and geopolitical-energy risk. These variables would aid in the identification of the pathway in which climate risk and energy shocks affect asset values (Engle et al., 2020; Bolton & Kacperczyk, 2023; Giglio et al., 2021). Methodologically, future work can use regime-switching models, time-varying parameter models, high-frequency identification, local projections, copulas, dynamic connectedness models, downside beta models, and nonlinear machine-learning methods. As green-bond and ESG histories become longer, future research can also test more rigorously whether fixed-income sustainable assets provide more robust hedging benefits than clean-energy equities. The next frontier is not asking whether green assets outperform brown assets on average, but identifying which green assets hedge which risks, under which regimes, and for which investors.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/jrfm19080633/s1; Table S1: Asset Availability and Data Validation. Table S2. Full Correlation Matrix. Table S3. Full Portfolio and Risk Metrics. Table S4. Full Newey–West Regression Results. Table S5. Downside-Risk and Hedge Tests. Table S6. Green Bond and ESG Performance. Table S7. Machine-Learning Classification Results. Table S8. Variance Inflation Factor (VIF) Diagnostics.

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