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Dynamic Spillovers and Portfolio Construction:
A TVP-VAR Analysis of the S&P 500, SSE, ESG ETFs, and Commodities

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Abstract

Purpose - This study explores the dynamic return spillovers and portfolio implications of key global financial assets, including U.S. and Chinese equities, crude oil, and ESG-focused investments, with the aim of analyzing whether investors in the S&P 500 and Shanghai Stock Exchange can mitigate portfolio risk through strategic allocation to ESG and commodity assets. This research provides a quantitative framework for investors, portfolio managers, and policymakers to make evidence-based decisions on risk diversification, hedging strategies, and performance enhancement in both equity and multi-asset portfolios under conditions of financial and economic uncertainty.

Design/methodology/approach - A Time-Varying Parameter Vector Autoregressive (TVP-VAR) model is applied to examine evolving interdependencies among the S&P 500 Index, Shanghai Stock Exchange Composite Index, West Texas Intermediate (WTI) crude oil, and the SPDR S&P 500 ESG ETF (EFIV). Four dynamic portfolio optimization strategies—Minimum Variance, Minimum Correlation, Minimum Connectedness, and Risk Parity—are implemented and evaluated under varying market conditions.

Findings - Results indicate that the S&P 500 and EFIV consistently act as net transmitters of volatility, while WTI and SSE function predominantly as receivers. Portfolios optimized using Minimum Connectedness and Correlation strategies demonstrate superior cumulative returns, whereas those using Minimum Variance and Risk Parity approaches achieve better risk-adjusted performance. Bivariate hedging analyses highlight the effectiveness of ESG assets, especially in equity pairings.

Practical implications - Findings provide valuable insights for institutional investors and portfolio managers seeking to optimize diversification, manage risk, and incorporate ESG principles in asset allocation strategies, particularly under conditions of global financial uncertainty.

Originality/value - This study contributes to the literature by integrating ESG-focused instruments within a dynamic connectedness framework and demonstrating their role in portfolio risk mitigation and performance enhancement. Specifically, it introduces a novel combination of TVP-VAR modeling with multiple dynamic portfolio optimization strategies, demonstrating how ESG assets can systematically mitigate portfolio risk and enhance performance, offering new guidance for evidence-based decision-making in financial markets.

Keywords: Dynamic Connectedness, TVP-VAR Framework, Portfolio Optimization, Hedge Effectiveness, ESG, Equity Markets, Crude Oil

JEL Classifications: C01, C02, C32, C58, G11, G15

1. Introduction

The global financial system is undergoing a period of rapid transformation, driven by heightened market volatility, recurring macroeconomic shocks, and the accelerating shift toward sustainability. Traditional portfolio management strategies, often rooted in static correlation measures and stable asset roles, have proven increasingly inadequate in capturing the dynamic, nonlinear relationships that now characterize financial markets. As systemic risks evolve and investor behavior adjusts to new economic realities, including climate-related threats and geopolitical uncertainty, there is a growing demand for adaptive, data-driven frameworks that can inform both risk assessment and asset allocation. One of the most pressing challenges in this context is understanding how financial shocks propagate across markets and asset classes. Dynamic return spillovers, where shocks in one market affect returns in others, are not constant but vary significantly over time and across economic regimes. Recent studies have highlighted the importance of quantifying these time-varying interactions, especially during periods of heightened uncertainty. For instance, gold, oil, and ESG assets have demonstrated asymmetric spillover behaviors depending on the prevailing risk environment, while equity markets tend to amplify or absorb volatility differently based on their structural characteristics and investor profiles.

This study contributes to the evolving discourse in two principal dimensions. First, it focuses on four carefully selected financial assets that capture key dimensions of global market dynamics: the S&P 500 (representing developed markets and the U.S. as a global financial hub), the Shanghai Stock Exchange Composite Index (SSE) (capturing the influence and volatility of an emerging market powerhouse), West Texas Intermediate (WTI) crude oil (as a proxy for commodity and energy-driven macroeconomic shocks), and the SPDR S&P 500 ESG ETF (EFIV) representing the growing market shift toward sustainable investing). This asset selection is deliberate and strategic: it spans two of the world's largest economies (the U.S. and China), includes a key global commodity, and integrates an ESG-focused asset that embodies the structural transition toward socially responsible finance. Second, by integrating ESG-focused instruments within a dynamic connectedness framework and demonstrating their role in portfolio risk mitigation and performance enhancement. In particular, it introduces a novel combination of TVP-VAR modeling with multiple dynamic portfolio optimization strategies, illustrating how ESG assets can systematically reduce portfolio risk and enhance overall performance. The findings offer new and actionable guidance for evidence-based decision-making in financial markets, particularly for investors and policymakers seeking resilient, sustainability-oriented investment strategies.

Notably, this study offers direct relevance to financial and economic decision-making by providing a quantitative framework through which investors and portfolio managers can evaluate whether allocations to ESG and commodity assets can mitigate risks associated with U.S. and Chinese equities, enhance diversification, and improve performance under uncertain market conditions.

Specifically, the paper makes a distinct contribution to the literature by being one of the first to jointly analyze the dynamic spillover effects and diversification potential of this particular combination of assets (S&P 500, SSE, WTI, and an ESG ETF) using a unified TVP-VAR modeling framework during a period characterized by unprecedented global shocks. While prior studies typically examine isolated market pairs (e.g., oil–equity or U.S.–China equities) or largely omit ESG instruments, this study addresses an important gap by linking dynamic spillovers directly to portfolio optimization outcomes, thereby offering a more comprehensive understanding of hedging effectiveness.

This contribution is particularly valuable as it provides a rigorous, data-driven framework that integrates time-varying connectedness measures with actionable portfolio strategies, thereby supporting improved decision-making under uncertainty for investors, policymakers, and financial institutions.

To achieve these objectives, the study employs a two-step methodological approach. First, a Time-Varying Parameter Vector Autoregressive (TVP-VAR) model is used to estimate the evolving connectedness structure among the four assets through Generalized Forecast Error Variance Decompositions (GFEVDs) and Generalized Impulse Response Functions (GIRFs). Second, the resulting time-varying variance–covariance matrices are used to construct dynamic portfolios under four optimization strategies: Minimum Variance Portfolio (MVP), Minimum Correlation Portfolio (MCP), Minimum Connectedness Portfolio (MCoP), and Risk Parity Portfolio (RPP).

The empirical findings reveal several key insights. The S&P 500 and EFIV emerge as persistent net transmitters of volatility, underscoring their central role in global financial contagion. In contrast, WTI and the SSE often act predominantly as net receivers. From a portfolio perspective, MCoP and MCP strategies yield superior cumulative returns, while the MVP and RPP approaches outperform in terms of risk-adjusted outcomes. ESG assets, particularly EFIV, display strong hedging effectiveness in equity-based portfolios.

In sum, this paper links dynamic connectedness structures to forward-looking portfolio strategies, offering a comprehensive and quantitative framework for managing risk, enhancing diversification, and improving performance in an era defined by growing market interdependencies and sustainability transitions.

The remainder of the paper is organized as follows. Section 2 reviews the literature on dynamic spillovers, portfolio optimization, and ESG integration. Section 3 describes the data and methodological design, detailing the implementation of the TVP-VAR model and the four portfolio strategies. Section 4 presents and discusses the empirical results. Section 5 concludes with implications for investors and policymakers and suggests avenues for future research.

2. Literature Review

The interconnectedness among major equity markets, commodity prices, and ESG-oriented financial assets has become an increasingly prominent theme in recent financial research, particularly in the context of persistent systemic shocks and heightened global uncertainty. Empirical evidence consistently shows that the S&P 500 plays a dominant role in transmitting volatility and return spillovers across international markets. Studies such as Erdas and Caglar (2018), Akin et al. (2024), and Zeng et al. (2020) highlight the leadership of U.S. equity markets in shaping global financial dynamics, especially during periods of stress, reinforcing their position as major global risk transmitters. These characteristics underscore the relevance of dynamic connectedness modeling frameworks—such as VAR and TVP-VAR (Cogley & Sargent, 2005; Primiceri, 2005; Sims, 1980)—which capture regime-dependent transmission mechanisms shaping market interactions.

In contrast, the Shanghai Stock Exchange (SSE) tends to operate as a net receiver of shocks originating from global markets. Its sensitivity to external disturbances is most apparent in the short run, with multifractal and high-frequency analyses (Ghani et al., 2025; Ma et al., 2013) revealing strong short-term cross-correlations between international risk factors and SSE returns. Despite elements of partial segmentation—such as the relative independence of the Shanghai Gold Exchange—Chinese equity markets still offer diversification benefits during downturns (Hoang et al., 2015; Qian, 2020). Historical fluctuations linked to bubbles, policy reforms, and regulatory pressures further shape SSE dynamics (Hoang et al., 2015; Yao & Luo, 2009), positioning the market as regionally driven yet globally interconnected.

Commodity markets, particularly WTI crude oil, play a fundamental role in global risk transmission due to their sensitivity to geopolitical tensions, supply chain disruptions, and macroeconomic uncertainty. Research by Mensi et al. (2017, 2023), Smales (2021), and Zheng et al. (2023) demonstrates that oil often behaves as a volatility receiver in tranquil periods but may shift into a transmitting role during major supply-side shocks. These dynamic spillover patterns have important implications for both traditional and ESG assets, reinforcing the need for time-varying connectedness frameworks such as those proposed by Diebold and Yilmaz (2014) and Antonakakis et al. (2020).

ESG-focused indices such as EFIV have gained substantial prominence amid the growing shift toward sustainable finance. Their behavior is shaped by geopolitical risk, investor sentiment, sectoral dynamics, and macroeconomic conditions. Empirical studies (Sharma et al., 2024; Yang et al., 2024) indicate that ESG portfolios generally exhibit lower downside risk compared to conventional indices, although their performance remains sensitive to cyclical conditions and energy-related shocks. ESG stocks also show a low positive correlation with oil and a negative relationship with gold, reflecting their hybrid nature as both equity-like and sustainability-oriented assets. While ESG investing enhances portfolio resilience, it does not replace gold as a safe haven during episodes of severe market distress (Yang et al., 2024).

Recent research further highlights the behavioral and macro-financial dimensions underpinning ESG and equity market interactions. Evidence from Indian equity markets suggests that shifts in investor attention significantly affect trading volumes and returns, revealing the behavioral underpinnings of risk transmission (Bhuyan & Roubaud, 2022). Other studies emphasize the role of foreign direct investment (FDI) in shaping environmental outcomes, particularly under the N-shaped Environmental Kuznets Curve (Bekun et al., 2025). From a sustainability perspective, evaluating environmental pressures through alternative metrics such as the load capacity factor offers richer insights for emerging economies (Bekun et al., 2024). Similarly, financial development has been shown to support renewable energy deployment in BRICS countries (Yadav et al., 2024), while broader renewable energy adoption serves as a buffer against macroeconomic volatility (Yadav, 2024). Wavelet-enhanced quantile regression evidence further shows that firms with strong ESG profiles maintain higher value resilience during episodes of financial distress (Yadav & Asongu, 2025).

Intermarket dynamics involving WTI, SSE, and EFIV are similarly multifaceted. Gold is identified as a net transmitter of short-term volatility to WTI (Mensi et al., 2023), while gold and oil both provide diversification benefits, with gold delivering superior downside protection (Mensi et al., 2017). The influence of WTI on SSE is primarily short-term in nature (Ghani et al., 2025; Ma et al., 2013). EFIV, composed of environmentally and socially responsible firms, is indirectly exposed to oil shocks through the energy sector (AlGhazali et al., 2024). Its performance reflects broader developments in ESG investing, characterized by regional heterogeneity and strong environmental and governance orientations (Daugaard, 2020; Meira et al., 2022).

Geopolitical risk plays a significant role across these asset classes. Studies show that rising geopolitical uncertainty depresses returns and increases volatility for indices such as SSE and EFIV (Fiorillo et al., 2024; Xu et al., 2023). Structural breaks, limited institutional participation, and market fragility further heighten crash risk, although strong ESG performance may partially mitigate these effects. Additionally, investor sentiment—including fear and uncertainty—shapes short-term price dynamics (Seok et al., 2024), with fear-driven behaviors intensifying sell-offs and illiquidity (Chiu et al., 2014). Social media platforms such as Twitter amplify these effects by accelerating information diffusion and propagating volatility spillovers (Wilksch & Abramova, 2023).

3. Theoretical Framework

This section integrates the theoretical foundations relevant to the methodologies employed in this study. It provides a thorough background that supports the empirical approaches and analytical strategies used.

3.1 Vector Autoregression (VAR) and Time-Varying Parameter VAR (TVP-VAR)

The Vector Autoregression (VAR) framework, introduced by Sims (1980), is a flexible technique for modeling the dynamic interdependencies among multiple time series variables, treating all variables symmetrically as endogenous. However, traditional VAR models assume constant parameters and variances over time, which limits their ability to capture evolving economic or financial dynamics, especially during structural breaks or crises. Extensions by Cogley and Sargent (2005) and Primiceri (2005) led to the Time-Varying Parameter VAR (TVP-VAR) framework, which allows coefficients and covariance matrices to change over time. This enables the detection of structural breaks and regime-dependent behaviors, enhancing the modeling of systemic linkages over different economic phases.

3.2 Connectedness Measures based on the VAR Framework

Building on the VAR methodology, Diebold and Yilmaz (2014) developed a quantitative connectedness framework that measures the degree and direction of interdependence among financial variables through variance decompositions. This approach constructs directional and total connectedness indices, effectively capturing how shocks propagate across markets. Antonakakis et al. (2020) further refined this framework by incorporating TVP-VAR models and Kalman filter estimation, overcoming limitations of fixed rolling windows. Their approach allows for smooth and continuous evolution of connectedness measures, with robustness checks including variable window lengths, identification schemes, and forecast horizons to ensure reliability and empirical strength.

3.3 Portfolio Optimization Theories

The portfolio optimization strategies in this study rest on foundational financial theories. Markowitz's Modern Portfolio Theory (1952) underpins the Minimum Variance Portfolio (MVP), which aims to construct portfolios minimizing risk through diversification. The MVP model is suitable for risk-averse investors seeking the lowest possible portfolio variance. Complementing this approach, the Risk Parity strategy allocates weights to achieve equal risk contribution from each asset, emphasizing risk diversification rather than return expectation. This strategy manages portfolio concentration and volatility more effectively, particularly in multi-asset portfolios.

3.4 Hypothesis Development:

Building on the theoretical arguments and empirical insights presented above, this study develops four testable hypotheses that capture the dynamic interconnections and portfolio implications among the analyzed asset classes: Bitcoin, gold, the S&P 500, ESG indices (EFIV), WTI crude oil, and the Shanghai Stock Exchange (SSE).

H1. *The S&P 500 and ESG-oriented assets (EFIV) act as net transmitters of return and volatility spillovers to other major financial markets.*

This hypothesis is grounded in prior evidence that major equity and ESG markets dominate global financial dynamics. Studies by Erdas and Caglar (2018), Akin et al. (2024), and Zeng et al. (2020) show that the S&P 500 and ESG indices often lead cross-market transmission, especially during periods of market stress. Sharma et al. (2024) and Yang et al. (2024) further highlight that ESG assets, while providing resilience, often transmit shocks due to their exposure to macroeconomic and geopolitical events.

H2. Traditional commodities and emerging market assets, specifically WTI crude oil and the SSE, function primarily as net receivers of spillovers.

This is consistent with prior findings that commodities and regional equity markets tend to absorb rather than transmit global shocks (Ghani et al., 2025; Ma et al., 2013; Mensi et al., 2017). Oil's volatility spillovers are typically driven by macroeconomic events and technological market shocks, while the SSE remains sensitive to external transmission channels but is less influential globally.

H3. Portfolios optimized under connectedness-aware strategies (e.g., Minimum Connectedness Portfolio – MCoP) yield higher cumulative returns, whereas risk-based portfolios (e.g., Minimum Variance Portfolio – MVP and Risk Parity Portfolio – RPP) demonstrate superior risk-adjusted performance.

Empirical research supports this theoretical distinction. Mensi et al. (2023) and Zeng et al. (2020) reveal that connectedness-based diversification enhances performance by minimizing systemic contagion. Similarly, Attarzadeh et al. (2024) and Doumenis et al. (2021) show that accounting for asymmetric spillovers improves portfolio robustness.

H4. ESG-oriented ETFs (EFIV) provide effective hedging benefits when combined with traditional equity indices, particularly during volatile market phases.

This proposition aligns with Sharma et al. (2024), Yang et al. (2024), and Yadav and Asongu (2025), who demonstrate that ESG assets enhance resilience and offer downside protection under geopolitical or market uncertainty. Although they do not replace gold's safe-haven role (Kayral et al., 2024; Mensi et al., 2023), ESG ETFs contribute meaningfully to sustainable and adaptive portfolio strategies.

4. Methodology and Econometric models

This study employs a comprehensive two-step methodological framework. In the first step, we estimate a range of dynamic connectedness measures to capture the transmission mechanisms among the assets in our system. The analysis begins with the implementation of a multivariate Time-Varying Parameter Vector Autoregression (TVP-VAR) model using the Kalman filter, allowing for the evolution of both parameters and shocks over time. This model is then transformed into its moving average representation (TVP-VMA), which forms the basis for deriving Generalized Impulse Response Functions (GIRFs) and Generalized Forecast Error Variance Decompositions (GFEVDs). These tools are essential for quantifying the intensity and direction of spillovers, specifically, how much a given asset is influenced by others ("FROM" connectedness) and how much it influences the rest ("TO" connectedness). The difference between these two provides the net directional connectedness, while the average level of interconnectedness in the system is captured by the Total Connectedness Index (TCI). In line with the framework proposed by Gabauer (2021) and Chatziantoniou and Gabauer (2021), we ensure that own-variance shares dominate over cross-variance components, preserving consistency within the connectedness structure.

In the second step, we apply the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model introduced by Engle (2002). This model allows us to capture the time-varying volatility and conditional correlations between assets in a flexible yet parsimonious way. It operates in two stages. First, univariate GARCH models are estimated for each asset to model individual conditional volatilities; the best-fitting specification for each univariate GARCH model is selected based on standard information criteria. Second, the standardized residuals are used to estimate the dynamic correlations across assets. The DCC-GARCH model is particularly well-suited for identifying changes in volatility transmission and co-movement behavior over time, complementing the spillover analysis from the TVP-VAR framework.

In the third step, we turn to portfolio construction and performance evaluation. Leveraging the time-varying variance-covariance matrix derived from the TVP-VAR model, we assess historical investment performance through dynamic backtesting. Following Antonakakis et al. (2020), we construct optimal portfolios under different management strategies informed by connectedness dynamics. To evaluate the robustness of our findings, we implement four alternative portfolio optimization approaches grounded in the evolving interdependencies among assets.

Finally, we examine hedging effectiveness and Sharpe ratios to evaluate the contribution of each asset to portfolio risk mitigation.

4.1 Modeling Dynamic Connectedness based on a TVP-VAR Model

Building upon the seminal framework established by Diebold and Yilmaz (2014) and subsequently refined by Antonakakis et al. (2020), this study employs a Time-Varying Parameter Vector Autoregression (TVP-VAR) model. This econometric approach, which incorporates Bayesian estimation techniques as pioneered by Primiceri (2005) for such models, is particularly well-suited for capturing the dynamic nature of spillovers within bond markets. A key feature of the TVP-VAR model is its capacity to allow for temporal variation in both the autoregressive coefficients and the variance-covariance matrix of the structural shocks, thus reflecting the evolving interconnectedness of financial systems.

In line with established best practices in the empirical literature, the prior distributions for the initial state of the system, encompassing both the time-varying coefficients and the shock variances, are calibrated through a preliminary estimation of a static Vector Autoregression (VAR) model of order one, applied to an initial subsample of the data. To adequately reflect the adaptive and often non-linear nature of financial systems, the model assumes that its parameters follow a random walk process. This assumption enhances the model's flexibility in capturing potential structural changes and is consistent with the Bayesian estimation strategies employed in the works of Primiceri (2005), who demonstrate its robustness in monetary and financial contexts through extensive simulation-based validation. The Bayesian estimation of the TVP-VAR model is operationalized via a Kalman filtering algorithm. This recursive procedure not only dynamically updates the parameter estimates as new data becomes available but also strategically utilizes the Kalman gain to mitigate the undue influence of outliers. This latter characteristic is of critical importance when analyzing high-frequency financial data, which are frequently characterized by abrupt shifts and inherent noise. The selection of the appropriate lag order for the VAR and the forecast horizon for the spillover analysis is guided by the objective of accurately capturing short-run transmission dynamics. Finally, the dynamic connectedness measures are computed using time-varying generalized forecast error variance decompositions (GFEVDs), which are meticulously corrected for potential small-sample bias. This comprehensive methodological approach enables a nuanced and robust tracking of evolving interdependencies and directional spillovers within the highly volatile and globally integrated bond market. The TVP-VAR model[1] is presented as follows:

$$y_t = \beta_t y_{t-1} + \varepsilon_t, \qquad \left(\varepsilon_t \middle| F_{t-1} \sim N(0, H_t)\right), \tag{1}$$

$$vec(\beta_t) = vec\beta_{t-1} + v_t, \qquad \left(v_t \middle| F_{t-1} \sim N(0, \omega_t)\right), \tag{2}$$

where y_t is the return series, where vec (β_t) denotes the column-stacking operator applied to β_t; β_t is the time-varying coefficient matrix in the TVP-VAR model, F_{t-1} refers to all information up to $t-1$. ε_t corresponds to the error variance $m \times 1$ dimensional vectors. H_t refers to the time-varying conditional variance-covariance matrix of the return innovations. β_t and H_t refer to $m \times m$ dimensional matrices with accounting for changes in volatility. v_t and $vec(\beta_t)$ are $m^2 \times 1$ and ω_t is a $m^2 \times m^2$ dimensional matrix with v_t, the error term, captures the random fluctuations in the evolution of the VAR model parameters over time. To compute the GFEVD and GIRF, the TVP-VAR should be converted into its TVP-VMA framework based on the Wold representation, which reports that:

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[1] Based on the Bayesian information criterion, we use the first-order VAR model.

$$z_t = \sum_{i=1}^{p} \beta_{it} \, z_{t-i} + \varepsilon_t = \sum_{j=1}^{\infty} A_{it} \, \varepsilon_{t-j} + \varepsilon_t, \quad (3)$$

where z_t represents the vector of endogenous variables at time *t*, p corresponds to the order of the VAR process. This indicates the number of lags considered in the model. β_t is the coefficient matrix linked to z_t. ϵ_t refers to the vector of errors for the VAR model. A_{it} corresponds to the time-varying moving average coefficient matrices in the VMA representation associated with the error ϵ_t. GIRFs are not contingent on or affected by the framework or the order of the errors, where K is the forecast horizon. The GIRF approach captures the dynamics among and between all variables j effectively. This could be expressed by:

$$GIRF\left(\varphi_{ij,t}(K)\right),$$

$$GIRF\left(K, \sqrt{H_{jj}}, F_{t-1}\right) = H_{jj,t}^{-\frac{1}{2}} A_{K,t} H_t \varepsilon_{j,t}, \quad (4)$$

where $A_{K,t}$ denotes the coefficient matrix associated with the error ϵ_t up to horizon K, derived from the moving average representation of the TVP-VAR model. This matrix captures the dynamic propagation of shocks across the system over time. This implies how one variable (in percentage terms) affects the forecast error variance of another variable in the system. Then, the GFEVD shows each variable's distinct contribution to the forecast error variance of variable i. This could be presented as follows:

$$GFEVD_{ij,t}(K) = \frac{\sum_{t-1}^{K-1} GIRF_{ij,t}^2}{\sum_j^m GIRF_{ij,t}^2},$$

$$\sum_{j=1}^{m} GIRF_{ij,t}(K) = 1, \qquad \sum_{i,j=1}^{m} GIRF_{ij,t}(K) = m. \quad (5)$$

One might compute the effect of variable iii by others, as well as the reciprocal impact of variable i on all others. We can also evaluate if variable iii strongly affects others than it is affected by them. To do so, the following three metrics could be used:

The total directional connectedness FROM all others is computed as follows:

$$FROM_{i \leftarrow j,t} \frac{\sum_{j=1, i \neq j}^{m} GFEVD}{\sum_{i=1}^{m} GFEVD} * 100. \quad (6)$$

The effect of all the others on variable i should be strictly below 100% as the effect of i itself has been excluded.

The total directional connectedness TO all others is computed as follows:

$$TO_{i\to j,t} \frac{\sum_{j=1,i\neq j}^{m} GFEVD}{\sum_{j=1}^{m} GFEVD} * 100. \quad (7)$$

From the foregoing, one might compute the Total Connectedness Index (TCI), which indicates if the whole patterns of connectedness within the system are strong or weak. The TCI ranges in the interval of $\left[0, \frac{m-1}{m}\right]$. As we express the average level of network comovement (in percentage), it should range between 0 and 1. A slight adjustment of the TCI is required:

$$Net_{i,t}(K) = TO_{i\to j,t} - FROM_{i\leftarrow j,t}. \quad (8)$$

Finally, TCI could be changed to obtain pairwise connectedness index (PCI) scores between variables i and j as follows:

$$TCI_t^e(K) = \frac{\sum_{i,j=1,i\neq j}^{m} Adj - GFEVD}{k} \; with\, 0 < TCI_t^e(K) < 1, \quad (9)$$

where $TCI_t^e(K)$ is the extended version of the Generalized Forecast Error Variance Decomposition approach of Total Connectivity Index for forecast horizon K. This index measures the average amount of network co-movement between variables for this time horizon. Adj-GFEVD refers to the Adjusted-Generalized Forecast Error Variance Decomposition (Adj-GFEVD) among variables i and j for forecast horizon k. It computes the contribution of variable j to the forecast error variance of variable i, adjusted for the effect of other variables in the system.

4.2 DCC-GARCH Model Specification

We acknowledge that the empirical analysis presented in this study spans a period from January 2020 to March 2025, characterized by a confluence of extraordinary global economic conditions. This timeframe was marked by the profound and multifaceted shocks stemming from the COVID-19 pandemic, significant volatility in commodity markets, including oil price wars, and an unprecedented surge in the growth and mainstream adoption of Environmental, Social, and Governance (ESG) investments. These unique circumstances, while providing a rich and dynamic environment for observing market connectedness and portfolio behavior, may inherently limit the generalizability of our findings to other, more conventional market periods or different economic conjunctures. The distinct market reactions and investor sentiments prevalent during these years could have influenced the observed spillover dynamics and the relative performance of various assets and portfolio strategies in ways that might not be replicated under more stable conditions.

Recognizing these potential limitations is crucial for a nuanced interpretation of our results. Therefore, to enhance the credibility of our conclusions and assess their stability beyond the specific modeling choices made (i.e., the TVP-VAR framework), we propose to conduct a robustness check test. Specifically, we intend to re-evaluate the dynamic conditional correlations and volatility spillovers using an alternative, well-established econometric methodology: the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model, as pioneered by Engle (2002). The application of a DCC-GARCH model will allow us to ascertain whether the core findings regarding asset interconnectedness and hedging effectiveness persist when estimated through a different lens, thereby providing greater confidence in the broader applicability of our conclusions, even considering the exceptional nature of the study period.

To capture the time-varying conditional correlations between the financial assets under study, we employ the Dynamic Conditional Correlation (DCC) GARCH model proposed by Engle (2002). This model offers a flexible yet parsimonious approach to modeling multivariate volatility dynamics. The estimation process involves two main stages: estimating univariate GARCH models for each asset series and then estimating the parameters governing the dynamic correlation.

Stage 1: Univariate GARCH Estimation

In the first stage, a univariate GARCH model is fitted to each individual asset return series. Let y_{it}be the vector of *k* asset returns at time *t*. The return series for each asset y_{it} can be modeled as:

$$y_{it} = \mu_i + \varepsilon_{it}, \tag{10}$$

where μ_i is the conditional mean of the return for asset i, and ε_{it} is the error term, which can be expressed as:

$$\varepsilon_{it} = H_t^{\frac{1}{2}} z_{it}, \tag{11}$$

where z_{it} are independent and identically distributed (*i. i. d.*) random variables with zero mean and unit variance, often assumed to follow a specific distribution (e.g., Normal, Student's t, Skewed Student's t). $H_t^{1/2}$ represents the conditional variance of asset *i* at time *t*, which is modeled using a GARCH (p, q) process. A common specification is the GARCH (1,1) model:

$$h_{it} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \tag{12}$$

where h_{it} is the conditional variance of asset i at time t, ω_i is the constant term, α_i and β_i are the GARCH parameters, and $\varepsilon_{i,t-1}^2$ is the squared innovation from the previous period. The parameters ω_i > 0, $\alpha_i \geq 0$, and $\beta_i \geq 0$ to be estimated, satisfying the stationarity condition $\alpha_i + \beta_i < 1$. This stage yields the standardized residuals $z_{it} = \varepsilon_{it}/ h_{i,t-1}^{1/2}$ for each asset.

Stage 2: Dynamic Conditional Correlation Estimation

In the second stage, the dynamic conditional correlations are estimated using the standardized residuals obtained from Stage 1. Let $z_t = (z_{1t}, z_{2t}, \ldots, z_{kt})'$ be the vector of standardized residuals at time *t*. The conditional covariance matrix H_t of the original returns y_t can be decomposed as:

$$H_t = D_t R_t D_t, \tag{13}$$

where D_t is a *k x k* diagonal matrix of the time-varying conditional standard deviations obtained from the univariate GARCH models, $D_t = diag(h_{1,t}^{1/2}, \ldots, h_{k,t}^{1/2})$, and R_t is the *k x k* time-varying conditional correlation matrix.

The DCC model specifies the evolution of R_t through a GARCH-like process for a proxy matrix Q_t:

$$Q_t = (1 - a - b)\bar{Q} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1}, \quad (14)$$

where $\bar{Q}$ is the $k\ x\ k$ unconditional covariance matrix of the standardized residualsz_{it}, and a and b are non-negative scalar parameters satisfying $a + b < 1$. The parameter a captures the impact of past shocks on current conditional correlations, while b measures the persistence of correlations.

The conditional correlation matrix R_t is then obtained by rescaling the elements of Q_t:

$$R_t = diag\left(Q_t^{-\frac{1}{2}} Q_t\ diag\ Q_t^{-\frac{1}{2}}\right), \quad (15)$$

where $diag(Q_t)$ extracts the diagonal elements of Q_t. This ensures that R_t is a valid correlation matrix with ones on the diagonal and off-diagonal elements between -1 and 1. The parameters of the univariate GARCH models and the DCC model are typically estimated using Quasi-Maximum Likelihood Estimation (QMLE).

4.3. Portfolio Implications: Dynamic allocation and risk assessment

4.3.1 Minimum Variance Approach

The Minimum Variance Portfolio (MPV) is largely used for portfolio construction. It serves to establish a portfolio with the lowest possible volatility by including various assets. One might determine the portfolio weights by using the following formula:

$$OW^* = \frac{[Var - Cov]_t^{-1} I}{I\ [Var - Cov]_t^{-1} I}, \quad (16)$$

where OW^* is the portfolio weight vector, I is a m-dimensional vector of ones, and $[Var - Cov]_t^{-1}$represents the $m \times m$ conditional variance-covariance matrix for period t.

4.3.2 Minimum Correlation Approach

Christoffersen et al. (2014) developed a new approach for constructing a portfolio based on the conditional correlation matrix to determine portfolio weights. The matrix $[Corr]$ is a $m \times m$ dimensional matrix. One might compute the weights for the minimum correlation portfolio (MCP) as follows:

$$OW^* = \frac{[Corr]_t^{-1} I}{I\ [Corr]_t^{-1} I}. \quad (17)$$

4.3.3 Minimum Connectedness Approach

One might develop the minimum connectedness portfolio (MCoP) using the previous indicators. Instead of using the variance/correlation matrix, this approach employs pairwise connectedness indices. The portfolio tends to be less susceptible to network shocks by reducing the interconnectedness among variables and diminishing their spillovers. Therefore, investment tools that are not affected or impacted by others are assigned higher weights. This could be written as follows:

$$OW^* = \frac{[PWConnect]_t^{-1} I}{I\,[PWConnectCorr]_t^{-1} I}, \tag{18}$$

where $[PWConnect]_t^{-1}$ is the pairwise connectedness index matrix, and I is the identity matrix.

4.3.4 Risk-Parity Approach

Following Maillard et al. (2010), one might use the risk-parity portfolio approach. Such a method allows us to allocate portfolio weights. Therefore, each asset could contribute to the overall portfolio in an equal manner. The idea behind such an approach is that a portfolio with equal risk contributions is expected to perform better and tend to be more resilient during bearish phases. One might write the minimization problem:

$$min \sum_{i,j=1}^{N} (OW_{it}^*(Var - Cov)OW_t^*))i - OW_{jt}^*(Var - Cov)t\; OW_j^{*2}. \tag{19}$$

4.3.5 Portfolio Backtesting: Hedging Effectiveness

To assess portfolio performance, one might use the Sharpe ratio and hedge effectiveness score. The Sharpe ratio (or the reward-to-volatility ratio) proposed by Sharpe (1966) is calculated as follows:

$$SR = \frac{E(r_p)}{\sqrt{\text{var}}}, \tag{20}$$

where $\sqrt{Var_t}$ refers to daily portfolio's standard deviation and $E(r_{p\,(t)})$ is the daily expected portfolio return. Following Ederington (1979), we can also calculate hedge effectiveness as follows:

$$HE = 1 - \frac{Var(Hedg)}{Var(Unhedg)}, \tag{21}$$

where *Var(Unhedg)* is the variance of the unhedged asset and *Var(Hedg)* is the variance of the portfolio returns. *HE* refers to the percent reduction in the variance of the unhedged position. The higher the *HE* is the risk reduction.

5. Data and Descriptive Statistics

5.1 Data

This study examines a multivariate portfolio composed of four key asset classes: the S&P 500 Index, the Shanghai Stock Exchange Composite Index (SSE), West Texas Intermediate (WTI) crude oil, and the SPDR S&P 500 ESG ETF (EFIV), over the period from January 30, 2020, to March 31, 2025. These assets were selected to reflect the interaction between traditional stock markets, emerging economies, commodity markets, and investment strategies centered on ESG factors. Their inclusion enables a comprehensive assessment of hedging effectiveness, diversification potential, and interdependencies within a portfolio, particularly in the context of recent global economic disruptions, energy market volatility, and the accelerating transition toward sustainable finance. The S&P 500 Index serves as a benchmark for the U.S. equity market, capturing the performance of large-cap companies and acting as a key indicator of investor sentiment. The SSE Index offers exposure to one of the world's largest and most dynamic emerging markets, providing valuable insights into the Chinese economy. WTI crude oil acts as a proxy for global energy supply and demand shocks, which are frequently driven by geopolitical events and production policies. Finally, the SPDR S&P 500 ESG ETF (EFIV) incorporates environmental, social, and governance (ESG) criteria into investment decisions, reflecting the growing importance of responsible investing. Together, these assets offer a robust framework for analyzing portfolio performance amid shifting market conditions, regulatory developments, and evolving investor preferences for resilient and sustainable investment strategies.

5.2 Descriptive Statistics

Figure 1 displays the time-varying returns for all assets during the period sample. Results show that WTI depicts the most volatile return series, with frequent and pronounced spikes, especially around 2022. This visual impression is corroborated by its high variance (0.001), strong negative skewness (–0.565), and significant excess kurtosis (2.543), indicating a heavy-tailed, asymmetric distribution prone to sharp negative returns. In contrast, SSE appears much more stable in the figure, with limited fluctuations over the entire period. This is consistent with its low variance, near-zero skewness, and the highest excess kurtosis (7.208), suggesting rare but severe return shocks. The S&P 500 and EFIV series exhibit moderate volatility with noticeable return clustering, as seen in Figure 1, which aligns with their moderate excess kurtosis and negative skewness.

Figure 1. Daily returns

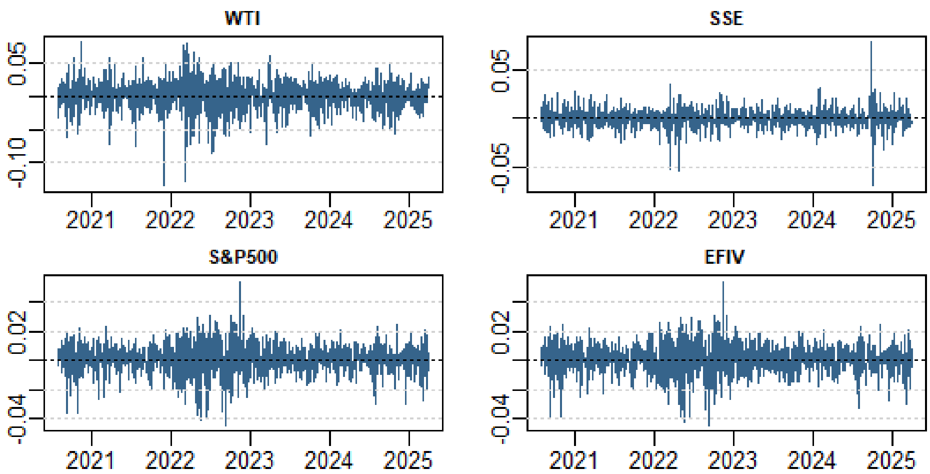


Table 1 presents the summary statistics of the S&P 500 Index, the Shanghai Stock Exchange Composite Index (SSE), West Texas Intermediate (WTI) crude oil, and the SPDR S&P 500 ESG ETF (EFIV). All assets deviate significantly from normality according to the Jarque-Bera test.

Table 1. Descriptive Statistics and Kendall's Tau Correlations for Asset Returns

Statistic / Asset	WTI	S&P500	SSE	EFIV
Mean	0.0005	0.0004	0.0000	0.0005
Variance	0.0227	0.0102	0.0097	0.0103

Skewness	-0.5657***	-0.3174***	0.0173	-0.2952***
Excess Kurtosis	2.5431***	1.9360***	7.2082***	1.8555***
Jarque–Bera (JB)	390.3451***	209.2021***	2619.5424***	191.0860***
ADF	-12.450**	-10.859***	-11.135***	-10.964***
ERS	-4.4310	-11.5171	-13.8962	-12.6401
Q(20)	23.0101***	13.5844	30.2612***	16.4766*
Q²(20)	152.7121***	217.3733***	209.8233***	209.1044***
Kendall WTI	1.0000***	0.0944***	0.0522***	0.0931***
Kendall S&P500	0.0942***	1.0000***	0.0655***	0.8955***
Kendall SSE	0.0522***	0.0656***	1.0000***	0.0722***
Kendall EFIV	0.0933***	0.8955***	0.0723***	1.0000***

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results demonstrate that the null hypothesis of a unit root can be rejected for each of the four asset return series at the 1% significance level. This confirms that all return series are stationary (integrated of order zero, I(0)), making them appropriate for Vector Autoregression (VAR) modeling and subsequent econometric analyses. Stationarity ensures that key statistical properties, such as the mean and variance, remain stable over time, thereby mitigating the risk of spurious regressions in time series modeling. The Q(20) and Q²(20) statistics further confirm the presence of serial correlation and volatility clustering, particularly in WTI. Finally, the Kendall rank correlation matrix in Table 1 highlights strong dependence between the S&P 500 and EFIV (0.895), a finding visually supported by their similar fluctuation patterns in Figure 1. Overall, the figure and table jointly emphasize the heterogeneous risk profiles and dynamic behaviors of the assets. The Jarque-Bera test results in Table 1 clearly indicate significant departures from normality for all asset return series, with exceptionally high test statistics and p-values of zero. This confirms the presence of non-normal features such as heavy tails and skewness in the data distributions. For instance, WTI exhibits pronounced negative skewness and excess kurtosis, indicative of asymmetric, fat-tailed behavior prone to extreme negative returns. Similarly, other assets show substantial kurtosis and skewness deviations from normality. These empirical characteristics justify the choice of using distributions with heavier tails, such as the Student's t distribution, in the specification of the GARCH models. Employing the Student's t distribution allows the models to better capture the observed leptokurtosis and tail risks inherent in the return data, thereby improving the accuracy and robustness of volatility estimation and forecasting. This approach aligns with best practices in financial econometrics when modeling return series that exhibit non-normality, providing a theoretically and empirically sound foundation for the subsequent analysis.

Before implementing the Time-Varying Parameter VAR (TVP-VAR) framework, it is essential to examine the statistical properties of the selected asset returns to ensure the appropriateness of the model. Following the descriptive statistics, we conduct diagnostic tests to assess potential nonlinearity and heteroskedasticity in the return series. These preliminary analyses provide a foundation for understanding the dynamic behavior of all assets and justify the subsequent application of a TVP-VAR approach to capture time-varying interdependencies and volatility spillovers across these key financial assets. **Table 2** illustrates that the Tsay test evaluates the presence of nonlinearity, while the ARCH test examines heteroskedasticity in the residuals.

Table 2. Diagnostic Tests for Nonlinearity and Heteroskedasticity in Asset Return Series

Series	Tsay Test Statistic	Tsay p-value	ARCH Chi-squared	ARCH p-value
WTI	1.7862	0.1400	97.2091	0.0000
S&P500	1.0061	0.3892	112.4455	0.0000
SSE	2.2172	0.1224	201.3920	0.0000
EFIV	0.49500	0.6860	106.6800	0.0000

The results of the diagnostic tests indicate that all series exhibit significant conditional heteroskedasticity, as evidenced by the ARCH test ($p < 0.01$ for all assets), while the Tsay test does not detect statistically significant nonlinearity at the 5% level. The presence of time-varying volatility in WTI, S&P 500, SSE, and EFIV returns underscores the inadequacy of static models and supports the use of a Time-Varying Parameter VAR (TVP-VAR) framework. The TVP-VAR is well-suited to capturing evolving interdependencies and dynamic spillovers across these financial assets, allowing for more accurate modeling of volatility transmission and portfolio risk under changing market conditions.

6. Empirical results analysis

6.1 Dynamic spillover risk results

The first set of results we present concerns the average connectedness measures among the four assets, as reported in Table 3.

Table 3. Dynamic Total Connectedness Index (TCI)

	WTI	SP500	SSE	EFIV	FROM
WTI	90.9700	3.6900	1.8600	3.4800	9.0300
SP500	2.0600	49.2000	0.8800	47.8600	50.8000
SSE	1.7200	3.5400	90.9900	3.7500	9.0100
EFIV	1.9500	47.8700	0.9700	49.2100	50.7900
TO	5.7300	55.1000	3.7200	55.0900	119.6400
Inc.Own	96.7000	104.3000	94.7000	104.3000	cTCI/TCI
NET	-3.3000	4.3000	-5.3000	4.3000	39.8800/29.9100
NPT	0.0000	3.0000	1.0000	2.0000	

Notes: Inc.Own (Including Own): Refers to the sum of "From" and the corresponding diagonal element (own variance share) for each variable, i.e., it reflects the total forecast error variance explained, including own contributions. NET: Calculated as the difference between "TO" and "FROM", this column measures the net directional connectedness for each variable. A positive value indicates a net transmitter, while a negative value indicates a net receiver. NPT (Net Pairwise Transmitter): Represents the number of pairwise relationships in which a given variable acts as a net transmitter of shocks.

The diagonal elements represent own-variable shocks (idiosyncratic shocks), whereas the off-diagonal elements reflect the directional spillovers between assets. According to the table, WTI and SSE exhibit a high level of self-dependence, with own-shock contributions reaching 90.97% and 90.99%, respectively. This indicates that these markets are largely influenced by their internal dynamics rather than by external spillovers.

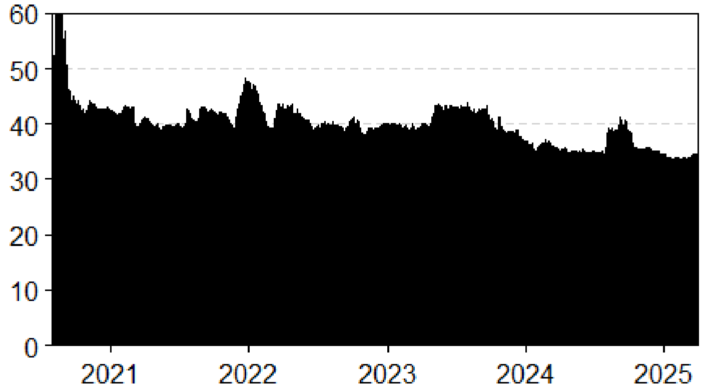
The forecast error variance decomposition (GFEVD) results presented in Table 2 underscore the prominent role of the S&P 500 and EFIV as central nodes in the volatility transmission network. Their relatively low own-shock shares of 49.20% and 49.21%, respectively, indicate that more than half of their forecast error variance is driven by external shocks, particularly from each other. This highlights their exposure to broader systemic influences and aligns with findings by Zeng et al. (2020) and Yang et al. (2024), who document strong bidirectional linkages between ESG and conventional equity indices during periods of financial instability.

The "TO" connectedness values, which capture each asset's role in propagating shocks, further emphasize this dynamic. Both the S&P 500 and EFIV contribute over 55% of total volatility to the other assets in the system, establishing them as the primary volatility transmitters. In contrast, WTI (5.73%) and SSE (3.72%) exhibit relatively weak outward spillovers, suggesting that these markets play more of a reactive or isolated role. These findings are consistent with the work of Mensi et al. (2023) and Ghani et al. (2025), who show that commodity and emerging markets often function as net receivers of shocks, particularly during periods of global financial stress or energy price disruptions. The "FROM" values, which measure the extent to which each asset is influenced by others, mirror the same structure. Both the S&P 500 and EFIV receive over 50% of their volatility from other assets, which, in combination with their high "TO" values, positions them as both systemic shock absorbers and transmitters. This dual role reflects their centrality in the global financial system and aligns with the conclusions of Attarzadeh et al. (2024), who highlight the feedback mechanisms between ESG indices and broader market dynamics.

The Net Connectedness (NET) metric provides further insight. While S&P 500 and EFIV are confirmed as net contributors to systemic risk (NET = 4.30 each), WTI (–3.30) and SSE (–5.30) emerge as net receivers, underscoring their relatively passive roles. These dynamics support the notion that traditional equity benchmarks and ESG ETFs are more integrated with systemic information flows, while commodity and emerging market indices are more insulated or responsive, as suggested by AlGhazali et al. (2024) and Xu et al. (2023).

The Total Connectedness Index (TCI), presented in Figure 2, captures the aggregate level of systemic integration. The adjusted TCI (excluding own effects) is approximately 29.91, while the unadjusted value reaches 39.88, indicating a moderate but persistent level of interconnectedness. This result is in line with Sharma et al. (2024), who argue that ESG-focused assets amplify market co-movements during periods of uncertainty, thereby increasing systemic risk despite their perceived resilience.

Figure 2: Dynamic total connectedness



Note: Results are based on a TVP-VAR (0.99,0.99) model with lag length of order 1 (BIC) and a 20-step-ahead forecast

Turning to Figure 3, which illustrates the Net Total Directional Connectedness (NPDC) over time, we observe significant variability in volatility spillovers among asset pairs between 2021 and 2025. The S&P 500 stands out as a dominant shock transmitter, especially in its pairwise relationships with SSE and EFIV, where the NPDC values remain consistently positive. This reflects the S&P 500's role as a global risk barometer, a finding echoed by Akin et al. (2024) in their analysis of cross-market volatility flows.

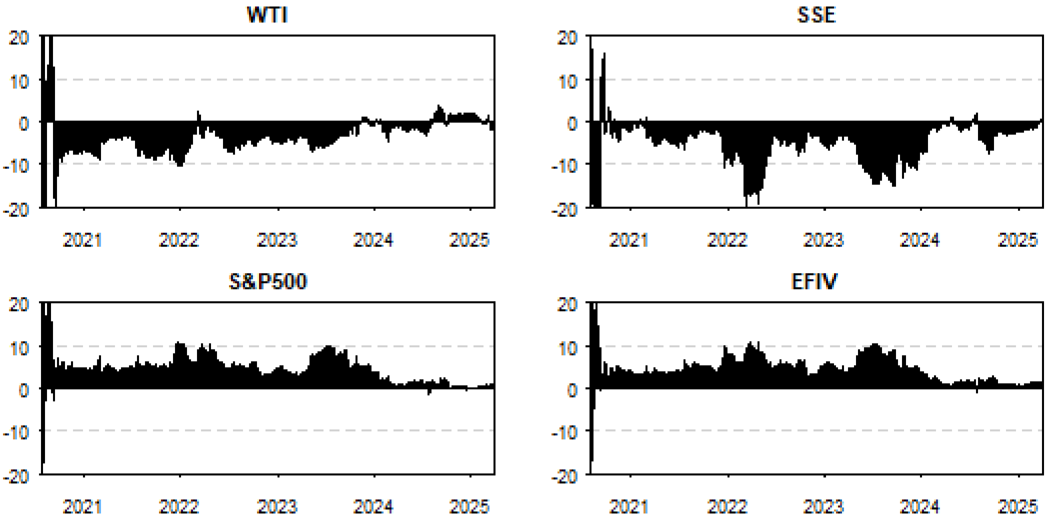
WTI, by contrast, consistently behaves as a net receiver of shocks, particularly in its relationships with both the S&P 500 and SSE. This suggests that energy markets are more responsive to financial market signals than active transmitters of risk. Interestingly, the WTI– EFIV relationship appears more balanced, with shifts in dominance over time, reflecting transitional periods of energy policy and ESG integration. A similar observation is made by Mensi et al. (2017), who report that oil and ESG indices influence each other cyclically depending on environmental policy shocks.

The SSE– EFIV connection exhibits increasing asymmetry, particularly in the later years of the sample. SSE emerges as a more influential transmitter in this dyad, potentially reflecting China's growing role in global ESG markets, as discussed in Meira et al. (2022). This evolving dynamic reinforces the importance of monitoring directional spillovers, as changes in geopolitical or regulatory regimes can shift hedging and diversification potential.

Lastly, Figure 2 confirms that the TCI varies between 30 and 60 throughout the sample period, reflecting both moderate and elevated systemic risk episodes. Notably, TCI peaks in late 2021 and mid-2023 coincide with global uncertainties such as post-pandemic economic adjustments and energy market disruptions. During these periods, the effectiveness of diversification decreases, emphasizing the need for dynamic portfolio adjustments. Toward the end of the period, a gradual decline in TCI suggests renewed opportunities for diversification as cross-asset linkages weaken. Nevertheless, the consistently high average level of interconnectedness affirms that structural market integration remains a defining feature of the modern investment environment.

We now turn our attention to the dynamics of net total directional connectedness. A key strength of the adopted econometric framework, the TVP-VAR model, lies in its ability to disentangle and classify the role of each market participant within the connectedness network, specifically, whether an asset predominantly acts as a net transmitter or net receiver of shocks over time. These dynamics are illustrated in Figure 3. As a guide to interpretation, when the shaded area in each subplot lies in the positive range, the corresponding asset is considered a net contributor of volatility spillovers to the system. Conversely, a negative shaded area indicates that the asset is absorbing more shocks than it is emitting, thus acting as a net receiver.

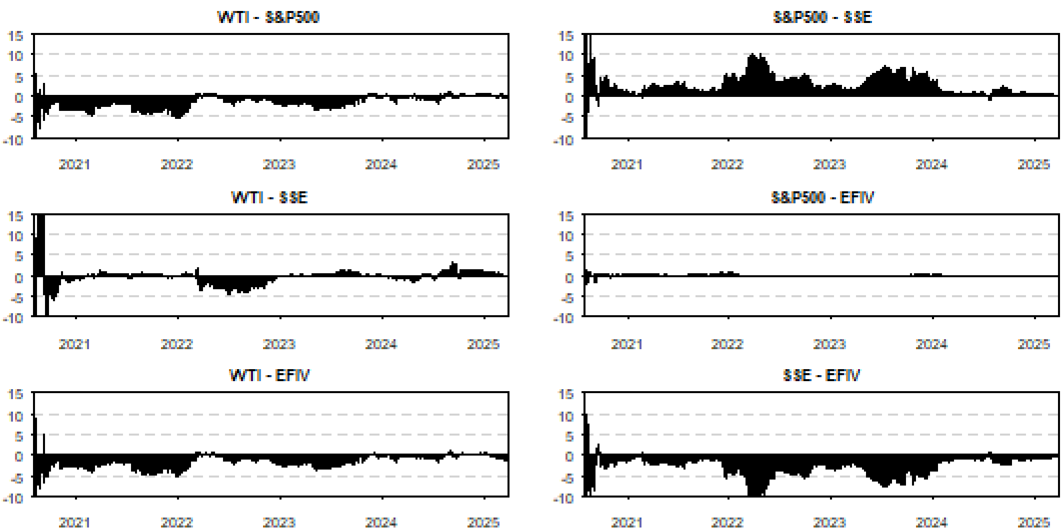
Figure 3. NET total directional connectedness



Notes: Results are based on a TVP-VAR (0.99,0.99) with one lag.

A clear pattern emerges from the figure: most assets in the system consistently exhibit one dominant role throughout the sample period. Notably, the SP500 and EFIV function predominantly as net transmitters, with sustained periods of positive net connectedness, particularly pronounced during turbulent market phases in 2022 and early 2023. In contrast, the SSE consistently registers as a net receiver, suggesting a heightened sensitivity to external volatility shocks, especially from developed markets. WTI shows more variable behavior, alternating between transmitter and receiver roles, though generally leaning toward a net recipient position. These findings provide important insights into the structural roles of different assets within the spillover network and offer valuable guidance for designing robust and responsive investment strategies.

Figure 4: Net pairwise directional connectedness



Notes: Results are based on a TVPVAR (0.99,0.99) with one lag

While the net total connectedness results are highly informative in distinguishing between net transmitters and net receivers within the network, they do not provide a complete picture of the underlying dynamics. Specifically, they fall short in capturing pairwise interactions, which can offer deeper insights into the evolving bilateral relationships between individual variables. Understanding these pairwise linkages is essential to identifying the precise role each asset plays within the system relative to others over time. To address this limitation and enhance our analysis of the interconnections among the markets under study, we now turn to the examination of bilateral connectedness patterns. These results are presented in Figure 4, allowing for a more granular perspective on the directional dependencies and spillovers within the network. For robustness, we performed residual diagnostic tests on the standardized residuals obtained from the estimated TVP-VAR model for each asset. Table 4 reports the results of the Ljung–Box Q(20) and $Q^2(20)$ statistics, confirming the absence of significant serial correlation and ensuring the adequacy of the model specification.

Table 4. Diagnostic Tests for TVP-VAR Model Residuals

Series	Q(20) Statistic	Q(20) p-value	$Q^2(20)$ Statistic	$Q^2(20)$ p-value
WTI	10307.9070	0.0921	1620.7120	0.2150
S&P500	8730.0150	0.1446	1753.9750	0.1130
SSE	9592.2030	0.3118	2009.6740	0.1260
EFIV	8128.6850	0.0425	2264.0520	0.2200

Notes: Q(20) and $Q^2(20)$ represent the Ljung–Box tests for serial correlation and ARCH effects up to 20 lags, respectively.

Overall, the diagnostic tests confirm that the TVP-VAR model is appropriately specified, as residuals for all series show no significant serial or conditional autocorrelation when both Q(20) and $Q^2(20)$ tests are considered. This suggests that the model effectively captures the temporal dynamics of all assets. For instance, the p-values for WTI (0.092), S&P 500 (0.145), and SSE (0.312) are well above the 0.05 threshold, confirming the absence of significant autocorrelation in their residuals. Although EFIV exhibits a slightly significant Q(20) statistic ($p = 0.043$), the $Q^2(20)$ statistic remains non-significant, indicating no remaining ARCH effects. This finding implies that any residual serial correlation in EFIV is statistically negligible and does not compromise the overall adequacy of the model. Consequently, the dynamic connectedness and volatility spillover estimates obtained from the TVP-VAR framework can be considered robust and reliable across all assets.

6.2 Robustness Analysis: Insights from the DCC-GARCH Approach

The findings are consistent with the broader connectedness analysis from our TVP-VAR model, particularly the sustained net transmitter behavior of assets like the S&P 500 and EFIV during crises. By presenting these complementary analyses, we aim to validate the connectedness patterns identified and provide a more robust empirical foundation for our conclusions. We believe that this approach, combining the nuanced insights of the TVP-VAR with the validation from GARCH and DCC-GARCH models, strengthens the credibility of our findings despite the unique characteristics of the study period. Table 5 presents a summary of the best-fitting GARCH specification selected for each asset, along with the corresponding estimated parameters of the DCC-GARCH model based on the optimal conditional volatility specification. The results show significant heterogeneity in conditional volatility dynamics among these assets. Notably, the ARCH coefficients (α) range from 0.072989 for SSE to 0.091886 for WTI, all statistically significant at the 1% threshold. Concurrently, the GARCH coefficients (β) present high values between 0.842356 (S&P 500) and 0.875334 (WTI), indicating strong volatility persistence across all studied assets. The conditional distribution parameters also reveal distinctive characteristics. SSE stands out with a particularly low shape value (1.191705) compared to other assets (>9), suggesting much thicker distribution tails and thus a higher propensity for extreme movements. Asymmetry (skew) is present in all assets, with values significantly below 1 for WTI (0.808308), S&P 500 (0.855023), and EFIV (0.868895), indicating a negative asymmetric distribution.

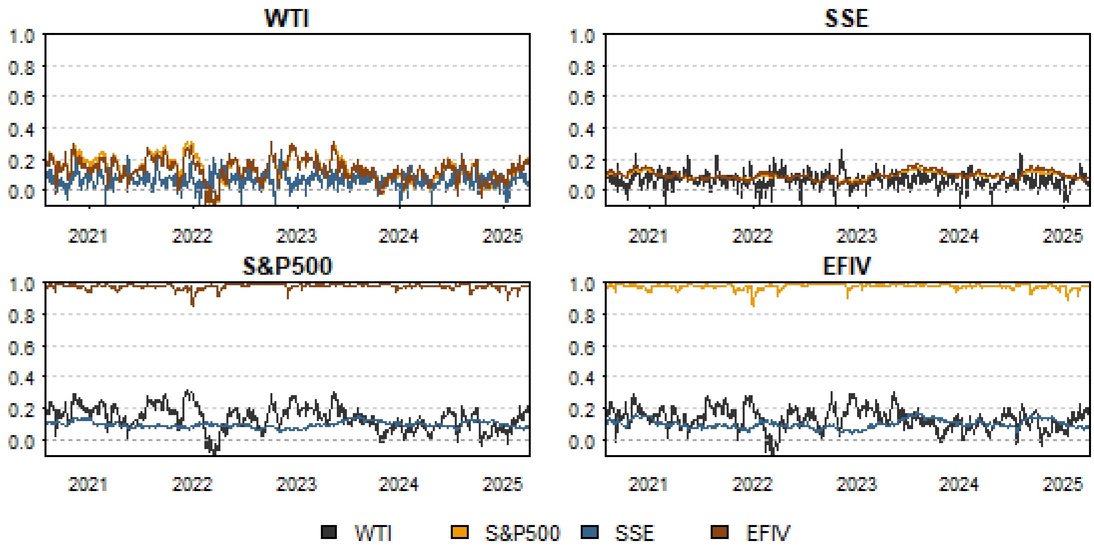
Table 5. Bivariate DCC-GARCH (1,1) with mixed univariate GARCH estimation table

Univariate GARCH parameters				
	WTI Model: s-GARCH Distribution:	S&P 500 Model: s-GARCH Distribution:	SSE: Model: f-GARCH Distribution:	EFIV Model: f-GARCH Distribution:
Parameters	Estimate (Pr(>|t|)			
μ	0.0008 (0.1461)	0.0003 (0.1924)	-0.0001 (0.0209)	0.0004 (0.1315)
ω	0.0000 (0.1126)	0.0004 (0.0004)	0.0000 (0.0000)	0.0004 (0.0001)
α	0.0918 (0.0002)	0.0893 (0.0000)	0.0729 (0.0000)	0.0818 (0.0000)
β	0.8753 (0.0000)	0.8423 (0.0000)	0.8604 (0.0000)	0.8525 (0.0000)
γ_1	-	0.7238 (0.0011)	-	0.7788 (0.0000)
γ_2	-	0.5774 (0.0006)	-	0.5312 (0.0000)
Conditional distribution parameters				
SSTD	SSTD	SGED	SSTD	
skew	0.8083 (0.0000)	0.8550 (0.0000)	0.9616 (0.0000)	0.8688 (0.0000)
shape	9.5209 (0.0016)	9.0198 (0.0001)	1.1917 (0.0000)	9.2431 (0.0002)
dcca1	0.0437	0.0120	3.6201	0.0002
dccb1	(0.8671)	(0.0581)	(14.9283)	(0.0000)

Notes: Estimation results of DCC-GARCH (Engle, 2002) with mixed univariate GARCH models (Antonakakis et al., 2020); while values in parentheses represent p-values. SSTD: skew Student's t; SGED: skew generalized error distribution,

The multivariate DCC-GARCH model estimation yields statistically significant parameters that further confirm the dynamic nature of correlations across the asset system. In fact, the DCC parameters capture the time-varying nature of the correlations between the assets. The parameter a (0.043748), which is statistically significant (p=0.000295), measures the short-term impact of past shocks (standardized residuals) on the current conditional correlation. Its positive value suggests that recent market shocks tend to slightly increase the co-movement between the assets. The parameter b (0.867157), highly significant (p=0.000), measures the persistence of the conditional correlations. Its value, being very close to 1, indicates a strong persistence in the correlation structure; correlations observed in the recent past tend to carry over into the near future, changing relatively slowly over time. The sum of dcca1 and dccb1 (approximately 0.91) is close to unity, further confirming the high degree of persistence in the dynamic correlations, implying that the correlation structure is quite stable but does evolve gradually.

Figure 5. Dynamic Conditional Correlations



Notes: The dynamic conditional correlations are retrieved from the DCC-GARCH framework (Engle, 2002) with mixed univariate GARCH models (Antonakakis et al., 2020).

These results are complementary to Figure 5, which presents the temporal evolution of conditional volatility for the four assets over the 2021-2025 period. The figure clearly illustrates the volatility clusters predicted by the high values of DCC coefficients. The more pronounced volatility peaks observed for SSE corroborate its exceptionally low shape value, thus confirming the model's ability to adequately capture extreme movements of this index.

The DCC parameters ($a = 0.043748$ and $b = 0.867157$), both statistically significant, reflect a persistent dynamic correlation structure between assets. This characteristic is visually perceptible in the figure through the partial synchronization of periods of increased volatility, particularly between the S&P 500 and EFIV.

In conclusion, the joint analysis of the results table and graphical representation demonstrates the relevance of the DCC-GARCH model for capturing not only individual volatility dynamics but also the temporal evolution of interdependencies among these four major financial indices.

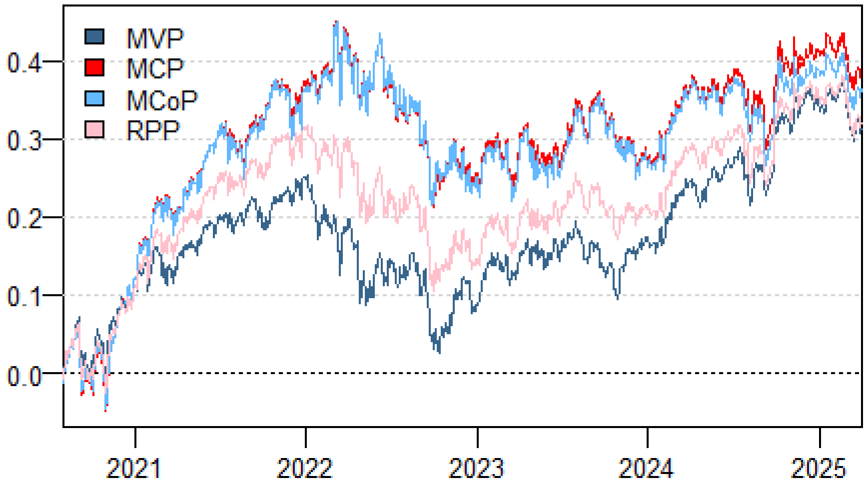
These findings have clear implications for portfolio construction and risk management. The stable yet dynamic nature of conditional correlations supports the use of adaptive diversification strategies, especially in environments characterized by systemic uncertainty. Moreover, the DCC-GARCH estimates are consistent with the broader connectedness analysis performed through the TVP-VAR model, where assets such as the S&P500 and EFIV exhibit sustained net transmitter behavior, particularly during crisis episodes. This consistency between the DCC-GARCH and connectedness approaches not only enhances the credibility of the results.

6.3 Dynamic Portfolios

The dynamic portfolio section is composed of two complementary analyses designed to enhance the robustness and reliability of the results. First, a multivariate analysis is conducted, encompassing both hedging and allocation dimensions, to provide a comprehensive understanding of portfolio efficiency and diversification within complex market environments. Alongside this, a bivariate analysis is performed to offer an additional layer of verification, testing the consistency and stability of observed performance and thus reinforcing the validity of the conclusions through cross-perspective evaluation. This dual approach ensures a thorough assessment of dynamic portfolio strategies by combining analytical depth with robust cross-verification.

Regarding the multivariate analysis, to evaluate the most suitable portfolio construction approach in light of these findings, we implement and compare four optimization strategies: (i) Minimum Variance Portfolio (MVP), (ii) Minimum Correlation Portfolio (MCP), (iii) Risk Parity Portfolio (RPP), and (iv) Minimum Connectedness Portfolio (MCoP). We assess each method using Sharpe Ratios and Hedging Effectiveness Scores, which serve as benchmarks for comparing their relative performance and risk-adjusted returns over time.

Figure 6. Time-varying Cumulative portfolio returns



Notes: Results are based on the time-varying variance covariance matrices retrieved from the TVP-VAR(0.99,0.99) with one lag. MVP refers to the minimum variance portfolio, MCP refers to the minimum correlation portfolio, RPP refers to the risk-parity portfolio, and MCoP refers to the minimum connectedness portfolio. The dotted gray lines depict returns on individual bond indices.

Figure 6 plots the cumulative returns of the four alternative portfolio strategies. The graph reveals that the portfolio methods perform with a visible degree of similarity, reflecting shared underlying dynamics throughout the observation period from January 30, 2020, to March 31, 2025. All portfolios experienced a sharp initial decline in early 2020, associated with the onset of the COVID-19 pandemic, followed by a period of sustained growth during 2021 and early 2022. Notably, while all strategies recover and trend upward, the MCP and MCoP portfolios maintain a consistently superior performance relative to the MVP and RPP portfolios, especially in the later stages of the sample. The dotted black line serves as a reference benchmark, and cross-comparison suggests that the connectedness- and correlation-based strategies outperform traditional risk and variance-based allocations in terms of cumulative returns. While this performance hierarchy is evident over the observed period, it is important to recognize that such relative rankings are subject to change across different market cycles and may not persist into the future.

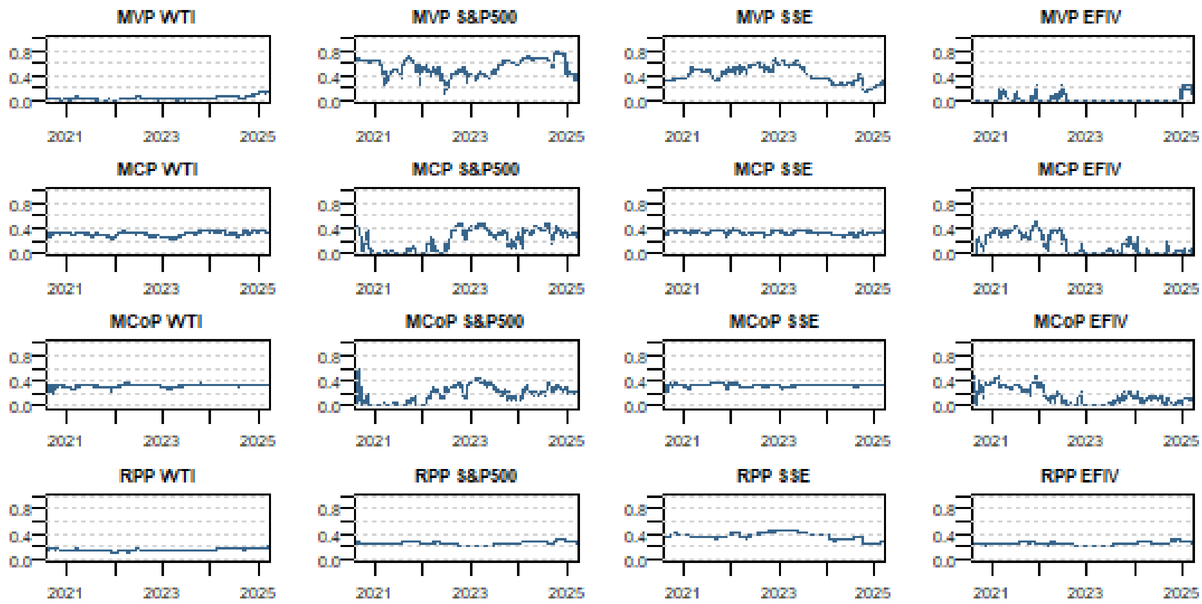
To provide a clearer picture of the internal composition of each portfolio strategy, Figure 7 illustrates the dynamic portfolio weights over time for portfolios constructed using the S&P 500, WTI crude oil (WTI), the SPDR S&P 500 ESG ETF (EFIV), and the Shanghai Stock Exchange Composite Index (SSE). This comprehensive visualization allows for a direct comparison of how each of the four assets contributes to the different portfolio construction methodologies across the sample period.

The MVP strategy, by its objective of minimizing portfolio variance, exhibits highly dynamic and often concentrated allocations. For the WTI, its weight in the MVP appears generally low and stable, suggesting it is often perceived as a more volatile component or offers less variance reduction benefits compared to other assets in this specific portfolio context. The S&P 500 shows fluctuating weights, likely increasing when its perceived contribution to overall portfolio variance is low or when it offers diversification benefits relative to other assets. The SSE also displays variable weights, potentially higher during periods where its volatility is comparatively lower or its correlation with other assets aids in variance reduction. The EFIV often commands a significant and sometimes dominant weight in the MVP, particularly during certain periods. This suggests that, within this four-asset universe, EFIV is frequently identified by the MVP strategy as a key component for achieving overall portfolio variance minimization, possibly due to lower individual volatility or favorable covariance characteristics with the other assets.

The MCP aims to minimize the average correlation between portfolio components. For WTI, its weight can vary, potentially increasing when its correlation with the equity and ESG components (S&P500, SSE, EFIV) is low, thus enhancing diversification. The S&P500 and SSE, as major equity indices, might see their weights adjusted based on their evolving correlation with each other and with WTI and EFIV. The EFIV's weight in the MCP will also be driven by its correlation profile; a lower correlation with S&P500, SSE, and WTI would lead to a higher allocation. The MCP strategy often results in a more diversified set of weights compared to MVP, as it focuses on inter-asset relationships rather than solely individual volatilities. The figure suggests that EFIV and WTI might often play important roles in achieving low portfolio correlation, while S&P500 and SSE weights are dynamically adjusted.

The MCoP strategy seeks to minimize the overall connectedness of the portfolio, based on spillover effects. The weight of WTI in the MCoP would be higher if it is identified as being less connected to the system or acting as a net receiver of spillovers, thus reducing the portfolio's overall exposure to systemic risk transmission. The S&P500 and SSE, often significant players in spillover networks, might see their weights managed to mitigate their contribution to portfolio connectedness. The EFIV's allocation will depend on its role in the connectedness network; if it acts as a diversifier by being less connected or by receiving spillovers rather than transmitting them, its weight could be substantial. Visually, the MCoP often shows allocation patterns similar to MCP, as high correlation can be a proxy for high connectedness, but MCoP specifically targets the spillover-based measure. The dominance of any single asset is less about its individual risk and more about its systemic risk profile within the TVP-VAR framework.

Figure 7. Time-varying multivariate portfolio weights



Notes: Results are based on the time-varying variance-covariance matrices retrieved from the TVP-VAR (0.99,0.99) with one lag. MVP refers to the minimum variance portfolio, MCP refers to the minimum correlation portfolio, RPP refers to the risk-parity portfolio, and MCoP refers to the minimum connectedness portfolio

The RPP aims to equalize the risk contribution from each of the four assets. This typically leads to more balanced weights compared to the MVP, as it avoids over-concentration in the least volatile assets. For WTI, if it is highly volatile, its capital allocation in the RPP will be lower to ensure its risk contribution is on par with other, less volatile assets. Similarly, the S&P500 and SSE weights will be inversely related to their respective volatilities. The EFIV, if it exhibits lower volatility compared to WTI or the broad equity indices, might receive a relatively larger capital weight in the RPP to achieve an equal risk contribution. The key characteristic of RPP is that no single asset should dominate in terms of risk contribution, leading to a diversified allocation where weights are primarily scaled by the inverse of their volatility.

Collectively, the dynamic weights in Figure 7, reveal distinct behaviors across the four portfolio construction strategies. The MVP often favors the asset(s) offering the lowest variance at a given time (frequently EFIV in this depiction). In contrast, MCP and MCoP make allocations based on minimizing inter-asset dependencies (correlation or connectedness), potentially leading to significant weights in assets like WTI or EFIV if they serve as diversifiers. The RPP provides the most structurally diversified approach by equalizing risk contributions, with weights inversely proportional to individual asset volatilities. These nuanced insights underscore the importance of selecting a portfolio strategy aligned with specific investment objectives and risk preferences, especially in a dynamic environment with diverse asset classes like developed equities, emerging market equities, commodities, and ESG investments.

Table 6: Dynamic Multivariate Portfolio Weights

	Mean	Std.Dev.	5%	95%	HE	p-value	SR
Minimum Variance Portfolio							
WTI	0.0400	0.0300	0.0000	0.1200	0.9100	0.0000	0.5500
S&P500	0.5300	0.1300	0.3300	0.6900	0.5300	0.0000	0.5500

SSE	0.4100	0.1200	0.2200	0.6000	0.4800	0.0000	0.5500
EFIV	0.0200	0.0600	0.0000	0.1700	0.5500	0.0000	0.5500
Minimum Correlation Portfolio							
WTI	0.3100	0.0300	0.2500	0.3500	0.8300	0.0000	0.4900
S&P500	0.2200	0.1600	0.0000	0.4500	0.1700	0.0000	0.4900
SSE	0.3300	0.0300	0.2800	0.3700	0.0800	0.1600	0.4900
EFIV	0.1400	0.1500	0.0000	0.3900	0.1900	0.0000	0.4900
Minimum Connectedness Portfolio							
WTI	0.3300	0.0200	0.2800	0.3500	0.8200	0.0000	0.4400
S&P500	0.1900	0.1300	0.0000	0.4000	0.1200	0.0300	0.4400
SSE	0.3300	0.0200	0.3000	0.3600	0.0200	0.7300	0.4400
EFIV	0.1600	0.1300	0.0000	0.3700	0.1400	0.0100	0.4400
Risk Parity Portfolio							
WTI	0.1400	0.0200	0.1200	0.1800	0.8900	0.0000	0.5300
S&P500	0.2500	0.0200	0.2100	0.2900	0.4700	0.0000	0.5300
SSE	0.3600	0.0600	0.2400	0.4500	0.4100	0.0000	0.5300
EFIV	0.2400	0.0200	0.2100	0.2900	0.4900	0.0000	0.5300

Notes: This table reports the estimated Multivariate-optimal portfolio weights under four portfolio strategies. The 5% and 95% columns correspond to the lower and upper quantiles of the weight distribution. *HE* represents the hedging effectiveness, while *SR* denotes the Sharpe ratio. *p-value* refers to the significance level of the hedging effectiveness test. The estimates build upon the modeling specifications outlined in Antonakakis et al. (2020). SSTD = skewed Student's *t* distribution; SGED = skewed generalized error distribution.

Table 6 presents the optimal portfolio weights, hedging effectiveness (HE), p-values, and Sharpe ratios (SR) for each asset under the four portfolio optimization strategies, highlighting their comparative risk-reduction and diversification performance. Under the MVP framework, the results indicate that the portfolio allocates, on average, 4% to WTI, 53% to the S&P 500, 41% to the SSE, and 2% to EFIV. The hedging effectiveness (HE) values reveal substantial volatility reductions, reaching 91% for WTI, 53% for the S&P 500, 48% for the SSE, and 55% for EFIV, suggesting that the MVP approach achieves a strong diversification effect and efficiently minimizes overall portfolio risk.

For the MCP approach, the optimal weights suggest an average allocation of 31% to WTI, 22% to the S&P 500, 33% to SSE, and 14% to EFIV. The HE coefficients show that the volatility of each asset in this portfolio is statistically significantly lowered by 83%, 17%, 8%, and 19%, respectively. These results imply that the MCP strategy effectively reduces systemic co-movements among assets while maintaining moderate diversification benefits. In the case of the MCoP strategy, the average portfolio composition—33% WTI, 19% S&P 500, 33% SSE, and 16% EFIV—is associated with volatility reductions of 82%, 12%, 2%, and 14%, respectively. This suggests that minimizing interconnectedness among assets improves stability, particularly when cross-market spillovers dominate traditional correlations. Finally, under the RPP, the weights are more balanced, with 14% allocated to WTI, 25% to the S&P 500, 36% to SSE, and 24% to EFIV. The corresponding HE values (89%, 47%, 41%, and 49%) confirm that the Risk Parity framework distributes risk more evenly across assets, ensuring consistent risk-adjusted performance and robust portfolio resilience.

Based on the multivariate results in Table 6, WTI consistently exhibits the highest hedging effectiveness (HE) across all portfolio strategies, with values ranging from 0.82 to 0.91, indicating its strong ability to reduce portfolio volatility. This suggests that WTI serves as the most effective hedging asset within the multivariate framework, providing substantial risk mitigation benefits when combined with other financial and ESG assets.

Table 7. Sharpe Ratio Results

	MVP	MCP	MCoP	RPP
Mean	0.0073	0.0093	0.0095	0.0071
StDev	0.0003	0.0003	0.0003	0.0003
SR	0.0365	0.0328	0.0316	0.0373

Notes: Sharpe ratios are calculated from the dynamic multivariate portfolio returns, using the corresponding estimated mean returns and standard deviations for each portfolio strategy. Mean and StDev refer to the multivariate portfolio mean returns and standard deviations, respectively.

Table 7 presents the Sharpe ratio results for the four multivariate portfolio strategies, summarizing their mean returns, standard deviations, and overall risk-adjusted performance. When evaluating the reward-to-volatility trade-off, the RPP portfolio achieves the highest Sharpe ratio (0.0373), suggesting superior risk-adjusted performance. This is followed by MVP (0.0365), MCP (0.0328), and MCoP (0.0316). These findings imply that although MCoP and MCP deliver higher average returns, RPP and MVP offer more efficient returns per unit of risk, highlighting their attractiveness for risk-averse investors.

Beyond the statistically significant volatility reductions achieved through various portfolio optimization strategies, a deeper look into the role of the ESG ETF (EFIV) reveals meaningful implications. The consistent hedging effectiveness of EFIV, especially when paired with traditional equity indices, suggests that its function may extend beyond simple correlation-based protection. While its performance could, in part, be attributed to its strong linkage with the S&P 500, the persistence of risk reduction across multiple portfolio strategies and market conditions points to a potentially distinct risk-return profile. This could indicate that ESG integration contributes to a more resilient portfolio structure by buffering systemic shocks and promoting volatility smoothing. Thus, rather than being a mere statistical artifact, the ESG ETF's performance may reflect evolving market dynamics in which sustainability factors contribute to more stable asset behavior during periods of stress. These findings align with recent literature that highlights the stabilizing role of ESG investments in times of market turbulence.

Building on the insights gained from the multivariate portfolio analysis, we now shift our focus to a bivariate framework to evaluate the hedging effectiveness of each individual asset. This approach allows for a more granular assessment of the risk mitigation potential of specific asset pairings, thereby providing valuable information for investors seeking tailored hedging strategies. By isolating the dynamics between each portfolio component and its potential hedge, we can better understand the relative importance and contribution of each asset in enhancing overall portfolio resilience (Table 8).

Table 8. Dynamic bivariate portfolio hedge ratio

Pair	Mean	Std.Dev.	5%	95%	HE	p-value	Return	Std.Dev	SR
WTI/S&P500	0.3500	0.2800	-0.0300	0.8000	0.0500	0.0000	0.0100	0.3500	0.0200
WTI/SSE	0.2300	0.1400	0.0000	0.4400	0.0200	0.6900	0.0500	0.3600	0.1400
WTI/EFIV	0.3200	0.2600	-0.0400	0.7600	0.0400	0.0000	0.0000	0.3500	0.0100

S&P500/WTI	0.0700	0.0500	-0.0100	0.1400	0.0400	0.4600	0.0800	0.1600	0.4900
S&P500/SSE	0.0900	0.0700	-0.0400	0.2000	0.0200	0.6900	0.1100	0.1600	0.6600
S&P500/EFIV	0.9700	0.0100	0.9300	0.9900	0.9700	0.0000	0.0000	0.0300	-0.0200
SSE/WTI	0.0300	0.0200	0.0000	0.0600	0.0200	0.4600	-0.0200	0.1500	-0.1000
SSE/S&P500	0.0900	0.0600	-0.0200	0.1900	0.0200	0.0000	-0.0200	0.1500	-0.1500
SSE/EFIV	0.1000	0.0700	-0.0100	0.2200	0.0200	0.0000	-0.0200	0.1500	-0.1500
EFIV/WTI	0.0700	0.0500	-0.0100	0.1300	0.0400	0.4600	0.0800	0.1600	0.5100
EFIV/S&P500	1.0100	0.0200	0.9800	1.0400	0.9700	0.0000	0.0000	0.0300	0.0500
EFIV/SSE	0.1000	0.0700	-0.0200	0.2300	0.0200	0.6900	0.1100	0.1600	0.6800

Notes: This table reports the estimated Bivariate-optimal portfolio weights. The 5% and 95% columns correspond to the lower and upper quantiles of the weight distribution. *HE* represents the hedging effectiveness, while *SR* denotes the Sharpe ratio. *p-value* refers to the significance level of the hedging effectiveness test. The estimates build upon the modeling specifications outlined in Antonakakis et al. (2020). SSTD = skewed Student's *t* distribution; SGED = skewed generalized error distribution.

The hedge ratio quantifies the proportion of one asset needed to hedge against the risk exposure of another within a bivariate portfolio. A higher hedge ratio indicates a stronger co-movement and potentially greater hedging effectiveness, whereas a lower ratio suggests weaker risk mitigation. As reported in Table 6, the WTI/SP500 pair exhibits a hedge ratio of 0.35, implying that 0.35 units of WTI are required to hedge one unit of SP500. This denotes a moderate level of hedging effectiveness, supported by a statistically significant p-value of 0.00, confirming the reliability of the hedge. Similar findings are reported by Mensi et al. (2023), who observe that oil-based assets provide moderate but variable hedging capacity depending on market volatility regimes, particularly during geopolitical or macroeconomic shocks.

In evaluating the broader results, one of the most consistent findings is the robust hedging capacity of the SPDR S&P 500 ESG ETF. Among the different pairings, EFIV frequently registers the highest hedge ratios. For example, the EFIV /SP500 combination exhibits a hedge ratio of 1.01, implying near-perfect coverage, i.e., one unit of SPEG is sufficient to hedge one unit of S&P500. The statistically significant p-value (0.00) reinforces the validity of this relationship. This outcome corroborates the work of Yang et al. (2024) and Sharma et al. (2024), who document that ESG-focused ETFs, particularly those linked to U.S. equities, can act as effective hedging instruments due to their stability, lower downside risk, and sensitivity to sentiment-driven shocks. These assets often provide enhanced diversification, especially during periods of heightened uncertainty or ESG-aligned market transitions.

Conversely, certain asset pairs such as SSE/WTI and S&P500/SSE report low hedge ratios of 0.03 and 0.09, respectively. These low ratios reflect weak co-movement and limited hedging capacity, indicating that these combinations are less suitable for portfolio risk mitigation. The associated p-values (0.46 and 0.00) provide mixed evidence of statistical significance. This is consistent with findings by Ghani et al. (2025) and Ma et al. (2013), who emphasize the limited short-term volatility spillover from WTI to Chinese equity markets, suggesting that energy assets offer little diversification benefit in portfolios dominated by Chinese stocks.

Overall, EFIV emerges as the most reliable hedge among the assets studied, combining high hedge ratios with statistical significance across multiple pairings. Its performance highlights the growing role of sustainability-aligned assets in reducing portfolio risk. In contrast, while assets like WTI and S&P500 can offer moderate hedging benefits, their effectiveness is more context-dependent. These insights align with the broader literature on asset connectedness and hedging dynamics, reinforcing the strategic importance of including ESG assets in diversified portfolios aimed at maximizing hedging effectiveness and downside protection.

We now delve into potential underlying mechanisms, such as shifts in investor behavior driven by growing awareness of sustainability factors, regulatory changes promoting ESG integration, and the specific sectoral compositions of the ESG ETFs. For instance, the dual role of ESG ETFs, acting simultaneously as significant market players due to their increasing capitalization and liquidity, which could imply a capacity to transmit shocks, while also offering hedging properties, can be further elucidated by recent academic findings. Their inherent focus on companies with better risk management practices and resilience can explain their hedging properties, particularly during periods of market stress or specific types of crises. This is supported by studies such as Fung et al. (2024), who found that ESG-tilted indices demonstrate greater resilience to market volatility spikes and possess lower downside risks, attributing this to a more stable investor base less prone to speculative trading during stressful market situations. While the increasing market capitalization and liquidity of ESG ETFs could theoretically position them as potential transmitters of shocks, current research tends to emphasize their shock-absorbing or resilient characteristics. The specific sectoral compositions and the emphasis on companies with robust governance and risk management frameworks might mitigate their role as net shock transmitters. Instead, their growing presence might alter market dynamics by rewarding sustainable practices. We also consider how information flows and market sentiment towards ESG themes might influence these dynamics. The heightened awareness and preference for ESG investments can create a positive feedback loop, where increased investor demand not only bolsters the market for ESG assets but also encourages companies to improve their ESG performance, potentially leading to a financial system that is both more sustainable and more resilient to certain types of shocks. This contributes to a more nuanced understanding of their evolving role in the financial system.

6. Conclusion

In an increasingly complex and interconnected global financial environment, understanding dynamic market spillovers has become crucial for effective risk management and portfolio design. Recent geopolitical tensions, energy market disruptions, and the accelerating shift toward ESG-oriented investment practices have significantly altered asset behavior, reinforcing the need for advanced analytical frameworks. In response to these challenges, this study employs a Time-Varying Parameter Vector Autoregression (TVP-VAR) model to examine return spillovers among four key asset classes: the S&P 500, the Shanghai Stock Exchange (SSE), West Texas Intermediate (WTI) crude oil, and the ESG-focused EFIV ETF.

Our empirical results reveal several important patterns. The S&P 500 and EFIV consistently act as dominant volatility transmitters, while WTI and SSE primarily serve as net receivers. Portfolio optimization findings further indicate that Minimum Connectedness (MCoP) and Minimum Correlation (MCP) strategies yield superior cumulative returns, whereas Minimum Variance (MVP) and Risk Parity (RPP) provide stronger risk-adjusted performance. Bivariate portfolio analyses confirm the effectiveness of ESG ETFs, particularly SPEG and EFIV, as reliable hedging instruments, especially during periods of elevated uncertainty.

These findings generate several policy and managerial implications. For institutional investors and asset managers, the results highlight the need to move beyond static allocation models and adopt dynamic, spillover-aware strategies. The consistently strong hedging performance of ESG ETFs suggests that reallocating capital toward ESG-aligned instruments during market stress can enhance downside protection without compromising long-term returns. The context-dependent hedging ability of traditional assets like WTI and the S&P 500 further reinforces the importance of adaptive portfolio frameworks, potentially supported by regime-switching or machine learning techniques.

From a regulatory and macroprudential perspective, the study underscores the systemic relevance of ESG assets. Given their stabilizing properties, regulators, central banks, and financial stability boards could benefit from monitoring ESG asset flows as part of broader systemic risk surveillance. Additionally, ESG rating agencies may consider integrating measures of dynamic connectedness and hedging performance into their assessment methodologies to better reflect real-world financial resilience.

Looking ahead, future research could extend this analysis to a wider spectrum of ESG instruments, commodities, or regional markets to test the robustness of these findings. Examining the influence of major macroeconomic or policy events on connectedness dynamics may also provide deeper insights. Finally, exploring hybrid portfolio optimization frameworks that incorporate spillover forecasts could yield more sophisticated risk-management tools for an era of persistent uncertainty.

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