

Article

Not peer-reviewed version

A Comparative Analysis of Green and Brown Stocks: The Impact of Uncertainty Indices on Tail-Risk Forecasting

[Antonio Naimoli](#) and [Giuseppe Storti](#) *

Posted Date: 19 March 2026

doi: 10.20944/preprints202603.1499.v1

Keywords: value-at-risk; expected shortfall; realized ES-CAViaR; climate risk; geopolitical risk; economic policy uncertainty; green and brown assets; tail-risk forecasting



Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a [Creative Commons CC BY 4.0 license](#), which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

Article

A Comparative Analysis of Green and Brown Stocks: The Impact of Uncertainty Indices on Tail-Risk Forecasting

Antonio Naimoli  and Giuseppe Storti * 

Department of Economics and Statistics (DISES), University of Salerno, Via Giovanni Paolo II, 132, 84084, Fisciano, SA, Italy

* Correspondence: storti@unisa.it

Abstract

This paper examines whether climate, geopolitical and economic policy uncertainty indices improve Value-at-Risk (VaR) and Expected Shortfall (ES) forecasts for green and brown stocks. We extend the Realized-ES-CAViaR framework by incorporating physical and transition climate risk, geopolitical risk and economic policy uncertainty indices alongside a high-low range volatility estimator. Using daily data for the iShares Global Clean Energy ETF (ICLN) and the iShares Global Energy ETF (IXC) over the period January 2012 - December 2024, we evaluate alternative model specifications at the 1% and 2.5% risk levels through backtesting procedures, strictly consistent scoring rules and the Model Confidence Set methodology. Results reveal a pronounced asymmetry in the predictive content of risk indices across asset classes and quantile levels. Transition climate risk dominates tail-risk forecasting at the 1% level for both asset classes, while geopolitical risk and economic policy uncertainty emerge as the leading factors at the 2.5% level for green and brown stocks, respectively. These findings highlight the heterogeneous channels through which uncertainty shocks propagate into financial tail-risk, with direct implications for risk management and regulatory oversight during the low-carbon transition.

Keywords: value-at-risk; expected shortfall; realized ES-CAViaR; climate risk; geopolitical risk; economic policy uncertainty; green and brown assets; tail-risk forecasting

1. Introduction

The global transition towards a low-carbon economy is reshaping the risk structure of financial markets. Climate change, environmental regulation and technological innovation related to decarbonization have led to new and interacting sources of uncertainty that affect firms and investors in heterogeneous ways. These factors are particularly relevant for assets sensitive to climate transition risks, which are jointly influenced by policy developments, geopolitical events and macroeconomic conditions. Consequently, understanding how climate transition dynamics propagate into financial risk has become a key concern for both investors and regulators.

An important implication of the climate transition is the growing heterogeneity between environmentally sustainable ("green") assets and fossil-fuel-intensive ("brown") assets. Green firms and clean energy investments are generally expected to benefit from decarbonization policies and technological innovation, while brown assets face increasing exposure to regulatory tightening, stranded asset risk and changes in investor preferences. A growing empirical literature documents that climate-related shocks affect these two groups asymmetrically, with important consequences for returns and volatility (Ardia et al. 2023; Bolton and Kacperczyk 2021; Pástor et al. 2022). However, these effects may manifest differently in the tails of the return distribution, which capture extreme losses.

The measurement of extreme financial losses is a central concern for risk management, regulatory supervision and portfolio allocation. Since the global financial crisis, Value-at-Risk (VaR) and Expected Shortfall (ES) have become core metrics for quantifying tail-risk, with ES now playing a key role in regulatory capital requirements under the Basel III framework (Basel Committee on Banking Supervision

2017). Despite their widespread adoption, the accurate forecasting of VaR and ES remains challenging, particularly during periods of high uncertainty and structural change, when the distribution of asset returns may deviate substantially from standard modeling assumptions.

Recent advances in econometric modeling have addressed these challenges by developing a coherent framework that jointly models VaR and ES. The ES-CAViaR class of models represents a significant step in this direction, allowing for semi-parametric estimation of tail-risk while ensuring consistency between the two risk measures (Taylor 2019). To further enhance the ability of these models to capture changing market conditions, recent extensions incorporate realized volatility measures derived from high-frequency data, providing additional information about volatility dynamics and improving the accuracy of tail-risk forecasts (Peiris et al. 2024; Wang et al. 2023).

Despite their widespread use, traditional VaR and ES forecasting models often fail to capture the full complexity of tail-risk dynamics, particularly during periods of heightened market stress. A growing body of research provides evidence that external risk factors, including measures of uncertainty, sentiment and macroeconomic conditions, contain valuable predictive information that can substantially enhance volatility and tail-risk forecasts (Jiang et al. 2025; Leirvik 2025; Li et al. 2023; Naimoli 2023). This recognition has spurred interest in developing models that systematically incorporate such information while maintaining the flexibility to adapt to time-varying market conditions.

Among the various sources of risk that may drive extreme market movements, three factors have recently gained particular prominence: climate risk, geopolitical risk and economic policy uncertainty. Each of these factors operates through distinct channels and may affect different segments of financial markets with varying intensity.

Climate risk is commonly decomposed into physical and transition components. Physical risk arises from extreme weather events and long-term climatic changes, while transition risk reflects the economic and financial consequences of moving towards a low-carbon economy (Campiglio et al. 2023). Recent developments in text-based analysis have enabled the construction of high-frequency indicators that capture innovations in these two dimensions. Bua et al. (2024) propose the daily Physical Risk (PRI) and Transition Risk (TRI) indices based on Reuters news, providing timely measures of climate risk shocks relevant for financial markets. Several studies emphasize the role of climate policy uncertainty in the dynamics of returns and volatility across green and brown assets (see, e.g., Bouri et al. 2022, 2023; Sarker et al. 2023, among others).

Geopolitical risk constitutes a second critical dimension of risk with profound implications for volatility and tail-risk forecasting. Caldara and Iacoviello (2022) define geopolitical risk as threats, realizations and escalations of adverse events associated with wars, terrorism and interstate tensions that disrupt international relations. The Geopolitical Risk (GPR) index, constructed through automated text analysis of major international newspapers, captures the intensity of geopolitical tensions in real time. Geopolitical uncertainty has intensified in recent years, from the US-China trade war (2018–2020) to Russia's invasion of Ukraine (February 2022) and the Israel–Hamas conflict (October 2023), affecting energy supply chains, commodity prices and financial markets (De Luca et al. 2025; Hu and Borjigin 2024; Sweidan 2021; Zaremba et al. 2022).

In addition, economic policy uncertainty (EPU) represents a further source of macro-financial risk, reflecting uncertainty surrounding government policy actions. This channel is particularly relevant in a context where climate and energy policies play a central role in shaping economic outcomes. Baker et al. (2016) introduce a widely used EPU index based on newspaper coverage that captures uncertainty related to economic policy decisions. A large body of literature shows that policy uncertainty significantly affects stock returns, risk premia, investment decisions and market volatility (Chen et al. 2021; Pástor and Veronesi 2013; Xu et al. 2021). Empirical evidence further indicates that EPU also influences energy market volatility and the connectedness between fossil fuel and renewable energy markets (Evrin Mandaci et al. 2025; Jiang et al. 2024; Ma et al. 2022).

In this framework, climate, geopolitical and policy uncertainty measures may contain incremental predictive information for tail-risk forecasting that is not captured by traditional volatility-based

models. Because green and brown assets are differentially exposed to regulatory and transition-related shocks, understanding how uncertainty affects their tail-risk dynamics is essential for both portfolio management and financial stability assessment. Motivated by these considerations, this paper investigates whether climate, geopolitical and policy uncertainty indices can enhance VaR and ES forecasts for green and brown assets and whether their predictive power differs across asset classes and quantile levels.

This study contributes to the literature in several ways. First, it provides new evidence on how climate transition dynamics and uncertainty shocks affect financial tail-risk forecasting of green and brown stocks, moving beyond traditional analyses focused on volatility measures. Second, we analyze the distinct and combined impacts of physical climate risk, transition climate risk, geopolitical risk and economic policy uncertainty on VaR and ES dynamics for both green and brown stocks, allowing for a deeper understanding of how different types of risk differentially affect extreme losses depending on asset characteristics. Third, the paper advances the methodology for tail-risk forecasting by proposing an enriched specification of the Realized ES-CAViaR model that combines range-based volatility measures with a comprehensive set of external risk indices. The resulting framework allows for the systematic inclusion of exogenous risk drivers and can be flexibly extended to different asset classes and risk-factor configurations. Finally, by covering a sample period marked by major climate agreements, pandemic disruptions and geopolitical conflicts, the analysis sheds light on the differential vulnerability of green and brown assets during episodes of extreme market stress, providing insights that are highly relevant for investors, risk managers and policymakers.

Our empirical investigation uses daily data for the iShares Global Clean Energy ETF (ICLN) and the iShares Global Energy ETF (IXC) as representative proxies for green and brown stocks, respectively, covering the period from January 2012 to December 2024. This sample period is particularly informative as it covers multiple episodes of elevated climate, geopolitical and policy uncertainty, including the Paris Agreement (2015), various COP conferences, the US-China trade war, the COVID-19 pandemic, Russian invasion of Ukraine and the Israel-Hamas conflict. Specifically, geopolitical risk is measured by the daily GPR (GPRD) of [Caldara and Iacoviello \(2022\)](#), climate risk is captured by the Physical (PRI) and Transition (TRI) Risk Indices of [Bua et al. \(2024\)](#), economic policy uncertainty is measured by the EPU index of [Baker et al. \(2016\)](#), and volatility is estimated using the high-low range (HLR) estimator.

The adequacy of VaR forecasts is assessed using standard backtesting procedures based on the empirical Violation Rate (VR) and the Dynamic Quantile (DQ) test of [Engle and Manganelli \(2004\)](#). Forecasting accuracy across competing specifications is further evaluated using the Quantile Loss (QL) function, which allows for an economically meaningful comparison and ranking of alternative VaR models.

The joint evaluation of VaR and ES forecasts relies on the class of strictly consistent scoring functions introduced by [Fissler and Ziegel \(2016\)](#), complemented by the Strict ES Regression (ESR) backtest of [Bayer and Dimitriadis \(2022\)](#), which provides a powerful diagnostic framework for detecting ES misspecification. Finally, differences in predictive performance are formally assessed using the Model Confidence Set (MCS) procedure of [Hansen et al. \(2011\)](#), which identifies the subset of models that cannot be statistically distinguished from the best-performing specification.

Overall, the empirical results reveal a heterogeneous impact of uncertainty and climate-related risk indicators on tail-risk forecasts for green and brown stocks. Transition climate risk emerges as the most informative factor for extreme risk at the 1% quantile for both asset classes, highlighting the relevance of transition-related shocks for the most severe market conditions. At the 2.5% quantile, the predictive importance shifts across assets: geopolitical risk plays a central role for green stocks, while economic policy uncertainty becomes the key driver for brown energy stocks. These findings indicate that the informational content of uncertainty indices varies not only across risk levels but also across asset classes, suggesting that different sources of uncertainty propagate into financial tail-risk through distinct channels.

The remainder of the paper is organized as follows. Section 2 reviews VaR and ES and introduces strictly consistent loss functions for their joint evaluation. Section 3 presents the modeling framework, while Section 4 discusses model estimation. Section 5 describes the data and the construction of volatility and risk indices. Section 6 reports the forecasting design and empirical results. Finally, Section 7 concludes the paper.

2. VaR, ES and Scoring Functions

Financial risk management is a fundamental component of operational frameworks within financial institutions. Among the quantitative tools available for assessing and controlling market risk, the VaR has emerged as a standard metric.

Let $\mathcal{F}_t$ denote the information set available at time t and let

$$F_t(r) = \Pr(r_t \leq r \mid \mathcal{F}_{t-1})$$

be the cumulative distribution function (CDF) of return r_t conditional on $\mathcal{F}_{t-1}$. Under the assumption that $F_t(\cdot)$ is strictly increasing and continuous on $\mathbb{R}$, the one-step-ahead α -level VaR at time t , for a given risk level $\alpha \in (0, 1)$, is formally defined as

$$Q_{t,\alpha} = F_t^{-1}(\alpha).$$

Despite its widespread adoption, VaR presents well-known shortcomings as a risk measure. In particular, it fails to capture the severity of losses beyond the α -threshold and does not satisfy the sub-additivity property, thus lacking mathematical coherence and potentially discouraging portfolio diversification. To overcome these limitations, Artzner et al. (1999) proposed the ES as a coherent alternative, quantifying the expected loss conditional on the return falling below the VaR threshold. Recent regulatory developments, particularly the Basel III Accord, have reinforced the role of ES as the primary metric for market risk measurement. The one-step-ahead α -level ES is defined as the tail conditional expectation of r_t (see Acerbi and Tasche 2002, among others)

$$ES_{t,\alpha} = E(r_t \mid r_t \leq Q_{t,\alpha}; \mathcal{F}_{t-1}).$$

To simplify notation, unless otherwise stated, we adopt the following conventions throughout the paper: $Q_{t,\alpha} \equiv Q_t$ and $ES_{t,\alpha} \equiv ES_t$.

Consistent estimation of VaR and ES requires the choice of appropriate objective functions. Several parameterizations of the pair (Q_t, ES_t) have been proposed in the literature, with parameters that can be consistently estimated by minimizing strictly consistent scoring functions. When interest focuses exclusively on VaR, a natural estimator is obtained by minimizing the quantile loss (QL) function

$$QL(r_t, Q_t; \alpha) = (\alpha - \mathbb{I}_t)(r_t - Q_t), \quad (1)$$

where $\mathbb{I}_t = \mathbb{I}(r_t < Q_t)$ denotes the indicator function. This approach admits a quasi-likelihood interpretation under an Asymmetric Laplace (AL) distribution for r_t (Koenker and Machado 1999). Building on this foundation, Taylor (2019) shows that incorporating ES_t into the scale parameter of the AL distribution yields the joint conditional density

$$p(r_t \mid \mathcal{F}_{t-1}) = \frac{\alpha - 1}{ES_t} \exp\left(\frac{(r_t - Q_t)(\alpha - \mathbb{I}(r_t < Q_t))}{\alpha ES_t}\right), \quad (2)$$

which depends on both Q_t and ES_t , enabling their simultaneous estimation.

Fissler and Ziegel (2016) characterize a broad class of scoring functions that are strictly consistent for the pair (Q_t, ES_t) . This family takes the general form

$$S_t(r_t, Q_t, ES_t) = (\mathbb{I}_t - \alpha) G_1(Q_t) - \mathbb{I}_t G_1(r_t) + G_2(ES_t) - \left(ES_t - Q_t + \frac{\mathbb{I}_t}{\alpha} (Q_t - r_t) \right) H(ES_t) + a(r_t), \quad (3)$$

where $G_1(\cdot)$ is an increasing function, $G_2(\cdot)$ is strictly increasing and strictly convex, $H(\cdot)$ satisfies $H'(x) = G_2(x)$ with $\lim_{x \rightarrow -\infty} G_2(x) = 0$, and $a(\cdot)$ is a real-valued integrable function. A prominent special case is obtained by setting $G_1(x) = 0$, $G_2(x) = -1/x$, $H(x) = -\log(-x)$ and $a = 1 - \log(1 - \alpha)$, under the assumption of zero-mean return innovations, yielding the AL log-score (Taylor 2019)

$$S_t(r_t, Q_t, ES_t) = -\log\left(\frac{\alpha - 1}{ES_t}\right) - \frac{(r_t - Q_t)(\alpha - \mathbb{I}_t)}{\alpha ES_t}, \quad (4)$$

whose negative coincides with the log-likelihood of the density in (2), thereby guaranteeing strict consistency for the joint estimation of VaR and ES.

A further specification of practical interest is the FZ0 loss function proposed by Patton et al. (2019), obtained under the assumption that both VaR and ES are strictly negative by setting $G_1(x) = 0$, $G_2(x) = -1/x$ and $a(x) = 0$ in (3)

$$FZ0_t = \frac{1}{\alpha ES_t} \mathbb{I}_t (r_t - Q_t) + \frac{Q_t}{ES_t} + \log(-ES_t) - 1. \quad (5)$$

The FZ0 loss exhibits homogeneity of degree zero, a property that enhances the power of comparative forecast evaluation tests (Diebold and Mariano 1995), as documented in volatility forecasting applications (Patton and Sheppard 2009). In what follows, the AL log-score (4) is adopted for model estimation, while the FZ0 loss (5) serves as an additional criterion for forecast comparison.

3. Modelling Framework for VaR and ES Forecasting

Taylor (2019) introduces the semi-parametric ES-CAViaR family of models, designed to jointly characterize the dynamics of VaR and ES. Building on this framework, Gerlach and Wang (2020) augment the joint VaR-ES quantile regression approach by incorporating a realized volatility measure as a proxy for tail-risk dynamics, leading to the ES-X-CAViaR-X specification

$$\begin{aligned} Q_t &= \beta_0 + \beta_1 x_{t-1} + \beta_2 Q_{t-1}, \\ w_t &= \gamma_0 + \gamma_1 x_{t-1} + \gamma_2 w_{t-1}, \\ ES_t &= Q_t - w_t, \end{aligned}$$

where x_t denotes a realized volatility measure and w_t is an additive, time-varying component linking the dynamics of Q_t and ES_t . The constraints $\gamma_0 \geq 0$, $\gamma_1 \geq 0$ and $\gamma_2 \geq 0$ are imposed to prevent the VaR and ES series from crossing.

Several contributions have extended this framework by incorporating measurement equations for realized volatility. Wang et al. (2023) introduce the Realized ES-CAViaR model, while Peiris et al. (2024) propose the more general Realized-ES-CAViaR-M specification, which accommodates multiple realized measures through their respective measurement equations. The Realized-ES-CAViaR-M is given by

$$\log(-Q_t) = \omega + \beta \log(-Q_{t-1}) + \delta_1 \epsilon_{t-1} + \delta_2 \epsilon_{t-1}^2 + \gamma' u_{t-1}, \quad (6)$$

$$w_t = \nu_0 + \nu_1 w_{t-1} + \psi' |u|_{t-1}, \quad (7)$$

$$ES_t = Q_t - w_t, \quad (8)$$

$$\log(x_{j,t}) = \zeta_j + \varphi_j \log(-Q_t) + \tau_{j,1} \epsilon_t + \tau_{j,2} \epsilon_t^2 + u_{j,t}, \quad j = 1, \dots, K, \quad (9)$$

where $\epsilon_t = r_t/Q_t$ and K denotes the number of realized measures, with $K = 1$ reducing to the log-Realized-ES-CAViaR model. Equations (6)–(9) correspond, respectively, to the quantile equation, the VaR–ES spread equation, the ES equation and the measurement equations. The log specification in (6) ensures that Q_t remains strictly negative, as required for left-tail modeling, while the constraints $\nu_0 \geq 0$, $\nu_1 \geq 0$ and $\psi \geq 0$ prevent the VaR and ES series from crossing.

To further enhance forecasting performance, additional regressors can be incorporated into the model. Following Naimoli (2023), variables with a dynamic relationship to volatility or returns are included via dedicated measurement equations. In this spirit, we extend the Realized-ES-CAViaR-M framework by introducing measurement equations for various risk indices, related to climate, geopolitical, and economic policy uncertainty.

4. Estimation of ES-CAViaR Models

Parameter estimation for the ES-CAViaR model class is performed by maximizing the AL quasi log-likelihood introduced in Section 2. The negative of the AL log-score in (4) is strictly consistent for the joint pair (Q_t, ES_t) (Fissler and Ziegel 2016), providing a coherent foundation for the simultaneous estimation of VaR and ES. Formally, the model parameters are obtained by maximizing

$$\ell(\mathbf{r}; \boldsymbol{\theta}) = \sum_{t=1}^T \left(\log\left(\frac{\alpha-1}{ES_t}\right) + \frac{(r_t - Q_t)(\alpha - \mathbb{I}(r_t \leq Q_t))}{\alpha ES_t} \right), \quad (10)$$

where $\mathbf{r} = (r_1, \dots, r_T)'$ denotes the vector of observed returns, T is the sample size and $\boldsymbol{\theta}$ collects all model parameters.

For the Realized-ES-CAViaR-M model, which incorporates measurement equations with $\mathbf{u}_t \stackrel{iid}{\sim} N(\mathbf{0}, \Sigma)$, the full quasi log-likelihood augments (10) with the Gaussian contribution from the realized measures

$$\ell(\mathbf{r}, \mathbf{x}; \boldsymbol{\theta}, \Sigma) = \ell(\mathbf{r}; \boldsymbol{\theta}) + \ell(\mathbf{x}|\mathbf{r}; \boldsymbol{\theta}, \Sigma), \quad (11)$$

where $\mathbf{x}$ represents the realized measures and Σ is the covariance matrix of $\mathbf{u}_t$. The complete objective function can be expressed as follows

$$\begin{aligned} \ell(\mathbf{r}, \mathbf{x}; \boldsymbol{\theta}, \Sigma) &= \sum_{t=1}^T \left(\log\left(\frac{\alpha-1}{ES_t}\right) + \frac{(r_t - Q_t)(\alpha - \mathbb{I}(r_t \leq Q_t))}{\alpha ES_t} \right) \\ &\quad - \frac{1}{2} \sum_{t=1}^T \left(K \log(2\pi) + \log(|\Sigma|) + \mathbf{u}_t(\boldsymbol{\theta})' \Sigma^{-1} \mathbf{u}_t(\boldsymbol{\theta}) \right). \end{aligned} \quad (12)$$

Following Hansen and Huang (2016), for any fixed $\boldsymbol{\theta}$, the Gaussian component admits a closed-form solution for Σ

$$\hat{\Sigma}(\boldsymbol{\theta}) = \frac{1}{T} \sum_{t=1}^T \mathbf{u}_t(\boldsymbol{\theta}) \mathbf{u}_t(\boldsymbol{\theta})', \quad (13)$$

so that the joint maximization problem reduces to

$$\arg \max_{\boldsymbol{\theta}} \ell(\mathbf{r}, \mathbf{x}; \boldsymbol{\theta}, \hat{\Sigma}(\boldsymbol{\theta})). \quad (14)$$

This simplification follows from

$$\sum_{t=1}^T \mathbf{u}_t(\boldsymbol{\theta})' \hat{\Sigma}(\boldsymbol{\theta})^{-1} \mathbf{u}_t(\boldsymbol{\theta}) = \text{tr} \left\{ \hat{\Sigma}(\boldsymbol{\theta})^{-1} \sum_{t=1}^T \mathbf{u}_t(\boldsymbol{\theta}) \mathbf{u}_t(\boldsymbol{\theta})' \right\} = TK, \quad (15)$$

which is invariant with respect to $\boldsymbol{\theta}$, allowing the outer optimization to be conducted over $\boldsymbol{\theta}$ alone.

5. Data Description

To assess the impact of climate, geopolitical risk and economic policy uncertainty indices on tail-risk forecasting for green and brown stocks, we rely on daily financial market information. Specifically, we use close-to-close log-returns and the HLR volatility computed from the ICLN and IXC ETFs as proxies for green and brown equity markets, respectively. The full sample period spans from January 2012 to December 2024, chosen to align with the availability of the risk indices considered. To ensure temporal consistency with financial variables, all risk measures are adjusted to exclude non-trading days.

To enhance comparability with the HLR volatility estimator, all risk indices are transformed to be non-negative and interpretable as measures of uncertainty intensity. The absolute value is applied directly to the PRI and TRI indices, which already capture short-run innovations in climate risk. For the GPRI and EPU indices, which are level variables, we compute first differences and then take absolute values in order to capture the magnitude of risk shocks. All indices are finally rescaled to match the scale of the HLR to mitigate potential computational issues.

Contrary to high-frequency data, daily high (H) and low (L) prices are widely available and can be effectively used to estimate volatility. [Parkinson \(1980\)](#) proposed the High-Low Range as an approximately unbiased variance estimator, scaled by the factor $4 \log(2)$, defined as

$$HLR_t = \frac{(\log H_t - \log L_t)^2}{4 \log 2},$$

where H_t and L_t denote the intraday high and low prices for day t , respectively. Through theoretical derivation and simulation, [Parkinson](#) showed that the HLR is a more efficient estimator than the conventional squared return. Empirical evidence further confirms that the HLR performs well with real-world data ([Chou et al. 2010](#)) and outperforms the standard GARCH(1,1) model in both in-sample fit and out-of-sample forecasting ([Molnár 2016](#)).

Our empirical analysis incorporates climate-related risks using the PRI and the TRI¹ proposed by [Bua et al. \(2024\)](#). Both indicators are constructed through a text-based methodology based on the textual analysis of European news sourced from Reuters News, quantifying the frequency of articles discussing climate-related topics. The PRI captures media coverage related to physical climate risks, including extreme weather events, natural disasters and long-term environmental degradation, thus reflecting market perceptions of the direct impacts of climate change. The TRI instead measures news coverage associated with transition risks, such as regulatory changes, decarbonization policies, technological shifts and broader adjustments linked to the transition toward a low-carbon economy. Both indices provide daily measures of climate-risk salience in the public information set, making them particularly suitable for applications involving high-frequency financial data.

To investigate the role of GPR in tail-risk forecasting, we employ the GPRD index² of [Caldara and Iacoviello \(2022\)](#) as a proxy for geopolitical uncertainty. The GPRD is a news-based measure that quantifies the intensity of geopolitical tensions by tracking the share of articles in major international newspapers reporting on events such as wars, terrorist attacks, military conflicts and diplomatic disputes. Higher values correspond to periods of elevated geopolitical risk. The daily GPRI captures fluctuations in geopolitical conditions, making it particularly suitable for analyses involving financial variables.

To examine the role of economic policy uncertainty in tail-risk forecasting, we employ the daily EPU index³ developed by [Baker et al. \(2016\)](#). The EPU index is a news-based measure constructed by quantifying the frequency of articles in major US newspapers that simultaneously contain terms related to economic conditions, uncertainty and policy-relevant topics such as legislation, regulation, fiscal and monetary policy. By construction, higher values correspond to periods of heightened uncertainty

¹ The data were retrieved from the authors' public repository <https://sites.google.com/view/lavinia-rognone-library>
² The dataset used in this study was downloaded from <https://www.matteoiacoviello.com/gpr.htm>
³ The dataset used in this study was downloaded from <https://www.policyuncertainty.com>

regarding government actions and their potential economic consequences. Accordingly, the daily EPU index captures short-run fluctuations in the macroeconomic policy environment, which may affect green and brown assets differently given their heterogeneous exposure to regulatory interventions, fiscal incentives and environmental legislation.

Table 1 reports summary statistics for the daily log-returns of brown (IXC) and green (ICLN) stocks over the period January 2012 to December 2024. Both series exhibit nearly identical mean returns and comparable unconditional volatility levels, with standard deviations of 1.601 and 1.640 for brown and green stocks, respectively. However, the two series display markedly different tail behavior. Brown stocks exhibit substantially higher kurtosis (25.138 versus 9.243) and more pronounced negative skewness (-1.093 versus -0.350), indicating a greater propensity for extreme negative returns. The minimum daily return for brown stocks (-21.631%) is considerably more extreme than that of green stocks (-13.709%), while the maximum return is also larger (15.970% versus 10.800%). These stylized facts confirm the presence of fat tails and asymmetries in return distributions typical of financial time series, with brown energy stocks exhibiting more pronounced tail behavior than green stocks. This heterogeneity in tail-risk characteristics motivates the need for asset-specific VaR and ES forecasting models.

Table 1. Descriptive statistics for daily log-returns (in percentage) of brown stocks (iShares Global Energy ETF, IXC) and green stocks (iShares Global Clean Energy ETF, ICLN). Sample period: January 2012 – December 2024. **SD**, denotes standard deviation; **Skew**, denotes skewness and **Kurt**, denotes kurtosis.

	Mean	SD	Median	Min	Max	Skew	Kurt
IXC returns	0.016	1.601	0.060	-21.631	15.970	-1.093	25.138
ICLN returns	0.016	1.640	0.000	-13.709	10.800	-0.350	9.243

Figure 1 displays the time series of daily log-returns (top panels) and HLR volatility estimates (bottom panels) for brown (left) and green (right) energy stocks over January 2012 to December 2024. Both return series exhibit volatility clustering, with pronounced spikes during periods of market stress, most notably during the COVID-19 pandemic in early 2020, Russia’s invasion of Ukraine in early 2022 and the October 2023 geopolitical tensions. The volatility patterns reveal that both asset classes experienced elevated risk during these episodes, though the magnitude and persistence of volatility spikes differ across green and brown stocks. Brown stocks exhibit particularly large volatility spikes during energy-market-specific events (2020 oil price collapse, 2022 energy supply disruptions), reflecting their direct exposure to fossil fuel price dynamics and geopolitical tensions affecting oil and gas supplies. Green stocks, by contrast, show more persistent elevated volatility during periods characterized by regulatory uncertainty and policy shifts, such as the 2016-2017 period of policy reversals in renewable energy support programs. Consequently, the volatility patterns suggest that tail-risk dynamics may be driven by different factors across the two asset classes, motivating our investigation of whether climate risk, geopolitical risk and policy uncertainty indices provide differential predictive content for VaR and ES forecasting in green versus brown stocks.

Figure 2 displays the transformed risk indices, normalized to the [0,1] interval for visual comparison. The four panels show substantial time variation in all risk dimensions, with several notable spikes corresponding to major events. The TRI (top panel) exhibits pronounced increases during key climate policy developments, including the Paris Agreement (2015), various COP conferences and the 2021-2022 acceleration of net-zero commitments. The PRI (second panel) displays spikes associated with extreme weather events, including major hurricanes, wildfires and flooding episodes. The EPU (third panel) shows increases during the 2016 US election, the COVID-19 pandemic and various episodes of fiscal and monetary policy uncertainty. The GPRD (bottom panel) captures sharp elevations during the US-China trade war, Russia’s invasion of Ukraine and the Israel-Hamas conflict. The heterogeneous temporal patterns across these indices suggest they may contain distinct information relevant for tail-risk forecasting.

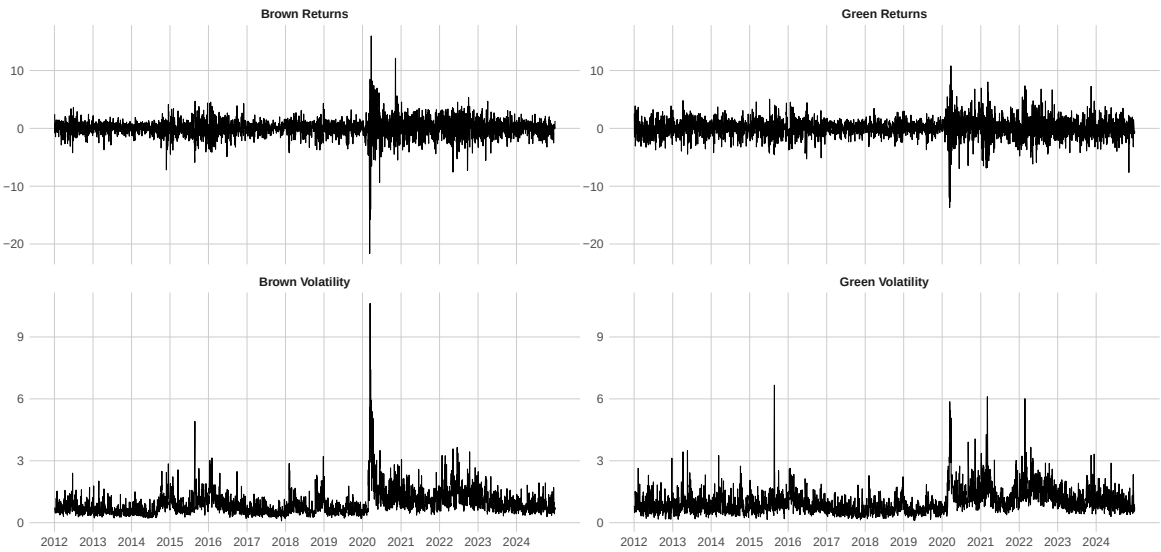


Figure 1. Daily log-returns and high-low range volatility over the period January 2012 – December 2024. Left panels: iShares Global Energy ETF (IXC, brown stocks). Right panels: iShares Global Clean Energy ETF (ICLN, green stocks). Top panels show returns, bottom panels show volatility.

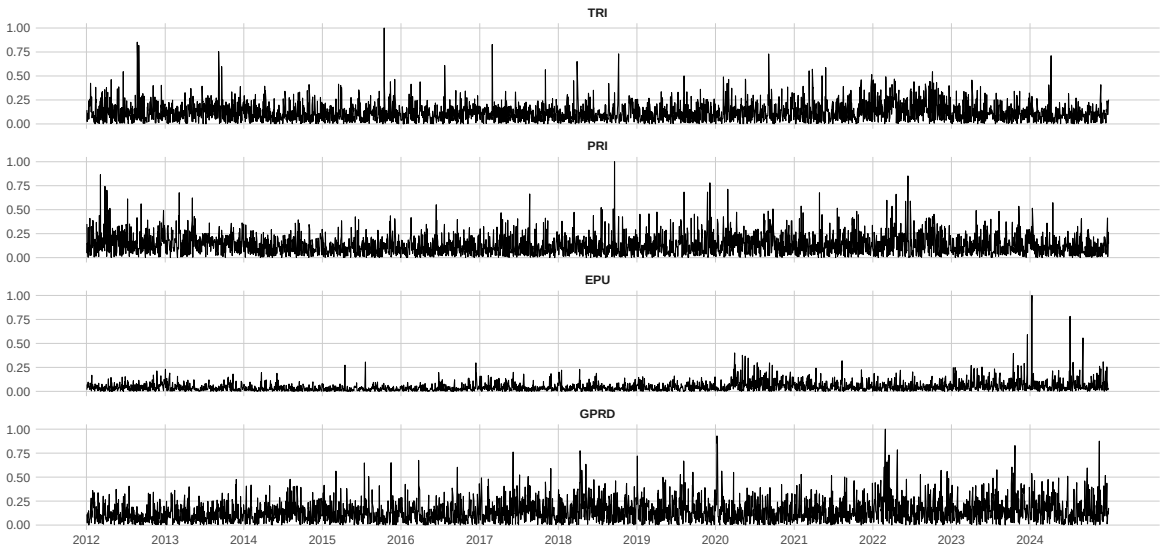


Figure 2. Transformed risk indices over the sample period January 2012 – December 2024. First panel: absolute values of the Transition Risk Index (TRI). Second panel: absolute values of the Physical Risk Index (PRI). Third panel: absolute first differences of the Economic Policy Uncertainty Index (EPU). Fourth panel: absolute first differences of the daily Geopolitical Risk (GPRD) Index. For enhanced visual comparison, all series displayed here are normalized to the [0,1] interval. Model estimation uses the series rescaled to the high-low range volatility scale.

6. Forecasting Results

6.1. Forecasting Design and Evaluation Strategy

The empirical analysis employs a recursive estimation strategy with a six-year rolling window, balancing parameter stability with adaptability to structural changes in tail-risk dynamics. Starting with an initial window from January 2012 to December 2017, parameters are re-estimated daily as the window advances one day at a time. This recursive procedure produces a sequence of one-step-ahead VaR and ES forecasts for the out-of-sample period from January 2018 to December 2024.

The out-of-sample period encompasses severe financial dislocations, including the December 2018 equity selloff triggered by trade tensions and monetary tightening, the February 2022 market disruption

following Russia's invasion of Ukraine, the March 2023 banking turmoil involving Silicon Valley Bank and Credit Suisse and elevated volatility in 2024 driven by persistent inflation and monetary policy uncertainty.

Geopolitical shocks during the sample period include the escalation of the US-China trade war in mid-2018, the January 2020 crisis between the US and Iran, the August 2021 withdrawal from Afghanistan, Russia's February 2022 invasion of Ukraine, the October 2023 Hamas-Israel conflict and heightened tensions in 2024 involving Red Sea shipping disruptions and increased strategic competition in the Taiwan Strait.

Physical climate events include the November 2018 Camp Fire, the 2019–2020 Australian bushfires, the February 2021 Texas blackout, Hurricane Ian in September 2022, the 2023 Canadian wildfires and recurrent European heatwaves and droughts between 2022 and 2024. Transition-related developments encompass the October 2018 IPCC 1.5°C report, the December 2019 EU Green Deal, the August 2022 US Inflation Reduction Act, the December 2023 COP28 fossil fuel transition commitments and COP29 climate finance negotiations in November 2024.

Economic policy uncertainty surged during the 2018-2019 US government shutdown, the pandemic-era fiscal and monetary interventions of 2020-2021, the 2021-2022 inflation spike and Federal Reserve tightening cycle, debates over cryptocurrency regulation and the 2024 presidential election cycle, which influenced expectations regarding energy, climate and trade policies.

This sample period provides a suitable setting to assess whether variations in climate, geopolitical and economic policy uncertainty indices improve tail-risk forecasting beyond standard volatility measures and whether their predictive power differs between green and brown stocks across risk levels. Accordingly, VaR and ES forecasts are generated at the 1% and 2.5% quantiles.

VaR forecast adequacy is evaluated through a comprehensive backtesting procedure. The empirical VR, computed as the fraction of VaR violations over the out-of-sample period, offers a simple measure of unconditional calibration. To assess whether violations occur at the expected frequency and exhibit serial independence, we implement the DQ test of [Engle and Manganelli \(2004\)](#), which combines the unconditional coverage test of [Kupiec \(1995\)](#) and the conditional coverage test of [Christoffersen \(1998\)](#) within a regression-based specification. Model ranking based on VaR performance is performed using the quantile loss (QL) function, which allows for a statistical comparison of predictive accuracy across competing specifications.

For the joint evaluation of tail-risk forecasts, we adopt two complementary approaches. First, we employ the class of Fissler–Ziegel (FZ) loss functions, which are strictly consistent for the joint (VaR, ES) pair and therefore suitable for comparative forecast evaluation. In particular, we implement the FZ0 loss function, which exhibits the desirable property of homogeneity of degree zero, shown by [Patton and Sheppard \(2009\)](#) to enhance the power of forecast comparison tests. Second, we apply the Strict Regression-Based Expected Shortfall backtest (BD) proposed by [Bayer and Dimitriadis \(2022\)](#), which provides a powerful diagnostic for detecting ES misspecification.

Statistical significance of performance differences is assessed using the MCS methodology of [Hansen et al. \(2011\)](#), which identifies the set of superior models (SSM) that remain statistically indistinguishable from the best-performing specification at a given confidence level. MCS results are reported at the conventional 25% significance level for both QL and FZ0 loss functions.

6.2. Forecast Evaluation

The forecast evaluation encompasses sixteen Realized-ES-CAViaR model specifications, ranging from the baseline model using only HLR volatility to the full specification incorporating all four risk indices (HLR, PRI, TRI, EPU, GPRD).

Table 2 reports out-of-sample forecasting results for green stocks (ICLN) at the 1% risk level. All specifications pass backtesting procedures, with DQ p -values well above the conventional 5% significance level and empirical VRs clustering around the nominal 1% level. In addition, the BD test confirms ES adequacy, with p -values exceeding 53%.

Table 2. Out-of-sample forecasting performance for green stocks (iShares Global Clean Energy ETF, ICLN) at the $\alpha = 1\%$ risk level. The table reports results for 16 Realized-ES-CAViaR model specifications over the period January 2018 – December 2024. VR denotes the empirical Violation Rate (in percentage). DQ reports p -values (in percentage) for the Dynamic Quantile test of [Engle and Manganelli \(2004\)](#). BD reports p -values (in percentage) for the Strict regression-based Expected Shortfall backtest of [Bayer and Dimitriadis \(2022\)](#). QL and FZ0 represent the Quantile Loss and FZ0 Loss functions, respectively, with lower values indicating superior forecasting performance. Shaded cells indicate models included in the 75% Model Confidence Set. Bold values denote the best-performing specification.

Measures	VR	DQ	QL	FZ0	BD
(HLR)	0.795	88.362	100.987	2991.382	64.138
(HLR, EPU)	0.852	82.877	101.413	3016.452	61.839
(HLR, GPRD)	0.852	94.060	102.112	2999.506	54.935
(HLR, PRI)	0.909	97.602	101.434	2999.800	60.422
(HLR, TRI)	0.625	72.426	100.072	2971.836	69.985
(HLR, EPU, GPRD)	0.682	73.211	102.186	3010.880	59.887
(HLR, PRI, EPU)	0.852	43.874	103.748	3018.375	64.198
(HLR, PRI, GPRD)	0.852	45.765	103.742	3015.617	59.538
(HLR, PRI, TRI)	0.682	85.102	100.652	2972.425	84.066
(HLR, TRI, EPU)	0.625	70.937	100.175	2974.834	76.334
(HLR, TRI, GPRD)	0.739	95.276	100.989	2966.790	75.618
(HLR, PRI, EPU, GPRD)	0.795	93.418	102.486	3013.471	64.176
(HLR, PRI, TRI, EPU)	0.795	29.635	104.497	3030.253	59.191
(HLR, PRI, TRI, GPRD)	0.852	43.493	104.428	3021.736	53.655
(HLR, TRI, EPU, GPRD)	0.795	44.055	101.535	2985.545	63.948
(HLR, PRI, TRI, EPU, GPRD)	0.852	47.720	104.252	3023.658	55.916

Regarding VaR forecasting performance, the QL-based MCS includes only two specifications: (HLR, TRI) achieving the best performance minimizing the QL and (HLR, TRI, EPU). This extreme selectivity indicates that TRI is particularly informative for VaR forecasting of green stocks in extreme tails. In particular, the baseline (HLR) specification is excluded from 75% MCS, highlighting the critical role of transition climate risk information in ensuring accurate VaR forecasts.

According to the joint performance criterion for VaR-ES, the FZ0-based MCS expands to nine models, including the benchmark and specifications with GPRD and PRI. The best ES model is (HLR, TRI, GPRD) with the lowest FZ0 value. This MCS expansion from QL to FZ0 indicates that ES forecasting benefits from a broader set of risk factors than VaR. It is worth noting that among the eight MCS FZ0 models integrated with risk indices, five contain TRI, thereby confirming its central role. In contrast, GPRD and PRI add value specifically for the ES metric.

Table 3 presents results at the 2.5% α -level for ICLN. At the less extreme quantile, coverage remains well calibrated across all models, with VR values tightly clustered around the nominal 2.5% level and very high DQ p -values, confirming adequate VaR dynamic specification. The BD test results similarly indicate robust ES performance, with all p -values exceeding 60%.

From a loss-function perspective, specifications including GPRD achieve the best performance according to both QL and FZ0. In particular, relying on QL, the 75% MCS includes only 2 models, namely (HLR, GPRD) showing best performance and (HLR, EPU, GPRD). Interestingly, GPRD replaces TRI as the dominant factor at the 2.5% quantile. This suggests that geopolitical risk is a more informative factor in explaining moderate tail-risk for green assets. Finally, the benchmark (HLR) is excluded from the SSM, though it achieves competitive performance.

The FZ0 MCS includes all model specifications, indicating statistical homogeneity in joint VaR-ES forecasts at the 2.5% risk level. Consistent with the QL results, the best-performing model is the (HLR, GPRD) specification. However, the differences across models are relatively small, suggesting that the baseline HLR model already captures most of the relevant tail-risk dynamics at this quantile. The

universal inclusion of all models in the MCS further implies that the addition of external risk indices provides limited incremental value for ES forecasting at the 2.5% level.

Table 3. Out-of-sample forecasting performance for green stocks (iShares Global Clean Energy ETF, ICLN) at the $\alpha = 2.5\%$ risk level. The table reports results for 16 Realized-ES-CAViaR model specifications over the period January 2018 – December 2024. VR denotes the empirical Violation Rate (in percentage). DQ reports p -values (in percentage) for the Dynamic Quantile test of [Engle and Manganelli \(2004\)](#). BD reports p -values (in percentage) for the Strict regression-based Expected Shortfall backtest of [Bayer and Dimitriadis \(2022\)](#). QL and FZ0 represent the Quantile Loss and FZ0 Loss functions, respectively, with lower values indicating superior forecasting performance. Shaded cells indicate models included in the 75% Model Confidence Set. Bold values denote the best-performing specification.

Measures	VR	DQ	QL	FZ0	BD
(HLR)	2.329	98.629	198.868	2533.103	69.397
(HLR, EPU)	2.329	97.935	199.789	2541.516	73.788
(HLR, GPRD)	2.329	98.700	197.725	2521.343	63.091
(HLR, PRI)	2.329	99.959	200.207	2546.062	68.589
(HLR, TRI)	2.273	97.266	199.955	2534.497	71.749
(HLR, EPU, GPRD)	2.329	98.466	198.440	2527.050	69.742
(HLR, PRI, EPU)	2.386	98.819	200.736	2543.834	73.485
(HLR, PRI, GPRD)	2.329	99.977	199.237	2534.894	62.234
(HLR, PRI, TRI)	2.329	99.949	200.614	2538.218	72.971
(HLR, TRI, EPU)	2.329	98.298	200.073	2541.018	78.055
(HLR, TRI, GPRD)	2.216	99.777	199.266	2527.383	65.557
(HLR, PRI, EPU, GPRD)	2.329	98.177	199.389	2529.534	72.820
(HLR, PRI, TRI, EPU)	2.273	99.804	201.832	2543.776	67.267
(HLR, PRI, TRI, GPRD)	2.273	99.804	200.330	2533.257	72.321
(HLR, TRI, EPU, GPRD)	2.273	97.295	199.787	2533.915	75.656
(HLR, PRI, TRI, EPU, GPRD)	2.329	99.933	201.016	2535.250	75.397

Table 4 reports the out-of-sample forecasting results for brown stocks (IXC) at the 1% risk level. In contrast to green stocks, models for brown stocks face greater specification challenges at the 1% quantile. Although the VRs are reasonably close to the nominal 1% level, several specifications exhibit DQ test p -values below 5%, including the benchmark (HLR) model, indicating residual dynamic misspecification when only limited information is used. Notably, the specifications that include TRI, namely (HLR, TRI), (HLR, PRI, TRI), (HLR, TRI, GPRD) and (HLR, PRI, TRI, GPRD), are the only ones that pass the DQ test. This suggests that transition risk information improves the forecasting accuracy of VaR models also for brown stocks. By contrast, the Strict ESR backtesting results are uniformly strong, with all models passing the test, indicating well-calibrated ES forecasts across specifications.

Performance improvements are also evident in terms of QL and FZ0 when climate-related variables are incorporated into the modeling framework. In particular, the (HLR, TRI) specification achieves the lowest QL, while the model combining PRI and TRI provides the best FZ0 value.

Regarding the QL-based MCS, twelve specifications are included, a substantially larger set than for green stocks, where only two models entered the MCS at the 1% risk-level. This broader inclusion indicates a more homogeneous VaR forecasting performance across model specifications for brown stocks. Nevertheless, consistent with the green case, the best-performing specification is (HLR, TRI). Interestingly, several multi-index models that do not include TRI also enter the MCS, such as (HLR, EPU), (HLR, PRI) and (HLR, GPRD). At the same time, the baseline model also enters the MCS, suggesting that HLR-based volatility alone provides reasonably accurate VaR forecasts for brown stocks. This contrasts with the results for green stocks, where the baseline specification was excluded from the MCS. The four specifications excluded from the QL-based MCS are all relatively complex models incorporating four or five risk factors: (HLR, PRI, EPU, GPRD), (HLR, PRI, TRI, EPU), (HLR, TRI, EPU, GPRD) and (HLR, PRI, TRI, EPU, GPRD).

Table 4. Out-of-sample forecasting performance for brown stocks (iShares Global Energy ETF, IXC) at the $\alpha = 1\%$ risk level. The table reports results for 16 Realized-ES-CAViaR model specifications over the period January 2018 – December 2024. VR denotes the empirical Violation Rate (in percentage). DQ reports p -values (in percentage) for the Dynamic Quantile test of [Engle and Manganelli \(2004\)](#). BD reports p -values (in percentage) for the Strict regression-based Expected Shortfall backtest of [Bayer and Dimitriadis \(2022\)](#). QL and FZ0 represent the Quantile Loss and FZ0 Loss functions, respectively, with lower values indicating superior forecasting performance. Shaded cells indicate models included in the 75% Model Confidence Set. Bold values denote the best-performing specification.

Measures	VR	DQ	QL	FZ0	BD
(HLR)	1.080	3.511	106.760	3001.448	78.697
(HLR, EPU)	1.193	4.471	106.567	3013.494	75.323
(HLR, GPRD)	1.023	3.836	107.611	2997.866	72.331
(HLR, PRI)	1.136	4.482	106.519	2996.003	86.512
(HLR, TRI)	1.023	57.220	105.814	2938.655	88.851
(HLR, EPU, GPRD)	1.136	4.270	107.831	3034.177	74.610
(HLR, PRI, EPU)	1.364	2.874	106.194	2982.199	74.780
(HLR, PRI, GPRD)	1.136	4.878	107.711	2995.935	67.761
(HLR, PRI, TRI)	1.023	49.117	106.205	2933.334	84.836
(HLR, TRI, EPU)	1.250	5.014	107.042	3014.323	83.437
(HLR, TRI, GPRD)	0.909	46.436	106.623	2943.938	85.961
(HLR, PRI, EPU, GPRD)	1.307	2.695	108.157	3035.360	71.562
(HLR, PRI, TRI, EPU)	1.307	4.787	108.384	3020.838	82.384
(HLR, PRI, TRI, GPRD)	1.023	47.361	107.323	2956.161	79.998
(HLR, TRI, EPU, GPRD)	1.250	4.057	108.398	3032.160	74.455
(HLR, PRI, TRI, EPU, GPRD)	1.364	1.771	108.348	3023.486	79.608

The FZ0-based MCS includes seven specifications, a substantial reduction compared with the twelve-model QL MCS, indicating that ES forecasting is more challenging than VaR prediction for brown stocks at the 1% risk-level. Notably, the baseline (HLR) model is excluded from the FZ0 MCS, despite being included in the QL MCS. This indicates that volatility alone is adequate for VaR forecasting but less effective in capturing ES dynamics. In contrast, external risk indices, particularly PRI and TRI, provide valuable information for modeling extreme losses in brown stock markets. The best-performing specification in terms of FZ0 is (HLR, PRI, TRI), achieving a 2.3% improvement over the benchmark (HLR), the largest gain observed across all model settings. This result highlights the importance of jointly accounting for physical and transition climate risks when characterizing the tail distribution of losses in brown markets. Among the seven models included in the 75% MCS, six incorporate either PRI or TRI (or both), reinforcing the relevance of climate-risk indicators for accurate joint VaR–ES forecasting. Overall, TRI-augmented models are consistently retained in the MCS, underscoring the importance of transition risk in capturing extreme risk dynamics in brown assets, which are inherently more exposed to policy, regulatory and technological shifts associated with the low-carbon transition.

Table 5 presents the forecasting results for brown stocks at the 2.5% risk level. Although VRs are slightly above the nominal level in several cases, VaR coverage remains substantially adequate but less uniform than for green stocks at the 2.5% quantile. DQ test p -values indicate that VaR models for brown stocks face greater specification challenges than those observed for green stocks at this quantile, possibly reflecting the more complex risk profile of fossil fuel companies exposed to multiple sources of tail-risk, including physical climate events, geopolitical supply shocks, policy uncertainty and technological disruption. Finally, the BD test results indicate no evidence of ES misspecification.

Table 5. Out-of-sample forecasting performance for brown stocks (iShares Global Energy ETF, IXC) at the $\alpha = 2.5\%$ risk level. The table reports results for 16 Realized-ES-CAViaR model specifications over the period January 2018 – December 2024. VR denotes the empirical Violation Rate (in percentage). DQ reports p -values (in percentage) for the Dynamic Quantile test of [Engle and Manganelli \(2004\)](#). BD reports p -values (in percentage) for the Strict regression-based Expected Shortfall backtest of [Bayer and Dimitriadis \(2022\)](#). QL and FZ0 represent the Quantile Loss and FZ0 Loss functions, respectively, with lower values indicating superior forecasting performance. Shaded cells indicate models included in the 75% Model Confidence Set. Bold values denote the best-performing specification.

Measures	VR	DQ	QL	FZ0	BD
(HLR)	2.671	28.194	204.112	2518.669	85.766
(HLR, EPU)	2.954	15.027	203.405	2523.388	64.204
(HLR, GPRD)	2.727	29.225	204.170	2523.816	76.345
(HLR, PRI)	2.671	28.351	204.817	2521.658	78.624
(HLR, TRI)	2.671	25.603	206.228	2530.689	69.361
(HLR, EPU, GPRD)	2.898	11.619	203.060	2519.820	66.353
(HLR, PRI, EPU)	2.841	24.093	203.892	2526.233	64.798
(HLR, PRI, GPRD)	2.727	29.295	204.902	2523.370	77.401
(HLR, PRI, TRI)	2.671	4.809	206.494	2535.490	67.509
(HLR, TRI, EPU)	2.784	20.031	204.662	2521.516	61.852
(HLR, TRI, GPRD)	2.671	25.684	206.177	2529.926	68.871
(HLR, PRI, EPU, GPRD)	2.841	22.518	203.390	2516.241	72.402
(HLR, PRI, TRI, EPU)	2.727	11.108	204.709	2520.919	59.620
(HLR, PRI, TRI, GPRD)	2.614	26.401	205.970	2527.152	64.272
(HLR, TRI, EPU, GPRD)	2.727	22.243	203.928	2515.459	64.368
(HLR, PRI, TRI, EPU, GPRD)	2.671	24.140	204.369	2521.765	55.299

Regarding predictive accuracy, models combining EPU and GPRD perform best. The (HLR, EPU, GPRD) specification minimizes QL, while the model including TRI, EPU and GPRD achieves the lowest FZ0.

The QL-based MCS includes four specifications, namely (HLR, EPU), (HLR, EPU, GPRD), (HLR, PRI, EPU, GPRD) and (HLR, TRI, EPU, GPRD). A key feature is the prominence of EPU, which appears in all specifications entering 75% MCS, indicating that economic policy uncertainty plays a central role in VaR forecasting for brown stocks at the 2.5% level. This contrasts with green stocks, where EPU plays a more limited role and with brown stocks at the 1% level, where TRI drives QL minimization. GPRD is also highly relevant, appearing in three of the four superior specifications, consistent with the exposure of brown stocks to geopolitical risks affecting energy supply chains and international energy markets. By contrast, climate risk indices play a more limited role at this quantile: TRI and PRI appear in only one specification each, suggesting that they add limited incremental information beyond policy uncertainty and geopolitical risk. Finally, the baseline (HLR) is excluded from the QL MCS, indicating that external risk indicators are necessary for effective VaR forecasting at the 2.5% risk-level.

The FZ0-based MCS includes all model specifications, mirroring the pattern observed for green stocks at the 2.5% quantile. Although (HLR, TRI, EPU, GPRD) achieves the lowest FZ0 value, the inclusion of all models indicates a high degree of statistical homogeneity in joint VaR–ES forecasting performance at this risk level. The presence of numerous multi-factor specifications in the MCS suggests that moderate tail-risk for brown assets reflects the influence of several uncertainty channels rather than a single dominant driver.

In summary, the results reveal a heterogeneous pattern of predictive gains that varies systematically across asset classes and quantile levels. For both green and brown stocks, transition climate risk emerges as the dominant predictor at the 1% level: it is the only factor entering the QL-based MCS for green assets and the only one ensuring adequate dynamic VaR specification for brown stocks. For brown markets, the joint inclusion of physical and transition climate risks provides the largest improve-

ment in joint VaR–ES forecasting performance across all settings. At the 2.5% quantile, the dominant drivers change. Geopolitical risk becomes most relevant for green assets, whereas economic policy uncertainty plays the leading role for brown stocks, reflecting their different exposure to regulatory interventions and disruptions in energy supply.

Finally, when using the QL to rank VaR forecasts, volatility-only benchmarks are generally excluded from the SSM, while parsimonious two- or three-factor specifications consistently outperform more complex multi-index models. On the other hand, using the FZ0 to evaluate VaR and ES forecasts can lead to more uncertain rankings. However, models that include information on other risk factors often perform better than volatility-only benchmarks.

7. Concluding Remarks

This paper examines whether climate, geopolitical and economic policy uncertainty indices improve VaR and ES forecasts for green and brown stocks, using the iShares Global Clean Energy ETF (ICLN) and the iShares Global Energy ETF (IXC) as representative proxies for the two asset classes.

Extending the Realized-ES-CAViaR framework, we incorporate four external risk indicators, namely physical and transition climate risk, geopolitical risk, and economic policy uncertainty, alongside a high–low range volatility estimator and evaluate sixteen model specifications at the 1% and 2.5% risk levels. The risk indices are transformed to capture the magnitude of uncertainty shocks and rescaled to ensure comparability with the volatility measure. Forecast adequacy and relative performance are assessed using VaR and ES backtesting procedures, strictly consistent scoring rules, and the MCS methodology.

Our empirical analysis over the 2018–2024 out-of-sample period yields several interesting findings. First, external risk indices lead to statistically significant and economically meaningful improvements over volatility-only benchmarks in most settings. This finding suggests that volatility measures alone do not fully capture the tail-risk dynamics of energy assets during periods of elevated macro-financial uncertainty. Second, transition climate risk emerges as the primary driver of extreme tail-risk at the 1% level for both asset classes. It is the only factor ensuring adequate dynamic VaR specification for brown stocks and the only external risk index whose standalone inclusion is sufficient to enter the QL-based MCS for green stocks. Specifications incorporating TRI achieve the lowest QL and FZ0 values for both green and brown assets at this risk level, confirming its dominant role in capturing extreme loss dynamics. Moreover, the joint inclusion of physical and transition climate risks produces the largest improvement in joint VaR–ES performance across all settings, highlighting their complementarity in modeling extreme losses in energy markets. Third, at the 2.5% quantile the dominant drivers shift: geopolitical risk becomes the most relevant factor for green assets, while economic policy uncertainty emerges as the key driver for brown stocks, reflecting their differential exposure to geopolitical tensions, regulatory interventions and energy supply disruptions. Fourth, adding more risk factors does not necessarily translate into better forecasts. Parsimonious two- or three-factor specifications systematically outperform more complex multi-index models, underscoring the importance of targeted and parsimonious model design.

These findings carry important implications along several dimensions. For risk managers and portfolio allocators, the results suggest that different sources of uncertainty should be monitored depending on whether portfolios are exposed to green or brown assets and whether the focus is on extreme or moderate tail events. For regulators, the evidence that volatility-only models may be dynamically misspecified highlights the importance of incorporating uncertainty measures into internal risk assessment frameworks. More broadly, the findings contribute to the growing literature on climate-related financial risk by showing that the informational content of uncertainty indices is both quantile- and asset-specific, a dimension that conventional volatility measures alone fail to capture.

Future research could extend the framework to individual stocks to explore heterogeneity within green and brown portfolios or apply it to other asset classes with differential exposure to climate-related risks. In addition, alternative volatility measures and text-based climate risk proxies represent promising avenues for further improving tail-risk forecasting performance.

Author Contributions: Conceptualization, Antonio Naimoli and Giuseppe Storti; Methodology, Antonio Naimoli and Giuseppe Storti; Software, Antonio Naimoli; Validation, Antonio Naimoli; Formal analysis, Antonio Naimoli and Giuseppe Storti; Investigation, Antonio Naimoli and Giuseppe Storti; Writing – original draft, Antonio Naimoli; Writing – review and editing, Antonio Naimoli and Giuseppe Storti; Supervision, Giuseppe Storti. All authors have read and agreed to the published version of the manuscript.

Funding: The authors acknowledge financial support under the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 104 published on 2.2.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union – NextGenerationEU– Project Title: Methodological and computational issues in large-scale time series models for economics and finance (ID: 20223725WE) – CUP D53D 2300610 0006 - Grant Assignment Decree No. n. 967 of 30/06/2023.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Acerbi, Carlo and Dirk Tasche. 2002. Expected shortfall: a natural coherent alternative to value at risk. *Economic notes* 31(2), 379–388.
- Ardia, David, Keven Bluteau, Kris Boudt, and Koen Inghelbrecht. 2023. Climate change concerns and the performance of green vs. brown stocks. *Management Science* 69(12), 7607–7632.
- Artzner, Philippe, Freddy Delbaen, Jean-Marc Eber, and David Heath. 1999. Coherent measures of risk. *Mathematical finance* 9(3), 203–228.
- Baker, Scott R, Nicholas Bloom, and Steven J Davis. 2016. Measuring economic policy uncertainty. *The quarterly journal of economics* 131(4), 1593–1636.
- Basel Committee on Banking Supervision. 2017. Basel iii: Finalising post-crisis reforms. Technical report, Bank for International Settlements, Basel, Switzerland.
- Bayer, Sebastian and Timo Dimitriadis. 2022. Regression-based expected shortfall backtesting. *Journal of Financial Econometrics* 20(3), 437–471.
- Bolton, Patrick and Marcin Kacperczyk. 2021. Do investors care about carbon risk? *Journal of financial economics* 142(2), 517–549.
- Bouri, Elie, Najaf Iqbal, and Tony Klein. 2022. Climate policy uncertainty and the price dynamics of green and brown energy stocks. *Finance Research Letters* 47, 102740.
- Bouri, Elie, Lavinia Rognone, Amin Sokhanvar, and Zhenkun Wang. 2023. From climate risk to the returns and volatility of energy assets and green bonds: A predictability analysis under various conditions. *Technological Forecasting and Social Change* 194, 122682.
- Bua, Giovanna, Daniel Kapp, Federico Ramella, and Lavinia Rognone. 2024. Transition versus physical climate risk pricing in european financial markets: A text-based approach. *The European Journal of Finance* 30(17), 2076–2110.
- Caldara, Dario and Matteo Iacoviello. 2022. Measuring geopolitical risk. *American economic review* 112(4), 1194–1225.
- Campiglio, Emanuele, Louis Daumas, Pierre Monnin, and Adrian von Jagow. 2023. Climate-related risks in financial assets. *Journal of Economic Surveys* 37(3), 950–992. <https://doi.org/https://doi.org/10.1111/joes.12525>.
- Chen, Zhenxi, Donald Lien, and Yaheng Lin. 2021. Sentiment: The bridge between financial markets and macroeconomy. *Journal of Economic Behavior & Organization* 188, 1177–1190.
- Chou, Ray Yeutien, Hengchih Chou, and Nathan Liu. 2010. Range volatility models and their applications in finance. In *Handbook of quantitative finance and risk management*, pp. 1273–1281. Springer.
- Christoffersen, Peter F. 1998. Evaluating interval forecasts. *International economic review*, 841–862.
- De Luca, Giovanni, Belinda Laura Del Gaudio, and Anna Pia Di Iorio. 2025. Geopolitical risk and financial stress. *The North American Journal of Economics and Finance*, 102510.
- Diebold, Francis X. and Roberto S. Mariano. 1995. Comparing predictive accuracy. *Journal of Business and Economic Statistics* 13(3), 253 – 263. Cited by: 4964, <https://doi.org/10.1080/07350015.1995.10524599>.
- Engle, Robert F and Simone Manganelli. 2004. Caviar: Conditional autoregressive value at risk by regression quantiles. *Journal of business & economic statistics* 22(4), 367–381.

- Evrin Mandaci, Pinar, Efe C. Cagli, Dilvin Taşkin, and Birce Tedik Kocakaya. 2025. Quantile-on-quantile connectedness of uncertainty with fossil and green energy markets. *Renewable Energy* 249, 123235. <https://doi.org/https://doi.org/10.1016/j.renene.2025.123235>.
- Fissler, Tobias and Johanna F. Ziegel. 2016. Higher order elicibility and osband's principle. *The Annals of Statistics* 44(4), 1680 – 1707. <https://doi.org/10.1214/16-AOS1439>.
- Gerlach, Richard and Chao Wang. 2020. Semi-parametric dynamic asymmetric laplace models for tail risk forecasting, incorporating realized measures. *International Journal of Forecasting* 36(2), 489–506.
- Hansen, Peter Reinhard and Zhuo Huang. 2016. Exponential garch modeling with realized measures of volatility. *Journal of Business & Economic Statistics* 34(2), 269–287.
- Hansen, Peter R, Asger Lunde, and James M Nason. 2011. The model confidence set. *Econometrica* 79(2), 453–497.
- Hu, Zinan and Sumuya Borjigin. 2024. The amplifying role of geopolitical risks, economic policy uncertainty, and climate risks on energy-stock market volatility spillover across economic cycles. *The North American Journal of Economics and Finance* 71, 102114.
- Jiang, Kunliang, Pengfei Luo, Wenxiao Gan, Jiashan Song, and Yuejing Wang. 2025. Does climate policy uncertainty affect expected shortfall (and value-at-risk) in the chinese sector? evidence from the mixed-frequency dynamic semi-parametric approach. *The North American Journal of Economics and Finance*, 102555.
- Jiang, Wei, Lingfei Dong, Xutang Liu, and Liming Zou. 2024. Volatility spillovers among economic policy uncertainty, energy and carbon markets—the quantile time-frequency perspective. *Energy* 307, 132683.
- Koenker, Roger and Jose AF Machado. 1999. Goodness of fit and related inference processes for quantile regression. *Journal of the american statistical association* 94(448), 1296–1310.
- Kupiec, Paul H. 1995. Techniques for verifying the accuracy of risk measurement models. Technical Report 95–24, Division of Research and Statistics, Division of Monetary Affairs, Board of Governors of the Federal Reserve System, Washington, DC.
- Leirvik, Thomas. 2025. Interactive effects of economic, geopolitical, and climate risks on commodity volatility. *Journal of Commodity Markets*, 100518.
- Li, Haohua, Elie Bouri, Rangan Gupta, and Libing Fang. 2023. Return volatility, correlation, and hedging of green and brown stocks: is there a role for climate risk factors? *Journal of Cleaner Production* 414, 137594.
- Ma, Rufei, Zhenhua Liu, and Pengxiang Zhai. 2022. Does economic policy uncertainty drive volatility spillovers in electricity markets: Time and frequency evidence. *Energy Economics* 107, 105848.
- Molnár, Peter. 2016. High-low range in garch models of stock return volatility. *Applied Economics* 48(51), 4977–4991.
- Naimoli, Antonio. 2023. The information content of sentiment indices in forecasting value at risk and expected shortfall: a complete realized exponential garch-x approach. *International Economics* 176, 100459.
- Parkinson, Michael. 1980. The extreme value method for estimating the variance of the rate of return. *Journal of business*, 61–65.
- Pástor, L'uboš, Robert F Stambaugh, and Lucian A Taylor. 2022. Dissecting green returns. *Journal of financial economics* 146(2), 403–424.
- Pástor, L'uboš and Pietro Veronesi. 2013. Political uncertainty and risk premia. *Journal of financial Economics* 110(3), 520–545.
- Patton, Andrew J and Kevin Sheppard. 2009. Evaluating volatility and correlation forecasts. In T. G. Andersen, R. A. Davis, J.-P. Kreiß, and T. Mikosch (Eds.), *Handbook of financial time series*, pp. 801–838. Springer.
- Patton, Andrew J, Johanna F Ziegel, and Rui Chen. 2019. Dynamic semiparametric models for expected shortfall (and value-at-risk). *Journal of Econometrics* 211(2), 388–413.
- Peiris, Rangika, Chao Wang, Richard Gerlach, and Minh-Ngoc Tran. 2024. Semi-parametric financial risk forecasting incorporating multiple realized measures. *Quantitative Finance* 24(12), 1823–1837.
- Sarker, Provash Kumer, Elie Bouri, and Chi Keung Lau Marco. 2023. Asymmetric effects of climate policy uncertainty, geopolitical risk, and crude oil prices on clean energy prices. *Environmental Science and Pollution Research* 30(6), 15797–15807.
- Sweidan, Osama D. 2021. The geopolitical risk effect on the us renewable energy deployment. *Journal of Cleaner Production* 293, 126189.
- Taylor, James W. 2019. Forecasting value at risk and expected shortfall using a semiparametric approach based on the asymmetric laplace distribution. *Journal of Business & Economic Statistics* 37(1), 121–133.
- Wang, Chao, Richard Gerlach, and Qian Chen. 2023. A semi-parametric conditional autoregressive joint value-at-risk and expected shortfall modeling framework incorporating realized measures. *Quantitative Finance* 23(2), 309–334.

- Xu, Yan, Xinyu Wang, and Hening Liu. 2021. Quantile-based garch-midas: Estimating value-at-risk using mixed-frequency information. *Finance Research Letters* 43, 101965.
- Zaremba, Adam, Nusret Cakici, Ender Demir, and Huaigang Long. 2022. When bad news is good news: Geopolitical risk and the cross-section of emerging market stock returns. *Journal of Financial Stability* 58, 100964.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.