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ETF Resilience to Uncertainty Shocks: A Cross-Asset Nonlinear Analysis of AI and ESG Strategies

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Abstract

This study investigates the asymmetric responses of AI and ESG Exchange Traded Funds (ETFs) to geopolitical and financial uncertainty, with a focus on resilience across market regimes. The NASDAQ-100 and MSCI ESG Leaders indices are used as proxies for thematic ETFs, and their dynamic interlinkages are examined in relation to volatility indicators (VIX, GPR), alternative assets (Bitcoin, Ethereum, gold, oil, natural gas), and safe-haven currencies (CHF, JPY). A daily dataset spanning the 2016–2025 period is analyzed using Quantile-on-Quantile Regression (QQR) and Wavelet Coherence (WCO), enabling a granular assessment of nonlinear, regime-dependent behaviors across quantiles. Results reveal that ESG ETFs demonstrate stronger downside resilience under extreme uncertainty, maintaining stability even during periods of elevated geopolitical and financial risk. In contrast, AI-themed ETFs tend to outperform under moderate-risk conditions but exhibit greater vulnerability during systemic stress, reflecting differences in asset composition and investor risk perception. The findings contribute to the literature on ETF resilience and cross-asset contagion by highlighting differential behavior patterns under varying uncertainty regimes. Practical implications emerge for investors and policymakers seeking to enhance portfolio robustness through thematic diversification during market turbulence.

Keywords: thematic ETFs; artificial intelligence; ESG investing; financial uncertainty; geopolitical risk; safe-haven assets; quantile-on-quantile regression; wavelet coherence

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1. Introduction

In recent years, global financial markets have been shaped by two major structural transformations: the transition towards sustainability and the accelerated integration of artificial intelligence (AI)-based technologies. Institutional investors, regulators, and portfolio managers are increasingly prioritizing environmental, social, and governance (ESG) factors, amid growing concerns over climate change, reputational risks, and ethical standards in investment decisions (Muhammad and Huang 2025). Simultaneously, AI is redefining financial decision-making models, enhancing data processing capabilities and offering advanced tools for dynamic asset allocation and risk management (Bouri and Jalkh 2024).

This dual transformation has facilitated the proliferation of thematic Exchange-Traded Funds (ETFs), offering targeted exposure either to leading AI-oriented firms or to corporations with strong sustainability credentials. While such ETFs are promoted as innovative

instruments aligned with global megatrends, the literature offers limited and inconclusive evidence regarding their ability to function as safe-haven assets or effective buffers during periods of systemic stress (Cui et al. 2024).

Most existing studies have concentrated on traditional safe-haven assets such as gold (Rao et al. 2022), stable currencies like the Japanese yen and Swiss franc (Aliu et al. 2024), and sovereign bonds (Mensi et al. 2023; Rabbani et al. 2024), as well as alternative assets such as cryptocurrencies (Bouri and Jalkh 2024). Recent contributions have examined the effects of geopolitical and financial uncertainty on ESG-related assets (Shaik et al. 2023; Yang et al. 2024) and interactions between renewable energy ETFs and traditional energy markets (Yousfi and Bouzgarrou 2024). However, ETFs with AI exposure remain underexplored, particularly in relation to how their performance varies with the intensity of geopolitical (GPR) and financial (VIX) uncertainty, and how they correlate with traditional and alternative assets. A systematic, comparative analysis addressing these dimensions remains lacking, especially within a methodological framework that accommodates nonlinearity and regime-specific behavior. While conventional ETFs provide a useful benchmark for market performance, this study focuses specifically on ESG-themed ETFs due to their growing prominence in institutional portfolios and their strategic alignment with global sustainability objectives. ESG ETFs incorporate unique screening criteria and sector allocations that may influence their behavior under systemic stress differently from conventional broad-market ETFs (Ullah et al. 2024). By narrowing the focus to ESG funds, the aim is to assess whether these thematic investments offer distinct resilience patterns or vulnerabilities during major economic and geopolitical disruptions, an area that remains underexplored in the literature.

To address this gap, the present study explores the differentiated responses of AI and ESG ETFs to systemic uncertainty. The NASDAQ-100 Index is employed as a proxy for AI exposure due to its high concentration of technology-oriented firms, including leading corporations in artificial intelligence, data analytics, and digital infrastructure (Aiche et al. 2024). These firms are key drivers of AI innovation and are frequently included in AI-themed ETF portfolios. Meanwhile, the MSCI ESG Leaders Index serves as a representative benchmark for ESG-themed investments, as it applies rigorous selection criteria to include companies with strong ESG performance relative to their sector peers. Both indices are widely used in the financial industry and academic research, offering transparent methodologies and broad acceptance as proxies for their respective thematic domains. These indices are examined in relation to a diverse set of financial instruments, including gold, Bitcoin, Ethereum, WTI crude oil, natural gas, and safe-haven currencies (CHF/USD and JPY/USD), alongside two widely used uncertainty indices (VIX and GPR).

Methodologically, the study combines two complementary approaches to capture the nonlinear and regime-dependent dynamics of co-movements between ETFs and risk factors: Quantile-on-Quantile Regression (QQR), which estimates relationships conditioned simultaneously on the distributions of variables (Zada et al. 2025), and Wavelet Coherence (WCO), which offers a time–frequency perspective on the synchronization between financial time series (Yadav et al. 2024). This integrated approach addresses the limitations of traditional linear models and enables the identification of asymmetric relationships and spillover effects during periods of systemic stress.

The contribution of this study is threefold. First, it offers a comparative evaluation of AI and ESG ETFs under conditions of geopolitical and financial uncertainty. Second, it situates this analysis within a cross-asset framework that includes conventional, alternative, and currency-based safe-haven assets. Third, it applies a reproducible methodological design suited to capture nonlinearities, time-varying dependencies, and risk-sensitive behavior. Preliminary results suggest marked differences between the two ETF categories:

ESG-themed ETFs exhibit greater robustness to geopolitical risk, while AI-themed ETFs display stronger performance during moderate volatility, but heightened vulnerability in the presence of extreme shocks. These findings are relevant for financial practitioners aiming to optimize portfolio resilience, as well as for policymakers concerned with systemic risk in the context of the digital and green transitions.

Understanding the resilience of ETFs during periods of financial crisis is critical for several reasons. First, in an era marked by increasing geopolitical tensions, economic shocks, and climate-related risks, investors are seeking assets that can preserve capital and mitigate downside exposure (Zhao et al. 2023; Ahmed et al. 2025). Thematic ETFs, particularly those centered on AI and ESG themes, are often promoted as future-proof solutions, yet their actual performance under stress conditions remains insufficiently examined. From a theoretical perspective, assessing their behavior under systemic stress enhances our understanding of nonlinear asset dynamics and regime-dependent interactions. Practically, these insights are highly relevant for institutional investors, portfolio managers, and policymakers aiming to design robust investment strategies and regulatory frameworks that ensure financial stability in the face of the accelerating digital and green transitions.

This paper is organized into six sections: Section 2 synthesizes prior literature and highlights key theoretical shortcomings. Section 3 details the data sources and outlines the methodological design. Section 4 presents and interprets the main empirical findings. Section 5 discusses the implications for financial practitioners and regulatory bodies. Finally, Section 6 summarizes the main conclusions and proposes directions for future inquiry.

2. Literature Review

Within the framework of modern portfolio theory, assets regarded as safe havens, due to their tendency to preserve or enhance value during market downturns, have played a central role in strategies aimed at mitigating systemic risk and enhancing portfolio resilience. According to Baur and McDermott (2010), a safe-haven asset is one that shows zero or negative correlation with risky assets during sharp market downturns. This operational definition has been widely used to assess the hedging potential of traditional and alternative financial instruments. Nevertheless, empirical evidence has increasingly shown that these relationships are not static but exhibit significant variability across market regimes, asset classes, and crisis typologies (Das et al. 2020; Urquhart and Zhang 2019). This perspective underscores the importance of incorporating regime-switching or quantile-based analytical frameworks to capture the heterogeneous behavior of safe-haven assets under different systemic stress conditions.

Building on this theoretical foundation, the financial literature has explored various instruments for their potential to mitigate portfolio risk during times of financial, geopolitical, or health-related uncertainty. Early empirical research primarily examined traditional safe-haven assets such as gold (Baur and McDermott 2010; Ali et al. 2022), sovereign bonds (Habib et al. 2020; Tiwari et al. 2022), and major reserve currencies like the Swiss franc and Japanese yen (Aliu et al. 2024), which are historically recognized for their role in conservative hedging strategies and their resilience across diverse crisis episodes.

In response to the structural shifts triggered by the COVID-19 crisis and intensifying geopolitical tensions, the academic focus has expanded to include alternative assets such as cryptocurrencies (Bouri et al. 2020), thematic ETFs (Ozcelebi et al. 2024), and sustainability-oriented financial instruments (Albuquerque et al. 2019). These developments reflect a broader transformation of the global financial ecosystem, where portfolio risk mitigation strategies are increasingly assessed not only for their financial performance but also for their alignment with sustainability principles and their integration of technological innovation.

A rising number of studies have examined how ESG assets perform under various market conditions, highlighting their potential for greater stability in the face of exogenous shocks (Broadstock et al. 2021). Sustainable ETFs have been evaluated for their risk-adjusted returns (Nagy et al. 2016), informational efficiency, and capacity to absorb systemic volatility (Gillan et al. 2021; Capelle-Blancard et al. 2019). However, empirical findings are mixed, with evidence ranging from strong defensive performance to heightened vulnerability. Some studies support the defensive function of ESG investments, while others document increased exposure to macroeconomic uncertainty, particularly in emerging markets (Sabbaghi 2023; ElBannan 2024). Moreover, Cepni et al. (2023) emphasize the role of climate uncertainty in amplifying shock transmission between conventional and ESG assets, reinforcing the notion that the safe-haven capacity of ESG instruments is highly context- and regime-dependent. Delays in ESG rating updates, especially for firms with intermediate environmental or governance scores, further undermine their defensive utility during fast-moving crises (Wang 2025), indicating a potential mismatch between real-time market conditions and the information incorporated into ESG metrics.

In contrast, ETFs with exposure to AI have received limited direct scrutiny. Frequently treated as part of the broader tech sector, AI-themed ETFs are rarely evaluated as standalone instruments in terms of their performance during systemic shocks or their role in portfolio diversification. This research gap is particularly important given the strategic role of AI in redefining financial modeling, data analytics, and investor behavior (Bouri and Jalkh 2024). As AI becomes integral to digital transformation, previous studies have largely overlooked its crisis-period dynamics, making it increasingly relevant to understand its financial implications, particularly during crisis episodes.

From a methodological perspective, the recent literature calls for more flexible and robust approaches to studying cross-asset linkages under uncertainty. Classical linear models are increasingly complemented by tools that account for nonlinearities and asymmetric responses, such as QQR and WCO. These techniques allow researchers to capture complex co-movements that vary across distributions and time–frequency domains (Sim and Zhou 2015; Shahzad et al. 2019). Prior studies have shown that these advanced methods can reveal dynamics that remain hidden under traditional linear frameworks. For example, Umar et al. (2022) demonstrate that the impact of geopolitical risk on financial markets is highly regime-sensitive, while Han (2025) highlights that only a cross-asset perspective can reveal the true nature of contagion between ETFs and commodities under systemic pressure. Similarly, Elsayed et al. (2022) document spillover effects between thematic ETFs and cryptocurrencies in response to geopolitical shocks, reinforcing the need for integrating uncertainty indicators such as GPR, VIX, and EPU into volatility modeling to achieve a more comprehensive risk assessment.

Regarding alternative assets, gold continues to be regarded as a robust safe haven (Arfaoui et al. 2023), while cryptocurrencies and energy commodities have been shown to exhibit conditional hedging potential during high-volatility episodes (Bossman et al. 2022). The empirical evidence from these studies reinforces the necessity of adopting dynamic econometric models that can capture regime dependence, nonlinear behavior, and cross-asset heterogeneity, particularly when assessing emerging instruments such as AI and ESG ETFs.

Despite these valuable contributions, two significant gaps remain underexplored in the literature. First, comparative and risk-conditioned analyses of AI and ESG ETFs under financial and geopolitical uncertainty, particularly across distinct market regimes, are largely absent. While ESG investments have been more extensively studied, AI ETFs remain largely untested as potential hedging tools or shock absorbers. Second, empirical evidence is scarce regarding the interaction of these thematic ETFs with both traditional

and alternative assets, such as gold, cryptocurrencies, energy commodities, and safe-haven currencies, within an integrated analytical framework designed to capture heterogeneous, asymmetric, and time-varying dynamics.

To address these research gaps and contribute to a better understanding of portfolio resilience during crises, the present study formulates the following hypotheses, each grounded in established theoretical reasoning and prior empirical findings: The first hypothesis builds on the notion that asset classes with different sectoral exposures and investment narratives exhibit heterogeneous sensitivities to shocks. ESG ETFs, rooted in sustainability principles, may attract long-term investors less prone to short-term trading, whereas AI ETFs, positioned within the technology and innovation sphere, are often more sensitive to market sentiment and cyclical fluctuations. As VIX and GPR influence these sectors differently, it is expected that their responses will diverge depending on prevailing market regimes.

H1: *AI and ESG ETFs respond differently to financial and geopolitical uncertainty (VIX and GPR), with sensitivities varying across market regimes.*

The second hypothesis draws from the literature on cross-asset linkages, which emphasizes the asymmetric and regime-dependent nature of interdependence between thematic and alternative assets. Gold, safe-haven currencies, cryptocurrencies, and energy commodities exhibit distinct risk–return profiles, and their correlation structures with ETFs vary in calm versus turbulent markets. Given their contrasting investment profiles, AI and ESG ETFs are likely to display heterogeneous co-movement patterns with such assets, particularly under stress conditions.

H2: *AI and ESG ETFs display asymmetric and regime-dependent linkages with alternative assets, reflecting heterogeneous patterns of interdependence.*

3. Methodology and Data

3.1. Conceptual Framework and Variable Selection

This research adopts an integrated multi-asset conceptual framework to explore the relationships between two thematic ETFs and a diversified set of explanatory variables that reflect systemic uncertainty, safe-haven dynamics, and cross-asset market stress. Following recent advances in the literature (Das et al. 2020; Umar et al. 2022), thematic ETFs are treated as dependent variables, while financial, geopolitical, and commodity-related risk factors are modeled as regime-sensitive explanatory variables. This framework builds on the premise that investor responses to uncertainty are not linear or static, but conditional upon prevailing market regimes.

To capture AI-related exposures, the NASDAQ-100 Index is selected due to its high concentration of companies actively involved in the development and application of artificial intelligence technologies. This choice is empirically supported by semantic and textual analysis conducted by Ante and Saggu (2025), who document the significant AI-related orientation of this index's constituents. Similarly, the MSCI ESG Leaders Index is employed as a proxy for sustainability-focused portfolios, as it reflects high ESG performance and is widely adopted in both academic and industry analyses of ESG asset behavior.

The set of explanatory variables comprises well-established measures of global uncertainty and widely accepted safe-haven assets. These include the VIX index, widely regarded as a proxy for implied volatility and investor sentiment; the GPR index by Caldara and Iacoviello (Iacoviello 2025), which quantifies news-based geopolitical tensions; and alternative assets frequently evaluated for their hedging potential. Gold (XAU/USD),

the Japanese yen (JPY/USD), and the Swiss franc (CHF/USD) are included due to their documented roles as safe havens (Baur and McDermott 2010; Arfaoui et al. 2023). Bitcoin and Ethereum are selected to represent the cryptocurrency market, increasingly discussed as digital substitutes for traditional stores of value (Urquhart and Zhang 2019). Additionally, WTI oil and natural gas are incorporated as proxies for commodity price shocks and global energy uncertainty. Table 1 provides the definitions, calculation methods, and sources for each variable.

Table 1. Variables' descriptions and data sources.

Variable Name	Code	Calculation Method	Data Source
NASDAQ-100 ETF (technology focus)	NDX	Daily closing price returns (log-differenced)	Bloomberg Terminal
MSCI ESG Leaders ETF (sustainability focus)	MSCI ESG	Daily closing price returns (log-differenced)	Bloomberg Terminal
Geopolitical risk index	GPRD	Caldara and Iacoviello index	https://www.matteoiacoviello.com/gpr.htm (accessed 7 July 2025).
Financial volatility index	VIX	CBOE volatility index (daily close)	Investing.com/CBOE
Gold price	XAU	Spot price per ounce (USD), daily returns	Bloomberg Terminal
Swiss franc exchange rate	CHF	USD/CHF daily returns	Bloomberg Terminal
Japanese yen exchange rate	JPY	USD/JPY daily returns	Bloomberg Terminal
Bitcoin	BTC	Daily closing price returns	CoinMarketCap/Investing.com
Ethereum	ETH	Daily closing price returns	CoinMarketCap/Investing.com
WTI crude oil	WTI	Spot price per barrel (USD), daily returns	Bloomberg Terminal
Natural gas	NG	Henry Hub natural gas spot price (USD), daily returns	Bloomberg Terminal
NASDAQ-100 ETF (technology focus)	NDX	Daily closing price returns (log-differenced)	Bloomberg Terminal

Note: This table reports the name, code, calculation method, and data source for each variable used in the empirical analysis.

Importantly, the selection of these variables is not based on assumptions of direct causality but reflects a regime-conditioned conceptual framework grounded in the literature on investor behavior under uncertainty (Cepni et al. 2023; Han 2025). The central premise is that market participants rebalance their portfolios in response to external shocks, with thematic ETFs acting as sensitive indicators of these reallocations. In this sense, the ETFs' co-movements with alternative assets and uncertainty indices provide insights into broader patterns of contagion, hedging, or substitution.

While the NASDAQ-100 and MSCI ESG Leaders indices serve as widely recognized proxies for AI-related and ESG-focused exposures, it is important to acknowledge their inherent limitations. The NASDAQ-100 is a technology-heavy index that includes many firms involved in AI development, but it is not a dedicated AI index. As such, it may capture broader innovation trends rather than offering pure exposure to AI-specific dynamics. Similarly, the MSCI ESG Leaders Index selects only companies with top-tier ESG ratings based on sector-relative performance, potentially excluding firms that are transitioning or improving their ESG practices but have not yet reached leader status. This best-in-class approach introduces a selection bias that may not reflect the full spectrum of ESG strategies.

Moreover, ESG ratings themselves are subject to time lags and methodological inconsistencies across rating agencies. These limitations should be considered when interpreting the generalizability of the findings, particularly in policy or investment contexts.

By simultaneously including traditional, digital, and commodity-based instruments, this framework enables the detection of nonlinear, asymmetric, and regime-dependent relationships. This complexity cannot be captured by linear models, thus justifying the use of advanced methods such as QQR and WCO. The design serves as a robust platform to test whether AI- and ESG-focused ETFs exhibit differentiated responses to external shocks, and whether such responses are contingent upon the source and intensity of perceived risk.

3.2. QQR Method

To capture the nonlinear, asymmetric, and regime-dependent relationships between thematic ETFs and systemic uncertainty factors, the analysis employs the quantile regression (QR) model developed by Koenker and Bassett (1978). Unlike classical linear models, QR estimates the effects of covariates across different points of the conditional distribution, enabling the examination of how NASDAQ-100 and MSCI ESG Leaders Index returns respond to varying levels of financial and geopolitical uncertainty under different market regimes, such as severe downturns, moderate fluctuations, or high gains. This framework reveals how ETF sensitivities shift across stress levels, highlighting heterogeneity in investor responses.

The standard QR model is specified as follows:

$$\hat{\beta}_\tau = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{n} \rho_\tau(y_i - x_i\beta), \tag{1}$$

where $\rho_\tau(u) = u\left(\tau - I_{\{u<0\}}\right)$ denotes the check loss function, and $\tau \in \{0.05, 0.50, 0.95\}$ denotes the quantiles of interest. This model captures how the effects of uncertainty vary across different ETF return regimes.

Before exploring the QQR framework, it is important to acknowledge alternative approaches for modeling nonlinear and asymmetric relationships. Traditional nonlinear models, such as nonlinear autoregressive distributed lag (NARDL) models, capture short- and long-run asymmetries but are limited to static, unidirectional effects. Markov-switching models identify regime shifts, yet they rely on discrete state changes and parametric assumptions. Standard QR offers flexibility across the conditional distribution of the dependent variable, yet it does not account for how the quantiles of the independent variable influence the dependent variable's distribution.

However, standard QR evaluates covariates only at specific quantiles of the dependent variable, limiting the analysis of bidirectional cross-distribution effects. To address this, we adopt the QQR model introduced by Sim and Zhou (2015), which estimates how the τ-quantile of the dependent variable Y is affected by the θ-quantile of the predictor X. This is achieved by using locally weighted regressions based on a cubic Epanechnikov kernel.

$$QQR_{(\tau,\theta)} : Q_{Y|\tilde{X}_\theta}(\tau) = \alpha(\tau,\theta) + \beta(\tau,\theta) \cdot x \tag{2}$$

$$K(u) = \left(1 - u^3\right)^3, \text{ for } |u| < 1 \tag{3}$$

The resulting surface $\beta(\tau,\theta)$ allows a detailed assessment of cross-quantile dependence by visually and quantitatively mapping the regimes where the relationships between ETFs and risk factors are positive, negative, significant, or unstable. This provides deeper insight into the resilience or vulnerability of thematic ETFs under varying risk environments.

The adoption of QQR is in line with recent studies that explore nonlinear financial dynamics. For example, Umar et al. (2022) examine asymmetric responses of conventional and crypto-assets to uncertainty using QQR, while Zeng et al. integrate QQR in an ESG technology context, revealing regime-contingent interdependencies between sustainable and innovation-driven instruments (Zeng et al. 2025).

3.3. WCO Method

To complement the nonlinear and asymmetric insights provided by the QQR model, we introduce a time–frequency domain analysis based on wavelet coherence. This extension enables the exploration of how the relationships between thematic ETFs and uncertainty indicators (VIX, GPR), as well as alternative assets (gold, cryptocurrencies, energy commodities, and safe-haven currencies), exhibit co-movement across time and multiple investment horizons (short-, medium-, and long-term).

We employ WCO to detect localized, scale-specific correlations between time series. Unlike classical spectral methods that assume stationarity, WCO is particularly suited to contexts marked by structural breaks and episodic volatility, as it reveals transient and regime-dependent dependencies (Aguiar-Conraria and Soares 2014; Torrence and Compo 1998).

Wavelet coherence is defined as follows:

$$R^2(a,b,s) = \frac{\left|S\left(s^{-1}W_{x,y}(a,b)\right)\right|^2}{S\left(s^{-1}|W_x(a,b)|^2\right) \cdot S\left(s^{-1}|W_y(a,b)|^2\right)} \tag{4}$$

where $W_x(a,b)$ and $W_y(a,b)$ denote the continuous wavelet transforms of the time series x(t) and y(t), respectively, and $W_{xy}(a,b) = W_x(a,b) \cdot \overline{W_y(a,b)}$ denotes the cross-wavelet spectrum. Here, s represents the scale (frequency), the temporal location, and S(·), a smoothing operator applied in both frequency and time domains.

The coherence coefficient, R^2, varies between 0 and 1, where values close to 1 indicate strong dependence at a specific scale and time point, and values near 0 suggest weak or no connection. Directionality and causality insights are further derived from the phase difference, computed as follows:

$$\varphi(a,b) = \arg\left(W_{xy}(a,b)\right) \tag{5}$$

A phase angle near 0° (pointing right) implies that the series are in-phase and move synchronously, while a phase near 180° (pointing left) indicates an inverse relationship. The vertical orientation of phase arrows can additionally signal lead–lag dynamics, enabling the identification of dominant information transmitters under uncertainty shocks (Han 2025).

As a robustness check, we also apply the standard Wavelet Transform Coherence (WTC) method, which confirms the existence of strong co-movements between ETFs and asset classes, especially in low-frequency bands during systemic crises. This dual-wavelet framework enhances the reliability and interpretability of our findings by capturing both the intensity and directionality of financial connectivity in a dynamic setting.

3.4. Data Sources and Period of Analysis

This study employs daily data spanning the period 2016 to 2025 (Bloomberg 2025; Investing.com 2025; Nasdaq 2025; Yahoo Finance 2025), a timeframe that encapsulates multiple episodes of geopolitical turbulence (the Russia–Ukraine war, US–China trade disputes, the Israel–Palestine conflict, and renewed China–US tensions) and financial instability (including the COVID-19 crisis, cryptocurrency crashes, and global inflation shocks). Such a periodization allows for the identification of regime shifts and asymmetries, which are central to testing H1 (quantile dependence) and H2 (cross-asset co-movement dynamics).

By incorporating the QQR method, we estimate the conditional effects across both the distribution of ETF returns and the distribution of predictors, providing a flexible framework for exploring nonlinear, regime-dependent relationships. This approach has recently been validated in studies focusing on green bonds, ESG indices, and alternative assets (Maheu and Zamenjani 2025; Gubareva et al. 2023). In parallel, the WCO analysis captures local co-movements in time and frequency, enhancing the robustness of the results and revealing potential lead-lag effects in risk transmission (Shrestha and Naysary 2023). All econometric analyses were conducted using EViews 12 (IHS Markit, 2021) and MATLAB R2023a (MathWorks, 2023). Full command scripts and parameter settings are available from the authors upon request to ensure full reproducibility.

Figure 1 illustrates the price evolution and volatility patterns for the variables included in the analysis.

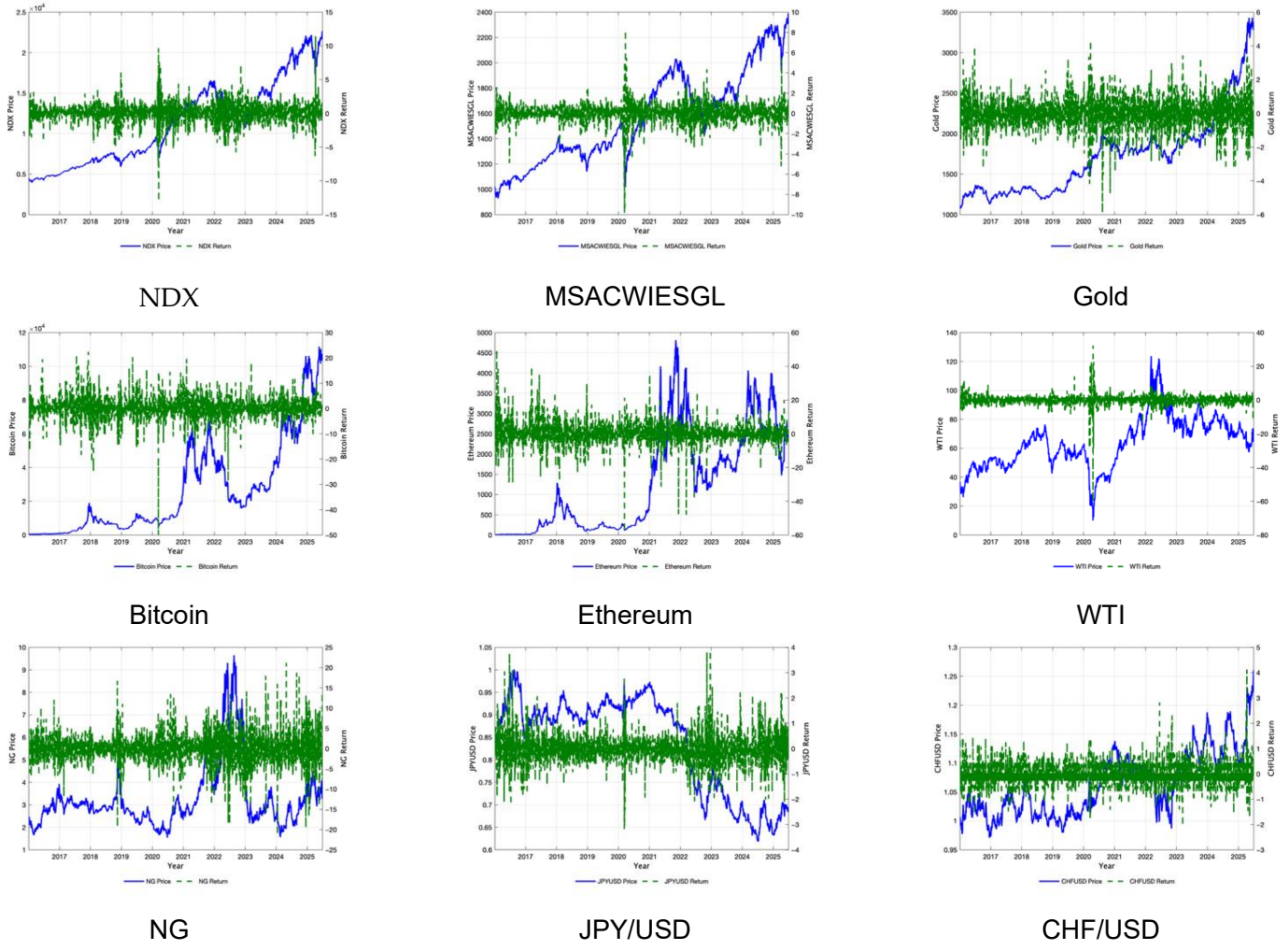

Figure 1. Price and volatility evolution of the analyzed assets (2016–2025). Note: This figure displays the historical evolution of asset prices (blue line, left axis) and their corresponding returns (green line, right axis) over the sample period.

The descriptive statistics reveal significant differences among the analyzed assets. For a normal distribution, skewness should be close to zero and kurtosis close to three. The results in Table 2 indicate that most series deviate substantially from these benchmarks. For instance, WTI and NG exhibit extreme kurtosis values (79.41 and 69.11, respectively), reflecting the presence of fat tails and high-impact shocks. Cryptocurrencies, especially Ethereum, combine elevated skewness and kurtosis, suggesting asymmetric reactions to

market events. VIX displays a marked positive skewness (2.49) and high kurtosis (14.85), consistent with its spike-driven dynamics in periods of turmoil. These departures from normality confirm the presence of heavy-tailed and asymmetric distributions, reinforcing the choice of econometric techniques that do not rely on the Gaussian assumption.

Table 2. Descriptive statistics.

Index	Mean	Median	Max	Min	Std. Dev.	Skew-Ness	Kurtosis	Jarque–Bera	Prob.	IQR
NDX	0.07	0.11	11.35	−13.00	1.43	−0.38	11.32	7113.37	0.000	1.26
MSACWIESGL	0.03	0.07	8.18	−9.85	0.93	−1.04	19.71	28,931.95	0.000	0.83
VIX	18.55	16.78	82.69	9.14	7.46	2.49	14.85	16,858.32	0.000	8.28
GPR	121.86	112.53	581.54	9.49	56.43	1.93	11.26	8473.97	0.000	62.77
Gold	0.05	0.07	4.30	−5.89	0.90	−0.23	5.85	847.45	0.000	0.97
Bitcoin	0.22	0.19	22.17	−49.73	4.30	−0.76	14.30	13,269.29	0.000	3.59
Ethereum	0.32	0.11	49.76	−57.99	6.43	−0.19	13.76	11,830.42	0.000	5.30
WTI	0.02	0.14	31.96	−60.17	3.09	−2.94	79.41	599,092.40	0.000	2.55
NG	0.02	0.00	21.06	−21.34	3.75	−0.03	6.91	1557.24	0.000	3.79
JPYUSD	−0.01	−0.02	3.87	−3.16	0.58	0.44	7.84	2469.19	0.000	0.60
CHFUSD	0.01	−0.01	4.10	−2.05	0.47	0.53	7.01	1753.31	0.000	0.55

Note: The table summarizes key statistical metrics for each variable, including central tendency (mean, median), dispersion (standard deviation, IQR), distribution shape (skewness, kurtosis), and the Jarque–Bera normality test. All variables exhibit significant deviations from normality ($p < 0.01$).

To assess the stationarity of the time series, we apply the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. For the ADF and PP tests, we consider specifications with intercept and with intercept plus linear trend, selecting the appropriate form for each series based on visual inspection and information criteria. The KPSS test is conducted with both intercept and trend to complement the unit root tests. The results of the ADF and PP tests indicate that all return series are stationary at level, with *p*-values below 0.01. In parallel, the KPSS test fails to reject the null hypothesis of stationarity in most cases, further supporting the absence of unit roots and deterministic trends (Table 3). These results validate the use of QQR and wavelet methods without concerns of spurious regressions or distorted dependencies.

Table 3. Stationarity test results.

Index	ADF				PP			
	Level		1st Diff		Level		1st Diff	
	t-Stat.	Prob.	t-Stat.	Prob.	Adj. t-Stat	Prob.	Adj. t-Stat	Prob.
NDX	−16.00	0.00	−21.00	0.00	−57.08	0.00	−676.16	0.00
MSACWIESGL	−14.98	0.00	−20.95	0.00	−47.81	0.00	−591.57	0.00
VIX	−5.47	0.00	−59.60	0.00	−6.04	0.00	−63.13	0.00
GPR	−9.24	0.00	−23.58	0.00	−36.40	0.00	−278.38	0.00
Gold	−49.46	0.00	−23.62	0.00	−49.51	0.00	−1325.41	1.00
Bitcoin	−51.07	0.00	−23.95	0.00	−51.06	0.00	−1746.74	1.00
Ethereum	−49.96	0.00	−26.16	0.00	−50.07	0.00	−716.95	0.00
WTI	−25.08	0.00	−19.11	0.00	−52.60	0.00	−856.28	0.00
NG	−54.00	0.00	−19.74	0.00	−54.09	0.00	−558.24	0.00

Table 3. *Cont.*

Index	ADF				PP			
	Level		1st Diff		Level		1st Diff	
	t-Stat.	Prob.	t-Stat.	Prob.	Adj. t-Stat	Prob.	Adj. t-Stat	Prob.
JPY/USD	−50.58	0.00	−21.06	0.00	−50.57	0.00	−1602.84	1.00
CHF/USD	−48.54	0.00	−19.82	0.00	−48.56	0.00	−811.97	0.00

Note: This table reports the stationarity test outcomes for all variables. Results from the ADF and PP tests are provided at both levels and first differences. Variables are considered stationary at first difference based on rejection of the null hypothesis at conventional significance levels.

Index	KPSS							
	Level				1st Diff			
	LM-Stat.	Asymptotic Critical Values			LM-Stat.	Asymptotic Critical Values		
		1%	5%	10%		1%	5%	10%
NDX	0.04	0.74	0.46	0.35	0.02	0.74	0.46	0.35
MSACWIESGL	0.03	0.74	0.46	0.35	0.04	0.74	0.46	0.35
VIX	0.86	0.74	0.46	0.35	0.02	0.74	0.46	0.35
GPR	1.56	0.74	0.46	0.35	0.04	0.74	0.46	0.35
Gold	0.17	0.74	0.46	0.35	0.09	0.74	0.46	0.35
Bitcoin	0.16	0.74	0.46	0.35	0.18	0.74	0.46	0.35
Ethereum	0.57	0.74	0.46	0.35	0.04	0.74	0.46	0.35
WTI	0.06	0.74	0.46	0.35	0.05	0.74	0.46	0.35
NG	0.04	0.74	0.46	0.35	0.04	0.74	0.46	0.35
JPY/USD	0.22	0.74	0.46	0.35	0.08	0.74	0.46	0.35
CHF/USD	0.09	0.74	0.46	0.35	0.15	0.74	0.46	0.35

Note: This table reports the stationarity test outcomes for all variables. Results from the KPSS tests are provided at both levels and first differences. Variables are considered stationary at first difference based on rejection of the null hypothesis at conventional significance levels.

4. Results

4.1. QQR Results for the NDX ETF

The QQR analysis uncovers a pronounced nonlinear and asymmetric relationship between the NDX ETF and the examined predictors, highlighting the regime-dependent nature of these interactions. In particular, the link between NDX returns and the VIX index demonstrates a significant negative dependence across the lower quantiles of the NDX distribution, with effects becoming more severe when financial market volatility reaches its upper extremes. This pattern indicates that financial uncertainty disproportionately affects the ETF during pessimistic or crisis-prone regimes, reinforcing the asymmetric transmission of risk. The effect of GPR on NDX returns is similarly pronounced. When geopolitical risk is situated in its upper quantiles, coinciding with major global tensions such as the 2020 pandemic onset or the 2022 Ukraine crisis, the negative effect on NDX returns intensifies, particularly when the ETF itself is in a lower-return regime. This suggests a marked aversion to technology-related assets during geopolitical shocks, reflecting the sensitivity of AI-oriented equities to macropolitical disruptions. Table 4 reports the complete QQR coefficient estimates for NDX across all predictor variables, providing a detailed view of the nonlinear and regime-dependent relationships.

Table 4. QQR results for NDX.

Quantile τ	**0.05**		**0.5**		**0.95**	
Intercept	0.792	(0.000)	0.435	(0.000)	−0.254	−(0.060)
VIX	−0.148	(0.000)	−0.019	(0.001)	0.103	(0.000)
GPR	0.000	(0.703)	0.000	(0.447)	0.003	(0.003)
Gold	0.175	(0.012)	0.062	(0.137)	0.038	(0.660)
Bitcoin	0.013	(0.382)	0.027	(0.000)	0.029	(0.017)
Ethereum	0.020	(0.009)	0.009	(0.013)	0.021	(0.000)
WTI	0.043	(0.064)	0.055	(0.000)	0.070	(0.001)
NG	−0.014	(0.309)	0.010	(0.156)	0.002	(0.902)
JPY/USD	−0.495	(0.000)	−0.359	(0.000)	−0.334	(0.006)
CHF/USD	0.197	(0.132)	0.214	(0.002)	0.227	(0.094)

Note: Values in parentheses represent *p*-values for each coefficient estimate.

Gold exhibits countercyclical behavior, with a negative and significant effect on NDX returns during periods of financial stress and when the ETF experiences low performance. This finding aligns with gold's role as a traditional hedge, particularly in times of heightened risk aversion.

The relationship between Bitcoin and NDX appears unstable and regime-specific. Intermediate quantiles indicate episodes of co-dependence, but this relationship weakens or reverses in extreme scenarios. Such dynamics suggest that Bitcoin may offer limited diversification benefits during systemic shocks. Ethereum, while sharing some of Bitcoin's characteristics, displays stronger positive co-movements in bullish regimes, highlighting its potential alignment with technology sentiment in more optimistic market conditions.

WTI crude oil exerts a negative influence on NDX returns in high-volatility regimes, especially when oil prices are elevated, implying that rising energy costs and inflationary pressures may erode profitability expectations in technology sectors. Similarly, natural gas prices exhibit a weak yet adverse effect in extreme regimes, signaling indirect exposure through input cost volatility and geopolitical uncertainty.

The defensive status of the Japanese yen and Swiss franc is confirmed. Both currencies negatively impact NDX performance under high-risk conditions, with the yen displaying a more robust inverse relationship. These effects reflect capital flight towards traditional safe assets during global turmoil, to the detriment of high-growth, high-risk sectors like AI and technology.

Collectively, these results provide empirical support for H1, underscoring the asymmetric and regime-contingent dependencies between the NDX ETF and key sources of financial and geopolitical uncertainty, as well as traditional and alternative asset classes. The evidence confirms that thematic AI-based ETFs are particularly vulnerable to external shocks, especially under bearish or high-volatility market conditions (Figure 2).

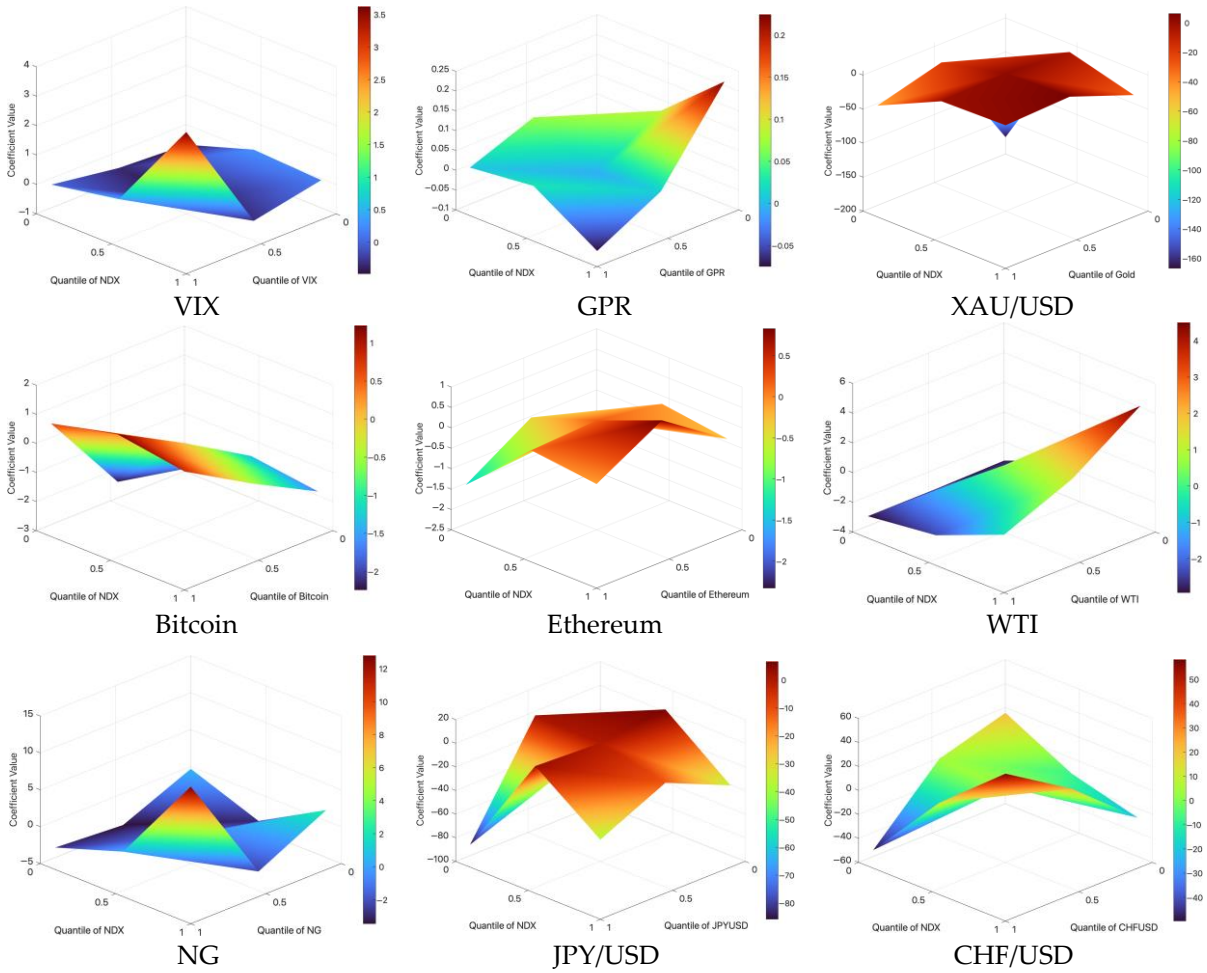

Figure 2. QQR results for the NDX ETF. Note: The surface plots show how the quantiles of the NDX distribution respond to varying quantiles of other financial and commodity market variables. Color gradients reflect the strength and direction of the estimated coefficients.

4.2. WCO Results for the NDX ETF

The WCO analysis reveals statistically significant and frequency-dependent co-movements between the NDX ETF and the selected explanatory variables, especially during major episodes of global turbulence (Figure 3).

With regard to VIX, the coherence is particularly strong in the low-frequency (long-run) domain, coinciding with times of systemic volatility such as the COVID-19 crisis and recent geopolitical escalations. Coherence with GPR becomes evident during geopolitical shocks, most notably in 2022, but appears more intermittent and episodic than that of VIX. This suggests that geopolitical risk exerts an irregular but impactful influence on AI-related equity performance.

In relation to gold, elevated coherence is concentrated during crises, especially at medium and long-term frequencies, reinforcing its role as a countercyclical safe haven that performs well when tech stocks falter.

For cryptocurrencies, coherence with NDX intensifies post-2020, highlighting growing interlinkages between digital assets and the tech sector. Ethereum displays more consistent coherence in optimistic phases, whereas Bitcoin's relationship is more fragmented and volatile across time–frequency domains, pointing to regime-dependent co-movements.

Coherence with WTI oil prices spikes between 2022 and 2023, aligning with global energy price shocks and suggesting indirect cost-related vulnerabilities for technology firms.

In contrast, natural gas displays lower coherence overall, though it becomes more relevant during localized stress events, reflecting sporadic exposure to energy-driven volatility.

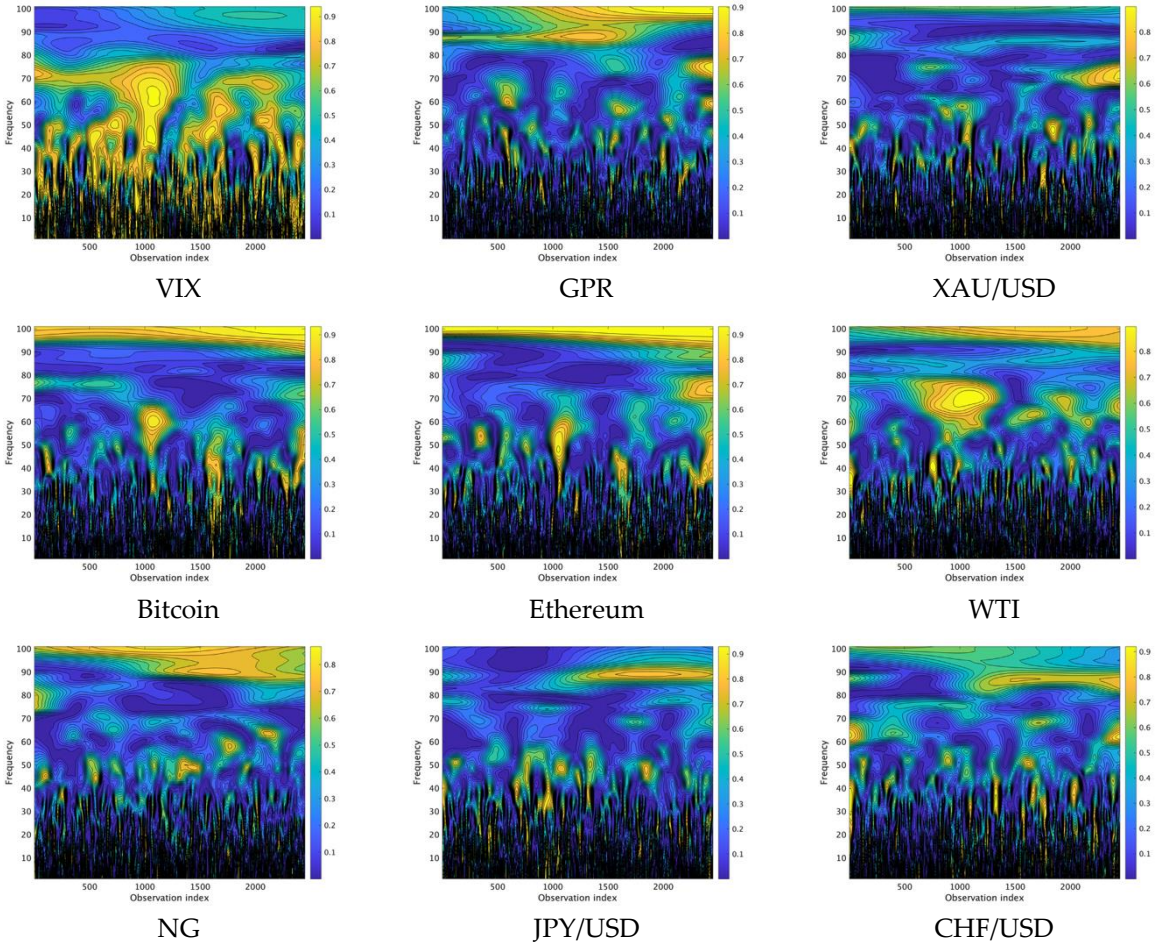

Figure 3. WTC results for the NDX ETF. Note: WTC plots display the time–frequency co-movement between the NDX ETF and other selected variables. Warmer colors indicate stronger coherence. The X-axis shows the time (observation index), and the Y-axis represents frequency (short- to long-term cycles).

Safe-haven currencies, such as the Swiss franc and Japanese yen, exhibit moderate but significant coherence under risk-off conditions, supporting the interpretation that investors rebalance toward defensive currencies when uncertainty surrounding tech assets intensifies.

In summary, the WCO results validate the QQR findings, highlighting that the dynamics of NDX returns are strongly influenced by uncertainty indicators and alternative asset classes, especially during market stress and transition regimes. These results reinforce the regime-sensitive behavior of AI-themed ETFs and their exposure to cross-asset risk transmission during crises.

4.3. QQR Results for the MSCI ESG Leaders Index

The linkage between the MSCI ESG Leaders Index and VIX reveals a consistently negative and statistically significant effect of financial uncertainty on returns, particularly in bearish market regimes. The adverse effect is most pronounced when ESG returns are in the lower quantiles and VIX is elevated, underlying the heightened sensitivity of sustainable portfolios to episodes of systemic stress.

In contrast, the influence of GPR appears more nuanced. While elevated geopolitical uncertainty dampens ESG performance in adverse conditions, its impact becomes muted or statistically insignificant in neutral or bullish regimes. This asymmetric response suggests that ESG assets may partially decouple from geopolitical noise during upward market trends, possibly due to investors' long-term strategic allocation to sustainability and regulatory tailwinds favoring ESG themes. Table 5 summarizes the average and peak coherence values across frequency bands for each explanatory variable.

Table 5. QQR results for MSCI ESG Leaders Index.

Quantile τ	**0.05**		**0.5**		**0.95**	
Intercept	0.780	(0.000)	0.397	(0.000)	−0.203	(0.218)
VIX	−0.101	(0.000)	−0.018	(0.000)	0.066	(0.000)
GPR	0.000	(0.628)	−0.001	(0.107)	0.002	(0.014)
Gold	0.076	(0.108)	0.055	(0.085)	0.001	(0.984)
Bitcoin	0.005	(0.520)	0.014	(0.008)	0.017	(0.027)
Ethereum	0.010	(0.005)	0.006	(0.062)	0.011	(0.123)
WTI	0.055	(0.000)	0.058	(0.000)	0.047	(0.068)
NG	0.005	(0.546)	0.005	(0.297)	0.007	(0.436)
JPY/USD	−0.313	(0.000)	−0.264	(0.000)	−0.217	(0.000)
CHF/USD	0.244	(0.003)	0.325	(0.000)	0.339	(0.000)

Note: Values in parentheses represent *p*-values for each coefficient estimate.

Gold plays a stabilizing role in bearish quantiles, reinforcing its traditional role as a safe haven during turbulent periods. However, its marginal benefit wanes in bullish regimes, reflecting its limited upside potential in thriving market environments where ESG equities already perform well (Figure 4).

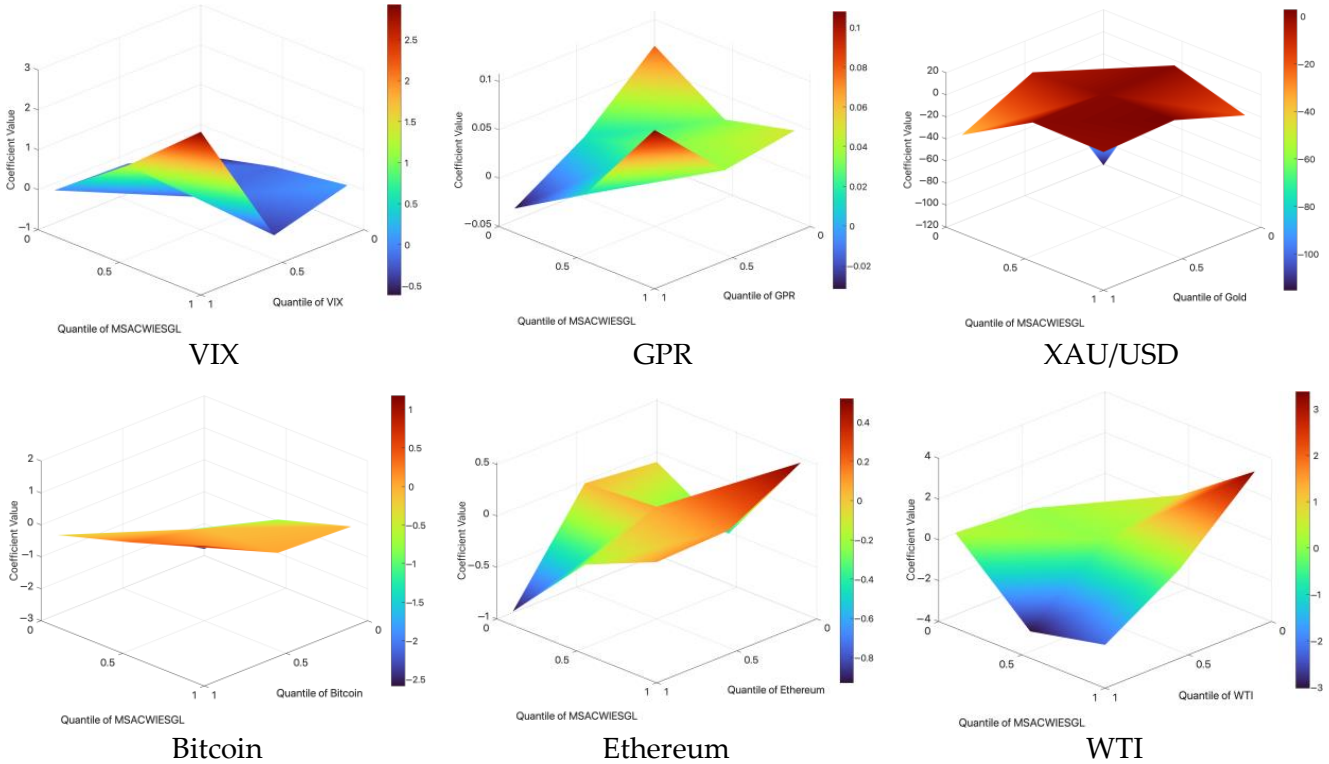

Figure 4. *Cont.*

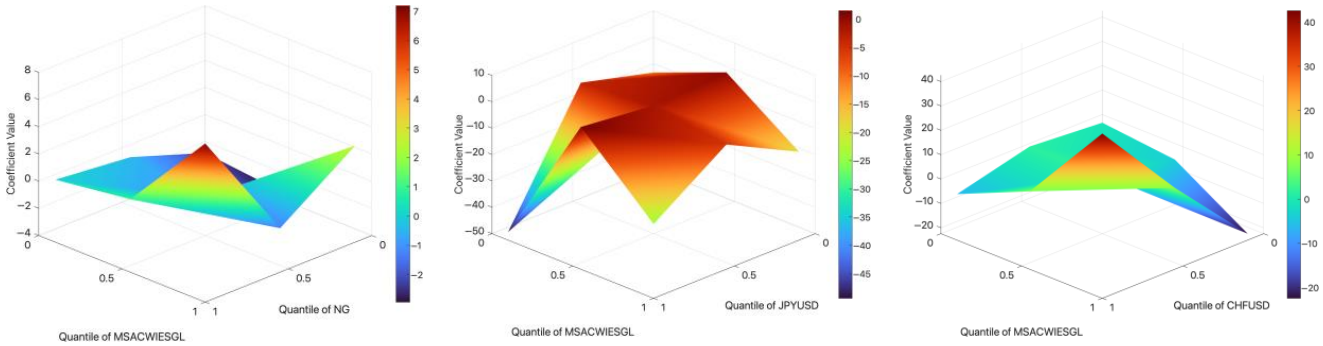

Figure 4. QQR results for MSCI ESG Leaders Index. Note: Each 3D surface reflects the coefficient variations across joint quantiles of the index and each independent variable.

Bitcoin demonstrates a nonlinear and regime-contingent relationship with ESG returns. Weak or negative dependencies under financial distress indicate that cryptocurrencies may not offer effective downside protection, while stronger co-movements in mid or upper quantiles suggest increased alignment in optimistic or stable conditions. Ethereum exhibits a similar behavior but displays more stable co-movement in mid-quantiles, potentially reflecting investor perceptions of its technological affinity with ESG innovations and the green digital economy.

WTI oil prices exhibit a pronounced negative impact, particularly when oil is in the upper quantiles and ESG returns are depressed. This finding is consistent with the structural aversion of ESG funds to fossil fuel exposure and emphasizes the vulnerability of such portfolios to energy price shocks. Natural gas shows a weaker, yet still negative influence, particularly under extreme scenarios, suggesting residual sensitivity to energy market volatility even among sustainability-focused assets.

Safe-haven currencies exert negative pressure on ESG returns during risk-off episodes. However, this impact is less severe compared to the NDX ETF, pointing to relatively greater resilience of ESG portfolios when investors reallocate towards defensive assets.

Overall, the QQR analysis supports H1, revealing that the MSCI ESG Leaders Index exhibits asymmetric, nonlinear, and regime-dependent linkages with systemic uncertainty factors and alternative asset classes. These findings not only confirm statistical patterns but also have important economic implications, demonstrating that while ESG investments are not immune to exogenous shocks, they may offer partial robustness and long-term defensiveness in diversified portfolios.

4.4. WCO Results for the MSCI ESG Leaders Index

The WCO results for the MSCI ESG Leaders Index reveal dynamic, scale-sensitive interactions with systemic uncertainty and alternative asset classes over the 2016–2025 period, displaying both similarities and contrasts with the patterns observed for the NDX ETF. Coherence patterns are concentrated in low-frequency bands, indicating persistent and structural relationships that shape the long-term performance of ESG investments, while short-term reactions are less pronounced except during major crises (Figure 5).

In relation to the VIX, coherence peaks in the low-frequency range during systemic crises such as COVID-19 and the 2022 geopolitical turmoil, confirming the vulnerability of ESG-oriented portfolios to financial market instability. While this mirrors the NDX response, ESG shows slightly more persistent long-run coherence, suggesting that sustainable portfolios may take longer to recover from liquidity pressures and volatility spikes. This resilience gap could stem from the broader sectoral composition of ESG indices, which often includes industries more exposed to macroeconomic cycles.

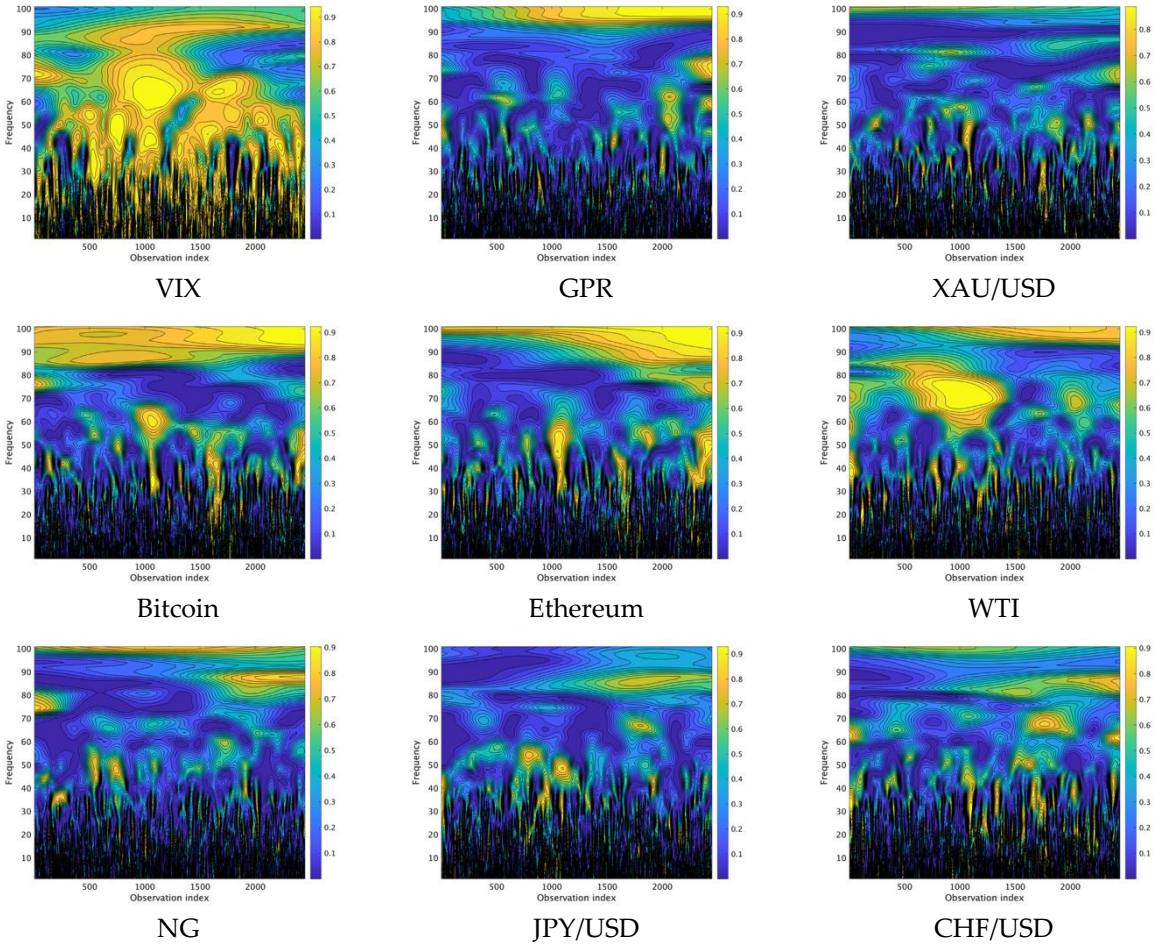

Figure 5. WTC results for MSCI ESG Leaders Index. Note: The WTC plots analyze the dynamic correlation structure between the index and external variables across different time horizons.

The GPR index exhibits sustained long-run coherence with ESG returns, particularly during geopolitical escalations, underscoring the influence of political risk on capital flows into sustainable assets. Compared to NDX, the ESG index displays stronger and more consistent low-frequency coherence with GPR, suggesting that ESG strategies are more sensitive to geopolitical stability and may experience prolonged periods of capital inflows or outflows depending on the global political climate.

Gold shows intermittent but statistically meaningful coherence in both low- and mid-frequency bands, especially in crisis periods. While both indices benefit from gold's defensive role, ESG portfolios appear to rely more heavily on gold as a store of value during equity market downturns, as indicated by more extended coherence intervals compared to NDX. In contrast, Bitcoin and Ethereum exhibit limited and irregular coherence with ESG returns, mostly confined to high-frequency bands and narrow time windows. This mirrors their speculative and volatile profile observed in the NDX case, but ESG portfolios display even weaker and shorter-lived coherence, implying a minimal diversification benefit from cryptocurrencies in a sustainable investment context.

Energy commodities, particularly oil and natural gas, show stronger coherence with ESG returns after 2020 in both medium- and low-frequency ranges. This is more pronounced than in the NDX case and is likely due to the dual role of energy markets for ESG strategies, as both a risk factor through fossil fuel volatility and a driver of policy shifts in the global energy transition narrative. These dynamics highlight that ESG portfolios are doubly exposed to fluctuations in traditional energy markets and changes in renewable energy policy frameworks.

Safe-haven currencies, notably the Swiss franc and Japanese yen, display stable and persistent long-term coherence, especially during stress regimes. This confirms their defensive role in times of global uncertainty for both indices, but ESG portfolios exhibit slightly stronger low-frequency coherence, reinforcing the relevance of such currencies for enhancing the resilience of sustainable investments.

Overall, the WCO results highlight that the MSCI ESG Leaders Index is embedded in a complex web of interdependencies with uncertainty indicators and alternative assets, with certain channels being more influential compared to the NDX ETF. These relationships are nonlinear, time-varying, and regime-dependent, reinforcing the importance of adopting time–frequency methodologies to capture the evolving risk landscape surrounding sustainable investments.

The complete outputs of the supplementary WTC and QR analyses, conducted to validate and complement the main findings, are available in the supplementary repository at https://doi.org/10.5281/zenodo.15270073.

5. Discussions

The results clearly highlight a nonlinear and regime-dependent relationship between the analyzed thematic ETFs and sources of global uncertainty, reinforcing evidence from previous studies that systemic volatility and geopolitical risks actively influence different asset classes depending on market conditions. The QQR methodology facilitated the investigation of quantile-dependent interactions between VIX, GPR, and the two ETFs, NDX and MSCI ESG Leaders, and the findings are complemented by frequency-based coherence analysis via WTC and WCO. The QQR methodology revealed nonlinear and asymmetric relationships, a pattern further corroborated by WCO and, additionally, by WTC, which confirmed the robustness of the observed synchronizations under high-volatility regimes.

For the NDX, the relationship with the VIX is generally negative and significant in extreme regimes, with a stronger effect observed in the lower quantiles of returns. This finding is supported by persistent low-frequency coherence waves identified during systemic crises such as the COVID-19 epidemic and more recent geopolitical conflicts, indicating a slow but persistent transmission of systemic risk. According to Dimpfl and Schweikert (2023), one possible explanation for this delayed reaction lies in the fact that thematic ETFs like those tracking the NDX contribute less to the price discovery process, as futures markets incorporate real-time information, whereas ETFs react within limited trading windows.

In the case of the GPR index, the relationship with NDX is also negative in stress regimes, indicating investors' clear aversion to technology assets during periods of geopolitical uncertainty. This observation aligns with the findings of Kamal et al. (2022) and Lai et al. (2023), which show that the effect of geopolitical events on financial assets is regime-dependent and more pronounced during high-volatility periods.

The relationship between NDX and gold is negative in pessimistic regimes, suggesting a partial hedging function. However, Bitcoin and Ethereum exhibit a positive relationship in favorable regimes but an ambiguous or weakly negative one during stress periods, indicating a more opportunistic than defensive integration into portfolios. This supports recent literature findings that cryptocurrencies do not consistently fulfill the role of safe haven assets (Lu et al. 2024). The Japanese yen and Swiss franc remain effective defensive assets in response to VIX shocks, although they do not respond uniformly to GPR, a finding also supported by Lu et al. (2024). The WCO dynamics confirm negative synchronization during stress episodes, indicating capital rotation into these currencies at the expense of the technology sector.

For the MSCI ESG Leaders ETF, the relationship with the VIX is also negative but more stable, with slightly lower sensitivity in extreme regimes. QQR reveals a greater shock absorption capacity compared to the NDX, in line with Meehan and Corbet (2025), who conclude that ESG ETFs offer better protection against volatility and generate more stable returns during crises. This resilience is confirmed by WCO waves in low-frequency bands, with lower amplitude than those observed for NDX. A more diffuse but persistent synchronization between ESG returns and geopolitical uncertainty is evident, indicating that investors may perceive these instruments as partially defensive against non-financial risks.

One possible explanation for the slower and more moderate reaction of the ESG ETF lies in significant delays in updating ESG ratings. According to Wang (2025), AI-based assessments of 10-K reports indicate lags of up to two years between ESG scores and actual corporate practices, particularly on the Environmental and Social dimensions. This latency can delay institutional investors' portfolio adjustments, increasing the risk of unintended exposure to systemic risk.

The ESG–GPR relationship is observable in intermediate regimes rather than during extreme uncertainty. A negative effect is evident in the lower-return intervals, suggesting that in bear markets geopolitical risk may affect the selection of sustainable companies. This does not contradict the overall resilience of the ESG ETF, but it suggests that its protective function is partially conditional on the nature and magnitude of external shocks. Unlike NDX, the ESG ETF appears to benefit from a more defensive perception among investors, consistent with Yang et al. (2024), who find hedging properties of ESG stocks in bearish regimes. These results validate H2, showing that thematic ETFs display distinct levels of connectivity with traditional and alternative safe-haven assets, depending on the market regime. While the tech-focused ETF NDX shows stronger and more volatile correlations with these assets during stress periods, the ESG ETF demonstrates more stable but weaker connectivity, reflecting a partially defensive profile and superior diversification potential. These differences underscore the importance of volatility regimes in assessing the hedging efficiency of thematic ETF-based strategies. Such differences underscore the necessity of incorporating volatility regimes into assessments of the hedging efficiency of thematic ETF-based strategies.

Regarding relationships with safe-haven assets, gold maintains a complementary role, especially in low-return regimes, supporting portfolio stability for sustainable investments during stress. Positive QQR coefficients in low-return zones confirm this relationship. In contrast, cryptocurrencies, particularly Ethereum, show more opportunistic integration, with positive relationships in bullish regimes but instability during stress periods. This reflects growing interest in blockchain technologies with ESG themes, but also the inherent volatility of these assets.

Negative correlations with CHF and JPY in stress regimes reinforce the idea of a defensive rotation of capital for this ETF as well, though with less intensity than for NDX. WCO results indicate stable and frequently negative coherence with traditional safe assets, particularly in low frequencies, supporting the diversification potential of ESG ETFs. The weak link with WTI and natural gas prices confirms that the ESG ETF is deliberately decoupled from direct exposure to conventional energy markets, which can offer protection during periods of energy market volatility.

These findings complement those of Mohammed et al. (2023), who show that during periods dominated by geopolitical and energy shocks, connectivity across asset classes increases significantly, but thematic ETFs offer a high degree of diversification relative to traditional markets. They also align with Sahadudheen and Kumar (2024), who emphasize the persistent transmission of gold and oil volatility into portfolios, particularly in low-frequency ranges.

Overall, the analysis confirms the hypothesis that thematic ETFs, especially sustainable ones, may offer partial protection against geopolitical and financial risks, but their effectiveness is regime-dependent, asymmetric, and influenced by institutional and structural market latencies. Investment strategies that ignore these asymmetries may underestimate systemic volatility exposure, particularly during periods of global contagion. Neglecting these asymmetries in portfolio construction may result in underestimation of systemic volatility exposure, especially during global contagion episodes.

6. Conclusions

This study explored how thematic ETFs focused on technology (NDX) and sustainability (MSCI ESG Leaders) respond to financial volatility, geopolitical risk, and a diverse set of safe-haven assets, both traditional (gold, CHF, and JPY) and alternative (Bitcoin, Ethereum). Using advanced econometric and time–frequency methods (QQR, WCO), the analysis reveals that the relationships between these ETFs and the explanatory factors are nonlinear, asymmetric, and regime-dependent, becoming more pronounced during episodes of elevated financial or geopolitical stress.

The results show that the NASDAQ-100 ETF is more sensitive to systemic uncertainty, with marked declines in performance under stress regimes, while the ESG ETF demonstrates relatively greater resilience and shock absorption capacity. These differences highlight distinct behavioral patterns between growth-oriented and sustainability-linked ETFs. However, the interaction with safe-haven assets is not uniformly stabilizing and varies significantly depending on the source and intensity of uncertainty, suggesting that the protective role of thematic ETFs is conditional rather than absolute.

From a practical perspective, the findings suggest that portfolio managers should dynamically adjust their exposure to AI- and ESG-themed ETFs according to prevailing market regimes. During periods of heightened financial volatility, reducing allocation to AI-focused ETFs in favor of ESG ETFs or traditional safe-haven assets may enhance portfolio resilience. Conversely, during stable or recovery phases, AI-themed ETFs may offer superior growth potential. For policymakers, the results underscore the need to consider the systemic implications of thematic ETFs in financial stability assessments, as their co-movement patterns with safe-haven assets reveal potential channels of contagion during crises.

The practical implications emphasize the importance of dynamic diversification strategies that consider not only the type of asset but also the prevailing regime of market volatility and the dominant source of systemic risk. ESG ETFs may contribute to portfolio stability during persistent geopolitical uncertainty, but their protective efficacy is affected by delays in ESG rating adjustments and the strategic behavior of institutional investors. In this context, ESG ETFs may serve as partial substitutes for traditional safe-haven assets during geopolitical stress, though their effectiveness is contingent on timely and transparent ESG rating methodologies.

This study is not without limitations. It focuses on two representative ETFs, which constrains the generalizability of findings across the broader universe of thematic funds. Furthermore, the GPR index captures geopolitical risk in aggregate form without distinguishing between different geopolitical dimensions, and ESG scores are treated as exogenous, omitting analysis of scoring inconsistencies or methodological biases among providers. Cryptocurrencies are considered in aggregate terms, without exploring structural divergences or network effects.

Future research could refine this analysis by incorporating ESG ETFs rated by different agencies (MSCI, S&P Global, Sustainalytics), by disaggregating sources of geopolitical or climate-related risk, and by employing machine learning techniques to improve regime

classification and forecasting accuracy. Investigating the temporal misalignment between ESG practices and market perceptions could also provide further insights into the lagged responsiveness of sustainable investment vehicles.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
ETFs	Exchange Traded Funds
ESG	Environmental, social, and governance
NDX	NASDAQ-100 Index
MSACWIESG	MSCI ESG Leaders Index
XAU/USD	Gold
JPY/USD	Japanese yen
CHF/USD	Swiss franc
WTI	WTI oil
NG	Natural gas
GPR	Geopolitical risk
VIX	Financial uncertainty
QQR	Quantile-on-Quantile Regression
WCO	Wavelet Coherence
QR	Quantile regression
WTC	Wavelet Transform Coherence
ADF	Augmented Dickey–Fuller
PP	Phillips–Perron
KPSS	Kwiatkowski–Phillips–Schmidt–Shin

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