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Volatility in U.S. Natural Gas Prices: Exploring Market Dynamics and Economic Policy Uncertainties

Bahram Adrangi[1*], Ales Kresta[2], Kambiz Raffiee[3], and Tomas Tichy[4]

Abstract

We investigate the association between the Henry Hub natural gas pricFe (HHNGP) short-and long-run volatilities in the US and Global economic policy uncertainties, and crude oil market uncertainties (GEPU, OVX, respectively). Our findings from a GARCH-MIDAS methodology that takes the US industrial production and the US economic policy uncertainty (EPU) into account, Markov switching regressions (MSR) and Quantile Granger causality tests suggest that the association of realized short-term and long-term volatilities and global policy and oil market uncertainties are stable over time. Both the short- and long-term volatilities (STV and LTV, respectively) are Granger caused by GEPU and OVX at some quantiles. These findings have significant ramifications for policy makers and natural gas users in US.

JEL classification: Q31, Q39, G10.
Keywords: Natural gas price volatility, GARCH-MIDAS, Economic policy uncertainty, Economic uncertainty, Quantile Regression Granger causality, Markov Switching Regression.

[1*] W.E. Nelson Professor of Financial Economics University of Portland, Portland, Oregon. *Corresponding author.
[2] Department of Finance, Faculty of Economics VSB–Technical University of Ostrava, Ostrava, Czech Republic.
[3] Foundation Professor of Economics and Associate Dean, College of Business Administration, University of Nevada, Reno.
[4] Department of Finance, Faculty of Economics, VSB–Technical University of Ostrava, Ostrava, Czech Republic.

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1. Introduction

Natural gas is a pivotal U.S. energy input, underpinning activity in manufacturing, chemicals, refining, electric power, and services. In 2021, consumption totaled roughly 30.66 Tcf (≈31.73 quads), about 32% of total U.S. energy use; the electric power sector accounted for 37%, industry 33%, commercial 11%, and transportation 4%. Economic expansions typically raise energy demand—including natural gas—through higher industrial and commercial output, strengthening the observed correlation between natural gas use and growth. On the supply side, U.S. production has rebounded to pre-pandemic levels and is projected to keep rising through 2050, led by shale gas and associated gas from oil plays (notably the Appalachian Basin and the Permian). LNG exports are expected to expand with global demand; scenario analysis suggests higher oil prices or lower U.S. gas prices boost LNG exports, whereas the reverse dampens them. Still, uncertainty about end-use demand, LNG trade, oil prices, and recoverable reserves tempers the long-run outlook (EIA projections).

A broad literature documents macroeconomic and sectoral benefits from the shale revolution. Studies such as Bilgili et al. (2016), Bjï and Zhulanova (2018), and Arora and Lieskovsky (2014) report positive spillovers to investment, employment, and production, with production-side shocks to gas exerting meaningful effects on U.S. industrial output. Related work (Krupnick et al., 2013; Jenkins et al., 2018; Spigelmyer, 2014) highlights contributions to electricity generation, jobs, tax revenues, and lower energy costs, while noting natural gas is not a complete long-term decarbonization solution (Jenkins et al., 2018).

Retail energy prices, including natural gas, are volatile relative to many production inputs. Price formation depends on global crude oil supply–demand conditions (OPEC near 40% of world output; the U.S. and Russia around 10–12% each), geopolitics, and domestic market structure. U.S. crude and gas production has grown, yet shocks—policy, economic, and geopolitical—continue to propagate through energy markets and the broader economy.

To maintain parsimony, we use the CBOE Oil Volatility Index (OVX)—an options-implied gauge of expected 30-day crude volatility—as a compact proxy for oil-market uncertainty that also informs natural gas dynamics. OVX helps investors and firms manage risk and price options, though its short-horizon design and dependence on options-market liquidity limit its ability to capture long-run structural changes. Despite these caveats, OVX remains a practical indicator of oil-market vagaries for our purposes.

Foundational work on decision-making under uncertainty (Sandmo, 1971; Galbraith, 1977; Bernanke, 1983; Pindyck, 1990; Dixit & Pindyck, 1994; Flacco & Kroetch, 1986; Adrangi & Raffiee, 1999) explains why firms adjust investment, production, and pricing when risk rises. More recent contributions (Bloom, 2007, 2009, 2014; Fernández-Villaverde et al., 2011; Basu & Bundick, 2017; Jurado et al., 2015; Baker & Wurgler, 2006, 2007; Baker et al., 2012a, 2012b, 2016, 2019, 2021; Adrangi et al., 2015, 2019, 2023a,b, 2024a,b,c, 2025a,b,c), Kyriazis et al. (2025), and Sun and Li (2025), among others show that uncertainty shocks are key drivers of business-cycle fluctuations. Text-based indices (e.g., Baker et al., 2016) link policy uncertainty to lower investment, output, and employment across advanced economies, though a universally accepted definition of "uncertainty" remains elusive.

Kyriazis et al. (2025) examine how various forms of U.S. uncertainty—monetary, regulatory, financial regulatory, and national security—affect the S&P 500 index between January 1985 and August 2022, distinguishing between crisis and non-crisis periods. Using vector autoregressive models, the analysis finds that during market crashes, all four types of uncertainty negatively impact the S&P 500 in the short term, while in normal periods, only monetary and national security uncertainties have a significant negative effect. Conversely, the S&P 500 helps reduce most uncertainty types in stable periods but only temporarily lowers financial regulation uncertainty during downturns. The results highlight the strong and complex bidirectional relationship between financial regulation uncertainty and stock market stability, suggesting that increased regulatory uncertainty fosters competition from alternative investments and heightens market instability. Overall, the study provides valuable insights for policymakers and investors into how distinct sources of uncertainty interact with financial markets under different economic conditions.

Sun and Li (2025) construct a provincial-level economic policy uncertainty (EPU) index for China using text analysis and combines it with micro-level data from the China Household Finance Survey (CHFS) to examine how policy uncertainty affects the effectiveness of household investment portfolios. The analysis reveals that higher EPU significantly reduces portfolio efficiency by lowering households' risk preference and increasing income risk, leading to overly conservative asset allocations and weaker diversification. The study further finds that the adverse effects of EPU are moderated by regional and institutional factors—specifically, higher levels of marketization, financial development, and financial literacy help mitigate the negative impact of policy uncertainty on household portfolio performance. By linking localized policy uncertainty with household financial behavior, the research provides new insights into the mechanisms through which macro-level policy instability influences micro-level financial decisions and underscores the importance of institutional and educational factors in enhancing household financial resilience.

Following Su et al. (2017, 2018, 2019), we model volatility with a GARCH-MIDAS decomposition that separates short-run (daily) from long-run components driven by low-frequency uncertainty indicators. Su et al. combine equity-market uncertainty measures—EPU, FU, and NVIX—and find EPU positively associated with equity volatility in industrialized countries, mixed results for NVIX, and little added value from FU for long-horizon prediction. Extensions using quantile methods show asymmetric effects of uncertainty on commodity volatility (Dutta et al., 2021) and VaR for oil returns (Xu et al., 2021), though single-covariate specifications risk omitted-variable bias. Evidence that multiplicative GARCH-MIDAS outperforms many alternatives (Conrad & Kleen, 2020) motivates our adoption of multi-covariate MIDAS terms.

Our contribution is twofold. First, for Henry Hub natural gas prices (HHNGP), we estimate short- and long-run volatility via a two-covariate GARCH-MIDAS model that embeds demand and supply fundamentals (e.g., industrial production and crude-oil production) to improve conditional volatility measurement. Second, we examine how uncertainty metrics (e.g., OVX and GEPU/EPU) relate to these volatility components using Markov-switching regressions and quantile-regression Granger causality tests, thereby mitigating misspecification concerns in one-covariate MIDAS designs (e.g., Su et al., 2019; Pan et al., 2017; Conrad & Kleen, 2020).

Volatility is central to asset pricing and derivatives (Ball & Roma, 1994), while implied measures (e.g., VIX) are widely used as "fear" gauges (Whaley, 1993, 2009). In futures markets, volatility relates to contango and backwardation: oil's term structure responds to volatility conditions (Robe & Wallen, 2016); analogous effects appear in agriculture (Beckmann & Czudaj, 2014) and shipping rates (Alizadeh & Nomikos, 2011).

Methodologically, research has progressed from early GARCH variants toward frequency-mixing approaches. Notable milestones include Ding & Granger (1996), Engle & Lee (1999), and application-oriented studies on hedging and forecasting (Javaheri et al., 2004; Awartani & Corradi, 2005; Liu & Hung, 2010; Hajizadeh et al., 2012; Carnero et al., 2012). Engle et al. (2013) formalize GARCH-MIDAS; subsequent work (Asgharian et al., 2013; Conrad & Loch, 2015; Lindblad, 2017, 2019; Amendola et al., 2017, 2019; Pan et al., 2017, 2021; Conrad et al., 2018; Borup & Jakobsen, 2019; Altig et al., 2020; Krol, 2014; Dutta et al., 2021; Jiang et al., 2019; Xu et al., 2021; Amado et al., 2019) shows that including low-frequency macro variables materially improves volatility forecasts.

Cross-market and uncertainty linkages are strong: Qadan et al. (2020) find oil prices and OVX are shaped by uncertainty shocks and investor risk appetite; Kang et al. (2021) document that VIX and OVX dominate U.S. sector ETF dynamics at multiple horizons; Fang et al. (2018) show NVIX adds to GARCH-MIDAS performance for G7 equities (with caveats about potential endogeneity when including realized volatility). For China, Wen et al. (2019) report short-run links between macro variables and U.S. EPU/VIX/OVX, with longer-run effects dominated by VIX.

Work directly on natural gas volatility and uncertainty is sparse relative to oil. Scarcioffolo & Etienne (2021a) uncover regime-dependent volatility for oil and natural gas, with policy uncertainty raising the odds of turbulent regimes—an effect that weakens post-shale. During COVID-19, wavelet-based analyses (Sharif et al., 2020) indicate significant coherence between pandemic dynamics, oil volatility shocks, geopolitical risk, EPU, and U.S. equities, with policy implications for crisis management. Broader connectedness studies (Adekoya et al., 2022; Bouri et al., 2023; Abiad & Qureshi, 2023; Assaf et al., 2021) reinforce the role of EPU, GPR, and OVX in shaping returns, volatility, and macro activity across assets and regions, often with asymmetric and state-dependent effects.

Given natural gas's centrality and the projected growth of U.S. supply, volatility in HHNGP can arise from fundamentals (production, demand), policy regimes, and global shocks. Because agents exhibit risk aversion, uncertainty shocks propagate through investment and spending; salience and perception of events (Edwards et al., 1995) shape these responses. Our two-covariate GARCH-MIDAS design, followed by MSR and quantile-Granger analysis, is intended to capture both frequency-domain structure and state dependence while reducing misspecification risk.

Section II reviews the methodology for volatility measurement and uncertainty–energy links, emphasizing GARCH-MIDAS, regime switching Markov Chain and quantile regressions. Section III describes data sources and the empirical findings. Section VI offers conclusions with policy implications regarding volatility management and the design of uncertainty-sensitive energy and macro policies.

2. Methodology

Building on the multiplicative GARCH–MIDAS framework of Conrad and Kleen (2020), and its implementation in Adrangi et al. (2023, 2024a,b, 2025a,b), we decompose the conditional variance of Henry Hub natural gas returns into short- and long-run components. The high-frequency block uses daily HHNGP returns, while the MIDAS (low-frequency) drivers include weekly crude-oil inputs to refineries and monthly industrial production, yielding short-term volatility (STV) and long-term volatility (LTV) estimates for HHNGP.

With STV and LTV in hand, we then estimate a set of regressions that relate each volatility measure to the chosen explanatory variables. Equation (1) states the baseline specification used throughout the empirical analysis.

$$\text{HHNGP volatility} = f(\text{GEPU}, \text{OVX}) \tag{1}$$

Before relating HHNGP volatility to GEPU and OVX, we first assess the time-series properties of STV, LTV, and the uncertainty measures (EPU, GEPU, OVX), checking for unit roots and structural breaks. Visual diagnostics suggest approximate stationarity, though plots indicate potential regime shifts in EPU. We address these issues below.

2.1 Structural breaks and stationarity

We implement Bai and Perron's (2003) multiple-break procedure and test for unit roots using the augmented Dickey–Fuller (ADF; Dickey and Fuller, 1979) and Phillips–Perron (PP; Perron and Phillips, 1987) tests. Because these methods are well documented in the literature, we omit further detail for brevity.

2.2 GARCH–MIDAS

For the volatility model, we follow the exposition in Adrangi et al. (2023, 2024a, 2024a,b, 2025b). To capture volatility clustering typical of financial returns, we adopt the GARCH framework introduced by Bollerslev (1986). Market variance is known to evolve over time, with high-volatility episodes often coinciding with crises and calmer periods during steady expansions.

We estimate a component GARCH model with MIDAS terms (Ghysels et al., 2004, 2016), which permits mixed-frequency drivers and delivers separate short- and long-run volatility components. Specifically, daily Henry Hub natural gas returns anchor the high-frequency block, while weekly crude-oil inputs to refineries and monthly industrial production (both from FRED) enter the low-frequency MIDAS filter to produce short-term (STV) and long-term (LTV) volatility for HHNGP. The MIDAS specification, detailed in Adrangi et al. (2023a,b, 2024a,b, 2025b), is presented in Equation (2).

$$y_{t+k} = \alpha_0 + \alpha_1 x^m{}_t + \varepsilon_t^m, \tag{2}$$

where y_{t+k} denotes the k-step-ahead value of the dependent variable observed at time t at the highest sampling frequency; $x^m{}_t$ denotes the (possibly vector-valued) regressors at time t, measured at frequency m that matches the frequency of y; ε_t^m is the random innovation at time t at frequency m; and α_0, α_1 are, respectively, the intercept and a conformable vector of coefficients. Under a GARCH(1,1) specification, the disturbance and its conditional variance are

$$\varepsilon_t = (\varepsilon_{t-j})\sqrt{\sigma_{\varepsilon,t}{}^2}$$

and

$\sigma_{\varepsilon,t}^2 = f(\varepsilon_{t-1}, \sigma_{t-1}^2)$, for GARCH (1,1) specification.

Following Engle et al. (2013), Ghysels et al. (2016), and Conrad & Kleen (2019), we integrate high-frequency (daily) and low-frequency (monthly) information within a GARCH–MIDAS framework. In this setup, the innovation's conditional variance is factorized into short- and long-run components,

$$\sigma_{\varepsilon,t}^2 = h_{i,t}\tau_t,$$

Where h and τ denote the short-term volatility of the high-frequency and the long-term volatility of the low-frequency data series, respectively, expressed in equations (3) and (5):

$$h_{i,t} = a_0 + a_1 \frac{\varepsilon_{t-1}^2}{\tau_t} + a_2 h_{i-1,t}. \tag{3}$$

The short-term volatility component h_{it} accounts for daily volatility clustering and is derived from a mean-reverting unit-variance GJR-GARCH(1,1) process. It varies daily within period t that signifies the lower frequency. Equation (3) may be expanded into its components as equation (4).

$$h_{i,t} = (1 - \alpha - \gamma / 2 - \beta) + (\alpha + \gamma\,|_{\varepsilon_{i-1,t}<0}) \frac{\varepsilon_{t-1}^2}{\tau_t} + \beta h_{i-1,t}. \tag{4}$$

The long-term realized volatility is smoothed over K periods, then expanded by adding low frequency covariate as

$$\tau_t = m + \theta \sum_{k=1}^{K} \phi_k(w_1, w_2) x_{t-k}, \tag{5}$$

The short-term component of GARCH-MIDAS in this paper is due to Engle et al. (2013) i.e., the GARCH process of Bollerslev (1986). It is designed to capture volatility clustering in the daily HHNGP returns. The long-term component is constant across days consistent with low frequency monthly series in the GARCH-MIDAS model. Equation (5) is expanded with other variables and their variances.

The weights in equation (5) are formulated as

$$\phi_k(w_1, w_2) = \frac{(k/K)^{w_1-1}(1-k/K)^{w_2-1}}{\sum_{j=1}^{K}(j/K)^{w_1-1}\sum_{j=1}^{K}(1-j/K)^{w_2-1}}, \tag{6}$$

Where

$$\sum_{k}^{K}\phi_k(w_1,w_2)=1\,.$$

The weighting scheme in (6) results in convex weights. Following Su et al. (2017), Fang et al. (2018), Conrad and Kleen (2020) w_1 is restricted to 1. Thus it leads a decaying weight pattern based on parameter W_2. The restricted weighting version of (6) boils down to
The relationship between U.S. economic performance and natural gas usage is multifaceted and shaped by macroeconomic conditions, policy, technological change, and market structure; consequently, it can shift over time. By the same logic, the association between Henry Hub natural gas price (HHNGP) short- and long-run volatility (STV and LTV) and the uncertainty measures GEPU and OVX is likely time-varying. Periods of low time-varying correlation for any pair may imply weak coherence and limited causal transmission. To capture this evolution in comovement, we estimate Dynamic Conditional Correlations (DCC) and report pairwise DCCs between STV/LTV and GEPU/OVX, based on the GARCH estimates, as follows:

$$\rho_{ij}(t)=M_{ij}(t)/\sqrt{M_{ii}(t)M_{jj}(t)}\,,$$

where M denotes the modified diagonal covariance matrix from the GARCH model. In the interest of brevity, we do not report the GARCH model estimates.

2.3 Regime Switching Markov Chain Regression

s_t. The switching model accommodates distinct regression models for each regime. The conditional mean of y_t in regime m, a vector of switching regressors x, and coefficients β_m and non-switching vectors of regressors z_t and coefficients ϕ is given by equation (7).

$$\mu_t^{(m)}=x_t{}'\beta_m+z_t{}'\phi\,. \tag{7}$$

Consistent with Adrangi et al. (2023a, b; 2024a, b, c; 2025a,b), we provide a concise overview of Markov-switching regression (MSR) to orient readers rather than a full textbook treatment. In MSR, the observed variable y_t is governed by an unobserved, discrete state s_t. that indexes distinct “regimes.” When the data-generating process alternates across regimes, the regression allows regime-specific relationships.
At each date t, the system occupies some regime m∈{1,…,M}. The conditional mean of y_t in regime m depends on a vector of **s**witching regressors x_t with regime-dependent coefficients and on non-switching regressors regressors z_t and coefficients ϕ; this specification is given in Equation (8).

$$\mu_t^{(m)}=x_t{}'\beta_m+z_t{}'\phi\,. \tag{8}$$

Assuming i.i.d. regression errors ε_t, (with variance potentially varying by regime), the full regime-switching model is written in Equation (9).

$$y_t=x_t{}'\beta_m+z_t{}'\phi+\sigma_m\varepsilon_t\,. \tag{9}$$

Following Adrangi et al. (2023a, b; 2024a, b; 2025a), regime probabilities are modeled as functions of exogenous information. The multinomial-logit form for these probabilities appears in Equation (10),

$$P(s_t=m\,|\,\Omega_{t-1},\psi)=p_m(E_{t-1},\psi)=\frac{\exp(E'_{t-1},\psi_m)}{\sum_{j=1}^{M}\exp(E'_{t-1},\psi_j)} \tag{10}$$

where:
m is a given regime,
p_m is the regime probabilities,
Ω_{t-1} is the information set at time t-1,
E_{t-1} is the vector of exogenous observable variables, and
ψ represents model coefficients.
Model parameters are obtained by maximizing the log-likelihood implied by Equations (9) and (10), as summarized in Equation (11).

$$l(\beta,\phi,\sigma,\psi)=\sum_{t}^{T}\log\left\{\sum_{m=1}^{m}\frac{1}{\sigma_m}\varpi[\frac{(y_t-\mu_t(m))}{\sigma_m}].P(s_t=m\,|\,\Omega_{t-1},\psi)\right\}. \tag{11}$$

Estimation proceeds via iterative, nonlinear optimization; regime probabilities are filtered concurrently during likelihood maximization.
A common variant imposes a first-order Markov structure, in which the probability of being in regime mmm depends on the regime realized at t−1t-1t−1. The resulting transition probabilities are shown in Equation (12),

$$p(s_t=j\,|\,s_{t-1}=i)=p_{ij}^{t}. \tag{12}$$

and the M×M transition matrix is presented in Equation (13).

$$p(t)=\begin{pmatrix} p_{11}^{t} & \cdots & a^{t}{}_{1M} \\ \vdots & \ddots & \vdots \\ a^{t}{}_{M1} & \cdots & a^{t}{}_{Mn} \end{pmatrix}. \tag{13}$$

Each row of the transition matrix follows a multinomial-logit form analogous to Equation (9). Using one-step-ahead regime probabilities and the transition matrix yields the joint density of data and states; integrating over the latent states gives the period-t likelihood in Equation (14). The likelihood is then maximized numerically to recover the parameter estimates.

$$l(\beta,\phi,\sigma,\psi)=\sum_{j=1}^{M}f(x_t{}'\beta_m+z_t{}'\phi+\sigma_m\varepsilon_t,s_t\,|\,\Omega_{t-1},\psi), \tag{14}$$

2.4 Quantile Regression

The pronounced shifts and structural disruptions observed in the Economic Policy Uncertainty series could potentially exert asymmetric influences on the short and long-term volatility of HHNGP. Stakeholders and investors not only respond to the overall correlation between EPU and HHNGP volatility but are also concerned about the repercussions of extreme upward and downward movements in EPU and their connection to HHNGP volatility. Structural breaks have the potential to be a contributing factor to extreme fluctuations in volatility. Additionally, both short and long-term volatility in HHNGP exhibit Autoregressive Conditional Heteroscedasticity (ARCH) effects, indicating the presence of periods with extreme volatility and heteroscedasticity.
Following the approach of Adrangi et al. (2023a,b,2024a,b,c, 2025a,b) and Scarcioffolo and Etienne (2021b), we employ Quantile regressions (QR), which are suitable for examining the conditional median rather than the conditional mean of volatility. While the QR methodology is well documented in the literature and in the above cited papers we offer a brief explanation of the methodology for the readers' benefit. These regressions are particularly well-suited for accommodating asymmetric dependence between

the volatility measures of HHNGP and explanatory variables. QR models, known for their nonlinearity (as seen in Galvao et al., 2020), exhibit robustness in the presence of extreme events and asymmetric dependence, where linearity assumptions may be inadequate (as observed in Geraci, 2019; Yu et al., 2003). Additionally, they outperform Ordinary Least Squares (OLS) estimates by allowing coefficient estimates to vary with the distribution of the dependent variable, providing an accurate representation of the relationship between explanatory variables and the dependent variable. The following provides a concise overview of Quantile Regression (QR).

Pronounced shifts and structural breaks in the Economic Policy Uncertainty series can induce asymmetric effects on both short- and long-run volatility of HHNGP. Market participants care not only about average comovement between EPU and volatility but also about tail behavior—large upward or downward moves in EPU and their connection to volatility spikes. Moreover, the short- and long-run volatility measures exhibit ARCH-type dynamics, implying episodes of pronounced heteroskedasticity.

Following Adrangi et al. (2023a, b; 2024a, b, c) and Scarcioffolo & Etienne (2021b), we employ quantile regression (QR), which characterizes conditional quantiles rather than the conditional mean. QR is well suited to asymmetric dependence and tail sensitivity (Galvão et al., 2020) and remains robust under heavy-tailed outcomes where linear mean models can be inadequate (Geraci, 2019; Yu et al., 2003). By allowing slope coefficients to vary across quantiles, QR often outperforms OLS when relationships differ across the distribution of the dependent variable.

Let $F(y)$ = Prob($Y \leq y$) denote the distribution of HHNGP volatility. For 0<τ<1 the τ-quantile is the minimum y with $F(y) \geq \tau$: where

$$Q(\tau) = \inf\left\{y : F(y) \geq \tau\right\}.$$

The empirical quantile can be written as the solution to a loss-minimization problem based on the "check" (pinball) function

$$Q_n(\tau) = \arg\min\left\{\sum_i \rho_\tau (Y_i - \omega)\right\}$$

that weights positive and negative residuals asymmetrically as

$$\rho_\tau(w) = w(\tau - 1(w < 0))$$

Extending to covariates X, the conditional τ-quantile of volatility given X is specified linearly (Equation 14), with the coefficient vector indexed by τ as follows

$$Q(\tau \mid X_i, \beta(\tau)) = X_i^{'}\beta(\tau)\,, \tag{15}$$

where $\beta(\tau)$ is the vector of coefficients associated with the τ th quantile.

As shown in Adrangi et al. (2023a, b; 2024a, b, c), the QR estimator solves a linear-programming problem; we implement the Koenker & D'Orey (1987) adaptation of the Barrodale & Roberts (1973) simplex algorithm. Under mild regularity conditions, the estimator is asymptotically normal (Koenker & Ng, 2005).

$$\sqrt{n(\hat{\beta}(\tau) - \beta(\tau)}$$

We allow for i.n.i.d. disturbances and use a Huber "sandwich" covariance (Hendricks & Koenker, 1992).

$\tau(1-\tau)H(\tau)^{-1}JH(\tau)^{-1}$, in which $J=\lim_{n\to\infty}(\sum_i X_iX_i^{'}/n)$,

The conditional density (sparsity) at the τ-quantile i.e.,

$H(\tau)=\lim_{n\to\infty}(\sum_i X_iX_i^{'}f_i(q_i(\tau))/n)$, and $f_i(q_i(\tau))$,

is estimated nonparametrically using Powell's (1986) kernel method, with bandwidth chosen following Hall & Sheather (1988) and Koenker & Ng (2005) and deriving the residulas from the initial estimate of the H function

$\hat{H}=1/n\sum b_n^{-1}K(\vartheta(\tau)/b_nX_iX_i^{'}$.

Model fit is summarized using the pseudo- a pseudo R-squared of Koenker & Machado (1999), which is the standard goodness-of-fit measure in the QR literature.

3. Data and Empirical Findings

Our sample spans March 3, 1997–December 30, 2022. We use daily HHNGP; monthly U.S. industrial production; daily U.S. news-based EPU from FRED (constructed from >1,000 newspapers via term counts normalized by article totals and standardized across outlets); and monthly GEPU and daily OVX (from September 2009 onward), also from FRED. Baker et al. (2019) provide the EMV construction aligned to VIX using newspaper content.

3.1 Structural Breaks and Stationarity

The Bai–Perron test shows breaks in GEPU, OVX and LTV in 2005, 2006 and 2007. In 2005, Hurricane Katrina significantly impacted the Gulf Coast, and the aftermath and recovery efforts extended into 2006. The Gulf experienced a reduction in oil production capacity, and the refining capacity of the Gulf States suffered damage, causing a shock to crude oil and natural gas supplies. This sudden decline in oil production led to increased demand, resulting in spot oil prices surging to over $70 a barrel. A staff report by Federal Energy Regulatory Commission in 2005 highlighted the disruptions caused by Hurricane Katrina, including the shutdown of offshore gas platforms, onshore refineries, and gas processing plants, each with varying patterns of disruption. While Hurricane Katrina initially caused a rapid increase in natural gas prices from $9.80 to as high as $12.69/MMBtu at Henry Hub, a subsequent decline to $11.03/MMBtu by September 11 indicated that the damage was less severe than initially feared. However, Hurricane Rita continued to exert upward pressure on prices as the full extent of the damage became apparent.

Following Hurricane Rita—when prices spiked to $15.22/MMBtu—Henry Hub was offline until October 4, 2005, temporarily removing the principal U.S. natural gas pricing reference during a critical window. Forward markets surged: NYMEX January 2006 natural gas futures closed September at $13.90/MMBtu at Henry Hub; on October 3, 2005, NYMEX ClearPort basis swaps for New York City reached $8.27/MMBtu; and traded forward power swaps exceeded $190/MWh for on-peak January deliveries in both New York City and New England.

Data gaps observed in 2006 are plausibly linked to layered global and natural sources of uncertainty: intensifying conflict and insurgency in Iraq after the 2003 invasion; the broader campaign against terrorism (e.g., Al-Qaeda); diplomatic tensions over nuclear programs in Iran and North Korea; and ongoing recovery from the 2004 Indian Ocean tsunami and 2005 Hurricane Katrina. Domestically, the United States remained engaged in military operations in Afghanistan and Iraq while continuing large-scale reconstruction along the Gulf Coast in Katrina's aftermath.

Conditions in 2007 further reshaped crude oil and natural gas markets. Strong world growth lifted energy demand, especially for oil and gas, while persistent geopolitical frictions in the Middle East—concerns over Iran's nuclear program and instability in Iraq—added risk premia. Late in the year, early signs of financial stress and fears of an impending downturn emerged, feeding through to energy pricing. Natural hazards, including hurricanes and tropical storms, underscored exposure to production disruptions in the Gulf of Mexico and elsewhere. Price formation remained highly sensitive to the global balance of supply and demand, with rising attention to climate change and policy support for renewables beginning to influence expectations. Rapidly expanding demand from China and India also played a prominent role. Volatility intensified into 2008, when oil set record highs; in response to supply concerns and escalating prices, the U.S. drew from the Strategic Petroleum Reserve. OPEC production and quota decisions continued to exert substantial influence. These forces interacted in complex ways, with effects that differed across short and long horizons.

Visual inspection of GEPU, OVX, and the Henry Hub volatility measures (STV and LTV) suggests mean and covariance stationarity. To corroborate the plots (omitted for brevity), we conduct formal tests. Table 1, Panel B reports augmented Dickey–Fuller and Phillips–Perron statistics indicating stationarity for all series. The final panel of Table 1 provides summary statistics, showing that both short- and long-run volatility display conditional heteroscedasticity.

Table 1: Break Points, Diagnostics and Summary

Panel A: Bai Perron Test of Structural Breaks					
	GEPU	OVX	STV	LTV	Critical
Break Test	F-Stat	F-Stat	F-Stat	F-Stat	Value
0 vs. 1	20.19[a]	423.54[a]	9.09	11.93[a]	11.47
1 vs. 2	7.03	42.47[a]	11.63		12.95
2 vs. 3		4.02			14.03
	Dates	Dates	Dates	Dates	
0 vs. 1	5/31/2006	10/24/2005		7/5/2006	
		10/19/2007			
* Bai-Perron (Econometric Journal, 2003) critical values					
Unit Root Tests					
Panel B: Levels					
	GEPU	OVX	STV	LTV	
ADF	-2.999b	-5.282[a]	-7.155[a]	-3.000	
PP	-3.108b	-7.471a	-9.269[a]	2.099	
With Structural Break	-5.332[a]	-9.791[a]	-14.961[a]	-3.044	
Panel C: Summary descriptive statistics for model variables. All variables are in level					
Mean	185.453	37.456	0.989	21.438	
Stand Dev	75.562	17.859	2.964	7.622	
Skewness	0.850	5.259	13.411	0.647	
Kurtosis	2.926	52.154	234.053	1.976	
J-B	420.223	353323.0[a]	7565671.0[a]	381.363[a]	
LM ARCH test			50.412 [a]	4.697[b]	

Notes: Bai and Perron (2003) (Econometric Journal), critical values. The null hypotheses for ADF and PP tests is that a series is nonstationary. Intercepts were included in the PP tests. The ADF test is performed with breakpoint possibility and includes both a trend and an intercept. Unit root tests with break points tests include a trend and intercept in regressions. Break selection is based on Dickey-Fuller t statistic minimization. Insignificant test statistic means that the null hypothesis is not rejected. [a,b] represent significance at 1and 5 percent levels.

3.2 GARCH-MIDAS and Markov Switching Regression Results

Table 2 shows the estimates of the GARCH-MIDAS model that produce the short-term and long-term volatility components of the realized volatility in HHNGP. The estimates of β are 0.9793 and 0.886 based on two sets of covariates, respectively and are statistically significant, suggesting strong persistence in the short-term volatility component. The coefficient α is statistically significant in equation (4) with the first set of covariates. The θ and θ_2 coefficients represent the changes in the long-term volatility stemming from the lagged effects of the industrial production and EPU. The coefficients are statistically significant in specification (1), therefore the long-term volatility is positively and negatively associated with the industrial production and EPU, respectively. Both weights, i.e., w2 and w2_2 in equation (5) are statistically significant in specification (1). Mostly statistically significant coefficients in specification (1) shows that the short-and long-term volatilities in HHNGP are driven by the industrial production and EPU in the US.

Table 2: GARCH -MIDAS with two covariates, change in industrial production with News-Based Economic Policy Uncertainty (1), and with Equity Market Volatility Index (2)

	(1)	(2)
μ	-0.006	-0.013
	(0.041)	(0.081)
α	0.197 [a]	0.123
	(0.037)	(0.012)
β	0.793[a]	0.886 [a]
	(0.028)	(0.008)
ϒ	-0.021	-0.020
	(0.036)	(0.020)
m	3.009 [a]	-2.325[a]
	(0.386)	(0.963)
θ	0.537[a]	0.288
	(0.202)	(0.192)
w2	1.000 [a]	4.098[a]
	(0.178)	(1.492)
θ_2	-0.004[a]	1.622
	0.001	(1.230)
w2_2	6.542 [b]	3.889
	3.852	(3.281)
Note: [a,b] significant at 1 and 10 percent levels.		

Table 3 displays the results of the MSR estimation. The findings indicate the salience of GEPU in the minds of market participants under both volatility regimes. The association of the GEPU with short- and long-term volatilities is statistically significant and positive during low and high volatility regimes. Therefore, regardless of the volatility regimes, the global economic policy uncertainties contribute to volatility in the HHNGP market both in the short-and long-term.

The statistically significant and negative association of the oil market volatility index (OVX) with short-term volatility is observed in high volatility regime. However, OVX significantly and positively impacts Long-Term Volatility (LTV) only under both volatility regimes.

Table 3: Markov Switching Estimation of Equation (1)

	Regime	C	GEPU	OVX	LN(σ)
STV	Regime 1	0.518[a]	$0.19*10^{-3}$ [a]	-0.0004	-1.264[a]
		(0.015)	$(07.59*10^{-5})$	(0.0002)	(0.0165)
STV	Regime 2	1.827[b]	0.020[a]	-0.078[b]	1.847[a]
		(0.898)	(0.003)	(0.031)	(0.030)
LTV	Regime 1	7.163[a]	0.050[a]	0.050	0.571[a]
		(0.266)	(0.002)	(0.003)	(0.040)
LTV	Regime 2	15.340[a]	0.249[a]	0.001[c]	1.108[a]
		(0.696)	(0.010)	(0.0006)	(0.029)

Notes: Simple switching regressions are estimated by BFGS/Marqurdt steps. [a,c] represent significance of Z statistic at 1 and 10 percent levels. Numbers in parentheses are standard errors. STV and LTV represent short- and long-run volatilities in HHNGP from GARCH-MIDAS model.

It is plausible that market participants form rational expectations regarding unexpected OVX movements and take necessary steps to cope with them in the short run. This rationality aligns with the way market participants anticipate non-market-determined policies, similar to Federal Reserve (FED) policies, which may or may not materialize. For example, during acute crude oil market crises, the US government tends to inject crude oil supplies from the strategic petroleum reserves (SPR). While these steps may carry symbolic weight, their psychological impact on the markets can be substantial. Following the onset of the Ukraine conflict in February 2022, Brent crude prices surged past $107 a barrel to reach a seven-year high. The announcement of a 1 million barrel release of crude oil from the SPR by the US, coupled with similar actions by other nations, appeared to have a calming effect on crude oil markets.
It is noteworthy that GEPU increases long-term volatility levels in HHNGP under both volatility regimes. Consequently, global policy risks contribute to heightened volatility in the long-term HHNGP. Natural gas end users may face challenges in predicting unsettling global events and deploying hedging strategies in a timely manner.
Table 4 provides an overview of the transition probabilities and duration of high and low variance periods for both short-term and long-term volatility series. It is noteworthy that the probabilities of transitioning from regime 1 to regime 2 are quite high. In regime 2, characterized by a high absolute value of LN(σ), shorter periods of short-term HHNGP volatility (STL) are observed compared to regime 1 (low variance).

Table 4: Short term volatility Transition summary:
Constant Markov transition probabilities and expected durations

	STV		LTV	
	Low volatility	High volatility	Low volatility	High volatility
Low volatility	0.992	0.008	0.657	0.343
High volatility	0.037	0.963	0.657	0.343
Constant expected durations	127.76	27.203	2.916	1.521

Notes: STV and LTV represent short- and long-run volatilities in HHNGP from GARCH-MIDAS model.

A similar pattern is evident in the long-term volatility of HHNGP. Our volatility forecasts were derived from data that encompassed a period of extreme shock and volatility—the COVID-19 pandemic. Historically, equity markets have rebounded from shocks such as avian influenza and the severe acute respiratory syndrome coronavirus. The S&P500, for instance, demonstrated a remarkable recovery following the initial impact of the COVID-19 outbreak. As a result, the behavior of short- and long-term volatility in HHNGP is anticipated to exhibit variations. It is crucial to acknowledge that the fossil fuel industry experienced demand and supply shocks, contributing to volatile markets for crude oil and its distillates. However, the detailed exploration of these factors is beyond the scope of this paper.

Figures 3 and 4 plot the predicted one-step transition probabilities of being in regime 1 and regime 2 as well as the length of high and low variance periods in both short- and long-term HHNGP volatility series.

3.3 Quantile Regression Results

The QR regression estimates presented in Table 5 reveal that Short-Term Volatility (STV) in HHNGP is influenced by both Global Economic Policy Uncertainty (GEPU) and OVX, particularly when short-term volatility is heightened, i.e., at higher quantiles of the STV. This observation suggests a plausible scenario where market participants in the natural gas market become more responsive to additional market turbulence in the crude oil market (as indicated by OVX) and geopolitical risks (as indicated by GEPU) during periods of elevated short-term volatility.

Table 5: Quantile Regression Estimation of Equation (1), Short-Term Volatility of HHNGP Granger Causality

STV	1^{st} Q	C	GEPU	OVX	Ps_R2	Quasi_LR	No Causality	
		0.217^a	$8.38*10^{-5}$	$--2.52*10^{-5}$	0.0003	0.233		
		(0.011)	$(5.84*10^{-5})$	(0.0002)				
STV	5^{th} Q	0.444^a	0.0005^a	-0.001^a	0.002	28.470	GEPU[a]	OVX[a]
		(0.023)	(0.0001)	(0.0003)				
STV	9^{th} Q	0.712^a	0.008^a	-0.013^a	0.053	214.163	GEPU[a]	OVX[a]
		(0.129)	(0.001)	(0.001)				
STV	OLS	-0.135	0.009^a	-0.014^a	0.047	82.870		
		(0.344)	(0.003)	(0.005)				

Notes: [a] represents significance at 1 percent level. The values of R-sq and likelihood ratio functions for the OLS estimates and pseudo R-sq and quasi-likelihood ratio functions are in the last two columns. OLS estimates are by the Newey-West HAC method. Huber sandwich standard errors and covariances. Method of Epanechnikov kernel, and Hall–Sheather residuals bandwidth (bw = 0.025648). STV and LTV represent short- and long-run volatilities in HHNGP from GARCH-MIDAS model. Granger (1969) causality tests test the causality from GEPU and OVX to STV up to a week as determined by several information criterion.

Drawing on the insights of Edwards et al. (1995), who demonstrated the dynamic nature of saliency in the minds of decision-makers depending on prevailing conditions, it is conceivable that decision-makers in the natural gas market, especially during periods of high short-term volatility become exceptionally attuned to news and risks emanating from the crude oil market and the global landscape.

The QR Granger causality tests presented in Table 6 reveal that long-term volatility (LTV) in HHNGP is not influenced by the oil volatility index (OVX). This lack of influence is unsurprising given that OVX is specifically designed to signal short-term market volatilities. However, noteworthy findings emerge as, across all levels of long-term volatility—ranging from low quantiles to high quantiles in LTV—Global Economic Policy Uncertainty (GEPU) significantly impacts the volatility in HHNGP. This suggests that market participants in the natural gas market remain responsive to geopolitical risks even in the context of varying long-term volatility levels.

Table 6: Quantile Regression Estimation of Equation (1), Long-Term Volatility of HHNGP Granger Causality

LTV	1st Q	C	GEPU	OVX	Ps_R2	Quasi_LR	
		6.077[a]	0.047[a]	0.047[a]	0.305	2054.691	GEPU[a]
		(0.167)	(0.001)	(0.002)			
LTV	5th Q	5.029[a]	0.080[a]	0.020[a]	0.445	5544.009	GEPU[a]
		(0.172)	(0.001)	(0.003)			
LTV	9th Q	3.189[a]	0.112[a]	0.136[a]	0.352	1566.434	GEPU[a]
		(0.939)	(0.007)	(0.022)			
LTV	OLS	5.848[a]	0.077[a]	0.043[a]	0.607	2595.694	
		(0.664)	(0.003)	(0.014)			

Notes: [a] and [b] represent significance at 1percent level. The values of R-sq and F statistic for the OLS estimates and pseudo R-sq and quasi-likelihood ratio functions are in the last two columns. OLS estimates are by the Newey-West HAC method. Huber sandwich standard errors and covariances. Method of Epanechnikov kernel, and Hall–Sheather residuals bandwidth (bw = 0.025648). STV and LTV represent short- and long-run volatilities in HHNGP from GARCH-MIDAS model. Granger causality tests test the causality from GEPU and OVX to LTV up to five months as determined by several information criterion.

This observation aligns with the dynamic nature of issue saliency highlighted by Edwards et al. (1995), emphasizing that the significance of issues in the minds of decision-makers is subject to change over time and may be driven by different factors at different times.

The observation that causality from both OVX and GEPU is more pronounced at the middle and upper quantiles suggests the limited risk-hedging efficacy of natural gas risks during normal and bullish market states. In essence, the study urges against neglecting uncertainties, particularly those tied to global economic policy and oil market risks, in the analytical frameworks designed for modeling and forecasting Henry Hub natural gas prices. The nuanced insights provided by the research shed light on the intricate dynamics between uncertainties and natural gas prices in the US, offering valuable considerations for investors and analysts alike.

The findings from Granger causality tests in quantiles revealed compelling evidence that GEPU significantly Granger-cause LTV in HHNGP volatility across all quantiles. LTV does not appear to respond to OVX in any quantile. This finding is plausible indicating that the long-term volatility in HHNP are not dependent on short-term risks in crude oil market as reflected by OVX. However, LTV is not immune to global uncertainties. Thus, available hedging strategies may not be effective given the unpredictability of global and geopolitical risks.

The statistical results indicating that both short- and long-run volatility in the HHNGP market display conditional heteroscedasticity are reasonable and align with the inherent structural and behavioral features of the natural gas market. Conditional heteroscedasticity—where volatility depends on past variances or shocks—is a natural property of energy markets characterized by recurrent supply-demand imbalances, storage limitations, and sensitivity to macroeconomic and policy developments. The high and statistically significant β coefficients in the GARCH-MIDAS estimations (0.9793 and 0.886) imply that current volatility is heavily influenced by its own past, which is consistent with the persistence of volatility clustering observed in natural gas prices. This persistence reflects the way market participants adjust expectations gradually to evolving information about weather conditions, production, and global economic activity, leading to serial correlation in volatility rather than instantaneous adjustment.

Moreover, the significant impact of industrial production and EPU on long-term volatility accords well with the economic underpinnings of natural gas demand. Industrial production captures cyclical energy consumption patterns, where expansions increase baseline demand and amplify volatility through capacity constraints. Conversely, higher EPU often suppresses investment and industrial activity, dampening long-term volatility by reducing demand uncertainty. The opposite signs of these coefficients in the long-term volatility equation therefore reflect the offsetting forces of real economic activity and policy-driven uncertainty in shaping market expectations. This dynamic produces the conditional heteroscedasticity pattern observed in both the short and long horizons—periods of economic expansion amplify volatility persistence, whereas high uncertainty moderates it over longer intervals.

The Markov-Switching results further substantiate the statistical plausibility of conditional heteroscedasticity in the HHNGP market. Transition probabilities between low- and high-volatility regimes suggest that shocks are not transient but tend to propagate through expectations and inventory decisions. This regime-dependent structure mirrors rational behavior among producers, distributors, and traders who adjust contract lengths, storage, and hedging positions asymmetrically across regimes. In tranquil periods, volatility remains subdued and mean-reverting, but in high-volatility states, self-reinforcing mechanisms—such as speculative positioning or precautionary storage—amplify variance persistence. This dual structure naturally generates conditional heteroscedasticity and supports the theoretical foundation of using GARCH-type and regime-switching models for HHNGP volatility dynamics.

Finally, the inclusion of global and oil-related uncertainty measures (GEPU and OVX) provides additional justification for these statistical results. Global uncertainty shocks transmit indirectly to the U.S. gas market through macro-financial channels, influencing expectations of economic growth, liquefied natural gas (LNG) export demand, and cross-market substitution with oil. As a result, both short- and long-term volatility in HHNGP respond conditionally to the intensity of global uncertainty and commodity-market turbulence. These patterns make the observed conditional heteroscedasticity entirely consistent with the economic realities of a partially globalized but still regionally constrained natural gas market.

The volatility behavior observed in the Henry Hub Natural Gas Price market shares important parallels—and some clear contrasts—with those in the electricity and crude oil markets.

In both the crude oil and natural gas markets, volatility dynamics exhibit strong persistence, with significant short-term clustering and long-term components driven by macroeconomic variables such as industrial production and policy uncertainty. The GARCH-MIDAS findings for HHNGP align closely with evidence from the crude oil market, where both demand-side factors (industrial activity) and uncertainty shocks (EPU or GEPU) shape volatility at different horizons. However, while the oil market often transmits global shocks more directly—owing to its higher liquidity and geopolitical exposure—natural gas volatility tends to respond with a lag and shows greater sensitivity to domestic production cycles and weather-related demand shifts. This reflects the more regionally segmented nature of natural gas trade relative to the globally integrated crude oil market.

In contrast, the electricity market behaves differently due to its limited storability and high sensitivity to short-term supply-demand imbalances. Electricity price volatility is typically more episodic and characterized by sudden spikes rather than persistent clustering. Unlike HHNGP, where long-term volatility responds strongly to global policy uncertainty, electricity market volatility is more often driven by local operational factors—such as outages, grid constraints, and renewable intermittency—though policy uncertainty still plays a role through regulatory reforms or carbon pricing schemes. Thus, while both electricity and gas prices are influenced by energy-sector fundamentals, the persistence and predictability of volatility are generally stronger in natural gas than in electricity.

Another important distinction concerns regime behavior. The Markov-Switching results for HHNGP show clear transitions between high- and low-volatility regimes that mirror crude oil market dynamics, particularly during geopolitical shocks (e.g., the 2022 Ukraine conflict). By contrast, electricity markets exhibit more frequent but shorter volatility bursts, corresponding to system constraints or demand peaks rather than macroeconomic cycles. In this sense, HHNGP's volatility regimes resemble those of crude oil—driven by broad macro-financial and policy uncertainties—while electricity volatility is more microstructural and transitory.

While all three markets share nonlinear and regime-dependent volatility features, natural gas occupies an intermediate position: less globally synchronized than oil but far more persistent and policy-sensitive than electricity. These comparisons imply that policy measures or hedging strategies effective in crude oil markets—such as macro-hedging against policy uncertainty—may be more transferrable to gas than to electricity markets, where localized and physical-market interventions dominate.

4. Summary and Conclusions

The association of U.S. natural gas price volatility with global economic uncertainty and the Oil Volatility Index (OVX) represents a critical aspect of market dynamics in both the short and long run. Using daily Henry Hub Natural Gas Prices (HHNGP), U.S. industrial production, and economic policy uncertainty (EPU) data from March 1997 through December 2022, alongside global EPU and OVX data available since 2009, we examined these relationships through GARCH-MIDAS estimation, Markov-switching regressions, and quantile regression (QR) Granger causality tests. Structural break tests further revealed notable shifts in GEPU, OVX, and long-term volatility (LTV) during 2005–2007, plausibly linked to Hurricanes Katrina and Rita and broader geopolitical risks.

The results demonstrate that short-term volatility (STV) in HHNGP is strongly influenced by both GEPU and OVX, especially during periods of elevated volatility. At higher quantiles of STV, natural gas market participants appear particularly sensitive to shocks in the crude oil market and to geopolitical risks. Interestingly, OVX shows a negative association with STV in low-volatility regimes, suggesting that oil market dynamics affect natural gas differently during calmer periods. In contrast, LTV is consistently driven by GEPU across all quantiles, while OVX loses significance in the long run—consistent with its design as a short-term volatility measure.

These findings underscore the multifaceted relationship between natural gas prices, oil market risks, and global policy uncertainty. Short-term dynamics reflect heightened sensitivity to immediate oil market shocks, while long-term volatility is shaped primarily by global policy uncertainty. The evidence suggests that natural gas markets are not insulated from global risks and that available hedging strategies may be limited in their effectiveness, particularly under conditions of heightened uncertainty.

The findings of this study offer several important policy lessons for regulators, energy exporters, and market participants.

Global economic policy uncertainty exerts a persistent influence on both STV and LTV, underscoring the importance of monitoring international policy shifts and geopolitical events. The negative association between OVX and STV during low-volatility regimes highlights the potential for oil market developments to exert spillover effects on natural gas, even when overall volatility is subdued. Investors may reduce exposure through diversification across energy commodities or by employing options strategies tailored to the observed interplay between GEPU, OVX, and STV. More broadly, risk management strategies should integrate both market-specific factors and global economic indicators to better anticipate and mitigate volatility.

For monetary and fiscal regulators, the evidence underscores the need for a coordinated policy framework to counteract the amplification of oil-market shocks through domestic policy channels. Central banks should maintain policy credibility by anchoring expectations and avoiding excessive liquidity expansion during periods of high oil price volatility. Fiscal authorities, in turn, should adopt countercyclical spending strategies—saving windfalls in stabilization funds during high-price periods and deploying reserves strategically when prices fall. Such measures would help smooth inflationary pressures and mitigate the procyclicality observed in oil-exporting economies.

For energy market regulators and state-owned enterprises, the nonlinear effects identified in this study highlight the importance of developing hedging and diversification mechanisms to reduce exposure to extreme oil volatility. Establishing transparent pricing frameworks, forward-contract markets, and robust risk-management tools can enhance market stability and investor confidence, particularly in economies where energy exports are the main source of revenue.

For LNG exporters and corporate decision-makers, understanding the asymmetric and time-varying relationship between oil volatility and inflation can inform long-term contracting, investment timing, and inventory management. Firms can use the study's insights on lagged effects to optimize hedging strategies and minimize adverse balance-sheet impacts during turbulent market phases.

For hedge funds and institutional investors, the cross-quantile and wavelet findings indicate that inflation responses to oil volatility are strongest under extreme market conditions. This suggests that energy-linked assets and inflation-sensitive instruments (such as TIPS or commodity futures) can be strategically reweighted across volatility regimes. Incorporating such regime-switching signals into quantitative trading models may improve risk-adjusted returns.

To summarize, these policy and market implications underscore that maintaining macro-financial stability in oil-dependent economies requires adaptive, data-driven regulation and proactive risk management. The integration of time- and frequency-sensitive analytical approaches—such as those employed in this study—can enable both policymakers and market participants to better anticipate and mitigate the cascading effects of global commodity shocks.

In conclusion, the evidence highlights the interconnectedness of global economic policy, oil market dynamics, and U.S. natural gas price volatility. Recognizing these linkages is essential for accurate modeling and forecasting, and for designing policies and investment strategies that are resilient to both short-term shocks and long-term geopolitical risks.

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Figures

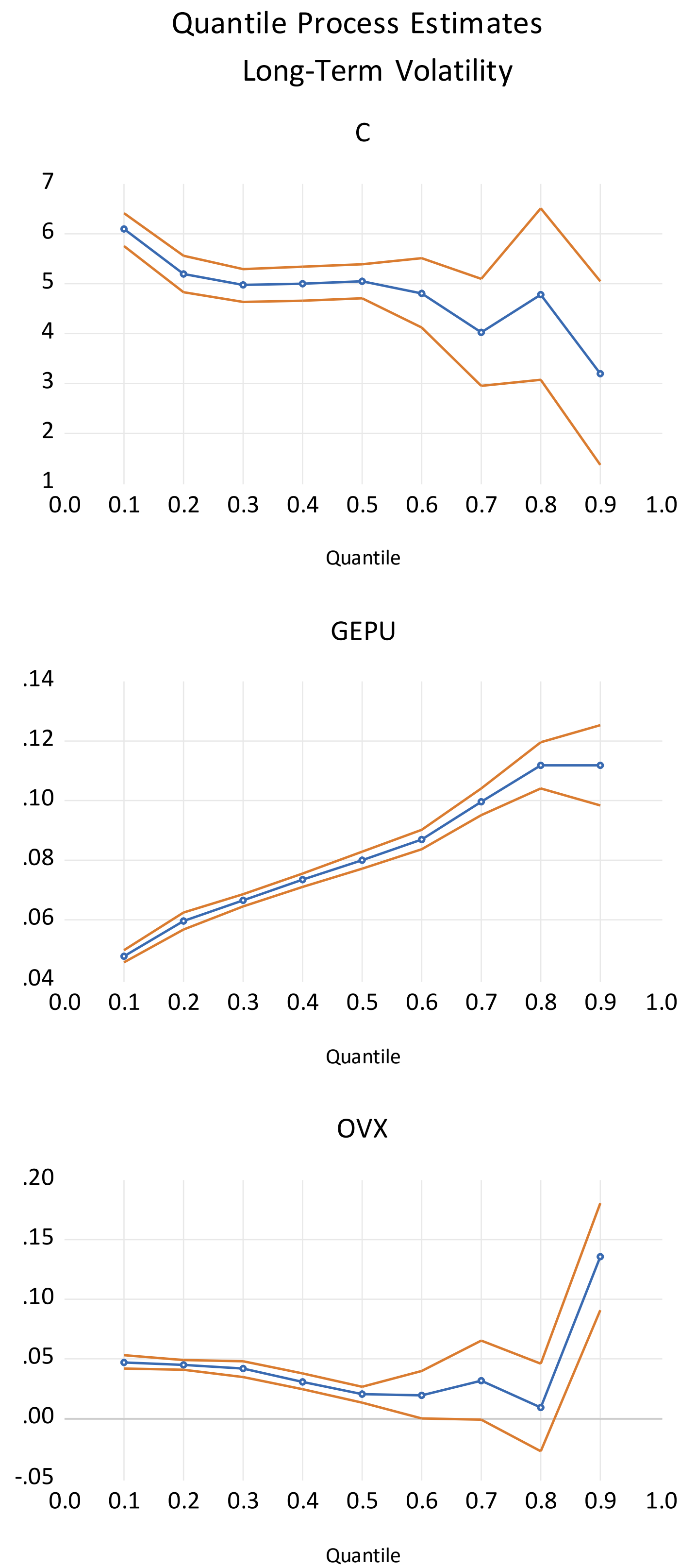

Figure 1: Coefficient estimate process for STV regressions through quantiles

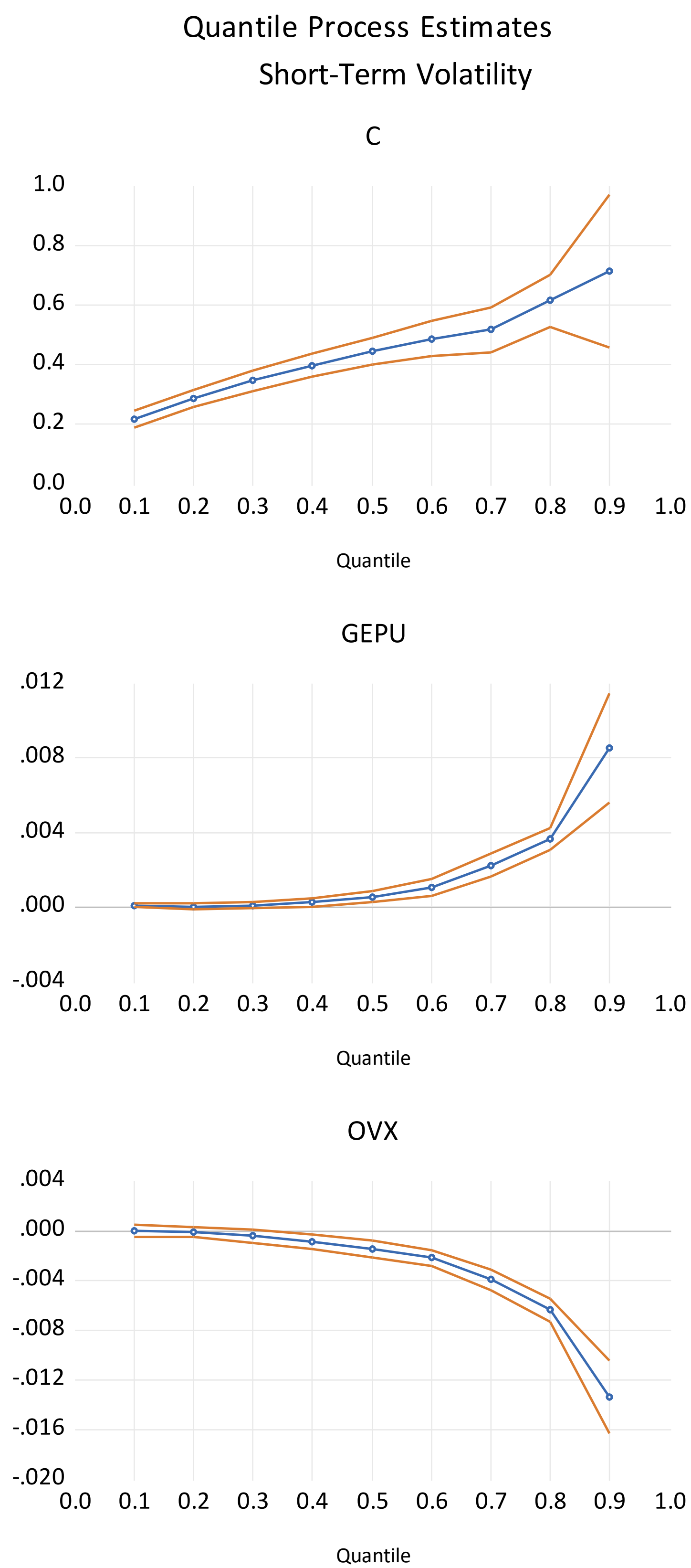

Figure 2: Coefficient estimate process for LTV regressions through quantiles

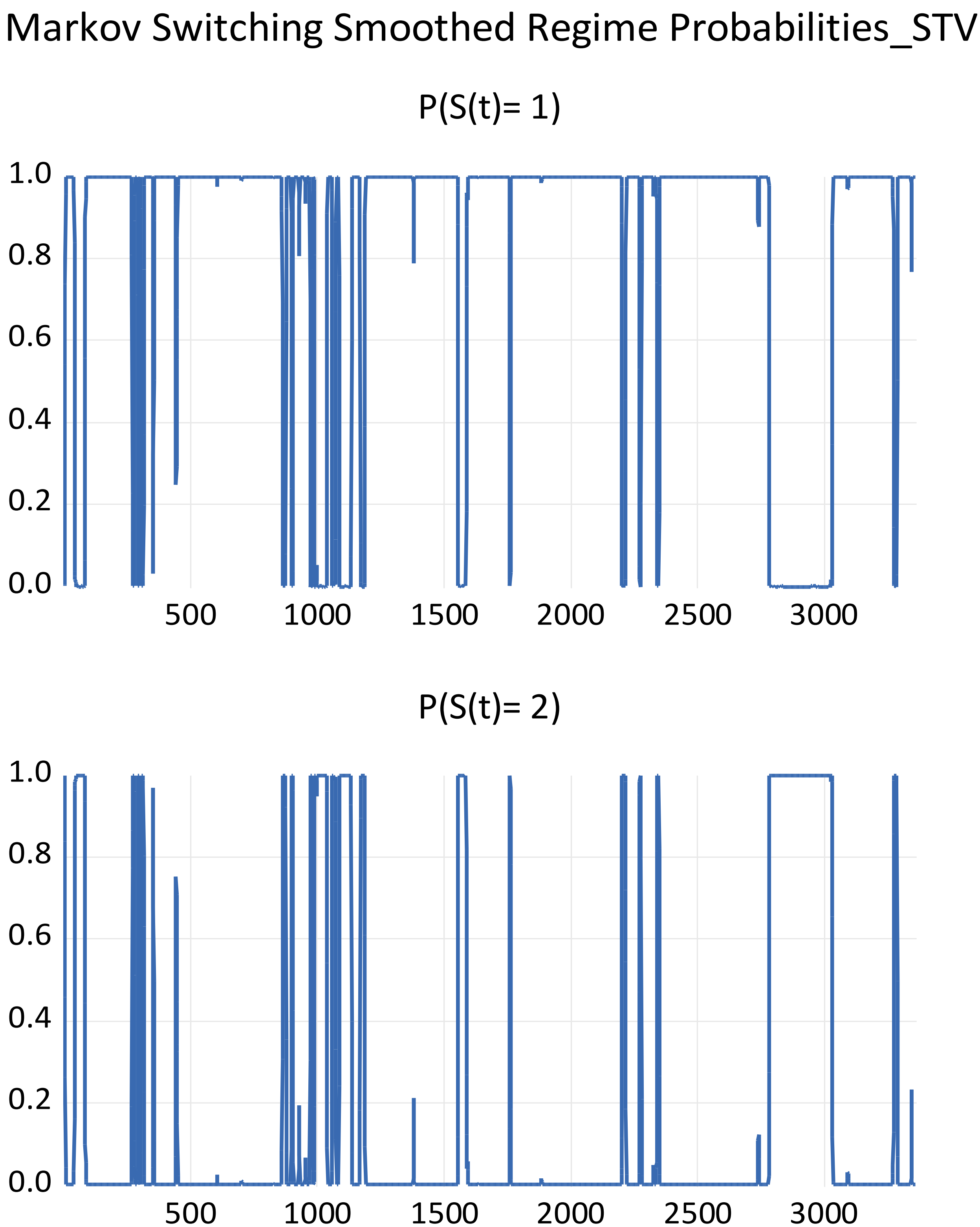

Figure 3: Markov switching transition probabilities for short-run HHNGP volatility

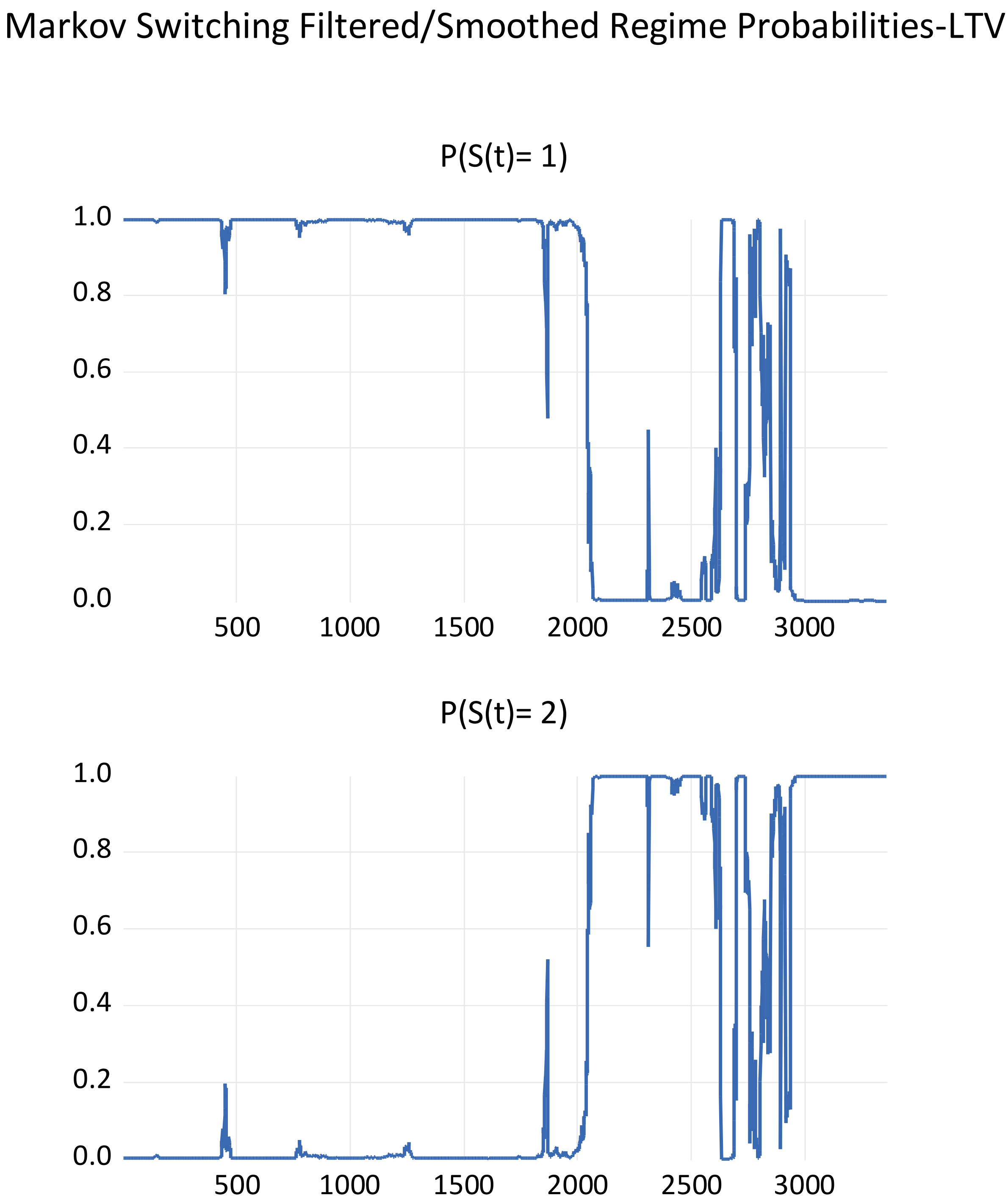

Figure 4: Markov switching transition probabilities for long-run HHNGP volatility