

A Multiresolution Investigation of How Macro Uncertainties Influence Natural Gas Price Dynamics

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Abstract

The price dynamics within the energy complex appear independently state-dependent; for instance, it is well documented that the price of natural gas (crude) is especially susceptible to large swings in Winter (Summer), when demand is elevated. The influence flowing from crude price dynamics to the energy complex must therefore be considered a multiresolution problem. In this paper we use quantile-on-quantile (QOQ) regressions and wavelet coherence analysis to assess the response of natural gas price return volatility (HHNG) to two macro influences – economic polity uncertainty (EPU) and crude oil volatility (OVX). The QOQ regressions show that the response of natural gas volatility to uncertainty is strongly regime dependent. In tranquil states, when both volatility and uncertainty lie in lower or middle quantiles, shocks to EPU and OVX have little effect and may even slightly dampen volatility. In contrast, once markets enter turbulent regimes, even modest increases in uncertainty generate disproportionate and persistent volatility surges. Long-horizon dynamics show smoother but sustained effects, with high-quantile EPU and OVX jointly contributing to prolonged volatility elevation. Wavelet coherence analysis reinforces the QOQ regression findings by identifying periods of strong, in-phase co-movement between gas volatility and uncertainty indicators and by showing that leadership can shift: gas volatility often leads uncertainty at high frequencies, while EPU or OVX lead gas volatility at medium-term horizons. On the other hand, HHNG emerges as a regime-dependent process shaped jointly by domestic fundamentals, policy uncertainty, and oil-market sentiment. The evidence points to the importance of recognizing the nonlinear and state-contingent dynamics in the statistical evaluation of energy prices; consistent with our choice of methodology, a general and flexible form of state-contingent evaluation appears appropriate.

JEL classification: Q31, Q39, G10.

Keywords: Natural Gas, Volatility, EPU, OVX, Wavelet Analysis, Quantile Regression.

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1. Introduction

Natural gas occupies a central position in the U.S. economy, serving as a critical source of energy and a driver of industrial production, employment, and exports. It provides over one-third of the nation's total energy supply and accounts for the largest share of electricity generation, surpassing coal and renewables combined. Its role extends far beyond power plants: natural gas is a key input in manufacturing, petrochemicals, and fertilizers, while also heating millions of households across the country. Because of this pervasive reach, the price of natural gas is not a narrow market concern as it bears directly on macroeconomic stability.

Natural gas prices are known to be sensitive to weather, storage, and infrastructure constraints, but over the past two decades the market has become increasingly financialized and globally interconnected. Its price dynamics respond not only to local fundamentals but also to shifts in investor sentiment, regulatory expectations, and global uncertainty. Among the macro-level drivers, two forces stand out: economic uncertainty and oil-market volatility, represented in this paper by economic policy uncertainty (EPU) and the "oil fear index" (OVX), respectively. EPU captures fluctuations in the policy environment—changes in fiscal and regulatory outlooks that influence investment and consumption decisions, while OVX reflects risk perceptions and stress levels in global energy finance. Both can transmit shocks to the natural gas market, altering expectations and prompting cascades of volatility. Yet their effects are unlikely to be linear or uniform. The same level of policy uncertainty may have little impact in calm markets but cause large disruptions when volatility is already elevated. Capturing these subtleties requires moving beyond conventional linear time-series models. The purpose of this paper is to examine the potentially varying influence that oil price and economic uncertainty have on natural gas prices.

The present study adopts two main econometric approaches—quantile-on-quantile regression (QOQ) and wavelet coherence analysis—to uncover these nuanced relationships. The QOQ framework allows the effect of uncertainty to vary across the entire joint distribution of natural gas volatility and the uncertainty measures, identifying how extreme or moderate states interact rather than assuming a single average response. This method highlights asymmetry and state dependence—how uncertainty may dampen volatility in tranquil conditions yet amplify it in turbulent regimes. Complementing this, wavelet coherence combines time-series and frequency-domain analysis to trace the co-movement between variables across different time horizons. It reveals when and at what frequencies Henry Hub volatility and uncertainty measures move together or diverge, and the directionality of their relationship through phase arrows. The integration of these two methods offers a richer, multidimensional view of market behavior: the quantile-on-quantile results expose nonlinearities in distributional space, while the wavelet coherence uncovers evolving synchronization and lead-lag patterns over time.

By applying these complementary tools, the analysis provides new evidence on how domestic policy uncertainty and global oil-market fear jointly shape the dynamics of U.S. natural gas prices. We demonstrate that volatility transmission in the gas market is conditional, asymmetric, and time-varying—driven by both structural fundamentals and financial sentiment. These insights have direct relevance for investors, hedgers, policymakers, and energy suppliers seeking to understand and manage the risks associated with one of the most important commodities in the modern U.S. economy.

The remainder of the paper is organized as follows. In Section II, we review background of the methods employed in context of energy price dynamics. Section III describes the data and methodologies deployed, emphasizing GARCH-MIDAS, quantile-on-quantile regressions, and wavelet and cross Wavelet analyses. Section IV reports the empirical results. Section V offers conclusions with policy implications regarding volatility management and the design of uncertainty-sensitive energy and macro policies.

2. Assessment of Energy Price Volatility and Economic Uncertainty

Economic uncertainty influences business cycle, prices, investment and hedging decisions. Building upon foundational work that explains why firms adjust their production, investment, and pricing strategies when perceived risk increases (see Sandmo, 1971; Galbraith, 1977; Bernanke, 1983; Pindyck, 1990; Dixit & Pindyck, 1994; Flacco & Kroetch, 1986; Adrangi & Raffiee, 1999, among others) this paper examines techniques that incorporate the influence of uncertainty.

Two forms of macro uncertainty are assessed in context of their influence on natural gas. First, we employ the U.S. news-based economic policy uncertainty index (EPU) as a proxy of economic uncertainty. Research utilizing text-based indices (see Baker et al., 2016)), such as those focusing on policy uncertainty, suggests a link to reduced output, investment, employment, and business-cycle fluctuations across developed economies, though a universally agreed-upon definition of "uncertainty" remains elusive. Nonetheless, the EPU provides a convenient and standardized means to quantitatively assess economic uncertainty (e.g., 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, and Sun and Li (2025)). Second, we deploy crude oil uncertainty. The formation of crude oil prices is influenced by a combination of global supply and demand conditions—given that OPEC accounts for nearly 40% of world output and the U.S. and Russia each contribute about 10–12%—along with geopolitical factors and the structure of domestic markets. The CBOE Oil Volatility Index (OVX), derived from options and gauges expected 30-day crude volatility. While OVX assists firms and investors in risk management and option pricing, its short-term focus and dependence on the liquidity of the options market limit its capacity to capture profound, long-term structural shifts.

Methodologies for modeling volatility have advanced from earlier GARCH models to more sophisticated frequency-mixing approaches. Notable contributions include Ding & Granger (1996), Engle & Lee (1999), and to 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) who deploy the GARCH-MIDAS methodology. Further research (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) confirm that including low-frequency macro variables materially improves volatility forecasts. This study employs a GARCH-MIDAS decomposition, following previous research work of Su et al. (2017, 2018, 2019), to separate the long-run and short-run (daily) components of volatility, where the long-run component is driven by low-frequency uncertainty indicators. The adoption of multi-covariate MIDAS terms is supported by evidence that multiplicative GARCH-MIDAS often outperforms many alternative modeling techniques. Other researchers show asymmetric effects of uncertainty on commodity volatility (Dutta et al., 2021) and oil returns (Xu et al., 2021). Conrad & Kleen, 2020 show evidence that multiplicative GARCH-MIDAS outperforms many alternatives.

The connections between cross-market factors and uncertainty are widely documented: for example, Qadan et al. (2020) find that oil prices are influenced by investor risk appetite and uncertainty shocks, and both VIX and OVX significantly impact U.S. sector ETF dynamics across various time horizons. For China, Wen et al. (2019) discover that short-term connections exist between macro variables and U.S. indices like VIX, EPU, and OVX, with VIX dominating the longer-run effects. Sharif et al., 2020 deploy wavelet analyses to show a significant coherence between pandemic dynamics, oil volatility shocks, geopolitical risk, EPU, and U.S. equities, with policy implications for crisis management. Broader studies on market connectedness confirm the influential role of OVX, EPU, and Global Geopolitical Risk (GPR) in shaping macro activity, volatility, and returns across different regions and assets, often with asymmetric and state-dependent impacts (see Adekoya et al., 2022; Bouri et al., 2023; Abiad & Qureshi, 2023; Assaf et al., 2021). Other researchers focus on volatility spillover across commodities rather than volatility triggered by economic policy or crude oil market uncertainty. For instance, Koulis & Kyriakopoulos (2023) discuss volatility transmission and contagion between gold and silver markets.

However, research focused specifically on natural gas volatility and its relation to uncertainty is limited compared to that for oil. Prior work by Scarciuffolo & Etienne (2021a) reveal a regime-dependent volatility for both oil and natural gas, where policy uncertainty increases the likelihood of turbulent periods, an effect that has diminished since the rise of shale production. Given the crucial importance of natural gas and the anticipated increase in U.S. supply, volatility in Henry Hub Natural Gas prices can stem from global shocks, policy frameworks, and fundamental factors such as demand and production. Since economic agents are typically risk-averse, uncertainty shocks influence spending and investment decisions, with the perception and prominence of events shaping these market responses (Edwards et al., 1995). Consequently, the behavior of natural gas price volatility is dynamic and non-uniform, reflecting complex and evolving market conditions. Therefore, natural gas price volatility must be understood as fundamentally dependent on the prevailing market regime. For all participants, including hedgers, investors, policymakers, and suppliers, it has become essential to adopt a framework that explicitly views volatility as regime-dependent and linked to OVX and EPU.

The study's design, combining a two-covariate GARCH-MIDAS model with subsequent Wavelet and Quantile-on-Quantile analyses, is specifically crafted to capture both the frequency-domain structure and the state dependence of volatility while mitigating the risk of misspecification. GARCH-MIDAS is deployed here to obtain short and long-duration volatility measures. These measures are then used in estimating the relationships using QOQ regressions. QOQ offers several key advantages over ordinary least squares (OLS) and OLS-based multivariate frameworks such as VARs, particularly when analyzing the relationship between uncertainty measures (EPU and OVX) and short- and long-term natural gas volatilities. Traditional OLS models focus on average effects and therefore mask the heterogeneous responses that may occur across different segments of the volatility distribution. Similarly, VARs—despite capturing dynamic interactions—still rely on conditional means and assume symmetric responses unless explicitly modified. As a result, both approaches can overlook important nonlinearities, tail behaviors, and regime-specific sensitivities. By contrast, QOQ regressions allow the effect of an independent variable's quantile (e.g., high or low EPU or OVX) to be mapped onto the dependent variable's quantile (e.g., high or low volatility). This dual-quantile structure enables a far richer characterization of how uncertainty shocks transmit under different market conditions. For example, QOQ estimations can reveal whether EPU or OVX have disproportionately strong effects on the lower percentiles of short- or long-term volatility—periods associated with calm, stable regimes—or whether their influence intensifies in the upper percentiles, corresponding to stress, turbulence, or crisis regimes.

This flexibility provides insight into regime-dependent behavior that conventional approaches cannot capture. If the impact of EPU or OVX is found to be muted in low-volatility states but amplified in high-volatility ones, QOQ regressions make this pattern directly visible. Conversely, if uncertainty shocks exert stronger influence during tranquil market regimes—perhaps by altering expectations or precautionary behavior—QOQ models will detect such asymmetries. In this way, the methodology is well suited to explaining how the EPU–volatility or OVX–volatility relationship evolves as volatility itself transitions across regimes. In sum, QOQ regression delivers a nuanced, distribution-aware view of uncertainty transmission that is unattainable with traditional OLS or VAR frameworks. It highlights the heterogeneity, asymmetry, and nonlinear dependence structures that are essential for understanding volatility dynamics in markets characterized by frequent regime shifts.

This study also applies the continuous wavelet transform (CWT), following the recommendations of Aguiar-Conraria and Soares (2014), to identify underlying patterns and structural dynamics in the data. The theoretical foundations and analytical procedures are based primarily on the frameworks developed by Aguiar-Conraria and Soares (2014), Rua (2012), Torrence and Compo (1998), and Röscher and Schmidbauer (2018). Unlike traditional time-series techniques—which typically operate either in the time domain (e.g., VARs, GARCH models) or the frequency domain (e.g., spectral analysis)—wavelet transforms provide a unified framework that captures localized, nonlinear, and time-varying dependence structures. Building on works by Aguiar-Conraria and Soares (2014), Torrence and Compo (1998), and others, this method decomposes time series into components that reveal both short-term fluctuations and long-term cycles. This capacity is particularly valuable in markets such as natural gas, where volatility dynamics respond to

evolving macroeconomic uncertainty, policy shifts, and global risk sentiment. Applied to EPU and OVX, wavelet-based methods illuminate how the intensity, timing, and persistence of uncertainty shocks differ across volatility horizons. Short-run volatility may exhibit high-frequency coherence with OVX during global financial stress, while long-run volatility may display stronger low-frequency coherence with EPU during extended policy uncertainty episodes. By capturing these scale-specific causal and co-movement structures, wavelet and cross-wavelet analysis provide a rigorous and flexible framework for understanding the nonlinear and regime-dependent effects of uncertainty on natural gas markets. More detailed treatment of the subject can be found in Percival and Walden (2000).

3. Data and Methodology

The data for the empirical investigation is comprised of the mixed frequency sample of observations spanning May 1st 2007 through June 1 2025. The daily price series of Henry Hub Natural Gas prices in U.S. Dollars per Million Metric British Thermal Unit is taken from FRED database at the St. Louis Federal Reserve Bank. The US monthly average temperature in Fahrenheit degrees is provided by the National Oceanic and Atmospheric Administration (NOAA). The monthly US industrial production series is taken from the FRED database of the Federal Reserve Bank of St. Louis. The short- and long- term HHNG is estimated by deploying a two-variate GARCH-MIDAS methodology. The daily data for crude oil volatility index (OVX) created by the Chicago Board of Exchange (CBOE) are available from Yahoo Finance. The daily news-based economic uncertainty index for the US (EPU) are from the FRED data base of the Fed of St. Louis.

Our empirical strategy consists of two interconnected stages designed to isolate, characterize, and interpret the effects of uncertainty on Henry Hub natural gas volatility across multiple dimensions.

In the first stage, we employ a two-covariate GARCH-MIDAS framework to jointly extract short-term (high-frequency) and long-term (low-frequency) volatility components of natural gas prices. This model is well suited for commodity markets, as it accommodates heterogeneous volatility dynamics and allows macro-level uncertainty indicators to influence the long-run volatility component while preserving the daily structure of short-run fluctuations. Equation (1) states the specification used in the GARCH-MIDAS (Conrad and Kleen (2020)) estimation of STV and LTV.

$$\text{HHNG} = f(\text{industrial production, temperature}) \quad (1)$$

In the second stage, we examine how these short- and long-run volatility measures respond to macroeconomic uncertainty (EPU) and global risk sentiment (OVX). To capture potential asymmetries and regime-dependent behavior, we adopt the Quantile-on-Quantile (QQQ) regression approach. This methodology allows the quantiles of EPU and OVX to map onto the quantiles of both volatility measures, thereby revealing whether uncertainty exerts stronger or weaker effects across tranquil, moderate, or turbulent volatility regimes. QQQ is particularly effective in non-linear environments where traditional mean-based models may obscure tail behavior or state-dependent sensitivities.

To broaden the analysis to the combined time–frequency space, we further apply wavelet coherence techniques. Wavelet methods, unlike conventional time-series models, decompose co-movements across multiple frequencies while preserving temporal localization. This enables us to detect whether the influence of EPU and OVX on HHNG is short-lived or persistent, contemporaneous or lagged, and whether these relationships strengthen or weaken during specific economic episodes. Importantly, wavelet coherence is robust to nonlinearity and does not require strict stationarity, making it an ideal complementary tool for validating the QQQ findings.

The, wavelet, cross-wavelet, and phase-difference analyses complement the conventional time-series methodologies by examining the relationships among the variables jointly across the time and frequency domains. Unlike conventional time-domain models, which generally summarize relationships over the sample or through a specified lag structure, wavelet methods decompose the dynamics across different frequencies while preserving their localization in time. Consequently, they can identify whether the

association between policy uncertainty and HHNG volatility is concentrated at short-, medium-, or long-term horizons and, importantly, whether these relationships remain stable or vary over the sample period. The continuous wavelet transform provides information about the evolution of the variability of an individual series across time and frequencies, whereas the cross-wavelet transform identifies regions of common power between two series. Wavelet coherence further measures the strength of their localized co-movement in time-frequency space. Thus, two variables may exhibit relatively weak association over the full sample while displaying substantial co-movement during particular periods and at specific frequencies. This feature is especially relevant to energy markets, where the response to policy uncertainty may differ between short-horizon market participants reacting immediately to new information and longer-horizon investors responding to more persistent changes in economic fundamentals.

An additional advantage is provided by phase-difference analysis. Because wavelet coherence itself measures the strength of co-movement but does not distinguish between positive and negative relationships, phase differences provide information about the direction of the association. An in-phase relationship indicates positive co-movement, whereas an out-of-phase relationship indicates negative co-movement. The orientation of the phase arrows can also provide evidence regarding which of the two variables leads the other at a particular time and frequency. Therefore, the phase analysis is particularly useful in the present study because it can indicate whether changes in policy uncertainty tend to precede movements in sector equity markets or whether movements in equity markets precede changes in measured policy uncertainty. These methods provide information that complements the threshold and other time-series models, including QOQ. The combination of the two approaches therefore permits a richer examination of nonlinear and time-varying dependence by distinguishing not only between low- and high-uncertainty regimes, but also between short-, medium-, and long-run market responses.

Together, the GARCH-MIDAS volatility extraction, QOQ regressions, and wavelet coherence analysis provide a comprehensive, robust, and internally consistent methodological framework. This multi-layered approach allows us to uncover both the distributional and the time-frequency characteristics of uncertainty transmission, reducing the risk of model misspecification and strengthening the credibility of the empirical conclusions.

We offer a brief explanation for the methodologies deployed in this research.

3.1 GARCH–MIDAS Model

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 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 the monthly average US temperature and monthly industrial production enter the low-frequency MIDAS filter to produce short-term (STV) and long-term (LTV) volatility for natural gas price. The MIDAS specification, detailed in Adrangi et al. (2023a,b, 2024a,b, 2025b), is presented in Equation (2).

$$y_{t+k} = \alpha_0 + \alpha_1 x_t^m + \varepsilon_t^m, \quad (2)$$

where y_{t+k} denotes the k -step-ahead value of the dependent variable observed at time t at the highest sampling frequency; x_t^m 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

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

Following Engle et al. (2013), Ghysels et al. (2016), and Conrad & Kleen (2020), 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).

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

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).

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

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

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

The short-term component of GARCH-MIDAS in this paper is due to Engle et al. (2013) i.e., the GARCH process of Bollerslev (1987). It is designed to capture volatility clustering in the daily natural gas price 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:

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

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

$$\phi_k(w_2) = \frac{(1 - k/K)^{w_2-1}}{\sum_{j=1}^K (1 - j/K)^{w_2-1}}.$$

The relationship between U.S. economic performance and natural gas usage is multifaceted—shaped by macroeconomic conditions, policy, technological change, and market structure—and therefore prone to shifting over time. By the same logic, the associations between short- and long-run HHNG (STV and LTV) and the uncertainty measures EPU and OVX are also likely to be time-varying. Periods of low correlation for any pair may reflect weak coherence and limited causal transmission.

Given these dynamics, QOQ regressions and Wavelet coherence offer powerful tools for modeling such complex relationships across different quantiles of their distributions and across time and frequency domains. These methodologies are briefly explained below.

3.2 Quantile-on-Quantile Regression

The Quantile-on-Quantile regression framework was first introduced by Sim and Zhou (2015) as an extension of the traditional quantile regression developed by Koenker and Bassett (1978). While quantile regression allows researchers to explore how independent variables influence the conditional distribution of a dependent variable at different quantiles, it does not fully capture the intricate interactions between the distributions of both the independent and dependent variables.

Sim and Zhou (2015) developed the QOQ regression approach to address this limitation by integrating quantile regression with nonparametric local linear estimation. This methodology enables researchers to investigate how the θ -th quantile of an explanatory variable affects the τ -th quantile of a response variable. In essence, QOQ regression maps the entire distribution of one variable onto the conditional distribution of another, offering a richer and more granular understanding of complex economic and financial relationships.

Since its introduction, the QOQ regression approach has been widely applied in empirical economics and energy research to analyze heterogeneous and nonlinear effects across variable distributions. For instance, it has been used to examine how various levels of economic growth influence energy consumption in major economies and how shocks propagate differently depending on whether variables are in their lower, median, or upper quantiles. Its flexibility makes QOQ regression particularly valuable for studying asymmetric, nonlinear, or distribution-specific relationships that conventional OLS or even standard quantile regression methods may overlook.

In this study, we employ the QOQ framework to examine the transmission of OVX and EPU to HHNG. By analyzing both low and high quantiles of distributions, we capture the heterogeneous effects of OVX and EPU that traditional models may fail to detect.

We analyze the impact of each independent variable separately—namely, EPU and OVX on short- and long-term HHNG. The QOQ model for a single independent variable $X_t \in \{EPU, OVX\}$ is expressed as:

$$Q_{HHNG}(\tau) = \alpha_\tau^\theta + \beta_\tau^\theta(Q_X^\theta) + \varepsilon_{t,\tau}^\theta,$$

where $Q_{HHNG}(\tau)$ represents the τ -th quantile of HHNG on the θ -th quantile of X , Q_X^θ . The coefficient β_τ^θ measures the slope of HHNG at the quantile τ when X is at quantile θ . while $\varepsilon_{t,\tau}^\theta$ denotes the quantile-specific residual.

The marginal effect of each independent variable at a given quantile is:

$$\frac{\partial HHNG(\tau)}{\partial X_t} = \beta_\tau^\theta \quad (7)$$

Where at the low EPU or OVX ($\tau = 0.10$) the marginal effects help assess how EPU or OVX influence the lower tail of HHNG. Similarly, at high states of EPU or OVX ($\tau = 0.90$), they reveal how these independent variables affect the upper tail of the HHNG, providing insights into extreme EPU and OVX pressures.

The paper provides a useful theoretical discussion of Quantile-on-Quantile regression, but additional information on the actual implementation would improve reproducibility. The authors should report the quantile grid employed, the bandwidth-selection procedure, the kernel function, and any other relevant estimation choices. These details are particularly important given that the empirical conclusions rely heavily on differences across quantile combinations.

To implement the QOQ estimation we use the same evenly spaced grid of 10 quantiles: $\tau, \theta \in \{0.1, 0.2, \dots, 0.9\}$ for both the response (dependent) and the conditioning variables (explanatory). This grid is chosen to capture the full distributional dependence while remaining computationally feasible; it includes the lower tail, the median, and the upper tail so that any nonlinear pattern (including asymmetries that are common in volatility-spillover studies) can be seen clearly.

The kernel used to define local neighborhoods around each θ is the standard Gaussian kernel. The weight for observation i at a given θ is:

$$w_i = \frac{\phi\left(\frac{x_i - \hat{\theta}}{h}\right)}{\sum_{j=1}^n \phi\left(\frac{x_j - \hat{\theta}}{h}\right)},$$

where $\phi(\cdot)$ is the standard normal density, $\hat{\theta}$ is the empirical quantile of variable at level θ , and h is the bandwidth.

The bandwidth is automatically with Silverman's rule-of-thumb:

$$h = 1.06 \cdot \text{SD}(x) \cdot n^{-1/5}.$$

To guarantee numerical stability (especially when the plug-in estimate is very small), we impose a hard floor: $h \geq 0.1 \cdot \text{SD}(x)$. This hybrid approach is standard in kernel-based nonparametric and semiparametric work when the data-driven estimate would otherwise cause problems.

For each of the 100 (τ, θ) pairs, we set the quantile level to exactly τ , apply the Gaussian kernel weights, and use the FN (Frisch-Newton) optimizer. We keep only observations whose weights exceed $1\text{E-}8$ (roughly the top 10 % of the data at each point) so that the local sample is large enough for reliable inference.

3.3 Wavelet, Cross Wavelet, and Phase Analysis

This study applies the continuous wavelet transform (CWT), following the recommendations of Aguiar-Conraria and Soares (2014). All normalization steps and parameter conventions follow the standards established in Röscher and Schmidbauer (2018).

The fundamental building block of wavelet analysis for a univariate discrete-time series $\{x_t\}$ where $t=1, \dots, T$ is the wavelet function,

$$W_x(\tau, \varphi) = \sum_{t=1}^T x_t \frac{1}{\sqrt{\varphi}} \Omega^*\left(\frac{t-\tau}{\varphi}\right), \quad (8)$$

which depends on the location parameter τ , representing the position in the time domain, and the scale parameter ϕ , which is inversely related to frequency and corresponds to the level of temporal resolution or period. This dual localization enables the wavelet transform to represent both short-term variations and long-term trends within the time series. In equation (8), the function $\Omega^*(\cdot)$ denotes the complex conjugate of the Morlet mother wavelet, which incorporates the imaginary unit $i = \sqrt{-1}$, is shifted in time by τ , and scaled by the factor ϕ . The angular frequency ω is conventionally fixed at $\omega=6$.

The main analytical measures derived from the basic wavelet include the amplitude

$$A_x(\tau, \phi) = \frac{1}{\sqrt{\phi}} |w_x(\tau, \phi)| \text{ and, more critically, the wavelet power spectrum}$$

$$\rho_x(\tau, \phi) = \frac{1}{\phi} |w_x(\tau, \phi)|^2, \text{ defined as the square of the amplitude.}$$

The wavelet power spectrum defines the intensity of periodic fluctuations at a particular scale (or period) ϕ and specific point in time τ . Averaging these values over time yields the mean power spectrum, which functions analogously to the traditional power spectrum in classical spectral analysis.

Another important tool derived from the basic wavelet is the wavelet phase angle,

$$\Phi_x(\tau, \phi) = \arctan\left(\frac{I(W_x(\tau, \phi))}{R(W_x(\tau, \phi))}\right), \text{ which defines the timing and synchronization of fluctuations.}$$

Functions $\text{Re}(\cdot)$ and $\text{I}(\cdot)$ denote the real and imaginary components, respectively. The wavelet phase angle $\phi_x(\tau, s) \in [-\pi, \pi]$ pinpoints the angular displacement of cyclical patterns relative to the time origin τ . We will utilize the phase angle concept in the context of the bivariate wavelet transform.

When examining the interaction of two time series $\{x_t\}$ and $\{y_t\}$ for $t=1, \dots, T$, one can compute the univariate wavelet transforms, $W_x(\tau, s)$ and $W_y(\tau, s)$. The cross wavelet power spectrum is computed using individual wavelet transforms as $w_{xy}(\tau, \phi) = \frac{1}{\phi} w_x(\tau, \phi) w_y^*(\tau, \phi)$, which explains the joint variability of the two time series in both time and frequency domains. While individual wavelet power spectra describe the temporal variation within each series, the cross wavelet power spectrum reveals their shared dynamics.

The wavelet coherence, which is based on the cross wavelet power spectrum, is computed and given in equation (9). It is used to quantify the strength of the local relationship between the two series across both time and frequency domains.

$$\rho_{yx}(\tau, \phi) = \frac{|S(W_{yx}(\tau, \phi))|^2}{S(P_x(\tau, \phi)) \cdot S(P_y(\tau, \phi))}, \quad (9)$$

The Wavelet coherence value ranges between 0 and 1 and is interpreted as the localized squared correlation in the time-frequency plane. The operator $S(\cdot)$ defines the smoothing process applied over time and scale dimensions (for further discussion, see Grinsted et al. 2004; Cazelles et al. 2007).

An essential component of the wavelet analysis is the wavelet phase difference, which reveals the lead–lag dynamics between leading indicators and the reference cycle, as well as the degree of temporal consistency in their relationship. The phase difference is formally expressed as:

$$\Phi_{xy}(\tau, \phi) = \arctan\left(\frac{I(W_{xy}(\tau, \phi))}{R(W_{xy}(\tau, \phi))}\right). \quad (10)$$

A phase difference of zero indicates that the two time series move together, sharing the same phase angle—thus, they are *in phase*. When the phase difference falls between 0 and $\pi/2$, the series remain in phase, but x_t leads y_t . If it lies between $-\pi/2$ and 0, they are still in phase, though y_t leads x_t . As the phase difference approaches $\pm\pi$, the series become *out of phase* (or *anti-phase*), meaning they move in opposite directions. In this case, a positive phase angle implies y_t leads x_t , while a negative one indicates that x_t leads y_t , even though they are out of phase.

The angular phase difference (ϕ_{xy}) can be converted into real time units, such as months, by dividing it by the angular frequency corresponding to a given scale (ϕ). This is commonly calculated as $\Delta t = \Phi_{yx} \cdot \phi / (2\pi f)$, where f represents the data frequency - for example, $f = 1/12$ for monthly series - and ϕ denotes either the specific wavelet scale under consideration or the average across selected relevant scales.

An important element of this study is the wavelet phase difference, which identifies the lead–lag relationship between leading indicators and the reference cycle while also evaluating the consistency of this relationship over time. When the phase difference i.e., $\Phi_{xy}(\tau, \phi) = \Phi_{xy}$ equals zero, the two series move together, sharing an identical phase angle. A major strength of wavelet analysis lies in its capacity to examine these lead–lag dynamics at particular frequency scales—here, those corresponding to business cycle periods.

When interpreting phase differences, it is essential to focus on regions within the time–scale domain that lie inside the cone of influence (COI) and display high wavelet coherence. As noted by Funashima (2017), interpretations of phase differences vary across the literature, and Ge (2008) emphasizes that no formal statistical tests for phase differences currently exist. Some studies therefore use block bootstrap methods to construct confidence intervals around the median phase difference.

In empirical applications, the *coherence and phase-arrow map* serves as a valuable visualization tool for analyzing relationships between two time series in both time and frequency dimensions. The color scale indicates the strength of coherence between variables: warm colors such as yellow, orange, or red denote strong co-movement, while cooler tones like blue or green indicate weaker or inconsistent relationships.

Phase arrows overlaid on the map provide further insight into the timing and direction of interaction. Arrows pointing to the right generally indicate that the variables move together (in phase), whereas arrows pointing to the left suggest that they move in opposite directions (out of phase). The tilt of the arrows—upward or downward—shows which variable leads or lags, and how that relationship evolves across time or frequency. For example, arrows pointing diagonally to the right and upward suggest one variable leads the other with synchronized movements, whereas arrows directed to the left and downward imply that the other variable leads but moves inversely.

Overall, the coherence and phase-arrow map allows researchers to assess not only the strength of interdependence between variables but also the timing, direction, and persistence of their interactions across different time horizons. This makes it a vital analytical instrument for investigating complex economic and financial relationships. Figure (1) summarizes the interpretation of phase-arrow directions.

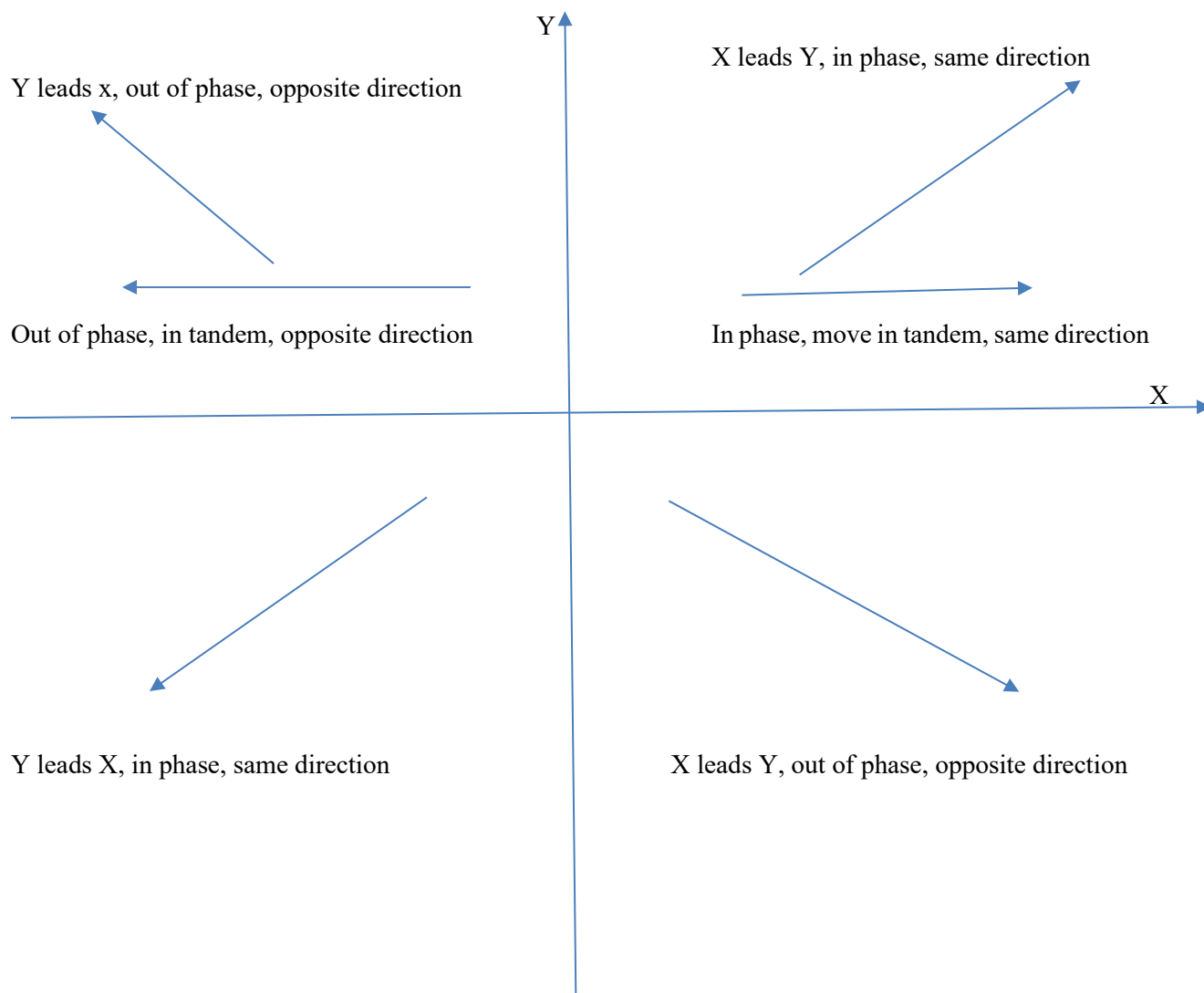


Figure 1: Graphic interpretation of the directions of the phase arrow. X is the HHNG, Y represents other variables like EPU and OVX

Together, these three methodological components create a strong and complementary empirical framework. The Quantile-on-Quantile regression offers detailed insights into how different segments of the HHNG-EPU(OVX) relationship behave under varying distributional conditions. The Wavelet Quantile Correlation adds a dynamic dimension, capturing how shocks transmit across quantiles over time with distinct lag and directional effects. The wavelet coherence analysis then provides a broader time–frequency perspective, situating the quantile-based results within their historical and structural contexts.

Integrating these methods yields a comprehensive, multidimensional understanding of the HHNG that incorporates distributional heterogeneity, temporal asymmetry, and frequency-dependent variation. This methodological synthesis is crucial for uncovering the policy-relevant implications of EPU and OVX for HHNG.

4. Empirical Findings

Table 1: Data sources and Summary statistics for key model variables

	EPU	OVX	LV	SV	IP	Temp
Mean	132.434	38.402	8.18	0.721	99.008	53.781
SD	100.861	17.101	0.412	0.767	4.649	15.237
Skewness	2.529	4.613	0.757	4.015	-1.369	-0.033
Exc. Kurtosis	9.255	42.17	-0.274	26.811	4.210	1.582
JB	21427.71	358876.2	456.045	150866.1	83.647	18.792
Frequency	Daily	Daily	Daily	Daily	Monthly	Monthly
Source	FRED	FRED	GMIDAS	GMIDAS	FRED	NOAA

Note: LV is derived on daily basis from the GARCH-MIDAS(GMIDAS) model and measures the monthly volatility. FRED is the Federal Reserve Bank of St. Louis Database. NOAA is the National Oceanic and Atmospheric Agency. IP stands for US industrial production. JB stands for the Jarque-Berra test of normality of distributions.

Table 1 reports the summary statistics for all variables. The Jarque–Bera (JB) test strongly rejects the null hypothesis of normality for each series. This conclusion is consistent with the JB test components: each variable exhibits non-zero skewness and positive excess kurtosis. Such departures from normality suggest that conventional ordinary least squares (OLS) estimation—which relies on mean-based relationships—may yield misleading or spurious inferences. By contrast, quantile regression is well suited for analyzing data with skewness and heavy tails because it captures relationships across the entire conditional distribution of the variables rather than relying on their means. Therefore, we employ QQQ regressions to investigate the nuanced associations between volatility and uncertainty across different quantiles of their distributions.

Table 2 shows the estimates of equations (4) and (5) of the GARCH-MIDAS model that produce the short-term and long-term volatility components of the realized volatility in natural gas price using the two sets of covariates, industrial production and average US contiguous states' monthly temperature. These covariates likely account for the variations of natural gas prices in the US. The coefficient α is statistically significant in equation (4) supporting asymmetric responses in volatility, specifically the "leverage effect" where negative shocks have a greater impact on volatility than positive shocks. The θ and θ_2 coefficients represent the changes in the long-term volatility stemming from the lagged effects of the covariate in the model. For instance, the coefficient is statistically significant, therefore, the long-term volatility is positively associated with the industrial production and temperature, respectively. Both weights, i.e., w_2 and w_{2_2} in equation (5), are statistically significant. Statistically significant coefficients in Table 2 show that the short- and long-term HHNG are driven by the included covariates as described in the note to the table.

Table 2: GARCH -MIDAS volatility estimation

Variable	Coefficients
mu	-0.0052. (0.0221)
alpha	0.1971 ^a (0.0284)
beta	0.8096 ^a (0.0273)
gamma	-0.0433 ^a (0.0218)
m	2.1255 ^a (0.3777)
theta	-0.0841 ^a (0.0193)
w2	6.5664 ^a (1.7322)
theta.two	-0.5781 ^a (0.2094)
w2.two	1.000 ^a (0.179)

Notes: ^a significant at 1 percent levels. The covariates in the GARCH-MIDAS model are the monthly series of industrial production and the average temperature in the US.

Table 3 presents the estimated coefficients from the QQQ regressions. For example, the first row shows that the 10th, 20th, and 80th percentiles of OVX significantly affect the 10th percentile of short-term HHNG volatility. The significance of the lower OVX quantiles suggests that relatively low levels of crude oil market volatility are significantly associated with low levels of Henry Hub natural gas price volatility. More notably, the 80th percentile of OVX is significant across most quantiles of the short-term HHNG volatility distribution. This finding indicates that periods of high crude oil market volatility are associated with natural gas price volatility across a broad range of market conditions. Thus, heightened uncertainty in the crude oil market appears to transmit to the natural gas market rather broadly, rather than being confined to periods of exceptionally high natural gas price volatility. The remainder of the tabulated coefficients may be interpreted in the same manner. Figures 2 through 4 present the values and significance of the coefficients visually. For instance, Figure 4 summarizes the first panel of Table 3 visually.

Table 3: Quantile-on-Quantile Coefficient Estimates and their Significance Levels

	$\hat{I}_s=0.1$	$\hat{I}_s=0.2$	$\hat{I}_s=0.3$	$\hat{I}_s=0.4$	$\hat{I}_s=0.5$	$\hat{I}_s=0.6$	$\hat{I}_s=0.7$	$\hat{I}_s=0.8$	$\hat{I}_s=0.9$
OVX & ST HHNG									
$\hat{I}_s=0.1$	-6e-04***	-4e-04**	-2.00E-04	0	0	0	0	6e-04***	-6.00E-04
$\hat{I}_s=0.2$	-0.0013***	-9e-04***	-4e-04**	-2.00E-04	0	1.00E-04	0	6e-04**	-5.00E-04
$\hat{I}_s=0.3$	-0.0025***	-0.0017***	-0.001***	-6e-04**	-3.00E-04	0	1.00E-04	7e-04**	-5.00E-04
$\hat{I}_s=0.4$	-0.0025***	-0.0024***	-0.0019***	-0.0013***	-4.00E-04	2.00E-04	5.00E-04	4.00E-04	-9.00E-04
$\hat{I}_s=0.5$	-0.0028***	-0.0029***	-0.0026***	-0.0017***	-5.00E-04	4.00E-04	5.00E-04	0.0012*	-9.00E-04
$\hat{I}_s=0.6$	-0.0024***	-0.003***	-0.0026***	-0.0015***	-6.00E-04	6.00E-04	6.00E-04	0.001	1.00E-04
$\hat{I}_s=0.7$	-0.0015*	-0.0024***	-0.0024***	-0.0017***	-9.00E-04	5.00E-04	0.0011*	0.0018	-1.00E-04
$\hat{I}_s=0.8$	-0.0014	-0.0029**	-0.0032***	-0.0028***	-0.0019**	0.0017	0.0015	0.0042**	0.0028
$\hat{I}_s=0.9$	3.00E-04	-0.0031	-0.0051**	-0.0057***	-0.0037**	6.00E-04	0.0055***	0.0068**	0.0065
OVX&LT HHNG									
$\hat{I}_s=0.1$	-0.0159***	-0.0189***	-0.019***	-0.018***	-0.0189***	-0.0202***	-0.0199***	-0.0103***	0.0149***
$\hat{I}_s=0.2$	-0.0143***	-0.0179***	-0.0212***	-0.0218***	-0.0198***	-0.0175***	-0.0157***	-0.0075*	0.0165***
$\hat{I}_s=0.3$	-0.0131***	-0.0191***	-0.0196***	-0.019***	-0.0166***	-0.0099***	-0.0032*	-0.0062*	0
$\hat{I}_s=0.4$	-0.01***	-0.0193***	-0.0194***	-0.0188***	-0.0145***	-0.0077***	-0.0052***	-0.0094***	0
$\hat{I}_s=0.5$	-0.0068***	-0.0178***	-0.0167***	-0.0151***	-0.0137***	-0.0092***	-0.007***	-0.0124***	0.0014
$\hat{I}_s=0.6$	-0.0024	-0.016***	-0.0191***	-0.0188***	-0.0133***	-0.0058***	-0.0039	-0.019***	3.00E-04
$\hat{I}_s=0.7$	0.01***	0.0066***	-0.0032	-0.0235***	-0.0218***	0.0092*	0.0165***	-0.0321***	-0.0037
$\hat{I}_s=0.8$	0.0165***	0.0175***	0.0028	-0.0142***	-0.0154***	0.0252***	0.0364***	-0.0232***	-0.0222*
$\hat{I}_s=0.9$	0.0549***	0.0379***	0.009**	0.0102***	0.0121***	0.01***	-0.0085***	-0.0137***	-0.016**
EPU & ST HHNG									
$\hat{I}_s=0.1$	-6e-04***	-4e-04**	-2.00E-04	0	0	0	0	6e-04***	-6.00E-04
$\hat{I}_s=0.2$	-0.0013***	-9e-04***	-4e-04**	-2.00E-04	0	1.00E-04	0	6e-04**	-5.00E-04
$\hat{I}_s=0.3$	-0.0025***	-0.0017***	-0.001***	-6e-04**	-3.00E-04	0	1.00E-04	7e-04**	-5.00E-04
$\hat{I}_s=0.4$	-0.0025***	-0.0024***	-0.0019***	-0.0013***	-4.00E-04	2.00E-04	5.00E-04	4.00E-04	-9.00E-04
$\hat{I}_s=0.5$	-0.0028***	-0.0029***	-0.0026***	-0.0017***	-5.00E-04	4.00E-04	5.00E-04	0.0012*	-9.00E-04
$\hat{I}_s=0.6$	-0.0024***	-0.003***	-0.0026***	-0.0015***	-6.00E-04	6.00E-04	6.00E-04	0.001	1.00E-04
$\hat{I}_s=0.7$	-0.0015*	-0.0024***	-0.0024***	-0.0017***	-9.00E-04	5.00E-04	0.0011*	0.0018	-1.00E-04
$\hat{I}_s=0.8$	-0.0014	-0.0029**	-0.0032***	-0.0028***	-0.0019**	0.0017	0.0015	0.0042**	0.0028
$\hat{I}_s=0.9$	3.00E-04	-0.0031	-0.0051**	-0.0057***	-0.0037**	6.00E-04	0.0055***	0.0068**	0.0065
EPU&LT HHNG									
$\hat{I}_s=0.1$	-6e-04***	-4e-04**	-2.00E-04	0	0	0	0	6e-04***	-6.00E-04
$\hat{I}_s=0.2$	-0.0013***	-9e-04***	-4e-04**	-2.00E-04	0	1.00E-04	0	6e-04**	-5.00E-04
$\hat{I}_s=0.3$	-0.0025***	-0.0017***	-0.001***	-6e-04**	-3.00E-04	0	1.00E-04	7e-04**	-5.00E-04
$\hat{I}_s=0.4$	-0.0025***	-0.0024***	-0.0019***	-0.0013***	-4.00E-04	2.00E-04	5.00E-04	4.00E-04	-9.00E-04
$\hat{I}_s=0.5$	-0.0028***	-0.0029***	-0.0026***	-0.0017***	-5.00E-04	4.00E-04	5.00E-04	0.0012*	-9.00E-04
$\hat{I}_s=0.6$	-0.0024***	-0.003***	-0.0026***	-0.0015***	-6.00E-04	6.00E-04	6.00E-04	0.001	1.00E-04
$\hat{I}_s=0.7$	-0.0015*	-0.0024***	-0.0024***	-0.0017***	-9.00E-04	5.00E-04	0.0011*	0.0018	-1.00E-04
$\hat{I}_s=0.8$	-0.0014	-0.0029**	-0.0032***	-0.0028***	-0.0019**	0.0017	0.0015	0.0042**	0.0028
$\hat{I}_s=0.9$	3.00E-04	-0.0031	-0.0051**	-0.0057***	-0.0037**	6.00E-04	0.0055***	0.0068**	0.0065

Notes: Horizontal I index stands for the quantiles of the OVX and EPU. Vertical i index represents the quantiles of the short-term and long-term HHNG (ST HHNG, LT HHNG). ***, **, * indicate significance at 1, 5, and 10 percent levels.

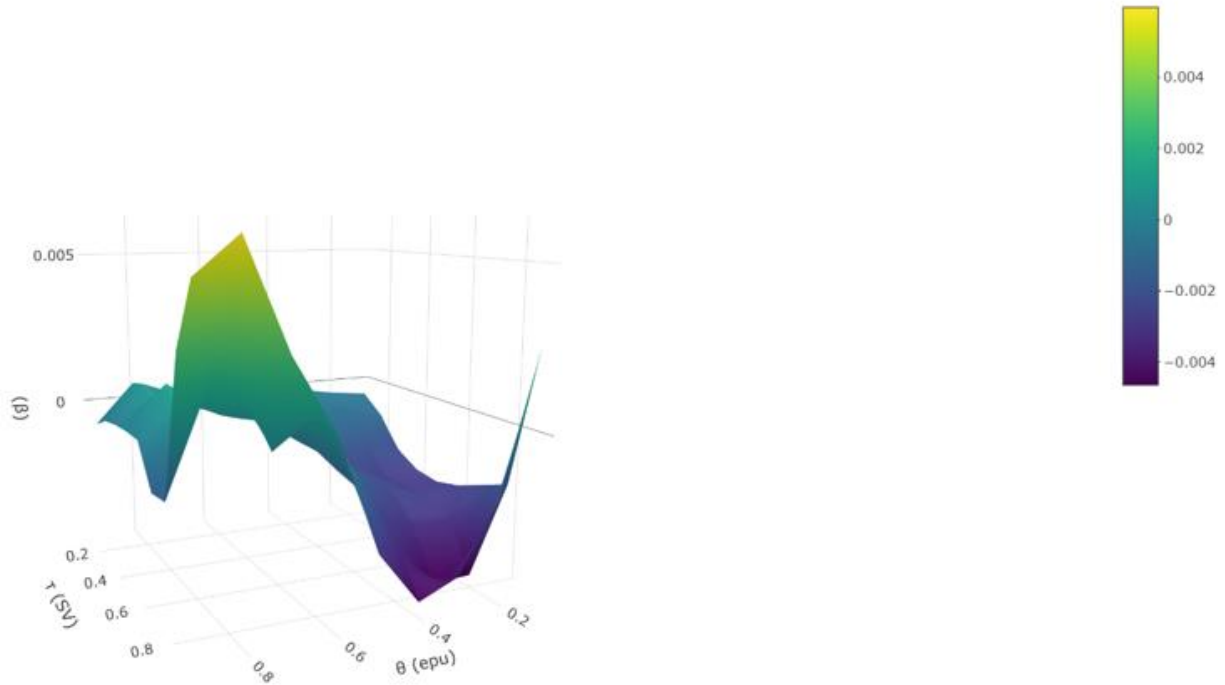


Figure 2: QOQ coefficients of short term HHNG and quantiles of EPU

The three-dimensional surface in Figure 2 illustrates how the short-term volatility of Henry Hub natural gas prices, derived from a GARCH model, varies across different quantiles of Economic Policy Uncertainty (EPU). The axes represent the quantiles of short-term volatility (τ , on the left) and the quantiles of EPU (θ , on the right), while the vertical axis (β) indicates the estimated coefficients of the quantile-on-quantile regression as in equation (7). The color gradient, ranging from deep purple (negative coefficients) to bright yellow (positive coefficients), provides a visual indication of the magnitude and direction of these relationships.

The surface demonstrates a nonlinear and asymmetric response of natural gas price volatility to shifts in EPU quantiles. At moderate quantiles of both volatility and EPU—approximately between 0.4 and 0.6—the coefficients become negative, suggesting that during periods of moderate uncertainty, the linkage between EPU and natural gas volatility weakens or even reverses. This behavior likely reflects the stabilizing effects of market expectations and hedging activities by industrial users and traders, who adjust to moderate policy fluctuations through storage and forward contracting. Conversely, the sharp peaks in the higher quantiles of short-term volatility and low-to-moderate EPU quantiles indicate that even mild policy uncertainty can elicit strong volatility responses when the market is already in a high-volatility state. This may correspond to situations where small policy signals trigger amplified speculative reactions, consistent with the highly financialized and weather-sensitive nature of the U.S. natural gas market.

In contrast, the lower-left region of the surface—representing low quantiles of both variables—shows near-zero or slightly positive coefficients, implying minimal transmission of policy uncertainty to price volatility in tranquil market conditions. This pattern aligns with the structural characteristics of the natural gas market, where price movements are primarily driven by seasonal demand, storage levels, and short-run supply constraints rather than by macroeconomic or policy news. However, at the extreme right of the surface, corresponding to high EPU quantiles, the coefficient sharply rises again, suggesting that in times of elevated policy uncertainty—such as during fiscal debates, regulatory transitions, or geopolitical disruptions—volatility in natural gas markets intensifies even when baseline volatility is moderate.

Figure 2 underscores the nonlinear nature of the EPU–volatility nexus in the natural gas market. It reveals that the market’s reaction to uncertainty is contingent on its prevailing volatility regime: calm markets remain largely insulated from policy noise, while already turbulent markets magnify even modest uncertainty shocks. This behavior reflects the dual structure of the Henry Hub market—anchored by physical supply-demand fundamentals yet increasingly responsive to financial sentiment and policy-driven expectations.

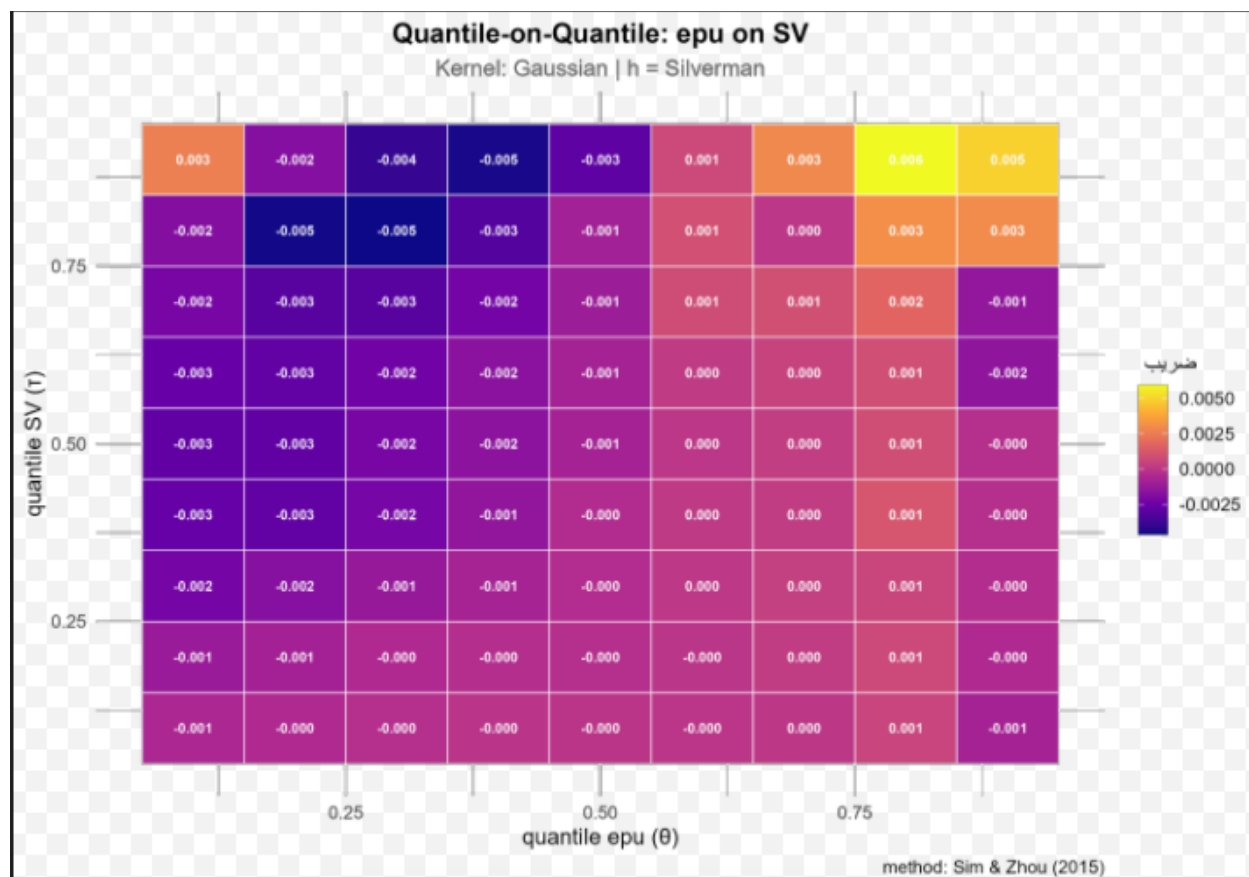


Figure 3: Heatmap of QOQ coefficients of short-term HHNG on quantiles of EPU

The heatmap in Figure 3 provides a two-dimensional view of the same quantile-on-quantile regression results linking the short-term volatility (SV) of Henry Hub natural gas prices, obtained from a GARCH model, to different quantiles of Economic Policy Uncertainty (EPU). The vertical axis (τ) represents the quantiles of natural gas volatility, while the horizontal axis (θ) corresponds to the quantiles of EPU. Each cell displays the coefficient of EPU’s effect on volatility for the specific combination of quantiles, with color intensity reflecting the magnitude and direction—ranging from deep blue for negative coefficients to bright yellow for positive ones.

The heatmap reveals a pattern consistent with the earlier 3D surface plot but with greater precision. The top-right and top-left corners display positive coefficients, represented in warmer colors (yellow to orange), indicating that at high quantiles of both volatility and EPU—or at high volatility and low EPU—the relationship between uncertainty and volatility is positive. In other words, during periods of extreme volatility, whether triggered by elevated or subdued policy uncertainty, the natural gas market tends to amplify price fluctuations. This behavior reflects the sensitivity of natural gas prices to speculative activity, storage adjustments, and expectations about policy-driven energy demand or regulation. Even minor policy signals, such as shifts in energy subsidies or carbon-related legislation, can prompt exaggerated responses in an already volatile market.

By contrast, the broad central region of the heatmap, shaded in blue and purple, corresponds to negative coefficients. These dominate the mid-quantiles of both volatility and EPU, implying that during moderate uncertainty and relatively stable market conditions, policy shocks exert a dampening effect on volatility. This may occur when traders and industrial participants can hedge effectively, and physical supply-demand dynamics—such as weather, storage levels, and pipeline capacity—dominate market behavior. Essentially, when the market operates in its typical regime, policy uncertainty adds limited new information and may even stabilize expectations through predictable adjustments in policy signaling.

The lower quantile region (bottom rows) exhibits values close to zero with faint color intensity, indicating weak or neutral relationships when both volatility and EPU are low. In such tranquil conditions, the natural gas market's short-term volatility is primarily governed by physical fundamentals rather than macro-policy dynamics.

The heatmap emphasizes the nonlinear and state-dependent transmission of EPU shocks to Henry Hub volatility. The positive responses at the extremes underscore how uncertainty amplifies volatility in turbulent times, while the negative coefficients across middle quantiles suggest that in moderate market conditions, participants absorb and neutralize uncertainty efficiently. This asymmetric pattern aligns with the characteristic behavior of the U.S. natural gas market—one that oscillates between stability driven by fundamental supply-demand factors and bursts of speculative volatility triggered by both policy uncertainty and exogenous shocks such as weather or geopolitical developments.

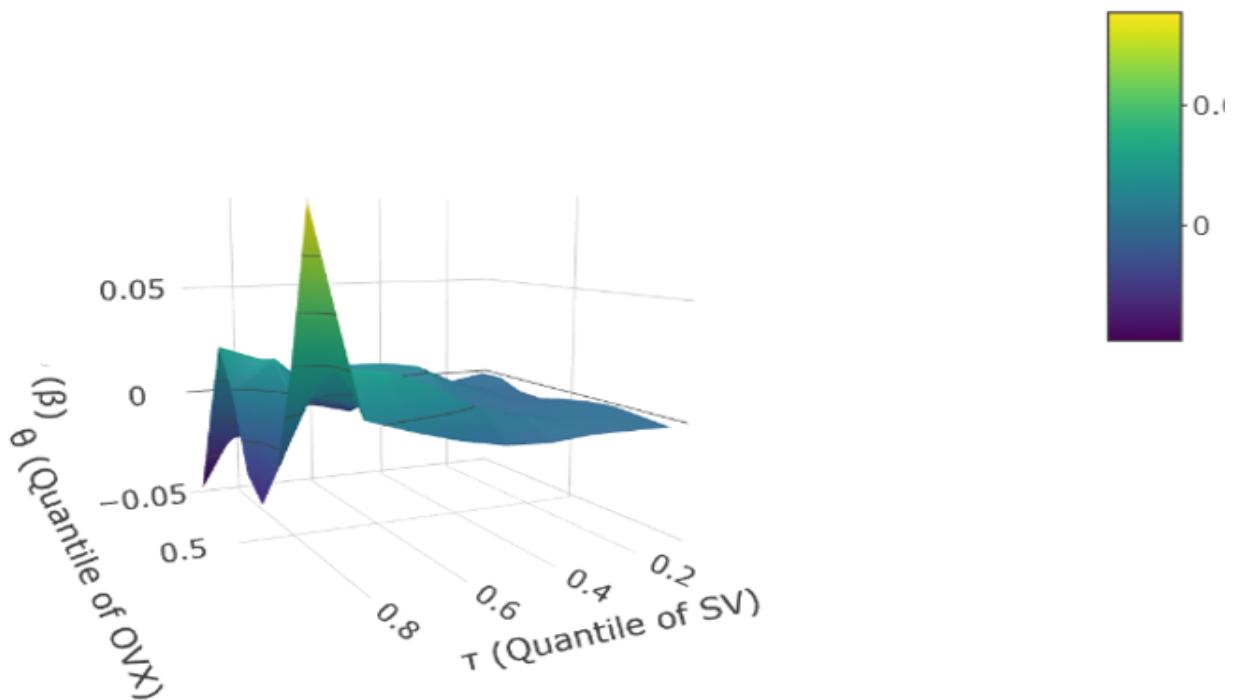


Figure 4: QOQ coefficients of the short-term HHNG on quantiles of OVX

Figure 4 reveals a pronounced nonlinear and asymmetric relationship between oil market uncertainty and natural gas volatility. The most striking feature is a sharp positive spike at high quantiles of both OVX and natural gas volatility. This peak suggests that during periods when both gas oil and natural gas markets experience extreme volatility, the influence of oil market fear on natural gas price fluctuations intensifies sharply. Such episodes typically coincide with global energy market stress—driven by geopolitical disruptions, supply shocks, or unexpected OPEC decisions—when investor sentiment and cross-market linkages amplify volatility transmission. The strong positive coefficients in this region reflect heightened

co-movement between oil and natural gas markets, consistent with the growing financial integration of energy commodities and the shared influence of macro-level uncertainty.

In contrast, the regions of moderate and low quantiles of both variables display near-zero or slightly negative coefficients, indicating a weak or inverse connection between OVX and Henry Hub volatility under stable market conditions. This outcome reflects the partially segmented nature of the natural gas market. Unlike crude oil, natural gas prices—particularly at Henry Hub—are strongly influenced by regional supply-demand fundamentals such as weather patterns, storage levels, and pipeline infrastructure. When both markets are calm, oil-related uncertainty exerts limited or no influence on U.S. natural gas volatility, as localized factors dominate price dynamics.

The modest negative coefficients observed at intermediate quantiles may also suggest a temporary decoupling effect, where oil market fear induces a flight of capital from oil futures to other commodities, momentarily reducing volatility in natural gas prices. This effect aligns with periods of relative insulation in the natural gas market, often observed when storage capacity is adequate and production from shale basins remains stable, dampening the influence of global oil sentiment.

Figure 4 underscores the nonlinear contagion pattern between oil and natural gas markets. The transmission of volatility from oil to natural gas is not constant—it emerges powerfully during crises and fades during stable periods. This asymmetric response mirrors the dual identity of the Henry Hub market: increasingly integrated with global energy finance yet still governed by domestic fundamentals. The results imply that extreme oil market stress functions as a volatility amplifier for U.S. natural gas prices, reinforcing the systemic risk interdependence of energy markets in times of uncertainty.

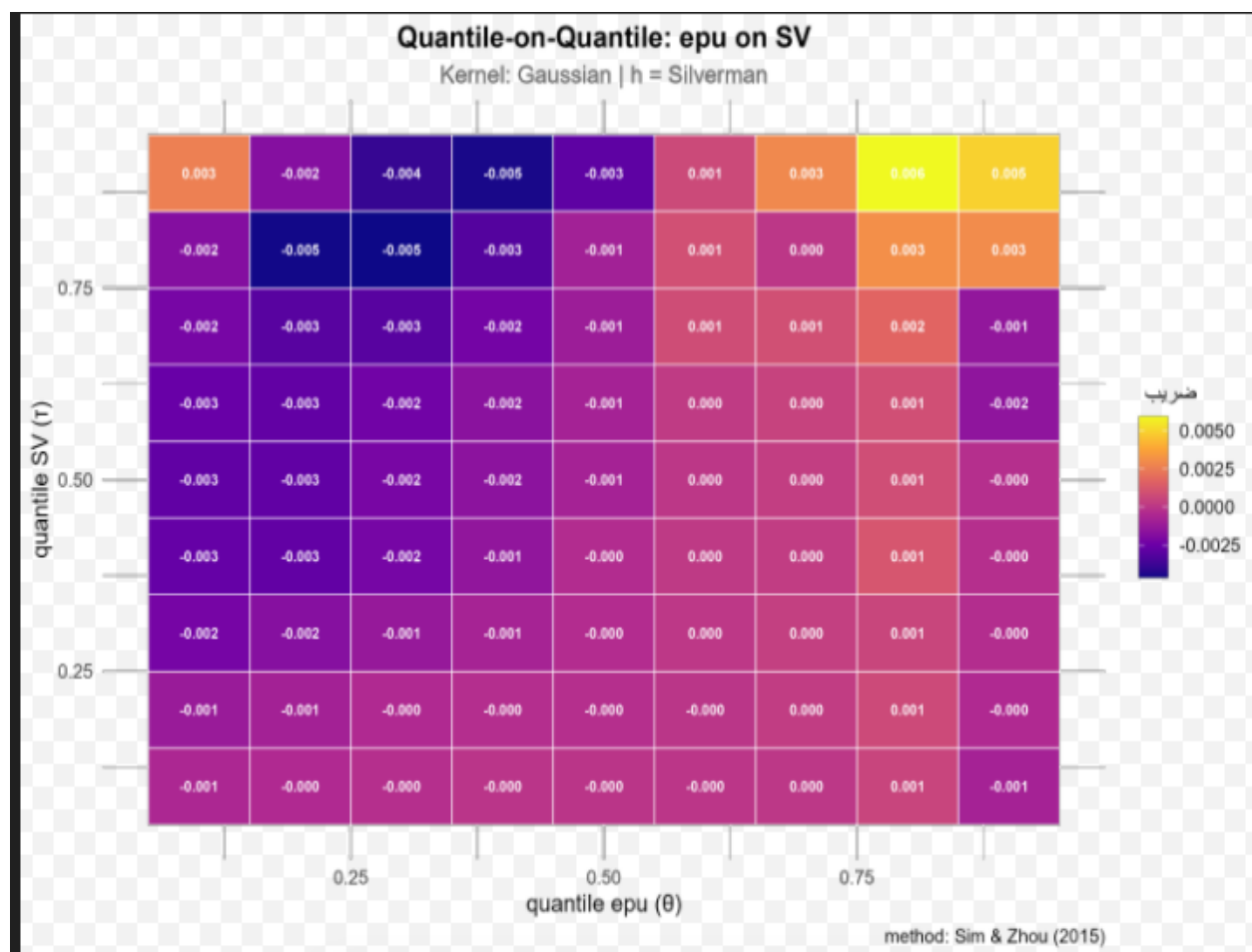


Figure 5: Heatmap QOQ coefficients of the two-period lagged short-term HHNG on quantiles of OVX

The heatmap in Figure 5 provides a two-dimensional representation of the quantile-on-quantile regression coefficients measuring how the short-term volatility of Henry Hub natural gas prices, estimated from a GARCH model, responds to various quantiles of the oil market volatility index (OVX), often described as the “oil market fear index.” The vertical axis represents the quantiles of natural gas volatility, while the horizontal axis shows the quantiles of the OVX. The color gradient ranges from deep purple for negative coefficients to bright yellow for strong positive ones, indicating the strength and direction of the relationship across different market states.

The heatmap reveals a distinctly asymmetric and nonlinear association between the two markets. The most pronounced positive coefficients, highlighted in yellow and red, are located in the upper-left region of the plot, corresponding to high quantiles of natural gas volatility and low-to-moderate quantiles of the OVX. This pattern indicates that when natural gas markets are already volatile but oil market uncertainty is still moderate, small increases in OVX lead to sharp rises in natural gas volatility. This is consistent with a spillover effect during the early stages of oil market distress, when investors and traders anticipate broader energy market disruptions and adjust their positions across related commodities. Such behavior is typical of the interconnected energy landscape, where futures markets for oil and gas react not only to actual supply disruptions but also to shifts in sentiment and expectations.

In the middle quantile region, represented by orange and pink shades, coefficients remain positive but moderate, suggesting a steady co-movement between oil and gas volatility under average market conditions. This relationship reflects the underlying structural linkages between oil and natural gas prices—both are influenced by global energy demand, macroeconomic indicators, and shared financial investors who manage cross-commodity portfolios. However, the effect is less intense here because the natural gas market retains a strong domestic character, with price movements often governed by regional factors such as storage capacity, pipeline flows, and weather patterns.

Toward the right-hand side of the plot, where OVX quantiles are high, the coefficients become negative, indicated by the blue areas. This suggests that when oil market fear reaches extreme levels, its marginal effect on natural gas volatility weakens or even reverses. Such decoupling is plausible given the partial segmentation of the U.S. natural gas market from the global oil trade. During extreme oil market distress—such as global geopolitical shocks or OPEC-driven supply disruptions—natural gas may temporarily behave as a substitute energy source or a relatively safer asset within the energy sector. Consequently, volatility transmission from oil to gas diminishes or turns negative, particularly when domestic supply and demand dynamics buffer the U.S. market against international oil shocks.

Overall, the heatmap illustrates a complex, state-dependent interaction between oil market fear and natural gas volatility. The positive relationships in low-to-moderate OVX states underscore the sensitivity of the natural gas market to early signals of oil-related uncertainty, while the muted or negative coefficients at higher OVX quantiles highlight the limited contagion effect once the oil market enters crisis mode. This nonlinear pattern mirrors the dual structure of the Henry Hub market—deeply linked to global energy sentiment through financial and speculative channels, yet ultimately governed by regional fundamentals that moderate the impact of extreme oil market turbulence.

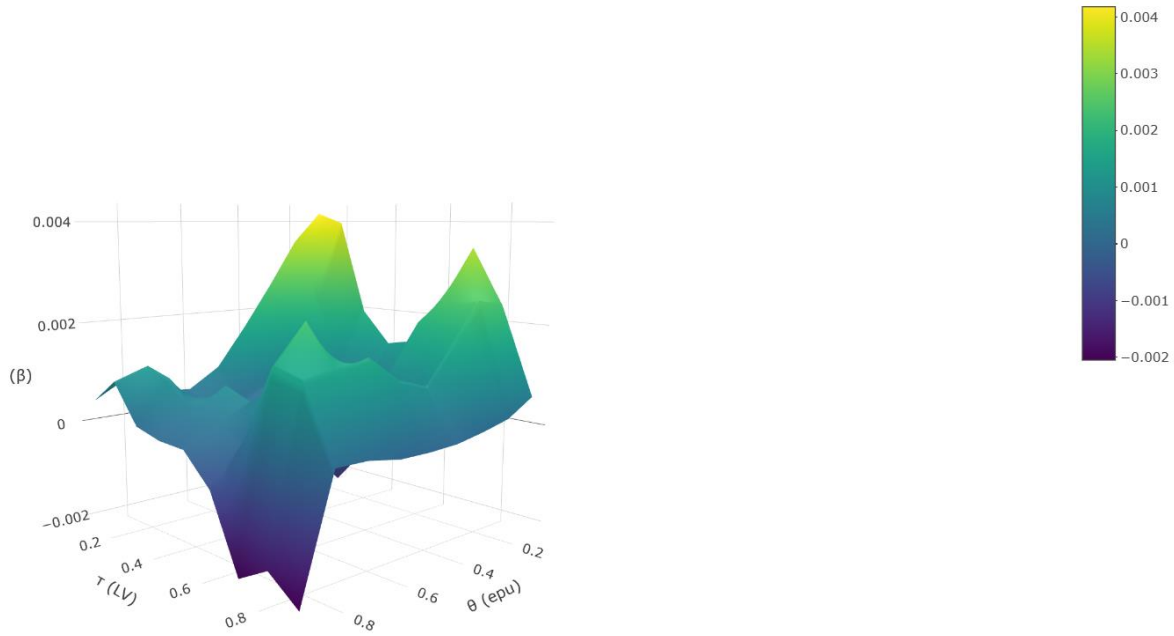


Figure 6: QOQ coefficients of long- term HHNG volatility and quantiles of EPU

The surface in Figure 6 reveals a more balanced and smoother pattern than that observed for the short-term volatility. While the short-term plot was marked by sharp spikes and abrupt changes in response to EPU shocks, this long-term surface suggests a more measured, cyclical, and persistent response of natural gas volatility to economic uncertainty. At moderate-to-high quantiles of both EPU and volatility, the coefficients rise gradually, forming two distinct positive peaks. This indicates that, over longer horizons, periods of sustained policy uncertainty are associated with higher volatility in natural gas prices. Such effects likely reflect the deeper structural adjustments in the energy market—such as investment delays, production realignments, or shifts in long-term demand expectations—that occur as firms and investors respond to an uncertain policy environment.

In contrast, low quantiles of both EPU and long-term volatility exhibit near-zero or slightly negative coefficients. This suggests that during tranquil policy and market conditions, uncertainty plays only a minor role in driving long-term volatility. The muted reaction in these regions underscores that the Henry Hub market, while increasingly integrated with global energy dynamics, remains fundamentally anchored in domestic supply-demand cycles. Long-term natural gas price behavior is shaped by physical infrastructure, production technologies, and consumption patterns, which evolve gradually and are less sensitive to transient policy disturbances.

Compared with the short-term results, where EPU shocks led to sharp but short-lived spikes in volatility, the long-term response reflects inertia and persistence. Short-term volatility captures traders' reactions to daily or monthly policy signals, speculation, and hedging behavior. In contrast, the long-term dynamics reflect the cumulative effects of uncertainty on investment and storage decisions, regulatory expectations, and production planning. This difference highlights the dual character of the natural gas market: in the short run, it behaves like a financialized commodity highly responsive to sentiment and news shocks, while in the long run, its volatility mirrors the structural adjustments of a resource-based industry.

To recap, the long-term surface suggests that economic policy uncertainty exerts a slower but more sustained influence on Henry Hub price volatility. The positive association at higher quantiles points to a form of volatility persistence—once policy uncertainty becomes embedded in market expectations, it takes time for confidence to recover and for volatility to normalize. This finding aligns with the broader nature of the natural gas market, where investment cycles, contract structures, and infrastructure constraints create long memory effects, making the market more resilient to transient shocks but more vulnerable to prolonged uncertainty.

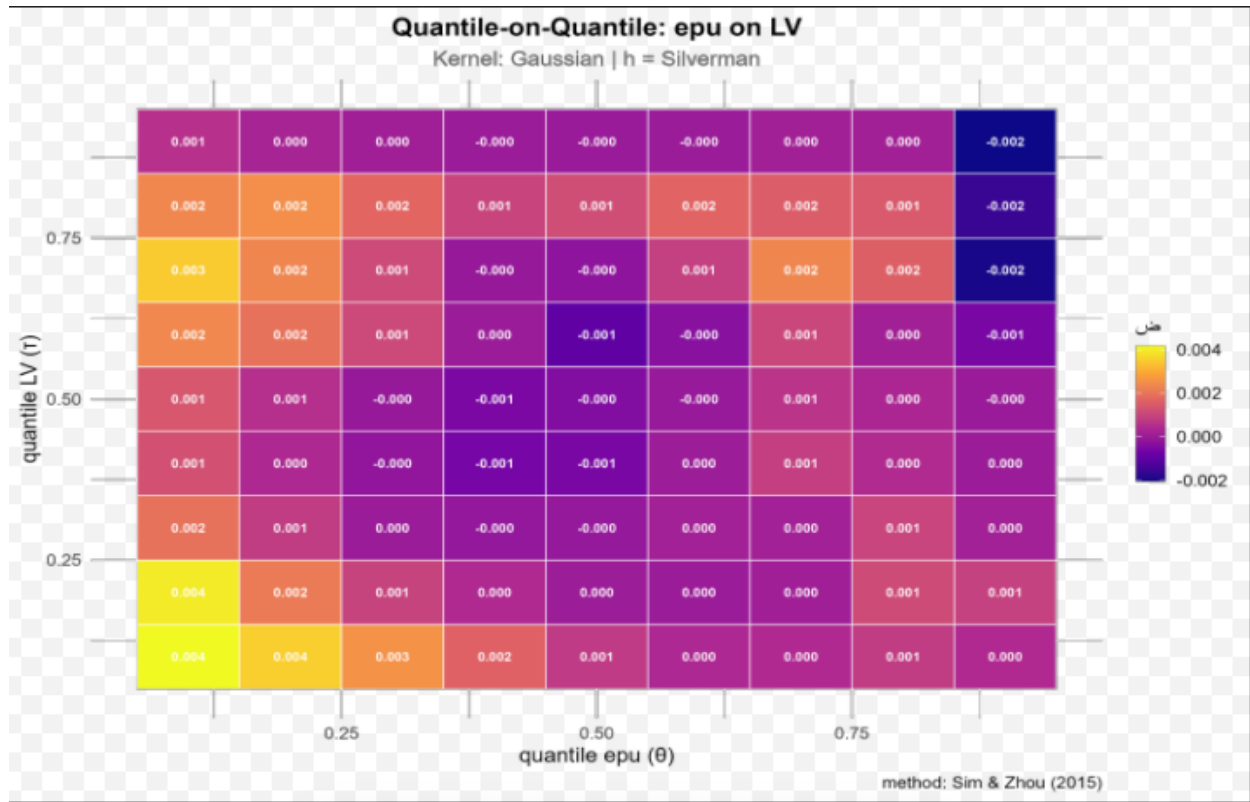


Figure 7: Heatmap of QOQ coefficients of long-term HHNG on quantiles of EPU

The heatmap in Figure 7 illustrates the quantile-on-quantile regression coefficients showing how the long-term volatility of Henry Hub natural gas prices, derived from a GARCH model, responds to different quantiles of Economic Policy Uncertainty (EPU). The vertical axis represents the quantiles of long-term volatility (τ), while the horizontal axis denotes the quantiles of EPU (θ). The color bar on the right translates these coefficients, with yellow indicating positive relationships, deep purple marking negative coefficients, and intermediate shades representing near-zero effects.

The heatmap reveals that, in contrast to the short-term dynamics, the long-term relationship between policy uncertainty and natural gas price volatility is smoother, more symmetrical, and considerably weaker in magnitude. The coefficients remain small and largely positive across most regions, especially at the lower and moderate quantiles of both EPU and long-term volatility. These warm-toned areas suggest that periods of modest uncertainty tend to be associated with slightly higher long-term volatility, implying that policy shifts—such as regulatory adjustments or fiscal debates—introduce mild, persistent uncertainty that filters gradually into natural gas market expectations. Unlike the immediate speculative reactions captured in short-term volatility, these long-term responses unfold more steadily, reflecting adjustments in investment decisions, infrastructure expansion, and storage management.

The concentration of slightly higher coefficients in the lower-left quadrant (low EPU and low volatility) and the upper-left quadrant (high volatility and low-to-moderate EPU) suggests that policy uncertainty can

sustain or mildly amplify price fluctuations even when uncertainty itself is not extreme. This finding is consistent with the structural behavior of the natural gas market, where long-term price dynamics are influenced by strategic factors such as production planning, capital investment, and evolving environmental and energy policies. These effects accumulate over time rather than generating sharp, short-lived shocks. By contrast, the darker shades toward the right edge of the heatmap, particularly in the upper-right region corresponding to high EPU quantiles, reveal weakly negative coefficients. This implies that under conditions of extreme policy uncertainty, the marginal effect on long-term volatility diminishes or even reverses. This outcome can be attributed to adaptive market mechanisms: when uncertainty remains high for extended periods, market participants tend to adjust expectations, secure long-term supply contracts, or diversify portfolios, thereby stabilizing volatility.

When compared to the short-term results, the difference is striking. In the short-term quantile-on-quantile analysis, volatility displayed pronounced spikes and nonlinear patterns—reflecting traders' rapid reactions to news shocks, financial speculation, and short-lived sentiment changes. The long-term heatmap, however, depicts a more contained and measured response. It reflects the structural resilience of the Henry Hub market, which is anchored in physical supply-demand fundamentals and infrastructure constraints. Over longer horizons, storage capacity, production flexibility from shale gas, and the relatively regionalized nature of U.S. natural gas pricing all contribute to smoothing the volatility response to macroeconomic and policy shocks.

In sum, the heatmap underscores that while economic policy uncertainty can amplify short-term volatility in natural gas prices through immediate financial channels, its influence on long-term volatility is more gradual, subdued, and adaptive. The natural gas market appears to absorb and internalize uncertainty over time, translating it into small but persistent adjustments rather than sudden fluctuations. This distinction highlights the market's hybrid nature: highly sensitive to short-run information shocks, yet grounded in physical and institutional structures that moderate long-term volatility.

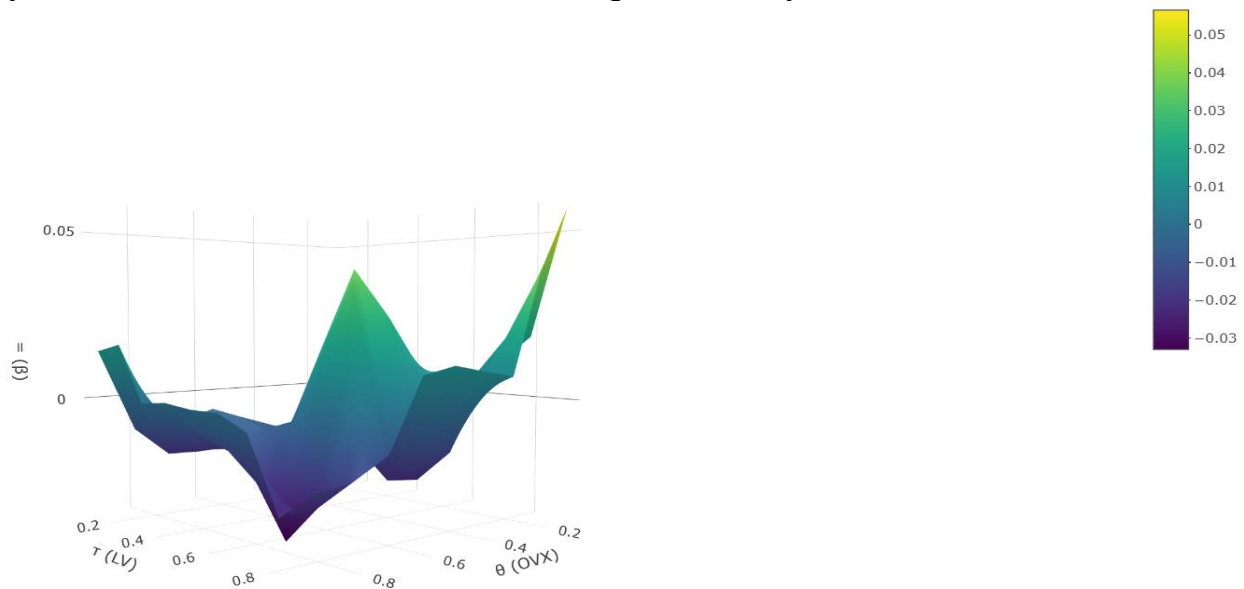


Figure 8: QOQ coefficients of Long-term HHNG and quantiles of OVX

Figure 8 suggests that the long-term link between oil market uncertainty and natural gas volatility is positive but nonlinear, with notable intensity concentrated at high quantiles of both OVX and natural gas volatility. The sharp peaks appearing in these upper quantile combinations indicate that when both oil and gas markets experience prolonged periods of high uncertainty and volatility, the influence of oil market fear on natural gas volatility becomes pronounced and sustained. This long-run interdependence reflects the broader integration of energy markets: over extended horizons, persistent oil market instability—driven by geopolitical risks, OPEC decisions, or structural shifts in energy policy—translates into higher uncertainty

and price variability in the natural gas market. These effects endure because long-term investment decisions, production planning, and storage strategies in the gas sector are sensitive to expectations about future energy prices and risk conditions across related markets.

In contrast, for lower and mid quantiles of both OVX and long-term volatility, the coefficients hover near zero or slightly negative, suggesting that when the oil market is stable, its long-run influence on natural gas volatility remains limited. This finding highlights an important structural feature of the Henry Hub market: while it is increasingly connected to global energy dynamics through financial and sentiment channels, its long-term price behavior is still grounded in regional fundamentals such as weather-dependent demand, production efficiency in shale basins, and pipeline capacity. These factors moderate the transmission of oil market fear into natural gas prices during calm or moderately volatile periods.

When compared with the short-term quantile-on-quantile results, the long-term pattern displays a smoother and more persistent structure. In the short term, oil market shocks triggered sharp, transient responses in natural gas volatility—reflecting speculative reactions, risk aversion, and liquidity shifts in futures markets. However, the long-term behavior indicates that volatility transmission becomes less abrupt but more enduring, as uncertainty in the oil market gradually influences natural gas through structural and financial channels. The persistence of positive coefficients in higher quantiles underscores how sustained oil market fear feeds into the longer-term expectations of energy market participants, shaping their risk assessments and pricing strategies over time.

In conclusion, the surface portrays the long-run interaction between the oil and natural gas markets as one of gradual yet durable contagion. While short-term volatility captures traders' reactions to immediate shocks, long-term volatility reflects the embedded expectations of market participants adjusting to a prolonged atmosphere of uncertainty. This behavior aligns with the dual character of the Henry Hub natural gas market: short-run sensitivity to financial sentiment and long-run adjustment to global energy conditions. It suggests that oil market fear acts as a slow-moving but persistent driver of natural gas price variability, reinforcing the idea that structural linkages between energy commodities strengthen over extended horizons even as short-term market reactions remain episodic and transient.

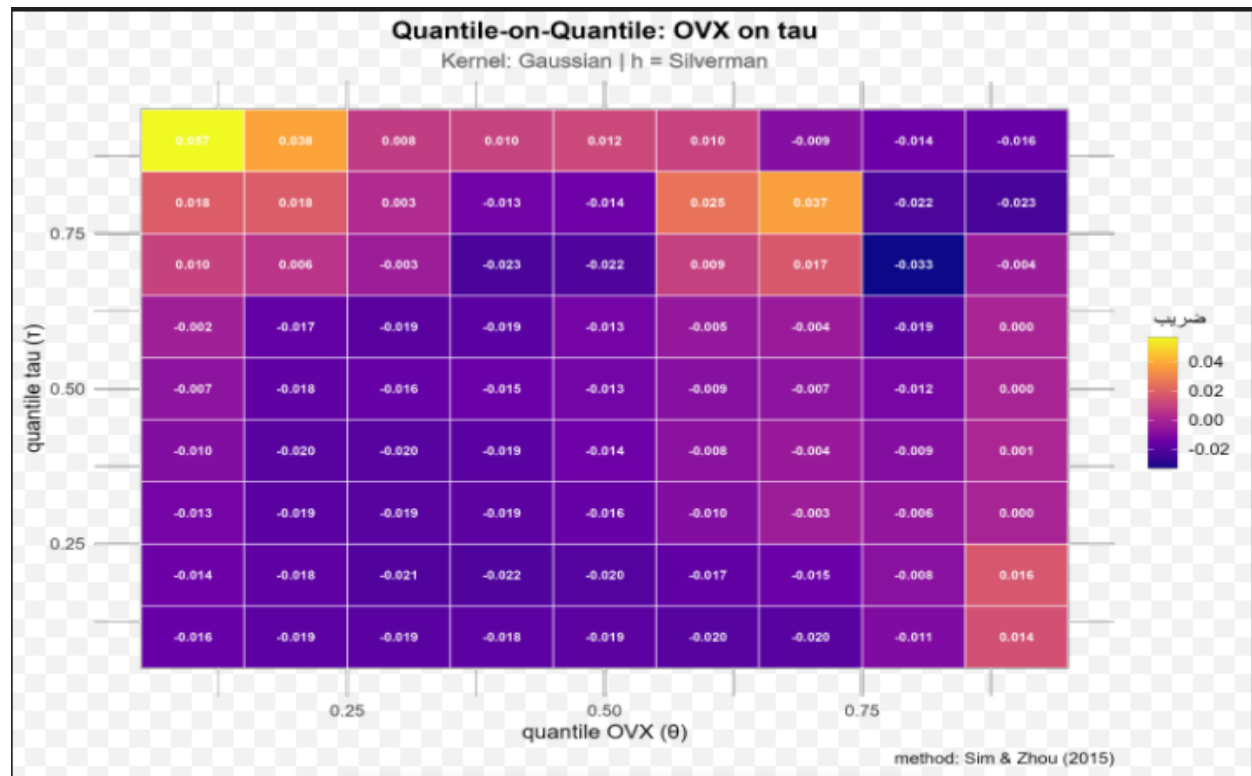


Figure 9: Heatmap of the QOQ coefficients of the Long-term HHNG on quantiles of OVX

The heatmap in Figure 9 illustrates the quantile-on-quantile regression coefficients describing how the long-term volatility of Henry Hub natural gas prices, derived from a GARCH model, responds to different quantiles of the OVX—the oil market volatility index, often referred to as the “oil market fear gauge.” The horizontal axis represents the quantiles of OVX (θ), while the vertical axis denotes the quantiles of long-term natural gas volatility (τ). The color gradient on the right ranges from purple for negative coefficients to yellow for positive ones, indicating the intensity and direction of the relationship across different quantile combinations.

The heatmap displays a clear asymmetry and state-dependent relationship between oil market volatility and long-term natural gas price volatility. The most intense positive coefficients, shown in bright yellow and orange, appear in the upper-left quadrant where both long-term volatility and OVX quantiles are high but not extreme. This pattern indicates that when the oil market is moderately to highly volatile, the long-term volatility of natural gas prices tends to rise as well. Such positive associations reflect the integrated nature of energy markets: persistent oil market uncertainty, often driven by global supply disruptions, OPEC policy shifts, or geopolitical tensions, tends to spill over into the natural gas market through shared investor sentiment, cross-commodity portfolio adjustments, and broader energy-sector risk repricing. Over the long run, this linkage becomes structural rather than transient, as producers and consumers adjust investment horizons and contractual arrangements based on the evolving expectations of global energy volatility.

However, as the heatmap moves toward the middle and lower quantile ranges, the coefficients gradually shift into negative territory, depicted by dark blue and purple shades. These areas suggest that when both OVX and natural gas volatility are moderate or low, the long-term relationship weakens or even turns inverse. This decoupling reflects the structural independence of the U.S. natural gas market, where domestic factors—such as shale gas production efficiency, storage capacity, and seasonal weather-driven demand—exert a stronger influence than international oil market uncertainty. During tranquil energy market conditions, the Henry Hub price dynamics are largely shaped by localized fundamentals rather than by fluctuations in global oil volatility.

Interestingly, the top-right region of the heatmap shows a subtle reappearance of small positive coefficients, suggesting that in periods of extreme oil market fear, long-term natural gas volatility can again increase slightly. This behavior may correspond to episodes when systemic uncertainty dominates, such as during major global crises, when financial contagion across energy commodities becomes unavoidable. Even then, however, the coefficients remain weaker compared to those seen in short-term analyses, indicating that while shocks in oil volatility influence the gas market in the long run, they do so in a slower and more muted fashion.

When compared to the short-term quantile-on-quantile results, the contrast is striking. In the short term, the relationship between OVX and Henry Hub volatility was far more volatile and nonlinear, characterized by sharp spikes and stronger coefficients concentrated in the high quantile regions. Those short-run dynamics captured traders’ rapid responses to oil market news, speculative adjustments, and shifts in market sentiment. The long-term heatmap, by contrast, depicts a smoother and more measured relationship. Volatility transmission from oil to natural gas becomes more persistent but less intense—reflecting gradual adjustment processes such as long-term investment decisions, hedging strategies, and infrastructure responses that take time to materialize.

Collectively, the heatmap underscores that while the short-term linkage between oil and gas markets is dominated by speculative and financial forces, the long-term relationship is more structural and fundamentally driven. Over extended horizons, sustained oil market uncertainty influences natural gas price volatility through slow-moving channels—capital allocation, energy substitution expectations, and regulatory responses—rather than immediate trading reactions. This aligns with the broader characteristics of the Henry Hub market: a system increasingly connected to global energy sentiment yet still anchored in regional production, consumption, and logistical constraints that moderate the full impact of oil market shocks over time.

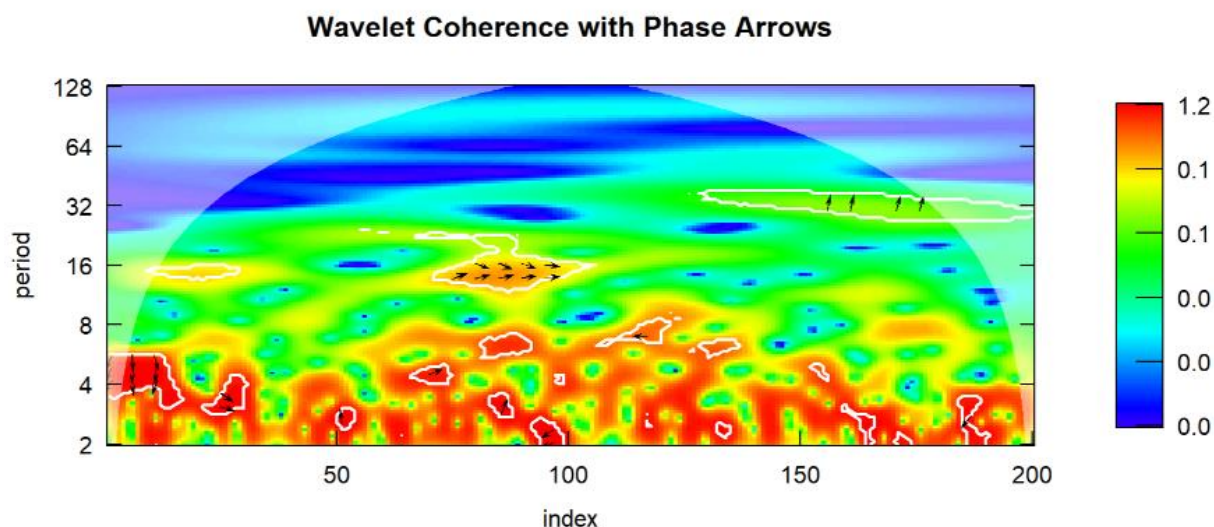


Figure 10: Wavelet Coherence and Phase Arrows of the short-term HHNG and EPU

The wavelet coherence diagram with phase arrows in Figure 10 offers a dynamic view of how the short-term volatility of Henry Hub natural gas prices co-moves with economic policy uncertainty (EPU) across both time and frequency domains. In this figure, the horizontal axis represents the time index, while the vertical axis corresponds to the period, which captures the frequency of oscillations. The warmer colors, especially yellow and red, indicate stronger coherence between the two series, suggesting intervals during which the two variables move closely together, while the cooler blue and green regions reflect weak or no coherence. The black phase arrows embedded in the coherent regions provide an important layer of interpretation—they indicate the direction and timing of movement between the two series. Arrows pointing to the right imply that the two series move together (in phase), while arrows pointing left signify an inverse relationship (anti-phase). When arrows tilt downward, it means that the natural gas volatility leads the EPU, and when they tilt upward, EPU leads the volatility series.

The wavelet coherence plot shows clear regions of high coherence at intermediate to short periods, roughly corresponding to cycles of 4 to 16 units on the vertical scale. These warm zones are particularly important because they represent time spans when Henry Hub natural gas volatility and EPU are synchronized. The phase arrows within these regions mostly point toward the right and slightly downward, suggesting that the two series are positively correlated and that natural gas volatility tends to lead policy uncertainty. This means that shifts in volatility in the gas market occur slightly before comparable changes in EPU, implying that the gas market may anticipate or react quickly to economic and policy conditions. In other sections of the plot, particularly around longer periods and higher frequencies, the coherence weakens, and the arrows become more scattered, reflecting an unstable or lagged relationship. This variability indicates that the influence of policy uncertainty on gas price volatility is not constant but depends on the time scale and the intensity of external shocks.

These findings correspond closely to the patterns revealed in the quantile-on-quantile regression results for short-term volatility of Henry Hub natural gas prices. The regression results demonstrated that the relationship between natural gas volatility and EPU is nonlinear and asymmetric. During tranquil market conditions, when both volatility and uncertainty are low, the connection is weak, and the market remains largely insulated from policy news. However, when volatility is already high, even moderate levels of uncertainty can trigger strong responses in gas prices. This pattern matches the wavelet coherence results: periods of high coherence and rightward arrows are consistent with the idea that in high-volatility regimes, natural gas markets respond strongly and rapidly to uncertainty shocks, amplifying their effects.

Conversely, the lower coherence regions in the wavelet plot align with the negative or insignificant coefficients in the regression model for moderate quantiles, suggesting that under stable conditions, the linkage between volatility and uncertainty dissipates.

At the same time, the wavelet analysis adds an important temporal and frequency-based dimension to the quantile findings. While the quantile regression results capture the cross-sectional and regime-dependent aspects of the volatility–uncertainty relationship, the wavelet analysis highlights its dynamic nature over time. It reveals that the connection between Henry Hub volatility and EPU strengthens or weakens at different frequencies, showing that their association fluctuates with the broader macroeconomic environment and energy market cycles. The downward-tilted phase arrows, indicating that natural gas volatility leads EPU, provide a meaningful interpretation: in the short run, traders and market participants in the natural gas market may react to expectations of policy changes before those uncertainties are formally realized in broader economic indicators. This leading behavior is typical of a financialized commodity market, where expectations and speculative positioning often precede the actual unfolding of macroeconomic uncertainty.

In summary, the wavelet coherence and quantile-on-quantile regression analyses converge in showing that the link between Henry Hub natural gas volatility and economic policy uncertainty is both nonlinear and state-dependent. The wavelet plot captures the same amplifying effects of uncertainty in high-volatility regimes that the quantile regression identified, while also illustrating when and over what time horizons this relationship is strongest. Both methods portray the natural gas market as one that oscillates between stability dominated by physical supply-demand forces and periods of heightened sensitivity to financial and policy-driven shocks. The coherence at shorter periods and the rightward phase arrows reinforce the view that the Henry Hub market, though grounded in physical fundamentals, behaves like a forward-looking and sentiment-driven market when uncertainty rises, anticipating and transmitting policy-related risks into volatility cycles.

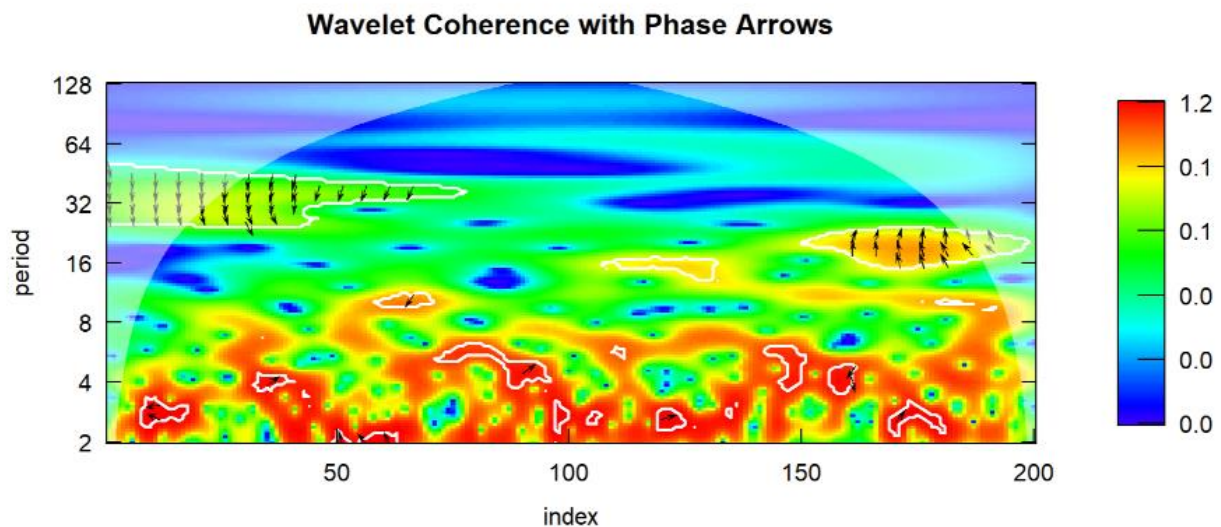


Figure 11: Wavelet Coherence and Phase Arrows of the short-term HHNG and OVX

The wavelet coherence plot with phase arrows in Figure 11 provides a time–frequency view of how short-term Henry Hub natural gas volatility moves with the OVX, the oil market fear index. Along the horizontal axis is the time index of the sample, while the vertical axis shows the period: values near the bottom correspond to high-frequency, short-lived movements; values higher up represent lower-frequency, longer-horizon cycles. Colors mark the strength of coherence between the two series, with warmer colors indicating periods and frequencies where natural gas volatility and OVX co-vary strongly. The curved boundary is the cone of influence, reminding us that results near the top corners are less reliable because of edge effects.

The arrows embedded in the high-coherence regions are crucial. In standard wavelet coherence, arrows pointing to the right indicate that the two series are in phase, moving in the same direction at that time scale;

arrows pointing left indicate anti-phase, or movements in opposite directions. When arrows tilt down and to the right, the first series (here, short-term gas volatility) slightly leads the second; arrows tilting up and to the right indicate that OVX leads natural gas volatility.

In this plot, the most striking feature is a broad, warm band of coherence at relatively long periods, roughly in the 32–64 range, stretching across a central portion of the sample. The arrows in this band are mostly rightward, with only a slight tilt, which means that on these longer cycles the OVX and Henry Hub short-term volatility move largely in phase. Neither market clearly and persistently leads the other; instead, both respond almost synchronously to common shocks, such as major global energy news or shifts in broader risk sentiment. This is consistent with the idea that in times of elevated but persistent stress, oil and gas markets are jointly driven by macro-level uncertainty and cross-market portfolio rebalancing, rather than by idiosyncratic, commodity-specific factors.

Closer to the bottom of the figure, at shorter periods (roughly 2–8), the coherence is more fragmented. We see isolated red patches separated by cooler colors, indicating episodes when gas volatility and OVX are tightly linked for a short time and then decouple. In some of these patches arrows deviate from the horizontal. Where they tilt slightly downward and to the right, Henry Hub volatility appears to lead OVX at that frequency, suggesting that turbulence in the gas market can emerge a bit earlier than comparable spikes in oil-market fear. That is consistent with a picture in which weather shocks, storage surprises, or pipeline issues first disturb gas prices and only later feed into a broader perception of energy-market risk captured by OVX. In other small regions arrows may tilt up and to the right, implying that sudden jumps in OVX precede and help trigger short bursts of gas volatility. These alternating lead–lag patterns highlight that directionality is not stable; leadership can switch depending on the episode and time scale.

When we compare these wavelet coherence findings with the quantile-on-quantile regression results, several common threads emerge. The QOQ analysis showed a strongly nonlinear, asymmetric relationship: a pronounced positive spike in the coefficients at high quantiles of both OVX and natural gas volatility, and near-zero or even negative coefficients in the middle and lower parts of the joint distribution. That pattern implies that during crises—when both series are in their upper tails—oil-market fear acts as a powerful amplifier of gas volatility, whereas in more typical conditions the connection is weak or occasionally dampening. This behavior matches the coherent, in-phase band at long periods in the wavelet plot. The long-period coherence with rightward arrows suggests that, over extended stretches characterized by heightened market stress, OVX and gas volatility move together and reinforce each other, exactly as the large positive QOQ coefficients at joint high quantiles would suggest.

The fragmented structure at short periods in the wavelet plot also resonates with the QOQ finding that at moderate quantiles the effect of OVX on gas volatility can be small or even negative. Patchy coherence and occasional anti-phase or ambiguous arrow directions at high frequencies correspond to episodes where the two series are not systematically aligned. In those states, regional fundamentals of the U.S. gas market—weather-driven demand, storage availability, and pipeline bottlenecks—dominate price dynamics, while oil-market sentiment plays only a secondary role. The modest negative QOQ coefficients at intermediate quantiles can be interpreted as reflecting these decoupled or even offsetting episodes, where capital moves away from oil or where gas responds to local shocks that are not mirrored in OVX.

There are, however, also nuances and mild tensions between the two approaches. The wavelet coherence at long periods suggests a fairly persistent, structural co-movement between OVX and gas volatility over a sizeable part of the sample, whereas the QOQ results emphasize that the strongest effects are concentrated in the joint upper tails. That difference arises because wavelet coherence weights sustained cyclical co-movement at specific frequencies, even if the underlying amplitudes are not always extreme, while the QOQ framework is explicitly focused on conditional behavior in the distribution tails. In other words, wavelets say “these two series cycle together for quite a long time at certain horizons,” while QOQ adds “and when both of them are in extreme states, the strength of that link jumps dramatically.”

In sum, the two perspectives reinforce the view that Henry Hub natural gas is a hybrid market. In ordinary times, its short-term volatility is governed mainly by domestic supply–demand fundamentals and idiosyncratic shocks, which explains the weak coherence and small or negative QOQ coefficients at moderate quantiles. Yet in periods of pronounced oil-market fear and broader financial stress, the gas

market becomes tightly synchronized with OVX, as seen in both the strong long-period wavelet coherence with nearly horizontal phase arrows and the sharp positive QOQ coefficients in the upper-tail regimes. In those phases, oil-market uncertainty and gas volatility form a tightly coupled system, underscoring how deeply integrated U.S. natural gas has become with global energy finance, even while retaining its traditional anchoring in regional fundamentals.

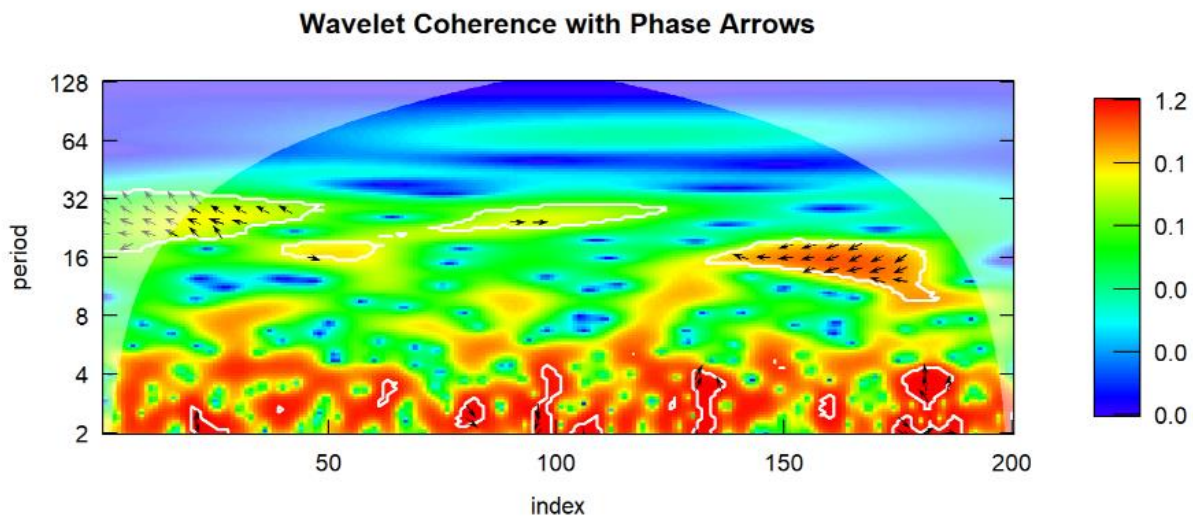


Figure 12: Wavelet Coherence and Phase Arrows of the long-term HHNG and EPU

Figure 12 gives a time–frequency view of how the long-term component of Henry Hub natural gas returns volatility moves with economic policy uncertainty. On the horizontal axis we have the time index of the sample, on the vertical axis the period: values close to 2–4 at the bottom correspond to high-frequency, short cycles, while values around 16, 32 or 64 represent progressively slower, long-run oscillations. The color scale shows the strength of local coherence between the two series. The red and orange bands mark periods and dates where long-term volatility and EPU are tightly linked, while green and blue areas indicate a weak or unstable association. The cone-shaped boundary reminds us that results near the upper corners should be treated cautiously because of edge effects.

The black arrows superimposed on the colored surface encode the phase relationship between the two series. Following the usual convention for wavelet coherence, an arrow pointing directly to the right indicates that the two series are in phase, rising and falling together at that time and frequency. An arrow pointing left implies that they move in opposite directions. When arrows tilt downwards and to the right, the first variable in the analysis – here the long-term volatility of Henry Hub – leads EPU by roughly a quarter cycle. When they tilt upwards and to the right, EPU leads the long-term volatility component.

In this figure, the most persistent and visually striking feature is the red-orange belt near the bottom of the plot, around periods of roughly 2–6, and several coherent patches extending into periods of about 8–16. These warm colors show that even the long-term volatility component shares strong short- to medium-horizon co-movements with EPU at various times in the sample. Within some of these red patches, especially around periods near 8 and indices around 80–110, the phase arrows tend to point to the right with a slight upward tilt. That pattern signifies a positive, in-phase relationship in which EPU slightly leads the long-term volatility cycles: extended episodes of higher policy uncertainty are followed by, and move together with, elevated long-run volatility in the gas market. This fits the interpretation that sustained policy uncertainty encourages firms and investors to reassess long-horizon investment and storage plans, so that the slow component of volatility adjusts after uncertainty has risen and remains high for some time.

Elsewhere in the lower-period band some arrows lean down-right rather than up-right, suggesting intervals where long-term volatility leads changes in EPU. In those episodes the gas market’s volatility appears to react earlier, possibly to sector-specific shocks or to information that later becomes visible in the broader

uncertainty index. This hints at a feedback loop rather than a one-way EPU-to-volatility channel: gas-market turmoil may at times contribute to an environment of heightened macroeconomic policy uncertainty. At longer periods, particularly above 16 and toward 32, the colors shift from red and yellow to green and light blue, and the coherent patches become more sporadic. The arrows in these regions often remain approximately rightward but are sparse and sometimes absent, indicating that the long-run co-movement between EPU and the slow component of volatility is weaker and less consistently identified at very low frequencies. This is consistent with the idea that, over multi-year horizons, the long-term volatility of Henry Hub is driven largely by structural factors internal to the gas market – infrastructure build-out, shale productivity, contract design, and long-run demand trends – which only partially overlap with broad policy uncertainty.

When we compare this wavelet picture with the long-term quantile-on-quantile regression results, several common themes stand out. The quantile surface shows a gradual build-up of positive coefficients at moderate to high quantiles of both EPU and long-term volatility, indicating that persistent high uncertainty is associated with elevated long-run volatility. The wavelet coherence diagram echoes this by revealing extended time–frequency regions with strong coherence and mostly rightward arrows, especially around medium periods. Both methods therefore point to a slower, persistent co-movement between EPU and the long-run volatility of Henry Hub: once uncertainty is elevated and remains so, volatility does not spike briefly and vanish but instead stays high in tandem with the uncertain environment.

The quantile surface also shows near-zero or slightly negative coefficients when both EPU and long-term volatility sit in their lower quantiles. That suggests that under tranquil policy and market conditions, uncertainty has a limited role in shaping the slow component of volatility. In the wavelet diagram, this corresponds to the many green and blue regions and the absence of coherent arrow fields across large parts of the plot. For those times and frequencies, there is little statistical evidence of a systematic link between long-term volatility and EPU; the Henry Hub market appears to be governed by its own domestic supply–demand forces rather than by macro-policy news. In that sense, the two methods tell the same story: long-run volatility is largely insulated from uncertainty when both are low.

There are yet some nuances and mild points of tension between the two perspectives. The quantile regression is cast explicitly as the response of long-term volatility to EPU, and it emphasises that the relationship is strongest in the upper quantiles. The wavelet coherence, in contrast, is symmetric: it does not impose direction and shows times when EPU leads volatility and times when volatility leads EPU. The presence of downward-tilted arrows in several coherent patches indicates that long-term volatility sometimes precedes changes in EPU, an aspect the quantile regression, by construction, does not highlight. This suggests a more complex, potentially bidirectional interaction in which energy-market conditions feed back into perceptions of overall policy uncertainty.

Another difference is that the wavelet diagram shows strong coherence at relatively short periods as well, even though we are examining the long-term component of volatility. This may mean that the process used to extract the slow component still retains some higher-frequency structure that co-moves with EPU, or that EPU itself has multi-scale fluctuations that affect both short- and long-run volatility simultaneously. The quantile surface, by focusing on the distribution of the long-run component, stresses the level of volatility rather than the specific time scale of its oscillations. As a result, wavelets can make the long-run association appear more pervasively present across frequencies, whereas the quantile approach concentrates the effect in particular regions of the joint distribution.

Despite these nuances, the two approaches reinforce a coherent narrative about the Henry Hub natural gas market. Over long horizons, policy uncertainty and gas-market volatility are linked in a slow, persistent way: the wavelet coherence shows in-phase movements with EPU often leading at medium periods, and the quantile surface shows higher long-run volatility in the upper quantiles of sustained uncertainty. In calm times, both methods find the relationship weak. And at certain intervals the wavelet arrows hint that volatility can lead uncertainty, suggesting feedback from energy-market stress to the broader policy environment. Together they portray a market that, in the long run, internalises prolonged uncertainty into its volatility structure, while still being anchored in the physical and institutional realities of natural gas production, infrastructure, and consumption.

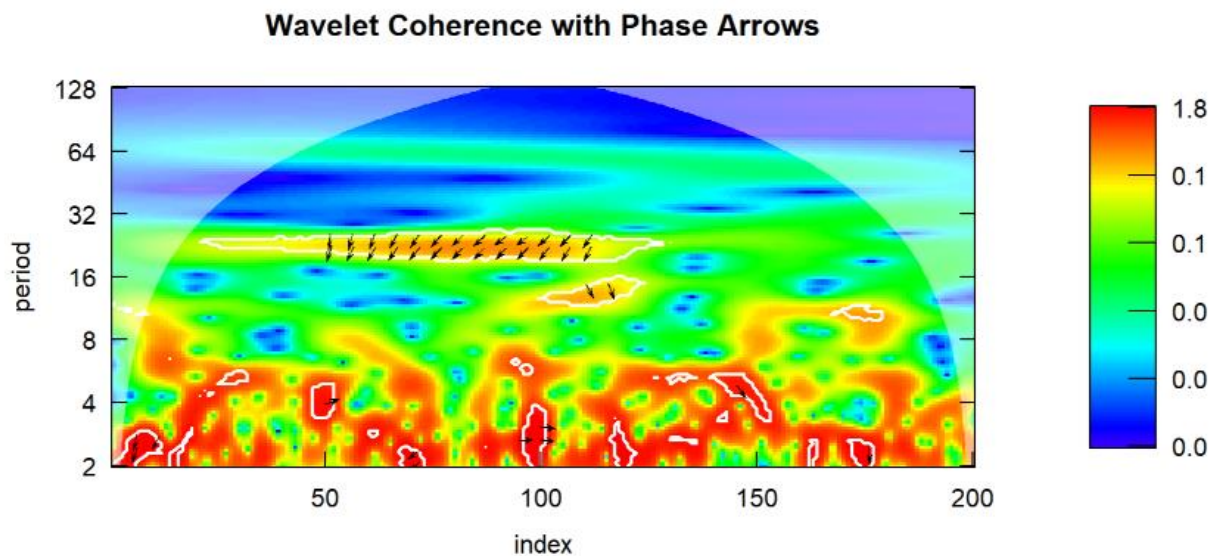


Figure 13: Wavelet Coherence and Phase Arrows of the long-term HHNG and OVX

Figure 13 illustrates how the long-term volatility of Henry Hub natural gas prices co-moves with the OVX—the oil market fear index—across both time and frequency dimensions. The horizontal axis represents the time index of the sample, while the vertical axis shows the period, indicating the duration of oscillations: shorter periods near the bottom reflect high-frequency, short-lived movements, while longer periods toward the top represent persistent, slow-moving cycles. The color scale at the right measures the strength of coherence, where red and orange areas signify strong correlation between the two variables and blue or green areas indicate weak or no relationship. The phase arrows reveal the directional relationship between the series. Arrows pointing to the right indicate that the two series move together (in phase), arrows pointing to the left denote opposite movements (anti-phase), downward-pointing arrows suggest that Henry Hub volatility leads the OVX, and upward-pointing arrows indicate that the OVX leads Henry Hub volatility.

In Figure 13, the key area of strong coherence lies around the 16–32 period range, marked by a yellow-green band stretching across much of the time index. The arrows in this zone mostly point to the right, some with a slight upward tilt, suggesting that over these longer horizons the OVX and natural gas volatility move in phase, with OVX marginally leading. This pattern implies that oil market fear—an indicator of broader energy market uncertainty—tends to precede and influence long-term volatility in the Henry Hub natural gas market. The finding is consistent with the notion that in times of sustained oil market anxiety, natural gas volatility gradually adjusts to evolving risk conditions across interconnected energy markets. Rather than reacting immediately, the natural gas market internalizes uncertainty over time, reflecting the slower adjustment processes tied to production, storage, and infrastructure investment decisions.

At shorter periods (roughly between 4 and 8), the coherence is weaker and more fragmented, showing patches of red and orange interspersed with cooler colors. In these regions, the phase arrows are more dispersed and occasionally point downward, which indicates intervals when gas volatility leads changes in the OVX. This suggests that during short-lived episodes, fluctuations in natural gas volatility may anticipate changes in oil market fear, potentially through early signals of supply disruptions or shifts in energy demand expectations that later reverberate across the oil market. Such episodes reinforce the idea that causality in energy market interactions is not one-directional but evolves over time depending on prevailing market conditions and the frequency band under consideration.

The overall coherence pattern reveals that the relationship between long-term natural gas volatility and the OVX is strongest in the medium-frequency domain, where the two variables oscillate together in a slow,

persistent rhythm. This interpretation aligns well with the quantile-on-quantile regression results, which also found a positive but nonlinear and persistent relationship at higher quantiles of both variables. The regression analysis showed that during periods of sustained uncertainty and volatility in both markets, the link between OVX and Henry Hub volatility strengthens markedly. This same tendency is captured by the wavelet diagram's broad, high-coherence region with rightward arrows at medium periods: both results point to a durable long-run contagion effect between oil and natural gas markets.

At the same time, both methods indicate that this link weakens or becomes negligible during tranquil market phases. In the quantile regression, low and moderate quantiles of OVX and long-term gas volatility yielded near-zero or even slightly negative coefficients, suggesting that during stable periods, the influence of oil market fear on gas volatility is minimal. Similarly, the wavelet plot shows extensive regions of low coherence (blue and green areas) outside the 16–32 period band, implying that over certain stretches of time and at some frequencies, the connection between oil and gas markets dissipates. These calmer phases correspond to times when the Henry Hub market's domestic fundamentals—such as storage dynamics, weather-driven demand, and shale gas output—overshadow broader energy market sentiment.

There are, nevertheless, some subtle distinctions between the two approaches. The quantile-on-quantile regression is inherently distribution-based, emphasizing how the conditional relationship between OVX and volatility changes across the joint quantiles of the two variables. It isolates the strength of co-movement under specific volatility regimes but does not explicitly account for how these relationships evolve over time or across frequencies. In contrast, the wavelet coherence captures temporal and spectral variations simultaneously, showing not only that the link between OVX and gas volatility strengthens during high-uncertainty phases but also when and over what time horizons these links occur. The phase arrows add another dimension by revealing directionality, which the quantile regression does not provide. The upward tilt of the arrows in the coherent band suggests that OVX tends to lead long-term gas volatility, supporting the interpretation that oil market fear transmits gradually into natural gas volatility through long-horizon expectations rather than immediate speculation.

Collectively, the wavelet and quantile results tell a cohesive story. Both reveal that the connection between oil market fear and Henry Hub natural gas volatility is state-dependent, nonlinear, and persistent. The wavelet analysis adds temporal depth, showing that this interdependence manifests most strongly at medium-to-long frequencies and that the oil market's uncertainty often leads the natural gas market's response. The quantile regression reinforces this by quantifying the strength of the effect across volatility regimes, particularly under conditions of sustained market stress. In combination, they depict a market that is increasingly intertwined with global energy sentiment: responsive and sensitive to prolonged oil market fear, yet still anchored in its own domestic fundamentals. Over long horizons, oil market uncertainty acts as a slow but steady driver of natural gas volatility, deepening the structural integration between the two energy markets and shaping expectations, risk assessments, and investment behavior across the broader energy landscape.

5. Summary and Conclusions

We use quantile-on-quantile regressions on mixed-interval data from May 2007 to June 2025 to assess the response of natural gas price return volatility to two macro influences – economic policy uncertainty and crude oil volatility. The evidence points to the importance of recognizing the nonlinear and state-contingent dynamics in the statistical evaluation of energy prices; consistent with our choice of methodology, a general and flexible form of state-contingent evaluation appears appropriate. Wavelet coherence investigations reinforce the QOQ results.

The empirical findings show that the Henry Hub Natural Gas price volatility is highly state-dependent and sensitive to the broader risk environment. Short-term volatility reacts nonlinearly to both economic policy uncertainty and the oil-market fear index: in calm regimes, policy and OVX shocks barely move gas volatility and may even have a mild dampening effect, but once the market is already turbulent, even modest increases in uncertainty produce outsized swings. Over longer horizons, the linkages become smoother and more persistent. Policy uncertainty and oil-market fear still matter, but instead of short, sharp bursts they show up as gradual drifts in long-term volatility, especially when both uncertainty and volatility are in their upper quantiles. Wavelet coherence analysis reinforces this story by showing bands of strong, in-phase co-movement at specific time scales and by revealing that leadership can alternate: at some high-frequency intervals gas volatility tends to lead uncertainty measures, while at medium horizons EPU or OVX often lead the gas market.

For portfolio managers, these findings argue for a regime-switching view of natural gas risk rather than a single, constant beta to “uncertainty.” In tranquil periods when both EPU and OVX sit in lower or middle quantiles, the results suggest that Henry Hub price return volatility is largely governed by weather, storage, and infrastructure constraints, so standard factor models based on fundamentals may perform well. In those states, adding gas exposure can provide diversification relative to broad policy or equity risk, because policy shocks transmit only weakly. In contrast, when measures of policy uncertainty or oil-market fear move into their upper quantiles, the study shows that both short-term and long-term volatility respond strongly and persistently.

Hedgers such as power utilities, industrial gas users, and LNG exporters can use these insights to refine the timing and structure of their hedging programs. The evidence that moderate uncertainty in otherwise calm markets does not necessarily translate into higher volatility suggests that systematic, mechanical hedging every time a policy headline hits may be costly and unnecessary. Instead, hedging intensity might be scaled to the joint state of gas volatility and uncertainty indicators: when both are in mid-range quantiles, firms may rely more heavily on operational flexibility and storage, while reserving heavier use of options and longer-dated futures for episodes when EPU or OVX move into their upper quantiles and the joint distribution implies much larger volatility responses. The long-term results also emphasize persistence: once the system enters a high-uncertainty state, volatility tends to remain elevated even after the initial shock has faded. That argues for hedging strategies that extend beyond the immediate news window, using layered or rolling positions that cover not just days or weeks but quarters in which regulatory or geopolitical uncertainty may remain unresolved.

For U.S. energy policy makers, the results are a reminder that macro and regulatory uncertainty are not neutral background noise for the gas market. When uncertainty is moderate and the market is stable, policy debate may have only minor or even stabilising effects on volatility, perhaps because firms have learned to hedge routine risks and markets have priced in expected regulatory paths. But when uncertainty becomes elevated and persists, both the short-term and long-term components of gas volatility respond more strongly, potentially feeding into electricity prices, industrial costs, and export competitiveness. That suggests a premium on policy clarity and predictable rule-making in periods of stress. Transparent communication of regulatory intentions and credible timetables for climate, infrastructure, and export decisions can help keep the system in the part of the joint distribution where volatility responses are modest. At the same time, the evidence that oil-market fear can feed into gas volatility over long horizons underscores the importance of monitoring global oil dynamics when crafting gas policy; LNG export

approvals, pipeline regulation, and strategic storage decisions should all be stress tested under states where OVX and EPU are jointly high, not just under average conditions.

Suppliers of natural gas—upstream producers, midstream pipeline operators, and LNG exporters—operate at the intersection of these financial and physical forces. The empirical findings suggest that during prolonged episodes of high oil-market fear and policy uncertainty, their revenue streams will face not only higher volatility but volatility that is more tightly linked to external risk factors beyond their operational control. That reality strengthens the case for robust balance sheets, diversified contract structures, and flexible capital budgeting. Producers might respond by increasing the share of output sold under long-term contracts or price collars when uncertainty indicators move into the upper tails, protecting investment programs from being whipsawed by volatility that is driven more by macro sentiment than by local fundamentals. Midstream firms, whose revenues often depend on volumes rather than prices, can still be affected if volatility spills over into shut-ins or curtailments; for them, the long-term results may support geographically diversified systems that buffer region-specific shocks. LNG exporters, finally, must navigate both U.S. domestic volatility and international demand swings; understanding how Henry Hub volatility responds to global oil fear and U.S. policy uncertainty helps them negotiate contract terms, such as destination flexibility and price indexation, that are resilient to the high-quantile regimes identified in the study.

Declarations: The authors declare that there are no conflicts of interest regarding this research. This research did not receive any specific grant or funding from public, commercial, or not-for-profit agencies. Data supporting the findings of this study are available from the authors upon request.

Acknowledgement: The authors are grateful for the constructive comments provided by the anonymous reviewers. Any remaining errors remain the sole responsibility of the authors.

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