Dependence Structure between Indian Financial Market and Energy Commodities: A Cross-quantilogram based Evidence

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Abstract

Given the developing nations are moving towards attaining the sustainable energy future, the reliance on renewable energy solutions is rising. Therefore, the dependence on traditional fossil fuel-based solutions is getting reduced, and this might have an impact on the energy market commodities. Analyzing this impact might divulge several insights regarding the portfolio decisions, in presence of the transformations in developmental trajectory. In this study, we analyze the cross-quantile dependence of the returns on the energy market commodities and the market returns for Indian financial market over July 31, 2008 to March 31, 2020. For this purpose, we adopt a novel three-stage methodology comprising Dynamic Conditional Correlation GARCH, Cross-quantilogram, and Wavelet Coherence-based models. We find that the market returns have negative effect on returns on the energy market commodities. This impact has been found to be asymmetric in nature. Moreover, the moderating impact of policy uncertainty has been analyzed has been analyzed through partial cross-quantilogram approach, and the outcome shows that the impact remains same under extreme market conditions. The findings have significant portfolio decisions in an energy transition context.

Keywords: India; Energy market commodity; Cross-quantilogram; Uncertainty; Volatility

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1 Introduction

Since the 2000s, there has been a rising concern about environmental health across the nations. Myopic industrialization over the ages has already resulted in increased pollution and depletion of non-renewable resources. Especially, the depletion of fossil fuels poses a serious question mark over civilization and industrial growth. Currently, fossil fuels contribute an overwhelming 90% of the world's energy consumption.[2] The current consumption rate indicates a gloomy future that the world will be out of all the fossil fuels by the next 50-70 years.[3] Recognizing the importance of this alarming condition, all the nations have started devising the appropriate measure to combat this crisis. Sustainable Development Goals (SDG) adopted by United Nations in 2015 depict this global initiative.[4] In this context, exploration and use of alternative or renewable energy resources emerge as one of the most effective solutions. Specifically, SDG 7 aims at achieving the global use of 175-gigawatt renewable sources by 2022.[5] Various government as well as business organizations have started taking appropriate measures. For instance, the use of renewable energy led to around 26 % of the global electricity generation in 2018 and is expected to rise to 45 % by 2040.[6]

Though the renewable energy sources can bring a desirable solution to the environmental crisis, it causes another problem in the energy market. The increasing use of renewable energy sources can lead to a huge demand-supply mismatch in the oil and gas sector. Already, the global financial crisis along with the great recession in 2008 left an unprecedented negative impact on the oil and gas sector. It led to a price drop of USD 150 to 35 per barrel, a fall in the stock price, and reduced consumption of fossil fuels in 2008.[7] Further, SDGs of the business practices have already raised the investors'' uncertainty, leading to a 14-percentage point decrease in the foreign direct investment to the developing economy countries in 2017.[8] In this background, the extensive use of renewable energy sources can add more uncertainty to the investment decisions in the energy portfolio design. These real-life phenomena signify the

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[4] Retrieved from: https://www.undp.org/content/undp/en/home/sustainable-development-goals.html
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[8] Retrieved from: https://unctad.org/news/investor-uncertainty-looms-over-sustainable-development-goals

importance of investigating the effect of the rising adoption of renewable energy sources on the uncertainty in the oil and gas sector.

The uncertainty in the oil and gas market has remained an area of interest for scholars over the ages. Researchers focus on different issues such as the relationship between financial stress and policy uncertainty (Reboredo and Uddin, 2015), the dynamic relationship between crude oil returns and uncertainty indices (Aloui et al., 2016), the co-movement and causality of economic policy uncertainty and crude oil prices (Sun et al., 2020), etc. However, it highlights several interesting research opportunities. For instance, as per the SDG Progress Report (United Nations, 2019), emerging economies around the world are moving towards attaining the objectives of SDG 7. In this pursuit, these nations are trying to achieve the full potential of renewable energy solutions. As a result, dependence on fossil fuel-based solutions is gradually decreasing. Further, if we look at the Indian scenario, then it can be observed that the Indian economy is striving to achieve sustainable development by gradually shifting away from fossil fuel-based solutions, as reliance on this energy solution is turning out to be a predicament to achieve the SDG objectives (ADB, 2019; UNESCAP, 2019). Looking at the persisting energy security and energy poverty issues in India, NITI Aayog (2019) has mentioned that the dependence of the Indian economy on fossil fuel-based solutions might create a hindrance in attaining the developmental trajectory. Moreover, reliance on fossil fuel-based solutions might make the Indian economy vulnerable to price fluctuations, which are majorly driven by global demand and supply considerations. To tackle this issue, the policymakers might need to introduce import substitution policies that can incentivize organizations to shift from existing imported fossil fuel-based production processes to renewable energy solutions-based ones. The recent report by World Bank (Artuc et al., 2019) highlights this issue and opines this solution in the Indian context should be benchmarked for other emerging economies in Asia. However, this initiative might have implications for the prices of the energy market commodities. Also, it might have a consequential impact on the market dynamics. In contrast, it can also be hypothesized that the prevailing market dynamics exert a negative externality on the energy commodity prices. Therefore, while India is treading along the path of attaining the objectives of SDG 7, the financial market might react to it differently. These conflicting objectives might influence the portfolio decision of the investors. Further, it is worthwhile to mention that the economic and socio-political stability of India is uncertain following the financial crisis in 2008, the economic slowdown in 2011, political transformation in 2014, and the growing unemployment scenario. It motivates us to address the following research question:

Research question: What are the possible dynamics between financial market and energy commodities under policy uncertainty?

The contributions of this work are as follows:

Given India is making progress towards attaining the objectives of SDG 7, the traditional energy sector is facing a demand shrinkage, while it is a major driver of Indian economic growth. At the same time, renewable energy solutions are also garnering considerable attention. A reflection of this situation might be experienced in the energy market, as well as in the associated portfolios. Hence, in this work, we investigate the relationship between the financial market and energy commodities under policy uncertainty. Here, we analyze the dependence structure of the returns on the energy market commodities and the market returns for the Indian financial market over July 31, 2008, to March 31, 2020. For this purpose, we adopt a novel three-stage methodology comprising Dynamic Conditional Correlation GARCH (DCC-GARCH), Cross-quantilogram, and Wavelet Coherence-based models to investigate the dependence structure of the return series, measure the tail-dependence in the correlational structure, and explore the lead-lag relationship between the series, respectively. The proposed approach ensures robustness. Our analysis reveals several important insights. First, there is a long-term relationship between energy commodities and energy index. Second, returns on energy commodity prices have a positive effect on market returns, while market returns negatively influence the returns on energy commodity prices. Third, still Indian industrial practices involve fossil fuel-based energy consumption, thus highlighting an obstacle to achieving the objectives of SDG 7. From the perspective of Indian investors, these insights can be useful to design their portfolio comprising energy stocks.

The article is organized as follows. Section 2 presents a summarized literature review. Section 3 describes the methodology. Section 4 explains data, results, and insights obtained from the analysis. Section 5 concludes the paper by discussing contributions and future research avenues.

2 Literature review

2.1 Scholarly works related to effect of uncertainty on the oil and gas sector

As per our exploration, a few researchers focus on the relationship between EPU and oil shocks (Rehman, 2018; Degiannakis et al., 2018). In the context of the USA, Andreasson et al. (2016) study the interaction between commodity futures returns (Energy, metal, and agricultural) and five driving factors, including the VIX and economic policy uncertainty for 1990-2014. In a similar background to the USA, Aloui et al. (2016) study the dynamic relationship between crude oil returns and uncertainty indices for 2000-2014. They find a unidirectional relationship between the VIX and commodity futures prices, and the policy uncertainty and commodity return (crude oil and natural gas). However, a bi-directional relationship is observed for heating oil. Andreasson et al. (2016) study the interaction between commodity futures returns (Energy, metal, and agricultural) and five driving factors, including the VIX and economic policy uncertainty for 1990-2014. Ji et al. (2018) investigate the impact of uncertainties (economic, financial, and energy) on the S&P 500 Global Clean Energy Index (CEX), crude oil and natural gas of the USA for 2007-2017. Uddin et al. (2018) investigate the casual interrelationships between various types of geopolitical, economic, and financial uncertainty indices and oil markets of the USA and Europe for 1990-2015. Badshah et al. (2019) investigate the relationship between the stock (S&P 500 index) and commodity markets (commodities included in Dow Jones Commodity Index) for 1999-2016 and observe a positive relationship between the economic policy uncertainty and commodity markets and a negative relationship between the VIX and commodity markets. Zhang et al. (2019) study the influence of the USA and China on key international markets, namely, stock, credit, energy, and commodity markets. They also investigate the interaction between economic policy uncertainty (as a measure of policy stance) and various markets and observe that the USA holds a dominant position in all the markets and China's economic policy uncertainties are found to be responsive to US economic policy uncertainties. They observe a negative (positive) dependence between uncertainty measures and oil returns (during certain periods such as before the financial crisis and Great Recession). Lee et al. (2019) study the impact of country risk (i.e., economic risk, financial risk, and political risk) on energy commodity futures prices using quantile regression for 1994-2017. They find that for crude oil and heating oil, the economic risks (financial risks) are significantly positive (negative) in the lower quantiles, but the effects turn significantly negative (positive) in the upper quantiles of the commodity returns. On similar lines, Zhu et al. (2020) demonstrate that the economic policy uncertainty of both domestic and other countries can affect crude oil prices. They study the effect of economic policy uncertainty on China's commodity futures (metal and agricultural) using the panel quantile regression approach. The EPU shocks (both local and US EPU) were differentiated into positive and negative components and the market conditions were classified as bearish, normal, and bullish. They find that the impact of EPU shocks (both local and US EPU) on commodities was heterogeneous across quantiles and sectors. They observe a common feature that the US EPU shocks have significant positive effects in bullish commodity markets (metal and agricultural).

Sun et al. (2020) perform a multi-country study to understand the relationship between uncertainty and crude oil. They study co-movement and causality of economic policy uncertainty and crude oil prices (West Texas Intermediate) on 10 countries (G7 countries, China, Brazil, and Russia) for 1997-2017 using wavelet coherence method and scale-by-scale linear Granger causality tests. They opine that the weak interaction between EPU and oil prices in the short-term and strong interaction in the mid-term and long-term. They also find a significant strong interaction at the financial and political events such as terrorist attack (2001), Iraq war (2003), global financial crisis (2008), Arab spring (2011), and European Sovereign Debt Crisis.

2.2 Scholarly works related to methodologies applied to measure the effect of uncertainty on the oil and gas sector

Our analysis reveals the existence of diverse approaches in the relevant scholarly works. For instance, Reboredo and Uddin (2015) study the impact of financial stress and policy uncertainty on conditional return distributions for the most tradable energy and metal commodities of the USA applying Quantile regression-based method for 1994-2015. Balcilar et al. (2017) investigate the predictive ability of economic policy uncertainty (EPU) and equity market uncertainty (EMU) on oil returns and volatility of oil returns of the USA applying bivariate quantile causality test-based method for 1986-2014. Yao and Sun (2018) examine the static tail dependence structure between the economic policy uncertainty (EPU) index and several financial markets of the USA applying copulas-based method for 1992-2016. Degiannakis et al. (2018) study the relationship between uncertainty (financial and economic) and oil shocks (supply-side, aggregate demand, and oil specific demand shocks) in the USA for 1994-2015 using the structural VAR (SVAR) model and a time-varying parameter VAR (TVP-VAR) model. They find that oil supply shocks do not exercise any significant impact on uncertainty indicators (SVAR model) and the uncertainty responses to the three oil price shocks are heterogeneous (TVP-VAR model). Ma et al. (2018) apply high-frequency tick data (West Texas Intermediate futures contract with a maturity of 1 month traded on NYMEX) for 2010-2014 to study the impact of economic policy uncertainty on the forecasting of crude oil futures relative volatility, and find that adding economic policy uncertainty to the Heterogeneous Autoregressive Model of the Realized Volatility (HAM-RV) increases the forecast accuracy of the crude oil futures markets. Chen et al. (2019) explore the dynamic relationship between the Brent oil market and EPU of Brazil, India, Russia, and China applying the Wavelet-based BEKK-GARCH approach for 2003-2018. Shaikh (2019) investigate the effect of economic policy uncertainty (EPU) on the 14 VIX-based volatility measures of the USA applying GARCHX and Markov switching models for 2001-2018. Shahzad et al. (2019) adopt a nonlinear auto-regressive distributed lag cointegration-based approach to investigate the impact of the oil price shocks on economic policy uncertainty, stock market uncertainty (VIX), treasury rates, and investor (bullish and bearish) sentiment in the USA for 1995-2015. They conclude that oil demand shocks affect economic policy uncertainty and stock market uncertainty, oil supply shocks affect treasury rates, and both oil demand shocks and oil supply shocks affect investor sentiment. To understand the change in the relationship between economic policy uncertainty and oil returns after the global financial crisis, Lei et al. (2019) apply the MIDAS quantile regression-based approach to study the risk perception of traders in crude oil spot and futures markets for 1986-2018. In the background of the USA, Qadan and Idilbi-Bayaa (2020) apply the threshold-GARCH, structural vector autoregression, and causality models for 1990-2017 to study the relationship between the economic uncertainty and the risk appetite of equity investors.

Our analysis of the existing literature review indicates that the Indian Financial market and energy commodities have not been paid enough attention. Also, most of the research articles adopt a single methodology. The summary of the existing scholarly works and contributions of this article is presented in Table 1.

Table 1 Summarized description of the literature.

[Insert Table 1 Here]

3 Methodology

In this study, we investigate the dependence structure between the Indian financial market and energy commodities. For this purpose, we incorporate a system of approaches. This system of approaches helps in addressing the research problem in several ways. First, the dependence structure might follow a dynamic time-dependent correlation structure contingent upon the market volatility. It facilitates the first-level understanding of the connectedness between the returns on market and selected indices. Second, after discovering the dynamic time-dependent correlation structure, it is important to explore whether the returns demonstrate any tail-dependence in their correlational structure or not. As the tail-dependence demonstrates the changes in the correlational structure based on market exigencies, it is important to understand this phenomenon. Third, after observing the correlational structure, the findings can be triangulated based on their co-movement pattern over the short-run and long-run. While the tail-dependence in the correlational structure might reveal the possible positive or negative association between the return series, the co-movement patterns also can disclose the lead-lag relationship between them.

Given the three ways the system of approaches will address the research problem, we select multiple methods as follows. First, we apply a Dynamic Conditional Correlation GARCH model (DCC-GARCH) model to capture the dependence structure of the return series. Next, upon confirmation of the dynamic time-dependent correlation structure revealed from the DCC-GARCH method, we incorporate a Cross-quantilogram approach to measure the tail-dependence in their correlational structure. Finally, after analyzing the correlational structure between the series with the dynamic and extreme conditions, we adopt a Wavelet Coherence-based approach to explore the lead-lag relationship between the series. Precisely, this methodological schema has been utilized in the study for attaining the research objective.

3.1 Description of DCC GARCH

Time-varying volatilities of financial assets move in tandem, and their closeness varies across assets and markets. This closeness is directly related to the systemic risk. For this reason, we apply a DCC-GARCH model to analyze the time-varying volatility of time series.

The variance fluctuates over time. Also, it shows properties such as the small volatility changes are followed by small changes and large volatility changes are followed by large changes and volatility tends to be autocorrelated which means today's volatility depends on past volatility. Based on these properties, Engle (1982) develops the ARCH model that captures the time-varying volatility. Later, Bollerslev (1986) introduces the GARCH models that capture the volatility clustering and forecast future volatilities. The idea that the conditional covariance matrix can be decomposed into conditional standard deviations and a conditional correlation matrix leads Bollerslev (1990) to introduce the Constant Conditional Correlation (CCC) model. Here, the conditional standard deviation is time-varying and the conditional correlation is assumed to be constant over time. Engle and Sheppard (2001) extend this model in the form of Dynamic Conditional Correlation (DCC), where both the conditional standard deviation and conditional correlation are time-varying. Thus, it can be deduced that the DCC-GARCH model is a generalization of the CCC-GARCH model, which allows the correlation matrix to depend on the time. DCC–GARCH model separate the volatility fluctuations from returns, leaving the standardized residuals, which are independently and identically distributed (i.i.d.).

The DCC-GARCH model can be defined as follows

$$r_t = \mu_t + a_t.$$

$$a_t = H_t^{1/2} z_t.$$
$$H_t = D_t R_t D_t.$$

where,

r_t is a $n \times 1$ vector of log returns of n assets at time t.

μ_t is a $n \times 1$ vector of conditional means that shows the expected value of the conditional r_t.

a_t is a $n \times 1$ vector of unpredictable residuals that shows mean-corrected returns of n assets at time t, i.e., $E[a_t] = 0$ and Cov $[a_t] = H_t$.

H_t is a $n \times n$ symmetric positive-definite matrix that shows conditional variances of a_t at time t.

$H_t^{1/2}$ is any $n \times n$ matrix at time t such that H_t is the conditional variance matrix of a_t. $H_t^{1/2}$ may be obtained by a Cholesky factorization of H_t.

D_t is a $n \times n$ diagonal matrix of conditional standard deviations of a_t at time t.

R_t is a $n \times n$ conditional correlation matrix of a_t at time t.

$z_t$is a $n \times 1$ vector of i.i.d errors such that $E[z_t] = 0$ and $E[z_t z_t^T] = I$.

The mean part of the DCC-GARCH model $[\mu_t]$ is independently modelled using Autoregressive Moving Average (ARMA) model as follows.

$$\mu_t = \mu + \sum_{i=1}^{P} A_i r_{t-i} + \sum_{j=1}^{Q} B_j \epsilon_{t-j}. \quad (1)$$

Where A_i and B_j are diagonal matrices.

The elements in the diagonal matrix D_t are standard deviations from univariate GARCH models and can represented in the following manner.

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sqrt{h_{nt}} \end{bmatrix}. \quad (2)$$

where, $h_{it} = \delta_{i0} + \sum_{q=1}^{Q_i} \delta_{iq} a_{i,t-q}^2 + \sum_{p=1}^{P_i} \gamma_{ip} h_{i,t-p}$.

R_t is the conditional correlation matrix of the standardized disturbances ϵ_t, i.e., $\epsilon_t = D_t^{-1} a_t \sim N(0, R_t)$. Since R_t is a correlation matrix, it is symmetric and can be expressed as follows.

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \cdots & \rho_{2n,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \rho_{n-1,n,t} \\ \rho_{1n,t} & \rho_{2n,t} & \cdots & \rho_{n-1,n,t} & 1 \end{bmatrix}. \quad (3)$$

The elements of $H_t = D_t R_t D_t$ can be expressed in the following manner

$$[H_t]_{ij} = \sqrt{h_{it}h_{jt}}\rho_{ij}. \tag{4}$$

where, ρii = 1.

Ensuring H_t and R_t to be positive definite, R_t can be decomposed into the following elements.

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{5}$$

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha\epsilon_{t-1}\epsilon_{t-1}^T + \beta Q_{t-1}. \tag{6}$$

where $\overline{Q}$ is the unconditional covariance matrix of the standardized errors ϵ_t.

$$\overline{Q} = \mathrm{Cov}[\epsilon_t\epsilon_t^T] = E[\epsilon_t\epsilon_t^T] = \frac{1}{T}\sum_{t=1}^{T}\epsilon_t\epsilon_t^T.$$

The parameters α and β are scalars, and Q_t^* is a diagonal matrix with the square root of the diagonal elements of Q_t at the diagonal. Q_t^{*-1} is the inverted diagonal matrix with the squared root diagonal elements of Q_t.

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{q_{nnt}} \end{bmatrix}. \tag{7}$$

Q_t^* rescales the elements in Q_t to ensure $\left|\rho_{ij}\right| = \left|\frac{q_{ijt}}{\sqrt{q_{iit}q_{jjt}}}\right| \leq 1.$

Further, Q_t has to be positive definite to ensure R_t to be positive definite. The scalars α and β must satisfy $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$.

The correlation structure can be extended to the general DCC (M, N)-GARCH model in the following manner.

$$Q_t = \left(1 - \sum_{m=1}^{M}\alpha_m - \sum_{n=1}^{N}\beta_n\right)\overline{Q_t} + \sum_{m=1}^{M}\alpha_m a_{t-1}a_{t-1}^T + \sum_{n=1}^{N}\beta_n Q_{t-1}. \tag{8}$$

The conditional correlation between energy market and uncertainty at time t can be defined as follows.

$$\rho_{ij,t} = \frac{(1-\alpha-\beta)\overline{q}_{ij} + \alpha\epsilon_{i,t-1}\epsilon_{j,t-1} + \beta q_{ij,t-1}}{[(1-\alpha-\beta)\overline{q}_{ii} + \alpha\epsilon_{i,t-1}^2 + \beta q_{ii,t-1}]^{1/2}[(1-\alpha-\beta)\overline{q}_{jj} + \alpha\epsilon_{j,t-1}^2 + \beta q_{jj,t-1}]^{1/2}}. \tag{9}$$

The parameters of H_t assuming the Gaussian distribution for the standardized error z_t are given by the following likelihood function as follows.

$$\ln\big(L(\theta)\big) = -\frac{1}{2}\sum_{t=1}^{T} n\ln(2\pi) + 2\ln(|D_t|) + \ln(|R_t|) + a_t^T D_t^{-1} R_t^{-1} D_t^{-1} a_t. \tag{10}$$

This is estimated in two steps. In the first step, R_t is replaced by I which results in a quasi-likelihood function as given below

$$\ln\left(L_1(\emptyset)\right) = \sum_{i=1}^{n}\left(-\frac{1}{2}\sum_{t=1}^{T}\left[\ln(h_{it}) + \frac{a_{it}^2}{h_{it}}\right] + \text{constant}\right). \tag{11}$$

The parameters set $\emptyset, h_{it}, \epsilon_t,$ and $\overline{Q}$ are calculated using the first function. The parameters α and β are estimated in the second step as follows.

$$\ln\left(L_2(\varphi)\right) = -\frac{1}{2}\sum_{t=1}^{T}(n\ln(2\pi) + 2\ln(|D_t|) + \ln(|R_t|) + \epsilon_t^T R_t^{-1}\epsilon_t). \tag{12}$$

3.2 Description of Cross-Quantilogram

Linton and Whang (2007) introduce quantilogram that measures the directional predictability in different parts of the distribution of a single stationary time series. Later, Han et al. (2016) introduce cross-quantilogram that measures the quantile dependence between two time series, predict one time series using other, and measures the systemic risk.

For two events $r_{1,t}$ and $r_{2,t-k}$, where $\{r_{1,t} < q_{1,t}(\tau_1)\}$ and $\{r_{2,t-k} < q_{2,t-k}(\tau_2)\}$, $q_{i,t}(\tau_i)$ being either τ_i conditional or unconditional quantile of $r_{i,t}$. The quantile hit is given by $\{1[r_{i,t} < q_{i,t}(.)]\}$ for $i = 1,2, \ldots$ where $1[.]$ denotes the indicator function that take the value one when its argument is true, and zero otherwise. The cross-quantilogram is the cross-correlation of the quantile-hit processes and is defined as follows:

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau 1}\left(r_{1,t} - q_{1,t}(\tau_1)\right)\psi_{\tau 2}\left(r_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau 1}^2\left(r_{1,t} - q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau 2}^2\left(r_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}}, \text{ for } k = 0, \pm 1, \pm 2, \ldots \tag{13}$$

Where, $\psi_{\tau i}\left(r_{i,t} - q_{i,t}(\tau_i)\right) = 1[r_{i,t} < q_{i,t}(\tau_i)] - \tau_1$.

A sample cross-quantilogram can be expressed in the following manner

$$\hat{\rho}_\tau(k) = \frac{\sum_{t=k+1}^{T}\psi_{\tau 1}\left(r_{1t} - \hat{q}_{1,t}(\tau_1)\right)\psi_{\tau 2}\left(r_{2,t-k} - \hat{q}_{2,t-k}(\tau_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\psi_{\tau 1}^2\left(r_{1t} - \hat{q}_{1,t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T}\psi_{\tau 2}^2\left(r_{2,t-k} - \hat{q}_{2,t-k}(\tau_2)\right)}}, \text{ for } k = 0, \pm 1, \pm 2, \ldots \tag{14}$$

The dependence between two events $\{q_{1,t}(\tau_1^l) < r_{1,t} < q_{1,t}(\tau_1^u)\}$ and $\{q_{2,t-k}(\tau_2^l) < r_{2,t-k} < q_{2,t-k}(\tau_2^u)\}$ for arbitrary quantile ranges $[\tau_1^l, \tau_1^u]$ and $[\tau_2^l, \tau_2^u]$ can be obtained by replacing τ_i with $[\tau_i^l, \tau_i^u]$ in $\psi_{\tau i}\left(r_{i,t} - q_{i,t}(\tau_i)\right) = 1[r_{i,t} < q_{i,t}(\tau_i)] - \tau_1$ in the following manner.

$$\psi_{[\tau_i^l, \tau_i^u]}\left(r_{i,t} - q_{i,t}([\tau_i^l, \tau_i^u])\right) = 1[q_{i,t}(\tau_i^l) < r_{i,t} < q_{i,t}(\tau_i^u)] - (\tau_i^u - \tau_i^l). \tag{15}$$

While considering dependence from an event $\{q_{2,t-k}(\tau_2^l) \leq r_{2,t-k} \leq q_{2,t-k}(\tau_2^u)\}$ to an event $\{q_{1,t}(\tau_1^l) \leq r_{1,t} \leq q_{1,t}(\tau_1^u)\}$, $\rho_\tau(k) = 0$, shows no dependence or directional predictability. $\rho_\tau(k) \neq 0$, shows existence of quantile dependence or directional predictability.

The null and alternative hypothesis for testing the directional predictability of events up to p lags $\{r_{2,t-k} \leq q_{2,t-k}(\tau_2) : k = 1, \ldots, p\}$ for $\{r_{1t} \leq q_{1,t}(\tau_1)\}$ are as follows

$$\textit{Null hypothesis } H_0: \rho_\tau(1) = \cdots = \rho_\tau(p) = 0$$

$$\textit{Alternative hypothesis } H_1 : \rho_\tau(k) \neq 0 \text{ for some } k \in \{1, \ldots, p\}$$

The hypothesis can be tested using Box-Pierce type test statistic $\widehat{Q}_\tau^{(p)} = T \sum_{k=1}^{p} \hat{\rho}_\tau^2(k)$ or Box-Ljung version $\widetilde{Q}_\tau^{(p)} \equiv T(T+2) \sum_{k=1}^{p} \hat{\rho}_\tau^2(k)/(T-k)$. Portmanteau test statistics $\widehat{Q}_\tau^{(p)}$ for a specific quantile is a special case of the sup-version test statistic:

$$\sup_{\tau \in T} \widehat{Q}_\tau^{(p)} = \sup_{\tau \in T} T \sum_{k=1}^{p} \hat{\rho}_\tau^2(k). \tag{16}$$

where T is the range of quantiles we are interested in evaluating the directional predictability, $\forall_\tau \in T$, and $(k, \tau) \in \{1, \ldots, p\} \times T$ with fixed p.

In order to control the impact of the exogenous factors on the hypothesized relationship between two events $r_{1,t}$ and $r_{2,t-k}$, the partial cross-quantilogram method is employed. This method is capable of encompassing the events between the temporal frame of t and $t-k$, such that $r_{1,t} \leq q_{1,t}(\tau_1)$ and $r_{2,t-k} - q_{2,t-k}(\tau_2)$. The control variables of the empirical model are introduced in this method as:

$$c_t \equiv [\psi\left(r_{3,t}\left(r_{3,t} - q_{3,t}(\tau_3)\right)\right), \ldots \psi\left(r_{n,t}\left(r_{n,t} - q_{n,t}(\tau_n)\right)\right)]^T \tag{17}$$

Where, n denotes the size of the matrix of exogenous control factors. Now, the correlation structure among the model parameters, in presence of exogenous control factors can be defined in expected values term as:

$$R_{\bar{\tau}}^{-1} = E(j_t(\bar{\tau}) j(\bar{\tau}))^{-1} = K_{\bar{\tau}} \tag{18}$$

Where, $j_t(\bar{\tau}) = [\psi(r_{1,t} - q_{1,t}(\tau_1)), \ldots \psi_{\tau,n}(r_{n,t} - q_{n,t}(\tau_n)]^\tau$ (19)

This mathematical specification signifies the quantile hit process. Following Han et al. (2016), $K_{\bar{\tau}}$ can be expressed as:

$$\rho_{\bar{\tau}|c}(k) = K_{\bar{\tau},12} / \sqrt{K_{\bar{\tau},11} . K_{\bar{\tau},22}} \tag{20}$$

This cross-quantile correlation method thus defined can take account of the moderating impact of the exogenous control parameters.

3.3 Description of wavelet coherence

As Fourier transform is able to entirely decomposing stationary time-series, wavelets might be utilized to analyze nonstationary time-series. This method allows for time conservation for localized information, and thereby, permitting comovement being computed in the frequency domain. The present study has adapted the wavelet coherence approach by Goupillaud et al. (1984) and Torrence & Compo (1998). The spectral properties of a time series data are discovered through the wavelet transform, while preserving the transformations in the temporal structures of the data. This method allows the time series data to be disintegrated into several frequencies. The Morlet wavelet function employed in this study can be represented as the following:

$$\varpi(t) = \pi^{-\frac{1}{4}} e^{-i\varpi t} e^{-\frac{1}{2}t^2} \tag{21}$$

Where, e represents the non-dimensional frequency. Tiwari et al (2013) divulged that the continuous wavelet transformation (CWT) is able to reveal the time series properties of the data. Besides, Aguiar-Conraria and Soares (2014) mentioned that the CWT helps the cross-wavelet analysis to unveil the frequency domain interface between two time series. The CWT for a discrete-time series can be explained as follows:

$$\varpi_{k,f}(s) = \frac{\rho t}{\sqrt{s}} \sum_{n'=0}^{N-1} x_{n'} \varpi^* \left((n' - m) \frac{\rho t}{s} \right) \tag{22}$$

$|W_n^x(s)|^2$ portrays the wavelet power spectrum, which divulges the variance of the data. At the borders of the finite length signals, the distortion of this spectrum creates the *Cone of Influence*. This power spectrum can be described as:

$$D\left(\frac{|W_n^x(s)|^2}{\rho_x^2} < p \right) = \frac{1}{2} P_f X_z^2 \tag{23}$$

Where, Fourier frequency describes the range of the mean spectrum (P_f), ρ signifies variance, and ${X_z}^2$ demonstrates two series, i.e., $p < P_f$, at 1 for real wavelets and 2 for the complex wavelets for z. The comovement between $r_{1,t}$ and $r_{2,t}$ is explored using the wavelet coherence:

$$R_n(s) = \frac{\left| S\left(s^{-1} W_n^{r_1 r_2}(s) \right) \right|^2}{S\left(s^{-1} |W_n^{r_1})|^{\frac{1}{2}} \right) S\left(s^{-1} |W_n^{r_2}|^{\frac{1}{2}} \right)} \tag{24}$$

Where, S is the levelling operator. The phase difference φ of series (r_1, r_2) is explored by the wavelet coherence as:

$$\varphi = \tan^{-1} \left(\frac{E\{W_n^{r_1 r_2}\}}{G\{W_n^{r_1 r_2}\}} \right) \text{and } \varphi \in [-\pi, \pi] \tag{24}$$

Where, the imaginary and real component operators are designated by G and E. r_1 leads r_2, when $\varphi \in \left[0, \frac{\pi}{2}\right]$. r_2 leads r_1, when $\varphi \in \left[-\frac{\pi}{2}, 0\right]$. On the other hand, the anti-phase alteration occurs, when r_1 leads r_2, $\varphi \in \left[-\pi, -\frac{\pi}{2}\right]$, and r_2 leads r_1, when $\varphi \in \left[\frac{\pi}{2}, \pi\right]$.

Now, analysis of the results of CWT entails understanding the phase diagram, which demonstrates the directional arrows for the hypothesized association. The Figure 1 depicts the phase diagram, which is having four quadrants. If the CWT between r_1 and r_2 is analyzed, then the direction arrows along the four quadrants will signify the following:

1. First quadrant: If the directional arrows are within the first quadrant, then it signifies that both the signals are in-phase, i.e., they will move in the same direction. Moreover, in this quadrant, r_1 will lead r_2.
2. Second quadrant: If the directional arrows are within the second quadrant, then it signifies that both the signals are out-of-phase, i.e., they will move in the opposite directions. Just like the previous case, in this quadrant also, r_1 will lead r_2.
3. Third quadrant: If the directional arrows are within the third quadrant, then it signifies that both the signals are out-of-phase, i.e., they will move in the opposite directions. Moreover, in this quadrant, r_2 will lead r_1, i.e., the lead-lag association will reverse.
4. Fourth quadrant: If the directional arrows are within the fourth quadrant, then it signifies that both the signals are in-phase, i.e., they will move in the same direction. Like the previous case, in this quadrant also, r_2 will lead r_1.

Fig.1 Phase diagram of the Wavelet transformation.

[Insert Figure 1 Here]

4 Data analysis and results

In this work, we analyze the cross-quantile dependence of the returns on the energy market commodities and the market returns for the Indian financial market over July 31, 2008, to March 31, 2020, using the proposed methodology presented in Section 3. For this purpose, daily percentage returns of crude oil, natural gas, energy index, economic policy uncertainty (EPU), volatility index (VIX), and stock market index are used. The daily closing prices for crude oil and natural gas are collected from National Commodity and Derivatives Exchange (NCDEX). The daily closing prices for energy are obtained from India Energy Exchange (IEX). The daily closing prices for the VIX and stock market index are collected from the National Stock Exchange (NSE). The monthly data for economic policy uncertainty is obtained from the www.policyuncertainty.com, and this data is converted into daily data using the quadratic match-sum process.

4.1 Results of DCC-GARCH model

We first analyze the time-varying correlations between the various time series using the DCC-GARCH model to understand the long-term relationship. Once the long-term relationship is established, we further probe the relationship between the time series at various quantiles using heat maps and cross quantilogram. This approach is useful to understand how the crude oil, natural gas, and energy index contribute to (and affected by) the systemic risk.

Table 2 Descriptive statistics.

[Insert Table 2 Here]

The descriptive statistics presented in Table 2 show negative mean returns for crude oil and natural gas. Negative mean returns are the result of sudden shocks that leads to high variability in the absence of autocorrelation and ARCH effects. The energy index returns are positive and vary less than the individual energy commodities. The specific composition of the energy index causes the less variability in returns. The energy index shows the autocorrelation and ARCH effects. The variability in the returns of the EPU and VIX is much lower than the individual commodities and energy index. Both EPU and VIX return series exhibits autocorrelation. The stock index returns are the least volatile across all the time series under study. Also, it shows autocorrelation and ARCH effects. The significant values of the skewness, kurtosis, and Jarque-Bera tests for all the time series reveal the non-normality in the returns.

Figure 2 depicts the returns of the time series. We observe that the variability in the returns for crude oil is more than the natural gas. The presence of shock in the natural gas returns attributes to a higher variance. The effect of the shock is reflected in the returns of the energy index too. The energy index returns and market returns highlight the presence of volatility clustering, i.e., high returns and low returns follow the high and low returns, respectively. The EPU and VIX seem to be regularly affected by the news leading to small shocks in both upward and downward directions. Initially, both EPU and VIX follow a similar path. Later, their paths reverse, i.e., the high variation in EPU coincides with the low variation in VIX. Also, Figure 2 reveals that the information in EPU does not reflect in the stock market. Similarly, less variation in the EPU parallels high variation in the stock market at the beginning of the analysis.

Fig.2 Plots of the return series.

[Insert Figure 2 Here]

The DCC-GARCH model reveals the long-term relationship between the energy commodities and energy index with the EPU, VIX, and stock market. Table 3 shows the short-term (dcca1) and long-term (dccb1) conditional correlation parameters (with covariance targeting) between the various return pairs. All the returns pairs show significant long-term dynamic conditional correlations. Five pairs, viz., OIL-MKT, GAS-EPU, EN-EPU, EN-VIX, and EN-MKT, show non-significant short-term dynamic conditional correlations. The association has been graphically represented in Figure 3a. This empirical evidence falls in the similar lines with the findings of Cevik et al. (2020), who used EGARCH approach and found crude oil prices have significant effects on stock market returns for Turkey.

Table 3 Joint conditional correlation between the returns of the time series.

[Insert Table 3 Here]

Fig. 3a Dynamic conditional correlation of crude oil, natural gas and energy index with EPU and VIX.

[Insert Figure 3a Here]

The dynamic correlation between the OIL-EPU pair moves between negative and positive values frequently. However, for the last one and half years the dynamic correlation has been positive. It shows that the uncertainty observed from the news influences the oil prices both positively and negatively. This piece of the findings extends the findings of Chen et al. (2019) for the BRIC economies. Dynamic conditional correlation between the OIL-VIX pair moves from a period of positive dynamic conditional correlation to periods of negative dynamic conditional correlation. Overall relationship is significant in the short and long-term. Dynamic conditional correlation between the GAS-EPU is near to zero with two positive and one negative instances, where the dynamic correlation moves between -0.4 to 0.4. Dynamic conditional correlation between the GAS-VIX is near to zero with one positive and negative instances where the dynamic correlation moves between -0.1 to 0.3. However, the appearances of sudden positive and negative dynamic correlation in the GAS-EPU pair are opposite to the GAS-VIX pair. Dynamic conditional correlation between the EN-EPU pair is positive and seems to be near 0.01 while the dynamic conditional correlation between the EN-VIX pair is negative (except once stance to be positive) and lies between 0.00 to -0.02. The direction of the dynamic conditional correlation between the EN-EPU and EN-VIX pairs is opposite. This can be caused by the diversified nature of the energy portfolio. The association has been graphically represented in Figure 3b. This section of the output can be considered as an extension of the findings by Ji et al. (2018), who used time-varying copula-GARCH model and found negative dependence between energy returns and uncertainty changes.

Fig. 3b Dynamic conditional correlation of crude oil, natural gas and energy index with stock market

[Insert Figure 3b Here]

Dynamic conditional correlation calculated using the volatility between oil and market is positive except for two instances. The dynamic correlation is near zero for the entire period and significant in the long-term. The dynamic correlation observed for the OIL-MKT pair is much smaller than the OIL-EPU and OIL-VIX pairs. Dynamic conditional correlation between gas and market is positive except for a few instances (lies between -0.01 and 0.02) and significant in both long-term and short term. The high fluctuations in the short-term exhibit the relationship between gas and market is different from the relationship between oil and market.

The dynamic conditional correlation between energy and market is positive (lies between 0.005 and 0.06) and significant in the long-term. The dynamic correlations in the three returns pairs, viz., OIL-MKT, GAS-MKT, and EN-MKT are significant in the long-term and show a distinct relationship with the stock market. From a larger macroeconomic perspective, this result extends the findings of Sinha (2017), who used multivariate GARCH and found rise in the oil import leads to depreciation of dollar-rupee exchange rate.

The dynamic correlation explains the time-varying relationship between the time series and shows how the two series are related. A significant long-term dynamic correlation between OIL-MKT, GAS-MKT, and EN-MKT pairs and the absence of the linear relationship adds more complexity to understand the relationship. The long-term significant dynamic correlation implies that oil, gas, and energy impact the market in the long-run. Here, it is interesting to observe how the energy commodities contribute to (and get impacted) the systemic risk.

After this, we analyze how cross-quantilogram (Han et al., 2016) between energy commodities and the stock market influence each other under extreme market conditions. First, the heatmaps reveal the quantile-based relationship. Second, cross-quantilograms between the energy commodities and market (with and without considering EPU and VIX as the state variables) unveil the systemic risk.

4.2 Cross-quantilogram estimates

Following the methodological framework adopted by Uddin et al. (2019), we apply the cross-quantilogram method for various quantiles of the returns on market prices $q_{MARKET}(r_{MARKET})$. Specifically, we focus on $r_{MARKET} = r_{ENERGY} = 0.05, 0.15\ldots\ 0.85, 0.95$. These selected quantiles individually specify different states of returns on market and energy prices and vice versa. Figure 4a explains how different lags of returns on market prices affect the returns on oil, natural gas, and energy prices. The heatmap in the diagram denotes the power of dependence between returns of the market and the returns of energy commodity prices, whereas quantiles of both the variables indicate different market conditions, i.e., low, middle, and high quantiles explain the bearish, normal, and bullish market conditions, respectively. Moreover, following Han et al. (2016) and Todorova (2017), the present study uses 1000 bootstrapping iterations. Also, the color bar on the right-hand side of the heatmap explains the strength and direction of the relationship between the market and different energy prices. In each of the heatmaps, the horizontal axis and the vertical axis show the quantile of returns on market prices and the quantiles of returns on different energy commodity prices, respectively.

We first focus on the impacts of returns on market prices [1 day period] ($r_{MARKET} = r_{ENERGY}$) and confirm that returns on market prices predict returns on energy prices. The findings confirm that the returns on market prices have a positive effect on returns on all energy commodity prices in the majority of the quantile combinations. This empirical outcome extends the finding of Ewing et al. (2018) for the US economy. However, the highest positive effect of returns on market prices on returns on energy commodity prices is reflected on the low to high quantiles, i.e., mostly during bearish and bullish market conditions. This effect turns negative and also persists in 5 lags [1 week period]. During this period, the effect of returns on market prices is negative on returns on energy commodity prices. Alongside the negative effect, the intensity is strong in the nexus of market-energy price returns compared to the returns on market vis-a-vis oil prices and returns on market vis-à-vis gas prices. Also, the effect of returns on market prices on returns energy commodity prices is almost the same in 22 and 66 lags [1 month and 1 quarter period]. In this period, the effect of returns on market prices is negative for the returns of all the three energy commodity prices. However, the effect is strong in the market-gas return relationship than the returns on other energy commodity prices. This directional nature of the market returns on the returns of energy commodity prices following a tail-dependence approach extends the finding of Scarcioffolo and Etienne (2021), who used cross-quantilogram and quantile Granger causality tests and found positive and significant spillover effects from crude oil to natural gas during bearish market conditions.

Fig. 4a Cross-quantilogram correlation between market returns (Y-variable) and returns on energy market commodities (X-variable).

[Insert Figure 4a Here]

In Figure 4b, the present study finds the directional predictability from oil, gas, and energy prices to market prices for lags of 1, 5, 22, and 66 days. The findings are positive for the entire quantile distribution. It signifies that the oil, gas, and energy prices have a positive effect on market prices returns. This specific finding extends the findings of Nusair and Al-Khasawneh (2018), who used quantile regression and found oil price shocks to have asymmetric effects on stock returns in case of the GCC countries. It suggests that an increase in oil, gas, and energy prices leads to market returns as well. Because of the substitution effect, the increase in the energy prices, the energy-dependent firms start looking for alternative inexpensive energy sources. This occurrence enhances the need for a market, which, in turn, raises the returns of energy-related firms. Alternatively, the decrease in the prices of oil, gas, and energy has a negative impact on market prices returns. This result is in similar lines with the findings of Kim et al. (2019), who used extreme bounds analysis and found before the financial crisis in 2008, energy prices exerted a moderate negative effect on future stock returns. As the oil, gas, and energy prices are an operational source for energy, in the situation of the energy price drop, energy-related firms are likely to swiftly substitute energy for market sources. This activity could decrease the need for stocks which eventually decreasing the market returns.

Fig. 4b Cross-quantilogram correlation between market returns (X-variable) and returns on energy market commodities (Y-variable).

[Insert Figure 4b Here]

4.3 Partial cross-quantilogram in presence of policy uncertainty and volatility

As mentioned earlier, to understand the true tail-dependence nature of correlation structure, the association needs to be analyzed with exogenous moderations. Following Uddin et al. (2019), we employ the partial cross-quantilogram method to investigate the moderating effect of other exogenous factors on the association between the series. In this section, we evaluate the predictability structure of market returns and different energy prices after adjusting policy uncertainty measures, i.e., the equity market volatility (VIX) and economic policy uncertainty (EPU). Notionally, EPU and VIX could impact the market returns through their influence on the projected cash flow and the interest rate. Figures 4a-4c of the study present the connection between market returns and energy commodity returns adjusted for the EPU and VIX. In the estimation of partial cross quantilogram, the EPU and VIX are integrated as a control variable to tackle any interdependence among the factors due to essential uncertainty linked with the fluctuation of the VIX or EPU. Moreover, Figures 5a-5c show the dependence strength for different lags (1 lag and 22 lag). In these figures, the initial two columns present the findings after adjusting for EPU, and the remaining columns explain the findings after adjusting VIX. We observe that the returns on oil, natural gas, and energy prices have positive effects on market price returns across all quantiles of conditional distribution after controlling for the EPU and VIX. On the other hand, it can also be seen that the negative impact of the returns on market on returns on energy commodity prices increases after controlling for the EPU and VIX. This segment of the findings extends the outcomes obtained by Uddin et al. (2019), who used cross-quantilogram approach and found cross-quantile dependence of renewable energy stock returns on aggregate stock returns is robust even after controlling for economic policy and equity market uncertainties. Similar results are also obtained for lag 22. Moreover, the current study also finds that the positive effects occurring in the extreme quantiles (i.e., bearish and bullish) are higher in the 1-day period, as compared to the 1-month period. It indicates that the maximum changes occur during the daily fluctuation as compared to monthly.

Fig. 5a Cross-quantilogram correlation between market returns and returns on oil prices after controlling for policy uncertainty and volatility index.

[Insert Figure 5a Here]

Fig. 5b Cross-quantilogram correlation between market returns and returns on gas prices after controlling for policy uncertainty and volatility index.

[Insert Figure 5b Here]

Fig. 5c Cross-quantilogram correlation between market returns and returns on energy prices after controlling for policy uncertainty and volatility index.

[Insert Figure 5c Here]

As we analyze the outcomes presented in Figures 5a-5c, we find the factors are not very overpowering. This subjective contrast may show that risk factors (EPU and VIX) convey no or few facts with respect to energy-market returns dependability. This outcome is in a similar line with the findings of Han et al. (2016). This outcome also shows that systemic risk is a major driver of the cross-quantile correlation. As the essential risk leftovers to a great extent unaltered even after adjusting the EPU and VIX, it can be inferred that the endogenous interrelationship across energy-market nexus (not the risk measures) is the significant contributor to the main risk.

4.4 Robustness check of the estimates

Finally, we use the wavelet coherence method to evaluate the robustness of the estimates. The main rationale behind the selection of this method is its capability of assessing the co-movement of the parameters over their respective frequency domains. As the DCC-GARCH and cross-quantilogram models are used over the temporal domain, analyzing the co-movement over the frequency domain helps in triangulating the study findings. The wavelet coherence between (a) market returns and oil price returns, (b) market returns and energy price returns, and (c) market returns and natural gas price returns are computed using 1000 iterations for each of the pairs. These results are reported in Figures 6a-6c. In the figures, the color code ranges from blue to red. This color range signifies the strength of the co-movement from being low to high, respectively.

We first explain the wavelet coherence between market returns and oil price returns presented in Figure 6a. It shows that the market returns and oil price returns are largely in-phase, both in the short-run and long-run. During the beginning of the study period, they are temporarily out-of-phase for two years. In the short-run, the market returns lead to oil price returns, while the oil price returns lead to market returns in the long-run. It indicates that market and oil price returns show significant co-movement both in the short-run and long-run. The directional nature of co-movement is negative during the first two years of the study period, and then it becomes positive. This finding falls in similar lines with the cross-quantilogram results for market returns and oil price returns. Similarly, the wavelet coherence between market returns and energy price returns presented in Figure 6b shows that the market returns and energy price returns are largely in-phase, both in the short-run and long-run. Just like the previous scenario, they are also out-of-phase for the initial two years. In the short-run, market returns lead to energy price returns, while the energy price returns lead to market returns in the long-run. It indicates that market and energy price returns exhibit significant co-movement for both in the short-run and long-run. The directional nature of co-movement is negative during the first two years of the study period, and then it becomes positive. This finding falls in similar lines with the cross-quantilogram results for market returns and energy price returns. Lastly, the wavelet coherence between the market returns and gas price returns presented in Figure 6c shows that the market returns and gas price returns are largely out-of-phase, both in the short- and long-run. During both periods, the market returns lead to gas price returns. The directional nature of co-movement is positive during the first one and half years of the study period, and then it becomes negative. This finding falls in similar lines with the cross-quantilogram results for market returns and gas price returns.

Fig. 6a Wavelet coherence between Market returns and Oil price returns.

[Insert Figure 6a Here]

Fig. 6b Wavelet coherence between Market returns and Energy price returns.

[Insert Figure 6b Here]

Fig. 6c Wavelet coherence between Market returns and Natural Gas price returns.

[Insert Figure 6c Here]

4.5 Insights and discussion

Our study presents several significant findings. We observe that the energy commodities show a positive impact on the market returns. This phenomenon signifies that Indian industrial growth is still dependent on fossil fuel-based energy consumption, thus highlighting the unsustainable growth pattern. This argument can be traced back to the famous "*Limits to Growth*" discourse (Meadows et al., 1972). This unsustainability characteristic might deter India from attaining the objectives of SDG 7. It has been identified by the Indian policymakers. The recent annual report of NITI Aayog (2021) discusses the development of the "*State Energy Index*" to measure the accessibility and affordability of clean energy solutions. In line with this policy reorientation, the Indian industries are gradually embarking on energy innovation to achieve energy efficiency. Also, the industries are bringing transformations in their existing production processes to accommodate cleaner energy solutions (Tiwari et al., 2021; Shahbaz et al., 2021). As a result of this industrial reorientation, the demand for commercial fossil fuel-based energy is gradually declining. A reflection of this scenario is visible in terms of the negative impact of the market returns on the returns on prices of the energy commodities. Even in the presence of policy uncertainty and volatility in the financial market, the industrial sentiment is turning out to be pro-clean energy.

These prevailing conditions in the Indian industrial sector divulge some probable indications regarding the movement of the Indian financial market. While the prevailing energy consumption pattern is accelerating industrial growth, the returns on energy commodity prices are driving the market returns. However, this driving force might not be sustainable, as this positive impact is not getting reciprocated. The growing demand of cleaner energy solutions creates a negative impact on the returns on energy commodity prices. Given the uncertainties in the Indian financial market, the rising negative impact might create a negative sentiment for the fossil fuel-based energy commodities and open up prospects for renewable energy commodities. Also, it is observed that the market-energy relationship is not contingent upon the exigencies, thus highlighting the robustness of this relationship. Hence, the findings might have significant implications for the portfolio decisions of Indian investors.

5 Conclusion

The gradually rising dependence on renewable energy solutions and the replacement of fossil fuel-based solutions have reshaped the investment scenario in India. This reorientation has been catalyzed by endogenous policy-level uncertainties. As the firms are gradually moving towards adopting renewable energy solutions and the economy is moving towards attaining the objectives of SDG 7, the mobilization of capital is directed towards the renewable energy generation firms. Contrary to the literature, this study looks into the dynamics of the energy commodity market, given the renewable energy adoption is on the rise. Methodologically, this study adds to the literature by divulging the quantile dependence structure for analyzing the dynamics at a granular level.

To achieve the research objectives of the study, we analyze the dependence structure of energy commodity returns on market returns. Here, we employ a novel cross-quantilogram correlation approach, which can capture the dependence structure at extreme market conditions. We also incorporate a novel partial cross-quantilogram correlation approach to assess the moderating impact of policy uncertainties captured through the economic policy uncertainty and volatility index. The study outcomes suggest that the market returns have a negative impact on the energy commodity returns under extreme market conditions. When the dependence structure is reversed, this impact is reversed. However, in the presence of policy uncertainty, it is observed that the market-energy associations do not change during extreme market conditions.

The findings divulge significant implications for the investors. As India is moving towards a sustainable energy future, investments are mobilized towards renewable energy generation projects. As a result, the firms are gradually embracing these solutions. Therefore, the economic growth trajectory depicted through the market movements demonstrates a negative impact on the fossil fuel-based energy commodity returns. Even under uncertain market conditions, firms try to rely on renewable energy solutions. It shows that even under extreme market conditions, the investors should avoid putting energy commodities and market index under a portfolio as it might increase the risk profile of the investor. Under normal market conditions, the energy commodities can be hedged against the market index, as the downside risk of the energy commodities can be averted under these circumstances. During bearish market conditions, downside systemic risk can be hedged against any of the energy commodities. This holding can provide profitable outcomes for a single-day trading window, as the dependence might diminish for longer holding durations. While saying this, it should also be noted that the investors might need to look into a long-term holding strategy, as the downside risk of the portfolio might be mitigated over a longer holding period. During a longer holding period, the dependence structure gradually diminishes. Therefore, the downside risk of the energy commodities can be averted. From this perspective, oil can serve as a safer investment compared to gas and energy, as the market-oil dependence is the lowest during the longer holding period. Lastly, we recommend that the investors need to shift towards renewable energy stocks, as the capital mobilization towards renewable energy firms might reduce the downside risk of the portfolio, as against holding the traditional fossil fuel-based energy commodities. Given the objective of the policymakers to attain the objectives of SDG 7, it can be expected that returns on fossil fuel-based energy commodities might face diminishing returns in the future. Hence, the market-energy dependence structure might change with larger development and diffusion of renewable energy solutions. From the perspective of long-term returns, the investors might progressively select to replace the fossil fuel-based energy commodities with renewable energy commodities.

Declarations

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Conflicts of interest/Competing interests: The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material: Data is available on request

Code availability: Code is submitted along with this study

Authors' contributions (optional: please review the submission guidelines from the journal whether statements are mandatory)

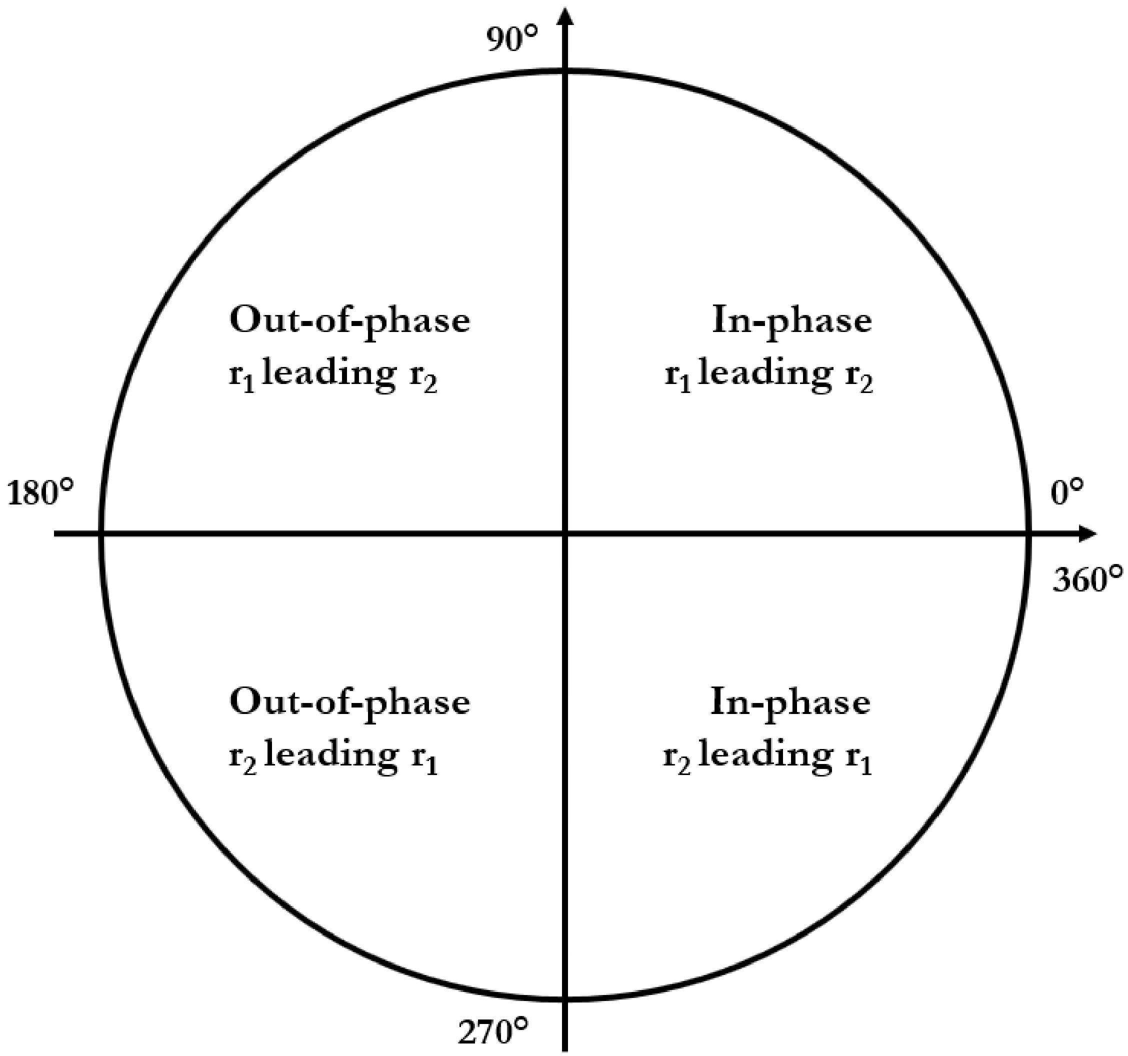


Figure 1: Phase diagram of the Wavelet transformation

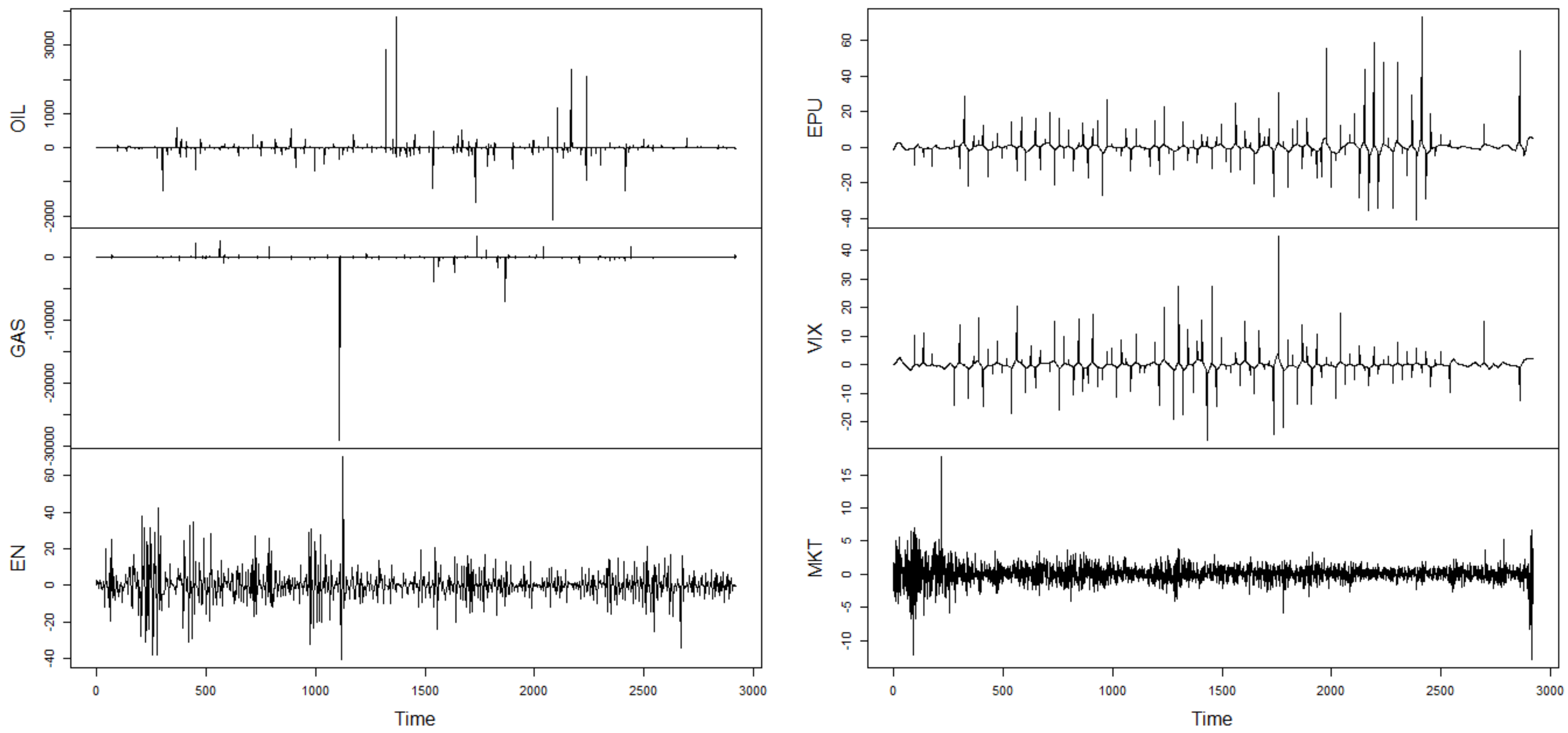


Figure 2: Plots of the return series

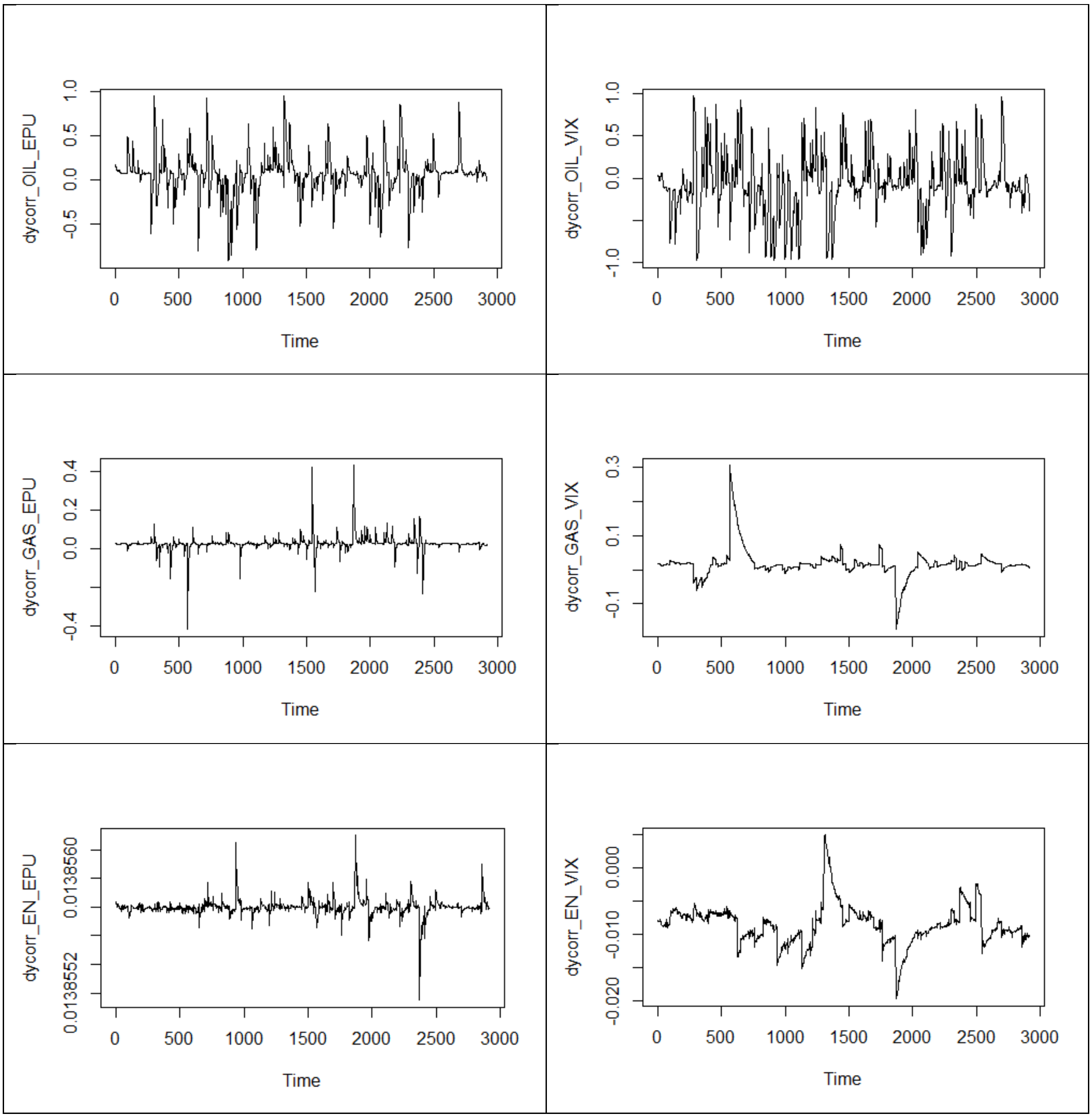


Figure 3a: Dynamic conditional correlation of crude oil, natural gas and energy index with EPU and VIX

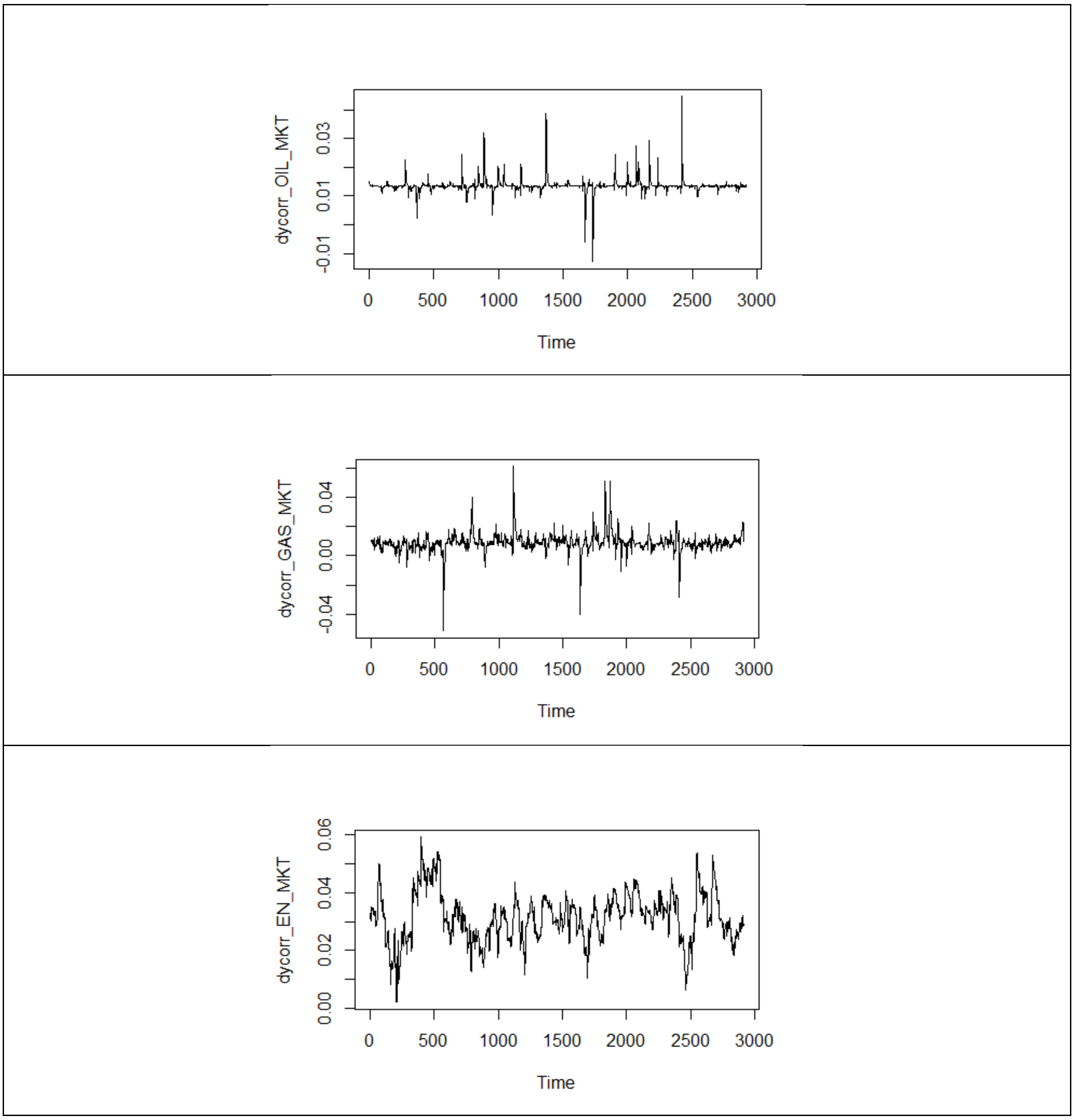
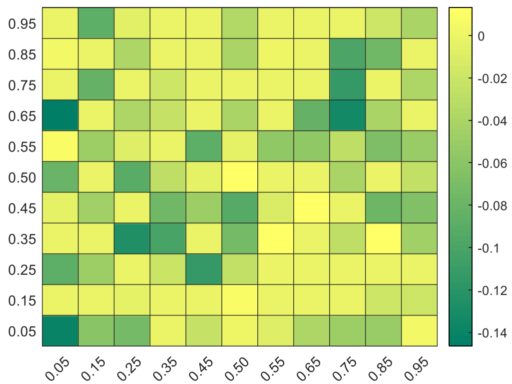
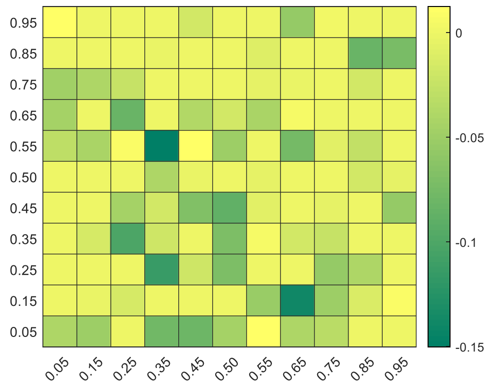
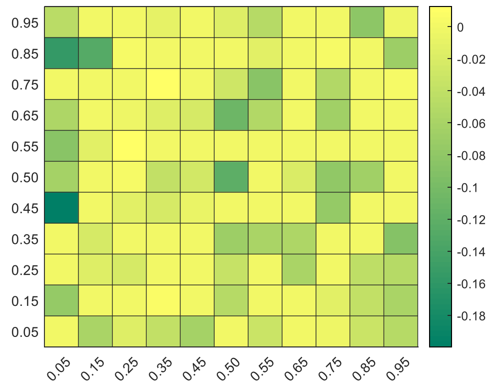
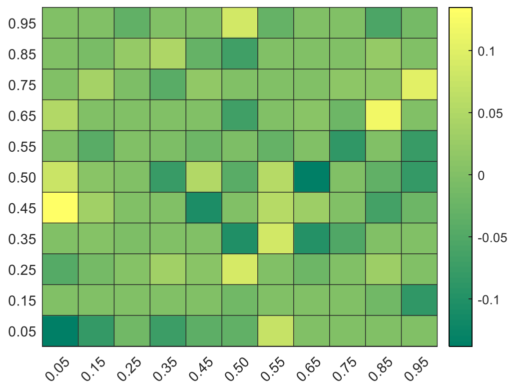
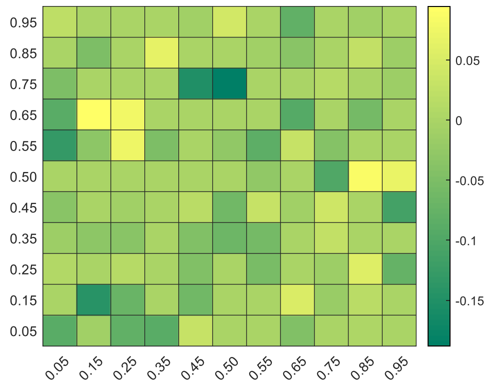
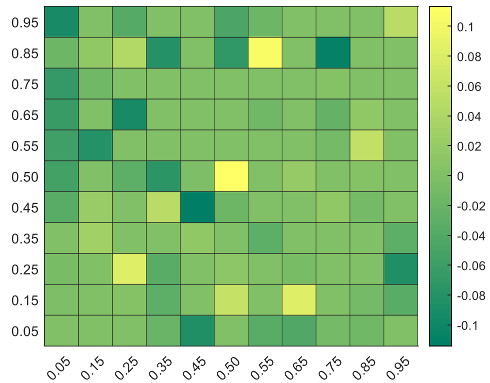


Figure 3b: Dynamic conditional correlation of crude oil, natural gas and energy index with stock market

Lags	A: OIL	B: GAS	C: ENERGY
MKT [1 day]			
MKT [5 days]			

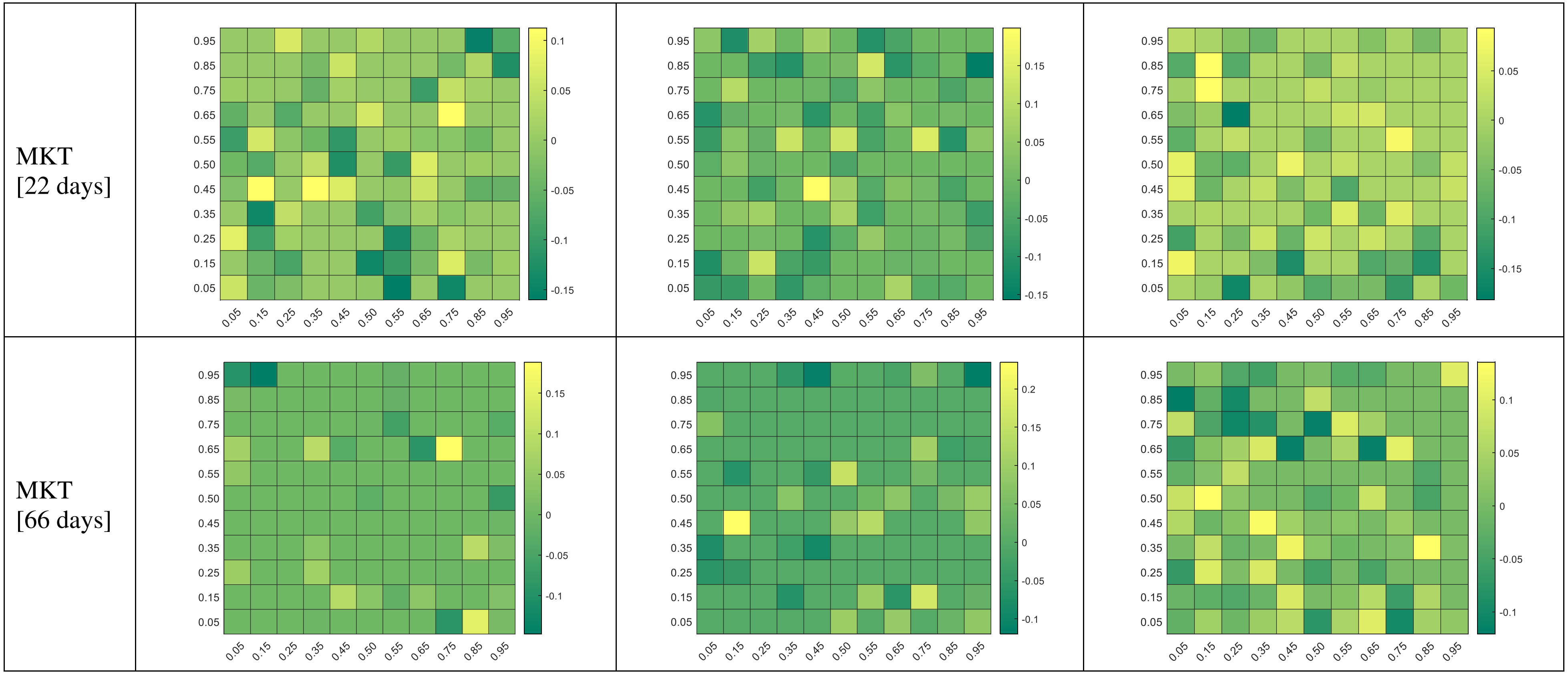
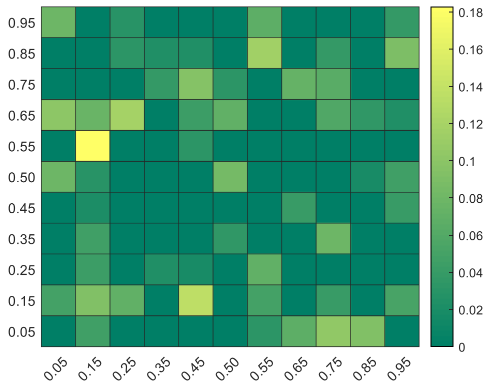
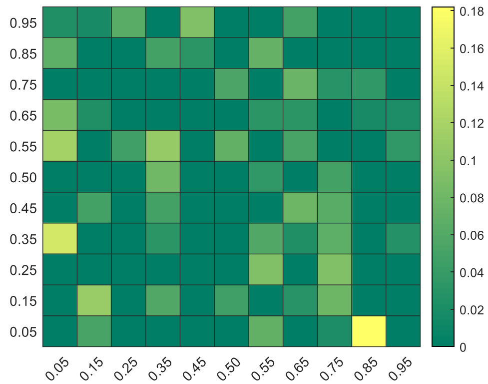
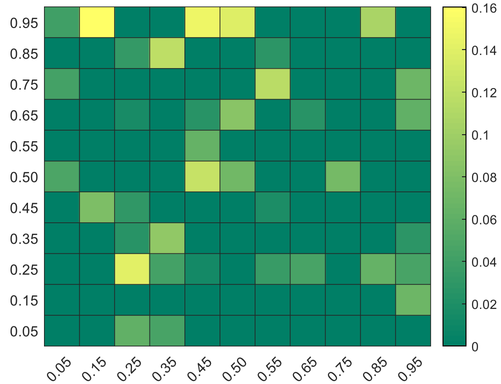
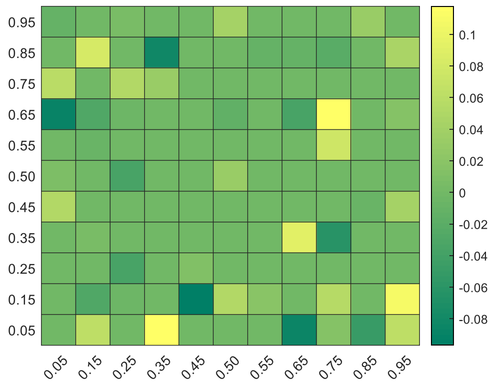


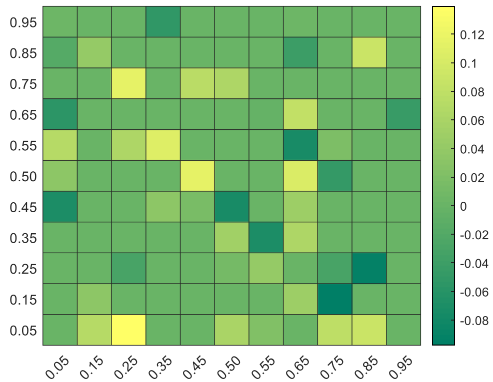
Figure 4a: Cross-quantilogram correlation between market returns (Y-variable) and returns on energy market commodities (X-variable)

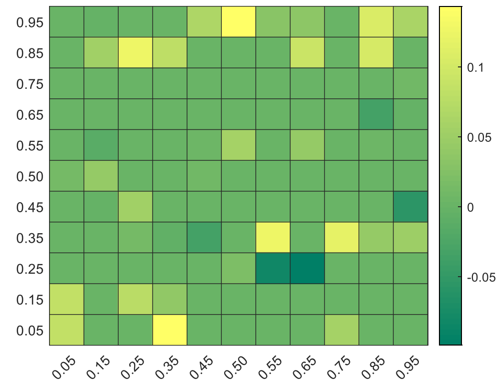
<table>
<tr><td>Lags</td><td>A: OIL</td><td>B: GAS</td><td>C: ENERGY</td></tr>
<tr><td>MKT</td><td>

[1 day]</td><td>

[1 day]</td><td>

[1 day]</td></tr>
<tr><td>MKT</td><td>

[5 days]</td><td>

[5 days]</td><td>

[5 days]</td></tr>
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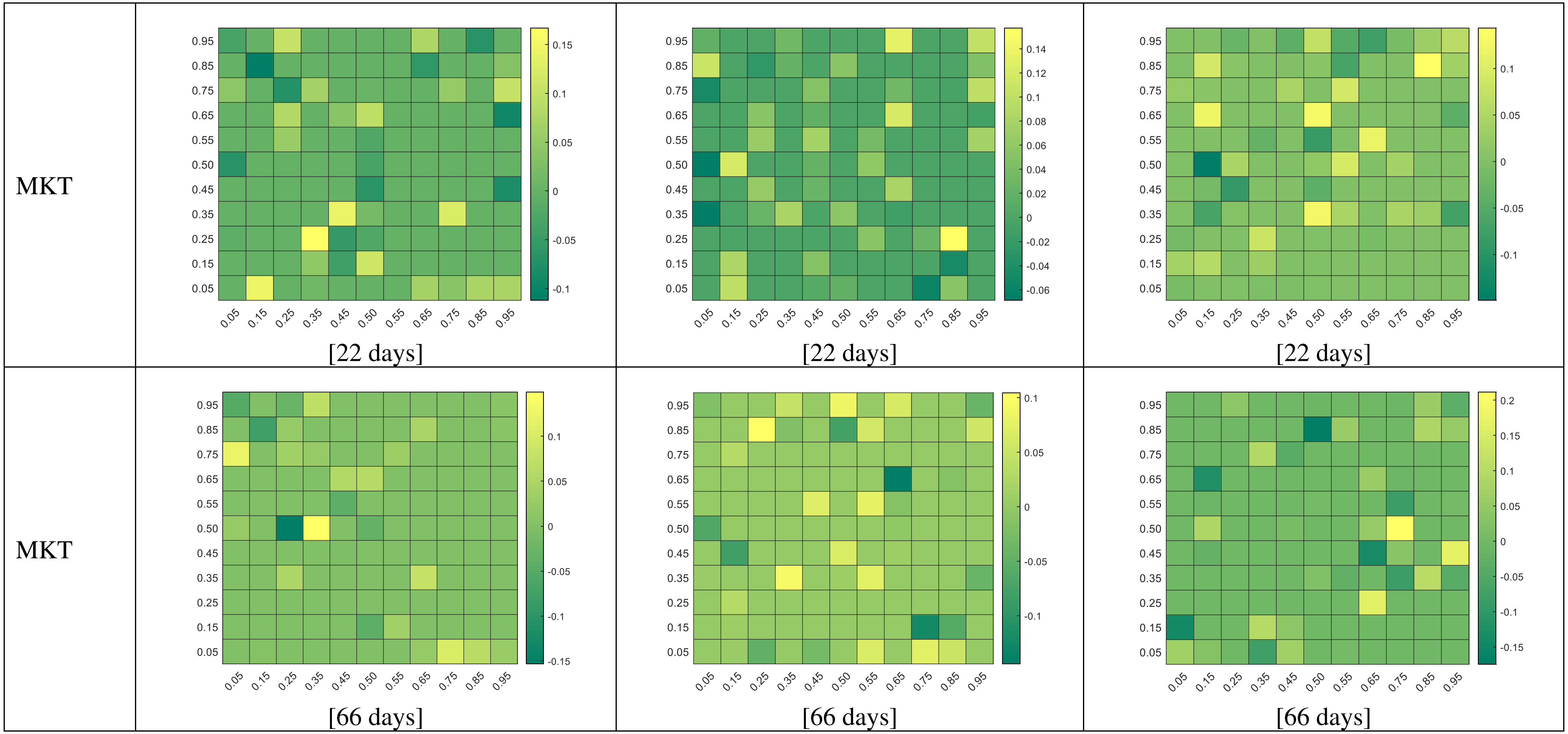

Figure 4b: Cross-quantilogram correlation between market returns (X-variable) and returns on energy market commodities (Y-variable)

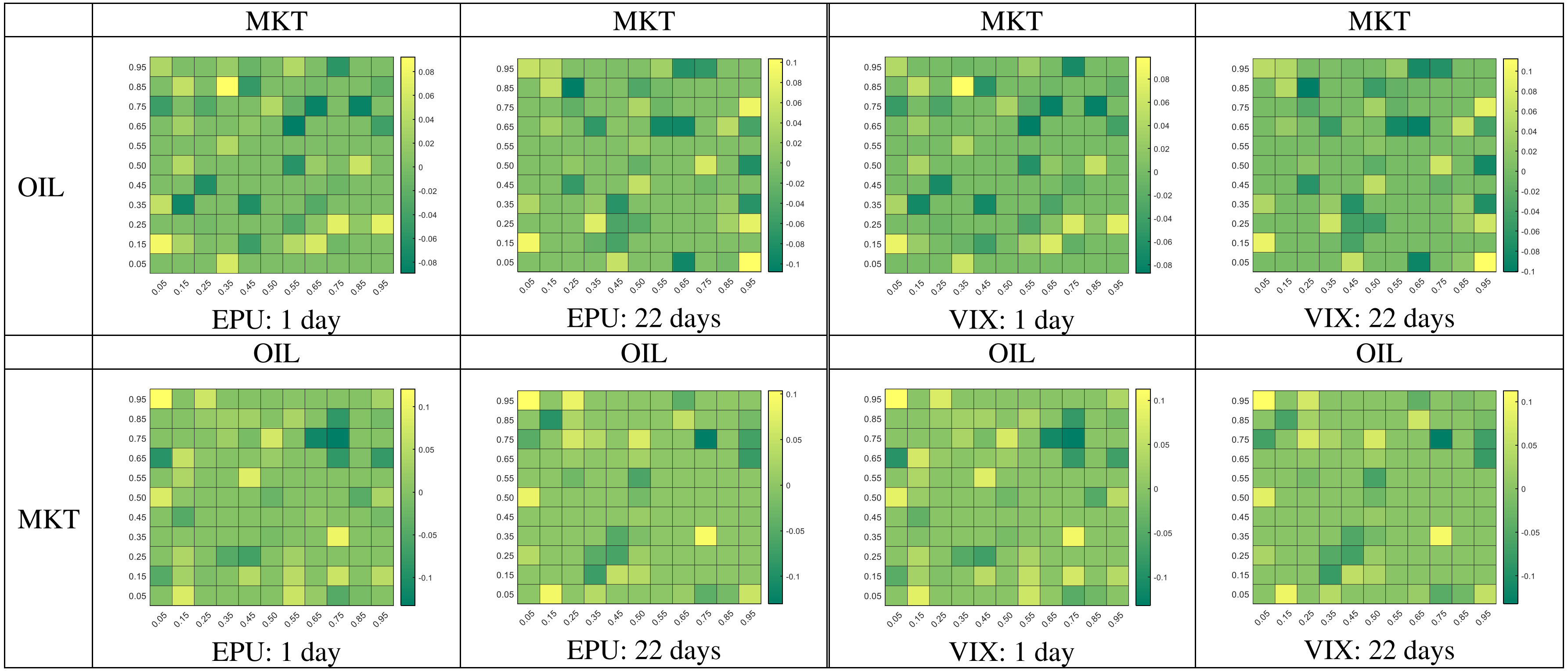

Figure 5a: Cross-quantilogram correlation between market returns and returns on oil prices after controlling for policy uncertainty and volatility index

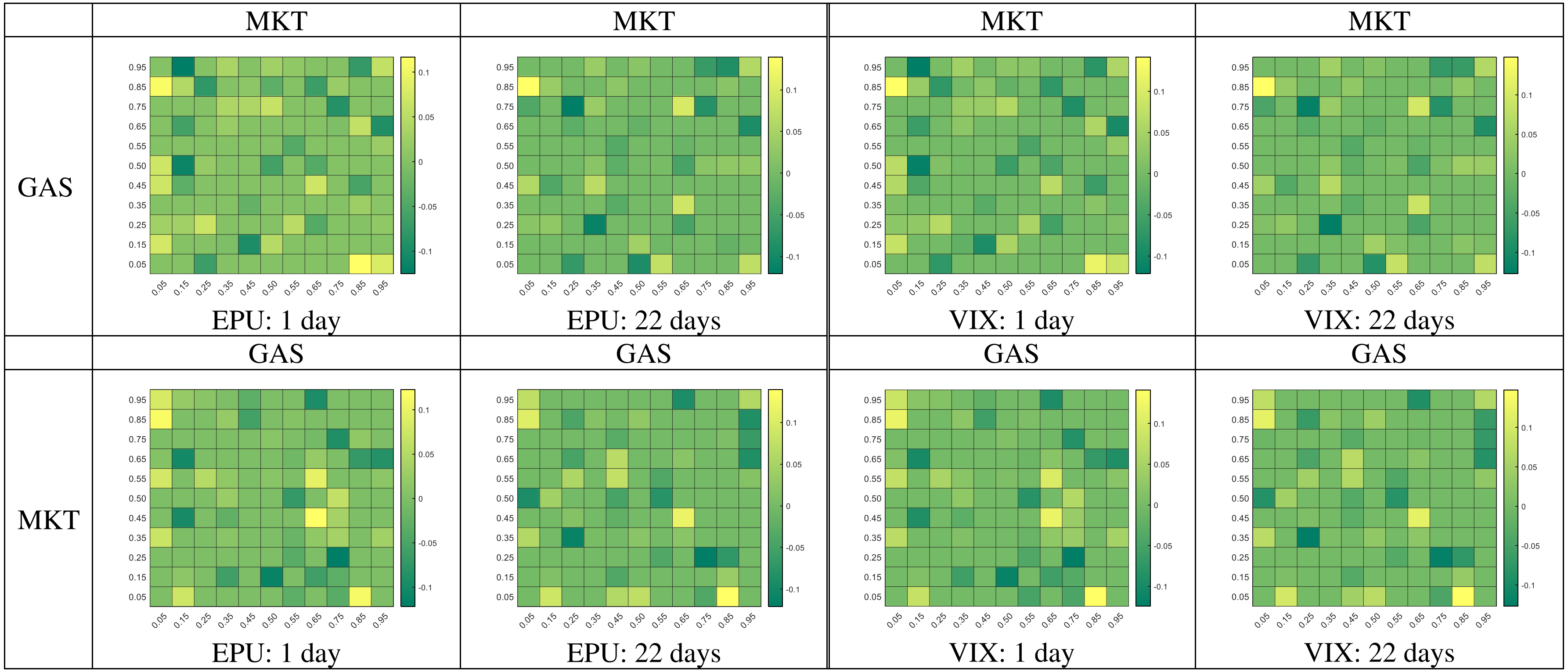

Figure 5b: Cross-quantilogram correlation between market returns and returns on gas prices after controlling for policy uncertainty and volatility index

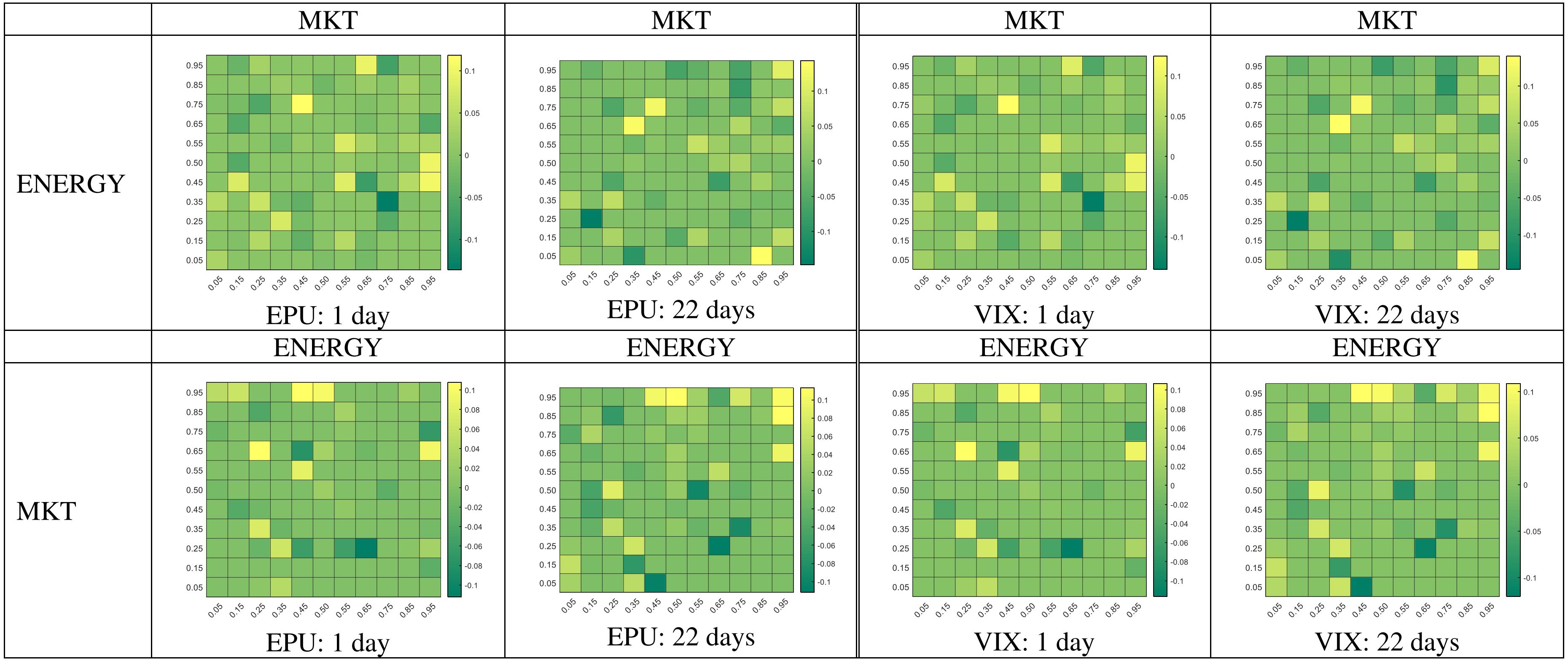

Figure 5c: Cross-quantilogram correlation between market returns and returns on energy prices after controlling for policy uncertainty and volatility index

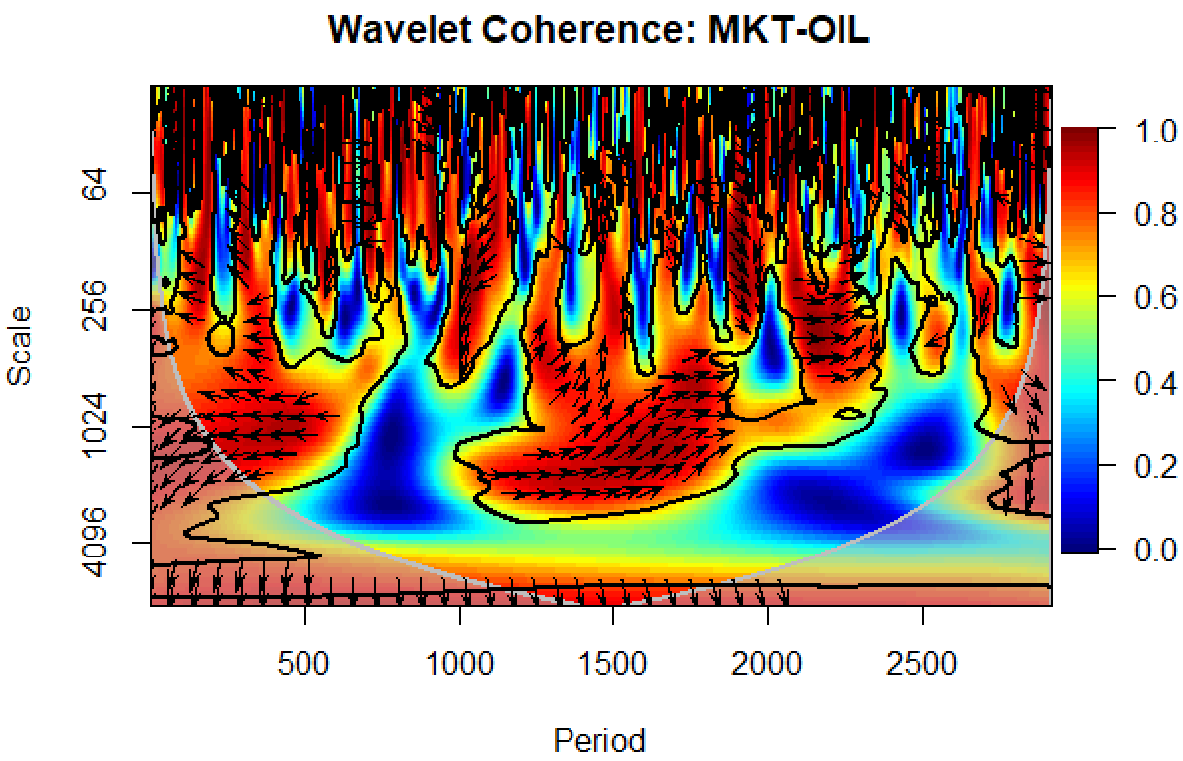

Figure 6a: Wavelet coherence between Market returns and Oil price returns

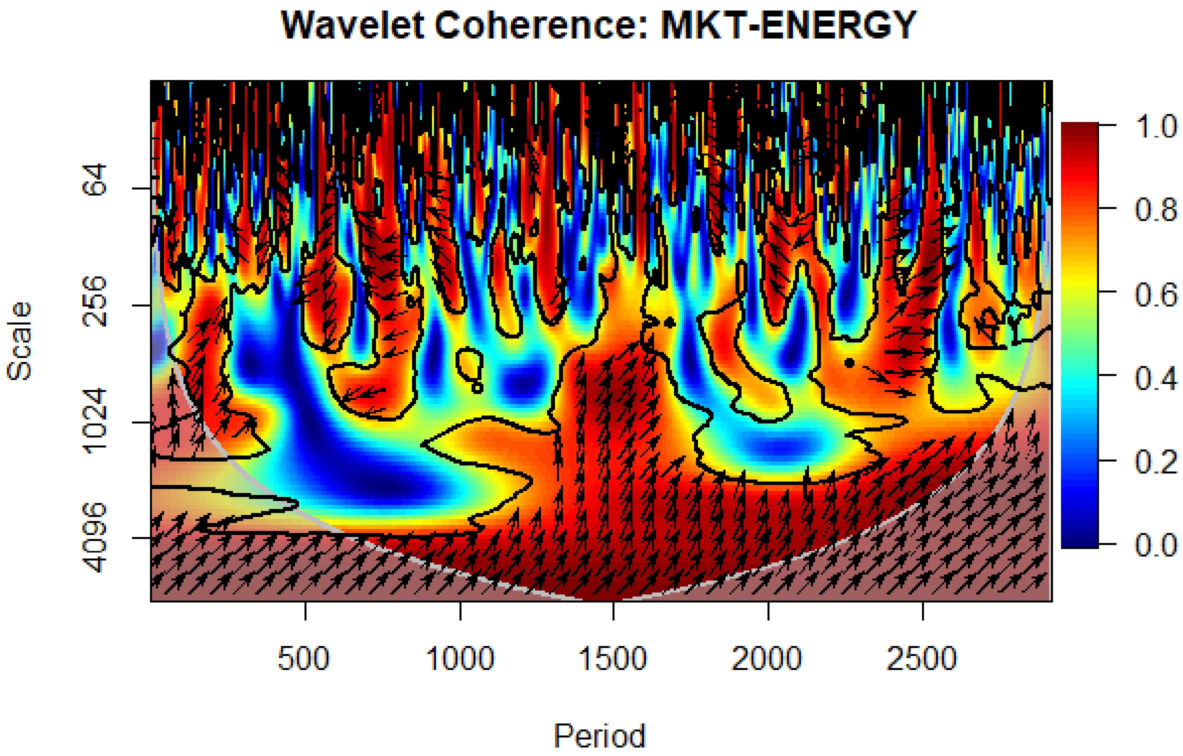

Figure 6b: Wavelet coherence between Market returns and Energy price returns

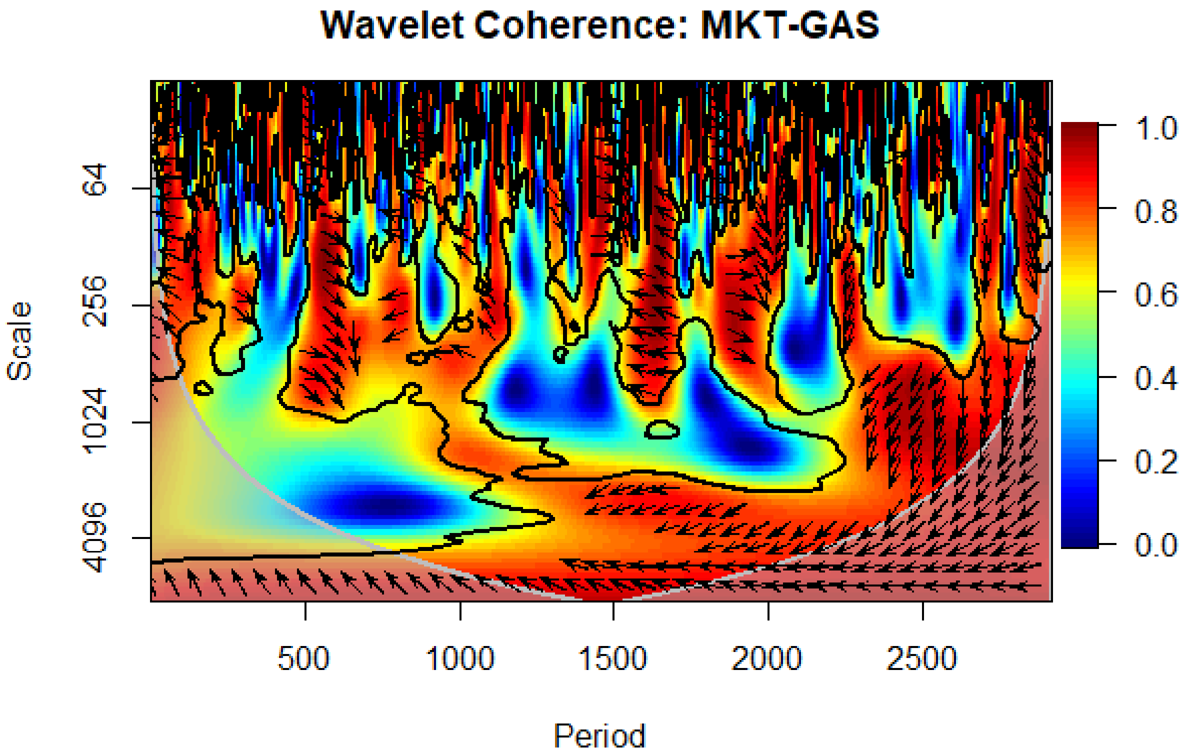

Figure 6c: Wavelet coherence between Market returns and Natural Gas price returns

Table 1: Descriptive statistics

	Mean	Minimum	Maximum	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	LB(10)	Arch LM Test
Crude Oil	-0.023	-2132.787	3834.499	137.459	10.818***	352.109***	15157046***	6.166	0.7277
Natural Gas	-12.600	-29110.079	3256.038	574.194	-45.234***	2265.716***	626212375***	0.0066	0.0067
Energy Index	0.093	-40.774	70.357	5.459	0.844***	21.566***	57005***	1806.3***	400.79***
EPU	0.124	-41.069	73.341	4.221	4.635***	92.728***	1057757***	816.01***	1.3166
VIX	0.030	-26.293	44.695	2.364	2.702***	85.426***	892397***	830.88***	1.0235
Stock Index	0.031	-12.980	17.744	1.355	0.118***	18.410***	41297***	35.086***	321.91***

Note:
LB (10) is Ljung-Box Q test statistics for 10 lags.

***, ** and * indicate the significance level at 1%, 5%, 10% respectively.

Table 2: Joint conditional correlation between the returns of the time series

		Estimate	Std. Error	t value	Pr(>|t|)
OIL-EPU	[Joint]dcca1	0.119*	0.069	1.728	0.084
OIL-EPU	[Joint]dccb1	0.835***	0.053	15.640	0.000
OIL-VIX	[Joint]dcca1	0.169***	0.037	4.574	0.000
OIL-VIX	[Joint]dccb1	0.815***	0.025	32.771	0.000
OIL-MKT	[Joint]dcca1	0.002	0.006	0.305	0.761
OIL-MKT	[Joint]dccb1	0.828***	0.126	6.562	0.000
GAS-EPU	[Joint]dcca1	0.018	0.026	0.698	0.485
GAS-EPU	[Joint]dccb1	0.839***	0.046	18.255	0.000
GAS-VIX	[Joint]dcca1	0.004*	0.002	1.934	0.053
GAS-VIX	[Joint]dccb1	0.980***	0.003	289.960	0.000
GAS-MKT	[Joint]dcca1	0.009***	0.002	4.008	0.000
GAS-MKT	[Joint]dccb1	0.876***	0.077	11.396	0.000
EN-EPU	[Joint]dcca1	0.000	0.003	0.000	1.000
EN-EPU	[Joint]dccb1	0.921***	0.224	4.118	0.000
EN-VIX	[Joint]dcca1	0.001	0.003	0.230	0.818
EN-VIX	[Joint]dccb1	0.988***	0.008	130.888	0.000
EN-MKT	[Joint]dcca1	0.002	0.005	0.359	0.720
EN-MKT	[Joint]dccb1	0.978***	0.017	56.758	0.000

*** and * indicate the significance level at 1% and 10% respectively.

Appendix 1: Summarized description of the literature

Authors	Data	Technique	Context	Objective
Reboredo and Uddin (2015)	4 January 1994 to 10 February 2015	Quantile regression	USA	Impact of financial stress and policy uncertainty on conditional return distributions for the most tradable energy and metal commodities
Badshah et al. (2019)	20 January 1999 to 30 September 2016	ADCC-GARCH model	USA	examine the effect of policy uncertainty and the state of the economy on the time-varying correlations between the stock and commodity markets
Andreasson et al. (2016)	May 1990 to April 2014	Linear and Non-linear Causality tests	USA	examine the influence of speculation and economic uncertainty on commodity prices
Chen et al. (2019)	January 2003 to January 2018	Wavelet-based BEKK-GARCH approach	Brazil, India, Russia and China	to investigate the dynamic relationship between the Brent oil market and EPU
Zhu et al. (2020)	March 2006 to May 2018	Panel quantile regression	China	to investigate the effect of economic policy uncertainty (EPU) on China's agricultural and metal commodity futures returns across quantiles
Zhang et al. (2019)	February 1995 to September 2017	Pairwise Granger-causality tests and VAR	USA and China	how the economic policy uncertainty of USA and China interact and affect the financial markets.
Aloui et al. (2016)	4 January 2000 to 12 May 2014	Copulas	USA	to examine the dynamic relationship between crude oil returns and uncertainty indices.
Yao and Sun (2018)	1 January 1992 to 31 December 2016	Copulas	USA	to examine static tail dependence structure between the economic policy uncertainty (EPU) index and several financial markets
Sun et al. (2020)	January 1997 to August 2017	Wavelet coherence method and scale-by-scale linear Granger causality tests	G7 countries, China, Brazil and Russia	to study the co-movement and causality of economic policy uncertainty and crude oil prices (West Texas Intermediate)
Degiannakis et al. (2018)	January 1994 to March 2015	Structural VAR (SVAR) model and a time-varying parameter VAR (TVP-VAR) model	USA	to study the relationship between uncertainty (financial and economic) and oil shocks (supply-side, aggregate demand, and oil specific demand shocks)
Rehman (2018)	January 1995 to December 2015	Structural VAR framework	China, India, US, Europe, France, Germany, Italy, UK, Spain , Japan	to investigate the oil shocks (global oil price shock, oil supply shock, and aggregate demand shock) on economic policy uncertainty in low and high volatility states
Shahzad et al. (2019)	January 1995 to December 2015	Nonlinear auto-regressive distributed lag cointegration approach	USA	to study the oil price shocks on economic policy uncertainty, stock market uncertainty (VIX), treasury rates, and investor (bullish and bearish) sentiment
Lei et al. (2019)	1 February 1986 to 30 June 2018	MIDAS quantile regression	USA	to study the risk perception of traders in the crude oil spot and futures markets
Qadan and Idilbi-Bayaa (2020)	January 1990 to September 2017	Threshold-GARCH, structural vector auto	USA	to study how the risk appetite affect oil returns and oil volatility

		regression, and causality models		
Balcilar et al. (2017)	2 January 1986 to 8 December 2014	Bivariate quantile causality test	USA	to analyze the predictive ability of economic policy uncertainty (EPU) and equity market uncertainty (EMU) on oil returns and volatility of oil returns
Ma et al. (2018)	2 January 2010 to 31 April 2014	Heterogeneous Autoregressive Model of the Realized Volatility (HAM-RV)	USA	to explore how EPU index can be effectively used to gain larger economic values in the oil futures market
Shaikh (2019)	January 2001 to March 2018	GARCHX and Markov switching model	USA	to study the impact of economic policy uncertainty (EPU) on the 14 VIX-based volatility measures
Uddin et al. (2018)	April 1990 to December 2015	Wavelet (Entropic MODWT)	USA and Europe	to study the casual interrelationships between various types of geopolitical, economic, and financial uncertainty indices and oil markets
Ji et al. (2018)	10 May 2007 to 13 April 2017	Copula-based CoVaR approach	USA	to study the impact of uncertainties (economic, financial and energy) on S&P 500 Global Clean Energy Index (CEX), crude oil and natural gas
Lee et al. (2019)	January 1994 to July 2017	Quantile regression	USA	to study the impact of country risk (i.e., economic risk, financial risk, and political risk) on energy commodity futures prices (crude oil, heating oil, and natural gas)

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