Quantile co-movement and dependence between energy-focused sectors and artificial intelligence

Urom, Christian; Ndubuisi, Gideon; Guesmi, Khaled; Benkraien, Ramzi

DOI
10.1016/j.techfore.2022.121842

Publication date
2022

Document Version
Accepted author manuscript

Published in
Technological Forecasting and Social Change

Quantile co-movement and dependence between energy-focused sectors and artificial intelligence

[1], Christian Urom[1], Gideon Ndubuisi[2], Khaled Guesmi[3], and Ramzi Benkraien[4]

[1] *Paris School of Business, Paris, France*
[2] *Delft University of Technology, Delft, The Netherlands*
[3] *Paris School of Business, Paris, France*
[4] *Audensia Business School, Nantes, France*

August 8, 2022

Abstract

This paper examines the dependence between Artificial Intelligence (AI) and eight energy-focused sectors (including renewable energy and coal) across different market conditions and investment horizons. This paper adopts both linear and non-linear models such as quantile regressions and quantile cross-spectral coherency models. Evidence from the linear model suggests that the performance of energy-focused corporations, especially those in the renewable energy sector depends strongly on the performance of AI. Results from the non-linear model indicate that dependence varies across both energy sectors, market conditions as well as investment horizons. By considering both negative and positive shocks on AI, we demonstrate that the dependence of energy corporations on AI also varies according to the direction of shocks on AI. Interestingly, negative and positive shocks on AI impact differently on the performance of energy corporations across different sectors and market conditions. Besides, we found that the dependence became stronger during the first wave of the COVID-19 pandemic. Our findings hold profound implications for portfolio managers and investors, who may be interested in holding the assets of AI and those of energy corporations.

Keywords: Tail dependence; Artificial intelligence; Energy corporations; Quantile-spectral coherence

1 Introduction

In this paper, we focus on the dependence structure between the stock returns of AI and those of energy-focused firms. This paper particularly aims to provide empirical evidence (if any) on the potential hedging and portfolio diversification opportunities AI assets may hold for those of energy-focused sectors across different investment horizons and market conditions. Following the seminal paper by Henriques and Sadorsky (2008), expansive literature examining the interdependence and connectedness between technology stocks, oil price changes, clean energy stocks has emerged. Among others, this literature has examined the market responses and volatility spillovers among crude oil prices, clean energy and technology stocks across different times and market conditions (Kumar et al., 2012; Sadorsky, 2012; Managi & Okimoto, 2013; Inchauspe et al., 2015; Bondia et al., 2016; Ahmad, 2017; Ferrer et al., 2019; Maghyereh et al., 2019; Nasreen et al., 2020; Niu, 2021). So far, results emerging from this literature show significant evidence of dependence, causality, and spillovers among these variables, although the strength of the correlation and directional predictability varies across these studies.

For instance, Henriques and Sadorsky (2008) employed the Vector Autoregressive (VAR) model and found that technology stock prices are influenced by changes in oil prices, while technology shocks exact more significant impact on clean energy stock prices compared to oil price shocks. Taking into account the time-dependent dynamics, Managi and Okimoto (2013) used a Markov-switching VAR model and found that in the post-structural break period, oil prices and technology stock prices impact positively on clean energy stock prices, whilst their pre-structural break period results are consistent with Henriques and Sadorsky (2008). Inchauspe et al. (2015) used a state-space multifactor model and found that the impact of oil prices on clean energy stock returns increased since 2007. They also found evidence of stronger effects of technology stocks on clean energy stocks compared to the effect of oil prices. Bondia et al. (2016) found that while the stock prices of clean energy companies are impacted by technology stock and oil prices in the short run, there is no causality running towards clean energy stock prices in the long-run. Ferrer et al. (2019) found evidence of pairwise connectedness between clean energy and technology stock prices, but mainly in the short-term. Ahmad (2017) found that there is a bilateral interdependency between clean energy and technology stocks, while crude oil exhibits limited interdependence with clean energy and technology. Maghyereh et al. (2019) used the wavelet and multivariate GARCH (MGARCH) techniques and found significant bidirectional return and risk transfer from oil and technology to the clean energy market. Results from the time-scale analysis further revealed that risk transmissions are more pronounced at longer time horizons.

While the above studies provide important insights on the nature of the relationship between technology and energy stocks, due consideration of the type of technology in question has remained unexplored in the literature. AI is one of the technologies that characterize modern technological advancement. It is the main driver of emerging technologies like big data, blockchain technologies, robotics, cloud computing, and the Internet of Things (IoT). Koroteev and Tekic (2021) note that AI is the most important general-purpose technology of today. Although AI has diverse applications across different industries and spheres of human life, the dependence of energy-focused sectors on AI has evolved with prominence (see Kalogirou, 2007; Zahraee, 2016; Hanga & Kovalchuk, 2019; Li et al., 2021; Gupta & Shah, 2021; Koroteev & Tekic, 2021; Jha et al., 2017; Boza & Evgeniou, 2021). For instance, while the growing application of AI in energy is interlaced within the recent concerns about fossil fuels depletion and climate change, Koroteev and Tekic (2021) note that the first applications of AI in a sector such as in oil and gas were as far as in the 1970s. Further, the overly reliance of clean energies on technological innovations as well as the entire energy sector's innate characteristic of being quicker to adopt new technologies than to experiment with and change their business models has strengthened this link in recent times.

Anecdotal evidence lends credence to the application of AI in both the production and distribution of energy across different energy sectors, with Lyu and Liu (2021) arguing that AI is probably the leading general-purpose technology adopted in the energy sector. As Lyu and Liu (2021) noted further, the characteristic of AI has made it possible for it to be applied easily to energy demand forecasting, generation and conservation, price forecasting, and the integration of more renewable energy, among others. Indeed, anecdotal evidence lends credence that AI has been widely applied in energy supply, trade, and consumption (Ahmad et al., 2021) and particularly in the Oil and Gas industry to minimize the cost of lifting, and strengthen the modeling of reservoirs and maintenance prevention (Rahmanifard & Plaksina, 2019; Gupta & Shah, 2021). It has also been used for predictive maintenance in the clean energy sector (Shin et al., 2021), and monitoring and risk assessment in the coal industry (Kuang et al., 2001; Zhu & Zhu, 2012; You et al., 2021). There is also available evidence suggesting that the application of AI in the energy sector leads to improved performance of the sector (Ahn & Cho, 2017; Fathi et al., 2020; Lyu & Liu, 2021; Zhang et al., 2021). However, whether AI as a tradable asset offers hedging and/or portfolio diversification opportunities to those of energy-focused sectors has remained unexplored. This is surprising given the well-established literature on the interdependence and connectedness between the stock returns of technology-intensive firms and energy-focused firms, on the one hand, and that AI is both the most important contemporary general-purpose technology and one of the major technologies that characterize modern technological advancement in AI, on the other hand. At best, the few extant studies that examined the hedging and portfolio diversification opportunities of AI have only focused on carbon prices, conventional and alternative asset classes such as bonds and cryptocurrencies (Huynh et al., 2020; Tiwari et al., 2021; Demiralay et al., 2021).

This study, therefore, advances the literature on the nexus between the stock returns of technology-intensive and energy-focused sectors/firms by paying particular attention to AI. Our paper particularly examines the dependence structure between AI and different energy-focused sectors across different market conditions and investment horizons. In an extended analysis, we also examine how asymmetric positive and negative shocks on AI as well as the recent COVID-19 pandemic affect the pattern of this relationship. Evidence from erstwhile literature on the nexus between energy and technology stocks, indicate heterogeneous relationships with stock returns of technology sectors/firms, with stronger positive co-movement and correlation with clean energy sector than dirty energy sector. The popular explanation for this finding is that investors consider clean energy stocks to be similar to those of technology as the success of clean energy companies depends upon the successful breakthrough or adoption of specific technologies (Bondia et al., 2016). Hence, technology stock prices would drive those of clean energy. Whereas this view cannot be entirely discredited such that one may expect the dependence between AI and energy-focused sectors is stronger for the clean energy sector, the application of AI across energy sectors in a bid to ensure environmental sustainability has become common. Hence, the strength and direction of the dependence between AI and the different energy-focused sectors becomes a matter of empirical question. One of the objective of our study is therefore to provide evidence on the structure of this dependence.

To address our research objectives, we use daily data covering the period from December 18, 2017 to June 14, 2021. As an empirical measure of AI, we rely on the NASDAQ AI price index following Huynh et al. (2020), Tiwari et al. (2021), and Demiralay et al. (2021). As noted by Huynh et al. (2020), The NASDAQ AI index was established to track the performance of firms that are active in AI and robotics, including technology, industrial, medical, and other economic sectors. Hence, it sufficiently reflects the industry and market dynamics associated with AI. Regarding the energy-focused sectors, on the other hand, we follow Corbet et al. (2020) that used eight energy-focused sectors defined based on their related TRBC Sector Code in the Datastream international. The eight sectors considered include Oil & Gas Exploration and Production, Oil & Gas Refining and Marketing, Integrated Oil and Gas, Oil-related Services and Equipment, Oil and Gas Transportation Services, Oil and Gas Drilling, Coal, and Renewable Energy. It suffices to note that by focusing on these different energy-focused sectors, our analysis offers substantial information on how the broad energy market dynamics are dependent on and predictable from the AI, thereby providing crucial information for potential portfolio diversification across these energy sectors.

Regarding our methodology, we employ both linear and non-linear models including the Ordinary Least Square (OLS), quantile regression (QR), and the quantile cross-spectral coherence (QCS) models, respectively. As we show in the next section, the latter two approaches enable us capture some interesting dynamics regarding the dependence between AI and each of the energy-focused sectors. In particular, whereas the linear model (OLS) allows us to capture the average level of dependence among these markets only, the flexible framework of the QR enables us to examine how this dependence differs across different quantiles of these markets' return distribution. These return quantiles are decomposed into bearish (i.e., left/lower tails), normal (i.e., shoulders of the distribution) and bullish (i.e., right/upper tails) market conditions. While the QCS method as developed by Barunik and Kley (2019) offers somewhat similar insights as the QR, it offers some additional advantages that enable us to explore the dependence between return quantiles across frequencies, which correspond to short, medium and long-term investment horizons. In line with our research objectives, therefore, we employ these research approaches jointly, although our preferred method is the QCS due to a more comprehensive results it presents.

The rest of the paper is structured as follows. The next section presents the data and the methods used for the empirical analysis. Section three presents and discusses the empirical results, while section four concludes.

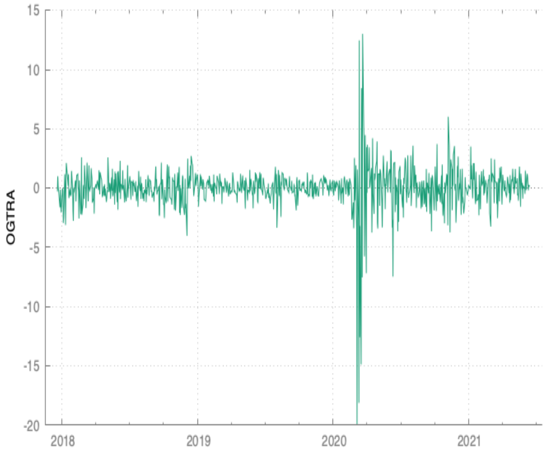
2 Data and empirical methods

2.1 Data

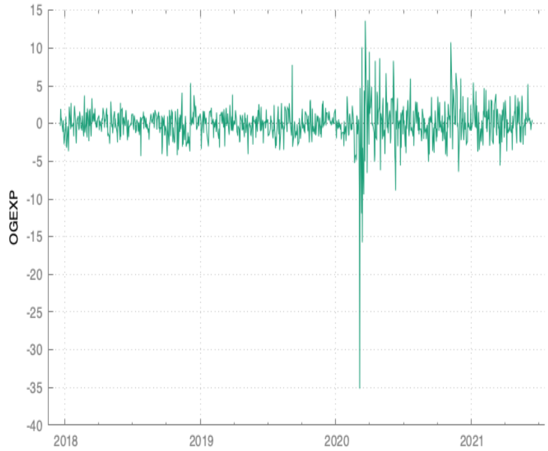
Our analysis relies on the NASDAQ AI price index as a measure of AI following two recent papers including Huynh et al. (2020) and Tiwari et al. (2021). The dataset covers the period from December 18, 2017 to June 14, 2021 and were retrieved from the Thomson International Datastream. The data begins from December 18, 2017 mainly because the NASDAQ AI price index is only available from this date. The NASDAQ AI index is established to track the performance of firms that actively apply artificial intelligence and robotics across technology, industrial, medical, and other economic sectors. Hence, the index captures the innovation level of the market as well as the performance of artificial intelligence and robotics industry. Regarding the energy-focused sectors, we follow Corbet et al. (2020) which used eight energy-focused sectors defined based on their related TRBC Sector Code in the Datastream international. The eight sectors considered include: (i) Oil & Gas Exploration and Production (OGEXP); (ii) Oil & Gas Refining and Marketing (OGREF); (iii) Integrated Oil & Gas (INTOG); (iv) Oil-related Services and Equipment (OGSEQ); (v) Oil & Gas Transportation Services (OGTRA); (vi) Oil & Gas Drilling (OGDRI); (vii) Coal (COAL); and (viii) Renewable Energy (REN).

Figure 1, Panel a - i displays the evolution of the energy-focused sectors and AI price returns over the sample period. Following past studies, we compute the daily returns as $r_t = 100 \times (lnp_t - lnp_{t-1})$. As expected, the plots show that across all energy sectors and AI, there is notable level of increased return volatility following the large drop in stock prices around the period of COVID-19 pandemic. Further, in Table 1, we provide the basic descriptive statistics for all the series. Table 1 shows that among the variables, renewable energy sector has the highest mean return while the Oil & Gas Transport sector has the least. It also shows that Oil & Gas drilling sector is the most volatile while AI is the least as implied from the standard deviation. Also, Table 1 indicates that all the series depart from normality conditions, as shown by the significant Jarque-Bera test for normality in the return distributions. Moreover, all the variables are negatively Skewed as shown by the Skewness coefficients. Basically, negative skewness conforms to the presence of asymmetry in return distributions. Additionally, all the return series exhibit excess Kurtosis, suggesting fatter tails than those of normal distribution.

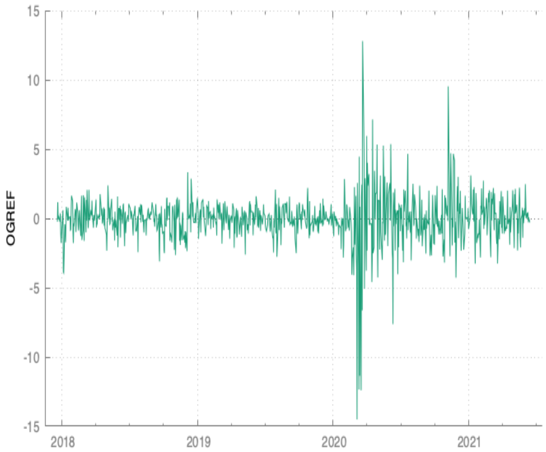
Lastly, as shown in Table 1, we examine the presence of unit roots using the Augmented Dickey-Fully (ADF) test statistic. The ADF coefficients indicate that all the return series are stationary at the first difference. The unit roots feature of the variables is particularly crucial given econometric techniques adopted in this study. Specifically, prior to implementing the quantile spectral approach, it is also necessary to test whether the energy sectors as well as AI exhibit nonlinear characteristics. Following this, Table 2 shows the results of BDS test proposed by Brock et al. (1996) on the VAR model's filtered residuals for all the time series in different dimensions (m = 2, 3, ..., 6). For all the variables, the null hypothesis of linearity is rejected, suggesting that the residual series of the selected energy sectors and AI exhibit nonlinear features. Hence, nonlinear models are more appropriate for examining the interactions between AI and energy-focused sectors.



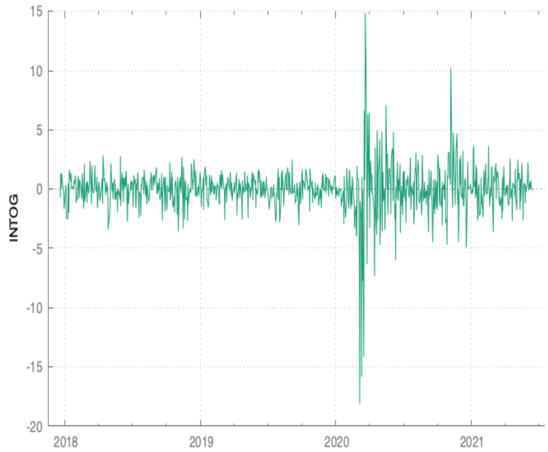
(a) Oil & Gas Transport Services



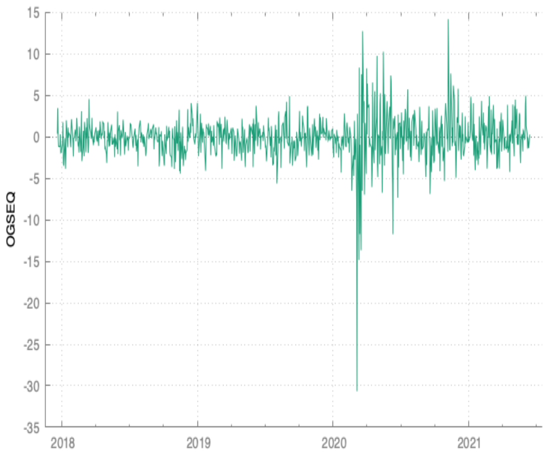
(b) Oil & Gas Exploration and Production



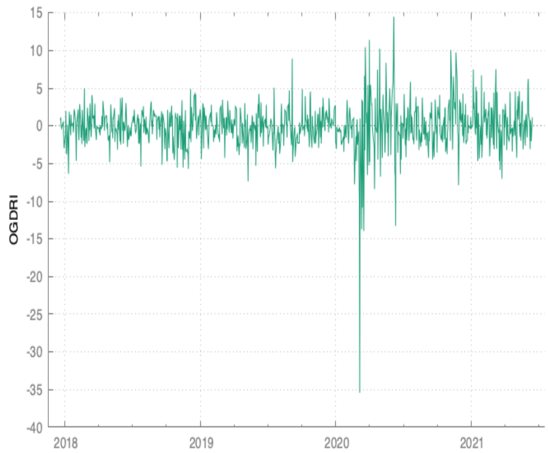
(c) Oil & Gas Refining and marketing



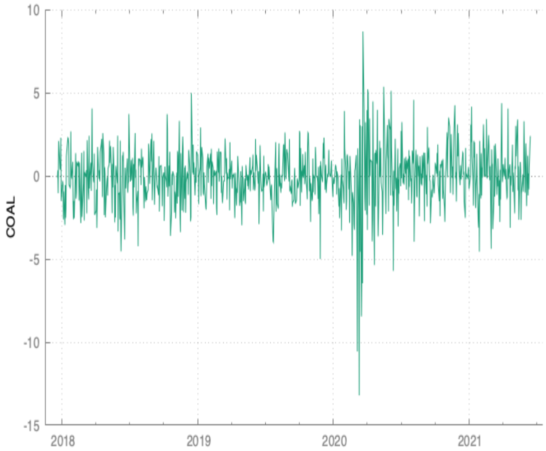
(d) Integrated Oil & Gas Services



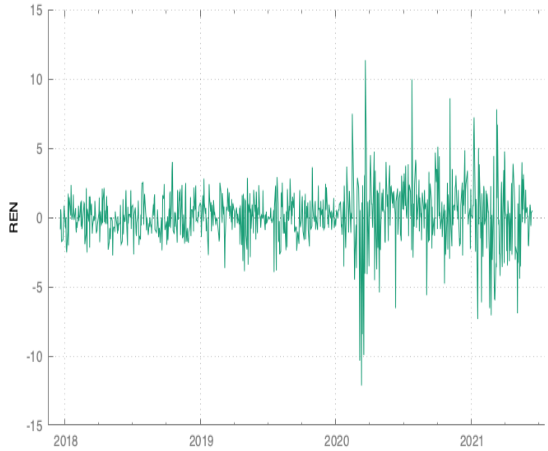
(e) Oil-related Services and Equipment



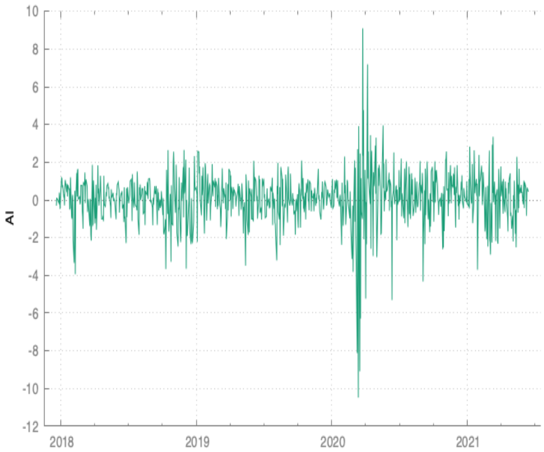
(f) Oil & Gas Drilling



(g) Coal



(h) Renewable



(i) Artificial intelligence

Figure 1: Plots of return series

Table 1: Descriptive statistics of AI and energy-sectors

Variable	Mean	Min.	Med.	Max.	Std. Dev.	Skew.	Ex. Kurt.	JB	ADF
AI	0.074	-10.480	0.177	9.101	1.391	-0.985	10.194	3979.8***	-17.99***
OGDRI	-0.113	-35.429	-0.075	14.498	2.989	-1.838	24.046	21845.3***	-25.90***
OGEXP	-0.034	-35.144	-0.007	13.639	2.557	-2.909	43.439	70907.7***	-19.10***
OGREF	-0.021	-14.512	0.006	12.857	1.755	-0.987	17.152	11004.5***	-18.95***
INTOG	-0.025	-18.103	0.012	14.882	1.904	-1.354	23.159	20071.2***	-18.65***
OGSEQ	-0.082	-30.650	-0.081	14.242	2.629	-1.756	24.599	22794.1***	-19.03***
OGTRA	-0.001	-19.976	0.069	13.033	1.860	-2.696	36.636	50622.7***	-20.11***
COAL	-0.033	-13.202	0.000	8.737	1.796	-0.661	5.639	1238.3***	-18.85***
REN	0.117	-12.129	0.156	11.412	2.043	-0.318	5.681	1206.4***	-17.61***

Note: Artificial Intelligence (AI); Oil & Gas Exploration and Production (OGEXP); Oil & Gas Refining and Marketing (OGREF); Integrated Oil & Gas (INTOG); Oil-related Services and Equipment (OGSEQ); Oil & Gas Transportation Services (OGTRA); Oil & Gas Drilling (OGDRI); Coal (COAL); and Renewable Energy (REN)

Table 2: BDS test for non-linearity from the vector autoregression (VAR) model filtered residuals.

Variable	Dimension				
	m = 2	m = 3	m = 4	m = 5	m = 6
AI	0.0215***	0.0456***	0.0640***	0.0761***	0.0813***
	(7.0618)	(9.4545)	(11.124)	(12.686)	(14.055)
OGDRI	0.0199***	0.0353***	0.0432***	0.0467***	0.0478***
	(6.5544)	(7.2882)	(7.4906)	(7.7617)	(8.2188)
OGEXP	0.0166***	0.0327***	0.0422***	0.0476***	0.0493***
	(5.3121)	(6.5900)	(7.1253)	(7.7059)	(8.2683)
OGREF	0.0325***	0.0630***	0.0843***	0.0948***	0.0978***
	(9.9651)	(12.159)	(13.662)	(14.737)	(15.765)
OGTRA	0.0331***	0.0642***	0.0853***	0.0992***	0.1044***
	(9.88411)	(12.014)	(13.404)	(14.961)	(16.331)
INTOG	0.0266***	0.0490***	0.0618***	0.0676***	0.0678***
	(8.3151)	(9.6178)	(10.172)	(10.676)	(11.101)
OGSEQ	0.0204***	0.0379***	0.0484***	0.0540***	0.0566***
	(6.4572)	(7.5753)	(8.1301)	(8.7014)	(9.4631)
COAL	0.0161***	0.0277***	0.0338***	0.0362***	0.0339***
	(5.9319)	(6.4252)	(6.5992)	(6.7948)	(6.6321)
REN	0.0197***	0.0444***	0.0625***	0.0731***	0.0784***
	(6.4927)	(9.2054)	(10.876)	(12.215)	(13.587)

Note: Artificial Intelligence (AI); Oil & Gas Exploration and Production (OGEXP); Oil & Gas Refining and Marketing (OGREF); Integrated Oil & Gas (INTOG); Oil-related Services and Equipment (OGSEQ); Oil & Gas Transportation Services (OGTRA); Oil & Gas Drilling (OGDRI); Coal (COAL); and Renewable Energy (REN)

2.2 Empirical methods

2.2.1 Quantile regression model (QR)

The first phase of our empirical analysis focuses on the effects of AI performance on the returns of different energy-focused sectors across different return distributions. To proceed with this objective, we adopt the QR analysis of Koenker and Bassett (1978). Although the QR follows a similar structure to linear regression analysis, it permits us to explore the existence of non-uniform effects of the independent variables on multiple quantiles of the outcome variable. Indeed, QR analysis offers several advantages as highlighted in previous studies that have employed this approach. Among others, Conyon and He (2017) argue that whereas the traditional OLS model predicts the average or conditional mean association between an independent variable X and the explained variable Y, the QR technique permits the prediction of specific parts of the distribution of the explained variable, including the conditional median effect on Y of a change in the independent variable X.

Beyond predicting the conditional median (50^{th} percentile) effect, the QR can also be used to predict different quantiles of the distribution of the explained variable including both the right and left tails of the distribution, which offers richer insights into the nature of effects during bullish (higher quantiles) as well as bearish (lower quantiles) market conditions. Therefore, the QR offers a comprehensive characterization of the data by enabling the effects of covariates to evolve throughout the entire distribution of the explained variable. For instance, using a simple case of one covariate, $\beta_{0.1} > 0$ denotes that an increase on the independent variable has a positive effect on the 10^{th} percentile of the explained variable while $\beta_{0.9} < 0$ implies that the effect of the same increase becomes negative on the 90^{th} percentile of the explained variable (Kaza, 2010). Further, as noted in Gallego-Alvarez and Ortas (2017), unlike the classical OLS model that may be inefficient if errors are non-normal, the QR approach is robust to non-normal errors and outliers. Besides, Baur (2013) argue that QR analysis permits changes in the degree of dependence to be tested across different quantiles of the distribution. Regarding the objectives of our study, the QR approach enables us to uncover potential non-monotonic effects of AI on the returns of energy-focused sectors across its different return quantiles.

Our QR model evolves from a baseline OLS specification as follows:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 \gamma_t + \psi D_t + \nu_t \tag{1}$$

where r_t is the return of each energy sector at time t while r_{t-1} is the return at time $t-1$. γ_t is the return of AI at time t while D_t represents a crisis dummy associated with the period of the first wave of the COVID-19. Specifically, the dummy variable is defined as $D_t = 1$ if the observation t falls within December 1, 2019 to July 1, 2020 and $D_t = 0$ if otherwise. ν_t is a random error term.

In Eq. 1, we assume that the relationship between the performance of AI and the energy-focused sectors are linear and that both increasing and declining changes in the performance of AI have symmetric effects on the performance of energy-focused sectors. However, there are several reasons to assume that this relationship may exhibit asymmetric/nonlinear tendency. For instance, increasing performance of AI is expected to lead to increasing application of AI in a wide range of processes, including the development of alternative energy sources. This may have adverse effects on the performance of corporations in the fossil energy industry if the adoption of AI improves the efficiency of alternative energy sources.

To accommodate possible asymmetries in the relationship between the performance of AI and the considered energy-focused sectors, γ_t is decomposed into positive γ_t^+ and negative γ_t^- changes, where $\gamma_t^+ = max(\gamma_t, 0)$ and $\gamma_t^- = min(\gamma_t, 0)$. Thus, Eq. 1 becomes:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta^+ \gamma_t^+ + \beta^- \gamma_t^- + \psi D_t + \nu_t \tag{2}$$

Eqs. 1 and 2 permit us to examine the extent to which the performance of AI may influence the returns of each energy sector. It also reveals whether positive and/or negative shocks on the performance of AI influence the performance of each energy sector differently. However, these models do not reveal whether this influence varies across different market conditions. That is, these models do not reveal whether the influence of the performance of AI on the energy sector is different during low market returns (bearish market) than during high market returns (bullish market). The models also do not show whether positive and negative shocks on the performance of AI impact differently on energy sector depending on whether market returns are low or high. The QR is very useful in determining whether the influence of a variable on another changes across different market conditions.

The QR technique expresses the conditional τth quantile of the dependent variable for some value of $\tau \in (0, 1)$. Thus, the conditional quantile model for q_t, given x_t, may be expressed as:

$$Q_{q_t}(\tau/x_t) = \alpha^\tau + x_t'\beta^\tau \tag{3}$$

where $Q_{q_t}(\tau/x_t)$ denotes the conditional τth quantile of the dependent variable q_t; α^τ represents the intercept, which is set to depend on τ. Also, β^τ is the vector of coefficients associated with τth quantile while x' is a vector of explanatory variables (which includes: one period lag of returns of the concerned energy-focused sector, AI, and the COVID-19 dummy). As noted in Koenker and Basset (1978) and Nusair and Olson (2019), the coefficients of the τth quantile of the conditional distribution are expressed as a solution to the minimization problem below:

$$\begin{matrix} min \\ \hat{\beta} \in \Re^k \end{matrix} \left[\sum_{t\,:\,q_t \geq \alpha^\tau + x_t'\hat{\beta}^\tau} \tau|q_t - \alpha^\tau - x_t'\hat{\beta}^\tau| \quad + \sum_{t\,:\,q_t < \alpha^\tau + x_t'\hat{\beta}^\tau} (1-\tau)|q_t - \alpha^\tau - x_t'\hat{\beta}^\tau| \right] \tag{4}$$

This may be re-written as a minimization of the weighted deviations from the conditional quantile as follows:

$$\begin{matrix} min \\ \hat{\beta} \in \Re^k \end{matrix} \sum_t \rho_\tau(q_t - \alpha^\tau - x_t'\hat{\beta}^\tau) \tag{5}$$

where ρ_τ represents a weighting factor known as a check function, expressed for any $\tau \in (0, 1)$ as:

$$\rho_\tau(\xi_t) = \begin{cases} \tau\xi_t, & if \quad \xi_t \geq 0 \\ (\tau - 1)\xi_t, & if \quad \xi_t < 0 \end{cases} \tag{6}$$

where $\xi_t = q_t - \alpha^\tau - x_t'\beta^\tau$. Hence, as noted by past studies, quantile regression represents a weighted regression with different weights assigned to data points, depending on whether the points fall above or below the line of best fit (e.g. Binder & Coad, 2011; Nusair & Olson, 2019).

Put differently, quantile regression technique minimizes the sum of residuals, given that the weight of τ is assigned to positive residuals while the weight of $1 - \tau$ is assigned to negative residuals.

To examine the effects of the performance of AI on the returns of energy-focused sectors using the QR approach, we specify the following models, inspired by the standard OLS framework:

$$Q_{q_t}(\tau/x_t) = \alpha_0^\tau + \alpha_1^\tau r_{t-1} + \alpha_2^\tau \gamma_t + \alpha_3^\tau D_t \tag{7}$$

$$Q_{q_t}(\tau/x_t) = \beta_0^\tau + \beta_1^\tau r_{t-1} + \beta^{\tau+}\gamma_t^+ + \beta^{\tau-}\gamma_t^- + \beta_2^\tau D_t \tag{8}$$

We estimate the QR models in Eqs. 7 and 8 following past studies by specifying nine quantiles (e.g. Tiwari et al., 2018; Nusair & Olson, 2019; Qin et al., 2020). The nine quantiles are ($\tau = 0.10$, 0.20,..., 0.90), which enables us to capture three market regimes, including low ($\tau = 0.10$, 0.20, 0.30), which corresponds to bearish market state; medium ($\tau = 0.40$, 0.50, 0.60), which is associated with normal market state; and high ($\tau = 0.70$, 0.80, 0.90), which corresponds to bullish market state. In this paper, bearish(bullish) market regime denotes periods of rapid decline(increase) in the performance of firms that are into AI, as implied by decrease(increase) in their stock prices.

2.2.2 Quantile cross-spectral (coherency) approach

In addition to determining the dependence between AI and energy-focused sectors across market conditions, an important aspect of our study is to determine the dependence structure across different investment horizons. To this end, the second phase of our analysis involves the quantile cross-spectral dependence technique proposed by Barunik and Kley (2019). This method permits us to examine the dependence structure of the quantile in the tails of the joint distribution and across frequencies. As posited by Maghyereh and Abdoh (2021), this technique captures the existence of dependence at different market conditions (e.g. lower quantiles, intermediate quantiles and upper quantiles) and across various investment horizons such as the short and long-term. Therefore, this methodology is a novel approach to measure the dynamic interdependence under different market conditions and varying investment horizons.

As in Barunik and Kley (2019), suppose that $(R_t)_{t \in Z}$ denotes a set of variables that are two strictly stationary process, with components $R_t = (R_{t,j1}, R_{t,j2})$, the quantile coherency between these two processes denoted as $(R^{j_1 j_2})$ may be represented as follows:

$$\Re^{j_1 j_2}(\omega; \tau_1, \tau_2) := \frac{f^{j_1 j_2}(\omega; \tau_1, \tau_2)}{(f^{j_1 j_1}(\omega; \tau_1, \tau_1) f^{j_2 j_2}(\omega; \tau_2, \tau_2))^{1/2}} \tag{9}$$

where ω is the time-frequency corresponding to $\omega \xi 2\pi 1/5; 1/22; 1/250$ respectively. Indeed, the coherency (co-dependence) across these three frequencies correspond to the short-run (one week), the intermediate run (one month) and the long run (one year). π denotes the periodic intervals of $\omega\xi(-\pi < \omega < \pi)$; τ_1 and τ_2 are the τth quantiles of R_{t,j_1} and R_{t,j_2} (i.e. 0.5, 0.05 or 0.95), consecutively, where $(\tau_1, \tau_2) \in [0,1], f^{j_1 j_2}, f^{j_1 j_1}$ and $f^{j_2 j_2}$ represent the quantile cross-spectral density and the quantile spectral densities of processes R_{t,j_1} and R_{t,j_2}, respectively generated from the Fourier transform of the matrix of quantile cross-covariance kernels denoted by $\Gamma(\tau_1, \tau_2) := (f\omega; \tau_1\tau_2)_{j_1 j_2}$, where

$$\gamma^{j_1 j_2} := Cov\left(I\{X_{t+k,j_1} \leq q_{j_1(\tau_1)}\}, I\{X_{t+k,j_2} \leq q_{j_2(\tau_2)}\}\right) \tag{10}$$

For $j_1, j_2 \in \{1, \cdots, d\}, k \in Z, \tau_1, \tau_2 \in [0,1]$, and $I\{A\}$ denote the indicator function of event A. To generate information about serial and cross-sectional dependence, we vary K while restricting $j_1 \neq j_2$. Further, the matrix of quantile cross-spectral density kernels $f(\omega; \tau_1, \tau_2) := (f(\omega; \tau_1, \tau_2))_{j_1 j_2}$, is realized from the frequency domain where:

$$f^{j_1 j_2}(\omega; \tau_1, \tau_2) := (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1, j_2}(\tau_1, \tau_2) e^{-ik\omega} \tag{11}$$

Quantile coherency is estimated by the smoothed quantile cross-periodogram as expressed below:

$$\hat{G}^{j_1,j_2}_{n,R}(\omega;\tau_1,\tau_2) := \frac{2\pi}{n}\sum_{s=1}^{n-1} W_n\left\{\omega - \frac{2\pi s}{n}\right\} I^{j_1,j_2}_{n,R}\left\{\frac{2\pi s}{n},\tau_1,\tau_2\right\} \tag{12}$$

where $I^{j_1,j_2}_{n,R}$ represents the matrix of rank-based copula cross periodograms (CCR-periodograms) while W_n is a sequence of weigth functions. Then, the estimator for the quantile coherency may be expressed as:

$$\Re^{j_1 j_2}_{n,R}(\omega;\tau_1,\tau_2) := \frac{\hat{G}^{j_1,j_2}_{n,R}(\omega;\tau_1,\tau_2)}{\left\{\hat{G}^{j_1,j_1}_{n,R}(\omega;\tau_1,\tau_1)\hat{G}^{j_2,j_2}_{n,R}(\omega;\tau_2,\tau_2)\right\}^{\frac{1}{2}}} \tag{13}$$

Following past studies including Maghyereh et al. (2019) and Maghyereh and Abdoh (2021), we examine the coherence matrices for three quantiles (0.05, 0.5 and 0.95) which correspond to lower, intermediate and upper quantiles respectively. We also consider the combinations of quantile levels of the joint distribution (0.05|0.05, 0.5|0.5, 0.95|0.95), which enable us to explore dependence under the left, intermediate and right tails of the distributions, respectively. Lastly, as detailed in Barunik and Kley (2019), the quantile cross-spectral density kernels $\{f^{j_1 j_2}(\omega;\tau_1,\tau_2)\}$ in Eq. 9 may be decomposed into real and imaginary parts. As noted in Maghyereh and Abdoh (2021), the real part represents the co-spectrum of the following processes: $(I\{R_{t,j_1} \leq q_{j_1}(\tau_1)\})_{t\in Z}$ and $(I\{R_{t,j_2} \leq q_{j_2}(\tau_2)\})_{t\in Z}$, while the imaginary part corresponds to the quadrature spectrum that circumvents several sources of noise coherence. To improve readability and clarity in presentation, we follow past studies including Barunik and Kley (2019), Maghyereh et al. (2019) and Maghyereh and Abdoh (2021) by presenting only the real part of the quantile coherence estimates.

3 Results and discussion

3.1 Quantile regression results

3.1.1 The linear model

The discussion of our empirical results begins with the linear model as presented in Table 3 and Figure 2. Table 3 displays the estimated coefficients from the baseline model. Following Nusair and Olson (2019), we first estimated both the standard OLS model as represented by Eq. 1 and QR model as represented by Eq. 7. We follow past studies that have adopted this empirical model in the interpretation of the estimated coefficients (see e.g., Mensi et al., 2014; Nusair & Olson, 2019). With the exception of Coal, results from the standard OLS model show that AI has statistically significant positive effect on all the energy-focused sectors. This suggests a positive co-movement between AI and energy-focused sectors. The results indicate that co-movement is weakest with Integrated Oil and Gas sector while it is strongest with renewable energy. This suggests that the dependence between AI and energy corporations is strongest with those in renewable energy sector. This result is in line with erstwhile literature that document stronger dependence between the returns of technology and clean energy firms (see e.g., Henriques & Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012). As noted in the introduction, this is expected since technology is a crucial input in renewable energy generation and deployment. Further, evidence in the result also shows significant and negative effects of the past COVID-19 crisis on the performance of conventional energy sectors including Oil and Gas Drilling, Oil and Gas Refining, Integrated Oil and Gas as well as Oil and Gas Servicing and Equipment. However, this effect is statistically insignificant for both coal and renewable energy sectors.

We proceed to examine the level of co-movement across the nine conditional quantiles for each energy sector using the QR model as described in Eq. 7. Fig. 2 plots the QR coefficient estimates for AI with 95% confidence interval along with the OLS estimates. The OLS estimates of the conditional mean effect, given by the blue solid line with 95% confidence interval (dashed lines), does not vary. As for the estimates of quantile coefficients, for each energy sector, we plot the nine QR estimates for $\tau = 0.1, ..., 0.9$ as the solid black curve with 95% confidence interval (shaded area). The QR model provides a quite different picture from the OLS model. This enables us to explore possible changes in dependence across the bearish, normal and bullish market conditions. Results from the QR model shows some interesting patterns of co-movement across the three market states. Particularly, results show that when the market is bearish, the effects of AI on the coal sector become significant but insignificant across all the quantiles with Oil and Gas Transport services. Also notable is the fact that dependence remains strongest with the renewable energy sector but least with Oil and Gas Refining. The strength of dependence with renewable energy sector, however, declines as we increase the quantiles. This suggests that during financial market downturns, the co-movement between the performance of AI stocks and those of energy corporations becomes stronger, especially those into renewable energy generation and deployment. The positive co-movement also suggests an absence of potential for diversification benefits from the inclusion of AI stocks with those of the energy sectors considered. However, the non significant co-movement with Oil and Gas Transport services suggests a likelihood that AI stocks may offer some diversification benefits for Oil and Gas Transport services stocks.

Furthermore, dependence under the normal and bullish market conditions appears to be weaker compared to the bearish market. In particular, the results show that AI has a statistically significant positive effects on Integrated Oil and Gas across all quantiles, but only the first quantile ($Q_{0.4}$) for renewable energy sector under the normal market state. In contrast, for Oil and Gas Services and Equipment, this effect is negative for the $Q_{0.4}$ but statistically insignificant for the remaining energy sectors across all quantiles under the normal market condition. These results imply that during calm market periods, there is positive co-movement between AI and Integrated Oil and Gas as well as renewable energy while the dependence is negative with Oil and Gas Services and Equipment. The absence of significant co-movement suggests some evidence of diversification benefits from the inclusion of AI stocks with energy stocks, except Integrated Oil and Gas stocks during normal market periods. The negative and significant co-movement with Oil and Gas Services and Equipment suggest that AI stocks has the potential of acting as safe-haven for Oil and Gas Services and Equipment during normal market times. Similarly, under the bullish market period, co-movement is positive and significant with Oil and Gas Transport services only. Similarly, this suggests that AI stocks may offer diversification benefits to the concerned energy sectors, except Oil and Gas Transport services when market condition become very bullish.

3.1.2 The asymmetric model

To allow for asymmetric co-movement between AI and the sampled energy-focused sectors, we decompose AI shocks into positive (γ^+) and negative (γ^-) changes. Then, the standard OLS model as represented in Eq. 2 and QR model as represented in Eq. 8 are estimated. Table 4 displays the estimated results from both models, while Figure 3 presents the graphs of asymmetric QR coefficients along with the OLS estimates with 95% confidence intervals. As with the previous results, the OLS estimates of the conditional mean effect, given by the blue solid line with 95% confidence interval(dashed lines), do not vary. As for quantile coefficient estimates, for each energy sector, we plot the nine QR estimates for $\tau = 0.1, ..., 0.9$ as the solid black curve with 95% confidence interval(shaded area). Indeed, introducing asymmetry in our analysis by differentiating between positive (γ^+) and negative (γ^-) shocks on AI provides slightly different results.

Specifically, the effects of negative shocks on AI (γ^-) is positive and statistically significant for all the energy-focused sectors while the effects of positive shocks on AI is not statistically significant across all the sectors. The effects are strongest on the renewable energy sector but weakest for the coal sector. Taken together, these results suggest that on average, there is significant positive co-movement between negative shocks on AI and the sampled energy-focused sectors. This implies that negative shocks on AI performance entail significant implications for the performance of investments in the energy sectors, especially investment in renewable energy. Regarding the results from the QR model, some interesting patterns evolve. First, across the three quantiles that depict the bearish market condition, both positive (γ^+) and negative (γ^-) shocks on AI exhibit significant effects on the energy-focused sectors, except for the coal, where the effect of positive shocks on AI is not significant. In particular, positive (γ^+) and negative (γ^-) shocks on AI have negative and positive effects across the energy-focused sectors. This implies that positive shocks on AI performance exhibit negative co-movement with the performance of energy investments while negative shocks on AI performance is associated with positive co-movement with the performance of energy investments when the financial market is bearish. However, the negative dependence between positive shocks on AI performance and those of renewable energy and Integrated Oil and Gas investment is only significant at the lowest quantile ($Q_{0.1}$).

Regarding the normal market condition, generally, the level of dependence is weaker relative to those of lower and upper tails of the distribution. Here, it is interesting to note that there are changes in the direction of dependence, positive and negative shocks on AI exhibit positive and negative effects on Oil and Gas Exploration as well as Oil and Gas Refining. This suggests that during normal market periods, the performance of investments in these two energy sectors may move in the same direction, showing no potential for diversification benefits. However, for Oil and Gas Drilling, Integrated Oil and Gas and the alternative energy sectors (coal and renewable energy), negative shocks on AI performance exhibit positive co-movement with their performance, suggesting a potential for diversification benefits. Lastly, both positive and negative shocks on AI performance have no significant effects on Oil-related Services and Equipment while positive AI shock has significant negative effects on coal at the median quantile ($\mathrm{Q}_{0.5}$).

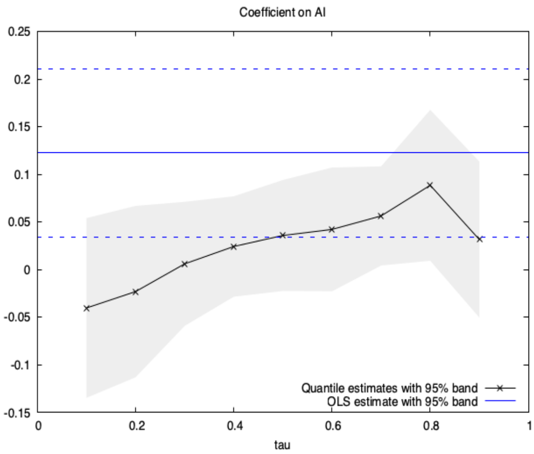
More so, when the market condition is bullish, results for the associated quantiles show that dependence strengthens significantly relative to those of normal market quantiles. For the renewable energy sector, both positive and negative shocks on AI performance have no significant effects while for coal, the negative effect of negative shocks on the performance of AI is only significant at the highest quantile. For the remaining energy sectors, positive and negative shocks on the performance of AI have positive and negative effects on their performance, respectively. This suggests that when market conditions are bullish, there is positive(negative) co-movement between positive(negative) shocks on AI performance, suggesting no potential for diversification benefits from the inclusion of AI stocks in the portfolio of these conventional energy stocks. In contrast, non significant co-movement with the renewable energy sector across all the relevant quantiles is an indication that AI stocks has the potential of offering some diversification benefits to portfolios of renewable energy stocks, when market condition is very bullish. Similar conclusion could be reached for the coal sector, however, this is only possible at the 70^{th} and 80^{th} percentiles of the return distribution.

It is also interesting to note that when we consider asymmetries in the interactions between AI and these energy sector, the dummy variable associated with the COVID-19 crisis period becomes insignificant in the standard OLS model but becomes significant across different quantiles under the asymmetric model. In particular, for all the considered energy-focused sectors, the effect of the crisis is negative and strongest during the bearish market, except for the renewable energy sector, where the effect is not significant for under bearish market condition. Lastly, following past studies such as Nusair and Olson (2019), Table 5 Panel A - B displays the critical values obtained from the F-test for quantile slope equality. The null hypothesis is that slope parameters are equal across the various quantiles. Thus, the rejection of the null hypothesis suggests that associated slope parameters are significantly different across quantiles. Also, we tested the slope equality of the decomposed positive and negative AI shocks ($\gamma^{+} = \gamma^{-}$) across all the quantiles as shown in Table 5 Panel B. The tests are repeated for every two quantiles (e.g., $\mathrm{Q}_{0.1} = Q_{0.2}$) and for lower quantile against the median ($\mathrm{Q}_{0.1} = Q_{0.5}$) and higher quantile against the median ($\mathrm{Q}_{0.5} = Q_{0.9}$). Generally, results mostly favour the rejection of the null hypothesis of slope equality across the different quantiles for all the energy sectors. The results confirm that the estimated coefficients are not constant but vary across the chosen quantiles.

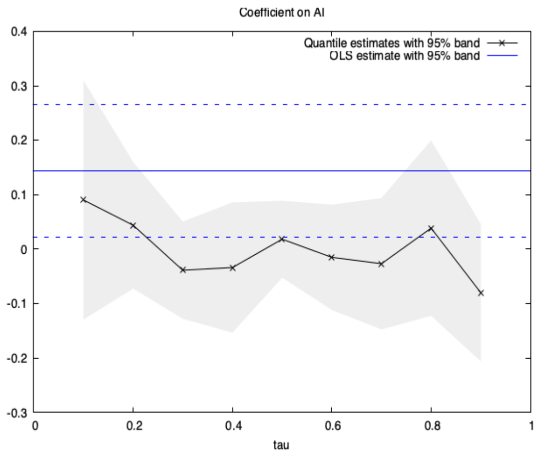
Table 3: Dependence Structure between AI and Energy-focused Sectors

Sector	Variable	OLS	Bearish market			Normal market			Bullish market		
			$Q_{0.1}$	$Q_{0.2}$	$Q_{0.3}$	$Q_{0.4}$	$Q_{0.5}$	$Q_{0.6}$	$Q_{0.7}$	$Q_{0.8}$	$Q_{0.9}$
OGEXP	Constant	0.011	-2.199***	-1.286***	-0.794***	-0.358***	-0.018	0.372***	0.763***	1.286***	2.053***
	OGEXP(-1)	0.033	0.114*	0.081**	0.067***	0.041	0.019	-0.017	-0.011	0.013	-0.024
	γ	0.143**	0.197*	0.044	-0.038	-0.033	0.018	-0.014	-0.026	0.038	-0.079
	D	-0.331	-2.598***	-0.816***	-0.352**	-0.111	0.013	-0.021	0.316	0.753**	1.587***
OGDRI	Constant	-0.028	-2.923***	-1.791***	-1.099***	-0.471***	-0.016	0.418***	0.983***	1.583***	2.762***
	OGDRI(-1)	0.101***	0.106**	0.053	0.072**	0.036	0.074***	0.061*	0.047	0.041	0.112**
	γ	0.133*	0.279***	0.191*	0.053	0.066	0.031	0.073	0.088	-0.04	-0.067
	D	-0.501*	-2.581***	-1.419***	-0.594**	-0.322	-0.340*	-0.114	0.131	0.734**	2.014***
OGREF	Constant	0.012	-1.327***	-0.863***	-0.452***	-0.209***	0.024	0.247***	0.502***	0.896***	1.370***
	OGREF(-1)	-0.02	0.026	0.044	-0.012	0.001	-0.018	-0.054*	-0.011	0.032	-0.011
	γ	0.126***	0.071	0.082**	0.018	0.013	0.036	0.014	-0.028	-0.054	-0.013
	D	-0.261*	-1.540***	-1.259***	-0.426***	-0.246**	-0.148*	-0.123	0.351***	0.975***	1.552***
INTOG	Constant	0.02	-1.505***	-0.873***	-0.471***	-0.164***	0.029	0.305***	0.597***	0.939***	1.485***
	INTOG(-1)	0.095***	0.158***	0.045	0.046*	0.018	0.034	0.049*	0.042*	0.054*	0.133***
	γ	0.088*	0.133***	0.095**	0.076**	0.076**	0.073**	0.071**	0.025	-0.065	-0.109**
	D	-0.289*	-1.805***	-0.947***	-0.618***	-0.526***	-0.121	-0.039	0.301**	0.706***	1.437***
OGSEQ	Constant	-0.023	-2.294***	-1.448***	-0.864***	-0.417***	-0.066	0.292***	0.772***	1.315***	2.308***
	OGSEQ(-1)	0.008	0.057	0.057	0.026	-0.004	0.003	0.001	0.022	-0.018	0.019
	γ	0.133**	0.167**	-0.018	-0.042	-0.082*	-0.052	-0.041	-0.022	0.049	0.002
	D	-0.414*	-2.505***	-1.015***	-0.526**	-0.227	-0.044	-0.168	0.168	1.000***	2.034***
OGTRA	Constant	0.032	-1.304***	-0.762***	-0.429***	-0.174***	0.048	0.292***	0.541***	0.834***	1.272***
	OGTRA(-1)	-0.125***	0.001	-0.044	-0.017	-0.060***	-0.057**	-0.060**	-0.046**	-0.023	-0.089***
	γ	0.122***	-0.04	-0.022	0.006	0.024	0.035	0.042	0.056**	0.088**	0.031
	D	-0.253	-1.986	-0.608	-0.083	0.13	0.138	0.213*	0.262***	0.537***	1.558***
COAL	Constant	0.0001	-1.952***	-1.181***	-0.695***	-0.309***	-0.009	0.284***	0.649***	1.224***	1.921***
	COAL(-1)	0.044	0.141**	0.125***	0.076*	0.063*	0.031	0.024	0.039	0.024	0.017
	γ	0.046	0.134	0.120**	0.094*	0.057	0.022	-0.0003	-0.008	-0.035	-0.097
	D	-0.21	-1.345***	-0.628***	-0.531***	-0.254	-0.009	0.087	0.087**	0.439**	1.175***
REN	Constant	0.098	-1.984***	-1.110***	-0.638***	-0.202***	0.072**	0.401***	0.845***	1.328***	2.175***
	REN(-1)	0.061*	0.052	0.106***	0.080***	0.086***	0.060***	0.019	0.022	0.043	0.121***
	γ	0.161***	0.305***	0.251***	0.175***	0.075*	0.038	0.047	-0.007	-0.038	-0.083
	D	0.001	-1.134***	-0.403*	0.028	0.285*	0.364***	0.194	0.352**	0.595**	0.386*

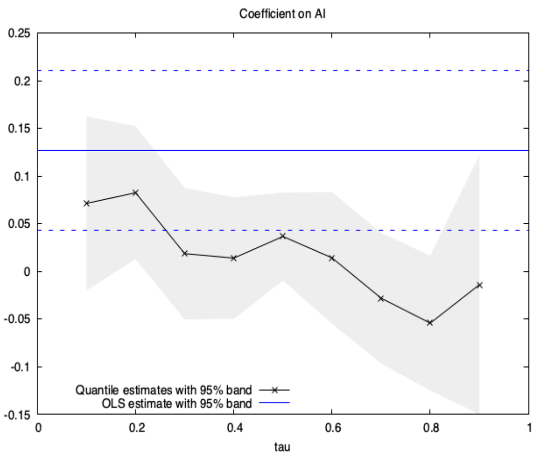
Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels. We choose nine quantiles ($\tau = 0.1, 0.2, \ldots, 0.9$) and divide them into three regimes: low ($\tau = 0.1, 0.2, 0.3$), medium ($\tau = 0.4, 0.5, 0.6$), and high ($\tau = 0.7, 0.8, 0.9$), which denote a bearish, normal, and bullish market, respectively. Also note that Artificial Intelligence (AI); Oil & Gas Exploration and Production (OGEXP); Oil & Gas Refining and Marketing (OGREF); Integrated Oil & Gas (INTOG); Oil-related Services and Equipment (OGSEQ); Oil & Gas Transportation Services (OGTRA); Oil & Gas Drilling (OGDRI); Coal (COAL); and Renewable Energy (REN)



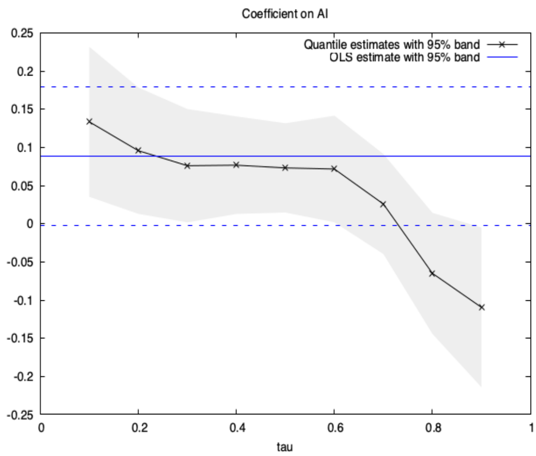
(a) Oil & Gas Transport Services



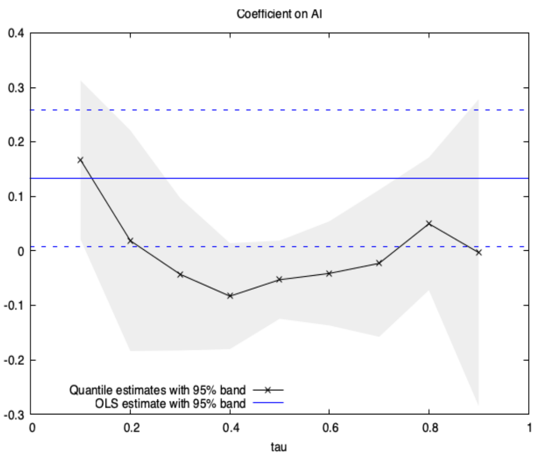
(b) Oil & Gas Exploration and Production



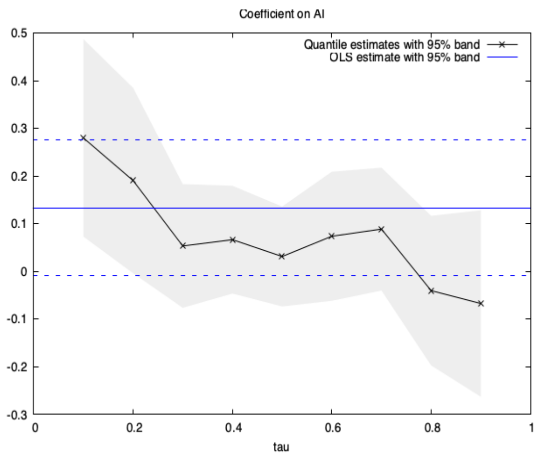
(c) Oil & Gas Refining and marketing



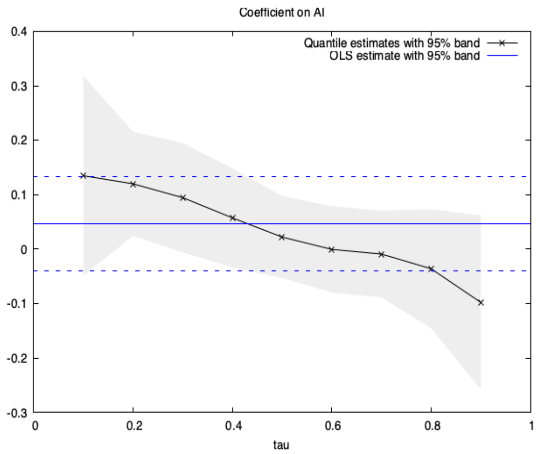
(d) Integrated Oil & Gas Services



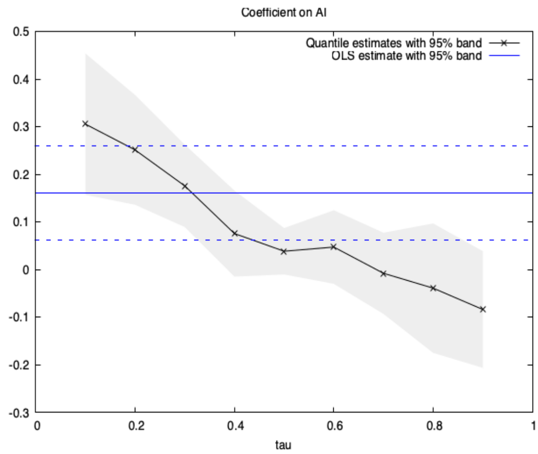
(e) Oil-related Services and Equipment



(f) Oil & Gas Drilling



(g) Coal



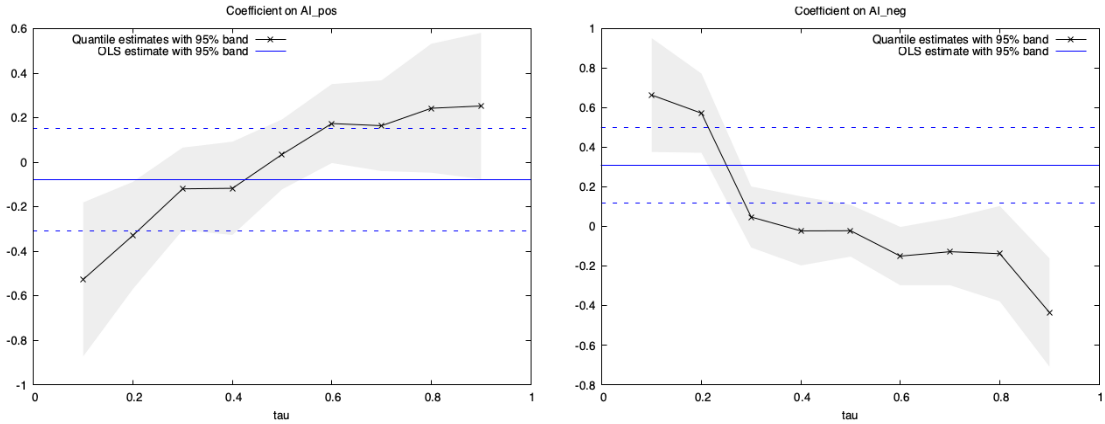
(h) Renewable

Figure 2: Quantile regression coefficient estimates for AI returns in the linear model. Estimates for $\tau = 0.1, \ldots, 0.9$ are given by the solid black curve with 95% confidence intervals (shaded area) for the effects of AI returns on returns of energy sectors. The OLS estimates of the conditional mean effect are given by the blue solid line with 95% confidence interval (dashed lines). Vertical axis displays the coefficient estimates of AI return changes over energy sectors' return distribution while horizontal axis shows the quantiles of the concerned energy sector (the dependent variable)

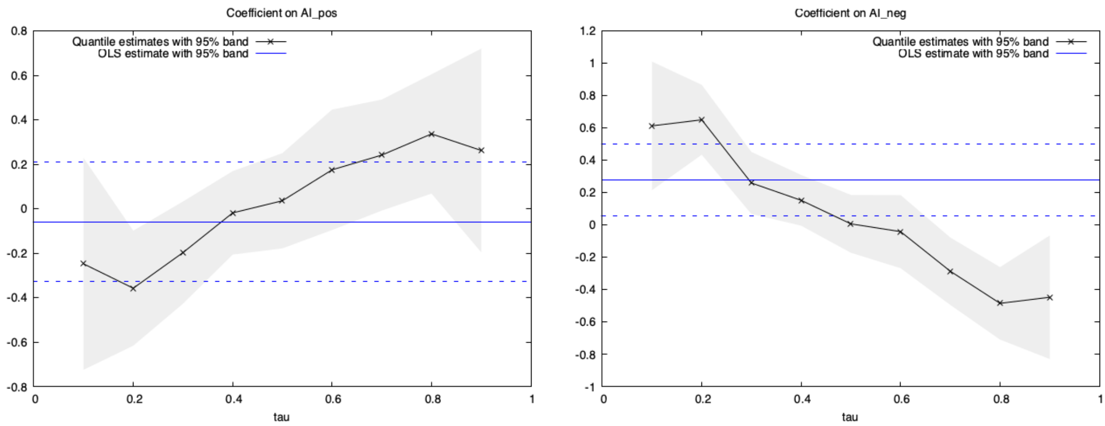
Table 4: Dependence Structure between AI and Energy-focused Sectors: Asymmetric Shocks on AI

Sector	Variable	OLS	Bearish market			Normal market			Bullish market		
			$Q_{0.1}$	$Q_{0.2}$	$Q_{0.3}$	$Q_{0.4}$	$Q_{0.5}$	$Q_{0.6}$	$Q_{0.7}$	$Q_{0.8}$	$Q_{0.9}$
OGEXP	Constant	0.178	-1.716***	-1.023***	-0.714***	-0.333***	-0.037	0.215**	0.626***	1.144***	1.872***
	OGEXP(-1)	0.034	0.117**	0.110***	0.057**	0.036	0.031	0.002	-0.023	0.023***	-0.01
	γ^+	-0.078	-0.525***	-0.328***	-0.119	-0.116	0.035	0.173*	0.164	0.242*	0.252
	γ^-	0.311***	0.664***	0.572***	0.048	-0.021	-0.02	-0.148**	-0.126	-0.136	-0.433***
	D	-0.212	-1.364***	-0.809***	-0.411**	-0.007	0.034	0.081	0.22	0.574*	1.218***
OGDRI	Constant	0.115	-2.475***	-1.363***	-0.903***	-0.394***	-0.022	0.360**	0.827***	1.293***	2.433***
	OGDRI(-1)	0.101**	0.108*	0.075**	0.081***	0.035	0.073***	0.056*	0.036	0.059*	0.130**
	γ^+	-0.057	-0.247	-0.356***	-0.196*	-0.018	0.036	0.175	0.241*	0.336**	0.262
	γ^-	0.278***	0.612***	0.650***	0.259***	0.152*	0.007	-0.04	-0.285***	-0.484***	-0.446**
	D	-0.398	-2.339***	-1.104***	-0.478**	-0.330*	-0.344	-0.224	0.036	0.351	1.868***
OGREF	Constant	0.136*	-0.969***	-0.665***	-0.337***	-0.187***	0.015	0.169***	0.298***	0.667***	1.115***
	OGREF(-1)	-0.017	0.119***	0.045	-0.014	0.002	-0.018	-0.038	0.014	0.027	0.011
	γ^+	-0.038	-0.597***	-0.172**	-0.150**	-0.0003	0.045	0.109*	0.282***	0.265***	0.236**
	γ^-	0.251***	0.566***	0.269***	0.176***	0.031	0.013	-0.103**	-0.272***	-0.270***	-0.294***
	D	-0.171	-1.372***	-1.039***	-0.334**	-0.259**	-0.151	-0.153	0.273**	0.596***	1.357***
INTOG	Constant	0.209**	-1.187***	-0.746***	-0.404***	-0.073	0.107*	0.282***	0.546***	0.780***	1.371***
	INTOG(-1)	0.099***	0.198***	0.052	0.056*	0.021	0.029	0.046*	0.027	0.082***	0.126
	γ^+	-0.163*	-0.454***	-0.076	-0.044	-0.039	-0.017	0.093	0.085	0.128*	0.014
	γ^-	0.278***	0.484***	0.283***	0.185***	0.191***	0.139***	0.059	-0.06	-0.230***	-0.238***
	D	-0.152	-1.690***	-0.904***	-0.599***	-0.513***	-0.143	-0.024	0.283**	0.605***	1.339***
OGSEQ	Constant	0.105	-2.002***	-1.076***	-0.630***	-0.404***	-0.095	0.235**	0.392***	1.089***	2.085***
	OGSEQ(-1)	0.009	0.081	-0.003	0.016	-0.009	0.004	0.007	0.016	-0.012	-0.0001
	γ^+	-0.037	-0.325*	-0.297**	-0.273***	-0.103	-0.015	0.051	0.388***	0.321***	0.078
	γ^-	0.263***	0.758***	0.541***	0.272***	-0.063	-0.079	-0.101	-0.327***	-0.264***	-0.212
	D	-0.321	-2.090***	-1.031***	-0.505***	-0.255	-0.046	-0.117	0.326*	0.505**	1.852**
OGTRA	Constant	0.215**	-0.919***	-0.534***	-0.349***	-0.174***	0.017	0.206***	0.431***	0.703***	1.112***
	OGTRA(-1)	-0.122***	0.012	-0.011	-0.034	-0.060***	-0.047**	-0.048**	-0.032	-0.043	-0.149***
	γ^+	-0.121	-0.509***	-0.405***	-0.095	0.022	0.087	0.168***	0.152***	0.252***	0.255**
	γ^-	0.306***	0.367***	0.236***	0.132**	0.024	-0.004	-0.063	-0.066	-0.027	-0.261***
	D	-0.122	-1.592***	-0.431***	-0.027	0.13	0.171	0.223**	0.309***	0.553***	1.226***
COAL	Constant	0.115	-1.796***	-1.050***	-0.537***	-0.155*	0.112*	0.319***	0.618***	1.201***	1.793***
	COAL(-1)	0.049	0.182***	0.101**	0.098**	0.090**	0.049*	0.012	0.042	0.025	0.048
	γ^+	-0.107	0.017	-0.062	-0.072	-0.123	-0.124*	-0.032	0.047	-0.017	0.068
	γ^-	0.161**	0.213*	0.302***	0.256***	0.219***	0.116**	0.023	-0.04	-0.066	-0.274***
	D	-0.126	-1.133***	-0.585***	-0.451**	-0.156	-0.05	0.152	0.318*	0.389*	1.111***
REN	Constant	0.295***	-1.426***	-0.808***	-0.455***	-0.123*	0.086*	0.401***	0.885***	1.251***	2.039***
	REN(-1)	0.061*	0.038	0.078*	0.107***	0.095***	0.058***	0.019	0.017	0.036	0.113**
	γ^+	-0.1	-0.532***	-0.189	-0.059	-0.015	0.032	0.047	-0.037	0.085	0.067
	γ^-	0.358***	0.718***	0.672***	0.524***	0.212***	0.082**	0.053	0.089	-0.101	-0.147
	D	0.141	-0.338	0.144	0.124	0.393***	0.353***	0.194	0.486***	0.558**	0.476*

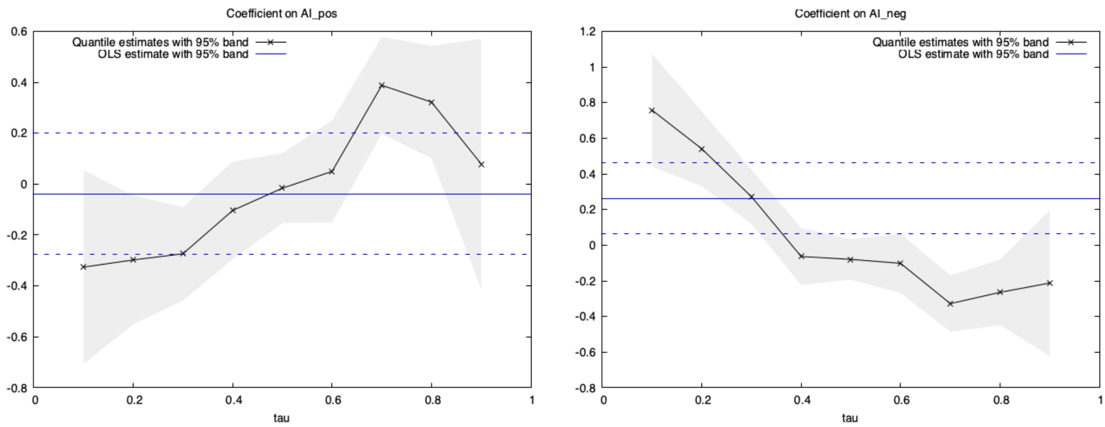
Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels. γ^+ and γ^- correspond to positive and negative changes in AI returns, respectively. Similarly, the three regimes: low ($\tau = 0.1, 0.2, 0.3$), medium ($\tau = 0.4, 0.5, 0.6$), and high ($\tau = 0.7, 0.8, 0.9$) denote the bearish, normal, and bullish markets, respectively. Also note that Artificial Intelligence (AI); Oil & Gas Exploration and Production (OGEXP); Oil & Gas Refining and Marketing (OGREF); Integrated Oil & Gas (INTOG); Oil-related Services and Equipment (OGSEQ); Oil & Gas Transportation Services (OGTRA); Oil & Gas Drilling (OGDRI); Coal (COAL); and Renewable Energy (REN)



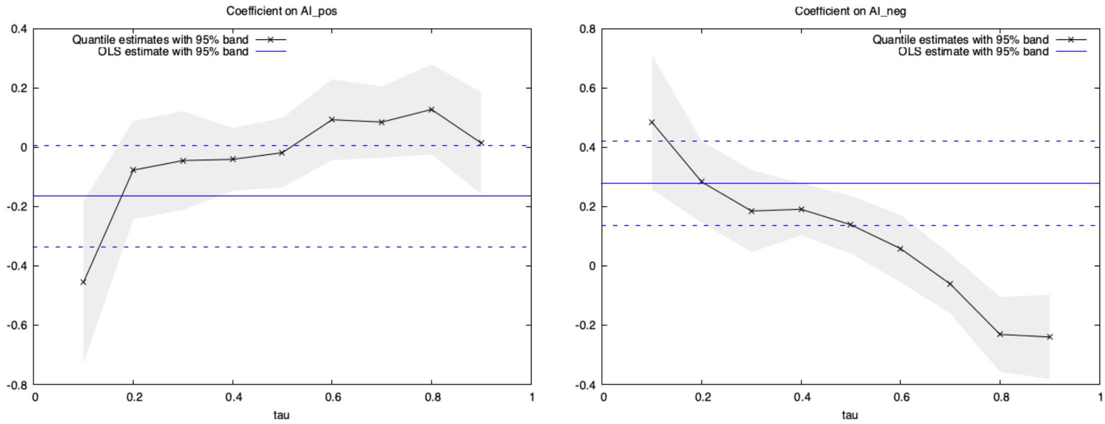
(a) Oil & Gas Exploration and Production



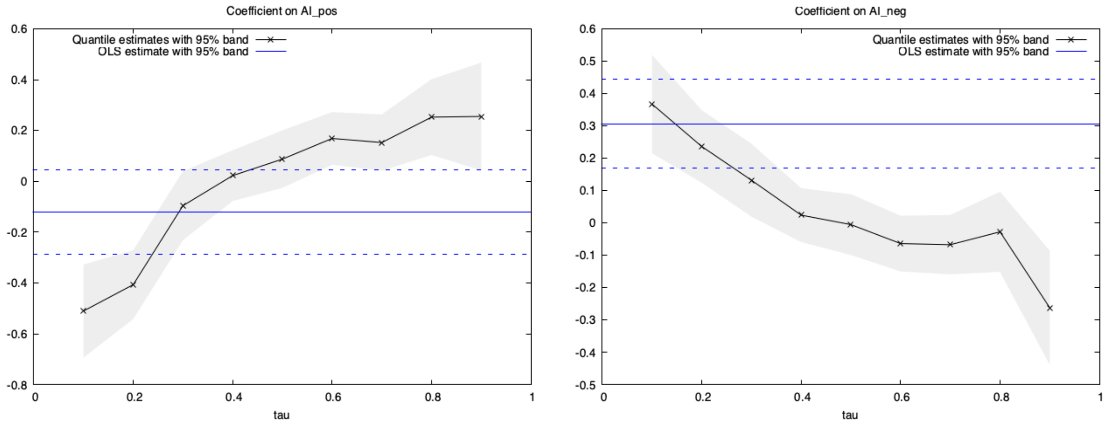
(b) Oil & Gas Drilling



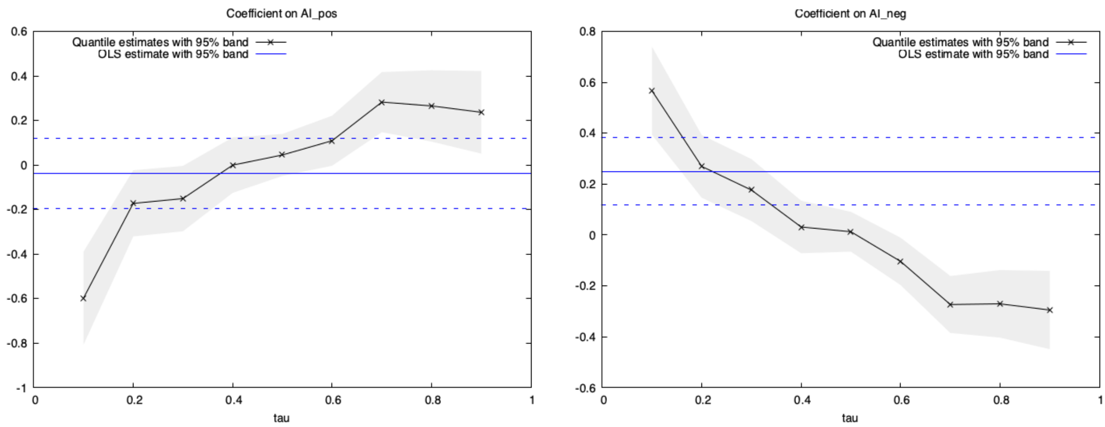
(c) Oil-related Services and Equipment



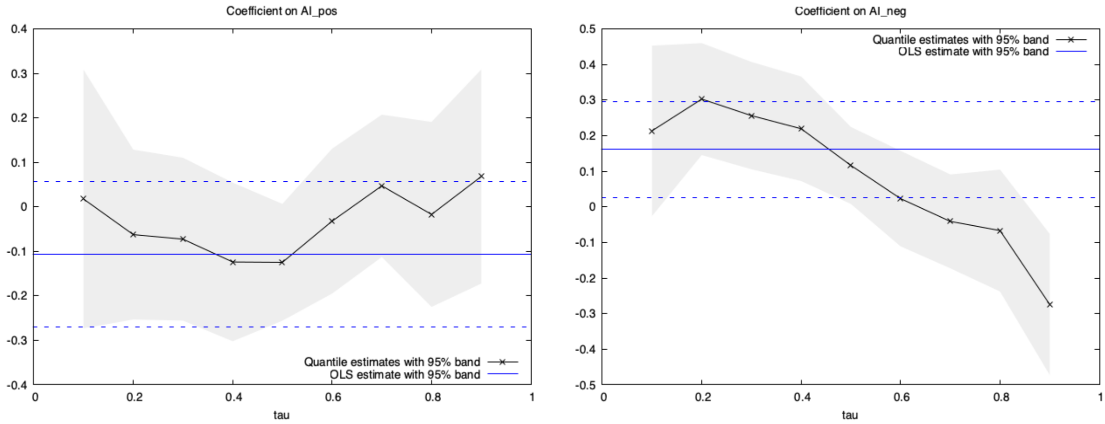
(d) Integrated Oil & Gas



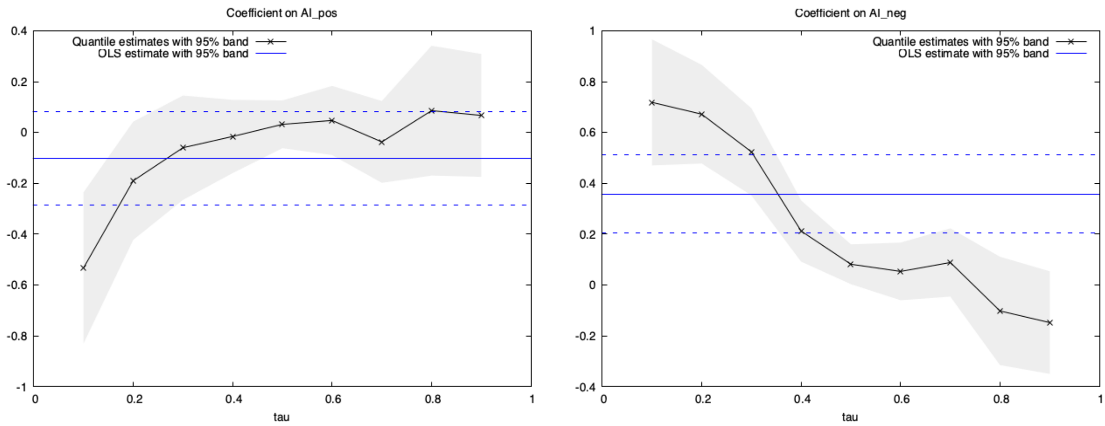
(e) Oil & Gas Transport Services



(f) Oil & Gas Refining and marketing



(g) Coal



(h) Renewable energy

Figure 3: Quantile regression coefficient estimates for γ^+ and γ^- returns in the asymmetric model. Estimates for $\tau = 0.1, \ldots, 0.9$ are given by the solid black curve with 95% confidence intervals (shaded area) for the effects of AI returns on returns of energy sectors. The OLS estimates of the conditional mean effect are given by the blue solid line with 95% confidence interval (dashed lines). Vertical axis displays the coefficient estimates of positive and negative AI return changes over energy sectors' return distribution while horizontal axis shows the quantiles of the concerned energy sector (the dependent variable)

Table 5: Quantile slope equality test

Sector	Variable	$Q_{0.1} = Q_{0.2}$	$Q_{0.2} = Q_{0.3}$	$Q_{0.3} = Q_{0.4}$	$Q_{0.4} = Q_{0.5}$	$Q_{0.5} = Q_{0.6}$	$Q_{0.6} = Q_{0.7}$	$Q_{0.7} = Q_{0.8}$	$Q_{0.8} = Q_{0.9}$	$Q_{0.1} = Q_{0.5}$	$Q_{0.5} = Q_{0.9}$	$Q_{0.1} = Q_{0.9}$
Panel A												
OGEXP	γ^+	0.04	1.47	2.66*	0.7	3.18**	0.07	0.61	0.08	6.21***	0.77	4.32**
	γ^-	0.01	4.04**	0.45	0.12	9.31***	0.09	0.01	1.94	7.60***	3.65**	11.13***
	D	0.29	0.62	6.08**	0.06	0.21	0.29	1.1	1.44	2.13*	3.06*	9.25***
OGDRI	γ^+	0.04	1.59*	0.42	0.96	1.22	0.48	0.54	0.28	3.43**	0.17	1.34*
	γ^-	0.05	2.25**	0.86	0.85	0.21	2.09*	0.51	0.01	7.50***	1.45	6.69***
	D	0.72	2.79**	0.24	0.03	0.01	1.79	0.65	5.12**	2.64***	7.98***	6.44**
OGREF	γ^+	7.15***	0.07	7.41***	0.19	2.59**	9.03***	0.02	0.06	12.9***	12.9***	18.2***
	γ^-	1.14	1.03	3.34**	0.02	1.82	3.50**	0.04	0.2	3.78**	5.45**	7.39***
	D	0.5	4.49**	1.01	1.23	0.15	3.67**	2.13*	5.08**	11.0***	15.3***	25.1***
INTOG	γ^+	4.93**	0.04	0.04	0.96	0.66	0.29	0.14	0.03	3.48*	0.26	3.46*
	γ^-	1.11	0.8	0.08	1.94*	1.57	1.37	2.07*	0.67	2.46*	12.7***	11.6***
	D	3.06*	5.14**	0.18	6.06**	0.71	3.61*	0.99	5.56**	8.81***	9.80***	22.1***
OGSEQ	γ^+	0.11	0.01	3.08*	1.53	0.33	5.12**	0.19	0.88	0.96	0.21	2.05
	γ^-	0.48	1.95*	6.54**	0.01	0.12	2.86*	0.02	0.05	4.37**	2.26**	4.74**
	D	2.32**	2.09*	1.2	0.86	0.36	2.69*	0.52	1.61	7.17***	2.34**	9.81***
OGTRA	γ^+	0.62	5.93**	3.04*	0.08	2.77*	0.18	1.71	0.81	12.99***	2.54**	14.43***
	γ^-	0.61	0.51	1.93*	0.63	0.93	0.2	0.3	1.49	1.33	2.49**	3.93***
	D	4.98**	2.58*	0.21	1.3	0.07	3.03*	2.93*	2.15*	12.79***	4.04**	12.6***
COAL	γ^+	2.18*	0.03	2.33*	0.14	0.16	2.73**	0.22	2.01*	1.74*	0.45	3.07**
	γ^-	0.54	0.19	0.1	7.12***	2.83**	2.37**	0.01	2.69**	0.09	3.02**	2.83**
	D	2.87*	1.11	2.23*	1.73	2.84*	1.12	0.06	3.84**	5.85**	14.7***	6.44**
REN	γ^+	2.08*	0.63	1.64	0.52	0.08	1.03	2.32*	1.12	4.01**	2.45**	2.32**
	γ^-	0.01	2.27*	7.76***	3.30**	3.01**	0.05	1.99*	0.04	16.5***	10.8***	4.94**
	D	2.56**	0.41	2.15*	0.02	2.97**	2.39*	0.16	3.46**	1.17	1.38	0.01
Panel B												
		$Q_{0.1} = Q_{0.1}$	$Q_{0.2} = Q_{0.2}$	$Q_{0.3} = Q_{0.3}$	$Q_{0.4} = Q_{0.4}$	$Q_{0.5} = Q_{0.5}$	$Q_{0.6} = Q_{0.6}$	$Q_{0.7} = Q_{0.7}$	$Q_{0.8} = Q_{0.8}$	$Q_{0.9} = Q_{0.9}$	$Q_{0.1} = Q_{0.9}$	$Q_{0.1} = Q_{0.5}$
OGEXP	$\gamma^+ = \gamma^-$	9.38***	8.03***	0.73	0.06	0.01	1.7	2.04*	2.18**	5.46**	2.04**	5.05**
OGDRI	$\gamma^+ = \gamma^-$	2.85*	4.30**	1.94*	0.25	0.05	1.94*	4.46**	11.53***	3.54**	0.06	2.76**
OGREF	$\gamma^+ = \gamma^-$	7.12***	2.81*	1.6	0.04	0.01	0.58	5.48**	10.86***	8.93***	1.65	6.52**
INTOG	$\gamma^+ = \gamma^-$	3.89**	3.30*	2.98*	2.73*	1.05	0.03	2.46*	1.87	2.76*	2.17*	2.97*
OGSEQ	$\gamma^+ = \gamma^-$	4.33**	12.78***	4.16**	0.08	0.25	3.55**	21.1***	5.91**	0.22	0.01	2.38*
OGTRA	$\gamma^+ = \gamma^-$	2.25*	2.80*	0.73	0.02	3.33**	3.10*	4.16**	2.89*	3.05*	1.43	3.86**
COAL	$\gamma^+ = \gamma^-$	0.02	2.26*	2.59**	2.14*	0.73	0.14	2.27*	0.03	2.12*	2.76**	4.07***
REN	$\gamma^+ = \gamma^-$	9.26***	20.8***	8.47***	1.28	0.01	0.02	2.27*	2.14*	0.05	2.43**	4.18**

Note: Reported are the critical values from the F-test of quantile slope equality, with the null hypothesis that slope parameters are equal across the various quantiles. ***, ** and * indicate the rejection of the null hypothesis of slope equality at the 1%, 5% and 10% significance levels, respectively. Also note that Artificial Intelligence (AI); Oil & Gas Exploration and Production (OGEXP); Oil & Gas Refining and Marketing (OGREF); Integrated Oil & Gas (INTOG); Oil-related Services and Equipment (OGSEQ); Oil & Gas Transportation Services (OGTRA); Oil & Gas Drilling (OGDRI); Coal (COAL); and Renewable Energy (REN)

3.2 Quantile coherency results

In Figures 4 - 6, we present the estimates of quantile coherency realized from the quantile cross-spectral. Following past studies such as Maghyereh and Abdoh (2021) and Maghyereh et al. (2019), horizontal axis displays the daily cycles over the interval while the measures of co-dependence of AI and the return of each of the energy sector is presented on the vertical axis. The weekly (W), monthly (M) and yearly (Y) frequency cycles in the upper label of the horizontal axis show how each pair of the return series are dependent across quantiles of the joint distribution. For instance, a sample frequency of 0.2 implies that there is 0.2 cycles per day, corresponding to a 5 days period. First, we present and discuss results for the full sample before proceeding with results for the COVID-19 sub-sample.

3.2.1 Quantile coherency for the full sample

In Figure 4 panel a - i, for all pairs of co-dependence between AI and each of the energy sectors, we use plots in (i), (ii) and (iii) to display the 0.05|0.05; 0.5|0.5 and 0.95|0.95 quantiles of the joint distribution, respectively. Figure 5 presents the dependence between the 0.05|0.95 quantiles of joint distribution for the full sample. As may be seen in Figure 4 panel a - i, results generally indicate that the level of coherency between AI and the energy sectors varies across both return quantiles and time scales. Basically, this suggests that dependence varies according to market situations and investment horizons. Particularly, during normal market condition as shown by the 0.5|0.5 return quantile in plot (ii), results indicate that dependence is mostly negative and strongest with renewable energy sector, but weakest with Oil and Gas Exploration and Production sector in the weekly horizon. However, dependence with Integrated Oil and Gas is mainly positive under this horizon. These results suggest that portfolios consisting of AI and the assets of the sampled energy sectors exhibit negative dependence, with high probability of short-term diversification benefits, except for Integrated oil and gas sector during normal market condition. Moreover, dependence is generally positive across monthly and yearly frequency cycles; strongest with renewable energy sector in the monthly cycle but with Oil and Gas Drilling in the yearly cycle. However, dependence is negative in the yearly cycle only with Oil and Gas exploration and production. These positive co-movements between AI and energy sectors generally suggest the absence or reduced potential for portfolio diversification opportunities in the mid- and long-term investment horizons.

Furthermore, notable differences may be seen across the left and right tails of the return distributions as shown by the 0.05|0.05 in plots (i) and the 0.95|0.95 in plots (iii). Specifically, results for the left tail (0.05|0.05) suggest that when market condition is bearish, similar to the normal market condition, dependence between AI and Coal, Oil and Gas Drilling, Integrated Oil and Gas, Oil-related Services and Equipment as well as Oil and Gas Transportation Services is mainly negative while dependence varies from positive to negative for the remaining energy sectors in the weekly cycle. In particular, towards the end of the weekly cycle, dependence becomes negative and strongest between AI and Oil and Gas Drilling, followed by the renewable energy sector. However, while dependence is generally positive and strongest with Oil and Gas Refining and Marketing in the yearly frequency cycle, in the monthly frequency cycle, results are mixed. For instance, dependence with Coal, Oil and Gas Exploration and Production, Integrated Oil and Gas, Oil and Gas Refining and Marketing and Oil and Gas Related Services are mostly positive while dependence with Oil and Gas Drilling, Renewable Energy and Oil and Gas Transport Services switches from positive to negative.

Regarding the upper tail of the return distribution as shown by the 0.95|0.95 in plots (iii), results indicate that when the market condition is bullish, in the weekly frequency cycle, the dependence between AI and Oil and Gas Refining and Marketing is positive while it is negative with Coal, Oil and Gas Exploration and Production as well as Oil and Gas Transportation Services. Besides, there are periods of positive and negative dependence between AI and the remaining energy-focused sectors across this cycle. Results for the monthly frequency cycle suggest that dependence is positive with Oil and Gas Drilling, Oil and Gas Exploration and Production, Renewable energy as well as Oil and Gas Transportation Services. However, dependence between AI and the remaining energy sectors switched from positive to negative under this frequency cycle. Concerning the yearly cycle, dependence between AI and all the considered energy-focused sectors is positive and strongest with

Renewable energy, followed by Oil and Gas Drilling. However, dependence is weakest between AI and Oil-related Services and Equipment.

Figure 5 presents the quantile coherency for the 0.05|0.95 quantiles of the joint distribution between AI and each of the energy-focused sectors. Indeed, this enables us to examine the evolution of dependence assuming that either AI or each of the eight energy-focused sectors is in a bearish market state while the other is in a bullish condition. Specifically, we study the dependence between a negative return (0.05 quantile) of AI and a high positive return (0.95 quantile) of each of the energy-focused sectors across the three frequency cycles. Results in Figure 5 indicate that during the weekly cycle, extreme dependence (0.05 for AI and 0.95 for energy sectors) is strongest with Coal. In terms of direction, dependence is mostly positive with Coal and Integrated Oil and Gas while it is negative with Oil-related Services and Equipment. However, for the remaining energy-focused sectors, extreme dependence switches from positive to negative.

Moreover, as the time frequency increases to monthly, extreme dependence becomes weaker between AI and Oil-related Services and Equipment, Oil and Gas Exploration and Production as well as Oil and Gas Drilling. However, dependence becomes positive with Oil and Gas Drilling and Oil-related Services and Equipment; negative with Renewable energy and Oil and Gas Exploration and Production while it changes between positive and negative for the remaining energy-focused sectors. When the time frequency is further increased to the yearly cycle, extreme dependence becomes strongest with renewable energy. However, extreme dependence at this time frequency is mostly negative, indicating that there is a likelihood of high positive returns for most energy-focused sectors following a negative return on AI. Particularly, dependence is negative between AI and Coal, Oil and Gas Refining and Marketing, Renewable energy, Oil and Gas Explorations and Production as well as Oil-related Services and Equipment. However, dependence is positive with Oil and Gas Drilling as well as Integrated Oil and Gas Services while it switches from negative to positive with Oil and Gas Transportation services.

3.2.2 Quantile coherency during the COVID-19 pandemic

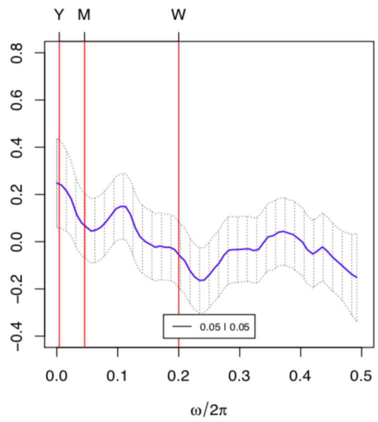
In this subsection, we are concerned with examining the changes in the strength and direction of dependence between AI and the energy-focused sectors due to changes in the global financial market during the COVID-19 pandemic. The results are shown in Figure 6 panel a - i. To save space, in each panel, plot (i) contains the evolution of dependence across the weekly, monthly and yearly time frequency cycles while plot (ii) displays the dependence for the extreme quantiles (0.05 for AI and 0.95 for energy sectors). As may be seen, results indicate that across all the return quantiles joint distributions, dependence between AI and energy-focused sectors became generally stronger during the peak of the pandemic, especially during the weekly and monthly time frequencies. This suggests a stronger short-term and mid-term dependence between AI and energy-focused sectors. In particular, under normal market condition, dependence between AI and energy-focused sectors is mostly negative with most sectors while it changes from negative to positive with only three sectors including Coal, Oil and Gas Transportation Services as well as Renewable energy in the weekly time frequency. With regards to diversification benefits, the observed increase in negative dependence suggests that during a health-induced financial market crisis, the inclusion of AI stocks in a portfolio of energy stocks may offer some portfolio risk reduction, especially in the short- and mid-terms.

However, for the monthly time frequency, dependence becomes positive with Oil and Gas Transportation Services, Renewable energy as well as Oil and Gas Refining and Marketing. For the remaining sectors, it switches from negative at the beginning of the cycle to become positive towards the yearly cycle. Besides, at the monthly cycle, dependence is strongest with the renewable energy sector. Similarly, when time frequency is further increased to the yearly cycle, results indicate that dependence remains positive and strongest with renewable energy. Dependence is also positive with Coal, Oil and Gas Transportation Services, Oil and Gas Drilling as well as Oil and Gas Exploration and Production. Hence, for portfolio optimization, the inclusion of AI stocks in portfolios of some energy sectors such as Oil and Gas Transportation Services, Renewable energy and Oil and Gas Refining and Marketing may lead to medium-term increase in portfolio risk and market losses during crisis periods such as the COVID-19 pandemic due to increase in positive dependence. This situation may also hold for the remaining energy sectors in our sample, but only for longer-term investment positions. However, dependence becomes negative with Oil-related Services and Equipment while it changes from positive to negative with Integrated Oil and Gas Services towards the end of the yearly cycle. In sum, these results underscore the short-term effects of the COVID-19 pandemic on the dependence between AI and energy sectors. Results posit a similar pattern in the direction of dependence, with AI exhibiting the strongest dependence with the renewable energy sector. Also, there is a general increase in the level of short-term dependence with all the energy sectors under the normal market condition.

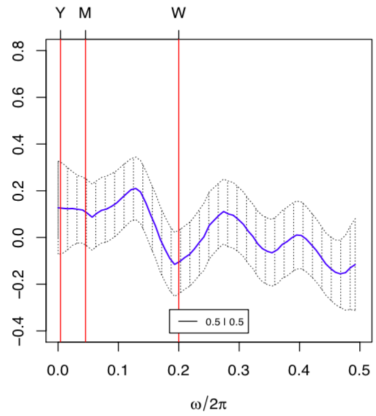
Regarding the level of dependence under the bearish market condition (0.05 quantiles), the dependence between AI and more energy sectors become negative. For instance, dependence with Oil and Gas Transportation Services sector becomes also negative while only the dependence with Renewable energy and Coal sectors change from negative to positive towards the end of the weekly cycle. However, as the time frequency increases towards the monthly cycle, the dependence between AI and renewable energy, Oil and Gas Transportation Services and Coal becomes positive while dependence with the remaining sectors changes from negative to positive towards the end of the monthly cycle. Furthermore, as the time frequency increases to the yearly cycle, unlike in similar time frequency under the normal market condition, dependence remains positive but becomes strongest between AI and the Oil and Gas Exploration and Production sector. These results suggest that although AI exhibited negative short-term dependence with most energy-focused sectors during the high volatile and low return market condition at the peak of the COVID-19 pandemic, dependence changed to positive from the intermediate-term towards the long-term. This corroborates our earlier findings in support of short-term diversification benefits of AI stocks in portfolios of energy stocks and suggests that this benefit may be higher during a high volatile and low return market situation created by a health crisis.

However, these results change when we consider the upper tail of the joint distribution (0.95 quantile). Specifically, at the weekly time frequency, dependence with AI mainly changed from negative to become positive before the end of the cycle, except the dependence with Oil and Gas Exploration and Production sector which is negative. As the time frequency is increased to the monthly cycle, dependence becomes positive with the renewable energy, Integrated Oil and Gas Services as well as Oil and Gas Transportation Services while it changed mainly from negative to positive with the remaining sectors towards the end of the cycle. Besides, as the time frequency is further increased to the yearly cycle, dependence between AI and all the energy sectors becomes positive and strongest with renewable energy sector, except with Oil-related Services and Equipment which changes from positive to become negative at the end of the cycle. In sum, these results show that across all the time frequencies and market conditions, the dependence between AI and energy-focused sectors increased substantially during the peak of the COVID-19 pandemic and was mainly positive, especially in the intermediate- and long-terms. Also, while dependence was positive and strongest with renewable energy sector, both during the normal and bullish market conditions, it was positive and strongest with Oil and Gas Exploration and Production during the bearish market condition.

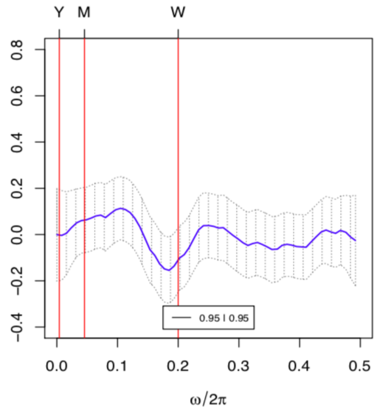
Similar to the full sample, we also examined the extreme dependence between AI and energy sectors using 0.05|0.95 quantiles of the joint distribution. Results in plots (ii) of panels a - i in Figure 5 suggest that extreme dependence is positive between AI and renewable energy, Integrated Oil and Gas as well as Coal while it changes from negative to positive with the remaining sectors in the weekly cycle. However, under the monthly cycle, only the dependence between AI and Oil-related Services is negative while dependence with other sectors changed from negative to positive before the end of the cycle. Besides, when the time frequency is increased to the yearly cycle, results become mixed. In particular, dependence between AI and Oil and Gas Exploration and Production, Oil and Gas Drilling, Oil and Gas Transportation Services becomes positive. However, dependence is negative with renewable energy and Oil-related Services but changes from positive to negative with the remaining sectors. Generally, the strongest extreme dependence is exhibited by AI and renewable energy under the yearly cycle, followed by Integrated Oil and Gas Services in the monthly cycle. In the weekly cycle, this may be found between AI and the renewable energy sector.



(i) 0.05|0.05

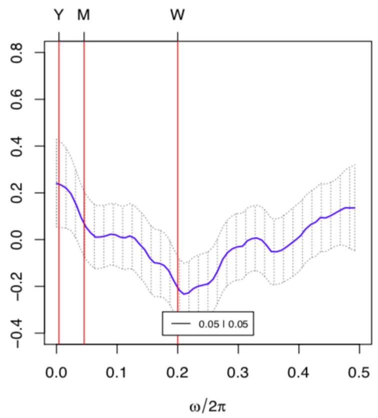


(ii) 0.5|0.5

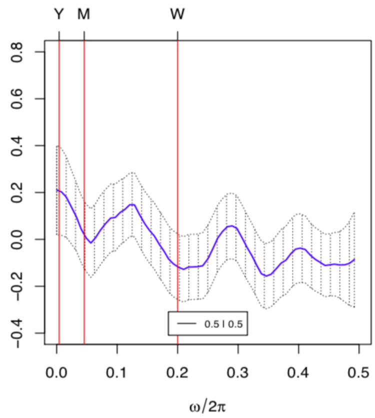


(iii) 0.95|0.95

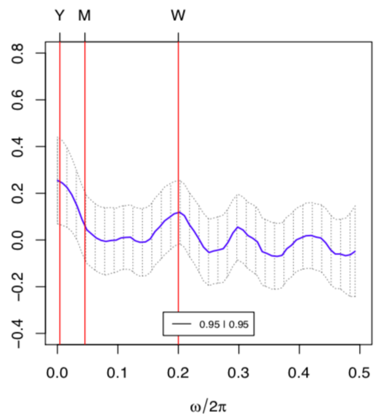
(a) AI vs Coal



(i) 0.05|0.05

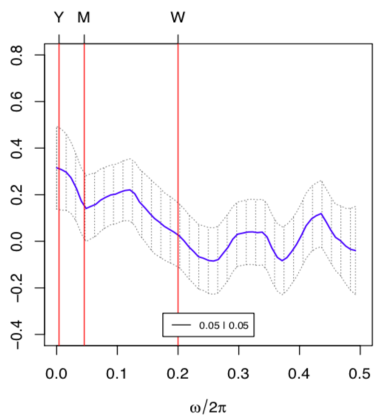


(ii) 0.5|0.5

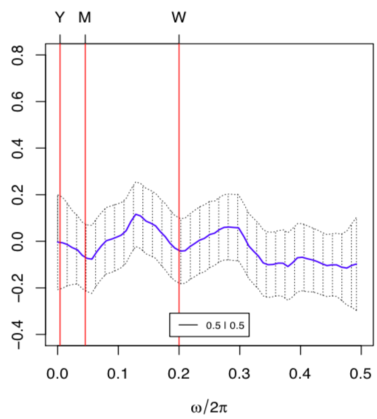


(iii) 0.95|0.95

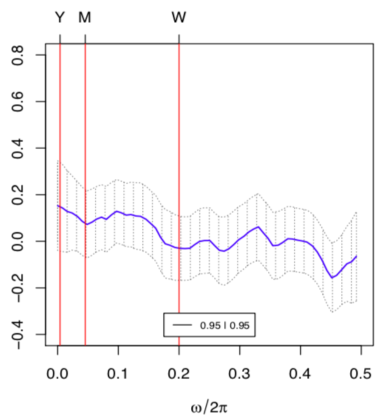
(b) AI vs Oil & Gas Drilling



(i) 0.05|0.05

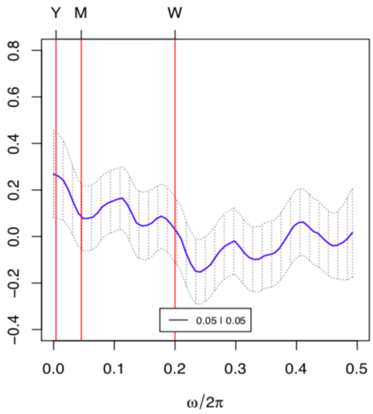


(ii) 0.5|0.5

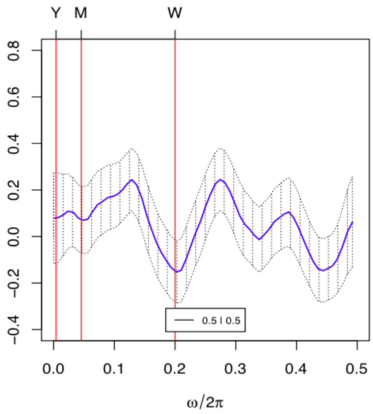


(iii) 0.95|0.95

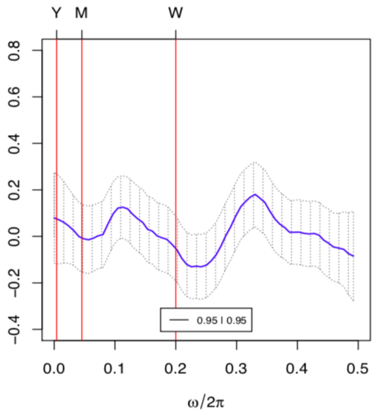
(c) AI vs Oil & Gas Exploration and Production



(i) 0.05|0.05

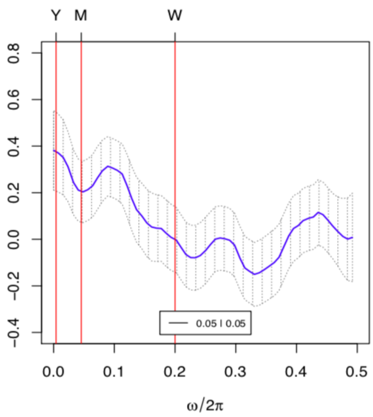


(ii) 0.5|0.5

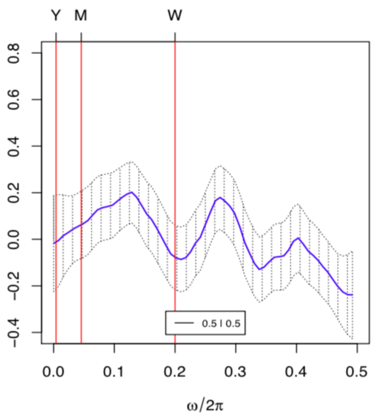


(iii) 0.95|0.95

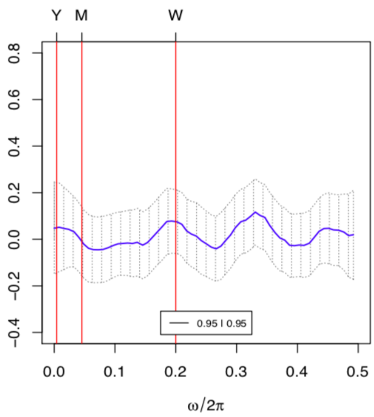
(d) AI vs Integrated Oil & Gas



(i) 0.05|0.05

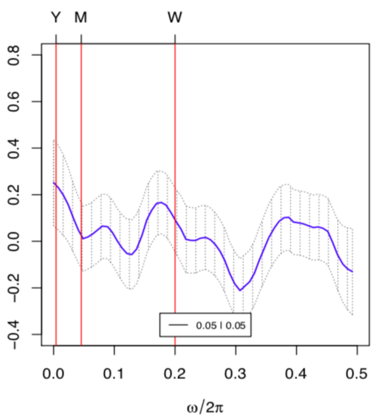


(ii) 0.5|0.5

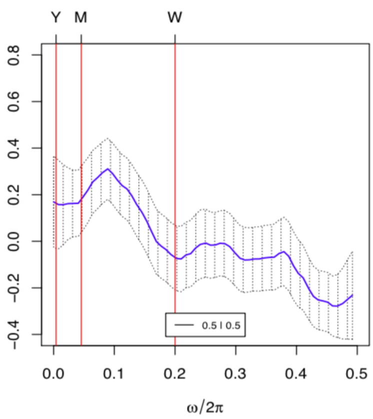


(iii) 0.95|0.95

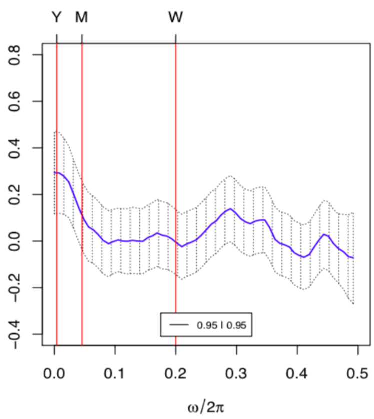
(e) AI vs Oil & Gas Refining and Marketing



(i) 0.05|0.05

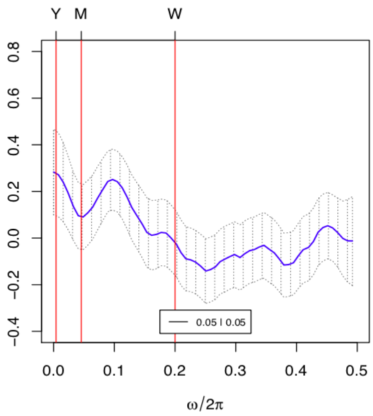


(ii) 0.5|0.5

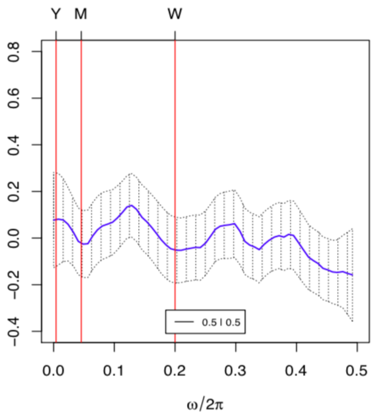


(iii) 0.95|0.95

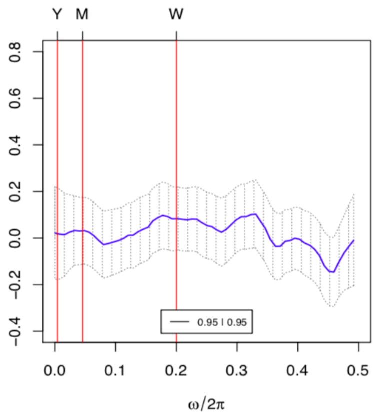
(f) AI vs Renewable energy



(i) 0.05|0.05

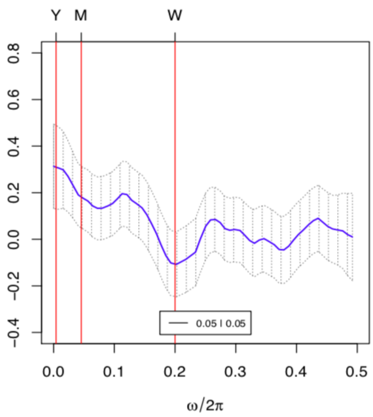


(ii) 0.5|0.5

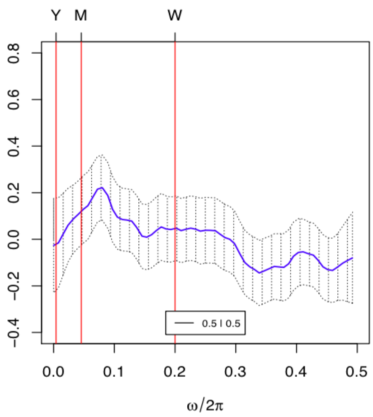


(iii) 0.95|0.95

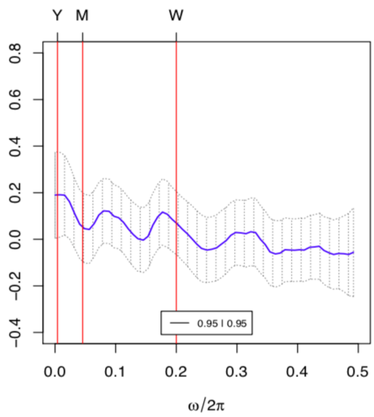
(g) AI vs Oil-related Services and Equipment



(i) 0.05|0.05



(ii) 0.5|0.5



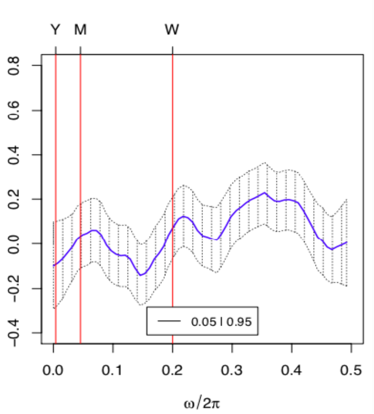
(iii) 0.95|0.95

(i) AI vs Oil & Gas Transportation Services

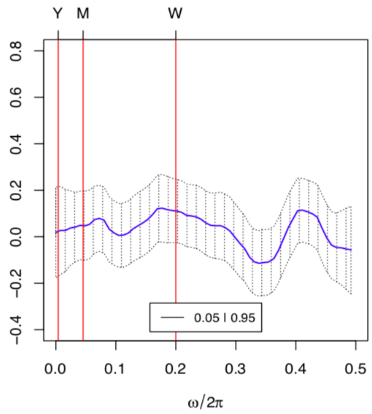
Figure 4: Quantile coherency estimates for the 0.05|0.05, 0.5|0.5 and 0.95|0.95 of the joint distribution across the different frequencies for the full sample

Note: Plots of the real part of the quantile coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The ——, - - - - and ...... line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively.

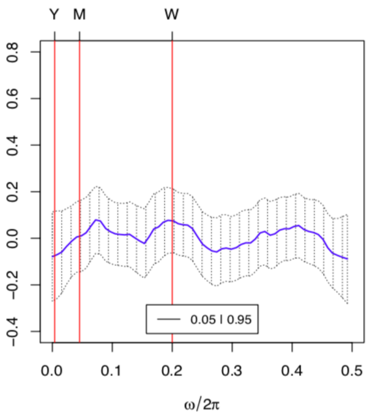
3.2.3 Dependence between the 0.05/0.95 joint distributions



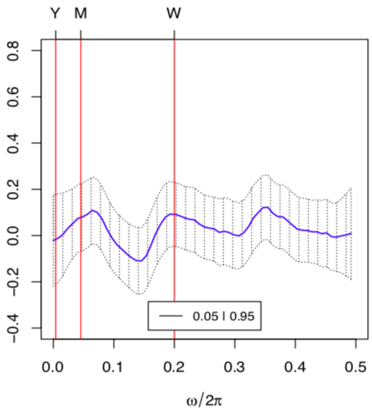
(i) AI vs Coal



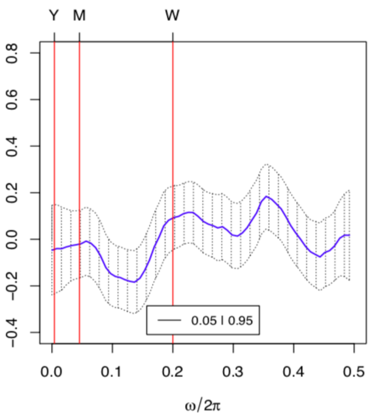
(ii) AI vs Oil & Gas Drilling



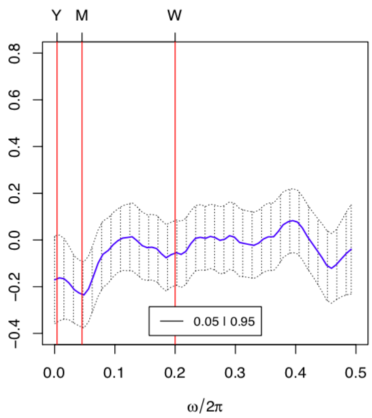
(i) AI vs Oil & Gas Exploration and Production



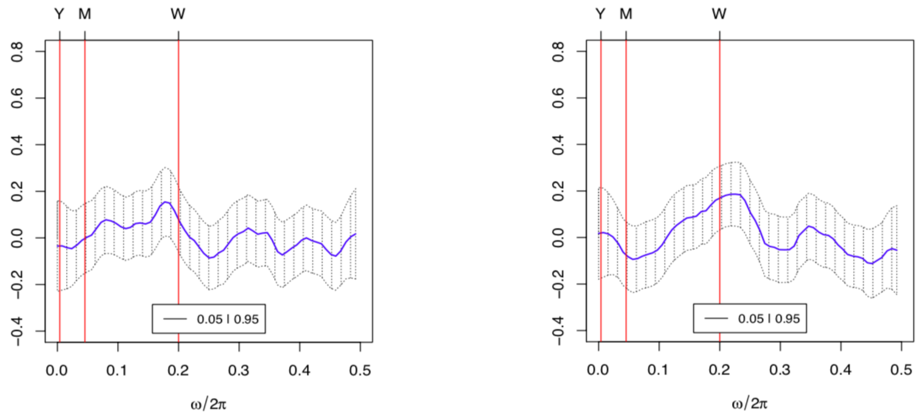
(ii) AI vs Integrated Oil & Gas Services



(i) AI vs Oil & Gas Refining and Marketing



(ii) AI vs Renewable energy

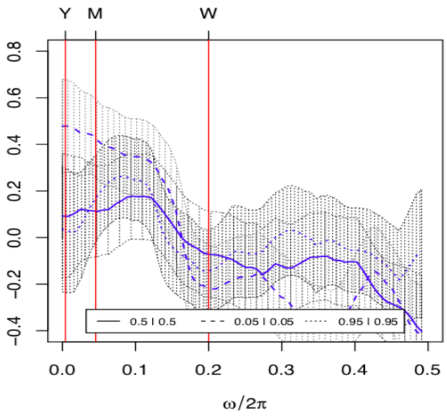


(i) AI vs Oil-related Services and Equipment

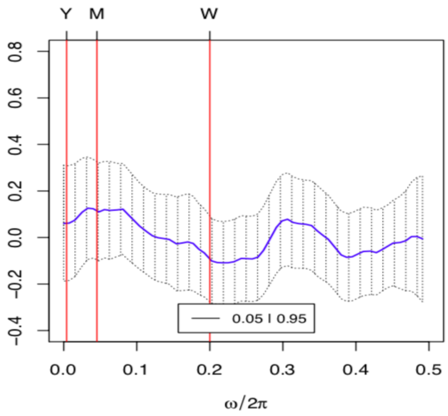
(ii) AI vs Oil & Gas Transportation Services

Figure 5: Dependence between the 0.05|0.95 quantiles of joint distribution for full sample

Note: Plots of the real part of the quantile coherency estimates of Baruník and Kley (2019) for the 0.05|0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The line corresponds to the 0.05|0.95 quantiles of the joint distribution.

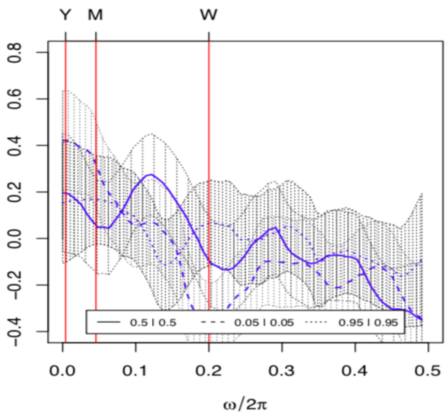


(i) 0.05|0.05; 0.5|0.5; 0.95|0.95

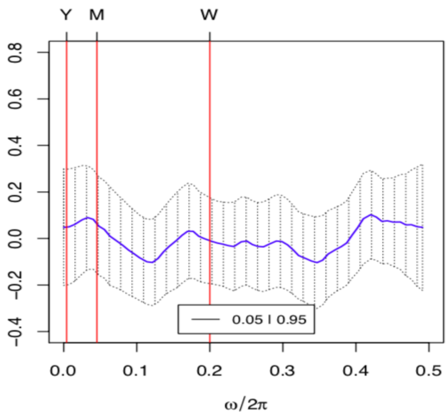


(ii) 0.05|0.95

(a)AI vs Oil & Gas Exploration and Production

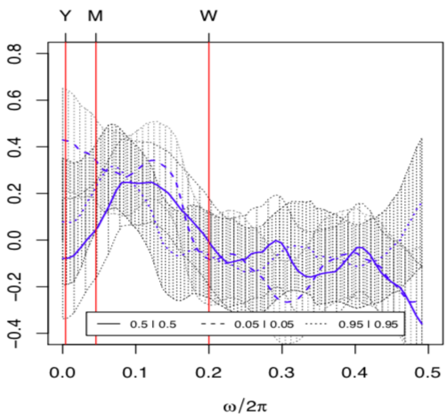


(i) 0.05|0.05; 0.5|0.5; 0.95|0.95

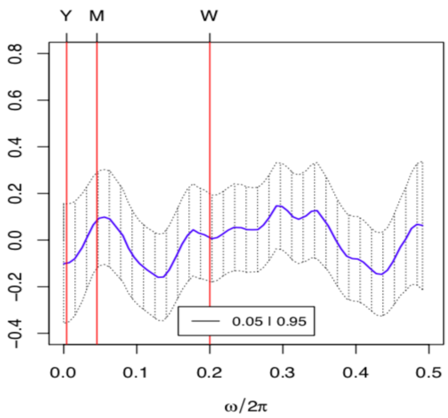


(ii) 0.05|0.95

(b)AI vs Oil & Gas Drilling

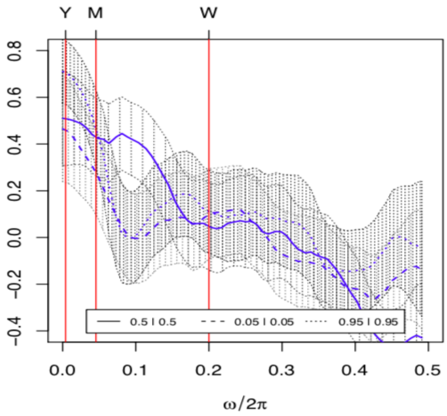


(i) 0.05|0.05; 0.5|0.5; 0.95|0.95

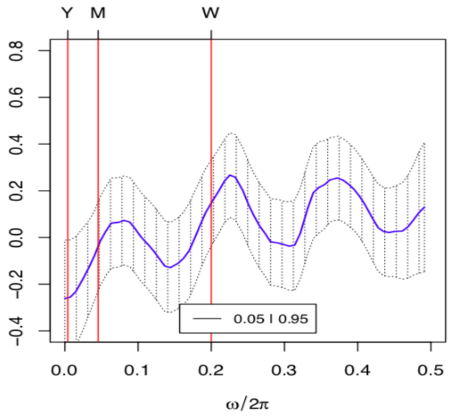


(ii) 0.05|0.95

(c)AI vs Oil & Gas Refining and Marketing

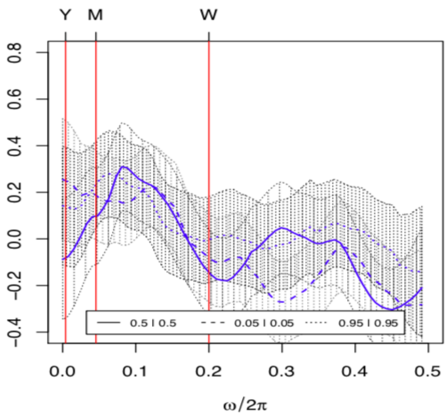


(i) 0.05|0.05; 0.5|0.5; 0.95|0.95

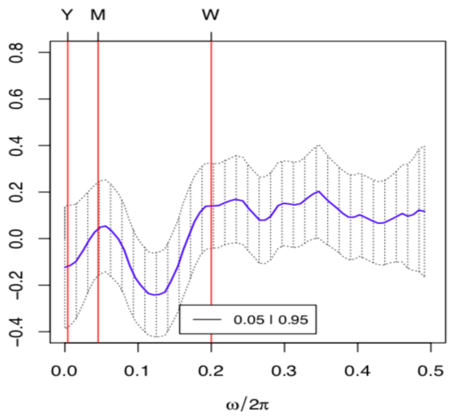


(ii) 0.05|0.95

(e)AI vs Renewable energy

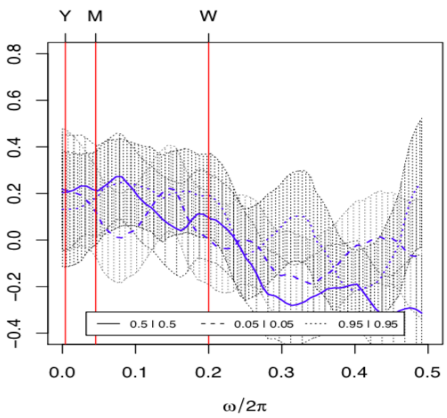


(i) 0.05|0.05; 0.5|0.5; 0.95|0.95

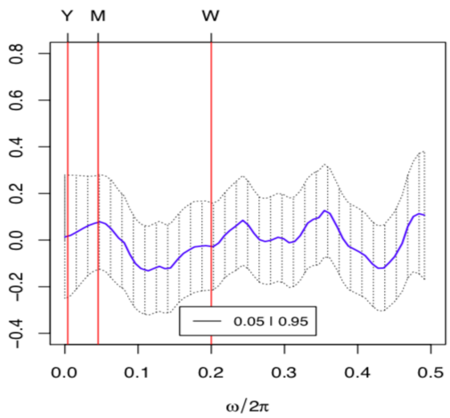


(ii) 0.05|0.95

(f)AI vs Integrated Oil & Gas services

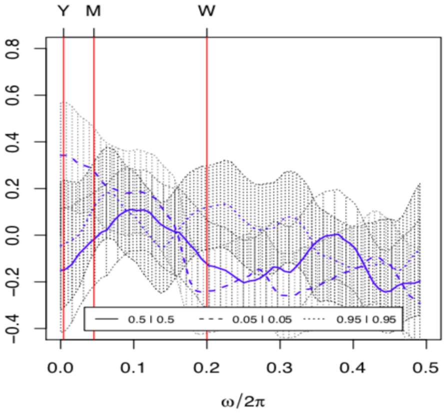


(i) 0.05|0.05; 0.5|0.5; 0.95|0.95

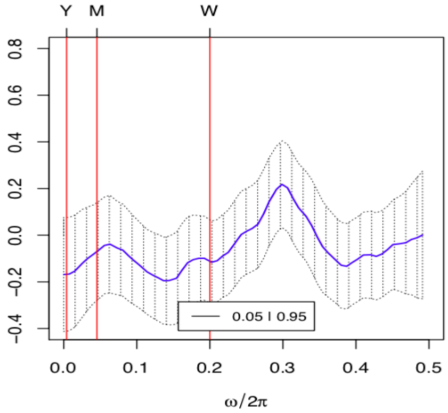


(ii) 0.05|0.95

(g)AI vs Oil & Gas Transportation Services

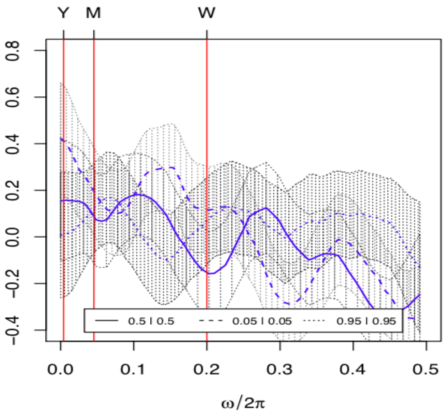


(i) 0.05|0.05; 0.5|0.5; 0.95|0.95

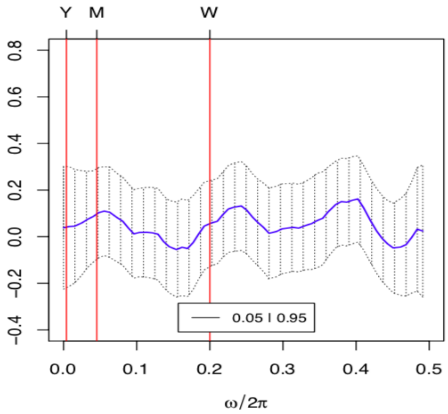


(ii) 0.05|0.95

(h)AI vs Oil-related Services and Equipment



(i) 0.05|0.05; 0.5|0.5; 0.95|0.95



(ii) 0.05|0.95

(i)AI vs Coal

Figure 6: Quantile coherency estimates for the 0.05|0.05, 0.5|0.5, 0.95|0.95 and the 0.05|0.95 of the joint distribution across the different frequencies for the COVID-19 period

Note: Plots of the real part of the quantile coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The , and line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively.

4 Conclusion

This paper relies on both linear and non-linear (including the OLS, quantile regression and quantile cross-spectral coherency) models to examine the dependence of eight energy-focused sectors on the performance of AI across different market conditions and investment horizons. The energy-focused sectors include: Oil and Gas Exploration and Productio; Oil and Gas Refining and Marketing; Integrated Oil and Gas; Oil-related Services and Equipment; Oil and Gas Transportation Services; Oil and Gas Drilling; Coal and Renewable energy. Overall, the linear model estimates show that the market returns of energy-focused sectors, especially those of renewable energy, depend strongly on the performance of AI. On the other hand, estimates from non-linear models indicate that the nature of this relationship varies across energy-focused sectors, market conditions and investment horizons. Further analysis also shows that the dependence of energy-focused sectors on AI became stronger during the COVID-19. Dependence also varies depending on whether there are positive or negative shocks on AI. In particular, when we do not consider negative or positive shocks on AI, results from the quantile regression model indicate that under a bearish market state, AI has a significant positive effect across the considered energy-focused sectors except for the Oil and Gas Transport sector. Regarding the bullish market condition, AI has a significant effect on only Integrated Oil and Gas and Oil and Gas Transport sectors. Besides, the effects on the former is negative while it is positive on the latter. When the market is in a normal state, AI has a positive effect on Renewable and the Integrated Oil and Gas sectors. For other sectors, it has a non-significant effect.

However, when we account for asymmetric positive and negative shocks on AI, we find that under a normal market condition, positive and negative shocks on AI exert significant negative and positive effects, respectively, on the stock returns of the Coal sector. Whereas we obtain opposite results for the Oil and Gas Exploration and Production as well as Oil and Gas Refining and Marketing, our results on the Oil and Gas Drilling, Integrated Oil and Gas, and Renewable energy sectors show that only negative shocks on AI exert significant (positive) effect on their returns. For Oil-related Services and Equipment sector, neither positive nor negative shocks exert any significant effect on their performance. Under the bullish market condition, we find that except for the Coal and Renewable energy sectors, positive and negative shocks on AI exert statistically significant positive and negative effects, respectively, across the considered energy-focused sectors. For Coal, only negative shocks on AI exert a significant (negative) effect on the returns of the sector whilst neither positive nor negative shocks on AI have any significant effect on the returns of Renewable energy sector. Under the bearish market condition, positive and negative shocks on AI have significant negative and positive effects, respectively, on the returns of the considered energy-focused sectors. As an exception, for the Coal sector, negative effects of positive shocks on AI are not significant.

Regarding the results from the quantile cross-spectral analysis, during normal market condition, we document evidence of negative dependence between AI and all energy-focused sectors in the weekly frequency, except for the Integrated Oil and Gas sector, which exhibit a positive dependence in this frequency. The negative dependence is strongest with the renewable energy sector but weakest with Oil and Gas Exploration and Production sector. However, under the monthly and yearly frequencies, except for the Oil and Gas exploration and production sector that shows negative dependence in the yearly frequency, other sectors show positive dependence across both time scales. Under bearish market condition, there is negative dependence in the weekly frequency, except for renewable energy, Oil and Gas Exploration and Production, and the Oil and Gas Refining and Marketing sectors. In the yearly frequency, however, dependence is generally positive while in the monthly frequency, results are mixed. As for the bullish market condition, we find that in the weekly frequency, dependence is positive for Oil and Gas Refining and Marketing sector; negative for Coal, Oil and Gas Exploration and Production, and Oil and Gas Transportation Services sectors but switches between positive and negative dependence for the remaining sectors. Results for the monthly frequency indicate that dependence is positive for the Oil and Gas Drilling, Oil and Gas Exploration and Production, Renewable energy, and the Oil and Gas Transportation Services sectors, while those of the remaining sectors switches from positive to negative. Concerning the yearly frequency, dependence is generally, positive.

Our findings hold profound and diverse implications for investors and portfolio managers. For instance, focusing on the quantile cross-spectral analysis, where weekly, monthly and yearly time scales approximated to short, medium and long-term investment horizons, our findings indicate that in the short-term under normal market condition, AI offers short-term diversification benefits to assets of the sampled energy-focused sectors, excluding those of the Integrated oil and gas sector. However, during the intermediate- and long-term, these benefits accrue only to Oil and Gas Exploration and Production. In the short-term, under bearish market condition, AI only offers diversification benefits to Coal, Oil and Gas Drilling, Integrated Oil and Gas, Oil-related Services and Equipment, and Oil and Gas Transportation Services. In the intermediate- and long-term, under bearish market condition, such diversification benefits hardly exist. During bullish market condition, our findings indicate that AI only offers diversification benefits to Coal, Oil and Gas Exploration and Production as well as Oil and Gas Transportation Services in the short term, while such diversification benefits hardly accrue across the energy-focused sectors both in the intermediate- and long-term. From a portfolio manager perspective, therefore, our findings imply that while AI may play a diversification role to the assets of energy-focused sectors, hedging decisions by portfolio managers should be sector as well as market condition specific.

Regarding investors, our findings also hold specific implications for traders and speculators that are more concerned with the short- and intermediate-term investment horizons, and institutional investors that are more concerned with the long-term investment horizon. For instance, our findings would imply that the diversification role of AI to energy-focused sectors only materializes during normal market condition, and is only beneficial to institutional investors who are interested in holding the assets of Oil and Gas Exploration and Production sector. Intuitively, our results also hold profound implications for the managers of portfolios containing stocks of AI and energy corporations during similar future financial market crisis periods like the situation created by the COVID-19 pandemic. In particular, our results show that dependence with AI stocks varies across energy sectors and investment horizons, suggesting the use of dynamic portfolio design during similar future health-induced crisis periods. Finally, our study opens up different avenues for further studies. For instance, whilst we focused on the dependence structure between the returns of AI and energy-focused sectors, future studies can focus on measuring and managing their cross-market risk transmission. Future studies could also examine the volatility dependence structure of the studied assets, which should be a direct extension of the current study while holding different implications, especially in the areas of portfolio risk monitoring and managing. Last but not the least, as indices for other types of technologies such as blockchain and Internet of Things (IoT) become available, it may also be interesting to see their dependence structure with the energy-focused sectors and compare how they vary with AI.

References

Ahmad, W., 2017. On the dynamic dependence and investment performance of crude oil and clean energy stocks. Research in International Business and Finance, 42 (2017), pp. 376-389, 10.1016/j.ribaf.2017.07.140

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., Chen, H., 2021. Artificial intelligence in sustainable energy industry: Status Quo, challenges, and opportunities. Journal of Cleaner Production, 289 (2021), 125834, 10.1016/j.jclepro.2021.125834

Ahn, J., Cho, S., 2017. Anti-logic or common sense that can hinder machine's energy performance: Energy and comfort control models based on artificial intelligence responding to abnormal indoor environments. Applied Energy, 204 (2017), pp. 117-130, 10.1016/j.apenergy.2017.06.079

Baruník, J., Kley, T., 2019. Quantile coherency: A general measure for dependence between cyclical economic variables. The Econometrics Journal, 222 (2019), pp. 131-152, 10.1093/ectj/utz002

Baur, D. G., 2013. The structure and degree of dependence: A quantile regression approach. Journal of Banking and Finance, 373 (2013), pp. 786-798, 10.1016/j.jbankfin.2012.10.015

Binder, M., Coad, A., 2011. From Average Joe's happiness to Miserable Jane and Cheerful John: using quantile regressions to analyze the full subjective well-being distribution. Journal of Economic Behavior and Organization, 793 (2011), pp. 275-290, 10.1016/j.jebo.2011.02.005

Bondia, R., Ghosh, S., Kanjilal, K., 2016. International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. Energy, 101 (2016), pp. 558–565, 10.1016/j.energy.2016.02.031

Boza, P., Evgeniou, T., 2021. Artificial intelligence to support the integration of variable renewable energy sources to the power system. Applied Energy, 290 (2021), 116754, 10.1016/j.apenergy.2021.116754

Broock, W. A., Scheinkman, J. A., Dechert, W. D., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econometric Reviews, 153 (1996), pp. 197-235, 10.1080/07474939608800353

Conyon, M. J., He, L., 2017. Firm performance and boardroom gender diversity: A quantile regression approach. Journal of Business Research, 79 (2017), pp. 198-211, 10.1016/j.jbusres.2017.02.006

Corbet, S., Goodell, J. W., Günay, S., 2020. Co-movements and spillovers of oil and renewable firms under extreme conditions: New evidence from negative WTI prices during COVID-19. Energy Economics, 92 (2020), 104978, 10.1016/j.eneco.2020.104978

Demiralay, S., Gencer, H. G., Bayraci, S., 2021. How do Artificial Intelligence and Robotics Stocks co-move with traditional and alternative assets in the age of the 4th industrial revolution? Implications and Insights for the COVID-19 period. Technological Forecasting and Social Change, 171 (2021), 120989, 10.1016/j.techfore.2021.120989

Fathi, S., Srinivasan, R., Fenner, A., Fathi, S., 2020. Machine learning applications in urban building energy performance forecasting: A systematic review. Renewable and Sustainable Energy Reviews, 133 (2020), 110287, 10.1016/j.rser.2020.110287

Ferrer, R., Shahzad, S. J. H., López, R., Jareño, F., 2018. Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. Energy Economics, 76 (2018), pp. 1-20. 10.1016/j.eneco.2018.09.022

Gallego-Álvarez, I., Ortas, E., 2017. Corporate environmental sustainability reporting in the context of national cultures: A quantile regression approach. International Business Review, 262 (2017), pp. 337-353, 10.1016/j.ibusrev.2016.09.003

Gupta, D., Shah, M., 2021. A comprehensive study on artificial intelligence in oil and gas sector. Environmental Science and Pollution Research, (2021), pp. 1-14, 10.1007/s11356-021-15379-z

Hanga, K. M., Kovalchuk, Y., 2019. Machine learning and multi-agent systems in oil and gas industry applications: A survey. Computer Science Review, 34 (2019), 100191, 10.1016/j.cosrev.2019.08.002

Henriques, I., Sadorsky, P., 2008. Oil prices and the stock prices of alternative energy companies. Energy Economics, 303 (2008), pp. 998-1010, 10.1016/j.eneco.2007.11.001

Huynh, T. L. D., Hille, E., Nasir, M. A., 2020. Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds, and cryptocurrencies. Technological Forecasting and Social Change, 159 (2020), 120188, 10.1016/j.techfore.2020.120188

Inchauspe, J., Ripple, D., Trück, S., 2015. The dynamics of returns on renewable energy companies: A state-space approach. Energy Economics, 48 (2015), pp. 325–335, 10.1016/j.eneco.2014.11.013

Jha, S. K., Bilalovic, J., Jha, A., Patel, N., Zhang, H., 2017. Renewable energy: Present research and future scope of Artificial Intelligence. Renewable and Sustainable Energy Reviews, 77 (2017), pp. 297-317, 10.1016/j.rser.2017.04.018

Kaza, N., 2010. Understanding the spectrum of residential energy consumption: A quantile regression approach. Energy policy, 38 (11) (2010), pp. 6574-6585, 10.1016/j.enpol.2010.06.028

Kalogirou, S., 2007. Artificial intelligence in energy and renewable energy systems. Nova Publishers.

Koenker, R., Bassett Jr, G., 1978. Regression quantiles. Econometrica: Journal of the Econometric Society, 46 (1978), pp. 33-50, 10.2307/1913643

Koroteev, D., Tekic, Z., 2021. Artificial intelligence in oil and gas upstream: Trends, challenges, and scenarios for the future. Energy and AI, 3 (2021), 100041, 10.1016/j.egyai.2020.100041

Kuang, Y. L., Deng, J. J., Liu, H. Y., 2001. Application of artificial intelligence in coal preparation. Zhongguo Kuangye Daxue Xuebao Journal of China University of Mining and Technology, 30 (2001), pp. 558-563,
https://www.osti.gov/etdeweb/biblio/20242639

Kumar, S., Managi, S., Matsuda, A., 2012. Stock prices of clean energy firms, oil, and carbon markets: A vector autoregressive analysis. Energy Economics, 34 (2012), pp. 215–226, 10.1016/j.eneco.2011.03.002

Li, H., Yu, H., Cao, N., Tian, H., Cheng, S., 2021. Applications of artificial intelligence in oil and gas development. Archives of Computational Methods in Engineering, 283 (2021), pp. 937-949, 10.1007/s11831-020-09402-8

Lyu, W., Liu, J., 2021. Artificial Intelligence and emerging digital technologies in the energy sector. Applied Energy, 303 (2021), 117615, 10.1016/j.apenergy.2021.117615.

Managi, S., Okimoto, T., 2013. Does the price of oil interact with clean energy prices in the stock market? Japan and the World Economy, 27 (2013), pp. 1-9, 10.1016/j.japwor.2013.03.003

Maghyereh, A., Abdoh, H., 2021. Tail dependence between gold and Islamic securities. Finance Research Letters, 38 (2021), 101503, 10.1016/j.frl.2020.101503

Maghyereh, A. I., Awartani, B., Abdoh, H., 2019. The co-movement between oil and clean energy stocks: A wavelet-based analysis of horizon associations. Energy, 169 (2019), pp. 895-913. 10.1016/j.energy.2018.12.039

Mensi, W., Hammoudeh, S., Reboredo, J. C., Nguyen, D. K., 2014. Do global factors impact BRICS stock markets? A quantile regression approach. Emerging Markets Review, 19 (2014), pp. 1-17, 10.1016/j.ememar.2014.04.002

Nasreen, S., Tiwari, A. K., Eizaguirre, J. C., Wohar, M. E., 2020. Dynamic connectedness between oil prices and stock returns of clean energy and technology companies. Journal of Cleaner Production, 260 (2020), 121015, 10.1016/j.jclepro.2020.121015

Niu, H., 2021. Correlations between crude oil and stocks prices of renewable energy and technology companies: A multiscale time-dependent analysis. Energy, 221 (2021), 119800, 10.1016/j.energy.2021.119800

Qin, Y., Hong, K., Chen, J., Zhang, Z., 2020. Asymmetric effects of geopolitical risks on energy returns and volatility under different market conditions. Energy Economics, 90 (2020), 104851, 10.1016/j.eneco.2020.104851

Rahmanifard, H., Plaksina, T., 2019. Application of artificial intelligence techniques in the petroleum industry: a review. Artificial Intelligence Review, 524 (2019), pp. 2295-2318, 10.1007/s10462-018-9612-8

Sadorsky, P., 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Economics, 34 (2012), pp. 248–255, 10.1016/j.eneco.2011.03.006

Şerban, A. C., Lytras, M. D., 2020. Artificial intelligence for smart renewable energy sector in Europe—smart energy infrastructures for next-generation smart cities. IEEE Access, 8 (2020), pp. 77364-77377, 10.1109/ACCESS.2020.2990123

Shin, W., Han, J., Rhee, W., 2021. AI-assistance for predictive maintenance of renewable energy systems. Energy, 221 (2021), 119775, 10.1016/j.energy.2021.119775

Tiwari, A. K., Jena, S. K., Mitra, A., Yoon, S. M., 2018. Impact of oil price risk on sectoral equity markets: Implications on portfolio management. Energy Economics, 72 (2018), pp. 120-134, 10.1016/j.eneco.2018.03.031

Tiwari, A. K., Abakah, E. J. A., Le, T. L., Leyva-de la Hiz, D. I., 2021. Markov-switching dependence between artificial intelligence and carbon price: The role of policy uncertainty in the era of the 4th industrial revolution and the effect of COVID-19 pandemic. Technological Forecasting and Social Change, 163 (2021), 120434, 10.1016/j.techfore.2020.120434

You, M., Li, S., Li, D., Xu, S., 2021. Applications of artificial intelligence for coal mine gas risk assessment. Safety Science, 143 (2021), 105420, 10.1016/j.ssci.2021.105420

Zahraee, S. M., Assadi, M. K., Saidur, R., 2016. Application of artificial intelligence methods for hybrid energy system optimization. Renewable and Sustainable Energy Reviews, 66 (2016), pp. 617-630, 10.1016/j.rser.2016.08.028

Zhang, Y., Li, R., Zhang, J., 2021. Optimization scheme of wind energy prediction based on artificial intelligence. Environmental Science and Pollution Research, 28 (2021), pp. 39966–39981, 10.1007/s11356-021-13516-2

Zhu, L.L. and Zhu, L.H., 2012. Application of Automated Artificial Intelligence to Monitor in Coal Industry. Meitan Jishu/ Coal Technology, 31(2012), pp.186-188.

Authors' Biographical Endnotes

Christian Urom is an Associate Professor of Economics at Paris School of Business, Paris, France. He holds a PhD in Economics from Université Paris 8. His interests are in International Macroeconomics, Energy Economics, Climate Change, Commodities and Global Financial Markets. Christian is published in leading peer-reviewed journals including *International Economics*, *Research in International Business and Finance*, *Economic Modelling*, *International Review of Financial Analysis* and *Energy Economics* etc.

Gideon Ndubuisi is an Assistant Professor of Economics at the Faculty of Technology, Policy and Management, Delft University. He has a PhD in Economics from Maastricht University. Gideon has worked and consulted for different institutions such as the German Development Institute/Deutsches Institut für Entwicklungspolitik (DIE), German Institute for Economic Research, Kiel Institute for World Economy, European Center for Economic Research, United Nations Industrial Development Organization, and World Bank.

Khaled Guesmi is the Director, Center of Research for Energy and Climate Change Change (CRECC). He is also the Director of Research Department, Economics, Energy & Policy at Paris School of Business. Khaled is also an Adjunct Professor at Telfer School of Management, University of Canada. He undertakes research and lectures on empirical finance, applied time-series econometrics, and commodity markets. Dr. Guesmi obtained his HDR (Habilitation for Supervising Doctoral Research) in July 2015. He earned a Ph.D in Economics from the University Paris Nanterre in 2011 and M.Sc in Finance from Paris I University of Sorbonne in 2005.

Ramzi Benkraien is the head of research partnerships with academic institutions and associations, and a Professor of Finance at Audencia Business School, France. He Holds a PhD from Toulouse Graduate School of Management and an HDR (State Habilitation for supervising Doctoral Research) from Western Brittany University.