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Exploring the coherency and predictability between the stocks of artificial intelligence and energy corporations

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Abstract

This paper employs wavelet coherence, Cross-Quantilogram (CQ), and Time-Varying Parameter Vector-Autoregression (TVP-VAR) estimation strategies to investigate the dependence structure and connectedness between investments in artificial intelligence (AI) and eight different energy-focused sectors. We find significant evidence of dependence and connectedness between the stock returns of AI and those of the energy-focused sectors, especially during intermediate and long-term investment horizons. The relationship has become stronger since the COVID-19 pandemic. More specifically, results from the wavelet coherence approach show a stronger association between the stock returns of energy-focused sectors and AI, while results from the CQ analysis show that directional predictability from AI to energy-focused sectors varies across sectors, investment horizons, and market conditions. TVP-VAR results show that since the COVID-19 outbreak, AI has become more of a net shock receiver from the energy market. Our study offers crucial implications for investors and policymakers.

Keywords: Artificial intelligence, Energy-firms, Quantile-dependence, Spillover

JEL Classification: O3, G10, G15, Q01, Q02, Q42

Introduction

Artificial Intelligence (AI) is impacting the future of virtually every sphere of human life. According to McKinsey Global Institute, around 70% of companies will adopt at least one type of AI technology by 2030, while less than half of large companies will deploy the full range (Inchauspe et al. 2015). It has also been estimated that the revenues of the AI market worldwide will exceed $US 3060 billion by 2024, compared to its previous value of about $US 260 billion in 2016. While these suggest the pervasiveness of AI, it is unlikely to slow down any time soon. Indeed, anecdotal evidence suggests that AI-related activities, measured either by the number of resources devoted to them or their outputs, have increased significantly in recent times (Furman and Seamans 2019; Vidya and Prabheesh 2020).

The emergence of AI is seen worldwide as a major platform for improving competitiveness and maintaining national security, and applying AI to energy is one of the priorities (Jha et al. 2017). With the growing concerns about the depletion of fossil fuels, climate change, and the need to achieve sustainable growth, various projects supporting the development and use of renewable energies are related to AI technologies. Technology might reduce the cost of greenhouse gases through product innovations, the higher energy efficiency of manufacturing processes, cost reductions in low-emission energy conversion, and improvements in fossil energy conversion (Tekic and Koroteev 2019). According Gupta and Shah (2021), AI has been used to increase the production rate, minimize the lifting cost, and enhance the modeling of reservoirs and maintenance prevention in the Oil and Gas industry. In the clean energy sector, it has been used for predictive maintenance, among others (Sadorsky 2012). AI plays a significant role in energy production, supply, and consumption (Ahmad et al. 2021). It has also successfully predicted and learned consumers' habits, values, motivations, and personalities, which help bolster the balancing and effectiveness of the energy system and allow for creating policies more effectively (McKinsey Global Institute 2018).

Previous literature focused on the interdependences and connectedness between technology stocks and clean energy reveal dependence, causality, and spillovers among these variables (Ahmad 2017; Bondia et al. 2016; Hanga and Kovalchuk 2019; Koroteev and Tekic 2021; Linton and Whang 2007; Maghyereh et al. 2019; Mensi et al. 2021; Nasreen et al. 2020; Politis and Romano 1994; Zhang et al. 2020). The view held in this literature is that increases in technological innovation and, hence, stock prices of technology companies would drive those of clean energy firms for at least two reasons. First, clean energy companies depend heavily on inputs from technology companies (Elsayed et al. 2020). Second, as the success of clean energy companies depends upon the successful breakthrough or adoption of specific technologies, investors may perceive clean energy stocks as similar to stocks of technology companies (Bondia et al. 2016). While these conjectures are specific to clean energy, they could be extended to other energy sources, such as Coal and oil and gas, as they are much quicker to adopt new technologies than to experiment with and change their business models (Shin et al. 2021).

Further, while the erstwhile literature does not specify the type of technology in question, a specific case can be made for AI as it is today's most crucial general-purpose technology (Koop and Korobilis 2014). Therefore, how investments in AI relate to those of the energy sector/market remains to be explored. Our current study aims to fill this gap. Specifically, we examine the potential implications of the recent surge in AI for the energy-focused sectors by analyzing the relationship between the stock returns of AI and energy-focused sectors. Our analysis considers the co-movement, lead-lag, tail dependence, and connectedness between AI and energy sectors. To the best of our knowledge, this is the first paper to analyze such relationships. We also consider the change that may have occurred from the COVID-19 pandemic by performing our analysis on two samples: the "pre-pandemic" and "during-pandemic" periods. The energy market was among the most hit and affected by the current pandemic due to supply chain disruption that pushed firms and economies to search for alternative energy sources (Ali et al. 2020; Uddin et al. 2019; Zahraee et al. 2016). This led to inefficiency in the energy market. It thus becomes imperative that analysis focused on the energy market differentiates between periods, as market fundamentals, as well as the behaviors and expectations of market participants, are likely to differ between both periods. Hence, our focus is on the two samples.

We address our research objectives using daily frequency time series data. Our empirical measure of AI relies on the NASDAQ AI price index following (Henriques and Sadorsky 2008) and (Tekic and Koroteev 2019), while our empirical measure of energy-focused sectors follows (Corbet et al. 2020) and uses eight energy-focused sectors defined based on their related TRBC Sector Code in the Datastream international (more on this in the data section). Concerning the empirical strategies, we rely on the Maximal Overlap Discrete Wavelet Transform (MODWT), for the co-movement and lead-lag dependence analysis. More generally, our motivation for adopting the Wavelet approach is because it allows the analysis of time series that contain varying power at different frequencies. Hence, it provides a unified framework to measure dependencies between two variables in a time–frequency space (see Akoum et al. 2012). We, however, focus on MODWT as it has been shown in previous studies to outperform the Discrete Wavelet Transform (DWT) (see Failed 2021; Linton and Whang 2007). Regarding the tail dependence analysis, we use the Cross-Quantilogram (CQ) approach of Gupta and Shah (2021). The importance of adopting this approach over other strategies, such as the vector autoregressive framework, multifactor asset pricing model, dynamic conditional correlation, and copulas that appear to be similar, cannot be over-overemphasized. While copulas and the CQ approach measure extreme-value dependence, the other approaches are only able to measure a mean-to-mean dependence. Nevertheless, the CQ approach is technically more informative than copulas as it permits the usage of arbitrary quantiles and very large lags, allowing us to jointly detect the direction, magnitude, and duration of the dependence between variables. Moreover, CQ is a model-free measure and is not reliant on any moment condition (Tiwari et al. 2021). Finally, we rely on the TVP-VAR spillover method of Antonakakis et al. (2020) to analyze the return connectedness between AI and the energy-focused sectors. We apply the TVP-VAR spillover method on the frequency components realized from the MODWT technique to enable us to examine the market return connectedness between AI and energy-focused sectors across frequencies corresponding to the short, intermediate, and long-term investment horizons.

The remainder of the paper is organized as follows. A preview of related literature is presented in the second section. The third section presents the data and empirical strategies, while the results are presented and discussed in section four. We conclude with Sect. 5.

Literature review

Our paper speaks directly to two strands of literature that have emerged independently. The first relates to the literature examining interdependences and connectedness between oil price, technology, and clean energy stocks (e.g., see (Ahmad 2017; Bondia et al. 2016; Huynh et al. 2020; Koroteev and Tekic 2021; Linton and Whang 2007; Maghyereh et al. 2019; Mensi et al. 2021; Nasreen et al. 2020; Politis and Romano 1994)). Studies within this literature have examined bilateral market responses and volatility spillovers among these variables across time, space, and market conditions. Hanga and Kovalchuk (2019), for instance, used the VAR model and found that changes in oil prices influence the stock prices of technology stock, while technology shocks have a more significant impact on clean energy stock prices compared with oil price shocks. Politis and Romano (1994) analyzed the dynamic correlation and risk transmission between oil prices, clean energy stock prices, and technology companies using several multivariate GARCH models and found results that are similar to those of Hanga and Kovalchuk (2019). More recently, Kalogirou (2007) investigated the degree to which firms' stock returns in the energy and technology sectors depend on oil demand and supply shocks by accounting for quantile dependence in shock transmission and causal linkages. They show that the substitution between oil and clean commodities occurs only in the long run when the oil market is subject to demand-driven shocks.

Maghyereh et al. (2019) used a Markov-switching VAR model to analyze the relationship between oil, clean energy, and technology stock prices. They found that in the post-structural break period, oil and technology stock prices positively impact clean energy stock prices, whilst their pre-structural break period results are consistent with (Hanga and Kovalchuk 2019). Bondia et al. (2016) found that while technology stock prices and oil prices impact the stock prices of clean energy companies in the short run, there is no causality running towards prices of alternative energy stock prices in the long run. Ahmad (2017) examines the directional spillover between returns and volatilities of crude oil prices and prices of clean energy and technology stocks. Among other things, the results showed bilateral interdependencies between clean energy and technology stocks, while crude oil exhibits limited interdependence with clean energy and technology.

In general, although the above studies show evidence of a significant relationship between technology and energy stocks, what remains under-explored in this literature is the technology type in question. Our paper, therefore, advances this literature by providing evidence on AI—a specific type of technology that characterizes modern technological advancement. Besides AI being an important general-purpose technology of today with a wide cross-sectoral application (Koop and Korobilis 2014), the need for such focus draws extensively from the increasing dependence of the energy sector on AI solutions (Boza and Evgeniou 2021; Gupta and Shah 2021; Hanga and Kovalchuk 2019; Jha et al. 2017; Kalogirou 2007; Li et al. 2020; Zahraee et al. 2016; Zhang et al. 2020).

The second literature our paper speaks to is the more nascent literature examining the relationship between AI and financial stock markets to detect potential hedging and/or diversification ability of AI for stocks (e.g., see (Demiralay et al. 2021; Henriques and Sadorsky 2008; Tekic and Koroteev 2019)). For instance, Henriques and Sadorsky (2008) analyzed the role of AI and green bonds in portfolio diversification via copulas and the Generalized Forecast Error Variance Decomposition methods. Results suggest that portfolios consisting of these assets exhibit heavy-tail dependence and high volatility transmission in the short term. Overall, they conclude that the NASDAQ AI and general equity indexes are not good hedging instruments for each other. On the other hand, Demiralay et al. (2021) examines the interdependence between AI stocks and traditional and alternative assets using wavelet coherence analysis in time–frequency space. Results suggest that co-movements between AI stocks and other assets significantly depend on the wavelet decomposition levels, suggesting time-scale-dependent investment benefits. Wavelet coherence and correlations have substantially increased, mostly in the low frequencies, during the COVID-19 pandemic. The study's conclusion highlights a fresh perspective on the potential hedging and diversification benefits of AI stocks.

Tekic and Koroteev (2019) investigate the dependence structure and dynamics between AI stocks and carbon prices in the era of the 4th industrial revolution by employing time-varying Markov switching copula models from December 2017 to July 2020. Findings show a negative and asymmetric dependence structure for the return series between AI stock prices and carbon prices, highlighting a stronger lower tails dependence. That said, the finding is similar to Demiralay et al. (2021), affirming that AI is a haven for carbon prices. This conclusion is maintained even with the introduction of the effect of economic policy uncertainty, equity market volatility, and the recent COVID-19 pandemic. Although these studies provide insights into the hedging and/or diversifying ability of AI for traditional assets, such a role in the context of energy-focused sectors and their assets still needs to be explored. Given the high application of AI solutions across different energy sectors, the need for an analysis that considers the interdependences and connectedness between AI and energy-focused sectors cannot be overstated. Our study fills this gap by empirically analyzing the tail dependence, co-movement, and directional predictability among AI and different energy-focused sectors' stock prices. Table 1 presents a summary of the above-reviewed related studies.

Data and empirical methods

Data

Two variables are important for our analysis: indicators of AI and energy-focused sectors. Inspired by Henriques and Sadorsky (2008) and Tekic and Koroteev (2019), we measure AI using the NASDAQ AI price index. The NASDAQ AI index was 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 the artificial intelligence and robotics industry. For the energy-focused sectors, we follow (Corbet et al. 2020) that uses 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 (EXP); (ii) Oil & Gas Refining and Marketing (REF); (iii) Integrated Oil & Gas (INT); (iv) Oil-related Services and Equipment (SEQ); (v) Oil & Gas Transportation Services (TRA); (vi) Oil & Gas Drilling (DRI); (vii) Coal (COAL); and (iii) Renewable Energy (REN). As noted in Corbet et al. (2020), the scale and dependence, as well as directional predictability, will offer substantial information about broad energy market dynamics during periods of economic downturn, but also potential channels through which diversification opportunities exist. The final dataset used for the analysis comprises daily frequency time series data that covers the period from December 18, 2017, to June 14, 2021.

Figure 1, panel i–ix, shows the trend of the daily returns of the energy-focused sectors and AI for the entire sample period. The daily returns is computed as $r_t = 100 \times (lnp_t - lnp_{t-1})$. The plots show that across all energy sectors and AI, the levels of return increased significantly following the large drop in prices during the COVID-19 pandemic. Inspired by this, we analyze dependence for the pre-COVID and the post-COVID pandemic periods by dividing our dataset into two sub-samples. The

Table 1 Related studies

Studies	Country	Period	Model	Variables
Henriques and Sadorsky (2008)	Global	2017—2020	Copulas	NASDAQ AI; Oil; Bitcoin; Green bond; MSCI World; MSCI USA; Gold; VIX
Demiralay et al. (2021)	USA	2017—2021	Wavelet	Nasdaq CTA AI & Robotics Index; S&P U.S. Government Bond Index; S&P U.S. Corporate Bond Index; S&P Commodity Index; CRIX; S&P 500 Index
Tekic and Koroteev (2019)	USA	2017–2020	Copula	AI Index; Carbon Price Index
Henriques and Sadorsky (2008)	Global	2017–2020	Copulas	NASDAQ AI index; oil; gold; VIX; MSCI equity indices
Linton and Whang (2007)	Global	2001–2018	Wavelet; DCCGARCH	WTI; WilderHill Clean Energy Index; FTSE ET50 Index
Huynh et al. (2020)	Global	2001–2014	multi-factor asset pricing model	WilderHill New Energy Global Innovation Index; WTI; MSCI World index
Mensi et al. (2021)	Global	2000–2017	Wavelet	Oil price;clean energy and technology companies price indices
Ahmad (2017)	USA	2005–2015	Diebold and Yilmaz (2012)'s method; DCCGARCH	WilderHill Clean Energy Index;NYSE Arca Technology Index;futures contracts of WTI
Bondia et al. (2016)	Global	2003–2015	Threshold cointegration approach	WilderHill New Energy Global Innovation Index;New York Stock Exchange Arca Tech 100 Index; WTI;10-Year Treasury Constant Maturity Rate
Hanga and Kovalchuk (2019)	USA	2001–2007	VAR	WilderHill Clear Energy Index; Arca Technology 100 index; S & P500;Oil
Maghyereh et al. (2019)	USA	2001–2010	MSVAR	WilderHill Clean Energy index;Arca Tech 100 index; WTI;US Treasury bill interest rate
Politis and Romano (1994)	USA	2001–2010	Multivariate GARCH	WilderHill Clean Energy Index; NYSE Arca Technology Index; WTI futures contract
Nasreen et al. (2020)	USA	2006–2018	EEMD;TDIC	WTI futures; WilderHill Clean Energy Index;NYSE Arca Technology Index
Koroteev and Tekic (2021)	Global	2005–2008	VAR	The Wilder Hill New Energy Global Innovation Index;S & P Global Clean Energy Index;WTI;carbon price; yield on a 3-month US Treasury bill;Arca Tech**100 index; S & P500

pre-COVID sample covers the period from December 18, 2017, to November 30, 2019, while the post-COVID-19 sample covers the period from December 1, 2019, to June 14, 2021. This enables us to explore and compare the degrees of dependence across these two sample periods. Table 2 Panel A–B, we show summary statistics for all the series under the two sample periods. Table 2 indicates that the mean return for AI and REN was higher in the post-COVID sub-sample. Also, while the remaining variables possess

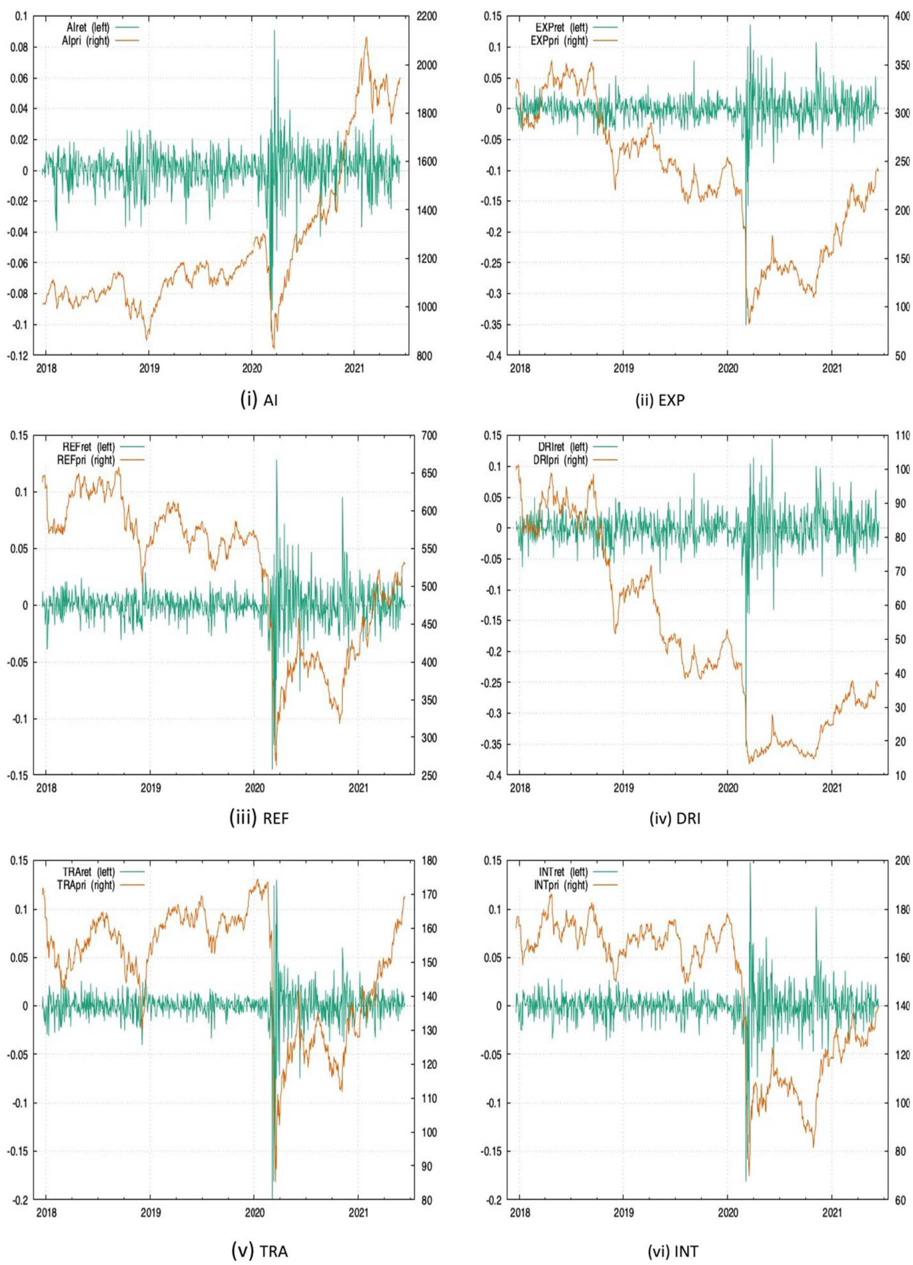


Fig. 1 Plots of prices and returns series for energy-focused firms and AI. Note: (i)AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN)

negative mean returns in the pre-COVID sample, the mean returns for EXP, TRA, and COAL become positive for the post-COVID subsample. However, across all the markets, risks became higher in the post-COVID sample, as shown by significant increases in their standard deviation.

Figure 2 Panel a–b presents the unconditional correlations among the variables for both samples using separate heatmaps. The heatmaps show that for all asset pairs, the level of correlation among the markets increased in the post-COVID sub-sample, except

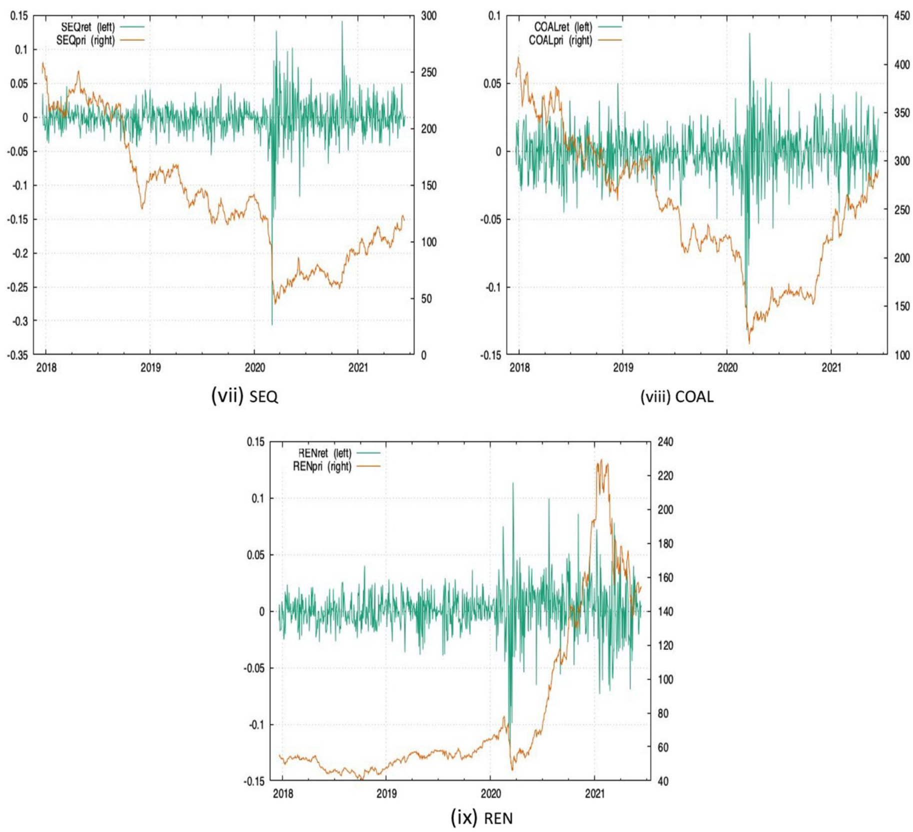


Fig. 1 continued

for the correlation between EXP and DRI, which remains approximately the same (0.88). Also, Table 2 indicates that across the two sub-samples, all the series depart from the normality condition as shown by the significant Jarque–Bera test for normality in the return distributions. Moreover, all the variables in both sub-samples are negatively skewed, as shown by the skewness coefficients, while they exhibit excess kurtosis, suggesting fatter tails than those of normal distribution. For both samples, 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 after the first difference. This feature is particularly crucial given the econometric techniques adopted in this study. Expressly, the cross-quantilogram and TVP-VAR models assume strict stationarity in the return series. Moreover, before implementing the cross-quantilogram approach, testing if all the variables exhibit nonlinear characteristics is necessary. Following this, Table 3 shows the BDS test proposed by Brock et al. (1996). The BDS test results on the VAR model's filtered residuals for all the time series in different dimensions (m = 2, 3, …, 6). For all variables, the null hypothesis of linearity is rejected, suggesting that the residual series of the selected energy sectors and artificial intelligence are nonlinear. Hence, the nonlinear models, such as the cross-quantilogram and frequency-based connectedness methods applied in this study, are appropriate for examining the interactions between AI and energy-focused sectors

Table 2 Descriptive statistics for the pre-and post-COVID sample

Variable	Mean	Min	Med	Max	Std. Dev	Skew	Ex. Kurt	JB	ADF
Panel A: pre-COVID									
AI	0.032	0.107	−3.939	2.653	1.041	−0.568	1.119	52.152***	−18.958***
EXP	−0.078	−0.007	−4.334	7.785	1.534	−0.104	1.435	43.131***	−20.598***
REF	−0.027	0.026	−3.902	3.375	0.962	−0.446	1.216	46.661***	−19.634***
INT	−0.008	0.034	−3.594	2.852	1.052	−0.396	0.644	21.388***	−20.467***
SEQ	−0.135	−0.079	−5.577	4.963	1.606	−0.068	0.390	34.901***	−19.688***
TRA	−0.008	0.000	−4.014	2.722	0.975	−0.372	1.043	38.151***	−20.662***
COAL	−0.128	−0.096	−4.982	5.020	1.444	−0.054	0.391	23.157***	−20.052***
DRI	−0.163	−0.075	−7.355	8.942	2.067	−0.078	0.913	17.587***	−19.577***
REN	0.017	0.021	−3.924	4.041	1.256	−0.056	0.319	23.437***	−20.032***
Panel B: post-COVID									
AI	0.126	0.261	−10.480	9.101	1.731	−1.054	8.830	1352.8***	−11.201***
EXP	0.021	−0.005	−35.144	13.639	3.432	−2.761	29.222	14,519.6***	−9.6683***
REF	−0.014	−0.025	−14.512	12.857	2.404	−0.837	9.780	1616.2***	−12.525***
INT	−0.045	0.001	−18.103	14.882	2.603	−1.141	13.706	3169.2***	−12.017***
SEQ	−0.017	−0.081	−30.650	14.242	3.511	−1.697	16.486	4650.9***	−12.383***
TRA	0.009	0.216	−19.976	13.033	2.569	−2.288	21.471	7912.1***	−10.097***
COAL	0.086	0.154	−13.202	8.737	2.153	−0.936	5.759	602.03***	−12.481***
DRI	−0.050	−0.088	−35.429	14.498	3.844	−1.968	19.022	6194.7***	−11.392***
REN	0.242	0.440	−12.129	11.412	2.720	−0.405	3.099	168.37***	−11.619***

JB denotes the Jarque–Bera test statistics for normality; ADF is the Augmented Dickey-Fuller test for stationarity while *** denotes significance at 1% level

Note: (i)AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN)

Empirical methods

In this paper, we are concerned with the dependence, directional predictability, and frequency-based connectedness among the returns of AI and energy-focused sectors. We employ recent novel econometric techniques, including the wavelet coherence, cross-quantilogram, and TVP-VAR connectedness approaches. This section describes these empirical strategies.

Wavelet coherence analysis

In line with our research objectives, we first provide evidence of dependence and co-movement between AI and each sector of energy-focused corporations across different time scales. We use the wavelet technique to retrieve the frequency domains using the Maximal Overlap Discreet Wavelet Transform (MODWT) to do this. It is well discussed in previous studies that the MODWT has some crucial advantages over the Discrete Wavelet Transform (DWT). For instance, Linton and Whang (2007) argues that the MODWT is more appropriate for handling a series of any sample size, including a non-dyadic length sample size. Failed (2021) has also shown that the MODWT does not institute phase shifts, which has the likelihood of altering the location of events in time, and it is translation-invariant given that a shift in signal does not substantially disrupt the pattern of wavelet transform coefficients.

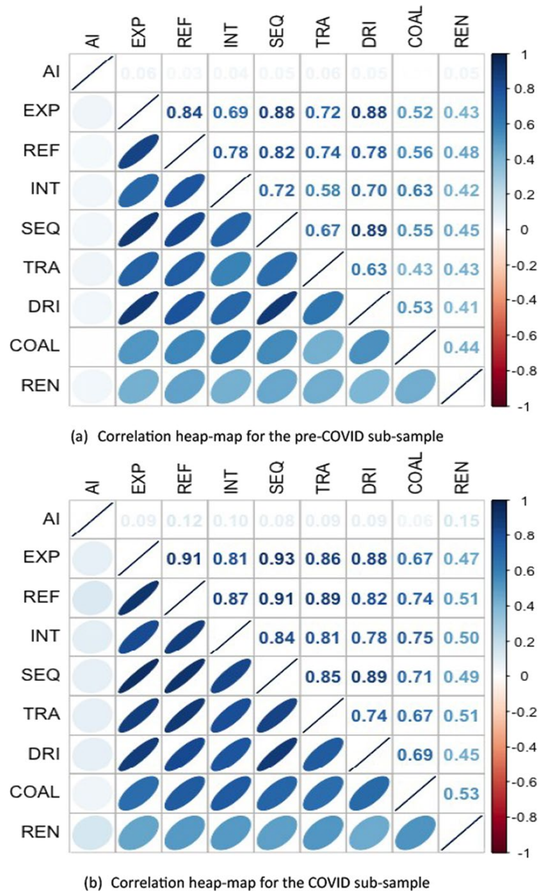


Fig. 2 Correlation heatmaps for the pre-COVID and post-COVID pandemic sub-sample periods. Note: (i)AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN)

Indeed, as described in Managi and Okimoto (2013), the MODWT wavelet and scaling coefficient $\tilde{w}_{j,t}$ and $\tilde{v}_{j,t}$ for a return series r_t may be written as:and

$$\tilde{w}_{j,t} = \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \tilde{h}_{j,l} r_{t-j}$$

$$\tilde{v}_{j,t} = \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \tilde{g}_{j,l} r_{t-j} \tag{1}$$

where L denotes the filter length. Relying on the least asymmetric decomposition technique of Daubechies (1998) and Antonini et al. (1992), we generate the multi-scale decomposed return series corresponding to a filter length, $L = 8$. Hence, the decomposed signals of the multi-resolution analysis in the MODWT may be expressed as:

$$r_t = S_j(t) + \sum_{j=1}^{J} d_j(t)$$

Table 3 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)
EXP	0.0166***	0.0327***	0.0422***	0.0476***	0.0493***
	(5.3121)	(6.5900)	(7.1253)	(7.7059)	(8.2683)
REF	0.0325***	0.0630***	0.0843***	0.0948***	0.0978***
	(9.9651)	(12.159)	(13.662)	(14.737)	(15.765)
DRI	0.0199***	0.0353***	0.0432***	0.0467***	0.0478***
	(6.5544)	(7.2882)	(7.4906)	(7.7617)	(8.2188)
TRA	0.0331***	0.0642***	0.0853***	0.0992***	0.1044***
	(9.88411)	(12.014)	(13.404)	(14.961)	(16.331)
INT	0.0266***	0.0490***	0.0618***	0.0676***	0.0678***
	(8.3151)	(9.6178)	(10.172)	(10.676)	(11.101)
SEQ	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)

(i) AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN)

where the smoothed representation of the series r_t at scale J, $S_J(t)$ and the wavelet scales, $d_J(t)$, which represents local fluctuation throughout returns associated with each scale j $\{j = 1, \cdots, J\}$ may be written as:

$$S_J(t) + \sum_{l=-\infty}^{+\infty} h(l) S_{J-1}\left(t + 2^{j-1} \times l\right) \tag{2}$$

and

$$d_J(t) + \sum_{l=-\infty}^{+\infty} g(l) S_{J-1}\left(t + 2^{j-1} \times l\right) \tag{3}$$

As in previous studies, including Linton and Whang (2007) and Managi and Okimoto (2013), we decompose all the nine-return series for this study into 5 wavelet scales (d_1, ..., d_5), which conform to the following: d_1 represents 2–4 days; d_2 captures 4–8 days; d_3 denotes 8–16 days, d_4 denotes 16–32 days while d_5 relates to 32–64 days. Following, we construct and examine dependence across three investment horizons such that the short-term, intermediate-term, and long-term horizons are as follows: d_1 represents the short-term; the sum of the series corresponding to d_2, $d_{3,}$ and d_4 denotes the intermediate-term, while the d5 denotes the long-term horizon.

Furthermore, the cross-wavelet transform and complementary wavelet coherency of two series $x(t)$ and $y(t)$ may be written as:

$$W_{xy}(\tau,s) = W_x(\tau,s)\tilde{W}_y(\tau,s) \tag{4}$$

and

$$R_{xy}(\tau,s)\frac{\left|s\left(W_{xy}(\tau,s)\right)\right|}{\sqrt{s(|W_{xx}(\tau,s)|)s\left(\left|W_{yy}(\tau,s)\right|\right)}} \tag{5}$$

where the wavelet transforms of x and y are denoted by $W_x(\cdot)$ and $W_y(\cdot)$, respectively, while $S(\cdot)$ is the smoothing operator in both scale and time. As expected, we move further to explore the dependence across time and frequency using the phase difference defined as follows:

$$\psi_{xy}(\tau,s) = tan^{-1}\left\{\frac{\Im\left(W_{xy}(\tau,s)\right)}{\Re\left(W_{xy}(\tau,s)\right)}\right\} \tag{6}$$

where $\Im(\cdot)$ and $\Re(\cdot)$ represent the real and imaginary parts of the cross-wavelet spectrum.

The cross-quantilogram (CQ) model

In line with the second research objective, we proceed to describe the CQ technique with which we examine dependence and directional predictability between AI and returns of energy-focused sectors. The CQ approach of Gupta and Shah (2021) extends the single time-series quantilogram of Li et al. (2020). Suppose that the conditional distribution function of the series θ_{1t} given θ_{2t} with density function $f_{\theta i|xi}(.|x_{it})$, and the associated conditional quantile function is stated as $q_{i,t}(\alpha_i) \equiv infv$: $F\theta_i|x_i(|x_{it} \geq \alpha_i)$ for $\alpha_i \in (0,1)$, for $i=1$, 2. We set θ_{1t} as AI and θ_{2t} as each energy corporation, respectively. If α represents the range of quantiles, the CQ measures the serial dependence between two events such as $\{\theta_{1t} \leq q_1(\alpha_1)\}$ and $\{\theta_{2t} \leq q_2(\alpha_2)\}$ for arbitrary quantiles. The quantile-hit or quantile-exceedance process for $i=1{,}2$ as in the literature may be written as: $\{1[\theta_{it} \leq q_i(\cdot)]\}$.

The CQ is specified as the cross-correlation of the quantile-hit process of α-quantile with k lags given as:

$$\rho_\alpha(k) = \frac{E\left[\Psi_{\alpha 1}\left(\theta_{1,t} - q_{1,t}(\alpha_1)\right)\Psi_{\alpha 2}\left(\theta_{2,t-k} - q_2(\alpha_2)\right)\right]}{\sqrt{E\left[\Psi^2_{\alpha 1}\left(\theta_{1,t} - q_{1,t}(\alpha_1)\right)\right]}\sqrt{\left[\Psi^2_{\alpha 2}\left(\theta_{2,t} - q_2(\alpha_2)\right)\right]}} \tag{7}$$

For $k=0,\pm1,\pm2,\ldots$, where $\Psi_\alpha(v) \equiv 1[v<0]-\alpha$, $1[\cdot]$ is the indicator function, and $1[\theta_{i,t} \neq q_i(\alpha_{\ i})]$ represents the quantile-hit or quantile-exceedance process. Assume $\alpha=(\alpha_1, \alpha_{\ 2})=(\alpha_{1N}, \alpha_{0N})$, $\rho_\alpha(1)$ denotes the cross-correlation between AI returns that are below or above quantile $q_{0N}(\alpha_{0N})$ on the day t and the return on eight energy corporations on the day t being below or above quantile $q_{1N}(\alpha_{IN})$. If $\rho_\alpha(1)=0$, returns on AI being below or above quantile $q_{0N}(\alpha_{0N})$ in day t does not always permit the prediction of whether the subsequent returns on energy corporations will be above or below quantile $q_{1N}(\alpha_{IN})$ in the next day. In contrast, $\rho_\alpha(1)\ \neq 0$ captures one-day directional predictability from the returns on AI to the returns on energy sectors at $\alpha=(\alpha_{1N}, \alpha_{\ 0N})$.

As documented in Zhang and Du (2017), formulating a sampled analog of the CQ given the series $\{\theta_1,\theta_2\}_{t=1}^{T}$, requires solving the given sets of minimization problems to compute the unconditional quantile functions:

$$\hat{q}_1(\alpha_1) = \arg min_{v1\in R} \sum_{t=1}^{T} \pi_{\alpha 1}(\theta_1 - v_1)$$

$$\hat{q}_2(\alpha_2) = \arg min_{v2\in R} \sum_{t=1}^{T} \pi_{\alpha 2}(\theta_2 - v_2)$$

where, $\pi_\alpha(\mu) \equiv \mu(\alpha - 1[\mu < 0])$. The CQ of the sample counterpart is computed as given below:

$$\hat{\rho}\alpha(k) = \frac{\sum_{t=k+1}^{T} \Psi_{\alpha 1}(\theta_{1,t} - \hat{q}_{1,t}(\alpha_1)\Psi_{\alpha 2}\left(\theta_{2,t-k} - \hat{q}_{2,t-k}(\alpha_2)\right)}{\sqrt{\sum_{t=k+1}^{T} \Psi_{\alpha 1}^2(\theta_{1,t} - \hat{q}_{1,t}(\alpha_1)}\sqrt{\sum_{t=k+1}^{T} \Psi_{\alpha 2}^2(\theta_{2,t-k} - \hat{q}_{2,t-k}(\alpha_2)}} \quad (8)$$

where $k = 0, \pm1, \pm2, \ldots, \rho_\alpha(\hat{k})=0$ represents no directional predictability from returns on AI to energy corporations. Furthermore, as documented in Gupta and Shah (2021), a quantile-based version of the Ljung-Box-Pierce statistics based on the hypothesis of H_0: $\rho_\alpha(k)=0$ for all $k \in 1, \ldots, p$ against the alternative $H1 : \rho_\alpha(k)6 = 0$ for some $k \in 1, \ldots, p$ may be written as:

$$\hat{Q}_\alpha^{(p)} \equiv \frac{T(T+2)\sum_{t=1}^{p} \hat{\rho}_\alpha^2(k)}{T-k} \quad (9)$$

where $\hat{Q}_\alpha^{(p)}$ conforms to the portmanteau test which may be applied in testing directional predictability of returns at a pair of quantiles $\{\theta_1, \theta_2\}$ from one series to another up to p Lastly since the asymptotic distribution of the CQ is not free of noise parameters under the assumption of no directional predictability, Gupta and Shah (2021) rely on the stationary bootstrap of Niu (2021) and to compute the distribution of the Portmanteau test statistics.

Frequency-based connectedness analysis

We analyze the degree of connectedness among AI and energy-focused sectors across different investment horizons using the frequency domains realized from the wavelets technique. Here, we rely on the TVP-VAR connectedness approach proposed by Antonakakis et al. (2020) on the frequency components generated from the wavelets technique. The TVP-VAR technique relates the distribution of a particular series to depend on its lags and those of other relevant covariates, which incorporates variations in the variances using the stochastic volatility Kalman Filter estimation of Khalfaoui et al. (2015).

Traditionally, the TVP-VAR model unfolds with a time-varying parameter $\mathrm{VAR}_{(p)}$ model defined as:

$$Y_t = \phi_{0t} + \delta_{1t}Y_{t-1} + \cdots + \delta_{pt}Y_{t-\mathrm{p}} + u_t \quad (10)$$

where $u_t \sim (N(0, \Sigma_t)$, with Σ_t representing an $M \times M$ covariance matrix. If $K \times 1$ vector $\beta_t = vec\left(\left[\varphi_{0t}\prime, \delta_{1t}\prime, \ldots, \delta_{pt}\prime\right]'\right)$, where $K = M(1 + Mp)$ while the $M \times K$ vector $z = 1 \otimes \left[1, Y_{t-1,}\prime \ldots, Y_{t-p}\prime\right]$. Also, due to constraints of limited information about parameter changes, β_t vector follows a random walk, which enables the evolution of richer patterns relative to a stationary autoregressive process. Hence, the TVP-VAR model may be re-stated as:

$$Y_t = \beta_t z_{t-1} + u_t \qquad u_t \sim N(0, \Sigma_t) \tag{11}$$

$$\beta_t = \beta_{t-1} + v_t \qquad v_t \sim N(0, \Pi_t) \tag{12}$$

where β_t is an $N \times N_p$ time-varying coefficients matrix while u_t represents an $N \times 1$ matrix of error terms; σ_t is an $N \times N$ time-varying variance–covariance matrix. Thus, β_t depends on their past values β_{t-1} and an $N \times N$ matrix of error terms v_t, with $N^2 \times N^2$ dimensional matrix of variance-covariances Π_t.

To realize the Generalized Impulse Response Functions (GIRFs) and the Generalized Forecast Error Variance Decomposition (GFEVD), the TVP-VAR model is re-written as a TVP-VMA (TVP-Vector Moving Average) using the Wold theorem defined as:

$$Y_t = \beta_t z_{t-1} + u_t = A_t u_t \tag{13}$$

$$A_{0,t} = I \tag{14}$$

$$A_{j,t} = \beta_{1,t} A_{j-1,t} + \cdots + \beta_{p,t} A_{j-p,t} \tag{15}$$

where $\beta_t = \left[\beta_{1,t}, \beta_{2,t} \cdots, \beta_{p,t}\right]\prime$ and $A_t = \left[A_{1,t}, A_{2,t} \cdots, A_{p,t}\right]\prime$ are $N \times N$ matrices of parameters. Based on the GFEVD, the GIRFs: $\omega_{ij,t}(h)$ accounts for the responses of all variables j to a shock on variable i. Using this, the h-step-ahead forecast in which variable i is shocked and another for which variable i is not shocked may be estimated. Thus, this variance relates to the shock in variable i, written as:

$$GIRF_t\left(h, \vartheta_{j,t}, F_{t-1}\right) = E\left(Y_{t+h} | d_j = \vartheta_{j,t}, F_{t-1}\right) - E\left(Y_{t+k} | F_{t-1}\right) \tag{16}$$

$$\Psi_{ij,t}((h) = \frac{A_{h,t} \sum_t d_j}{\sqrt{\Sigma_{jj,t}}} \frac{\vartheta_{j,t}}{\sqrt{\Sigma_{jj,t}}} \vartheta_{j,t} = \sqrt{\Sigma_{jj,t}} \tag{17}$$

$$w_{ij,t}(h) = \sum_{jj,t}^{-\frac{1}{2}} A_{h,t} \sum_t d_j \tag{18}$$

where d_j is an $n \times 1$ selection vector with 1 in the j^{th} position and zero otherwise. The $GFEV\ D(\tilde{\gamma}_{ij,t}\ (h))$ is calculated and normalized, explaining the share of variance that a variable exerts on the system. Thus, each roll sums up to 100, indicating that all the variables in the system mutually account for 100% of the variable's variance in forecast error. This is defined as:

$$\tilde{\gamma}_{ij,t}(h) = \frac{\sum_{t=1}^{h-1} \omega_{ij,t}^2}{\sum_{j=1}^{n} \sum_{t=1}^{h-1} \omega_{ij,t}^2} \tag{19}$$

where $\sum_{j=1}^{n} \tilde{\gamma}_{ij,t}^{n}(h) = 1$ while $\sum_{j=1}^{n} \tilde{\gamma}_{ij,t}^{n}(h) = n$. Essentially, the numerator term captures the total effect of a shock in variable i, while the denominator term accounts for the cumulative effect of all the shocks in the system. Hence, the Total Connectedness Index (TCI) is estimated as:

$$T_t(h) = \frac{\sum_{ij=1,i\neq j}^{n} \tilde{\gamma}_{ij,t}(h)}{\sum_{i,j=1}^{n} \gamma_{ij,t}(h)} \times 100 = \frac{\sum_{ij=1,i\neq j}^{n} \tilde{\gamma}_{ij,t}(h)}{n} \times 100 \tag{20}$$

Following, total directional connectedness "TO" others captures how a shock in one of the variables i transmits to all other variables j, written as:

$$T_{i\rightarrow j,t}(h) = \frac{\sum_{ij=1,i\neq j}^{n} \tilde{\gamma}_{ij,t}(h)}{\sum_{i,j=1}^{n} \gamma_{ij,t}(h)} \times 100 \tag{21}$$

Likewise, total directional connectedness "FROM" others relates to the shock variable i receives from other variables j, written as:

$$T_{i\leftarrow j,t}(h) = \frac{\sum_{j=1,i\neq j}^{n} \tilde{\gamma}_{ij,t}(h)}{\sum_{i=1}^{n} \gamma_{ij,t}(h)} \times 100 \tag{22}$$

We retrieve the Net Directional Connectedness (NDC) by subtracting the total directional connectedness "TO" others from the total directional connectedness "FROM" others, expressed as:

$$TCI_{i,t} = T_{i\rightarrow j,t}(h) - T_{i\leftarrow j,t}(h) \tag{23}$$

To shed more light on bidirectional risk spillovers between asset pairs, in the last step, we retrieve and plot the net directional pairwise connectedness, defined as:

$$NPDC_{ij}(h) = \left(\tilde{\gamma}_{jit}(h) - \tilde{\gamma}_{ijt}(h)\right) \tag{24}$$

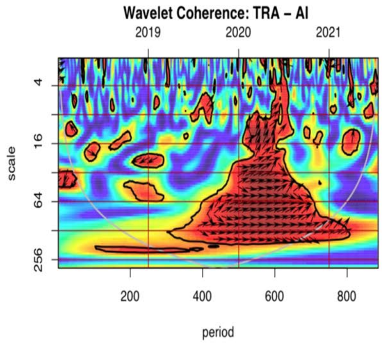
where $NPDC_{ij}(h) < 0$, signals that variable i is dominated by variable j while $NPDC_{ij}(h) > 0$ implies that variable i dominates variable j.

Results and discussion

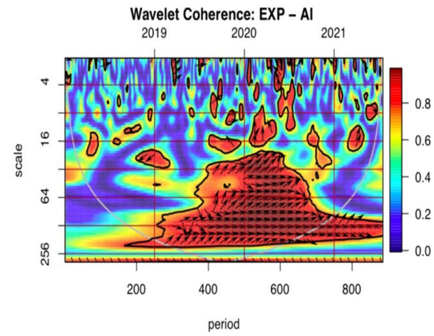
In this section, we present and discuss the results from our empirical analysis for both the pre-COVID-19 and COVID-19 period samples. First, we present the results of time–frequency dependence using wavelet coherence techniques. Second, we present the results of directional predictability using the cross-quantilogram while in the third section, we present the results of return connectedness using the TVP-VAR.

Dependence between AI and energy-focused sectors: wavelet coherence results

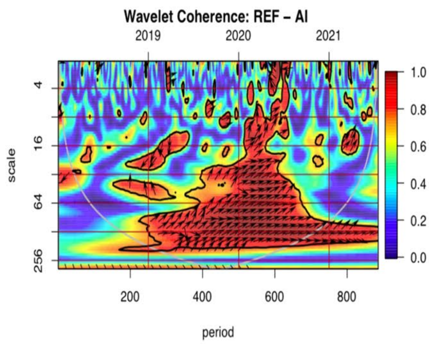
In this subsection, we are primarily concerned with analyzing the causal association between the returns of AI and those of the energy-focused sectors across time and frequency domains using wavelet coherence and phase difference as defined in Eqs. (5) and (6). This enables us to investigate the changing dependence and lead-lag co-movement between the returns of AI and those of energy-focused sectors across different frequencies and over time. As may be seen in Fig. 3 panel a–h, frequencies are reported on the vertical axis while time scales are shown on the horizontal axis. In all cases, thickly



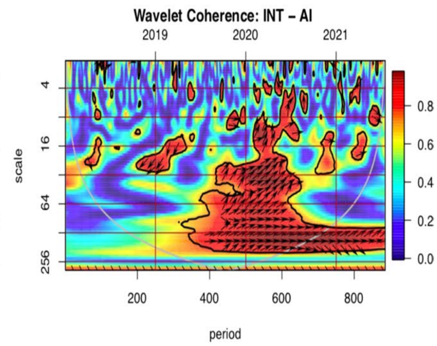
(a) AI vs TRA



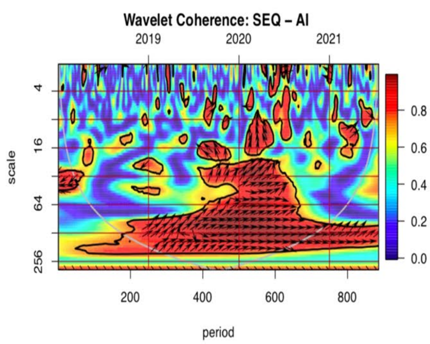
(b) AI vs EXP



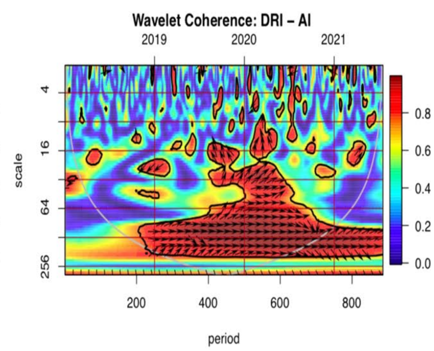
(c) AI vs REF



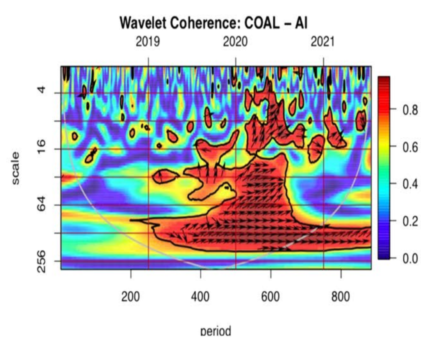
(d) AI vs INT



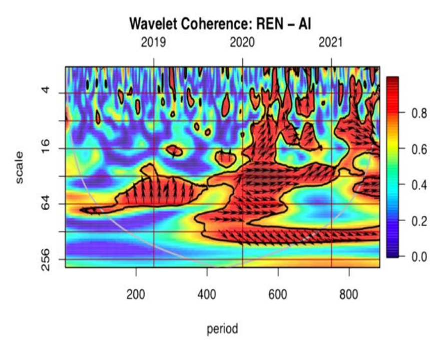
(e) AI vs SEQ



(f) AI vs DRI



(g) AI vs COAL



(h) AI vs REN

Fig. 3 Wavelet coherence between the performance of AI and energy sectors. Note: (i)AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN) shaded contours denote regions with significance at the 5% level. Also, colder colors (blue) represent regions where AI and each energy-focused sector are significantly less dependent, while regions of high significant dependence are indicated by warmer colors (red). The phase arrows also offer crucial indications of lead-lag phase relations between AI and the associated energy-focused sector. Right arrows (→) denote in phase, indicating the co-movement of two markets in a particular scale. Left arrows (←), on the other hand, denote anti-phase and suggest the opposite. The right-down (↘) and left-up (↖) arrows suggest that the associated energy sector leads AI, while the right-up (↗) or left-down (↙) arrows indicate that the concerned energy-focused sector is lagging and that AI leads.

The dominant message from the results in Fig. 3 panel a–h indicates that dependence between AI and energy-focused sectors becomes stronger towards the end of 2019 until the end of 2020 as shown by the warmer color (red), especially with Oil and Gas Exploration and Production, Oil and Gas Refining and Marketing, Oil and Gas Drilling. Results also generally suggest that dependence was stronger in the long-term, as shown by the thick color (red) mainly concentrated between the 64–256 days time scales. It also shows weaker short-term significant dependence, as indicated by the colder colors (blue) around the 2–32 days time scales across all the pairs. The dependence between AI and renewable energy (REN) also appears stronger across the intermediate- and long-term. It existed before the outbreak of the COVID-19 pandemic and continues towards the end of the sample period. This result is in line with the expectation of stronger dependence between AI's performance and the renewable energy sector, given the crucial application of technology in the development of renewable energy resources.

Even more, this supports the position expressed in past studies, arguing that the integration of novel AI approaches will improve the performance of renewable energy sources for the world's prosperity (see e.g. (Boza and Evgeniou 2021; Jha et al. 2017; Şerban and Lytras 2020)). Empirically, this is also consistent with the findings of past studies such as (Henriques and Sadorsky 2008), which document strong dependence between AI stocks and green bonds. Green bonds are a financial instrument used to mobilize financial resources for green energy companies, including renewable energy firms. The increasing demand for renewable energy should lead to an increase in the performance of technological sector stocks. On the other hand, increased deployment of technological innovation, including AI, is also expected to impact positively the performance of renewable energy stocks. Our findings also situate well within the second strand of papers discussed in the literature section. Particularly, our results relate well with the findings in Maghyereh et al. (2019) and Bondia et al. (2016), which document a stronger dependence between technology stocks and clean energy stocks than those of fossil fuel corporations.

Furthermore, some crucial information may be derived from the lead-lag phase relations. Between late 2018 to early 2019, there is a notable period of significant strong intermediate-term dependence between AI and energy sectors, except Coal and renewable energy sectors. During this period, arrows generally face left downwards, suggesting that these six energy sectors are lagging and AI leads. However, arrows are facing left-upwards for the Coal and renewable energy sectors, suggesting that Coal and renewable energy sectors lead AI. Regarding the period of significant strong dependence between

AI and the energy-focused sectors, which occurred around late 2019 till the end of 2020, the arrows are mainly facing right-upwards. This suggests that during the period of the COVID-19 pandemic, dependence between the stock returns of AI and those of energy-focused sectors became stronger in the long term, with the stocks of AI leading.

However, there are notable periods of right downwards facing arrows, as may be seen in the long-term dependence on the renewable energy sector and, to an extent, with Oil and Gas Transportation Services. This implies that during this period, the performance of these energy-focused sectors' stocks leads to the performance of AI stocks, especially renewable energy stocks. This is also exhibited by the phase relation between AI and Oil and Gas Drilling, although most of the arrows are out of the cone of influence, which indicates the zone affected by edge effects. Lastly, it is worth noting that towards the end of the sample period, the phase relation between AI and the renewable energy sector is dominated by right downwards facing arrows both in the intermediate and long-terms, indicating that renewable energy stocks lead AI stocks during this time scale. During the intermediate-term timescale, right downward arrows are also briefly exhibited by the phase relations between AI and Integrated Oil and Gas Services and Coal towards the end of the sample period. Taken together, these results indicate that although the dependence between AI and the chosen energy sectors became stronger in the intermediate- and long-term during the COVID-19 pandemic, with AI stocks leading the energy sectors, renewable energy stocks lead AI stocks in the long-term and the intermediate-term from early 2021 till the end of the sample period.

Dependence between AI and energy-focused sectors: cross-quantilogram results

In this section, we discuss the estimation results from the cross-quantilogram analysis as defined in Eqs. (12), (13), and (14). Table 4 presents the pre-COVID-19 sample results, while Table 5 shows the result for the post-COVID-19 period. Each table reports estimates of cross-quantilogram (as well as the Portmanteau test statistic) for each of the eight energy-focused sectors. We particularly consider the cross-quantilogram and Portmanteau test under nine quantiles covering both the bear and bull market states and the shoulders of the return distribution. We define the low quantiles, including 0.05, 0.1, and 0.2 quantiles, as the bear market state, whereas the high quantiles, including 0.8, 0.9, and 0.95, are considered bullish. On the other hand, the 0.3, 0.5, and 0.7 quantiles are defined as the shoulders of distribution. Each value in the tables represents the strength of an event of a decline in the performance of AI below a certain percentile, preceding the next day's decline in the performance of each of the eight energy-focused sectors below the corresponding percentile. This enables us to identify and differentiate the hedging and safe-haven role of AI for each of the eight energy-focused sectors considered. For instance, the values in the first row of each table show the strength of directional predictability from AI to returns of corporations in the Oil and Gas Exploration and Production under the nine quantiles considered.

Pre-COVID sample results using cross-quantilogram

Table 4 shows estimates of the pre-COVID-19 sample results using the CQ method, as described in Sect. 3.2.2. We find that the returns on AI stocks hardly predict those of energy-focused sectors across all quantiles under the frequencies corresponding

Table 4 Pre-COVID sample dependence and directional predictability

Quantiles →	**0.05**	**0.1**	**0.2**	**0.3**	**0.5**	**0.7**	**0.8**	**0.9**	**0.95**
Short-term									
EXP	− 0.002	0.002	0.002	0.004	− 0.003	**− 0.005**†	− 0.002	0.002	**0.004**†
REF	− 0.002	**0.003**†	**0.004**†	0.000	0.004	0.000	**− 0.005**‡	0.002	− 0.001
DRI	− 0.002	0.002	− 0.001	0.004	− 0.001	0.000	− 0.002	− 0.001	− 0.002
TRA	**− 0.007**†	**− 0.010**‡	**− 0.008**‡	− 0.004	0.001	0.005	0.004	**0.009**†	**0.006**†
INT	0.001	− 0.003	− 0.007	− 0.004	0.000	0.000	**0.006**†	**0.007**†	− 0.0001
SEQ	0.000	0.003	**0.008**‡	0.005	− 0.004	− 0.007	− 0.003	− 0.004	− 0.003
COAL	0.000	0.002	− 0.002	**− 0.006**‡	**− 0.005**†	0.001	**0.008**†	0.007	**0.005**†
REN	− 0.002	0.002	0.003	0.002	0.003	0.001	− 0.002	− 0.012	**− 0.005**†
% of sign. Predictability	*12.50%*	*25.0%*	*37.50%*	*12.50%*	*12.50%*	*12.50%*	*37.50%*	*25.0%*	*50.0%*
Intermediate term									
EXP	0.011	0.007	**0.008**†	**0.001**†	0.001	**− 0.002**†	0.001	− 0.008	− 0.011
REF	− 0.005	0.005	0.000	**0.001**†	− 0.005	**0.001**†	**− 0.004**†	**− 0.002**†	0.000
DRI	**0.005**†	**0.006**†	**− 0.002**†	**− 0.007**†	− 0.007	0.008	0.007	0.004	− 0.001
TRA	**0.029**‡	**0.023**‡	**− 0.007**†	− 0.011	− 0.034	**− 0.053**‡	− 0.043	**− 0.046**‡	**− 0.072**‡
INT	0.004	− 0.004	− 0.010	0.004	− 0.002	− 0.004	0.009	0.016	0.010
SEQ	0.006	0.000	0.009	0.006	− 0.002	**− 0.001**†	**− 0.001**†	**0.004**†	**− 0.009**†
COAL	− 0.016	− 0.009	− 0.004	− 0.001	**0.006**†	0.003	0.000	− 0.002	− 0.007
REN	0.002	0.002	− 0.003	0.004	− 0.001	**− 0.008**†	**− 0.011**‡	− 0.002	0.004
% of sign. Predictability	*25.0%*	*25.0%*	*37.50%*	*37.50%*	*12.50%*	*62.5%*	*37.50%*	*37.50%*	*25.0%*
Long-term									
EXP	**− 0.005**†	**0.006**†	**0.003**†	**− 0.031**‡	**− 0.028**‡	**− 0.011**	**− 0.007**†	**− 0.027**‡	**− 0.048**‡
REF	0.013	0.011	**− 0.021**‡	**− 0.036**‡	**− 0.028**‡	**− 0.034**‡	**− 0.050**‡	**− 0.044**‡	**− 0.055**‡
DRI	**0.033**‡	**0.014**‡	**− 0.027**†	**− 0.021**‡	**− 0.049**‡	**− 0.030**‡	**− 0.016**‡	**− 0.024**‡	**− 0.033**‡
TRA	**0.034**‡	**0.040**‡	**0.031**†	**− 0.005**†	**− 0.037**‡	**− 0.064**‡	**− 0.067**‡	**− 0.068**‡	**− 0.077**‡
INT	0.021	− 0.007	− 0.046	**− 0.049**‡	**− 0.038**‡	**− 0.011**†	**0.013**‡	**0.023**‡	0.001
SEQ	**0.029**‡	**0.023**‡	**− 0.007**†	**− 0.011**†	**− 0.034**‡	**− 0.053**‡	**− 0.043**‡	**− 0.046**‡	**− 0.072**‡
COAL	− 0.029	− 0.056	**− 0.047**†	**− 0.050**‡	**− 0.015**	**0.020**†	**0.042**‡	**0.029**‡	0.041
REN	**0.060**‡	**0.051**‡	**− 0.013**†	**− 0.043**‡	**− 0.018**‡	**− 0.031**‡	**− 0.034**‡	**− 0.074**‡	− 0.042
% of sign. Predictability	*62.5%*	*62.5%*	*87.50%*	*100%*	*100%*	*100%*	*100%*	*100%*	*62.5%*

Values in the table represent the mean strength of prediction under nine quantiles from AI to the eight sectors of energy-focused corporations. The closer the values to ± 1, the stronger the predictive ability under a particular quantile. Bold values are estimated significant coefficients, where † and ‡ denote significance at 5% and 1% respectively. (i)AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN)

to the short and intermediate-term investment horizons. This implies that the stock returns of energy-focused sectors hardly depend on those of AI during these investment horizons. This conclusion agrees with the last rows of the respective panels, showing the percentage of significant predictability under different quantiles that constitute the market conditions. Particularly, the panel for the short-term investment horizon shows that the percentage of considerable sample counterparts is only between 12.5 and 37.5% during bearish and normal market conditions and between 25 and 50% during bullish market conditions. Regarding the intermediate term, it is

Table 5 COVID sample dependence and directional predictability

Quantiles →	**0.05**	**0.1**	**0.2**	**0.3**	**0.5**	**0.7**	**0.8**	**0.9**	**0.95**
Short term									
EXP	**0.007†**	**0.008‡**	**0.012‡**	0.012	0.004	−0.011	−0.019	−0.005	**−0.015‡**
REF	**0.005†**	**0.008‡**	**0.009‡**	0.010	0.006	−0.011	−0.017	−0.005	**−0.011†**
DRI	**0.001†**	**0.004†**	0.018	0.016	−0.007	−0.017	−0.023	0.002	**−0.008‡**
TRA	**−0.003‡**	**0.003‡**	**0.001‡**	**0.005‡**	0.009	−0.007	−0.009	−0.001	**−0.007‡**
INT	**−0.004‡**	0.003	0.007	0.006	0.002	−0.008	−0.009	0.000	**−0.002‡**
SEQ	**−0.001‡**	**0.007‡**	**0.011‡**	0.011	0.004	−0.012	−0.016	**−0.005‡**	**−0.010‡**
COAL	**0.011‡**	0.011	0.014	0.010	−0.005	−0.009	−0.012	−0.001	**−0.018‡**
REN	−0.011	−0.002	**0.005‡**	**0.011‡**	**0.003†**	−0.008	−0.007	0.007	0.005
% of Sign. Predictability	*87.50%*	*62.50%*	*62.50%*	*25.00%*	*12.50%*	*0%*	*0%*	*12.50%*	*87.50%*
Intermediate-term									
EXP	**0.023‡**	**0.032‡**	**0.030‡**	**0.020‡**	**−0.002†**	**−0.011‡**	**−0.034‡**	**−0.042‡**	**−0.040‡**
REF	**0.035‡**	**0.041‡**	**0.037‡**	**0.025‡**	**−0.002†**	**−0.016‡**	**−0.042‡**	**−0.051‡**	**−0.051‡**
DRI	**0.010‡**	**0.016‡**	**0.020‡**	**0.010†**	−0.006	−0.002	−0.015	**−0.021‡**	−0.016
TRA	**0.042‡**	**0.047‡**	**0.042‡**	**0.030‡**	**0.0001†**	**−0.018‡**	**−0.043‡**	**−0.055‡**	**−0.057‡**
INT	**0.040‡**	**0.042‡**	**0.038‡**	**0.027‡**	**−0.004†**	**−0.021‡**	**−0.043‡**	**−0.056‡**	**−0.055‡**
SEQ	**0.020‡**	**0.032‡**	**0.031‡**	**0.024‡**	**0.002†**	−0.006	−0.027	**−0.038‡**	**−0.034‡**
COAL	**0.033‡**	**0.031‡**	**0.026‡**	**0.013†**	−0.010	**−0.020‡**	**−0.037‡**	**−0.040‡**	**−0.045‡**
REN	**0.028‡**	**0.034‡**	**0.023‡**	**0.017‡**	**−0.004†**	**−0.016‡**	**−0.029‡**	**−0.032‡**	**−0.038‡**
% of Sign. Predictability	*100%*	*100%*	*100%*	*87.50%*	75%	75%	75%	*100%*	*87.50%*
Long-term									
EXP	**0.030‡**	**0.019†**	**0.013‡**	**0.002‡**	**0.018‡**	**0.040‡**	**0.017†**	**−0.032‡**	−0.105
REF	**0.030‡**	**0.009†**	**0.016†**	**−0.003†**	**−0.004†**	**0.045‡**	**0.024‡**	**−0.033‡**	**−0.106‡**
DRI	**0.028‡**	**0.021‡**	**0.013†**	**0.0001†**	**0.007†**	**0.044‡**	**0.028‡**	**−0.029‡**	**−0.100‡**
TRA	**0.031‡**	**0.008†**	**0.008†**	**−0.011†**	**−0.010†**	**0.041‡**	**0.019†**	**−0.042‡**	**−0.118‡**
INT	**0.029‡**	**0.005†**	**0.047‡**	**0.039‡**	**0.028‡**	**0.059‡**	**0.032‡**	**−0.023‡**	**−0.093‡**
SEQ	**0.026‡**	**0.024‡**	**0.015†**	**0.004†**	**0.010†**	**0.045‡**	**0.030‡**	**−0.029‡**	**−0.095‡**
COAL	**0.013‡**	**0.029‡**	**0.043‡**	**0.044‡**	**0.037‡**	**0.048‡**	**0.023‡**	**−0.029‡**	**−0.080‡**
REN	**0.026‡**	**0.021‡**	**0.044‡**	**0.031‡**	**0.001†**	**0.006†**	**−0.043‡**	**−0.064‡**	**−0.080‡**
% of Sign. Predictability	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*87.50%*

Values in the table represent the mean strength of prediction under nine quantiles from AI to the eight sectors of energy-focused corporations. The closer the values to ± 1, the stronger the predictive ability under a particular quantile. Bold values are estimated significant coefficients, where † and ‡ denote significance at 5% and 1% respectively. (i) Oil & Gas Exploration and Production (EXP); (ii) Oil & Gas Refining and Marketing (REF); (iii) Integrated Oil & Gas (INT); (iv) Oil-related Services and Equipment (SEQ); (v) Oil & Gas Transportation Services (TRA); (vi) Oil & Gas Drilling (DRI); (vii) Coal (COAL); and (viii) Renewable Energy (REN)

between 25 and 37.5% during the bearish market condition, 12.5% to 62.5% during the normal market condition, and 25–37.5% during the bullish market condition.

In contrast to the estimates of the short and intermediate-term investment horizons, the panel for the long-term investment horizon shows evidence of strong dependence between AI and the energy-focused sectors across all quantiles. Indeed, compared to the relatively weak percentage of significant predictability obtained across quantiles during the short and intermediate-term investment horizons, the lowest percentage of significant predictability obtained across all quantiles during the long-term investment horizon is 62.5%, which was the maximum estimate during other investment horizons. We find that during normal and bullish market conditions in the long term, AI stock returns are a perfect directional predictor of those of energy-focused sectors, with the percentage of significant predictability in most cases being 100%. Except for Integrated Oil & Gas (INT) and Coal, evidence in the table also shows consistent patterns of negative dependence on and directional predictability from AI during the normal and bullish market conditions for six sectors including Oil & Gas Exploration and Production (EXP), Oil & Gas Refining and Marketing (REF), Oil & Gas Drilling (DRI), Oil & Gas Transportation Services (TRA), Oil-related Services and Equipment (SEQ), and Renewable Energy (REN). For these six energy-focused sectors, the result implies that when the returns on AI fall below the corresponding quantiles, the returns of these energy-focused sectors have a high likelihood of experiencing a substantial return in the following days. On the other hand, if these energy-focused sectors experience a significant loss, AI will likely experience a substantial gain in the next few days. In this case, investments in AI could serve a hedging role for investments in these energy-focused sectors during this market condition in the long term.

Per the exceptions, estimates for Integrated Oil & Gas (INT) show negative dependence during normal market conditions and positive dependence during a bullish state. The implication of the negative dependence aligns with those of the six energy-focused sectors given earlier. Positive dependence, however, implies that when the returns on AI rise, there is an increased likelihood of considerable gains in the Integrated Oil & Gas (INT). Results and implications of the bullish market condition for Coal are similar to those of Integrated Oil & Gas (INT). As for its estimates under normal market conditions, we find evidence of negative dependence except for the 0.7 quantiles. Further, results for the bearish market condition show consistent negative dependence of Coal on AI, although only the estimate at the 0.2 quantiles is statistically significant at the conventional significance level. Estimates of Oil & Gas Refining and Marketing (REF), Oil & Gas Drilling (DRI), Oil-related Services and Equipment (SEQ), and Renewable Energy (REN) are positive at the 0.05 and 0.1 quantiles but turn negative at the 0.2 quantiles, suggesting that for these energy-focused sectors, when the market becomes less bearish negative dependence takes precedence and lingers across the normal and bullish market conditions. Estimates of Oil & Gas Exploration and Production (EXP) show positive dependence at the 0.1 and 0.2 quantiles but negative dependence at the 0.05 quantiles. This suggests that once the market becomes highly bearish, the market reverses back to negative dependence. As for Oil & Gas Transportation Services (TRA), only positive dependence exists during the bearish market condition.

Post-COVID sample results using Cross-quantilogram

Table 5 shows the COVID-19 sample results for the CQ analysis. Overall, the results show that across both quantiles and frequencies, the returns of energy-focused sectors depend more strongly on those of AI. However, dependence and directional predictability are stronger in the long term and weaker in the short-term investment horizon, respectively. This result and conclusion are largely consistent with those obtained from the Wavelet coherence analysis, indicating that the dependence between AI and the energy-focused sectors becomes stronger from 2019 until the end of 2020, coinciding with the COVID-19 pandemic peak period. Moreover, consistent with the results obtained here, the wavelet coherence methods also suggested that the dependence was stronger in the longer term and weaker in the short term. Hence, the CQ provides a robustness check to our previous finding using the wavelet coherence method. That said, there are also some notable differences across the time scales and market conditions when we compare it to those of the pre-COVID-19 sample results that are worth mentioning.

Beginning with the short-term investment horizon, we find that the power of dependence and directional predictability are hardly significant at the conventional significance level, especially across quantiles corresponding to the normal market condition. Whereas this conclusion is consistent with that of the short-term pre-COVID-19 sample results, the intermediate-term results show stronger dependence on and directional predictability from AI across quantiles corresponding to the bear, normal, and bullish market conditions. These latter results differ from the intermediate-term results obtained for the pre-COVID-19 sample results. Indeed, compared to the intermediate-term pre-COVID-19 sample results, where the percentage of significant predictability across the quantiles was 12.50–62.5%, that of the COVID-19 sample is between 75 and 100%. It also suffices to note that in contrast to the intermediate-term pre-COVID-19 sample results, the intermediate-term COVID-19 sample results also show consistent patterns of directional predictability across different market conditions. A closer look at the intermediate-term results shows evidence of negative dependence among AI and the eight energy-focused sectors across all quantiles corresponding to the bullish market condition. On the other hand, positive dependence dominates across all quantiles corresponding to the bearish market condition. Under normal market conditions, however, there is evidence of both positive and negative dependence, depending on the quantiles. In particular, at the 0.3 quantiles, positive dependence dominates for all the energy-focused sectors in our sample. At the 0.5 and 0.7 quantiles, negative dependence dominates.

Moving on to the long-term investment horizon, we find that the returns on AI stocks are a perfect directional predictor of those of the eight energy-focused sectors. In fact, except for the estimates at the 0.95 quantiles, the percentage of significant predictability across all other quantiles during this period is 100%. Compared to the intermediate-term results, we find that positive dependence among AI and the energy-focused sectors continues to dominate all quantiles corresponding to the bearish market condition. However, notable differences occur across quantiles corresponding to normal and bullish market conditions. Beginning with the bullish market condition, except for Renewable energy (REN), which continues to show negative dependence across all quantiles corresponding to this market condition, the remaining seven energy-focused sectors show positive dependence at the 0.8 quantiles while their respective estimates at the 0.9 and 0.95 quantiles remain negative. This implies that negative dependence for these sectors on AI only takes precedence when the market is extremely bullish. Concerning the normal market condition, estimates for Oil & Gas Exploration and Production (EXP), Oil & Gas Drilling (DRI), Integrated Oil & Gas (INT), Oil-related Services and Equipment (SEQ), Coal and Renewable Energy (REN) all show a dominance of positive dependence across quantiles corresponding to this market condition, a result that is different from both the intermediate-term COVID-sample results as well as the long term pre-COVID 19 sample results. For Oil

& Gas Refining and Marketing (REF) and Oil & Gas Transportation Services (TRA), negative dependence dominates the 03 and 0.5 quantiles while positive dependence dominates the 0.7 quantiles.

Return connectedness between AI and energy-focused sectors across frequencies.

This section presents the results for the degree of connectedness among AI and energy-focused sectors for the pre-COVID and the COVID sample period, respectively. We report results across frequencies grouped into short, intermediate, and long-term investment horizons for each sample analysis. As discussed in Sect. 3.3, we attain this feat by applying the TVP-VAR spillover method of Antonakakis et al. (2020) on the frequency components realized from the MODWT technique.

Pre-COVID-19 sample return connectedness across frequencies

Table 6 presents the results of the pre-COVID sample degree of the return connectedness between AI and the chosen energy-focused sectors. Beginning with the total connectedness index (TCI) that measures how much, on average, a shock in one market is transmissible across the markets under study, evidence in the table indicates that TCIs are high across the investment horizons and strengthen as we move from the short to the long-term investment horizon. As can be seen in the table, however, own shock for AI is very high in the short term (86.31%) and intermediate-term (75.53%). Akin to this, the amount of shock either received from or contributed to the system by AI varies across both investment horizons. In the long-term, however, own shock for AI drops significantly to 15.41%, while the amount of shock AI either receives from or contributes to the system increases to 84.59% and 97.86%, respectively. Put together; these results suggest that the observed strong short-term and intermediate-term TCIs are largely driven by the strong return connectedness among the energy-focused sectors rather than the return connectedness between these energy-focused sectors and AI. However, the strong long-term TCI obtained is driven jointly by the strong return connectedness among the energy-focused sectors and the connectedness among AI and these energy-focused sectors. This result and conclusion are consistent with the pre-COVID sample results obtained using the cross-quantilogram methods. As a result in that section shows, the dependence structure between the stock returns of AI and those of the respective energy-focused sectors is stronger across all market conditions in the long term than either in the short or intermediate-term investment horizon.

Evidence in Table 6 also suggests that Oil & Gas Drilling (DRI) and Oil & Gas Exploration and Production (EXP) are net shock transmitters across all frequencies, while COAL and Oil & Gas Transportation Services (TRA) are net shock receivers. Portfolio and risk managers are more interested in assets that are driving the market than those that are being driven by the market, as the latter are exposed to more risk sources compared to the former. Hence, this makes investment in Oil & Gas Drilling (DRI) and Oil & Gas Exploration and Production (EXP) more attractive across frequencies of the pre-COVID-19 sample. Their roles and attractiveness vary across frequencies for AI and the remaining energy-focused sectors. In particular, AI and Renewable Energy (REN) are both net shock receivers in the short and intermediate-term but become net shock transmitters in the long term. Oil & Gas Refining and Marketing (REF) and SEQ are net shock transmitters in the short and intermediate-term but become net shock receivers

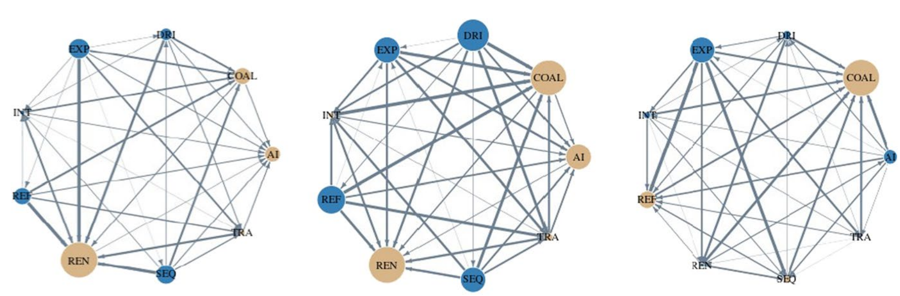
Table 6 Pre-COVID sample network connectedness across frequencies

	AI	COAL	DRI	EXP	INT	REF	REN	SEQ	TRA	FROM others
Short-term										
AI	86.31	1.85	1.60	1.67	1.48	1.84	1.31	1.81	2.13	13.69
COAL	0.24	35.46	9.12	9.04	14.16	9.13	6.69	9.77	6.38	64.54
DRI	0.27	6.09	22.87	17.27	10.52	13.34	3.87	17.05	8.73	77.13
EXP	0.27	6.06	16.51	21.77	9.60	14.98	3.66	15.79	11.36	78.23
INT	0.26	11.55	11.31	10.69	27.32	12.37	5.32	12.40	8.79	72.68
REF	0.31	5.98	13.52	15.56	11.39	22.64	4.07	14.55	11.99	77.36
REN	0.53	8.25	7.54	8.63	8.30	9.31	39.32	9.02	9.11	60.68
SEQ	0.31	6.56	16.01	16.06	11.31	14.32	4.12	21.35	9.96	78.65
TRA	0.43	6.30	10.18	14.13	9.16	14.08	5.77	11.92	28.02	71.98
TO others	2.61	52.63	85.80	93.04	75.92	89.38	34.81	92.30	68.45	594.94
Inc. own	88.92	88.10	108.66	114.81	103.24	112.02	74.13	113.66	96.46	
NDC	− 11.08	− 11.90	8.66	14.81	3.24	12.02	− 25.87	13.66	− 3.54	TCI = 66.10
Intermediate-term										
AI	75.53	2.39	3.50	4.09	2.04	3.12	1.98	3.30	4.05	24.47
COAL	0.44	34.09	11.04	9.34	12.68	10.18	4.82	9.97	7.44	65.91
DRI	0.59	5.94	23.88	15.95	10.75	13.53	3.09	17.89	8.39	76.12
EXP	0.65	4.54	16.52	21.93	9.15	16.00	3.67	15.64	11.89	78.07
INT	0.38	7.48	13.78	12.32	23.81	15.54	4.73	13.84	8.11	76.19
REF	0.46	5.35	14.69	15.69	12.05	21.31	4.29	14.74	11.41	78.69
REN	3.13	6.84	6.55	6.83	8.00	8.38	44.37	7.48	8.42	55.63
SEQ	0.47	5.62	18.73	15.30	10.32	14.94	3.81	22.25	8.54	77.75
TRA	1.29	4.31	12.50	15.76	7.41	15.74	4.95	11.51	26.52	73.48
TO others	7.41	42.48	97.31	95.29	72.41	97.43	31.34	94.39	68.25	606.32
Inc. own	82.94	76.57	121.19	117.22	96.23	118.74	75.71	116.64	94.76	
NDC	− 17.06	− 23.43	21.19	17.22	− 3.77	18.74	− 24.29	16.64	− 5.24	TCI = 67.37
Long-term										
AI	15.41	5.22	9.42	14.85	12.39	7.60	13.92	9.49	11.70	84.59
COAL	10.41	27.66	12.72	11.27	7.92	6.89	9.29	6.43	7.40	72.34
DRI	11.27	8.40	27.61	14.06	7.78	7.92	8.80	7.21	6.95	72.39
EXP	15.28	7.49	15.93	16.98	10.94	5.10	11.62	6.74	9.92	83.02
INT	13.48	4.13	6.93	13.86	14.02	10.50	11.48	12.34	13.27	85.98
REF	10.55	3.30	10.00	11.39	13.17	14.88	9.11	14.24	13.35	85.12
REN	11.97	4.55	12.96	14.83	11.82	7.67	16.25	9.38	10.58	83.75
SEQ	12.07	2.44	6.44	12.42	14.00	11.89	12.66	14.32	13.77	85.68
TRA	12.84	3.45	6.34	13.77	14.36	11.61	10.07	13.22	14.34	85.66
TO others	97.86	38.98	80.74	106.45	92.37	69.18	86.96	79.04	86.95	738.53
Inc. own	113.27	66.64	108.35	123.44	106.39	84.06	103.21	93.36	101.29	
NDC	13.27	− 33.36	8.35	23.44	6.39	− 15.94	3.21	− 6.64	1.29	TCI = 82.06

TCI and NDC denote the total connectedness index and Net directional connectedness, respectively. (i) AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN)

in the long term. Finally, Integrated Oil & Gas (INT) is a net shock transmitter in the short and long term, but a net shock receiver in the intermediate term. As per the pairwise directional connectedness, the results indicate that except in the long term, stock returns of AI are, on average, weakly connected to those of the energy-focused sectors in terms of the shocks it either receives from or transmits to them. In fact, in the short term, AI's highest shock receipt from the energy-focused sectors is 2.13% from Oil & Gas Transportation Services (TRA), while its highest transmitted shock is 0.53% to Renewable Energy (REN). In the intermediate term, its highest shock receipt is 4.09% from Oil & Gas Exploration and Production (EXP), while its highest transmitted shock is 3.13% to Renewable Energy (REN). However, in the long term, its highest shock receipt is 14.85% from the Oil & Gas Exploration and Production (EXP), while the highest transmitted shock is 15.28% to Oil & Gas Exploration and Production (EXP) which although low are both considerably higher than those of the short and intermediate-term.

Figure 4 plots the net pairwise directional return connectedness among the AI and energy-focused sectors for the pre-COVID-19 sample. Blue nodes in the figures illustrate net transmitters of risks, whilst yellow nodes illustrate net receivers. The sizes of the nodes represent weighted average net total directional connectedness. Hence, depending on whether a market is a net transmitter or net receiver of risks, the sizes of the nodes rank the net directional connectedness, with larger nodes being markets with stronger net directional connectedness. Vertices are weighted by averaged net pairwise directional connectedness measures. Evidence in the figures reiterates our prior discussions concerning the roles of each market when it comes to shock transmissions or receipts. However, it further shows that Renewable Energy (REN) is the major net shock receiver in the short and intermediate term, with respective values of −25.87% and −24.29%. However, Coal (−33.36%) is the major net shock receiver in the long term. On the other hand, Oil & Gas Exploration and Production (EXP) is the major net shock transmitter in the short (+14.82%) and long term (+23.44%). In the intermediate term, DRI with the NDC value of+21.19% is the major net shock transmitter. As per the net pairwise directional connectedness, the figures re-emphasize the varying structural characteristics among the AI and the energy-focused sectors across the different investment horizons. In particular, we observe that return connectedness among AI and the energy-focused sectors is weak in the short and intermediate term, with the former receiving more shocks than the latter. However, the reverse becomes the case in the long term, albeit not in the same order of magnitude.



(a) Short-term network connectedness (b) Intermediate-term network connectedness (c) Long-term network connectedness

Fig. 4 Pre-COVID sample net pairwise directional connectedness plots across frequencies. Note: Blue (yellow) nodes illustrate the net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness (NPDC) measures. The size of nodes represents weighted averaged net total directional connectedness. (i)AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN)

COVID-19 sample return connectedness across frequencies

Table 7 shows the results of the COVID-19 sample degree of return connectedness between AI and the chosen energy-focused sectors across frequencies grouped into short, intermediate, and long-term investment horizons. Similar to those of the pre-COVID-19 sample results, the TCIs are significantly high across the frequencies. It also

Table 7 COVID-sample network connectedness across frequencies

	AI	COAL	DRI	EXP	INT	REF	REN	SEQ	TRA	FROM others
Short-term										
AI	26.99	16.76	13.07	4.69	5.05	7.49	2.56	5.32	18.09	73.01
COAL	1.03	32.24	16.07	6.46	7.24	10.66	3.81	6.81	15.68	67.76
DRI	1.14	15.42	23.28	10.52	7.06	12.96	3.31	10.09	16.20	76.72
EXP	1.31	9.42	13.55	17.23	10.29	15.20	4.97	14.72	13.31	82.77
INT	1.61	8.86	10.14	12.33	21.57	15.64	6.36	15.12	8.37	78.43
REF	1.48	14.56	15.21	11.35	9.73	16.44	3.82	11.50	15.91	83.56
REN	3.16	10.28	8.54	8.38	8.76	10.07	32.27	10.42	8.11	67.73
SEQ	1.37	7.55	12.30	15.44	12.83	15.86	5.81	18.47	10.36	81.53
TRA	1.49	18.40	16.60	8.61	6.70	12.83	3.35	8.00	24.02	75.98
TO others	12.60	101.25	105.48	77.80	67.65	100.71	33.99	81.99	106.03	687.49
Inc. own	39.59	133.49	128.76	95.03	89.22	117.14	66.26	100.46	130.05	
NDC	− 60.41	33.49	28.76	− 4.97	− 10.78	17.14	− 33.74	0.46	30.05	TCI = 76.39
Intermediate-term										
AI	24.07	8.70	7.92	8.53	9.23	10.88	9.70	10.38	10.59	75.93
COAL	0.48	20.85	10.65	9.49	12.84	15.02	5.85	12.64	12.19	79.15
DRI	0.27	8.06	19.09	15.85	13.26	13.49	2.77	16.79	10.42	80.91
EXP	0.32	6.30	14.92	18.81	14.31	13.86	3.18	16.09	12.21	81.19
INT	0.48	8.02	12.19	14.00	19.18	13.87	6.23	13.52	12.51	80.82
REF	0.45	9.76	11.86	13.54	13.79	17.52	5.48	14.34	13.27	82.48
REN	3.71	7.88	8.01	7.94	11.40	9.04	34.19	8.36	9.47	65.81
SEQ	0.37	8.36	14.76	15.69	12.86	14.31	3.63	18.23	11.79	81.77
TRA	0.25	7.71	10.56	14.78	13.04	15.24	5.24	14.13	19.05	80.95
TO others	6.34	64.78	90.87	99.82	100.72	105.69	42.09	106.25	92.46	709.01
Inc. own	30.41	85.63	109.96	118.63	119.90	123.21	76.28	124.47	111.50	
NDC	− 69.59	− 14.37	9.96	18.63	19.90	23.21	− 23.72	24.47	11.50	TCI = 78.78
Long-term										
AI	12.01	11.39	12.15	9.35	10.37	11.90	9.84	12.56	10.42	87.99
COAL	8.79	12.45	12.54	11.91	11.78	8.71	10.46	10.94	12.42	87.55
DRI	10.30	12.14	12.68	10.19	11.33	10.43	9.91	11.50	11.51	87.32
EXP	12.29	7.42	7.93	18.96	7.84	12.75	6.43	18.05	8.34	81.04
INT	6.97	13.00	13.45	11.00	14.27	6.96	11.66	8.75	13.96	85.73
REF	11.17	11.51	12.17	9.87	10.61	11.32	10.15	12.31	10.89	88.68
REN	7.34	11.99	13.01	11.00	12.88	7.30	13.73	8.94	13.80	86.27
SEQ	12.53	10.84	11.32	10.59	9.44	12.75	8.99	13.91	9.63	86.09
TRA	9.24	11.00	11.68	13.22	11.09	9.46	9.73	12.50	12.09	87.91
TO others	78.62	89.29	94.26	87.12	85.34	80.26	77.18	95.55	90.96	778.58
Inc. own	90.63	101.74	106.94	106.08	99.61	91.58	90.91	109.46	103.05	
NDC	− 9.37	1.74	6.94	6.08	− 0.39	− 8.42	− 9.09	9.46	3.05	TCI = 86.51

TCI and NDC denote the total connectedness index and Net directional connectedness, respectively. (i) AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN) strengthens as we move from the short to the long term. However, the TCIs of the respective frequencies are higher than those of corresponding frequencies for the pre-COVID sample results. Evidence in the table also shows that shock received from or contributed to the system by either AI or any of the energy-focused sectors is higher across all the investment horizons when we compare them to their corresponding frequencies in the pre-COVID sample period. Indeed, the figures in the diagonal cells, which represent the magnitude of own shock spillovers, are much less than the value of the corresponding estimates obtained in the pre-COVID-19 sample. This includes AI which showed strong own shock dynamics in the preCOVID-19 sample estimates. Cumulatively, these imply that the share of own shock spillover decreases and system-wide shock increases, confirming the fact that external shock influences the return connectedness among AI and the energy-focused sectors' stocks. It suffices to note that across all frequencies, we also find that pairwise directional return connectedness between AI and those of the respective energy-focused sectors is also higher than their pre-COVID-19 sample estimates.

Put together, therefore, the above results suggest that COVID-19 has strengthened the level of return connectedness between AI and the energy markets, as well as the intra-connectedness among the energy markets. Again, these results correspond to those of cross-quantilogram and were compared to the pre-COVID-19 sample estimates. We found a strong dependence on and significant directional predictability from AI in the COVID-19 sample estimates across all market conditions and investment horizons. One of the plausible explanations for this result is that the COVID-19 pandemic was an unexpected accelerator of a structural shift toward adopting fourth-industrial revolution technologies such as AI. For instance, as people were forced to sit at home due to the COVID-19 outbreak, some firms readjusted production processes to become more automated. Such a watershed moment has far-reaching repercussions on the return connectedness between those AI and energy markets, as the latter's dependence on AI has only increased afterward.

Figure 5 plots the net pairwise directional connectedness among the AI and energy stocks understudy for the COVID-19 sample period. The description of the figures

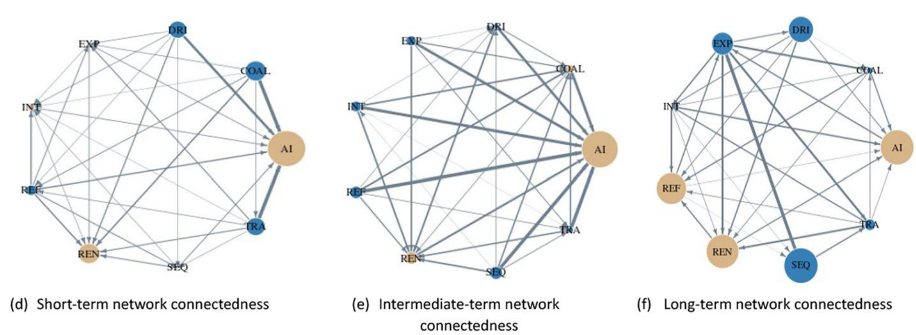


Fig. 5 COVID sample net pairwise directional connectedness plot sectors across frequencies. Note: Blue (yellow) nodes illustrate the net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness (NPDC) measures. The size of nodes represents weighted averaged net total directional connectedness. (i)AI (Artificial Intelligence); (ii) Oil & Gas Exploration and Production (EXP); (iii) Oil & Gas Refining and Marketing (REF); (iv) Integrated Oil & Gas (INT); (v) Oil-related Services and Equipment (SEQ); (vi) Oil & Gas Transportation Services (TRA); (vii) Oil & Gas Drilling (DRI); (viii) Coal (COAL); and (ix) Renewable Energy (REN)

follows that of Fig. 4a–c. The figures show that AI is a major shock receiver from the energy market across all frequencies during COVID-19. Energy markets such as Oil & Gas Refining and Marketing (REF) and Renewable Energy (REN) also come up prominently as net shock receivers in the long term. On the other hand, Coal is the major shock transmitter in the short term, while SEQ takes this role in the intermediate and long term. Besides this, the arrows highlight varying structural characteristics among the energy markets and between AI and energy stocks across the investment horizons.

Conclusion

Artificial intelligence (AI) is one of the most essential technologies of modern times, with diverse applications across different industries and spheres of human life. In this paper, we examine the potential implications the emergence of AI holds for the energy-focused sectors by analyzing the co-movement and lead-lag dependence and the dependence and directional predictability between the stocks of AI and those of eight energy-focused sectors. Along this line, the paper particularly examined the portfolio diversification role of AI stocks by considering average returns, possible risk, and correlations of the stocks of AI companies with those of energy-focused sectors. We addressed our research objectives by using a sample covering the period from December 18, 2017, to June 14, 2021, and by applying the Maximal Overlap Discrete Wavelet Transform (MODWT) for the co-movement and lead-lag analysis, the Cross-Quantilogram technique for the dependence and directional predictability analysis and the TVP-VAR technique for the network connectedness analysis.

Our results show that the stock returns of energy-focused sectors depend strongly on and are predictable from those of AI. However, the strength of this dependence and the direction of the prediction varies across the sectors, market conditions, and investment horizons. Beginning with our wavelet analysis, we find that the dependence between AI and energy-focused sectors was weaker in the short term and stronger in the intermediate- and long-term. The latter was significantly stronger for the renewable energy sector. Moreover, in the intermediate term, during which the degree of dependence is strong, the Coal and renewable energy sectors lead AI, while AI leads the remaining six energy-focused sectors. This suggests that returns on Coal and renewable energy investments hold some predictive power for AI investments. This is intuitive, especially for renewable energy, given the rising application of AI technology in their development and deployment. Similarly, in the long-term, when dependence is significantly strong, the renewable energy sector and, to an extent, the Oil and Gas Transportation Services sector lead AI. We also find that the co-movement and dependence between AI and energy-focused sectors strengthened during the COVID-19 peak period. This is in line with those of many past studies that document stronger co-movement and dependence among financial assets during the COVID-19 pandemic, as financial market risks rose to unprecedented levels following the restriction of movements and breakdown of economic activities.

Results from the CQ analysis correspond with those of the wavelet coherence analysis in suggesting a weaker (stronger) dependence between AI and the energy-focused sector in the short term (intermediate and long term) as well as the dependence between AI and energy-focused being stronger during the COVID-19 period. Besides this, the CQ analysis reveals notable differences in the directional predictability of the returns of the energy-focused sectors by that of AI across quantiles and frequencies that characterize the pre-COVID and COVID samples. For instance, whilst we find that negative directional predictability dominates the long-term pre-COVID sample period, positive directional predictability dominates the COVID sample period. TVP-VAR analysis shows strong return connectedness among AI and energy-focused sectors as we move from the short-term to long-term investment horizons in both the pre-COVID and COVID sample periods. Similar to the wavelet coherence and CQ results, however, the total connectedness between AI and the energy-focused sectors as a whole, and the net pairwise directional connectedness are both stronger during the COVID period. Moreover, we find that AI has been a net shock receiver from the energy markets since the COVID period.

Our findings offer three important implications for portfolio diversification managers, investors, and institutional investors who are more concerned with long-term investment horizons. First, under different investment horizons, investors are invited to make time-varying hedging strategies depending on whether the market is bearish, normal, or bullish. Second, traders and speculators that are more concerned with short- and intermediate-term investment horizons should consider that innovation in the AI market is more driven by innovations in the energy market since the COVID pandemic. Investment in AI yields diversification and hedging benefits to investment in the energy-focused sectors. Third, policymakers and financial regulators interested in market risk monitoring should pay attention to cross-market risk transmission between AI-based assets and those of energy-focused sectors, especially in the intermediate and long-term investment horizons.

Our study offers a premise for future directions. First, our findings may be sensitive to the chosen windows for the short-, intermediate- and long-term investment horizons. Therefore, we suggest that future studies may focus on further insights on these relationships by considering other window sizes for the various investment horizons. Future research could also extend our analysis to explore how the relationship understudy varies across different regions. Such analysis would create region-specific evidence and help ascertain if there are international diversification opportunities among the studied investment indices. Last but not the least, another interesting area would be to examine the dependence structure between the energy-focused sectors and other types of technologies such as blockchain and Internet of Things (IoT).

Abbreviation

AI	Artificial intelligence
ADF	Augmented Dickey-Fully
CQ	Cross quantiligram
DRI	Oil & gas drilling
DWT	Discreet wavelet transform
EXP	Oil & gas exploration and production
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
GFEVD	Generalized forecast error variance decomposition
GIRFs	Generalized impulse response functions
INT	Integrated oil & gas
JB test	Jarque–Bera test
MODWT	Maximal discreet wavelet transform
NASDAQ	National Association of Securities Dealers Automated Quotations
NDC	Net directional connectedness

NPDC	Net directional pairwise connected
VAR	Vector autoregssion
RE	Renewable energy
REF	Oil & gas refining and marketing
SEQ	Oil-related services and equipment
TRBC	The Refinitiv Business Classifications
TCI	Total Connectedness Index
TRA	Oil & gas transportation services
TVP-VAR	Time-varying parameter vector autoregression
TVP-VMA	Time-varying parameter vector moving average

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Declaration

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