Policy Impact Program: Driving UAE's Strategic Visions

Quantile Connectedness of Artificial Intelligence Tokens with Energy Sector

(Executive Summary)

Zaghum Umar

College of Business, Zayed University, Dubai, UAE
zaghum.umar@zu.ac.ae

Farooq Malik

Franke College of Business, Northern Arizona University, Flagstaff, Arizona 86011
farooq.malik@nau.edu

1. Introduction

Study Background: There has been an enormous recent interest in artificial intelligence (AI) because of the disruptive impact it has across many sectors of the economy. In financial industry, AI can potentially create optimal portfolios, offer investing advice and can even detect fraudulent activity. AI has the potential to enhance economic progress by increasing efficiency and productivity (Mokyr, 2018). Recent explosion in NVIDIA stock price, which is a key player in manufacturing chips used in AI computation, provides evidence of the AI potential. As a matter of fact, recently NVIDIA CEO crowned AI as a 'whole new industry' amid 'tipping point' after his company passed Google for third most valuable company in the world. Technological innovations in AI are expected to have a major influence on businesses by assisting financial decision-making under intricate settings (Ashta and Herrmann, 2021).

AI tokens are an offshoot of the AI technology, which are a new class of crypto assets which leverage the AI knowledge with enhanced security achieved through blockchain networks. AI tokens are digital assets that integrate AI capabilities by operating on decentralized networks using AI algorithms in order to automate tasks, make intelligent decisions, and have the ability to quickly adapt to changing datasets. In terms of applications, AI tokens can be used as digital currencies to function as a medium of exchange and store of value; can be used to power AI-based projects or AI-based investment strategies. Thus AI tokens have the ability to enhance functionality, introduce intelligent automation, establish decentralized intelligence, and enable adaptive learning.

Obviously, AI tokens are gaining widespread attention as investors hunt for alternative assets with superior performance but their value experience considerable volatility over time due to speculation, regulatory environment and investor sentiment. (See Sockin and Xiong, 2023; Malinova and Park, 2023). AI assets can improve the whole investment process by examining large datasets using AI algorithms to recognize patterns, gain insights, and select optimal investment opportunities. This can result in selection of optimal investments with better risk management and enhance overall performance. Additionally, AI assets have improved data analysis abilities which can allow investors to examine enormous data in real-time. This can quickly capture trends and sentiments more accurately, which can help investors with data-driven investment decisions. The popularity of AI tokens is evident from its market capitalization which has increased substantially over the last few years. As of March 13, 2024, the current market capitalization of SingularityNET is $1.5 billion, Fetch has a market cap of $2.7 billion, Ocean has a market cap of $729 million and Cortex has a market cap of $114 million.

Research Objective: A strand of literature has studied financial crisis, volatility spillover and tail risk among financial markets (See Billah et al., 2024; Hoque et al., 2023; Hoque et al., 2024a). Hoque et al (2024b) estimate the potential of gold-backed cryptocurrencies as a hedge and safe haven against global and regional financial stresses using dynamic conditional correlation and quantile coherency methodology using daily data from February 2020 to March 2023. They show that gold-backed cryptocurrencies serve as strong safe haven against US financial stress but are weak safe havens against global financial stress. Elsayed et al. (2024) study the relationship between assets related to the fourth industrial revolution versus dirty and clean energy markets. Their static connectedness analysis show weak integration between the fourth industrial revolution assets versus both clean and dirty energy markets with short term spillovers. Their time-varying connectedness analysis indicates that the connectedness is time-varying and responsive to external shocks. Kumar et al. (2023) study the connectedness and investment strategies among commodity prices, cryptocurrencies, and G-20 capital markets during COVID-19 and the Russian-Ukraine war. They document high connectedness during Covid-19 period with multidimensional effects.

However, recent research has focused on different aspects of cryptocurrencies especially how it correlates with traditional asset classes, how risk and return shocks are transmitted, its ability to diversify and hedge (see Corbet et al., 2018; Baur and Hoang, 2021; Le et al., 2021; Katsiampa et al., 2022; Shahzad et al., 2022; Chowdhury et al., 2022; Chen et al., 2022; Aharon et al., 2023). While some amount of research work is done on cryptocurrencies, very little research is performed to date on AI tokens. Jareno and Yousaf (2023) examine the quantile connectedness of AI tokens with the stock market. They report a low magnitude of connectedness although they report that the connectedness varies over time. Yousaf et al. (2024) study tail connectedness among AI tokens, ETFs based on AI with conventional assets. They report medium connectedness levels at median quantile and find ETFs based on AI as strong net transmitter of return spillovers, while AI tokens are weak receivers.

Our contribution to the literature is to answer the above important research questions since AI tokens are being used as investment assets, so it is important to understand how this new class of assets interacts with the traditional energy sector. Measuring the nature and strength of these financial market linkages is not only important for risk management strategies but also provides a policy response to potential systemic shocks. To the best of our knowledge, we are the first to study the relationship between popular AI tokens and the energy sector using quantile connectedness approach at both return and volatility level.

2. Research Question(s)

As the popularity of AI tokens is increasing, while these tokens consume significant amount of energy, a key question is how AI tokens and energy sector interact over time? It is important to decouple these two main catalysts of growth as the global economies switch their focus from traditional energy sources (fossil fuel energy sources like oil as well as clean energy sources like natural gas and biofuel) which had powered the industrial revolution to AI fueled technological revolution. Ross (1989) using a theoretical model shows that volatility in asset returns depends upon the rate of information flow, which suggests that information from one market can be incorporated into the volatility generating process of another market. Since information flows and the time needed to process that information is different across financial markets, one should expect different volatility spillover patterns across markets. Since return and volatility are intrinsically linked, we should expect returns across markets to be linked as well. Similarly, Fleming, Kirby, and Ostdiek (1998) document that cross-market hedging and sharing of common information can transmit volatility across markets over time. Based on the above theoretical models, we expect to find evidence of return and volatility spillover between the crypto and energy markets. Specifically, we are interested in the following three research questions. First, are there return and volatility spillovers across AI tokens and energy sector? Second, what is the direction of spillovers across these two important markets? Third, are these spillover effects more pronounced during extreme market conditions?

3. Research Methods

Approach:

In this paper, we use the methodology of Ando et al. (2022) as they extended the mean method of Diebold and Yilmaz (2012), by incorporating quantile regression framework of Koenker and Bassett (1978). Consequently, we estimate how y_t depends on x_t at different quantiles τ [τ ∈ (0, 1)] through the distribution of y_t/x_t for the order p for variable n of the quantile VAR process.

$$y_t = c(\tau) + \sum_{i=1}^{p} B\, i(\tau) y_{t-i} + et(\tau), t = 1, \dots, T \qquad (1)$$

After estimating the regression model at different quantiles, following Ando et al. (2022), we use Diebold and Yilmaz (2012) methodology to estimate connectedness at different quantiles. The above equation can be defined as moving average of the VAR process as MA (∞)

$$\mathrm{Y_t} = \Psi(\mathrm{L})\varepsilon_\mathrm{t} \qquad (2)$$

where $\Psi(\mathrm{L})$ is a $\mathrm{n} \times \mathrm{n}$ matrix of coefficients. The generalized forecast error variance decomposition for a variable is credited to shocks of different variables for a given forecasting horizon H:

$$(\theta_H)_{j,k} = ((\Sigma)_{k,k})^{-1} \sum_{h=0}^{H-1} \left((\Psi_h \Sigma)_{j,k}\right)^2 / \sum_{h=0}^{H-1} (\Psi_h \Sigma \Psi_h')_{j,j} \qquad (3)$$

where Ψ_h is a $\mathrm{n} \times \mathrm{n}$ coefficient matrix with lag h and $\sigma_{kk} = (\Sigma)_{k,k} . (\theta_H)_{j,k}$ which provides the generalized forecast error variance decomposition given by Pearson and Shin (1998), which has a beneficial property of yielding robust estimations if the order of the variables in the underlying vector autoregression is changed.

The total directional connectedness from a variable k to other variables is given as

$$\mathrm{C}_{j\leftarrow\blacksquare}(H) = 100 \times \sum_{j\neq k, j=1}^{\mathrm{n}} \mathrm{C}_{j,k}(H) / \sum_{j,k=1}^{\mathrm{n}} \mathrm{C}_{j,k}(H) \qquad (4)$$

The total directional connectedness from other variables to j is given as

$$\mathrm{C}_{\blacksquare\leftarrow k}(H) = 100 \times \sum_{j\neq k, k=1}^{n} \mathrm{C}_{j,k}(H) / \sum_{j,k=1}^{n} \mathrm{C}_{j,k}(H) \qquad (5)$$

The overall total system connectedness is provided as

$$\mathrm{C}_H = 100 \times \frac{\sum_{j\neq k}(\tilde{\theta}_H)_{j,k}}{\sum(\tilde{\theta}_H)_{j,k}} = 100 \times \left(1 - \frac{\mathrm{Tr}\{\tilde{\theta}_h\}}{\sum \tilde{\theta}_h}\right) \qquad (6)$$

The net directional connectedness of variable j with variable k is given as

$$C_{jk}^{g}(H) = \left(\frac{\bar{\theta}_{kj}^{g}(H) - \bar{\theta}_{jk}^{g}(H)}{N}\right) \times 100 \qquad (7)$$

The above measure of connectedness indicates if the variable receives or transmits shocks. Positive number indicates that the variable is transmitter of shocks while a negative value indicates that the variable is receiver of shocks in the system.

Data Collection:

In this paper, we use four major AI tokens (Cortex, Fetch, Ocean and SingularityNET) . For the energy sector, we use oil (S&P GSCI all crude), natural gas (S&P GSCI natural gas) and biofuel (S&P GSCI biofuel). These different instruments are widely used and provide us with range of instruments in the energy sector ranging from clean sources like natural gas to traditional fossil fuel source of oil. Consistent with earlier research, we use daily frequency data as it provides a richer information set which is essential for capturing intricate dynamics among variables. Our sample period ranges from June 5, 2019 to March 8, 2024, which provides 1264 observations. This sample period is significant to examine as AI sector has had an astonishing growth in the last few years coupled with extraordinary volatility. Additionally, this sample period is important to examine as it includes key global events like the COVID-19 pandemic and Russian-Ukraine war. Consistent with earlier studies, we use returns as the data in the level form had a unit root. Energy sector data is acquired from Datastream, while AI tokens data is obtained from coinmarketcap.com.

4. Key Findings

Our quantile connectedness investigation shows connectedness in the left and right tails of the distribution are greater (61%) than the center of the distribution (43%). This means that positive and negative shocks to AI tokens have bigger impact as the magnitude of the shock increases, which shows shocks to AI tokens spread more intensely under extreme market movements. We find that AI tokens are net transmitters of shocks while the entire energy sector is the net receiver of shocks at the return level. We further document that dynamic connectedness was considerably higher during the major significant events like COVID-19 pandemic and Russian-Ukraine war.

We further extend our study to consider connectedness of AI token shocks' with the energy sector at the volatility level. We see comparable results at the volatility level for total connectedness under different quantiles as we report higher level of connectedness (about 60%) in both tails relative to the center of the distribution (48%). This asymmetric impact response of volatility transmission is not captured in the traditional conditional mean estimation models. One interesting difference at the analysis at the volatility level is that oil is now also a net transmitter of shocks at the volatility level in addition to AI tokens. This means oil price risk is transmitted to the system. We do not see transmission of shocks from other two energy sectors (i.e. natural gas and biofuel). This finding could be attributed to the fact that oil is a fossil fuel while other two sources of energy are coming from clean sources. We also note that total connectedness at volatility level is different at median (48.46%) compared to a total connectedness at return level at median (43.29%). This underscores the need of analysis at different moments. These results show that under normal market conditions, contagion effect is stronger in volatility than returns.

5. Implications

Our results have major consequences for investors and policy makers. We show that investments in AI tokens are subject to contagion, which means they offer inadequate portfolio diversification when markets experience major movements. Our results can aid financial market participants to find optimal diversification strategies when large market changes occur, quite often caused by key global events. Moreover, financial market participants can optimize their allocation of assets and hedging effectiveness by adjusting for specific dynamics shocks to AI tokens. Given that we find that AI tokens are net transmitters of shocks while the entire energy sector is the net receiver of shocks at the return level, our research clearly implies that energy investors should keep a close on AI tokens' market to properly hedge and diversify their portfolios. Additionally, our research provides insight into the potential impact of adding AI tokens to an existing energy portfolio. Policy makers should understand that potential risks do transmit between AI tokens' market and energy markets, so they can mitigate risk. Because markets involving AI and the energy sector are a major part of the global economy, policy makers should prudently observe the transmission mechanism of shocks to pursue an optimal macroeconomic policy.

6. Conclusion

AI tokens are digital assets that integrate AI capabilities by operating on decentralized networks using AI algorithms in order to automate tasks, make intelligent decisions, and swiftly adapt based on data. Given that AI tokens are energy intensive assets, in this paper we explore how major AI tokens are connected to oil, natural gas and biofuel under extreme market movements using daily data from June 2019 to March 2024. We find that AI tokens are net transmitters of shocks while the energy sector is the net receiver of shocks at the return level but both AI tokens and oil are net transmitters of shocks at the volatility level. We also show that total dynamic connectedness significantly increased during the start of COVID-19 pandemic and the Russian-Ukraine war. Our quantile-based connectedness analysis shows that return connectedness is considerably higher at low and high quantiles, indicating that shocks to AI tokens spread more intensely during extreme market movements.

Our results indicate that AI tokens are subject to contagion and thus offer limited portfolio diversification benefits under major market movements. These results have important practical implications for investors and policy makers. Our results can aid financial market participants to find optimal diversification strategies when large market changes occur typically caused by key global events. Moreover, financial market participants can optimize their allocation of assets and hedging effectiveness by adjusting for specific dynamics shocks to AI tokens. Our research provides an insight into the potential impact of adding AI tokens to an existing energy portfolio. Policy makers should be aware that transmission of risk can occur between the AI tokens' market and the energy markets and this information can help them in devising better risk mitigating strategies. Because markets involving AI and the energy sector are very important for the global economy, policy makers should cautiously observe the transmission mechanism of shocks to follow optimal macroeconomic policy.