

Fear Risk transmission to AI Stocks, Tokens and Energy Investments: Connectedness in pre and post availability of COVID-19 Vaccine

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Abstract

The study aims to explore the COVID-19 risk transmission to AI, Tokens, AI stocks, and Fossil fuels during the vaccine non-availability and availability periods using the extended GFI. The outcomes of the GARCH-BEKK model reveal that lag shocks in the extended GFI significantly enhance the conditional volatility of FET-Fetch in both pre- and post-vaccine periods, and also enhance the conditional volatilities of Ocean-protocol, AMZN-Amazon, and all fossil fuel markets in the post-vaccine period. However, AGIX-Singularity NET and MSFT-Microsoft remain unaffected during both periods. With the application of the TVP-VAR model, the study uncovers the extent of connectedness. Similar spillovers are observed between GFI and AI tokens, AI stocks, and fossil fuel markets. The risk transmission character of such investments helps investors to avoid uncertainties during trading. The connectedness of GFI with AI tokens, stocks, and fossil fuel investments may uncover diversification opportunities for investors, especially during ups and downs in markets.

Keywords: GFI; AI Stocks; AI Tokens; Energy Investments; Connectedness

JEL Classification Codes: C40; G10; G12; G40

Introduction

Artificial Intelligence (AI) is becoming a big part of our everyday lives, especially in many industries. Businesses are always searching for new and creative ways to use AI to work better and develop fresh ideas. In the next ten years, we are likely to see even more significant changes due to AI, especially in the financial sector

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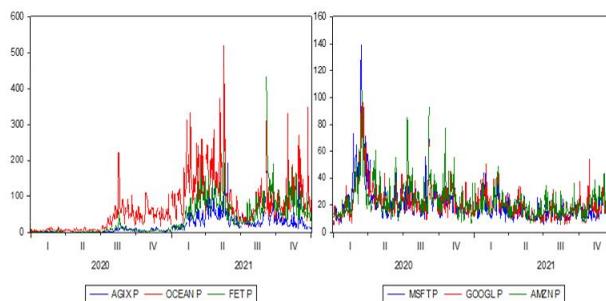
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(McKinsey, 2020). AI is making tasks more accessible, helping companies work more accurately, even predicting market trends, and changing the dynamics of banking operations and investment. As of 2023, the AI industry is worth about \$207.9 billion and growing rapidly, by around 42% yearly, potentially reaching \$1.8 trillion by 2030 (Bloomberg Intelligence report). Growing trends in AI are also influencing the energy industry. Energy companies are adapting to the changing dynamics of the financial world. AI-related activities use large amounts of energy to process information quickly, which helps connect essential market players, such as investors and government leaders. Some energy companies, including Shell, BP, and ExxonMobil, are pursuing AI exploration to manage oil and gas supply chains, analyze seismic data, spot anomalies and pollutants, and create payment solutions. Businesses may efficiently monitor and analyze enormous amounts of data with a level of accuracy, speed, and completeness that exceeds human capabilities by utilizing cutting-edge AI technologies. Thus, the intersection of AI with the energy industry creates links between market participants, such as producers, investors, legislators, and consumers. In the energy sector, artificial intelligence plays a key role in making our energy use smarter and more efficient. Companies are exploring ways to improve their planning and operations for power systems via AI to improve customer experiences (Deloitte, 2022). This technology helps share and examine information more effectively, bringing together different players in the energy market. Recently, there has been a growing interest in investments in artificial intelligence (AI), such as AI stocks and tokens.

Many investors see these as a way to diversify their investments, especially since AI stocks have significantly boosted the S&P 500 index. However, investing in these assets can be risky due to their instability and complexity. Additionally, the high energy consumption of AI raises concerns for investors. The energy needed for training AI also poses risks, impacting economies and global financial trends (Toews, 2020). At the same time, fossil fuel markets face divestment trends due to their harmful environmental impacts (Zori et al., 2022). Therefore, investors want to consider AI stocks and tokens to manage their portfolio risks and earn appropriate returns. As AI technology has spread across various sectors, it can offer benefits in terms of diversification. The rising demand for AI-related stocks and tokens has led to a substantial increase in their value. Thus, AI-based investments are getting the attention of investors to add to their portfolios for diversification benefits. Studies have suggested that tech-driven assets can act as safe havens during market downturns (Abakah et al., 2023a). However, Shahid (2022) argues

that global energy markets have been affected by COVID-19. The COVID-19-related fear has been badly transmitted to global energy investments (Shahid, 2024). During that time, no suitable vaccines were available, and subsequent waves caused a significant swing in market uncertainty (Baek & Lee, 2021). As a result, the COVID-19 news spreads uncertainty and panic among people, affecting the stock market (Shahid et al., 2022; Chen & QI, 2024). Several companies have tried to introduce appropriate vaccines to avoid COVID-19; however, the world's financial market conditions have been hit differently by the different waves of COVID-19.

Thus, the current study investigates the extent of fear transmission to AI financial markets, i.e., stocks, tokens, and fossil fuels, particularly during pre- and post-COVID vaccine periods. The study uncovers how these relationships change in different market conditions (pre-vaccine and post-vaccine). For robustness purposes, the study uncovers the connectedness of the fear index with investments. The study contributes to the literature in the following ways: a) It is first in its nature, uncovering the connectedness of AI financial markets with the global fear index. However, Earlier studies have shown how renewable energy tokens, carbon markets, cryptocurrencies, metals, and clean energy stocks interact with energy markets (Wei et al., 2022; Umar et al., 2022; Su et al., 2023; Chatziantoniou et al., 2023; Umar et al., 2023; Mohammed et al., 2023; Bai et al., 2023; Wei et al., 2023; Wang et al., 2023; Ren et al., 2023; Balash & Faizliev, 2024). As tokenization becomes more common in various industries, studying AI tokens could be helpful (Wang, 2022; 2022c; Wang et al., 2022; Ali et al., 2023); b) the study first time uncovers the COVID-related risk transformation to AI financial markets during Vaccination periods, c) the study utilizes an extended form of GFI proposed by Shahid (2024). The remainder of the study is expressed through the review of relevant literature in the following section. The methodology and data description are exhibited in section 3, while the results are displayed in section 4. Finally, the conclusions are furnished with practical implications in the last section.



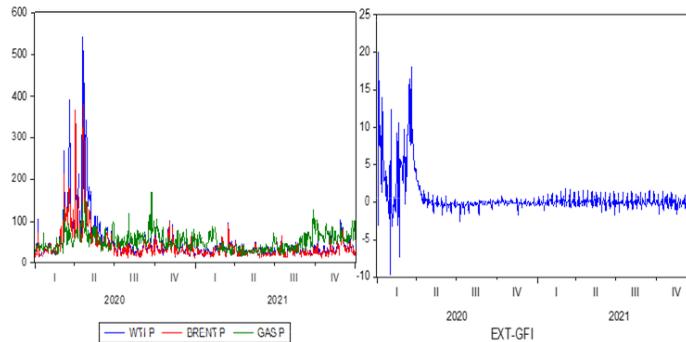


Figure 1. Prices of AI Tokens (AGIX, OCEAN, FET), AI Stocks (MSFT, GOOGL, AMZN), and Fossil Fuels (WTI, BRENT, GAS) over a full sample period. The behavior of extended GFI (EXT-GFI) is also presented. The alphabet “P” with each type of investment indicates prices.

Methodology and Data Description

To determine the effect of COVID-19 on AI stock, tokens, and energy investments, this study utilizes the extended GFI proposed by Shahid (2024), which is an extended version of the GFI prepared by Salisu and Akanni (2020) and used in the number of studies. Salisu and Akanni's (2020) GFI consisted of two primary components: the RCI and the RDI. However, Shahid (2024) has extended the GFI by adding the COVID stringency index (SI) to it and proposed a new GFI. The reported cases index (RCI) measures the dispersion between the current and predicted COVID-19 case counts over the following 14 days. Similarly, the RDI (reported death index) considers the current and projected daily death according to WHO proportions. However, Shahid (2024) claims that it is not only the RCI and RDI that transmit fear in investors; the nine matrices of the SI index also initiate uncertainties in investors. The number of COVID-19 cases and deaths, along with government responses such as lockdowns, mobility restrictions, and closures, have a significant impact on the economy and financial markets. The authors (Scher et al, 2022) state that these measures hit the financial markets hard. Restricted market activities are associated with lockdowns (Baig et al., 2021), and Lockdowns lead to narrower bid-ask spreads in the financial markets (Clancey-Shang, 2023). Therefore, the current study utilizes the extended version of the GFI of Shahid (2024), and we use the same criteria for its calculation in the current study. To investigate the risk transmission from extended GFI to AI tokens, stock, and energy induces, the study uses a multivariate BEKK-GARCH model developed by Engle and Kroner (1995). The

model has been applied in related studies to explain how price changes (volatility) in one market affect other markets (Chen et al., 2023). The model is particularly preferred since it is best suited to deal with the variance-covariance matrix, the tool used to analyze the variability and the degree of co-movement between different markets. The BEKK-GARCH model is deemed the most stable than the others in the heterogeneous group of multivariate GARCH models. The model has few convergence issues and is preferable to other models analyzing market relationships (Vo & Ellis, 2018; Chng, 2009).

The study determines the interaction between COVID-19 risk and AI stock, tokens, and energy investments using the multivariate BEKK-GARCH (1,1) model. The model also includes rules for positive definiteness concerning H_t .

$$H_t = \hat{C}C + \hat{A} e_{t-1}\hat{e}_{t-1}A + \hat{B}H_{t-1}B \quad 1$$

The following equation explains the model, which includes a lower triangular matrix named C, and square matrices are represented by A and B.

$$C = \begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix}, \quad A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, \quad B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \quad 2$$

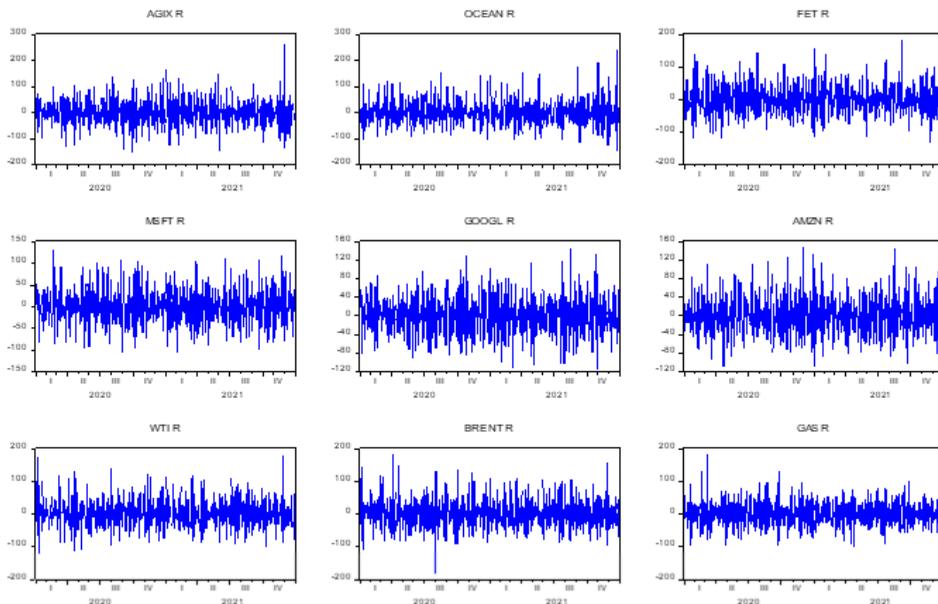
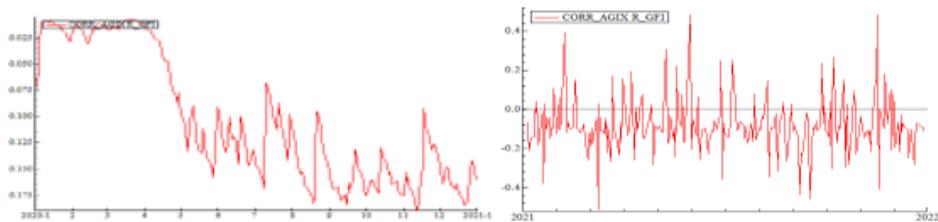


Figure 2. Returns from of AI Tokens (AGIX, OCEAN, FET), AI Stocks (MSFT, GOOGL, AMZN) and Fossil Fuels (WTI, BRENT, GAS) over full sample period. The alphabet “R” with each type of investment indicates returns.

Order (1) in above equation denotes GFI while respective AI investment is indicated in order (2) in equation 2. The coefficients of the ARCH term are represented with elements of matrix A. As the study uncovers the connections of GFI with AI investments, hence the relevant parameters are indicated with a_{12} and b_{12} , i.e., The prevailing conditional volatility of concerned AI investment affected by past COVID-19 shocks is indicated with a_{12} . The coefficients b_{12} indicates how the predominant conditional volatility of AI investments is affected by previous COVID-19 volatility shocks. The estimated parameters also yield the findings for past own shocks and volatility, which are shown as a_{22} and b_{22} , respectively. A multivariate BEKK-GARCH (1,1) model is utilized to measure the impact of COVID-19 risk spillovers on AI investments. In addition to estimating how AI investments assets co-move with GFI, the study employs TVP-VAR model mentioned under section 4.3.

Table 1
Summary Statistics of daily volatility.

	AGIX_R	OCEAN_R	FET_R	MSFT_R	GOOGL_R	AMZN_R	WTI_R	BRENT_R	GAS_R	EXT_GFI
Mean	0.582106	0.485483	0.522145	0.141589	0.145110	0.028715	0.066340	0.075878	0.240854	0.531969
Median	-0.637829	-1.869674	-0.024304	-2.096462	1.917647	-1.935535	-4.003664	-3.583237	-3.207918	-0.072098
Maximum	263.1512	241.0227	182.3678	131.6542	143.9413	147.9355	176.6461	180.5558	180.4602	20.07184
Minimum	-151.8304	-150.3687	-129.1136	-105.3386	-113.5508	-109.7691	-123.9326	-180.2531	-101.1269	-9.684183
Std. Dev.	53.13853	51.07318	50.30469	43.52596	43.58614	44.42184	46.77226	49.01570	40.27714	2.602207
Skewness	0.209186	0.630544	0.272631	0.210645	0.108009	0.380847	0.428334	0.418494	0.273258	3.546612
Kurtosis	4.207435	4.599007	3.039130	2.896019	3.011045	3.114521	3.486072	3.517952	3.502501	21.06837
Jarque-Bera	34.22358	86.91763	6.263240	3.946412	0.980557	12.43442	20.33261	20.30494	11.55197	7896.675
Probability	0.000000	0.000000	0.043647	0.139011	0.612456	0.001995	0.000038	0.000039	0.003101	0.000000
Observations	503	503	503	503	503	503	503	503	503	503



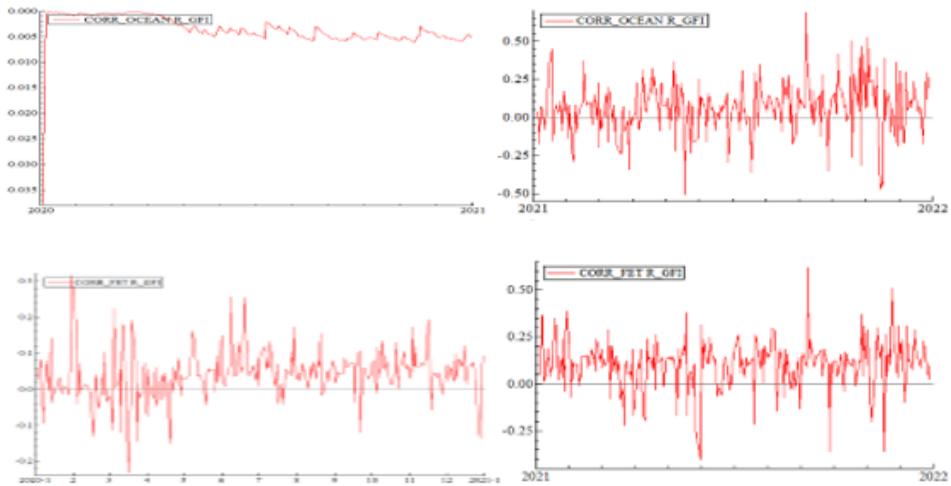


Figure 3. Time-varying correlations from multivariate BEKK-GARCH model between AI-Tokens and extended GFI (Shahid, 2024) for pre-vaccine (left-hand side graphs) and post-vaccine (right-hand side graphs) periods.

To reach the reality, the study collects the daily prices of AI tokens, stocks and energy investments from January 2020 to December 2021. To explore the extent of risk transmission, we divided the sample into pre-vaccine and post-vaccine periods, i.e., January 2020 to December 2020 and January 2021 to December 2021, respectively. For all AI stock, tokens and energy investments, the coefficient a_{22} is positive and significant. It implies that their own past shocks influence the current volatility of these indices during both pre- and post-vaccine periods.

Results and Discussion

For shock transmissions, the values of a_{12} indicate that lag shocks in the GFI (COVID-19 index) significantly enhance the conditional volatility of FET-Fetch from AI tokens (as coefficients are positive and significant) in both pre- post-vaccine periods. However, GFI enhances conditional volatilities of Ocean-protocol, AMZN-Amazon and all fossil fuel markets in the post-vaccine period. However, AGIX-Singularity NET and MSFT-Microsoft remain unaffected during both pre- and post-vaccine periods. The shock transmission is stronger from COVID-19 to AI tokens. The coefficients of b_{22} indicate that the past volatility of all these investments positively and significantly increases their current volatility except AI stocks and GAS-natural gas, which have negative coefficients in the post-vaccine period. The

coefficient values of b_{22} are significantly higher than those of a_{22} in the pre-vaccine period, implying that past own-volatility effects are more potent and higher than past own-shock effects. Such findings exhibit the significance of current volatility in predicting the future volatility of such investments.

All AI stocks, tokens, and energy indices show significant and positive cross-volatility transmission (see values of b_{12}) in both pre- and post-vaccine periods except AGIX (negative in the post-vaccine period). These values show that a rise in GFI enhances the volatility of the indices under study. These values show that only AGIX acts as a safe-haven asset during the post-vaccine period.

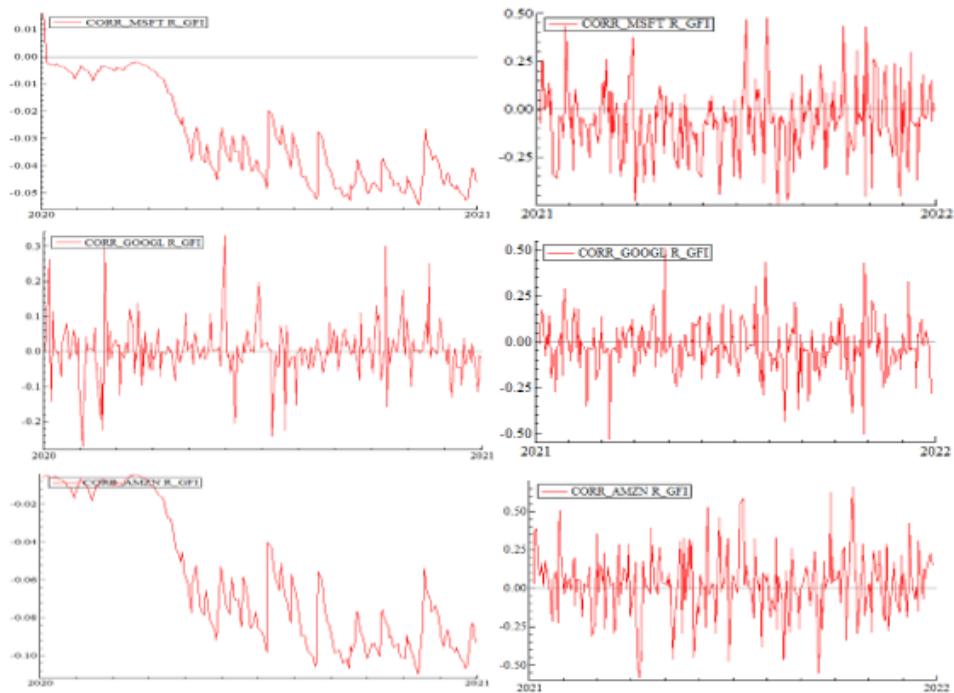


Figure 4. Time-varying correlations from multivariate BEKK-GARCH model between AI-Stocks and extended GFI (Shahid, 2024) for pre-vaccine (left-hand side graphs) and post-vaccine (right-hand side graphs) periods.

Table 2
Correlation Analysis.

Probability	AGIX_R	OCEAN_R	FET_R	MSFT_R	GOOGL_R	AMZN_R	WTI_R	BRENT_R	GAS_R
AGIX_R	1.000000								
OCEAN_R	0.357722	1.000000							
FET_R	0.0000	0.0000	1.000000						
MSFT_R	0.034480	0.050049	0.069385	1.000000					
GOOGL_R	0.4404	0.2626	0.1202	0.436712	1.000000				
AMZN_R	-0.027285	0.045904	-0.023968	0.436712	0.425725	1.000000			
WTI_R	0.5415	0.3042	0.5918	0.0000	0.0000	0.0000	1.000000		
BRENT_R	0.025871	0.060344	0.102024	0.440028	0.2701	0.3767	0.821386	1.000000	
GAS_R	0.5627	0.1766	0.0221	0.0000	0.0000	0.0000	0.0000	0.0000	1.000000
	0.155186	0.009205	0.045803	0.090800	0.049270	0.039497	0.051434	0.140734	0.140734
	0.0005	0.8368	0.3053	0.048	0.2701	0.3767	0.821386	0.0000	0.0016
	0.069513	0.013107	0.043860	0.097967	0.061349	0.051434	0.821386	0.0000	0.0016
	0.1195	0.7693	0.3263	0.0280	0.1695	0.2496	0.0000	0.0000	0.0016
	0.065441	-0.001319	0.038801	0.021689	0.062767	0.101292	0.164928	0.140734	0.0016
	0.1428	0.9765	0.3852	0.6275	0.1598	0.0231	0.0002	0.0016	0.0016

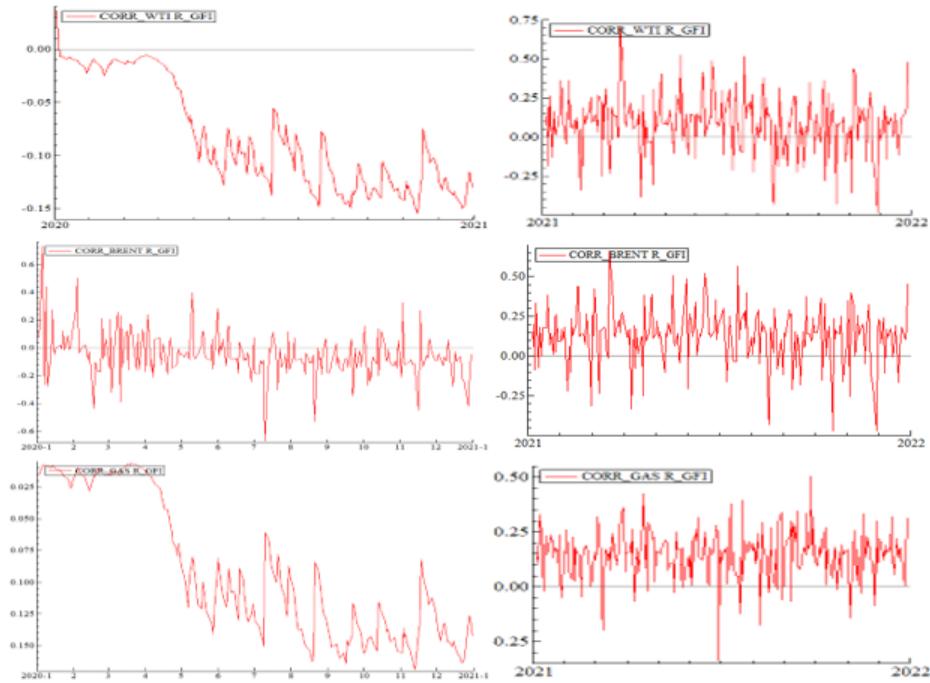


Figure 5. Time-varying correlations from multivariate BEKK-GARCH model between Fossil Fuels markets and extended GFI (Shahid, 2024) for pre-vaccine (left-hand side graphs) and post-vaccine (right-hand side graphs) periods.

Table 3

Risk Transmission from Extended GFI to AI Tokens, AI Stocks and Fossil Fuels during pre- and post-vaccine availability.

Period	c22	a12	a22	b12	b22
AI Tokens					
AGIX-SingularityNET					
Pre-Vaccine	50.402089 0.0000	-0.063532 0.1191	0.177118 0.0001	0.426182 0.0000	0.869951 0.0000
Post-Vaccine	45.310217 0.0000	-0.064020 0.1996	0.618778 0.0000	-0.321964 0.0001	0.001232 0.9407
Ocean Protocol					
Pre-Vaccine	46.509350 0.0000	-0.002395 0.9599	0.188358 0.0001	0.423323 0.0000	0.871044 0.0000
Post-Vaccine	45.813848 0.0000	0.037111 0.3360	0.526054 0.0000	0.675133 0.0002	0.050053 0.4212
FET-Fetch.ai					
Pre-Vaccine	50.467533 0.0000	0.028543 0.6628	0.188704 0.0004	0.425254 0.0000	0.869839 0.0000
Post-Vaccine	24.840509 0.0045	0.114488 0.1895	0.490157 0.0000	0.731992 0.0000	0.021981 0.3633
AI Stocks					
MSFT-Microsoft					
Pre-Vaccine	42.705377 0.0010	-0.020482 0.7560	0.187846 0.0001	0.423764 0.0000	0.870652 0.0000
Post-Vaccine	40.140743 0.0000	-0.037270 0.3106	0.531112 0.0000	0.653987 0.0000	-0.0000032 0.1932
GOOG-Alphabet					
Pre-Vaccine	40.707835 0.0000	0.002063 0.9610	0.188943 0.188943	0.432969 0.0000	0.868183 0.0000
Post-Vaccine	39.582513 0.0156	-0.018008 0.6788	0.499714 0.0000	0.746114 0.0000	-0.019037 0.7243
AMZN-Amazon					
Pre-Vaccine	44.557710 0.0000	-0.043813 0.3846	0.185015 0.0001	0.424504 0.0000	0.869914 0.0000
Post-Vaccine	38.396196 0.0000	0.016077 0.7334	0.534555 0.0000	0.656172 0.0000	-0.0000006 0.9394
Fossil Fuel Markets					
WTI					

Pre-Vaccine	47.673743 0.0000	-0.061871 0.2848	0.174663 0.0003	0.422916 0.0000	0.872489 0.0000
Post-Vaccine	28.352596 0.0000	0.060673 0.2837	0.553326 0.0000	0.438357 0.0001	0.063640 0.2069
BRENT					
Pre-Vaccine	43.982355 0.0000	-0.046604 0.4123	0.180568 0.0001	0.420641 0.0000	0.875431 0.0000
Post-Vaccine	42.885061 0.0000	0.067604 0.1021	0.525493 0.0000	0.660151 0.000	0.0000021 0.1608
GAS-natural gas					
Pre-Vaccine	43.393549 0.0000	-0.066362 0.8386	0.179435 0.1417	0.429075 0.0000	0.868108 0.0000
Post-Vaccine	20.996298 0.0090	0.137191 0.0862	0.484557 0.0000	0.737759 0.0000	-0.000798 0.9742

Figures 3–5 present the time-varying correlation of the BEKK-GARCH model between AI Tokens, stocks, fossil fuels and extended GFI for pre- and post-vaccine periods. Our findings are similar to the outcomes of recent studies; for example, Yousaf (2021) found that commodity markets act as safe-haven investments during COVID-19. Just and Echaust (2022) find increased uncertainty in global financial markets during crises. Guo et al. (2022) found that investment in natural resource commodities is volatile in the short run of the COVID-19 pandemic. Moreover, Bossman et al. (2023) found that COVID-19 risk has adversely affected the energy markets.

The connections between AI tokens, AI stocks, energy indices and GFI are presented in this section. To explore the connectedness, we apply the TVP-VAR model. All the return graphs (see Figure 1) provide evidence of some observable features; for example, all the series under study experienced high volatility during the first half of 2020 due to COVID-19. Table 2 presents a significant mean difference in returns and level of risk for all indices. Moreover, the negative skewness values indicate an asymmetric distribution of returns. Such preliminary analysis justifies the application of the TVP-VAR model to test connectedness (Antonakakis et al., 2020). Hence, to explore the dynamic return and volatility spillovers, we use the TVP-VAR model and present them through the following Equation (see Antonakakis et al., 2020)

$$A_t Z_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N(0, \Sigma_t) \quad 3$$

The equation above follows the Bayesian information criterion. The model can handle changes in structure and heterogeneous connections between the variables.

$$vec(A_t) = vec(A_{t-1}) + \xi_t \xi_t \sim N(0, \Xi_t) \tag{4}$$

In equations (3) as well as (4), the dimensional matrix data $K \times K$ are given with A_t and Σ_t while the dimensional vectors $K \times 1$ is given with y_t , Z_{t-1} and ξ_t . Whereas dimensional vectors $K^2 \times 1$ are presented with $vec A_t$ and ξ_t , and dimensional $K^2 \times K^2$ is indicated with Ξ . Diebold and Yilmaz (2012, 2014) explain that a moving average form of TVP-VAR can show the influence of the time-varying parameter vector of one series on another. The following equation presents the H-step ahead expression:

$$\theta_{ij,t}^g(H) = \frac{\sum_{h=0}^{H-1} (e_i^f A_{ht} \Sigma_t e_j^f)^2}{(e_j^f \Sigma_t e_j) \sum_{h=0}^{H-1} (e_i A_t S_t A_t^i e_i)} \tag{5}$$

$$\theta_{ij,t}^g(H) = \frac{\theta_{ij,t}^g(H)}{\sum_K \theta_{ij,t}^g(H)} \tag{6}$$

With unity in the i^{th} position, a dimensional zero-vector ($K \times 1$) is given with e_i . The unscaled GFEVD $\sum_{j=1}^K \xi_{ij,t}^g(H) \neq 1$ is indicated with $ij, t g(H)$. We divide $\theta_{ij,t}^g(H)$ by row sums to get scaled GFEVD, $\tilde{\theta}_{ij,t}^g(H)$ and normalize the unscaled GFEVD as suggested by Diebold and Yilmaz (2012, 2014). Being a core connectivity technique, scaled GFEVD facilitates computation of the total directional connectivity from (to) index (i.e. FI) to (from) all indices (AI tokens, AI stocks and fossil fuels. For total directional connectivity, “TO” indicates GFI has influence on all other indices, while “FROM” matrices indicate the impressions of all other indices on GFI. The TO and FROM connectivity are calculated through the following steps;

$$C_{i \rightarrow j,t}^g(H) = \sum_{j=1, i \neq j}^k \tilde{\theta}_{ij,t}^g(H) \tag{7}$$

$$C_{i \leftarrow j,t}^g(H) = \sum_{j=1, i \neq j}^k \tilde{\theta}_{ji,t}^g(H) \tag{8}$$

The TO and FROM connectivity are determined as follows.

$$C_{i,t}^g(H) = C_{i \rightarrow j,t}^g(H) - C_{i \leftarrow j,t}^g(H)$$

The results for returns and volatility spillovers are reported in the Tables below.

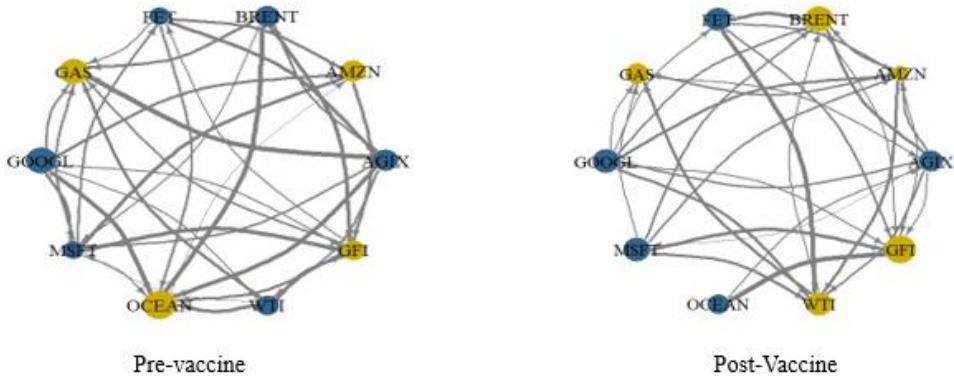


Figure 6: Network connectedness (returns spillovers) among energy cryptocurrencies and conventional assets.

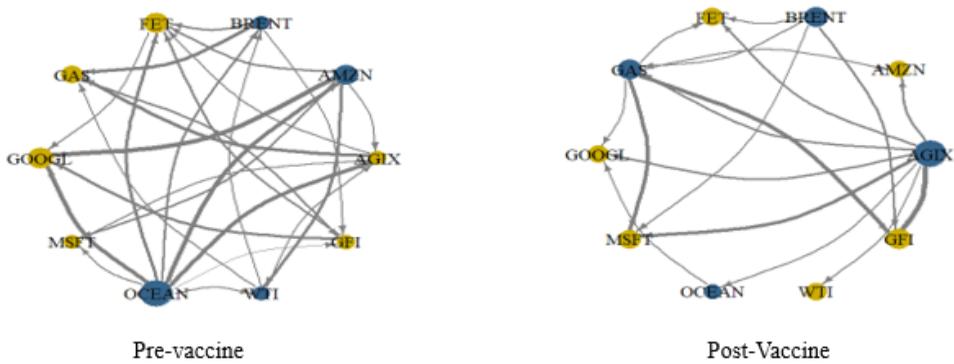


Figure 7: Network connectedness (volatility spillovers) among energy cryptocurrencies and conventional assets.

Table 4

Spillovers (Return) between Extended GFI to AI Tokens, AI Stocks and Fossil Fuels during the Pre-Vaccine availability. Total Network Connectedness is indicated with TNC.

Index	AGIX (AIT)	AMZN (AIS)	BRENT (FF)	FET (AIT)	GAS (FF)	GOOGL (AIS)	MSFT (AIS)	OCEAN (AIT)	WTI (FF)	GFI	FROM
AGIX	22.03	6.47	8.43	16.88	3.46	10.63	9.5	8.25	7.83	6.52	77.97
AMZN	8.12	39.38	5.13	9.32	3.59	9.19	11.62	4.77	5.05	3.83	60.62
BRENT	12.55	3.71	18.2	10.18	6.36	11.62	7.16	5.58	15.77	8.86	81.8
FET	10.36	4.23	10.98	23	3.81	10.24	11.26	6.06	10.43	9.61	77
GAS	11.73	2.96	11.43	6.3	24.27	10.38	9.03	4.56	11.31	8.04	75.73

GOOGL	10.11	4.03	9.89	8.67	6.97	30.57	8.2	6.17	9.31	6.08	69.43
MSFT	12.95	5.72	10.44	7.53	5.7	13.7	21.5	5.56	9.77	7.13	78.5
OCEAN	15.04	2.58	12.65	9.89	5.86	13.25	8.48	12.29	12.49	7.47	87.71
WTI	12.09	3.8	15.29	10.68	6.33	12.04	7.64	6.16	17.28	8.68	82.72
GFI	4.65	8.48	15.41	6.86	4.62	9.24	14.46	2.78	14.22	19.27	80.73
TO	97.6	41.99	99.66	86.3	46.71	100.3	87.35	49.89	96.19	66.23	772.21
Inc.own	119.6	81.36	117.86	109.3	70.98	130.87	108.85	62.18	113.47	85.49	TNC
NET	19.63	-18.64	17.86	9.3	29.02	30.87	8.85	-37.82	13.47	-14.51	77.22

Table 5

Spillovers (Volatility) between Extended GFI to AI Tokens, AI Stocks and Fossil Fuels during Pre-Vaccine availability period. Total Network Connectedness is indicated with TNC.

Index	AGIX (AIT)	AMZN (AIS)	BRENT (FF)	FET (AIT)	GAS (FF)	GOOGL (AIS)	MSFT (AIS)	OCEAN (AIT)	WTI (FF)	GFI	TNC
AGIX	18.15	6.45	5.54	12.78	10.15	12.58	10.82	11.97	6.58	4.99	81.85
AMZN	11.78	21.25	3.49	12.36	5.18	13.99	13.67	11.85	3.2	3.24	78.75
BRENT	11.24	8.31	9.32	13.06	10.77	10.27	11	11.04	10	4.99	90.68
FET	12.77	7.37	5.2	20.32	8.35	12.66	12.05	11	6.02	4.25	79.68
GAS	6.41	10.74	11.31	8.19	14.43	11.49	13.51	6.02	12.83	5.36	85.57
GOOGL	17.52	7.9	5.85	9.26	7.7	19.68	11.39	10.29	6.16	4.25	80.32
MSFT	13.48	8.39	6.08	10.75	10.2	12.82	15.43	12.19	6.71	3.96	84.57
OCEAN	8.85	11.57	8.94	12.93	6.12	11.33	13.37	12.85	9.16	4.89	87.15
WTI	11.53	10.02	7.09	14.71	6.01	12.63	12.48	11.18	9.96	4.4	90.04
GFI	7.92	7.31	8.82	8.7	4.86	7.51	11.63	15.33	4.89	23.04	76.96
TO	101.19	78.05	62.33	102.74	69.33	105.28	109.92	100.86	65.56	40.32	835.57
Inc.Own	119.34	99.3	71.64	123.07	83.76	124.96	125.35	113.71	75.52	63.36	TNC
NET	19.34	-0.7	-28.36	23.07	-16.24	24.96	25.35	13.71	-24.48	-36.64	83.56

Tables 4 and 5 present the outcomes for returns and volatility spillovers of GFI with AI tokens, AI stocks and fossil fuels with the application of TVP-VAR in pre-vaccine period. The researcher finds almost similar results for both returns and volatility spillovers. It is observed that all AI tokens, AI stocks and fossil fuels are the net receivers of innovations, with OCEAN (from AI tokens) being the least “net-connected” with GFI through returns (-37.82) and volatility (13.71). Similarly, AMZN

(from AI stock) being the least “net-connected” with GFI (returns = -18.64 and volatility = -0.7). On the other hands, GAS in returns (-29.02) and BRENT in volatility (-28.36) are least “net-connected” with GFI of COVID during pre-vaccine period. The FET in return and GAS in volatility is most connected with GFI with a value of 9.61 and 5.36 respectively during pre-vaccine period. The study finds 77.22 value (772.21/10) of returns and 83.56 value (835.57/10) of volatility for total network connectedness (TNC) during pre-vaccine period.

For post-vaccine period, the study observes different scenario, as FET (from AI tokens) being the least “net-connected” with GFI through returns (-20.76) and volatility (-26.14). From AI stock, GOOG (in returns = -22.02) and MSFT (in volatility = -30.9) are being the least “net-connected” with GFI. On the other hands, GAS in returns (-11.74) and WTI in volatility (-21.51) are least “net-connected” with GFI of COVID during post-vaccine period.

Table 6

Spillovers (Return) between Extended GFI to AI Tokens, AI Stocks and Fossil Fuels during Post-Vaccine availability period. Total Network Connectedness id indicated with TNC.

Index	AGIX (AIT)	AMZN (AIS)	BRENT (FF)	FET (AIT)	GAS (FF)	GOO G (AIS)	MSFT (AIS)	OCEAN (AIT)	WTI (FF)	GFI	FROM
AGIX R	16.05	9.17	6.58	6.13	7.54	8.43	10.83	15.58	9.74	9.94	83.95
AMZN R	6.6	24.65	4.05	8.72	3.01	9	11.94	15.27	4.95	11.8	75.35
BRENT R	8.34	5.6	22.93	5.55	8.36	7.21	6.03	11.22	16.74	8.01	77.07
FET R	9.44	12.86	9.32	18.63	8.36	5.31	8.66	11.6	10.45	8.38	81.37
GAS R	13.81	4.17	14.37	5.41	5.36	5.41	7.79	7.26	7.97	6.09	72.29
GOOGL R	9.4	17.35	5.3	8.17	5.92	14.56	11.18	13.42	4.86	9.86	85.44
MSFT R	7.85	16.12	7.09	7.04	8.52	9.97	16.53	12.76	5.93	8.18	83.47
OCEAN R	8.65	7.92	7.11	6.47	6.28	6.63	9.84	28.33	10.08	8.69	71.67
WTI R	6.44	9.45	13.53	8.45	5.18	6.43	7.22	12.91	24.15	6.25	75.85
GFI	11.77	10.43	10.73	4.67	10.39	5.03	8.91	10.84	6.94	20.29	79.71
TO	82.3	93.07	78.08	60.61	60.56	63.42	82.41	110.86	77.66	77.21	786.18
Inc.Own	98.36	117.72	101.01	79.24	88.26	77.98	98.95	139.19	101.81	97.49	TNC
NET	-1.64	17.72	1.01	-20.76	-11.74	-22.02	-1.05	39.19	1.81	-2.51	78.62

Table 7

Spillovers (Volatility) between Extended GFI to AI Tokens, AI Stocks and Fossil Fuels during Post-Vaccine availability period. Total Network Connectedness id indicated with TNC.

Index	AGIX (AIT)	AMZN (AIS)	BRENT (FF)	FET (AIT)	GAS (FF)	GOOGL (AIS)	MSFT (AIS)	OCEAN (AIT)	WTI (FF)	GFI	FROM
AGIX R	25.62	10.04	11.26	4.65	11.2	11.98	5.25	11.28	6.01	2.71	74.28
AMZN R	18.64	19.19	10.75	5.14	11.76	9.25	8.43	9.53	3.58	3.73	80.81
BRENT R	12.15	6.23	20.36	5.94	12.52	9.19	5.78	7.78	14.65	5.4	79.64
FET R	13.77	6.27	11.61	20.43	9.56	5.35	5.25	13.11	8.08	6.57	79.57
GAS R	19.22	4.95	19.15	4.09	25.62	3.9	5.21	5.24	9.98	2.63	74.38
GOOGL R	21.04	9.64	11.91	6.14	10.56	13.7	9.16	12.47	2.87	2.51	86.3
MSFT R	18.79	7.09	11.27	4.64	18.21	11.06	15.52	6.3	3.64	3.48	84.48
OCEAN R	18.25	5.88	12.08	13.49	6.2	5.41	3.99	27.02	3.8	3.87	72.98
WTI R	11.38	5.73	16.7	6.09	13.24	4.43	6.73	7.32	19.54	8.84	80.46
GFI	20.95	6.65	12.8	3.24	17.52	4.23	3.78	6.04	6.32	18.45	81.55
TO	154.21	62.49	117.53	53.42	110.75	64.8	53.58	79.07	58.94	39.74	794.54
Inc.Own	179.83	81.67	137.89	73.86	136.37	78.5	69.1	106.09	78.49	58.19	TNC
NET	79.83	-18.33	37.89	26.14	36.37	-21.5	-30.9	6.09	-21.51	-41.81	79.454

The AMZN in returns and WTI in volatility are most connected with GFI with a value of 11.8 and 8.84 respectively during post-vaccine period. The study finds 78.62 value (786.18/10) of returns and 79.454 value (794.54/10) of volatility for total network connectedness (TNC) during post-vaccine period. We observe consistent and dynamic results during pre- and post-vaccine periods respectively. Figures 6 and 7 corroborate our conclusions from Tables 3 & 5) and (4 & 6) respectively, certifying that the AI tokens, AI stocks and Fossil fuels are net receivers of innovations from GFI in both return and volatility during pre- and post-vaccine periods. However, most of tokens, stocks and fossil fuels offer diversification benefits during both pre- and post-vaccine periods.

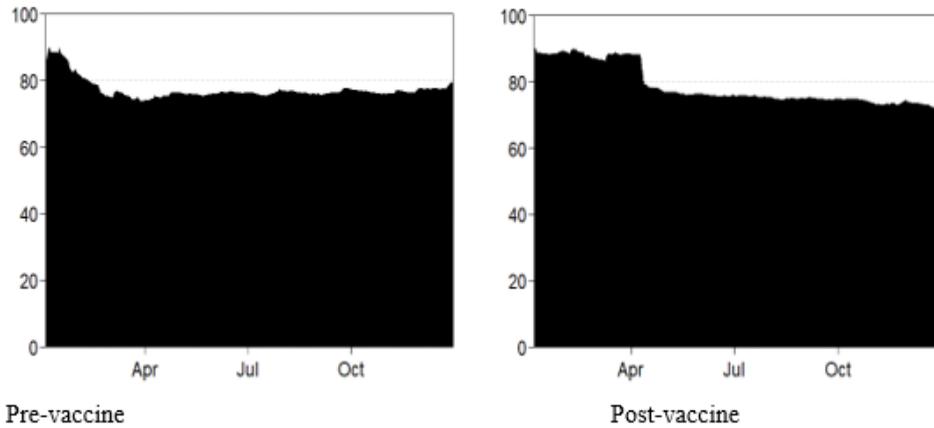


Figure 8: Dynamic connectedness in returns between energy cryptos and GFI

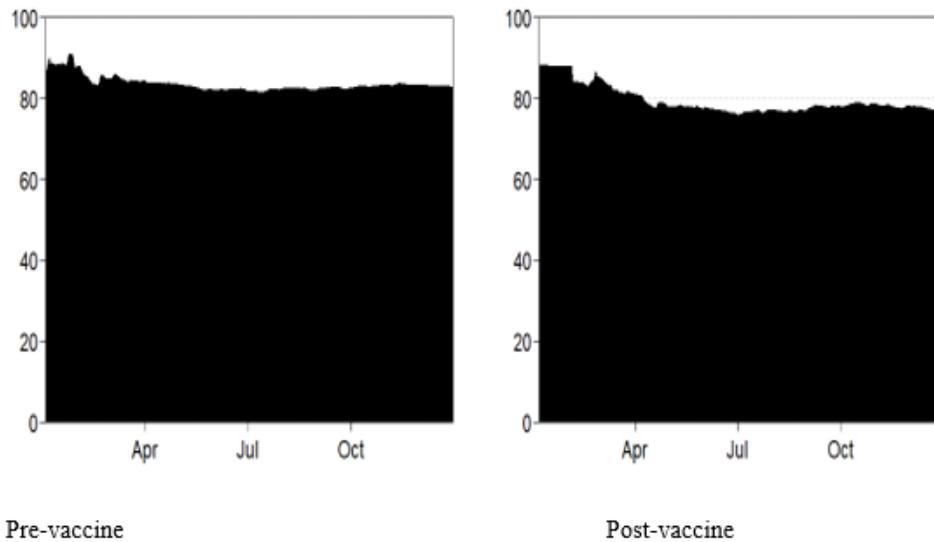


Figure 9: Dynamic connectedness in volatility between energy cryptos and conventional assets

Figures 8 and 9 present dynamic network connectedness in returns and volatility and express that all the indices are affected by GFI during pre- and post-vaccine periods, and the findings are in line with the outcomes of recent studies (see Aaron and Demir, 2021; Yousaf et al., 2022a; Shahid, 2024). The indices show more sharp

returns during post-vaccine periods due to the good news of vaccine successes. Both indices abruptly climb around the apogee of the COVID-19 slowdown in March 2020 and exhibit a sharp return to the pre-COVID-19 levels on good news regarding vaccine successes just before the end of 2020 (see Gubareva, 2021). Similarly, we observe sharp volatility in the post-vaccination period as well.

Conclusions, Limitations and Recommendations

The study uncovers the risk COVID-19 risk transmission to AI, Tokens, AI stocks and Fossil fuels during the pre and post availability of COVID vaccine using extended GFI of Shahid (2024). Moreover, the study explores the connectedness between extended GFI and AI tokened, AI stocks and fossil fuel markets over the period from January 2020 to December 2021. With the application of GARCH-BEKK model, we find that lag shocks in the extended GFI significantly enhance the conditional volatility of FET-Fetch in both pre- post-vaccine periods and also enhances conditional volatilities of Ocean-protocol, AMZN-Amazon and all fossil fuel markets in post-vaccine period. Moreover, AGIX-Singularity NET and MSFT-Microsoft are unaffected during both pre- and post-vaccine periods. We observe stronger shock transmission from COVID-19 to AI tokens. The outcomes exhibit the significance of current volatility in predicting the future volatility of such investment. Except AGIX, all AI stock, tokens and energy indices show significant cross-volatility transmission. Such findings show that only AGIX acts as safe haven asset during post vaccine period. For extent of connectedness, the study utilizes the TVP-VAR model. we observe similar spillovers, in bot returns and volatility between GFI and AI tokens, AI stocks and fossil fuel markets. The OCEAN, AMZN, BRENT and GAS are the least “net-connected” with GFI. We observe consistent and dynamic results during pre- and post-vaccine periods respectively.

By examining the links between GFI and AI tokens, stocks and fossil fuel investments, we hope to uncover diversification opportunities for investors, especially during ups and downs in markets. Since, AI assets are unique and come from a variety of sectors, they differ from traditional commodities due to having smaller information asymmetries. The findings provide valuable insights for investors looking to adapt their strategies by combining fossil fuels with AI investments to strengthen their portfolios. Connections between extended GFI and these markets during times of high volatility are analyzed while looking at different investment periods. Investors need to understand market trends. The findings offer

important insights to many market players, including portfolio managers, policymakers, and consumers. The sudden market shifts are affected by investment choices, which is crucial for investors and policymakers. Investors can use this research to improve their strategies and manage risks when the market gets tough. Policymakers can also utilize insights from this study to handle different market situations better. Many industries are expected to be affected by AI technology, and the research demonstrates how businesses and investors can adjust in response to these changes.

However, experts have raised concerns that AI models can have a large carbon footprint, similar to the impact of fossil fuels. This indicates that further research is needed to understand the relationship between these two areas better. Meanwhile, traditional fossil fuels are facing increasing scrutiny due to their environmental impacts, making AI stocks an attractive option for those looking for stability in a fluctuating market. However, we rest it for future researchers to uncover such issues.

We only cover 2020–21 and exclude high-frequency intraday data.” •Future research: Suggest two avenues (e.g., “Incorporate ESG-related fear indices” or “Extend analysis to 2022–24 with Omicron waves”).

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