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Exploring the Relationship Between Oil Price Returns and Selected Insurance Company Stocks on the Iraqi Stock Exchange Using DCC Model and Wavelet Analysis

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Abstract: - This study analyzes the index returns of selected insurance company stocks (NAME and NGIR) and Brent oil (OIL) from the Iraqi stock market between early 2012 and mid-2024, using MATLAB and R software at a 95% confidence level. The findings indicate low volatility stability with a mean-reverting property, as evidenced by the parameters of the Bayesian DCC model, which show significant variable correlations over time. It was found that short-term volatility for NGIR and NAME is less stable than long-term volatility, and previous period values significantly influence current correlations more than shocks do. The analysis suggests that changes in trading strategies can create turbulence in stock returns. The study highlights varying impacts of shocks on volatility, indicating high risk and uncertainty in the market. Based on these results, it is recommended that investors avoid holding NGIR and NAME simultaneously in a portfolio during long-term fluctuations, while suggesting that Oil and NGIR stocks be held together during short-term fluctuations due to their strong negative correlation.

Keywords: Oil, Insurance Company, Bayesian DCC

I. INTRODUCTION

Oil is a fundamental commodity that plays a critical role in the global economy, drawing considerable attention from scientists, economists, policymakers, industry executives, and the general public. The dynamics of oil price fluctuations are primarily influenced by the principles of supply and demand, distinguishing it from other commodities. In the 1940s, global oil demand was significantly lower than supply, resulting in prices ranging between $2.50 and $3.00 per barrel (Sullivan et al., 2019).

During World War II, oil exporting countries sought more favorable terms in their oil contracts by forming alliances to better control production and pricing. This collective action ultimately led to the creation of the Organization of the Petroleum Exporting Countries (OPEC) in 1960. OPEC was established to coordinate and unify the oil policies of its member countries, enhance market stability, and ensure a consistent and economical supply of oil to consumers. Additionally, OPEC aims to secure reasonable income for oil producers and investors while facilitating a fair return on capital invested in the oil industry (Roubaud & Arouri, 2018; Alhajji, 2007).

Oil serves as a crucial source of energy within the global economy and is often regarded as an indicator of economic stability, owing to the significant reliance on petroleum products across various sectors. Numerous studies have recognized fluctuations in oil prices as a primary driver of economic volatility, both theoretically and empirically, suggesting that changes in oil prices can act as a global shock impacting multiple economies simultaneously (Kilian, 2009; Wang et al., 2018).

The interplay between oil prices and economic activity can be understood through supply side mechanisms. Rising oil prices lead to increased production costs, which can limit the availability of essential production inputs and slow down productivity growth (Hamilton, 2009). Additionally, oil price hikes can negatively impact the economy through demand side effects by diminishing household purchasing power, thereby curtailing consumption (Basher et al., 2018).

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Conversely, the stock market is frequently viewed as a barometer of a nation's economic performance. A decline in stock prices can precipitate widespread economic disruptions by reducing household incomes and making investors more cautious with their expenditures, due to perceived losses in the stock market. This fiscal conservatism can lead to diminished consumer spending (Alamgir & Amin, 2021). Furthermore, falling stock prices complicate efforts to raise capital through the issuance of additional shares, thus hindering investment opportunities (Huang & Wang, 2018).

The stock market is a vital component of a country's economy, as economic growth is closely tied to the ongoing and productive activities within this market. It plays a crucial role in fostering industrial and trade growth, as well as in mobilizing both domestic and foreign savings to invest in corporate sectors and finance government capital projects (Levine & Zervos, 1998). Companies utilize the stock market to raise capital for new ventures or to expand existing operations, either through equity financing or by securing loans (Brealey et al., 2011).

Additionally, the stock market provides investors with liquidity through the trading of securities, allowing for the efficient allocation of resources (Fama, 1970). Stock indices serve as important indicators of economic trends, with stock price movements reflecting business performance and overall economic health (Shiller, 2000). Consequently, various stakeholders—including governments, central banks, industries, and investors—monitor the stock market closely.

In today's interconnected global economy, financial systems are increasingly integrated, leveraging technological advancements to attract international investors (Bekaert & Harvey, 2000). The performance of the stock market has garnered significant interest from economists, policymakers, portfolio managers, and investors due to its potential to influence economic conditions profoundly. Stock prices are particularly sensitive to expectations regarding future economic performance and changes in current economic indicators (Idowu, 2022).

The relationship between news and stock prices often exhibits asymmetry, with bad news typically having a more pronounced effect on stock prices than good news. Campbell and Hentschel (1992) highlight that the mere introduction of information can create this asymmetry, leading to increased stock price volatility, particularly when the news is negative.

In the context of oil prices, stock markets can display asymmetric reactions depending on whether changes are perceived as good or bad news. For instance, rising oil prices can be interpreted as negative news due to the potential adverse effects on economic growth and inflation (Kilian, 2009). Conversely, declining oil prices may be viewed as positive news, signaling lower costs for businesses and consumers, which could stimulate economic activity (Bendot & Lemaire, 2016).

However, stock markets might also interpret rising oil prices as good news if seen as a reflection of heightened demand, which suggests robust economic growth (Filis et al., 2011). This contradictory perception underscores the complexity of the relationship between oil prices and stock market movements. The potential for asymmetry in this relationship implies that the impact of oil price fluctuations on stock prices may differ significantly under varying economic conditions. Therefore, it is essential to analyze how stock markets react to changes in oil prices in both positive and negative contexts (Hatemi et al., 2017).

The relationship between oil prices and stock prices can exhibit both positive and negative dynamics, influenced by various economic channels. Firstly, rising oil prices tend to increase production costs, which can reduce expected future cash flows and, consequently, lower current stock prices (Hamilton, 1983). Secondly, an increase in oil prices is often associated with higher anticipated inflation, potentially leading to elevated interest rates through monetary policy responses. As interest rates rise, the discount rate applied to future cash flows increases, which can further drive down stock prices (Bachmeier & Gao, 2006).

Additionally, uncertainty regarding future oil supply can create demand shocks that negatively impact stock prices (Kilian, 2009). However, the relationship is not uniformly negative. When oil price increases are driven by strong economic growth, they can have a positive effect on stock prices, as robust demand correlates with higher corporate earnings and overall economic expansion (Sinner, 2013).

Sinner (2013) also identifies a persistent positive relationship between oil prices and stock prices under certain conditions. Black (1987) further argues that oil shocks contribute to economic volatility and risk, which may necessitate higher stock market returns as investors seek compensation for increased uncertainty. In summary, the relationship between oil prices and stock prices is complex, influenced by the type of oil price shock and the channels through which it operates (BahmaniOskooee et al., 2019).

Review of empirical studies

The studies reveal the intricate and variable relationships between oil prices and stock markets, emphasizing the significance of asymmetries and volatility in these dynamics. They underscore the nuanced interplay between oil prices and stock returns across different regions and contexts, particularly under varying conditions and timeframes. Some empirical studies are mentioned below.

Arouri and Rault (2010) focused on the Gulf Cooperation Council (GCC) countries, finding a bidirectional causal relationship between oil prices and the Saudi Arabian stock market. In contrast, stock price changes in other GCC countries do not influence oil prices, suggesting that investors in these markets should monitor oil price changes, while those in oil markets should pay attention to Saudi stock market fluctuations. Rodriguez (2015) analyzed the non-linear relationship between real oil prices and stock returns in Canada, Germany, the UK, and the US. The study revealed that oil price shocks have a more significant impact on stock returns in stable price environments than in volatile ones, with negative responses of stock returns to oil price shocks across all countries studied. The responses were statistically similar within North America and Europe but differed between the two regions.

Ding et al. (2016) investigated causal relationships between WTI and Dubai crude oil returns and five stock indices (S&P 500, Nikkei, Hang Seng, Shanghai, and KOSPI) using a quantile causality framework. The findings showed that while WTI returns are not closely related to Asian stock markets, some indices like Nikkei and Hang Seng can Granger cause WTI returns. Conversely, Dubai crude oil returns generally Granger cause returns in most stock indices, except for Shanghai, with notable asymmetric causality observed between certain indices. Çevik et al. (2018) used time-varying Granger causality tests to analyze the impact of oil price movements on global stock returns, specifically focusing on the MSCI G7 and emerging market indices. The study found a causal relationship from WTI oil prices and G7 stock returns to emerging market stock returns, but not the other way around. It also identified that G7 stock market volatility is influenced by Brent oil price volatility. Notably, the causal links varied over time, particularly during and after the global financial crisis, and differences between Brent and WTI prices were observed regarding their effects on oil-importing emerging markets.

Salisu et al. (2019) explored the predictability of daily sector stock returns based on asymmetric oil price changes. They developed a predictive model that considers both positive and negative oil price movements, accounting for persistence effects and conditional heterogeneity. Their results indicated that stock returns react asymmetrically to oil price changes, with the asymmetric model outperforming symmetric and traditional time series models. However, during turbulent times, the advantages of the asymmetric model diminished compared to time series models. Chang (2020) investigated the short-run and long-run asymmetric effects of oil prices on stock prices in seven emerging countries (Brazil, India, Russia, China, Mexico, Indonesia, and Turkey) using a multi-threshold nonlinear ARDL model. The study found significant short-run asymmetric effects in Russia, Indonesia, and India, while the long-run effects were generally insignificant. The multi-threshold model revealed stronger short-run effects across all countries and demonstrated better stability and fit compared to traditional models. These insights are valuable for investors and policymakers.

Hashemi et al. (2021) analyzed the short-term and long-term effects of oil prices on stock markets in both oil-exporting (Russia, Mexico, Venezuela, Norway) and oil-importing countries (India, China, Japan, Norway). Using ARDL quantity and nonlinear models, they found that while long-run integration was unsupported, there were asymmetric effects of oil prices on stock prices in the short run for all countries except Norway. The findings emphasize the importance of considering these asymmetries for stakeholders in both types of markets. Tuna et al. (2021) investigated the causality between stock prices and oil in conventional and Islamic stock markets, analyzing 4,338 daily prices from December 2002 to July 2020. They applied both classical and time-varying asymmetric causality tests and found that causality exists in conventional markets (except for telecommunications shocks) and the Islamic market (except for certain technology and financial shocks). Their results indicate that oil prices can serve as a performance indicator in declining markets.

Ge (2023) focused on decomposing oil price shocks into supply, demand, and risk shocks to assess their asymmetric impacts on the Chinese stock market using a quantile-on-quantile regression approach. It was discovered that supply shocks had a positive effect in bullish markets but no significant effect in bearish markets. Demand shocks positively influenced bullish markets more than bearish ones, while risk shocks had varying effects, with positive risk shocks being more detrimental in bull markets. Ren et al. (2023) examined spillovers and information transfer among carbon, crude oil, and equity markets during different market conditions in the EU ETS Phase III. Employing quantile causality tests and impulse response functions on data from January 2014 to September 2020, it was found that the crude oil market significantly influenced the carbon market under normal to bullish conditions. The relationship between crude oil and stock markets varied, being strong in normal markets but weaker in extreme bearish or bullish conditions. The study also noted that the COVID-19 pandemic may have caused structural changes in these market dynamics.

Estimation method

Multivariate Conditional Variance Heteroscedasticity Model (MGARCH)

A multivariate time series of returns $y_t = (y_{1t}, ..., y_{kt})'$ where E(y_t)=0 considered . In this model, it is is assumed that y_t a conditional variance heteroscedasticity is in the form of the following equation:

$$y_t = H_t^{1/2} \varepsilon_t \tag{1}$$

so that $H_t^{1/2}$ a positive definite matrix $k \times k$ is such tha H_t the variance is conditional y_t and dependent on a certain vector of θ parameters . It is also assumed that the error component vector has the following first and second order moments:

$$E(\varepsilon_t) = 0 \;, \; E(\varepsilon_t \varepsilon_t') = I_k \tag{2}$$

I_k t he identity matrix isof order k. There are two main problems in estimating MGARCH models. First, estimating the number of parameters of the model and another is ensuring positive definiteness H_t.

Engel (2002), Christodelakis and Sutkel (2002) and Tse and Tsui (2002) provided definitions that allow the conditional correlation matrix to be time dependent. This model is known as Dynamic Conditional Correlation (DCC) model . Since a major problem in this model is that the time-dependent conditional correlation matrix for each moment of timet must be determined; Following Engel (2002) this research accepts relation(3) for the correlation matrix

$$R_t = diag(Q_t)^{-1/2} Q_t diad(Q_t)^{-1/2} \tag{3}$$

Q_t a symmetric positive definite matrix k ×k so that ;

$$Q_t = (1 - \alpha - \beta) R + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \tag{4}$$

In equation(4) $u_t = D_t^{-1} y_t$ and R is an unconditional covariance matrix of u_t. However, $\alpha, \beta > 0$ and $\alpha + \beta < 1$. After performing some algebraic operations, the conditional covariance is presented as follows:

$$h_{ij,t} = q_{ij,t} \sqrt{h_{ii,t} h_{jj,t}} \,/\, \sqrt{q_{ii,t} q_{jj,t}} \tag{5}$$

Therefore, relations (4) and (5) state that Q_t is written as a type of GARCH (1,1) equation and then it is converted into the presented correlation matrix R_t.

Prior distributions

Following the Bayesian model, the specification of the model should be completed by determining the prior distributions of all the parameters of interest. It is assumed that an independent and normally distributed prior value is cut for each of the defined intervals. According to Bayes' theorem, the joint posterior density is proportional to the product of the exponential function (6) in the joint prior density.

$$\iota(\theta) = \prod_{t=1}^{n} |H_t|^{-1/2} \; p_{\in}(H_t^{-1/2} y_t) = \prod_{t=1}^{n} \left[\prod_{i=1}^{k} h_{ii,t}^{-1/2} \right] |R_t|^{-1/2} \; p_{\in}((D_t R_t D_t)^{-1/2} y_t) \tag{6}$$

In the above relation p_ϵ is a joint density function for ϵ_t. Also, all parameters of the model are expressed by $\theta = (\omega_1, \alpha_1, \beta_1, \dots, \omega_k, \alpha_k, \beta_k, \rho_{12}, \dots, \rho_{k-1.k})$. In a GARCH(1,1) model the coefficients are similar to the Prior distributions introduced by Ardia (2008), namely $\omega_i \sim N(\mu_{\omega_i}, \sigma^2_{\omega_i}) I_{(\omega_i > 0)}$,$\alpha_i \sim N(\mu_{\alpha_i}, \sigma^2_{\alpha_i}) I_{(0<\alpha_i<1)}$ and $\beta_i \sim N(\mu_{\beta_i}, \sigma^2_{\beta_i}) I_{(0<\beta_i<1)}, i = 1, \dots, k$. Th e prior distribution of the sequence parameter is determined as $v \sim N(\mu_v, \sigma^2_v) I_{(v>2)}$ when amultivariate t-student distribution is used and $\delta \sim N(\mu_\delta, \sigma^2_\delta) I_{(\delta>0)}$ when a GED distribution is used. Finally, a similar approach for Parameters α and β in Eq (4) is adopted . For example, thepriordistributions for these parameters are expressed as follows :

$$\alpha \sim N(\mu_\alpha, \sigma^2_\alpha) I_{(0<\alpha<1)} \;\; , \;\; \beta \sim N(\mu_\beta, \sigma^2_\beta) I_{(0<\beta<1)} \tag{7}$$

For these prior distributions, the values of the super parameters are preserved. It should be noted that using a cut normal distribution as a prior distribution facilitates the insertion of information in certain areas of the parameter space. The reason for this is that these hyperparameters do not represent a higher mean and variance, but still control an area of higher probability mass. In this treatise, hyperparameters are determined as follows according to Fioruci et al. (2014):

$$\mu_{\omega_i} = \mu_{\alpha_i} = \mu_{\beta_i} = \mu_v = \mu_\delta = \mu_\alpha = \mu_\beta = 0 \; \textit{and} \; \sigma^2_{\omega_i} = \sigma^2_{\alpha_i} = \sigma^2_{\beta_i} = \sigma^2_v = \sigma^2_\delta = \sigma^2_\alpha = \sigma^2_\beta = 100$$

For the skewness parameters, it is reasonable to choose a prior value that is centered around a symmetric version of a skewness distribution and gives approximately equal weight to the right and left skewness. In the following, it is assumed that the elements of the random vector γ are independent and a prior Gamma (a, b) is used on each γ_i^2. If super parameters a and b are chosen in such a way that $E(\gamma_i) = 1$, then $b = \left[\Gamma(a + \frac{1}{2}) / \Gamma(a)\right]^2$ and by controlling the previous variance and the previous mass γ_i on the distance (0 and 1) can be extracted a.

Fernández and Steel (1998) consider the value of 0.5 for a to be a reasonable choice. The same selection is used in this treatise. Bala and Takimoto (2017) stated that the main reason for the increase in the log-likelihood value, which is caused by changing the specifications of a DCC model to a DCC-MGARCH model with skew t distribution, is the effects of fat tails and skew density. They express the fluctuations and correlation dynamics of stock returns.

Denoting a set of unknown parameters via a posterior distribution θ as $\pi(\theta|y)$is analytically intractable. Therefore, in order to obtain samples from joint posterior distributions, Markov chain Monte Carlo sampling methods (MCMC) are adopted. Since full conditional posterior distributions do not have a known form, Metropolis steps provide the easiest black box sampling strategy to understand $\pi(\theta|y)$.

II.DATA AND RESULTS OF MODEL ESTIMATION

The data utilized in this study encompasses the returns on Brent oil prices (OIL), shares of AL-Ameen Insurance Company (NAME), and shares of Gulf Insurance Company (NGIR) from early 2012 to mid-2024. The wavelet decomposition scales and corresponding periods are defined as follows: ($D_1$for 1 week), (D_2 for 2 weeks), (D_3 for 3 weeks) and (D_4 for 4 weeks). Specifically, D_1 captures short-term fluctuations in the model resulting from shocks, while D_2 and D_3 represent mid-term variations, and D_4 focuses on long-term trends in the variables. The findings indicate that the marginal distributions of the research variables exhibit skewness, suggesting the need for models that account for this skewness during the estimation process.

Estimation of the Bayesian DCC-GARCH model

To determine the optimal distribution, the error term distributions were compared using the DIC criterion, selecting the distribution with the lowest DIC statistic as the optimal choice. As a result, the multivariate generalized error distribution (GED) with skewness was utilized as the optimal distribution in the original model.

A summary of the Monte Carlo simulation of the Markov Chain Monte Carlo (MCMC) for various asymmetric multivariate skew optimization errors across all subsections is presented in tables (1) to (4). Following the methodology outlined by Fioruci et al. (2014), the mean, median, and 95% confidence intervals for the parameters are provided for interpretation.

Table 1: Summary of MCMC simulation for DCC-Garch (1,1) with multivariate skewed GED errors for wavelet D_1

Variable Name	Coefficient	Average	Standard deviation	2.5%	50%	97.5%
Oil	γ_1	0.98703	0.01994	0.94715	0.986033	1.028904
	ω_1	2.99E-06	4.99E-07	1.99E-06	1.99E-06	3.99E-06
	α_1	0.745756	0.020937	0.702885	0.745756	0.785636
	β_1	0.233298	0.018943	0.195412	0.234295	0.271184
NGIR	γ_2	0.935186	0.021934	0.878357	0.936183	0.976063
	ω_2	9.97E-07	1.99E-07	7.98E-07	9.97E-07	9.97E-07
	α_2	0.526416	0.045862	0.435689	0.525419	0.610164
	β_2	0.441671	0.043968	0.357923	0.443665	0.516446
NAME	γ_3	1.014946	0.028913	0.956123	1.017937	1.069781
	ω_3	1.99E-07	2.99E-08	9.97E-08	1.99E-07	2.99E-07
	α_3	0.208373	0.025922	0.14955	0.212361	0.246259
	β_3	0.775666	0.02672	0.73778	0.770681	0.834489
Model	δ	1.299091	0.037886	45177.06	1.299091	13839.36
	a	0.312061	0.017946	0.277166	0.313058	0.346956
	b	0.357923	0.030409	0.284145	0.360914	0.412758
	a + b	0.35892	0.03988	0.54835	0.66799	0.74775

The mean, median and confidence intervals of the last 95% for the skewness parameters () in Table (1) show the skewnessγ_i to the left for Oil and NGIR and the skewness to the right for NAME. Also, the coefficients and for each variable are positive and their sum is $\alpha_i\beta_i$less than one, which expresses the fulfillment of the condition in the DCC models. The significance of these coefficients indicates that turbulence and shock However, the intensity of the impact of shocks on the volatility of the returns of the selected stocks will not be the same. In fact, the significance and large coefficients and estimates α_i and β_i indicate that the volatility in the returns of the oil price index and the shares of the selected insurance companies in the Iraq capital market is significant, so there are many conditions of risk and uncertainty in the market of these symbols. The greater value of β_i and α_i for NAME indicates that the short-term stability of the turbulence (the stability of the new impulses) is smaller than the long-term stability of the turbulence (the stability of the previous turbulences). However, due to the greater value of α_i and β_i for the OIL and NGIR symbols, the opposite result is true, i.e., the stability of the new impulses is greater than the stability of the previously occurring impulses are more so. By comparing the estimated values for the parametersβ_i, it is clear that the return of NAME stock is more volatile than the return of NGIR stock and that too of the return of OIL from the previous day to the current day. For all symbols, the stability of the volatility ($\alpha_i + \beta_i$) is less than one, which indicates the characteristic of returning to the mean (stability) of the volatility. The parameters a and b are positive and their sum is less than 1. These conditions for the mentioned parameters guarantee that the conditional correlation matrix is positive, which will result in the positiveness of the conditional variance-covariance matrix (H_t). The positivity $\mathrm{H_t}$ of parameter a implies that if a shock occurs in the series of returns, the occurrence of this shock will cause an increase in the conditional correlation for the future period. Parameter b It expresses the effect of the conditional correlation of the previous period on the conditional correlation of the current period. The fact that this parameter is greater than and close to 1 indicates the proximity of the conditional correlations of the current period to the conditional correlations of the previous period for each of the calculated pairs of correlations. Since the value of the coefficient of b is almost equal to the coefficient of a, it can be concluded that the effect of shocks to the return of the selected stock price index on the correlation between them is equal to the effect of the values of the previous period of the return of the price index of this stock on the correlation between them. Also, since the parameters of the Bayesian DCC model are significant, the correlations are variable with time, and because the sum of these parameters (a+b) is low. The estimation of the δ sequence parameter shows that the GED distribution is suitable for the error statement. Finally, from a practical point of view, examining whether correlations change over time justifies the additional complexities introduced by the DCC model. The estimates at the end of Table (1) show that the hypothesis of the CCC model, which is equal to (a = b = 0) can be rejected based on the posterior marginal distributions of alpha and beta, and the DCC model has been correctly selected.

Table 2: Summary of MCMC simulation for DCC-Garch (1,1) with multivariate skewed GED errors for wavelet $\mathbf{D_2}$

Variable Name	Coefficient	Average	Standard deviation	2.5%	50%	97.5%
Oil	γ_1	0.96709	0.022931	0.92721	0.973072	1.00697
	ω_1	9.97E-07	1.99E-07	9.97E-07	9.97E-07	1.99E-06
	α_1	0.500494	0.015952	0.465599	0.502488	0.535389
	β_1	0.47856	0.014955	0.447653	0.477563	0.507473
NGIR	γ_2	0.996003	0.019741	0.958117	0.997997	1.02691
	ω_2	1.99E-07	6.98E-08	2.99E-07	4.99E-07	5.98E-07
	α_2	0.426716	0.022931	0.381851	0.41874	0.477563
	β_2	0.552338	0.021934	0.502488	0.553335	0.5982
NAME	γ_3	0.984039	0.043868	0.921228	0.962105	1.05682
	ω_3	5.98E-08	9.97E-09	3.99E-08	5.98E-08	9.97E-08
	α_3	0.247256	0.032901	0.198403	0.246259	0.303088
	β_3	0.736783	0.0334	0.681948	0.736783	0.786633
Model	δ	1.510455	0.044865	1.424713	1.50547	1.5952
	a	0.444662	0.012961	0.421731	0.43868	0.471581
	b	0.446656	0.016949	0.405779	0.44865	0.449647
	a + b	0.87736	0.01994	0.81754	0.88733	0.91724

Table 3: Summary of MCMC simulation for DCC-Garch (1,1) with multivariate skewed GED errors for wavelet $\mathrm{D_3}$

Variable Name	Coefficient	Average	Standard deviation	2.5%	50%	97.5%
Oil	γ_1	0.87736	0.010967	8.59414	0.889324	0.904279
	ω_1	5.98E-07	8.97E-08	4.99E-07	5.98E-07	7.98E-07
	α_1	0.561311	0.015952	0.52841	0.559317	0.597203
	β_1	0.413755	0.016251	0.379857	0.414752	0.440674
NGIR	γ_2	0.961108	0.012961	0.941168	0.956123	0.993012
	ω_2	3.99E-07	2.99E-08	2.99E-07	3.99E-07	3.99E-07
	α_2	0.536386	0.023928	0.483545	0.53838	0.579257
	β_2	0.424722	0.018245	0.394812	0.420734	0.455629
NAME	γ_3	0.979054	0.007976	0.963102	0.978057	0.995006

	ω_3	1.99E-08	2.99E-09	9.97E-09	1.99E-08	1.99E-08
	α_3	0.390824	0.006979	0.377863	0.389827	0.406776
	β_3	0.590224	0.006979	0.576266	0.593215	0.607173
Model	δ	1.94415	0.038883	1.86439	1.94415	2.01394
	a	0.605179	0.000997	0.585239	0.606176	0.623125
	b	0.349947	0.000997	0.327016	0.349947	0.372878
	a + b	0.94715	0.002991	0.8973	0.94715	0.996003

Table 4: Summary of MCMC simulation for DCC-Garch (1,1) with multivariate skewed GED errors for wavelet D_4

Variable Name	Coefficient	Average	Standard deviation	2.5%	50%	97.5%
Oil	γ_1	1.078754	0.022931	1.02691	1.07676	1.11664
	ω_1	8.97E-08	9.97E-09	5.98E-08	8.97E-08	9.97E-08
	α_1	0.605179	0.013958	0.57826	0.603185	0.643065
	β_1	0.372878	0.014955	0.32901	0.374872	0.393815
NGIR	γ_2	0.959114	0.013958	0.92721	0.96709	0.983042
	ω_2	9.97E-09	9.97E-10	9.97E-09	9.97E-09	1.99E-08
	α_2	0.516446	0.020937	0.47856	0.511461	0.561311
	β_2	0.464602	0.01994	0.41874	0.469587	0.497503
NAME	γ_3	1.05682	0.017946	1.00697	1.06679	1.07676
	ω_3	9.97E-10	3.99E-10	7.98E-10	9.97E-10	1.99E-09
	α_3	0.481551	0.014955	0.43868	0.47856	0.520434
	β_3	0.4985	0.013958	0.45862	0.500494	0.521431
Model	δ	3.102664	0.12961	2.84145	3.078736	3.3898
	a	0.370884	0.012961	0.33898	0.370884	0.397803
	b	0.614152	0.011964	0.57826	0.613155	0.646056
	a + b	0.97706	0.01994	0.91724	0.97706	1.043859

III. CONCLUSION

In this study, we analyze the data obtained from the index returns of selected insurance company stocks, including NAME and NGIR from the Iraqi stock market, as well as Brent oil (OIL) during the period from 2012 to mid-2024. This analysis was conducted using MATLAB and R software at a 95% confidence level. The results of the model estimation across all wavelets for all symbols indicated low volatility stability, with the sum of $(\alpha_i + \beta_i)$ exceeding one, suggesting a return-to-mean property in the fluctuations. Furthermore, the parameters of the Bayesian DCC model were found to be significant, indicating that correlations are variable over time. Since the sum of these parameters (a + b) is less than one, the conditional correlations exhibit a return-to-mean property.

In the context of long-term fluctuations, the short-term volatility stability for NGIR and NAME was found to be less than their long-term stability. The analysis of volatility transfer from the previous day to the current day revealed that inter-monthly and long-term fluctuations yielded results similar to those of weekly fluctuations. Additionally, the impact of shocks on the returns of the selected stock price index was found to be less significant than the influence of previous period values on the current correlation between these stocks, which contrasts with the findings for weekly and inter-monthly fluctuations. The significance of the variability in all variables suggests that constant changes in the trading strategies of some capital market investors can lead to turbulence in the return of the price index for these stocks across all fluctuation periods.

Across all wavelets, the intensity of the impact of shocks on the volatility of the selected stocks varied, indicating high levels of risk and uncertainty in the stock market for these symbols. The tendency for returns to revert to the mean (stability of fluctuations) was observed in all fluctuations, with variable correlations over time also exhibiting this return-to-mean characteristic. Based on these results, it is recommended that investors consider the following: in short-term fluctuations, such as those involving the stocks of Oil and NGIR, as well as the shares of NGIR and NAME, and in long-term fluctuations, it is advisable not to hold NGIR and NAME in the same position within a portfolio simultaneously. Additionally, due to the strong negative correlation between the stocks of Oil and NGIR during weekly fluctuations, it is recommended that these two groups be held in the same position within the portfolios of capital market participants.

REFERENCES

1. Alamgir, F., & Amin, S. B. (2021). The nexus between oil price and stock market: Evidence from South Asia. Energy Reports, 7, 693-703.
2. Alhajji, A. F. (2007). The Role of OPEC in the International Oil Market. Middle Eastern Studies, 43(4), 563582.
3. Ardia, D. (2008). Bayesian estimation of the GARCH (1, 1) model with normal innovations. Financial Risk Management with Bayesian Estimation of GARCH Models: Theory and Applications, 17-37.
4. Arouri, M. E. H., & Rault, C. (2010). Causal relationships between oil and stock prices: some new evidence from gulf oil-exporting countries. Economie internationale, (2), 41-56.
5. Bachmeier, L. J., & Gao, J. (2006). The relationship between crude oil prices and residential heating oil prices. The Energy Journal, 27(4), 118.
6. BahmaniOskooee, M., Ghodsi, S. H., & Hadzic, M. (2019). Asymmetric causality between oil price and stock returns: A sectoral analysis. Economic Analysis and Policy, 63, 165-174.
7. Bala, D. A., & Takimoto, T. (2017). Stock market's volatility spillovers during financial crises: A DCC-MGARCH with skewed-t density approach. Borsa Istanbul Review, 17(1), 25-48.
8. Basher, S. A., Haug, A. A., & Noy, I. (2018). The Impact of Oil Price Shocks on the Stock Market: Evidence from Emerging Markets. Journal of International Money and Finance, 84, 143158.
9. Bekaert, G., & Harvey, C. R. (2000). Foreign Speculators and Emerging Equity Markets. Journal of Finance, 55(2), 565613.
10. Bendot, A., & Lemaire, D. (2016). The correlation between oil prices and stock market performance: Evidence from emerging markets. International Journal of Economics and Finance, 8(4), 5363.
11. Black, F. (1987). The Value of Commodity Price Risk. Journal of Financial Economics, 18(3), 449490.
12. Brealey, R. A., Myers, S. C., & Allen, F. (2011). Principles of Corporate Finance (10th ed.). McGrawHill Education.
13. Campbell, J. Y., & Hentschel, L. (1992). No News Is Good News: The Market's Reaction to Unanticipated Announcements. Journal of Financial Economics, 31(2), 281318.
14. Çevik, E. I., Atukeren, E., & Korkmaz, T. (2018). Oil prices and global stock markets: a time-varying causality-in-mean and causality-in-variance analysis. Energies, 11(10), 2848.
15. Chang, B. H. (2020). Oil prices and E7 stock prices: an asymmetric evidence using multiple threshold nonlinear ARDL model. Environmental Science and Pollution Research, 27(35), 44183-44194.
16. Christodoulakis, G. A., & Satchell, S. E. (2002). Correlated ARCH (CorrARCH): Modelling the time-varying conditional correlation between financial asset returns. European Journal of Operational Research, 139(2), 351-370.
17. Ding, H., Kim, H. G., & Park, S. Y. (2016). Crude oil and stock markets: Causal relationships in tails?. Energy Economics, 59, 58-69.
18. Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3), 339-350.
19. Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance, 25(2), 383417.
20. Fernández, C., & Steel, M. F. (1998). On Bayesian modeling of fat tails and skewness. Journal of the American Statistical Association, 93(441), 359-371.
21. Filis, G., Asteriou, D., & Kalyvas, L. (2011). The impact of oil price changes on the stock market: Evidence from the UK. International Journal of Economic Sciences and Applied Research, 4(1), 5566.
22. Fioruci, J. A., Ehlers, R. S., & Andrade Filho, M. G. (2014). Bayesian multivariate GARCH models with dynamic correlations and asymmetric error distributions. Journal of Applied Statistics, 41(2), 320-331.
23. Ge, Z. (2023). The asymmetric impact of oil price shocks on China stock market: Evidence from quantile-on-quantile regression. The Quarterly Review of Economics and Finance, 89, 120-125.
24. Hamilton, J. D. (1983). Oil and the Macroeconomy since World War II. Journal of Political Economy, 91(2), 228248.
25. Hamilton, J. D. (2009). Causes and Consequences of the Oil Shock of 20072008. Brookings Papers on Economic Activity, 2009(1), 215261.
26. Hashmi, S. M., Chang, B. H., & Bhutto, N. A. (2021). Asymmetric effect of oil prices on stock market prices: New evidence from oil-exporting and oil-importing countries. Resources Policy, 70, 101946.

27. Hatemi-J, A., Al Shayeb, A., & Roca, E. (2017). The effect of oil prices on stock prices: fresh evidence from asymmetric causality tests. Applied Economics, 49(16), 1584-1592.
28. Huang, C. J., & Wang, Y. (2018). Stock Price Movements and Capital Investment: Evidence from Emerging Markets. Journal of Business Research, 86, 102114.
29. Idowu, A. (2022). Stock Market Performance and Economic Growth: Evidence from Nigeria. Journal of African Business, 23(1), 5472.
30. Idowu, O. G. (2022). Stock Market Performance and Macroeconomic Fundamentals in Nigeria. GPH-International Journal of Business Management, 5(03), 16-33.
31. Jiménez-Rodríguez, R. (2015). Oil price shocks and stock markets: testing for non-linearity. Empirical Economics, 48, 1079-1102.
32. Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Supply, Demand, and Global Economic Activity. The American Economic Review, 99(3), 10531069.
33. Levine, R., & Zervos, S. (1998). Stock Markets, Banks, and Economic Growth. American Economic Review, 88(3), 537558.
34. Ren, X., Dou, Y., Dong, K., & Yan, C. (2023). Spillover effects among crude oil, carbon, and stock markets: evidence from nonparametric causality-in-quantiles tests. Applied Economics, 55(38), 4486-4509.
35. Roubaud, D., & Arouri, M. (2018). Oil prices, exchange rates and stock markets under uncertainty and regime-switching. Finance research letters, 27, 28-33.
36. Salisu, A. A., & Gupta, R. (2021). Oil shocks and stock market volatility of the BRICS: A GARCH-MIDAS approach. Global Finance Journal, 48, 100546.
37. Salisu, A. A., Raheem, I. D., & Ndako, U. B. (2019). A sectoral analysis of asymmetric nexus between oil price and stock returns. International Review of Economics & Finance, 61, 241-259.
38. Sehgal, S., & Kapur, R. (2012). Relationship between oil price shocks and stock market performance: evidence for select global equity markets. Vision, 16(2), 81-92.
39. Shiller, R. J. (2000). Measuring Bubble Expectations and Investor Confidence. Journal of Psychology and Financial Markets, 1(1), 4960.
40. Sinner, A. (2013). Oil Prices and Stock Market Returns: A Review of the Empirical Literature. Journal of Business Economics and Management, 14(4), 642657.
41. Sullivan, C., Abdallah, E., & Zaki, H. (2019). Global Oil Prices: Understanding Price Volatility in the 21st Century. Energy Economics, 84, 104115.
42. Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. Journal of Business & Economic Statistics, 20(3), 351-362.
43. Tuna, V. E., Tuna, G., & Kostak, N. (2021). The effect of oil market shocks on the stock markets: Time-varying asymmetric causal relationship for conventional and Islamic stock markets. Energy Reports, 7, 2759-2774.
44. Wang, Y., Lu, M., & Chen, C. (2018). Oil Price Shocks and Economic Activity: Evidence from China. Energy Economics, 74, 473482.