How Oil Price Shocks Affect the Egyptian Stock Market Performance in the Context of Recent Challenges

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Abstract

This study investigates the time-varying impact of oil price fluctuations on the performance of the Egyptian stock market from 1 January 2020 to 30 June 2022. During this period, the world witnessed two major shocks: COVID-19 and the Russian-Ukrainian crisis, which reconfigured the global oil situation and played a significant role in the functioning of stock markets. For an in-depth evaluation, the study assessed the impact of oil price fluctuations on stock performance for major sectors by utilizing GARCH and EGARCH models. Additionally, the BEKK-GARCH model measures the spillover transmission between oil prices and the stock market. The results revealed a significant adverse effect of oil prices and the fear index (VIX) on EGX100 and EGX30's daily returns and volatility. The banking, non-banking, and real estate sectors were the most affected. Moreover, a significant bidirectional volatility spillover between the oil and stock markets was detected. The results provide guidelines for investors and financial advisors to enrich their decision-making processes concerning how to efficiently reallocate resources among different economic sectors during periods of fluctuation. This study is among the first to address recent oil price fluctuations' impact on the Egyptian stock market returns and volatility, emphasizing sectoral performance.

Keywords: BEKK-GARCH, oil price, stock market returns and volatility, sectoral analysis, Egypt.

1. Introduction

After the global economy was breathing signs of relief from the repercussions of COVID-19, Russia's invasion of Ukraine led oil prices to rise, exerting a profound influence on economic and financial activities around the world. The fact that these two countries are major energy suppliers causes capital outflows from Emerging markets that suffered heavy losses in 2021 and 2022. In Egypt, EGX30 fell by 5.95% and EGX100 Equal Weight Index (EGX100 EWI) fell by 11.1% during the first quarter of 2022 (EGX quarterly report).

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Oil price fluctuations have a greater influence on stock markets in oil-importing countries than in oil-exporting ones (Asteriou et al., 2013). Cunando & Gracia (2014) observed a remarkable negative effect of oil price changes on stock market returns, while Perez (2020) showed that U.S. stock market returns did not highly respond to oil shocks, except for the energy sector. Since the available literature does not provide clear results concerning the relationship between oil price shocks and stock markets, the novelty of this study lies in examining the impact of oil price fluctuations on stock market performance in Egypt. Our contribution is twofold: first, it addresses the impact of recent oil price changes on the Egyptian stock market returns and volatility; second, it provides a preliminary assessment of the impact of oil price shocks on the performance of major economic sectors. This study tests three basic hypotheses: (i) oil price fluctuations have a significant impact on stock market returns and volatility; (ii) oil price fluctuations have varying effects on major sectors; and (iii) there is volatility transmission between oil and stock markets.

This paper proceeds as follows; Section 2 reviews theory and literature. Section 3 provides an overview of the Egyptian stock market performance before and after the recent surge in oil prices. Section 4 includes the analytical and econometric methods used. Section 5 analyzes the results. Section 6 provides a discussion of the findings and concluding remarks.

2. Theory and Literature

Oil price fluctuations are considered among the most important factors affecting stock market volatility, but there seems to be no clear pattern in stock market reactions (Bastianin et al., 2016; Zhang & Asche, 2014). The changes in oil prices during the global financial crisis of 2008 affected most Middle East/North Africa (MENA) stock markets differently, depending on whether the country was an oil importer or exporter, also on the level of analysis (aggregate, sectoral, or firm-level).

Oil price movements reflect the global economic situation because of their close ties to economic growth and, in turn, stock prices (Peiro, 2015). Baur et al. (2012) differentiated between positive and negative oil price shocks; increased oil prices result in weak economic growth prospects and, thus, lower stock prices and market returns. However, a decrease in oil prices is an indicator of a general economic slowdown due to increasing uncertainty, which appears in the form of postponing both investment and consumption decisions (Atil & Mahfoud, 2021; Brown & Yücel, 2002). At low oil price levels, stock markets in major oil-exporting countries in the Middle East share common fluctuations with oil markets; however, there is no evidence of such cyclical associations at higher levels (Onour, 2012).

Jones and Kaul (1996) clarified the direct and indirect negative effects of an increase in oil prices on stock market performance. The direct effect appears in the risk that such an increase exerts on financial markets; as it strongly influences the future cash flow, investment, and revenue of a firm. The indirect effect is reflected in the fact that inflation reduces investors’ earnings expectations from the stock market, resulting in stock market depreciation. Mokni (2020) noted that an oil price increase is expected to positively affect stock markets in oil-exporting countries, as their income increases. In contrast, oil price increases hurt stock markets in oil-importing countries because of the increasing cost of production (Arouri & Nguyen, 2010; Jones et al., 2014).

Osah & Mollick (2022) differentiated between the short- and long-term effects of oil price changes on stock returns and found a short-term negative effect on stocks for both oil exporters and importers. However, the relationship was reversed in the long run for oil exporters. Nevertheless, the effect might not appear at the aggregate level, as U.S. stock market returns respond slightly to oil market shocks, although the energy and materials sectors are affected (Perez, 2020). Therefore, it is important to note that the linkage between oil price volatility and stock market indices varies considerably across sectors (Badeeb & Lean, 2018; Fang & Egan, 2018). The energy-related sectors were positively affected by oil price changes, whereas other sectors were either negatively affected or unaffected. Banking stocks in Turkey benefited from the oil price increases from 2008 to 2016. In Europe, major sectors, such as energy, financial services, banking, and basic resources, were mostly influenced by oil prices from January to July 2020.

In summary, oil price volatility adversely affects stock market performance through three basic channels. First, a higher oil price increases the cost of production and reduces future cash flows and dividends, leading to a decline in stock returns. Second, inflationary pressures that accompany oil price hikes eventually lead to higher interest rates and depressing stock prices. Uncertainty provides a third channel through which oil price changes can alter stock market behavior.

3. Performance of the Egyptian Stock Market

In this section, a preliminary analysis of the influence of oil price fluctuations on the Egyptian stock market performance is presented through graphical interpretation, Pearson's correlation coefficient, and Kendall's tau, which are particularly suited for heavy tails in high-frequency financial data. Sectors may be affected more than others by changes in oil prices; aggregate analysis may mask the heterogeneous performance of various sectors. Therefore, examining the relationship between oil price and stock market performance at the disaggregated level is essential. As the relationship between oil prices and financial indicators could change depending on economic conditions, three successive periods were analyzed: the first period represents the outbreak of COVID-19 until the end of the first wave. The reason behind the differentiation between the first and other waves is the severe impact of the first one. The second period represents the subsequent waves of the pandemic. The third period represents the post-Russian invasion of Ukraine.

3.1 Oil prices and stock market indices during COVID-19's first wave

Part A in Figure (1) plots oil prices, EGX30, and EGX100, starting from January 1, 2020 (the pre-COVID period), followed by the first wave of the pandemic that spans from March 8, 2020, to November 22, 2020. In 2020, energy markets suffered negative supply and demand shocks, leading to severe oil price volatility. As China, the US, and Europe have undertaken several containment measures, including lockdown and travel restrictions, oil demand has drastically declined. A pandemic-triggered recession led to a supply shock due to the oil trade war between the major oil-producing nations. Saudi Arabia and Russia engaged in a price war, increasing oil production to gain market share.

The second quarter of 2020 marked a turning point in the history of the history of the oil market, and the crude oil price reached its minimum on April 28, 2020, approaching $12 per barrel, the lowest since 2002.

Eventually, the OPEC+ reached a historic agreement in April 2020 to adjust overall oil production downward. This agreement lowered the production scale and reduced the volume of oil made available by 9.7 million barrels per day traded on the world markets. Consequently, oil prices increased to $38.22 on May 30, 2020. By December 2020, oil stocks in OECD countries had fallen for the fifth consecutive year, stabilizing the oil market and accelerating the rebalancing process. EGX30 and EGX100 followed the same path as oil prices, experiencing a downward trend during the first quarter of 2020 and an upward trend during the second quarter.

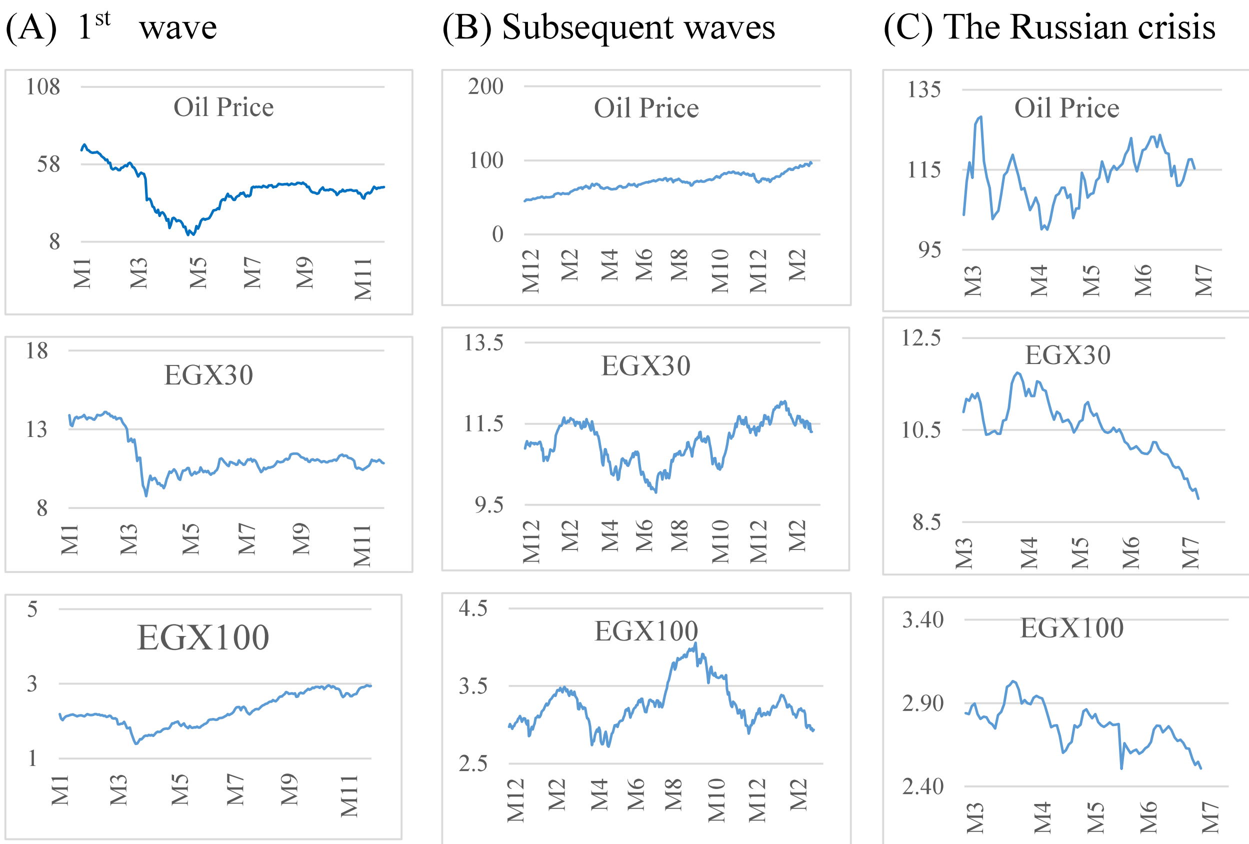


Figure 1: Oil price, EGX30 and EGX100

Source: US Energy Information Administration (EIA) and Egyptian Exchange (EGX) statistics.

The stock market indices began exhibiting the full effects of global turbulence in March; EGX30 recorded a 7% decline following the announcement of the first death on March 9. The closure of all schools and universities on March 15 constituted the worst decline (9%) since January. The indices improved during May, but the increase in new global COVID-19 cases by September 2020 (signifying the beginning of the second wave in the U.S.) sent bad signals to global stock markets; EGX30 declined by about 7% during the second half of October. Concerning the co-movement of oil price and stock market indices during the first wave of COVID-19, both Pearson and Kendall coefficients revealed a significant, strong positive correlation between oil price and EGX30, and the correlation was weaker in the case of EGX100, as shown in Part A of Table 1. Reduced oil consumption during this period decreased the barrel price, thus hurting the performance of stock markets worldwide.

3.2 The subsequent waves of the pandemic (November 22, 2020–February 23, 2022)

The rise in oil prices in the last quarter of 2020 followed an agreement among oil producers to extend lower production. Despite the good news about finding COVID-19 vaccines, crude oil prices fluctuated in 2021 as concerns were rising because of uncertain oil demand and a second wave of rising infections. The moderation of the second wave and the subsequent easing of restrictions caused the oil price to approach its pre-COVID values, reaching 73.6 per barrel by the middle of 2021. The EGX100 EWI index rose by 12.65% during the second quarter of 2021, as illustrated in Part B in Figure 1. OPEC+ started gradually increasing supply in June 2021 as economies came out of lockdown, putting an extra 400,000 barrels a day onto world markets. The highest monthly drop in the oil price since September 2020 was in August, following growing concerns about the Delta Coronavirus variant. The price decreased by 12% from $75 per barrel on August 1, 2021, to $66 on August 19, 2021. Consequently, EGX30 and EGX100 experienced a large decline in September 2021; EGX30 decreased by 7% and EGX100 by 8.5%.

As the third wave started, EGX30 witnessed a slight decline, but it rebounded quickly compared to the previous waves. There was a weak positive correlation between oil prices and both indices during the second and third waves of the pandemic, as the correlation coefficient did not exceed 26% (part A in Table 1). Oil prices have risen gradually since the beginning of 2022 because the increase in OPEC+ production was not enough to keep up with demand. At the same time, stock market indices declined because of concerns about the Russian-Ukrainian crisis.

3.3 The Post-Russian invasion of Ukraine (February 24, 2022–July 1, 2022)

The Russian invasion of Ukraine in February 2022 disrupted the energy supply and caused crude oil prices to jump to $128 per barrel on March 9, the highest level in almost ten years (EIA, 2022). Part C in Figure 1 shows the accompanying weak performance resulting from the increasing uncertainty that negatively affects global stock markets (Boungou & Yatie, 2022).

The results in Part A in Table 1 confirm the existence of a significant negative correlation between oil prices and the Egyptian stock market indices during this period. Oil prices had fallen by the end of March 2022 as China, the world's largest oil importer, began its most extreme COVID-19 lockdown in two years to control the growing number of cases in Shanghai. Consequently, the US, UK, European Union (EU), Australia, and some Asian nations immediately responded to international sanctions targeting Russia's economy.

However, the first round of sanctions imposed on Russia did not target oil supplies or energy payments.

On May 30, 2022, the EU agreed to ban seaborne imports of Russian oil (which makes up 90% of EU oil imports) with a transition period of six months for crude oil and eight months for refined products (Kajus et al., 2022). Eventually, the swift rise of the delta variant in the UK caused oil prices to fall by mid-June.

3.4 The Sectoral Analysis

The total market capitalization decreased by 11%, from EGP 708.1 billion in January 2020 to EGP 631.5 billion in July 2022 (according to the Egyptian Stock Exchange monthly reports). The major sectors include real estate, banking, non-banking, food, and basic resources, according to the highest share in market capitalization percentage. These sectors collectively represent 70% of the total market capitalization in January 2020.

Figure (2) shows that the share of the banking sector in total market capitalization decreased from 31.6% in January 2020 to 23.5% in July 2022, while that of the 'food, beverages, and tobacco' sector decreased from 9.6% to 8%. In contrast, the non-banking financial services sector share increased from 8.7% to 10.6% and the basic resources sector from 10.4% to 14.6%. The highest decline was found in the non-banking financial services sector (25% decrease during March 2020).

The Russian-Ukrainian crisis caused a sharp increase in oil prices; consequently, different sectors were distressed, but the intensity of this downturn was less than that of the pandemic. The correlation coefficients shown in Part B of Table 1 show a strong positive correlation between oil prices and stock prices in the five major sectors during the first wave of the pandemic. Hence, the pandemic exerted adverse effects on both oil prices and stock market prices. During the second and third waves, crude oil prices increased gradually, and the performance of the major sectors improved, except for banking and the "food, beverage, and tobacco" sectors.

The banking sector's market capitalization value experienced the largest decline compared to other sectors; it decreased from EGP 223 billion in January 2020 to EGP 196.8 billion just before the Ukrainian crisis, and it declined further to EGP 149 billion in July 2022. The food sector's market capitalization decreased by 23% from EGP 67.95 billion to EGP 52.3 billion in January 2022 and then decreased further to EGP 50.5 billion in July 2022.

After the Russian invasion of Ukraine, the sharp increase in oil prices and increasing uncertainty adversely affected stock market performance. Therefore, the correlation between oil prices and stock Prices in major sectors was negative and significant for all sectors except the basic resources sector.

Table 1: The correlation coefficient between oil price & other variables

A. Based on period:

	1st wave	**subsequent waves**	**After Ukrainian crisis**
EGX30			
Pearson	0.8629***	0.255***	-0.4251***
Kendall	0.6409***	0.1749***	-0.3512***
EGX100	0.3317***	0.1799***	-0.2193**
Pearson			
Kendall	0.2244***	0.1328***	-0.1722**

B. Based on Sector (January 2020 – July 2022)

	Bank	**Non-bank financial services**	**Basic resources**	**Food, Bev. & Tobacco**	**Real Estate**
1st wave	0.79***	0.89***	0.77***	0.86***	0.80***
Pearson					
Kendall	0.51***	0.70***	0.51***	0.68***	0.609***
Subsequent waves					
Pearson	0.60***	0.75***	0.73***	-0.53***	0.38***
Kendall	0.39***	0.51***	0.55***	-0.38***	0.29***
Ukrainian crisis					
Pearson	-0.45***	-0.40***	0.047	-0.331***	-0.39***
Kendall	-0.36***	-0.31***	0.004	-0.279***	-0.30***

Note(s): *, ** and * denote significance levels at 1%, 5% and 10%, respectively.**
Source(s): Author's calculations using e-views software.

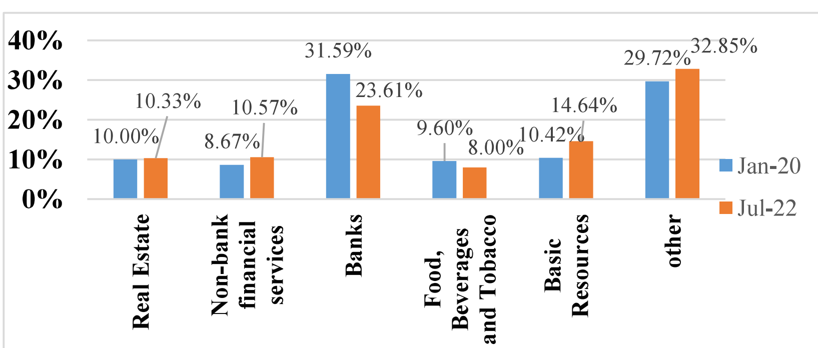


Figure 2: Market Capitalization (Jan. 2020 – July 2022)
Source: EGX data

4. Data and Methodology

This study employs several analytical and econometric tools to examine the influence of recent challenges and oil price variations on Egyptian stock market returns and volatility from January 1, 2020, through June 30, 2022. Furthermore, it provides unique insights into how variations in oil prices affect the major sectors.

4.1 Data Sources

The Egyptian Stock Market Exchange website provides the daily closing values for the EGX30 and EGX100 indices. For the analysis, returns were converted into price indices. The oil price data was retrieved from the Energy Information Administration. Daily data on the VIX closing prices was gathered from the Chicago Board Options Exchange website. The importance of the VIX is underlined in terms of the transmission of global market uncertainty (Dutta, 2018). A higher VIX reflects COVID-19 and the Ukrainian crisis, which depresses stock returns. Analyzing the volatility of stock market returns requires calculating the standard deviation of returns from the stock market index as follows: $SSdrt = \sqrt{\sum_{t=1}^{n} \quad (Rt - \bar{R})2\ /n - 1}$

As: $R_t = \text{Ln}(\text{index}_t/\text{index}_{t-1})$

Where R is stock returns, the index is EGX30 or EGX100 index, and t is time.

4.2 Methodology

Initially, the descriptive statistics of daily crude oil prices, EGX100, and EGX30 were analyzed to identify the characteristics of the variables. Also, the Jarque-Bera test was used to confirm the normal distribution of returns. The first step in the bivariate GARCH (p,q) methodology is to specify the conditional mean and variance equations as follows (Brooks & Rew, 2002):

The conditional mean equation is $R_t=\mu+\theta R_{t-1}+\varepsilon_t$

The conditional variance equation is $h^2_t= \omega+\alpha\varepsilon^2_{t-1}+\beta_1 h^2_t-1$

Where μ and ω are constants; α is the ARCH term, β_1 is the GARCH term, and ε_t is the error term. According to Bollerslev (1986), the parameters α and β_1 are assumed to be greater than zero for a positive variance.

We set p = 1 and q = 1 according to the lowest AIC. Additionally, this is usually the option that best fits financial time series and captures essential features of volatility. GARCH (1,1) strikes a balance between capturing volatility dynamics and avoiding excessive complexity (Bollerslev,1986)

Karmakar (2005) recommended using GARCH to record the conditional volatility in stock returns. (α+β) provides a measure of the persistence of the relevant time series, and thus, higher values for (α+ β) indicate more persistent volatility. Although the GARCH model captures many issues related to the financial time series, it fails to detect other volatility properties, such as the leverage effect. The negative shocks have a substantial impact on increasing volatility compared to the positive shocks of the same magnitude. This tends to build asymmetric GARCH models that capture the extent of availability for asymmetric distribution, parameter restrictions, and the leverage effect of stock returns. The issue of asymmetric conditions was first proposed by Black (1976), and then, over time, many empirical studies provided supporting evidence, such as the Exponential GARCH (EGARCH). This study employs the EGARCH model to capture the leverage effect of events on the Egyptian stock market. Awartani & Corradi (2005) found that the EGARCH model exhibited more fitness accuracy in the estimation of volatility in comparison to other types in the asymmetric GARCH family of models. EGARCH allows for the testing of asymmetries and is utilized to investigate the various effects of good and bad news on future volatility in the Egyptian stock market. Hence, the log of the variance is used, and the conditional variance for the EGARCH (1, 1)

$$Ln(\sigma_t^2) = \omega + \sum_{j=1}^{p} \beta_j Ln(\sigma_{t-j}^2) + \sum_{i=1}^{q} \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}$$

Where ω is a constant, α is the ARCH effect, β is the GARCH effect, and γ is the asymmetric effect.

To ensure that the stationarity assumption still holds, β must be positive and less than 1. Additionally, gamma (γ) indicates the leverage effect (asymmetric), and it must be both negative and significant. If γ is less than zero, the negative shocks will generate more volatility than positive shocks. Finally, following Gomes & Chaibi (2014) and Sahoo et al. (2017), the BEKK-GARCH model is used to detect the spillover effect between the crude oil market and the Egyptian stock market. The bivariate BEKK-GARCH model is used to capture the spillovers across the two markets, where the system of conditional mean equations consists of VAR(p) models (p=1,..,n). According to Schreiber et al. (2012), the bivariate BEKK-GARCH model has more advantages than the general MGARCH model because of the substantial decrease in several estimated parameters. The specification for conditional mean equation in VAR(p) form is: $\mathbf{Y}_t = \boldsymbol{\mu} + \sum_{i=1}^{P} \Gamma Yt - i + \varepsilon_t$

Where the parameter vector $\mu=(\mu_1,\mu_2)$ represents constants, and Γ is a 2×2 matrix of coefficients for autoregressive terms. The own market autoregressive terms (γ_{ii}) are used to eliminate linear dependency in the series, whereas cross-market autoregressive terms (γ_{ij}) are used to capture the mean spillover from market(i) to market j. The residuals $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ are normally distributed, $\varepsilon_t|\Omega t_{-1} \sim N(0, H_t)$, with its corresponding conditional variance-covariance matrix given by H_t, Ω_{t-1} as an information set at time t-1. The selection of lags in the above VAR models is based on Schwartz's criteria. The conditional variance equation of the BEKK-GARCH model is represented by:

$$H_t = CC` + A\,\varepsilon_{t-1}\,\varepsilon`_{t-1}\,A` + BH_{t-1}\,B`$$

Where H_t represents the conditional variance-covariance matrix, and C is the triangular matrix with three parameters. Matrix B depicts the extent to which the conditional variances are related to past conditional variances. A is a 2x2 square parameter that captures the effects of lagged shocks or events on volatility. The conditional variance for each equation in the bivariate BEKK-GARCH model can be derived by expanding system H_t as follows:

$$h_o^2 = \alpha_o + \beta_o^2 \varepsilon_{o-1}^2 + 2\beta_o\beta_{so}\varepsilon_{s-1}\varepsilon_{o-1} + \beta_{so}^2\varepsilon_{s-1}^2 + \delta_o^2 h_{o-1}^2 + 2\delta_o\delta_{so}h_{so-1} + \delta_{so}^2 h_{s-1}^2$$

$$h_{so} = \alpha_{so} + \beta_s\beta_o\varepsilon_{s-1}^2 + (\beta_{os}\beta_{so} + \beta_s\beta_o)\varepsilon_{s-1}\varepsilon_{o-1} + \beta_{os}\beta_o\varepsilon_{o-1}^2 + \delta_s\delta_o h_{s-1}^2 + (\delta_{os}\delta_{so} + \delta_s\delta_o)h_{so-1} + \delta_{os}\delta_o h_{o-1}^2$$

$$h_s^2 = \alpha_s + \beta_s^2\varepsilon_{s-1}^2 + 2\beta_s\beta_{os}\varepsilon_{s-1}\varepsilon_{o-1} + \beta_{os}^2\varepsilon_{o-1}^2 + \delta_s^2 h_{s-1}^2 + 2\delta_s\delta_{os}h_{so-1} + \delta_{os}^2 h_{o-1}^2$$

The above equations measure the spillover effects and volatility transmissions across variables throughout the study period. In other words, the conditional variance of the stock market (oil market) depends not only on its past variances and innovations but also on those of the oil market (stock market). Under the assumption of conditional normality, the parameters of a multivariate GARCH model can be estimated by maximizing the log-likelihood function:

$$Max \log L_T(\theta) = \sum_{t=1}^{T} l_t(\theta)$$

$$l_t(\theta) = -\frac{TN}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(\log|H_t| + \varepsilon'_t H_t^{-1}\varepsilon_t)$$

Where θ represents all unknown parameters, N is the number of variables, and T is the number of observations considered to be typically employed to produce the initial starting values for the estimation of the mean and variance-covariance matrix using the BFGS (Broyden, Fletcher, Goldfar-Shanoo) method. The final step in our analysis is verifying the efficiency of the models used by residual diagnostic tests.

5. Results

5.1 Descriptive statistics

According to Table (2), from January 1, 2020, to the 30th of June 2022, the average daily returns of the EGX30 and EGX100 were positive and approached zero, indicating that gains offset losses over the study period.

Table 2: Summary Statistics of EGX30 and EGX100

EGX100	Mean	Median	Max	Min	S.D	Skew.	Kurtosis
Price	2.84	2.918	4.06	1.39	0.56	-0.367	2.65
Return	0.0002	0.0026	0.06	-0.1	0.02	-1.327	7.568
EGX30	Mean	Median	Max	Min	S.D	Skew.	Kurtosis
Price	11.06	10.97	14.1	8.7	0.91	1.3	5.67
Return	-0.0007	0.00018	0.03	-0.1	0.01	-1.12	12.003

Source(s): Author's calculations using e-views software.

Additionally, a significant difference appears between the highest and minimum values, notably for EGX30, indicating severe fluctuations in price. Skewness is 0, and kurtosis is around 3 in a normally distributed series. The skewness of EGX100 and EGX30 returns is -1.32 and 24.6, respectively. Negative skewness indicates that the distribution deviates from normality and has a long left tail. EGX100 returns are leptokurtic because of the significant kurtosis statistics of 7.5, suggesting that the return is fat-tailed.

Table 3: The Jarque-Bera normality and ARCH effect

		J.B	**Prob**	**PP d(0)**	**ADF d(0)**	**ARCH effect (LM)**	
						F- stat.	**Prob**
EGX100	P	18.6	0.0				
	R	707.1	0.0	-18.8***	19.08***	58.1	0.0
EGX30	P	358.3	0.0				
	R	2179.5	0.0	-20.18	-20.2	63.3	0.0

Source: Author's calculations using e-views software.

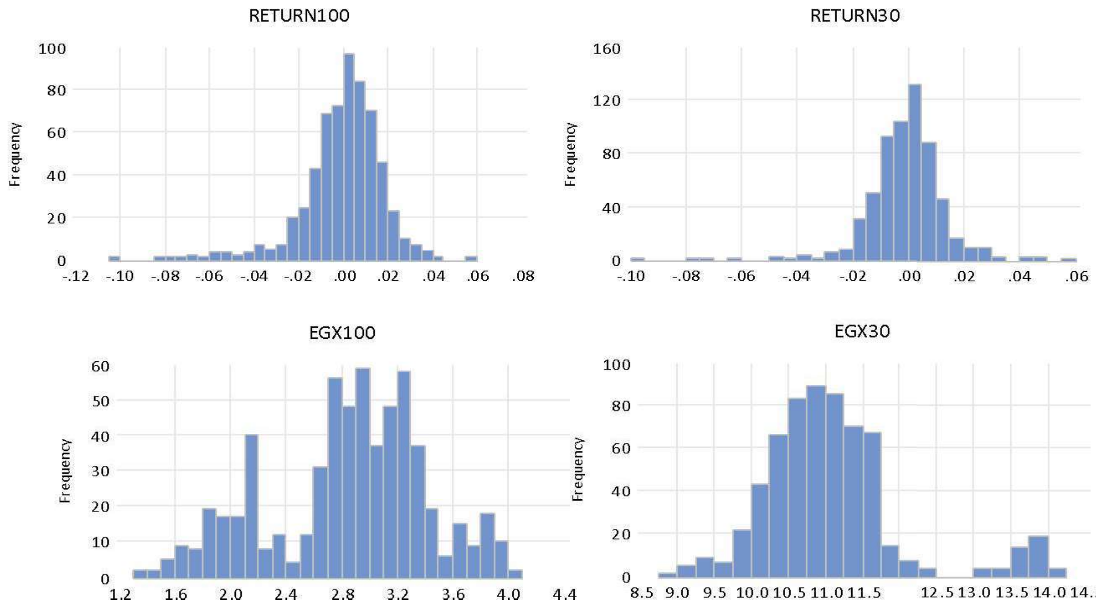


Figure 6: The Distribution of EGX100 and EGX30 Prices and Returns (Jan. 2020– July 2022)

The Jarque-Bera normality test results, as shown in Table 3 and Figure 6, are consistent with both kurtosis and skewness statistics. The returns are not normally distributed because the test result is significant at the 1% level. As the chosen data are leptokurtic, fat-tailed, and not normally distributed, this gives additional evidence for using the ARCH/GARCH model. Data stationarity was also tested before estimating the model using the Phillips-Perron, and Augmented Dickey-Fuller unit root tests.

The first step in the GARCH analysis procedure is to assess the residuals for heteroskedasticity and the presence of the ARCH effect. The following is the generalized autoregressive representation of the squared residuals:

$$\hat{u}_t^2 = b_0 + b_1\hat{u}_{t-1}^2 + b_2\hat{u}_{t-2}^2 + \cdots + b_q\hat{u}_{t-q}^2 + e_t$$

If the parameter estimate “bi” is significant and non-zero, this indicates the presence of an ARCH effect. The test statistics use the LM test in the following reduced form:

$$\hat{u}_t^2 = b_0 + b_1\hat{u}_{t-1}^2 + e_t$$

The null hypothesis states that there is no Arch effect on stock return volatility. Once the volatility of stock returns exhibits an Arch effect, the GARCH models are estimated to analyze changing volatility and assess whether EGX returns are affected by oil price swings.

5.2 GARCH Estimation Results

Because the EGX100 and EGX30 returns showed an Arch effect, the GARCH model was initially used to account for the changing variance. The null hypothesis of no change in volatility can be rejected based on the plain vanilla GARCH model findings in Table 4 since the change in volatility is considerable.

Table 4: Results of plain vanilla GARCH (1,1)

		R100		R30	
		coefficient	z-stat	coefficient	z-stat
Conditional mean equation	μ	0.0005	0.76	0.00016	0.4
	Return(-1)	0.23	5.04***	0.2088	4.36***
Conditional variance equation	ω	-0.0007	-4.5***	9.86E-06	3.658***
	α	0.18	3.5***	0.19	5.368***
	β	0.34	2.9***	0.75	17.4***
	α+β	0.52		0.94	
Loglikelihood		1655.26		1877.14	
AIC		-5.4		-6.16	

Source: Author's calculations using E-views software

The results of the GARCH models demonstrate that volatility from prior periods could explain the current volatility state at a 1% significance level. The coefficients of the ARCH effect are statistically significant in the conditional variance equation, suggesting that recent news influences stock market volatility. Furthermore, the GARCH effect coefficient is substantial, demonstrating that old news influences return volatility. Table 5 shows the findings of the GARCH model, which adds the natural logarithm of the oil price and the VIX variables to the conditional variance equation. As (α+β) is near one, the EGX100 and EGX30 return series have both volatility clustering and persistence.

Table 5 Results of GARCH (1, 1)

GARCH (1, 1) with independent Variables: Ln Oil and Ln VIX

		R100		R30	
		Coeff.	z-stat.	Coeff.	z-stat.
Conditional mean equation	μ	0.028	-1.8^{**}	0.02	2.2^{**}
	Return (-1)	0.21	4.6^{***}	0.18	3.56^{***}
	$(LnOil)_t$	-0.0049	-2.3^{***}	-0.002	-1.7*
	$(LnVIX)_t$	-0.0023	-0.8	-0.003	-2.05^{**}
Conditional variance equation	$(LnVIX)_t$	0.000176	4.4^{***}	2.35E-05	3.4^{***}
	$(LnOil)_t$	6.57E-05	3.2^{***}	3.34E-07	0.06
	ω	-0.0007	-4^{***}	-5.82E-05	-1.6^{*}

α	0.195	3.6***	0.16951	4.2***
β	0.359	3.1***	0.7068	13.4***
$\alpha+\beta$	0.554		0.87	
Log Likelihood	1659.2		1885.16	
Adjusted R^2	0.04		0.067	
AIC	-5.43		-6.18	
ARCH LM	f-stat	0.056	f-stat	0.26
	Prob	0.811	Prob	0.6
Autocorrelation	NO		NO	

Source: Author's calculations using E-views software.

The findings of GARCH demonstrated a strong negative influence of oil price movements and the fear index (LnVIX) on the daily returns and volatility of the EGX100 and EGX30. These findings are compatible with (Ulusoy & Özdurak (2018); and Alamgir & Amin (2021). Furthermore, strong GARCH coefficients indicate that conditional variance shocks take a long time to dissipate, and that volatility is persistent.

Finally, as indicated in table 6. To assess the efficiency and goodness of fit of GARCH models residual diagnostics tests were utilized. The Collegram Q-statistics and ACF and PACF plots for the squared residuals display no significant autocorrelation (probabilities >0.05. Also the probability of ARCH LM test (.81and 0.6 respectively) is greater than 0.05 indicating the absence of homoscedasticity (, the lowest Akaike criterion value, the largest adjusted R^2, and the highest log-likelihood. Lastly, in evaluating the presence of leverage effects in the standardized residuals, sign –bias test was utilized where the results indicate that the model adequately captures the impact of shocks on volatility.

The GARCH model's findings demonstrate how current global challenges have affected the Egyptian stock market. Due to bad events, the returns of the EGX100 and EGX30 are more negatively impacted than their volatility. The returns' volatility is modestly affected by the world oil price fluctuations, in contrast to its response to risks generated by COVID-19 and the Russian-Ukrainian crisis, reflected in the VIX. The weak effect of oil price fluctuations may be attributed to several factors, including the fact that the energy sector represents only 1% on average of total market capitalization. Oil price shocks can affect stock prices directly through listed energy-related stocks, and indirectly through general market risk related to macroeconomic variables such as GDP growth rates, inflation, and exchange rates (Demirer et al.,2014). Hence, the uncertainty accompanied by recent challenges has a higher impact on stock market performance than oil price changes. Additionally, with ongoing foreign investor sales, Egyptian stock market indices had a major decline in the second quarter of 2022. According to EGX monthly data, the non-

Arabs percentage decreased significantly while the percentage of Arabs barely changed. Egyptians', foreigners', and Arabs' respective percentages of the value traded in listed equities in January 2020 were 65.8%, 24.5%, and 9.7%; by July 2022, those percentages had dropped to 71.9% for Egyptians, 18.9%, and 9.2% for foreigners and Arabs.

Table 6: Standardized Diagnostics tests of GARCH (1, 1)

A)The Collegram plot of standardized residuals (ACF and PCF)

R100=F(LnOil,LnVix)

Sample (adjusted): 2/02/2020 9/30/2021
Q-statistic probabilities adjusted for 1 dynamic regressor

	AC	PAC	Q-Stat	Prob*
1	0.006	0.006	0.0204	0.886
2	-0.092	-0.092	5.1812	0.075
3	0.031	0.033	5.7883	0.122
4	0.091	0.083	10.828	0.029
5	-0.021	-0.017	11.102	0.049
6	-0.020	-0.005	11.342	0.078
7	-0.024	-0.033	11.689	0.111
8	0.013	0.005	11.792	0.161
9	0.006	0.005	11.815	0.224
10	0.082	0.088	15.962	0.101
11	0.010	0.013	16.019	0.140
12	-0.031	-0.021	16.634	0.164
13	-0.020	-0.026	16.881	0.205
14	0.002	-0.019	16.883	0.262
15	0.030	0.031	17.444	0.293
16	-0.081	-0.075	21.511	0.160
17	-0.039	-0.025	22.478	0.167
18	0.005	-0.012	22.493	0.211
19	0.016	0.007	22.662	0.253
20	0.010	0.019	22.727	0.302
21	-0.023	-0.020	23.055	0.341
22	0.045	0.052	24.319	0.331
23	0.032	0.023	24.961	0.352
24	0.073	0.085	28.347	0.246
25	-0.052	-0.054	30.052	0.222
26	-0.035	-0.020	30.823	0.235
27	-0.077	-0.090	34.584	0.150
28	-0.026	-0.043	35.031	0.169
29	-0.024	-0.027	35.412	0.191
30	-0.002	-0.005	35.416	0.228
31	0.028	0.052	35.912	0.249
32	0.015	0.002	36.061	0.284
33	-0.008	-0.009	36.100	0.326
34	0.026	0.007	36.551	0.351
35	-0.018	-0.016	36.756	0.387
36	-0.009	0.012	36.809	0.431

*Probabilities may not be valid for this equation specification.

R30=F(LnOil,LnVix)

Sample (adjusted): 2/02/2020 9/30/2021
Q-statistic probabilities adjusted for 1 dynamic regressor

	AC	PAC	Q-Stat	Prob*
1	0.013	0.013	0.0991	0.753
2	-0.058	-0.058	2.1423	0.343
3	0.045	0.047	3.3924	0.335
4	0.034	0.030	4.1180	0.390
5	-0.030	-0.025	4.6528	0.460
6	0.015	0.017	4.7893	0.571
7	-0.046	-0.053	6.0934	0.529
8	0.036	0.041	6.8983	0.548
9	0.028	0.021	7.3758	0.598
10	0.065	0.072	9.9555	0.444
11	-0.001	0.000	9.9560	0.534
12	0.013	0.013	10.058	0.611
13	0.004	-0.001	10.067	0.688
14	-0.026	-0.032	10.498	0.725
15	0.006	0.013	10.518	0.786
16	-0.058	-0.065	12.612	0.701
17	-0.015	-0.003	12.748	0.753
18	-0.002	-0.015	12.750	0.806
19	-0.077	-0.078	16.463	0.626
20	-0.010	-0.008	16.529	0.683
21	-0.040	-0.057	17.532	0.678
22	-0.021	-0.010	17.814	0.717
23	0.044	0.039	19.019	0.700
24	0.103	0.112	25.804	0.363
25	-0.043	-0.033	26.993	0.356
26	0.015	0.028	27.140	0.402
27	-0.091	-0.106	32.466	0.215
28	-0.037	-0.033	33.344	0.223
29	-0.013	-0.004	33.455	0.260
30	0.015	0.020	33.605	0.297
31	0.012	0.045	33.703	0.338
32	0.074	0.060	37.195	0.242
33	0.030	0.023	37.764	0.261
34	0.002	-0.021	37.765	0.301
35	0.014	0.005	37.891	0.339
36	-0.007	-0.020	37.920	0.382

*Probabilities may not be valid for this equation specification.

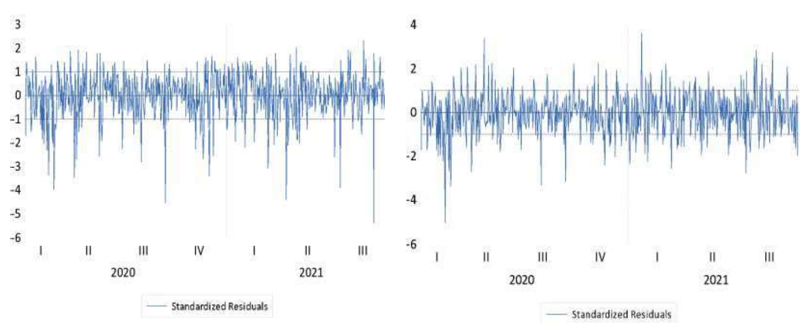
Source(s): Author's calculations using E-views software

b) Engle-Ng Sign-Bias Test

	t-Statistic	Prob.
Sign-Bias	-0.869228	0.3851
Negative-Bias	-0.780284	0.4355
Positive-Bias	-1.146567	0.2520
Joint-Bias	1.952693	0.5826

	t-Statistic	Prob.
Sign-Bias	0.316976	0.7514
Negative-Bias	-0.129666	0.8969
Positive-Bias	-0.202522	0.8396
Joint-Bias	0.502477	0.9183

Source: Author's calculations using E-views software



R100=F(LnOil,LnVix) ***R30=F(LnOil,LnVix)***

Figure (7) The standardized residual for GARCH(1,1)

Source: Author's calculations using E-views software

5.3 GARCH estimation results at the sector level

Recent global shocks have significantly impacted the stock returns of the banking, non-banking financial services, and real estate sectors, negatively affecting their performance. Interestingly, the volatility of returns within these sectors remained relatively unchanged. Following recent global challenges, the share of foreign ownership has increased in the banking, basic resources, and energy sectors. Conversely, the non-banking financial services industry experienced a decrease in foreign and Arab ownership. Specifically, the proportion of foreign ownership fell by 10.4%, while Arab ownership dropped by a more substantial 26%. The "food, beverages, and tobacco" industry was hit particularly hard. The percentage of foreign and Arab ownership plummeted by 32.2% and 61.8%, respectively. It's important to note that this decline was largely offset by a growing share of value traded in listed equities by Egyptians.

5.4 EGARCH (1,1) Estimation Results

Table 7 Results of EGARCH (1,1)

	R100		R30	
	Coeff.	z-stat.	Coeff.	z-stat.
ω	-1.8	-5.2^{***}	-0.54	-4.7^{***}
α	0.08	3.2^{***}	0.17	3.5^{**}
β	0.785	18.7^{***}	0.96	94.04^{***}
γ	-0.24	5.3^{***}	-0.16	-7.7^{***}
Log Likelihood	1647.7		1887.08	
Adjusted R^2	0.03		0.056	
AIC	-5.4		-6.2	

Source: Author's calculations using E-views software.

Table (7) reveals the existence of an asymmetric, a leverage, effect in the Egyptian stock market, where gamma γ has a negative value (-0.24) and is statically significant at the 1% level. Thus, stock returns are volatile, implying that negative shocks have a larger impact on future volatility than positive shocks. This is consistent with some previous studies such as Floros (2008), Emenike (2010) in Nigeria, Wasiuzzaman and Angabini (2011) in Malaysia, and Freedi et al. (2012) in KSA.

5.5 Bivariate BEKK-GARCH estimation results

The BEKK-GARCH estimation is conducted using two groups of variables: (i) EGX100 and EGX30, and (ii) oil price. Estimates of the bivariate asymmetric BEKK–GARCH parameters, along with various diagnostic test results, are reported.

a. *The crude oil price market and (EGX100)*

The mean equation:

$R_{t100}=0.02+0.17R_{100t-1}-0.005LnOil_{t-1}$….(1a)

$LnOil_t=0.012+0.99Ln\ Oil_{t-1}+0.08R_{100t-1}$….(2a)

The results of the conditional mean equations (1a) and (2a) indicate that the autoregressive coefficients for crude oil price and EGX100 returns are statistically significant at the 1% level. Therefore, the current returns of EGX100 and the oil prices depend to a great extent on their past values. Moreover, one-period lagged oil returns negatively affect current EGX100 returns significantly, implying that oil markets have price spillover effects on stock exchange market returns. The negative value of the coefficients indicates a decrease in the EGX100 returns due to an increase in oil prices.

The variance equation: The volatility transmission analysis between the oil and stock exchange markets (through EGX100) can be inferred from the estimated parameters in the conditional variance equations (Equations 3a ,4a, and 5a).

$h_{11,t}=0.00013+0.086RESID(-1)^2+0.421h_{11,t-1}$…..(3a)

$h_{22,t}=2.5e-05+0.29RESID2(-1)^2+0.73h_{22,,t-1}$….(4a)

$h_{12,,tv}=9.5e-06+0.16RESID1(-1)^*RESID2(-1)+0.56h_{12,,t-1}$….(5a)

Equations 3a to 5a reveal that the oil market has a higher ARCH effect (0.29) than the stock exchange market (0.086). Accordingly, volatility in the oil market is more sensitive to past market information than that in the stock exchange market. In both conditional variance equations, the estimated diagonal parameters A_{11}(0.29), A_{22}(0.539), B_{11}(0.65), and B_{22}(0.858) are statistically significant at the 1% level, indicating a strong GARCH process, which establishes that volatility in the stock market (through EGX100) and the oil market is driven by past shocks and volatility. Large magnitudes of GARCH coefficient, B_{11} and B_{22}, indicate strong volatility persistence. They indicate that the oil market has a high degree of volatility clustering as a higher possibility of the extent of its present volatility movement is related to its previous volatility movement.

In the covariance equation (5a), the ARCH coefficient presents the effect of the previous common information to the current covariance. The GARCH coefficient shows persistence regarding the covariance of return volatility. All off-diagonal parameters are significant, showing that all markets are affected by common information. A_{12}(0.16) is statistically significant at the 1% level, indicating a shock spillover from the oil to the stock market. Coefficient B_{12}(0.65) was statistically significant. These results establish volatility spillovers from the oil market to the stock market.

b. The crude oil market and Egyptian stock market (EGX30)

The mean equation:

$$R_{t30}=0.002+0.23R_{30t-1}{}^{***}-0.00004\text{Ln Oil}_{t-1}\ldots(1b)$$

$$\text{LnOil}_t=0.92+0.98\ \text{LnOil}_{t-1}{}^{***}+1.9R_{30t-1}\ldots(2b)$$

The conditional mean equations (1b) and (2b) show that the present EGX30 return, and the oil prices are heavily influenced by their prior values at the 1% level. However, there is little indication of spillover effects between the stock market return and the oil market.

The variance equation: The estimated findings of Equations 3b to 5b show that the oil market has a higher ARCH effect (0.79), indicating that volatility in the oil market is more sensitive to prior market information.

$H_{11,t}=8.62E\text{-}06+0.092\text{RESID1}(-1)^2+0.86\ h_{11,t-1}\ldots(3b)$ $h_{22,t}=0.325+0.63\text{RESID2}(-1)^2+0.41h_{22,,t-1}\ldots(4b)$

$h_{12,t}=0.00053+0.24\text{RESID1}(-1)^*\text{RESID2}(-1)+0.58h_{12,,t-1}\ldots(5b)$

The estimated diagonal parameters A11(0.3), A22(0.79), B11(0.92), and B22(0.62) are statistically significant at 1% in both conditional variance equations, indicating a strong GARCH process, establishing that volatility in the Egyptian stock market (through EGX30) and the oil market is driven by their past shocks and volatility. Furthermore, in the covariance equation(5b), all off-diagonal parameters are significant, indicating that common information affects all markets. At the 1% level, the A12;(0.24); is statistically significant, showing A shock spillover from the oil market to the stock market. These findings assert the volatility spillovers from oil to stock markets, with the coefficient B12(0.58) statistically significant.

The eigenvalues of the conditional covariance matrix in the BEKK-GARCH model are all less than one in absolute value. This ensures covariance stationarity, implying that the model captures the long-term behavior of the Egyptian stock market and isolates the effects of external variables like exchange rate volatility and interest rates.

6. Discussion and Conclusions

This study examined the impact of global oil price fluctuations on the Egyptian stock market's return and volatility between January 1, 2020, and June 30, 2022. This period witnessed significant financial market shocks due to the COVID-19 pandemic and the Russia-Ukraine conflict.

The research employed Pearson and Kendall coefficients to conduct a preliminary correlation analysis after dividing the study period into three sub-periods. A strong positive correlation emerged between oil prices and stock market indices during the initial wave of COVID-19. However, this correlation transitioned to negative after the Ukrainian crisis.

A comprehensive sectoral analysis of the Egyptian stock market was also performed. The analysis revealed an increase in the market capitalization of the basic resources sector, while the banking and "food, beverages, and tobacco" sectors experienced a decline. Notably, despite expectations of the food sector demonstrating greater resilience, the decrease in foreign and Arab investment during the crisis negatively impacted its performance.

The study then utilized GARCH, EGARCH, and a bivariate BEKK-GARCH model for further analysis. The GARCH model results indicated a significant negative impact of both oil prices and the fear index (LnVIX) on the returns and volatility of both the EGX100 and EGX30 indices. Interestingly, the impact of world oil prices on volatility was slightly weaker compared to the fear index.

Building upon the sectoral analysis, the study found that returns in the banking, non-banking financial services, and real estate sectors were negatively affected by fluctuations in oil prices, along with negative news related to COVID-19 and the Russia-Ukraine war. Furthermore, the research employed a BEKK-GARCH model to investigate the transmission of volatility and shocks between the oil and stock markets. The results revealed significant volatility spillovers in both directions between these markets.

Since the major sectors with the highest share of market capitalization percentage in Egypt are not highly oil-intensive, it is reasonable that oil price fluctuations had a slightly negative effect on their returns and volatility. However, the impact of recent challenges on variations in stock market returns outweighed that of oil prices.

These results have crucial implications for investors and policymakers, as they have to consider the effect of oil price variations on stock performance at both the aggregate and sectoral levels. Facing oil price fluctuations requires tightening monetary policies and increasing ex-ante real interest rates. The banking sector, brokerages, mortgage, and insurance companies are the most beneficial from interest rate hikes, because they can charge more for lending.

The present analysis can be extended to investigate more emerging markets and capture short and long-run asymmetries at the sectoral level. As Egypt recently shifted to a flexible exchange rate regime, which is expected to attract capital inflows and enable the economy to absorb real external shocks more easily, future work might consider the resulting stock market reaction.

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