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Crude Oil Prices and the Egyptian Economy Evidence from the Stock Market

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ABSTRACT

This paper investigates two important things; the role of crude oil prices in explaining the Egyptian stock market return, and what factors derive from Egyptian crude oil prices. Using 6 log difference time series variables this paper finds that multiple regression is an inappropriate model to test the two goals mentioned above. On the other hand, using Vector Autoregression (VAR Model) is much more profitable in achieving the paper's goals. Although the VAR model results are more reliable, crude oil price fails to explain the Egyptian stock market return because Egypt is not a big oil exporter. Furthermore, the VAR model shows that the Energy sector index, stock world index (S and P 500 the proxy), stock exchange index, exchange rate, and the global financial crisis are all factors that derive and determine the Egyptian crude oil price.

Keywords: Crude Oil Price, Vector Autoregression (VAR Model), Egyptian Stock Market Return, Oil Exporter, Energy Sector Index
JEL Classifications: G10, G11, G14

1. INTRODUCTION

Crude oil prices and the stock market are two linked factors that have a big impact on economies all over the world. Investor behavior and overall market mood can be significantly affected by variations in crude oil prices, hence highlighting the important relationship between the stock market and crude oil (Chang et al., 2013; Bataineh, 2022). This study aims to investigate the multiple causes and theories connecting these crucial components of the global economy. Crude oil serves as a vital energy source for transportation, electricity generation, and diverse industrial applications, making it indispensable to the global economy (Armeanu et al., 2019; Cao et al., 2020). Factors such as supply and demand dynamics, geopolitical tensions, market speculation, and global economic conditions intricately influence crude oil prices.[1] Consequently, comprehending the dynamics of crude oil prices is essential for understanding the implications they have on the stock market.

The stock market, often known as the equity market or share market, is a marketplace for purchasing and selling publicly traded company shares.[2] It allows individuals, institutions, and governments to invest in, trade-in, and raise funds for business expansion. The stock market, as an intrinsic component of modern economies, reflects investors' expectations, economic indicators, geopolitical events, and a variety of other factors that influence supply and demand for stocks (Filis et al., 2011; Jahan-Parvar and Mohammadi, 2013; Zhu et al., 2019; Uzun and Adali, 2021). The relationship between crude oil prices and the stock market has been the subject of much study and discussion. Several hypotheses and methods have been proposed to explain the relationship between these two variables:

Resource dependency theory: This theory suggests that high crude oil prices negatively impact the stock market, particularly in countries that heavily rely on oil imports (Kocaarslan and Soytas, 2019; Shahzad et al., 2021; Mahfouz et al., 2021). When crude oil

1 Federal Reserve Bank of St. Louis. (2020)

2 U.S. Energy Information Administration EIA. (2020)

prices rise, the increased costs of production and transportation can lead to reduced profit margins for businesses. Consequently, this may result in decreased corporate earnings and, thus, decreased stock market performance. Macroeconomic indicators: Crude oil prices considerably impact a country's macroeconomic indicators. As transportation and production expenses rise, high oil prices can lead to an increase in inflation. Higher inflation, in turn, reduces purchasing power, impacting consumer spending and overall economic growth (Gavanas, 2012; Kocaarslan and Soytas, 2019; Heshmati et al., 2020). These negative economic repercussions might lead to decreased investor confidence, resulting in stock market falls: Resource dependency theory: This theory suggests that high crude oil prices negatively impact the stock market, particularly in countries that heavily rely on oil imports (Khattab et al., 2016; Adekunle et al., 2020; Okoli et al., 2021). When crude oil prices rise, the increased costs of production and transportation can lead to reduced profit margins for businesses. Consequently, this may result in decreased corporate earnings and, thus, decreased stock market performance (Volkov and Yuhn, 2016; Shaoubi and El-Shawarby, 2017; Gu et al., 2020). Macroeconomic indicators: Crude oil prices have a significant impact on the macroeconomic indicators of a country. High oil prices often lead to an increase in inflation, as transportation and production costs rise. In turn, higher inflation erodes purchasing power, affecting consumer spending and overall economic growth. These adverse effects on the economy can translate into reduced investor confidence, leading to stock market declines (Al-Azzazy and Al-Gohary, 2019; Singhal et al., 2019; Kong et al., 2020).

The influence of the oil price on financial markets, particularly stock markets and returns, has gained significant importance in recent years, specifically after the financial crisis. Wei et al. (2019) have examined the long-term connections between crude oil futures prices and the Chinese stock market during the financial crisis, using a nonlinear threshold cointegration method within a multivariate framework. The study reveals a significant impact of the oil futures market on China's stock market. Additionally, it establishes significant long-term cointegration relationships between crude oil prices and the Chinese stock market. Jawadi and Serletis (2019) have analyzed the relationship between oil prices and stock market returns using the most frequent data. By employing daily data and structural VAR, they have found that positive oil price shocks have a negative effect on stock market returns.

In their study, Kocaarslan and Soytas (2019) explore the asymmetric relationships between oil prices, interest rates, and stock prices of clean energy and technology companies. They utilize the nonlinear auto-regressive distributed lag (NARDL) model and refute the notion that neglecting nonlinear relationships can lead to inaccurate outcomes. Moreover, their findings demonstrate substantial variations in positive and negative changes in oil prices, technology stock prices, and interest rates between the short-run and long-run. In the short-run, an increase in oil prices, coupled with speculative attacks, prompts greater investment in clean energy stocks, whereas the opposite holds true for the long-run, indicating an asymmetric impact. Similarly, Salisu et al. (2019) revisit the predictive powers of the oil-stock nexus by considering the role of macroeconomic variables in the US market. Utilizing both linear and nonlinear multi-predictive models to capture structural breaks and asymmetries, they affirm that asymmetries do not significantly enhance predictability. Additionally, they emphasize the significance of pre-tests for endogeneity and ARCH, as well as the robustness of their results under different forecast measures and horizons. These insights are valuable for facilitating effective hedging decisions in the US stock market.

2. LITERATURE REVIEW

Numerous studies have examined the correlation between oil and stock prices. During the 1970s and 1980s, it was found that oil price volatility had a negative impact on stock prices in the United States (Kaul and Seyhun, 1990; Sadorsky, 1999; Papapetrou, 2001). Fang and You (2014) further assert that oil price shocks affect the stock returns of emerging nations. Wei and Guo (2017) discovered various ways in which the stock market responds to oil shocks, finding a strong correlation with the underlying causes of oil price fluctuations. Sadorsky (2001) has observed a contradictory positive correlation between oil prices and Canadian stock returns in the 1990s, which goes against the majority of previous research. While the link between oil prices and stock market returns remains inconclusive, it is recognized that the volatility of oil prices significantly impacts stock market volatility. Additionally, the price of oil has ramifications for the stock prices of non-oil producing companies as it affects their profitability through fluctuations in raw material costs (Basher and Sadorsky, 2006). Furthermore, investigations into developing markets have supported the idea that oil price risk has an influence on stock returns, particularly in relation to stock prices and exchange rates.

Sari et al. (2010) carried out an investigation on the transmission of information and co-movements among various rare metals' spot prices, the exchange rate of USD to Euro, and the price of oil. Their findings indicate a slight long-term connection, but a notable equilibrium in the short term. Similarly, Basher et al. (2012) explored the correlation between oil prices, exchange rates, and stock markets. They concluded that positive oil price shocks can have a short-term impact on emerging market stock prices and USD exchange rates. Interestingly, they also observed that a positive shock to oil production leads to a decrease in oil prices, while a positive shock to actual economic activity raises oil prices. Lastly, Cheng et al. (2013) investigated the relationship between gold, oil, and the exchange rate. They determined the independence between these variables.

In their study, Jain and Ghosh (2013) investigated the long-term relationship and causality among global oil prices, precious metals prices, and the INR/USD exchange rate. They found a long-run link when considering gold price and exchange rate as dependent variables. Through Granger causality tests, the study concluded that the exchange rate drives rare metal and oil prices in India. Similarly, Aloui and Aïssa (2016) explored the relationship between crude oil prices, stock market indices, and exchange rates for the United States, developing economies, and oil exporter/importer countries. They discovered substantial and symmetric evidence of this relationship, noting that it varies over time. Contrarily, Kayalar et al. (2017) found that oil-exporting nations' exchange rates and stock indexes are more influenced by oil prices, while oil-importing emerging markets are less susceptible to oil price fluctuations. The study conducted by Jain and Biswal (2016) revealed that a decrease in gold and crude oil prices leads to a decrease in the value of the Indian rupee and the benchmark stock index.

Heavy studies have been done on the Mexican market as it is one of the most important emerging oil exporters, (Lizardo and Mollick, 2010).

This study examines the significance of the VAR model in addressing the issue of an insignificant multivariable regression model within the context of Egypt, one of the most important emerging markets in the MENA countries. Furthermore, we identify the key factors that drive the Egyptian crude oil price and analyze the impact of the global crisis on the return of the Egyptian stock market. The utilization of cointegration tests ensures robust and stable results. Notably, non-oil-producing firms' stock prices are observed to be influenced by oil prices, as fluctuations in oil prices have a direct effect on the costs of raw materials, consequently impacting firms' profitability.

2.1. Hypotheses

- H1: Oil price cannot explain the Egyptian stock market return
- H2: Oil price can explain the Egyptian stock market return
- H3: Our variables cannot derive the Egyptian crude oil price
- H4: Our variables can derive the Egyptian crude oil price.

3. DATA AND METHODOLOGY

The study sample is the Egyptian market; the paper uses annual data obtained from DataStream from 1998 to 2017.

Variables: Energy sector index as a dependent variable and other 5 independent variables as follows: crude oil price, stock world index (S and P 500 the proxy),[3] stock exchange index, exchange rate, and a dummy variable for Crisis.

The model applied is as follow:

$$LEnergyIndex=\alpha 0+\alpha 1LCrudeOilPrice+\alpha 2LWorldStockIndex+\alpha 3LStockExchangeIndex+\alpha 4LExchangeRate+\alpha 5Crisis \quad (1)$$

Where:

EnergyIndex: Is the log difference of the energy sector index of the country.

LCrudeOilPrice: Is the log difference of the crude oil price of the country.

LWorldStockIndex: Is the log difference of stock world index (S and P 500 the proxy). s: is the log difference of stock exchange index.

LExchangeRate L: Is the log difference of exchange rate of the country and the US dollar.

Crisis: Is α Dummy variable takes 1 before 2008 and 0 elsewhere.

This paper follows Bernanke's (2016) methodology. First of all, the log difference for all variables has been found to get stationary data. In addition, the paper runs the Dickey-Fuller test for unit root to make sure about stationarity. Secondly, multiple regression was estimated for variables. Thirdly, the paper tests for the appropriate number of lags for variables using the schwarz information criterion (SIC) following Narayan and Liu (2018) beginning with a maximum of 4 lags. Fourthly, the paper estimates the Vector Autoregression (VAR model). Finally, a robustness test of cointegration between variables was run to test for the stability and reliability of the VAR model results.

4. RESULTS AND DISCUSSION

Table 1 presents descriptive statistics for the study variables. The log difference of energy index has a slightly positive mean and high variability. The log difference of Crude oil price has a slightly negative mean and less variability compared to the log difference of energy index. The log difference of world stock index has a slightly positive mean and moderate variability. The log difference of stock exchange index has a positive mean and high variability. The log difference of exchange rate has a slightly positive mean and moderate variability. The crisis variable is binary and occurs half of the time in the dataset. Overall, the table provides a summary of the variables' central tendency, variability, range, and the occurrence of crises. Further analysis can be conducted for understanding relationships and patterns in the data.

Figure 1 presents a comprehensive exploration of various economic indicators, each segment weaving a unique narrative that collectively paints a vivid picture of the interconnectedness of global financial dynamics. The initial segment delves into the Egyptian energy sector index, revealing a stationary series marked by temporal fluctuations. Beginning in 2002, the sector experienced a pronounced upward trend, reaching its peak in 2006. However, the ensuing global financial crisis in 2008 cast a shadow, representing a low point for the sector. Post-crisis, a resilient recovery unfolded, showcasing the sector's ability to rebound from external economic challenges. Transitioning seamlessly to the second segment, the focus shifts to the global stock market index, exemplified by the S&P 500. This

3 International Monetary Fund (IMF). (2020)

Table 1: Descriptive statistics

Variable	Obs	Mean	SD	Min	Max
LEnergyIndex	19	0.1197916	0.4221087	−0.7665195	0.8419533
LCrudeOilPrice	19	−0.0149604	0.0466557	−0.1663437	0.0564528
LWorldStockIndex	19	0.0389949	0.1842298	−0.482295	0.3568811
LStockExchangeIndex	19	0.1644499	0.4986028	−0.8308029	0.9013357
LExchangeRate	19	0.0869138	0.1994088	−0.0561172	0.8395987
Crisis	20	0.5	0.5129892	0	1

portion of the graph unveils a stationary series with significant dynamics, notably a substantial decline in the index value during the global financial crisis of 2008. The negative values underscore the severity of the economic challenges, emphasizing the vulnerability of financial markets to external shocks. Continuing the narrative, the third section examines the Egyptian stock exchange returns index. From 2002 to 2007, the index experienced remarkable appreciation, influencing crude oil prices and associated trade dynamics. However, the onset of the financial crisis and the Arab Spring ushered in a decline, reflected in the descending trend of the index, symbolizing the challenges faced during these turbulent times. The fourth segment shifts the focus to crude oil prices, highlighting the most affordable prices in 2000. Post-2005, a transformative shift occurred, influenced by political events on domestic, regional, and global scales, including the global financial crisis. These multifaceted developments marked a departure from the earlier lower prices, signaling a significant transformation in the crude oil price landscape. Concluding the comprehensive analysis, the ultimate section scrutinizes the exchange rate between the Egyptian pound and the US dollar. This segment reveals a relatively stable effect until the substantial devaluation in 2016 when a notable 110% decrease occurred. This adjustment marks a noteworthy shift in the stability of the exchange rate dynamics, underlining the economic impact during this period. Collectively, the segments in Figure 1 create a cohesive narrative, showcasing the intricate interplay of various economic indicators over time.

Table 2 shows that all variables are stationary, after implementing the log difference for all of them. In addition, the P-values for all variables are below 0.01 which means we can reject the null hypothesis of unit root and conclude that all of them are stationary. We can see from the graphs that all of variables do not have increasing or decreasing trend with time, that's support what we already found from testing Dickey-Fuller test for unit root.

Table 2: Dickey-Fuller-test and stationary

Variable	Dickey-Fuller-test test statistics	P-Value	Variable status
LEnergyIndex	−3.450	0.0094	Stationary
LCrudeOilPrice	−3.434	0.0098	Stationary
LWorldStockIndex	−4.533	0.0002	Stationary
LStockExchangeIndex	−3.933	0.0018	Stationary
LExchangeRate	−4.317	0.0004	Stationary

Table 3 reposts the multiple regression results for our model that *LWorldStockIndex* is the only significant variable that explains the Egyptian stock market return (energy sector as a proxy). One notable thing to mention is that the crude oil price cannot explain or predict the Egyptian stock market return. So, because the of insignificant crude oil price with a P-value (0.697), we cannot reject our first null hypothesis that says oil price cannot predict the stock returns in Egypt, and we conclude that oil price cannot predict the stock returns in Egypt. Moreover, the dummy variable (Crisis) is insignificant, which means the performance of the Egyptian stock market return is the same before, during, and after the global financial crisis and this crisis has no effect on the Egyptian stock market return. On the other hand, the R-Square is 0.4662 and the Adj R-squared is 0.2610.

Table 4 examines five ways to select the appropriate number of lags for the variables (LR, FPE, AIC, HQIC, and SBIC). LR suggests 3 lags, while FPE suggests 2 lags. But for the other 3 ways they suggest 4 lags. I follow Narayan and Liu (2018) by using Schwarz Information criterion (SBIC) selection-order criteria, so my SBIC suggests 4 lags, and I will go with 4 lags.

Using the VAR model, Table 5 represents the first equation, where the *LEnergyIndex* is the dependent variable and the all 6 variables including the *LEnergyIndex* itself are independent variables with 4 lags for each we will have 24 coefficient. We obtain better results for explaining the Egyptian stock market return. Where, the 1st lagthe 3rd lags for

LEnergyIndex explains it significantly. The crude oil price again cannot explain the stock return. The 3rd and 4th lags for the world stock index explain the stock market significantly. For the whole

Table 3: Multiple regression

The dependent variable is *LEnergyIndex*						
Variable	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**(95% Conf. Interval)**	
LCrudeOilPrice	0.7027641	2.011047	0.35	0.732	−3.64183	5.047367
LWorldStockIndex	1.20603**	0.4748096	2.54	0.025	0.1802661	2.231794
LStockExchangeIndex	0.2733837	0.1878375	1.46	0.169	−0.132414	0.6791819
LExchangeRate	−0.3590989	0.4537041	−0.79	0.443	−1.33926	0.6210692
Crisis	0.0776335	0.1951612	0.40	0.697	-0.343986	0.4992536
Constant	0.0327552	0.1293878	0.25	0.804	−0.246770	0.3122805
R-Square=0.4662					Adj R-squared=0.2610	

**Indicate a statistical significance level of 5%

Table 4: Selecting the appropriate number of lags

Selection-order criteria Number of obs=15								
Lag	**LL**	**LR**	**df**	**P**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	20.9091	.	.	.	5.5e-09	−1.98788	−1.9909	−1.70466
1	82.6952	123.57	36	0.000	2.8e-10	−5.42603	−5.44715	−3.44349
2	1236.74	2308.1	36	0.000	7.4e-73*	−154.498	−154.537	−150.816
3	3065.31	3657.2*	36	0.000	.	−396.708	−396.754	−392.46
4	3073.5	16.383	36	0.998	.	−397.801*	−397.846*	−393.552*

**Indicate the appropriate number of lags

Table 5: Vector autoregression (VAR Model): *LEnergyIndex* as a dependent variable

LEnergyIndex as a dependent variable						
Variable	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
LEnergyIndex						
Lag 1	−0.5467665**	2.14e-15	2.14e-15	0.000	−0.5467665	−0.5467665
Lag 2	0	(omitted)				
Lag 3	−0.2557726**	5.11e-15	−5.0e+13	0.000	−0.2557726	−0.2557726
Lag 4						
CrudeOilPrice						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
LWorldStockIndex						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	0.2100162**	5.47e-15	3.8e+13	0.000	0.2100162	0.2100162
Lag 4	−0.4275355**	1.80e-15	−2.4e+14	0.000	−0.4275355	−0.4275355
LStockExchangeIndex						
Lag 1	0.8274164**	8.17e-16	1.0e+15	0.000	0.8274164	0.8274164
Lag 2	0.2473978**	1.54e-15	1.6e+14	0.000	0.2473978	0.2473978
Lag 3	−0.0307077**	3.03e-15	−1.0e+13	0.000	−0.0307077	−0.0307077
Lag 4	0.0353891**	2.17e-15	1.6e+13	0.000	0.0353891	0.0353891
LExchangeRate						
Lag 1	−0.0028401**	1.17e-15	−2.4e+12	0.000	−0.0028401	−0.0028401
Lag 2	1.505585**	5.42e-15	2.8e+14	0.000	1.505585	1.505585
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
Crisis						
Lag 1	0.3155516**	1.22e-15	2.6e+14	0.000	0.3155516	0.3155516
Lag 2	0	(omitted)	9.3e+12	0.000	0.0480386	0.0480386
Lag 3	0.0480386**	5.17e-15	−4.2e+13	0.000	−0.2017631	−0.2017631
Lag 4	−0.2017631**	4.84e-15	−2.4e+13	0.000	−0.0236606	−0.0236606
Constant	−0.0236606	9.85e-16	−2.4e+13	0.000	−0.0236606	−0.0236606

*** Indicate a statistical significance level of 1%

Table 6: Vector autoregression (VAR Model): *LCrudeOilPrice* as a dependent variable

LCrudeOilPrice as a dependent variable						
Variable	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**(95% Conf. Interval)**	
LEnergyIndex						
Lag 1	−0.129053**	7.41e-16	−1.7e+14	0.000	−0.129053	−0.129053
Lag 2	0	(omitted)				
Lag 3	0.263197**	1.77e-15	1.5e+14	0.000	0.263197	0.263197
Lag 4	−0.0042201**	5.27e-16	−8.0e+12	0.000	−0.0042201	−0.0042201
LCrudeOilPrice						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
LWorldStockIndex						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	−0.2329261**	1.89e-15	−1.2e+14	0.000	−0.2329261	−0.2329261
Lag 4	−0.0156496**	6.21e-16	−2.5e+13	0.000	−0.0156496	−0.0156496
LStockExchangeIndex						
Lag 1	0.0184936**	2.82e-16	6.6e+13	0.000	0.0184936	0.0184936
Lag 2	0.0592552**	5.31e-16	1.1e+14	0.000	0.0592552	0.0592552
Lag 3	−0.1340687**	1.05e-15	−01.3e+14	0.000	−0.1340687	−0.1340687
Lag 4	−0.068564**	7.49e-16	−9.2e+13	0.000	−0.068564	−0.068564
LExchangeRate						
Lag 1	−0.129157**	4.03e-16	−3.2e+14	0.000	−0.129157	−0.129157
Lag 2	−0.102474**	1.87e-15	−5.5e+13	0.000	−0.102474	−0.102474
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
Crisis						
Lag 1	0.0065533**	4.21e-16	1.6e+13	0.000	0.0065533	0.0065533
Lag 2	0	(omitted)				
Lag 3	0.210001**	1.79e-15	1.2e+14	0.000	0.210001	0.210001
Lag 4	−0.2485629**	1.67e-15	−1.5e+14	0.000	−0.2485629	−0.2485629
Constant	0.0537754	3.40e-16	1.6e+14	0.000	0.0537754	0.0537754

***Indicate a statistical significance level of 1%

Table 7: Vector autoregression (VAR Model): *LWorldStockIndex* as a dependent variable

LWorldStockIndex as a dependent variable						
Variable	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
LEnergyIndex						
Lag 1	−0.7171808**	1.75e-15	−4.1e+14	0.000	−0.7171808	−0.7171808
Lag 2	0	(omitted)				
Lag 3	0.4510221**	4.16e-15	1.1e+14	0.000	0.4510221	0.4510221
Lag 4	−0.0594533**	1.24e-15	−4.8e+13	0.000	−0.0594533	0.4510221
LCrudeOilPrice						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
LWorldStockIndex						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	0.0873019**	4.45e-15	2.0e+13	0.000	0.0873019	0.0873019
Lag 4	0.0873019**	1.46e-15	−1.2e+14	0.000	−0.1725761	−0.1725761
LStockExchangeIndex						
Lag 1	0.3516394**	6.65e-16	5.3e+14	0.000	0.3516394	0.3516394
Lag 2	0.4233692**	1.25e-15	3.4e+14	0.000	0.4233692	0.4233692
Lag 3	−0.2713399**	2.47e-15	−1.1e+14	0.000	−0.2713399	−0.2713399
Lag 4	−0.4359634**	1.77e-15	−2.5e+14	0.000	−0.4359634	−0.4359634
LExchangeRate						
Lag 1	−0.1288665**	9.50e-16	−1.4e+14	0.000	−0.1288665	−0.1288665
Lag 2	−1.156435**	4.41e-15	−2.6e+14	0.000	−1.156435	−1.156435
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
Crisis						
Lag 1	−1.156435**	9.93e-16	−2.8e+13	0.000	−0.0276606	−0.0276606
Lag 2	0	(omitted)				
Lag 3	0.1834831**	4.21e-15	4.4e+13	0.000	0.1834831	0.1834831
Lag 4	−0.1711539**	3.94e-15	−4.3e+13	0.000	−0.1711539	−0.1711539
Constant	0.1596445	8.02e-16	2.0e+14	0.000	0.1596445	0.1596445

***Indicate a statistical significance level of 1%

Table 8: Vector Autoregression (VAR Model): *LStockExchangeIndex* as a dependent variable

LStockExchangeIndex as a dependent variable						
Variable	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
LEnergyIndex						
Lag 1	−0.6938252**	2.47e-15	−2.8e+14	0.000	−0.6938252	−0.6938252
Lag 2	0	(omitted)				
Lag 3	−1.039234**	5.88e-15	−1.8e+14	0.000	−1.039234	−1.039234
Lag 4	−0.8864902**	1.76e-15	−5.0e+14	0.000	−0.8864902	−0.8864902
LCrudeOilPrice						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
LWorldStockIndex						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	0.4443603**	6.29e-15	7.1e+13	0.000	0.4443603	0.4443603
Lag 4	−0.3179847**	2.07e-15	−1.5e+14	0.000	−0.3179847	−0.3179847
LStockExchangeIndex						
Lag 1	−0.3187995**	9.40e-16	−3.4e+14	0.000	−0.3187995	−0.3187995
Lag 2	0.6800166**	1.77e-15	3.8e+14	0.000	0.6800166	0.6800166
Lag 3	−0.0485936**	3.49e-15	−1.4e+13	0.000	−0.0485936	−0.0485936
Lag 4	0.4558447**	2.49e-15	1.8e+14	0.000	0.4558447	0.4558447
LExchangeRate						
Lag 1	1.047581**	1.34e-15	7.8e+14	0.000	1.047581	1.047581
Lag 2	−0.2711528**	6.24e-15	−4.3e+13	0.000	−0.2711528	−0.2711528
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
Crisis						
Lag 1	−0.0743348**	1.40e-15	−5.3e+13	0.000	−0.0743348	−0.0743348
Lag 2	0	(omitted)				
Lag 3	0.9840666**	5.95e-15	1.7e+14	0.000	0.9840666	0.9840666
Lag 4	−0.2210948**	5.57e-15	−4.0e+13	0.000	−0.2210948	−0.2210948
Constant	0.0260434	1.13e-15	2.3e+13	0.000	0.0260434	0.0260434

*** Indicate a statistical significance level of 1%

Table 9: Vector autoregression (VAR Model): *LExchangeRate* as a dependent variable

LExchangeRate as a dependent variable						
Variable	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
LEnergyIndex						
Lag 1	0.9180595**	1.29e-14	7.1e+13	0.000	0.9180595	0.9180595
Lag 2	0	(omitted)				
Lag 3	−3.641822**	3.08e-14	−1.2e+14	0.000	−3.641822	−3.641822
Lag 4	−0.3626819**	9.21e-15	−3.9e+13	0.000	−0.3626819	−0.3626819
LCrudeOilPrice						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
LWorldStockIndex						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	2.690645**	3.30e-14	8.2e+13	0.000	2.690645	2.690645
Lag 4	1.275249**	1.09e-14	1.2e+14	0.000	1.275249	1.275249
LStockExchangeIndex						
Lag 1	−0.2856267**	4.93e-15	−5.8e+13	0.000	−0.2856267	−0.2856267
Lag 2	−0.6622711**	9.27e-15	−7.1e+13	0.000	−0.6622711	−0.6622711
Lag 3	2.179074**	1.83e-14	1.2e+14	0.000	2.179074	2.179074
Lag 4	1.695791**	1.31e-14	1.3e+14	0.000	1.695791	1.695791
LExchangeRate						
Lag 1	0.2640589**	7.04e-15	3.8e+13	0.000	0.2640589	0.2640589
Lag 2	1.667149**	3.27e-14	5.1e+13	0.000	1.667149	1.667149
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
Crisis						
Lag 1	0.3118181v	7.36e-15	4.2e+13	0.000	0.3118181	0.3118181
Lag 2	0	(omitted)				
Lag 3	−3.237017**	3.12e-14	−1.0e+14	0.000	−3.237017	−3.237017
Lag 4	−3.237017**	2.92e-14	1.0e+14	0.000	3.060178	3.060178
Constant	−0.3444888	5.94e-15	−5.8e+13	0.000	−0.3444888	−0.3444888

***Indicate a statistical significance level of 1%

Egyptian stock market index, the 4 lags explain the stock market return (energy sector) significantly which means the Egyptian stock market return was better before the financial crisis than during and after the crisis. So, the global financial crisis affects the Egyptian stock market return negatively. Furthermore, the 4 lags the in the exchange rate are also highly significant in explaining the stock return. Finally, for Crisis, we can see that 3 lags out of 4 are highly significant and can explain the stock market return.

Table 6 reports the second equation, where the *LCrudeOilPrice* is the dependent variable and all 6 variables including the *LCrudeOilPrice* itself are independent variables with 4 lags for each. We obtain the factors that derive the Egyptian crude oil price. Where the 1st and the 3rd and 4th lags for *LEnergyIndex* explain the crude oil price and reject the null hypothesis that we cannot decide the factors that derive the crude oil price, so we can conclude that *LEnergyIndex* is the first factor that drives the crude oil price. For the crude oil price again its lags cannot be a factor in deriving crude oil price. The 3rd and 4th lags for the world stock index explain crude oil prices significantly, so the world stock index is the second factor that derives the crude oil price. For the whole Egyptian stock market index, the 4 lags significantly explain the crude oil price, so the whole Egyptian stock market index is the third factor that derives the crude oil price. 1st and 2nd lags of the exchange rate are also highly significant in explaining the crude oil price, so the exchange rate is the fourth factor that derives the crude oil price.

For Crisis, we can see that 3 lags out of 4 are highly significant and can explain the crude oil price, so the global financial crisis is the fifth factor that derives the crude oil price in Egypt.

According to the findings presented in Table 7, it has been observed that the financial crisis has a negative impact on the world stock index. Moreover, it is worth noting that an increase in the exchange rate also contributes to the decrease of the world stock index. Interestingly, the data indicates that changes in the crude oil price do not provide a sufficient explanation for these shifts in the world stock index.

Table 8 shows the results of a Vector Autoregression (VAR) model with the dependent variable being the LStockExchangeIndex. From the coefficients and their associated statistics, it can be seen that some of the independent variables have a significant impact on the LStockExchangeIndex. For example, the Lag 1 value of LEnergyIndex has a statistically significant negative coefficient, indicating that higher energy index values in the previous period lead to lower values of the LStockExchangeIndex. Similarly, the Lag 3 and Lag 4 values of LWorldStockIndex have statistically significant positive and negative coefficients, respectively, indicating their influence on the LStockExchangeIndex. It is worth noting that some of the lag values for certain independent variables have coefficients of zero, indicating that they do not have a significant impact on the LStockExchangeIndex. For example,

Table 10: Vector autoregression (VAR Model): *Crisis* as a dependent variable

Crisis as a Dependent Variable						
Variable	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
LEnergyIndex						
Lag 1	−1.120371**	6.54e-15	−1.7e+14	0.000	−1.120371	−1.120371
Lag 2	0	(omitted)				
Lag 3	1.651904**	1.56e-14	1.1e+14	0.000	1.651904	1.651904
Lag 4	−1.174161**	4.66e-15	−2.5e+14	0.000	−1.174161	−1.174161
LCrudeOilPrice						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
LWorldStockIndex						
Lag 1	0	(omitted)				
Lag 2	0	(omitted)				
Lag 3	−1.68671**	1.67e-14	−1.0e+14	0.000	−1.68671	−1.68671
Lag 4	0.0435337**	5.49e-15	7.9e+12	0.000	0.0435337	0.0435337
LStockExchangeIndex						
Lag 1	−0.1930672**	2.49e-15	−7.7e+13	0.000	−0.1930672	−0.1930672
Lag 2	0.9920775**	4.69e-15	2.1e+14	0.000	0.9920775	0.9920775
Lag 3	−1.184582**	9.25e-15	−1.3e+14	0.000	−1.184582	−1.184582
Lag 4	−.6847076**	6.62e-15	−1.0e+14	0.000	−0.6847076	−0.6847076
LExchangeRate						
Lag 1	0.4940818**	3.56e-15	1.4e+14	0.000	0.4940818	0.4940818
Lag 2	−3.213692**	1.66e-14	−1.9e+14	0.000	−3.213692	−3.213692
Lag 3	0	(omitted)				
Lag 4	0	(omitted)				
Crisis						
Lag 1	0.3141675**	3.72e-15	8.4e+13	0.000	0.3141675	0.3141675
Lag 2	0	(omitted)				
Lag 3	2.274447**	1.58e-14	1.4e+14	0.000	2.274447	2.274447
Lag 4	−1.533543**	1.48e-14	−1.0e+14	0.000	−1.533543	−1.533543
Constant	0.2869453	3.01e-15	9.5e+13	0.000	0.2869453	0.2869453

***Indicate a statistical significance level of 1%

Figure 1: Egypt log difference variables

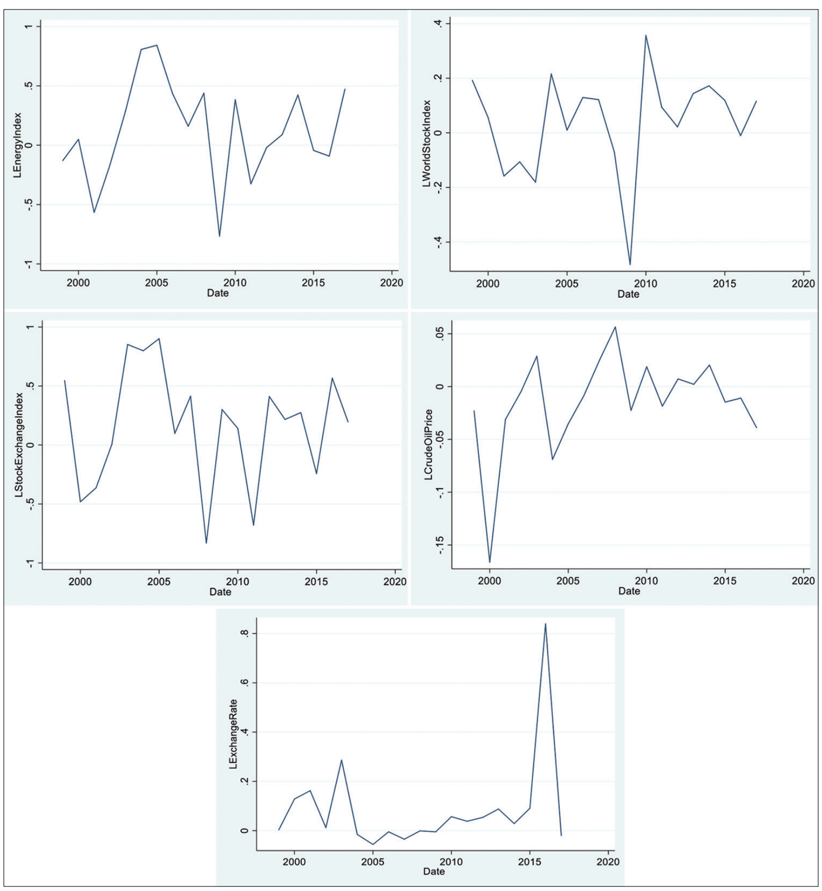

Table 11: Test of cointegration

Test	Test Statistics	P-value
Dickey-Fuller test for unit root	−4.892	0.0000

Lag 1 and Lag 2 of LCrudeOilPrice have coefficient values of zero, suggesting that these lagged values do not contribute significantly to predicting the LStockExchangeIndex.

Table 9 shows the results of a vector autoregression (VAR) model with the dependent variable being the logarithm of the exchange rate (*LExchangeRate*). The first lag of the Energy Index (*LEnergyIndex*) is statistically significant at the 1% level, with a coefficient of 0.9180595. This suggests that a one-unit increase in the first lag of the Energy Index is associated with a 0.9180595 unit increase in the logarithm of the exchange rate, all else being equal. The third and fourth lags of the Energy Index are also statistically significant, indicating that they have a negative impact on the exchange rate. The lagged variables for Crude Oil Price (*LCrudeOilPrice*), World Stock Index (*LWorldStockIndex*), and Stock Exchange Index (*LStockExchangeIndex*) do not have any statistically significant coefficients, as all their p-values are 0, indicating no relationship between these variables and the exchange rate. The lagged variables for the exchange rate itself have statistically significant coefficients. The first lag has a coefficient of 0.2640589, suggesting that the previous value of the exchange rate positively affects the current exchange rate. The second lag has a coefficient of 1.667149, indicating a stronger positive effect. The third and fourth lags are not statistically significant.

Based on Table 10, appears to be showing the results of a Vector autoregression (VAR) model, specifically with "Crisis" as the dependent variable. The coefficient values themselves indicate the direction and magnitude of the relationship between the dependent variable (*Crisis*) and the lagged variables. Positive coefficients suggest a positive relationship, while negative coefficients suggest a negative relationship. Some lagged variables have coefficients that are not statistically significant and are omitted in the table. This may indicate that these variables do not have a significant impact on the dependent variable.

To test for stability and reliability of the VAR model result we should test for cointegration, to test for cointegration the paper estimates multiple regression and save the residual of that regression, then test the Dickey-Fuller test for unit root for that residual.

According to the findings presented in Table 11, it can be concluded that the residual series exhibits stationarity. This suggests that there is indeed evidence of cointegration among all the variables considered in the analysis. Furthermore, we can confidently assert that a significant long-run relationship exists between these variables. Notably, the results obtained from the VAR model demonstrate a commendable level of reliability and stability, even when considering the long-term dynamics of the system. Hence, we can place substantial trust in the outcomes and implications derived from this model.

5. CONCLUSION

Conditions are different in emerging markets than in developed markets. Hence, the literature suggests that crude oil price is a key factor in explaining the stock market return (Wei et al. 2019; Alamgir and Amin, 2021), we find opposite results for the Egyptian market, neither multiple regression nor the VAR model can explain the issue in the Egyptian stock market, this sudden finding is due to the inefficiency in the Egyptian market. On the other hand, the VAR model is superior to the multiple regression in determining the relevant factors that derive the demand for the Egyptian crude oil price, these findings are compatible with Thorbecke (2019). In addition, the VAR model shows the effect of the global financial crisis on the Egyptian stock market. Moreover, VAR results are reliable and stable by the cointegration robustness test that shows a long-run relationship between variables and stationary residual for the model in the long run.

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