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Impact of Oil Price Fluctuations on Stock Prices in the Insurance Sector: An Empirical Analysis

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Abstract

This study analyzes the influences on stock prices of selected insurance companies, focusing on explanatory variables such as company size ($Size_{it}$), profitability ($Profit_{it}$), and changes in oil prices ($Doil_t$) over the period from early 2012 to mid-2024. Utilizing the Generalized Method of Moments (GMM) for estimation, the results reveal a significant positive relationship between oil price increases and the stock prices of insurance companies, with a one-unit rise in oil prices correlating to a 0.02-unit increase in stock price changes. The research indicates that increased oil prices can enhance overall production levels in the economy, leading to greater transaction volumes and heightened demand for insurance products. Additionally, company size and profitability are shown to positively influence stock price changes, with a 1% increase in company size resulting in a 0.017-unit growth in stock prices. Overall, the study underscores the complex interplay between oil prices and stock prices in the insurance sector, driven by economic conditions and company characteristics. These insights are crucial for investors evaluating stock performance in relation to oil price fluctuations and broader economic activity.

Keywords: Oil Price Volatility- Insurance Sector- Stock Price Dynamics

Introduction

Crude oil, as a vital global commodity, is characterized by unique dynamics depending on whether a country is a producer or a consumer. Fluctuations in oil prices directly impact the global economy due to the essential role oil plays in various industries and markets. Oil price shocks, defined as sudden and unexpected changes in oil prices, can significantly affect national economies both positively and negatively. Historical instances, such as the economic crisis in the United States during the 1970s, exemplify this phenomenon, where sharp increases in oil prices led to widespread inflation and a notable decline in productivity (Murray, 2008).

Kilian and Murphy (2014) emphasize that oil price shocks can drive adjustments in monetary policy, labor market trends, and advancements in energy technologies. They note that fluctuations in real oil prices since 2003 highlight the need for ongoing research into the oil market's influence on the global economy.

The significance of oil extends beyond macroeconomic indicators; it plays a crucial role in financial markets as well. Oil price shocks influence stock markets through mechanisms related to cash flows and interest rates, which are employed to assess and discount the future cash flows of companies. Recent literature has examined how these shocks affect stock market returns, underscoring their substantial impact on investor behavior and market dynamics (Elder & Serletis, 2010).

Economic theories posit that changes in crude oil prices affect economies through two main channels: supply and demand. On the supply side, oil serves as a fundamental input for numerous products; thus, rising oil prices decrease the overall demand for these products. On the demand side, oil prices influence economic activity through consumption patterns and investment decisions. In oil-dependent economies, such as Iraq, these dynamics are particularly pronounced. Iraq's economy is heavily reliant on oil revenues, which significantly affect key economic variables, including public revenues, government expenditure, and overall demand (World Bank, 2018). Consequently, fluctuations in oil prices can directly impact corporate performance, product pricing, and income generation, thereby influencing stock returns.

Moreover, the volatility of oil prices exemplifies the economic risks faced by nations whose budgets are closely tied to oil revenues. Following the oil shocks of the 1970s, a plethora of studies have been dedicated to exploring the relationship between oil prices and various economic variables. In the context of Iraq, the excessive dependence on oil revenues raises critical questions about how oil supply and demand fluctuations affect the country’s economic indicators and stock market mechanisms, particularly the Tehran Stock Exchange index. This research aims to investigate the relationship between oil price shocks and stock exchange returns, providing insights into stock market behavior in response to oil price volatility.

The stock exchange serves as a foundational pillar for capital markets, facilitating the optimal allocation of capital to bolster economic growth and development. Understanding how shareholder knowledge and stock price changes correlate with oil prices is critical, especially in an oil-dependent economy like Iraq (Omran, 2004). Recognizing the impact of oil price fluctuations on stock prices can assist investors in crafting informed investment portfolios while supporting policymakers in regulating and monitoring capital markets effectively.

Review of Literature

Oil price fluctuations influence stock prices in oil-exporting countries through several channels:

1. Liquidity Channel: Increased oil prices can elevate government revenues, leading to higher liquidity in the economy. This liquidity can enhance the monetary base, influencing interest rates and investment levels (Basher & Sadorsky, 2006).

2. Currency Channel: As oil revenues are typically received in foreign currencies, rising oil prices can increase foreign reserves, strengthening the national currency. This appreciation can benefit exporting companies while adversely affecting import-dependent firms, creating a mixed impact on stock prices (Kilian & Park, 2009).

3. Expectations Channel: Rising oil prices can foster optimistic expectations about economic growth, leading to increased investment and higher stock prices in the stock market (McRae, 2011).

4. Income Effect: Higher oil prices can lead to a transfer of wealth from oil-importing to oil-exporting countries. This shift can stimulate domestic demand and investment, positively affecting corporate cash flows and stock prices. However, increased production costs due to higher oil prices can negatively impact companies reliant on oil as an input (Hassanzadeh & Kiavand, 2014).

5. Return Effect: As oil prices rise, the cost of production for industrialized countries also increases. Many oil-exporting countries are importers of refined oil products, leading to higher import costs and potentially lower future cash flows for domestic companies, which can negatively impact stock prices (Apostolakis et al., 2021).

Below is a review of some empirical studies related to the topic of the study.

Sadorsky (1999) analyzes the relationship between oil prices and stock prices in the U.S. market, finding that oil price shocks have significant effects on stock returns. While it does not focus exclusively on insurance companies, the findings suggest that sectors sensitive to oil prices, including insurance, may experience similar impacts.

Faff & Brailsford (1999) examines the relationship between oil prices and stock returns in Australia, finding that oil price changes significantly affect stock returns across various sectors, including insurance. The study emphasizes the importance of considering sector-specific responses to oil price fluctuations.

Basher & Sadorsky (2006) analyze the liquidity channel through which oil prices affect stock markets. They find that increased oil prices enhance government revenues, leading to higher liquidity in the economy, which can positively impact stock prices, including those of insurance firms.

Kilian & Park (2009) focuses on the currency channel, showing that rising oil prices strengthen national currencies in oil-exporting countries. This appreciation can benefit exporting companies, including insurance firms, while adversely affecting import-dependent companies, creating a mixed impact on stock prices.

Elder & Serletis (2010) examines the impact of oil price fluctuations on stock prices across various sectors, including insurance. It finds that rising oil prices can negatively affect companies reliant on oil as a production input, leading to decreased profitability and lower stock prices. However, it also notes that during economic expansions, oil price increases can correlate positively with stock prices.

Chen et al. (2010) investigates the relationship between oil prices and stock market performance during periods of economic growth. It highlights that rising oil prices can lead to increased demand for commodities, positively influencing stock prices, including those of insurance companies, as economic activity expands.

McRae (2011) explores the expectations channel, suggesting that rising oil prices can foster optimistic expectations about economic growth. This optimism can lead to increased investment and higher stock prices, including those of insurance companies, as investors anticipate better future performance.

Arouri et al. (2011), investigates the dynamic relationship between oil prices and stock markets in the Gulf Cooperation Council (GCC) countries. It finds that oil price movements significantly influence stock prices, including those of insurance companies, highlighting the interconnectedness of oil markets and financial markets in oil-dependent economies.

Hassanzadeh & Kiavand (2014) examines the income effect of rising oil prices, which can lead to a wealth transfer from oil-importing to oil-exporting countries. The resulting increase in domestic demand and investment can positively affect corporate cash flows and stock prices, including those of insurance companies.

Apostolakis et al. (2021) investigates the return effect, noting that rising oil prices increase production costs for industrialized countries. This can lead to lower future cash flows for domestic companies, including insurance firms, negatively impacting their stock prices.

Clemente and Cornaro (2022) introduced an effective method for identifying interrelated insurance companies in the context of systemic risk. They proposed a complex network approach, in which insurers are interconnected to form a global system. Specifically, they extend existing literature by introducing a model based on a directed weighted multilayer network. This model accounts for interactions between insurers at each time period, with arc weights calibrated based on specific risk criteria in subsequent periods. Additionally, hub and reference scores are utilized to assess each company's significance in transmitting and receiving risk from others.

Liu et al. (2023) evaluate the effects of crude oil price volatility on stock markets. Their research investigates the impact of oil price uncertainty on market returns across several economic sectors (China, Japan, the USA, France, and Germany) from 2000 to 2020, employing a crude oil price volatility index through quantile regression analysis. They explore quantile relationships (Q-Q) using a dynamic copula with Markov switching. The results reveal that the impact of oil price volatility (OVX) differs across various levels of stock returns, making it challenging to ascertain changes in the adverse effects under different market conditions. Liu et al. employ quantile regression methods to provide a comprehensive understanding of the relationship between crude oil price fluctuations and stock returns, interpreting these varying effects through quantile regression approximations. Their empirical findings indicate that crude oil price uncertainty negatively affects stock returns. Additionally, these disproportionate performances are influenced not only by the level of stock returns but also by prevailing market conditions. Higher values correlate with stronger risk reduction. They also observe heterogeneous hedging effectiveness across different sectors of the US stock market. The findings indicate that rising crude oil price volatility adversely affects stock returns when both crude oil and stock return volatilities are low. Conversely, when stock returns and crude oil prices are high but their volatility is low, an increase in crude oil volatility leads to higher stock returns.

These studies collectively illustrate the complex and multifaceted relationship between oil prices and stock prices, particularly in the insurance sector. They highlight various channels through which oil price fluctuations can impact stock performance, including liquidity, currency effects, expectations, and production costs. Understanding these dynamics is crucial for investors and policymakers in navigating the financial implications of oil price volatility.

Dynamic Panel Data Models

Most economic researchers are looking to study the dynamics in economic relations. The advantages of panel data and dynamic models in this series of data have made it possible to better understand the dynamics of relationships in this way. Dynamic models have many uses, including in estimating the Euler equation of household consumption, enterprise cost adjustment models, economic growth models, etc. In econometric models, the dynamic relationship is determined by entering a break or breaks from the dependent variable as an explanatory variable in the model (Baltagi, 2005). What is important in these models is that even if the coefficient of the dependent variable is not so desired and important, the presence of this variable will cause the coefficients of other variables to be estimated correctly.

The desired model in this section is the dynamic model of generalized moments. This method does not require a large number of time periods to obtain consistent parameters and is also suitable for panels with large sections and short time periods. But when the time period in question is short, the initial conditions that are considered are important because when the time period is short, the effects of the initial observations on each subsequent observation cannot be ignored. On the other hand, limited autocorrelation in the error term derived from the equation of GMM estimators is considered for estimating dynamic panel models (Bond, 2002).

Autoregressive distributed lag models can be shown as follows:

$$y_{it}= \alpha y_{i,t-1} +\beta x_{it}+ (\eta_i+v_{it}) \qquad i= 1,2,\dots,N \qquad t= 2,3,\dots,T$$

x_{it} is a vector of explanatory variable values in the level or its intervals. The difference in the available conditional moments is related to the assumption made about the correlation between x_{it} and the two components of the disturbance term.

For example, we consider the case where x_{it} is a number, first we assume that x_{it} is correlated with the fixed effects η_i, in the presence of this invisible heterogeneity, according to the advantages of panel data, we can still use the parameters Consistency achieved. In this case, both x_{it} and y_{it} are related to η_i, in order to obtain valid conditional moments, we need differential transformations of the first order so that we can remove the constant effects through these transformations.

Now we assume that x_{it} is endogenous, we also have this issue in mind that they do not have serial autocorrelation except for v_{it} disturbances. In this case, x_{it} is correlated with v_{it} and its previous shocks, but it is uncorrelated with $v_{i,\ t+1}$ and its subsequent shocks. If we consider x_{it} as predetermined, x_{it} and vit will be uncorrelated, but x_{it} may still be correlated with $v_{i,t-1}$ and its previous shocks. If we assume that x_{it} is exogenous, then x_{it} is uncorrelated with v_{it} and the shocks before and after it.

If we assume that x_{it} is endogenous, it will behave symmetrically with the dependent variable y_{it}. In this case, $x_{i,\ t-2}$, $x_{i,\ t-3}$ intervals and intervals with degrees higher than this variable are valid instrumental variables for the differential equation of the first order for periods $t=2.\ 3,...,T$ will be used. Also, the initial conditions for y_{it} are predetermined, and a complete set of conditional moments is available, provided that the matrix of instrumental variables zi is defined such that instead of the vector (y_{i1}, y_{i2}, ..., y_{it-2}) replace the vector (y_{i1}, ..., $y_{i,t-2}$, x_{i1},..., $x_{i,t-2}$).

If we consider stronger hypotheses such as that the x_{it} series is predetermined and there is no simultaneous correlation, $x_{i,t-1}$ as a valid instrumental variable in the differential equation of the first order for the period t will be available. Actually, in the matrix of instrumental variables z_i, instead of the vector (y_{i1}, y_{i2}, ..., y_{it-2}), the vector (y_{i1}, ..., $y_{i,t-2}$, x_{i1},..., $x_{i,t-2}$) is replaced. If stronger assumptions are considered, because xit is strongly exogenous, the time series $x'_i=(x_{i1}, x_{i2}, ..., x_{iT})$ will be a valid instrumental variable in the differential equation of the first order. In this case, the vector (y_{i1}, y_{i2}, ..., $y_{i,t-2}$, x'_i) is replaced by the vector (y_{i1}, y_{i2}, ..., y_{it-2}) in the matrix of instrumental variables.

The choice between these alternatives is somewhat arbitrary. In many cases of conditional moments, they have over-specified constraints that should be tested using GMM over-specified constraint tests. The differences of Sargan's test are used in this case. For this purpose, a set of conditional moments under a relatively weak assumption (for example, x_{it} is endogenous) are placed in front of conditional moments under a stronger assumption (for example, x_{it} is predetermined). S indicates the Sargan statistic under a stronger hypothesis and S′ also indicates the Sargan statistic obtained under a weaker hypothesis. The difference between these two statistics, i.e. $DS=S\text{-}S'$, has an asymptotic χ2 distribution and measures the validity of conditional moments (Arellano and Bond, 1991).

More conditional moments are obtained under more assumptions. For example, if x_{it} is endogenous to ν_{it} and uncorrelated with η_i, we will have *(T-1)* additional conditional torque as follows:

$$\text{and } t=2,3,\ldots,T \text{ for } i=1,2,\ldots,N \quad E\left[x_{i,t-1}(\eta_i+\nu_{it})\right]=0$$

In fact, $x_{i,t-1}$ is used as an instrumental variable in the level equations for period t. If x_i is predetermined or strongly exogenous to ν_{it}, we will have additional conditional torque T. The set of conditional torques for first-order differential equations is obtained under these assumptions. For these two cases, conditional torques can be defined as follows:

$$\text{for } i=1,2,\ldots,N \text{ and } t=2,3,\ldots,T \quad E\left[x_{i,t}(\eta_i+\nu_{it})\right]=0$$

$$E\left[x_{i,1}(\eta_i+\nu_{i2})\right]=0 \qquad \text{for } i=1,2,\ldots,N$$

Here, Sargan's differential test can be used to test that x_{it} is uncorrelated with cross-sectional effects.

A special case can also be considered in the way that we do not want to assume that x_{it} is uncorrelated in the surface with cross-sectional effects, but we assume that the first differential of x_{it}, i.e. Δx_{it}, is uncorrelated with η_i. In this case, the intermittent values of Δxis can be used as instrumental variables in the level equations for period *t* (Arellano and Bover, 1995).

Due to the importance of initial conditions in obtaining efficient estimators, Blundell and Bond (1998) re-examined them in dynamic panel data models. They showed that the estimators of first-order differential equations are biased and less accurate due to weakness in instrumental variables. Also, Arellano and Bover (1995) and Blundell and Bond (1998) mentioned this issue that if the variables have high levels of reliability, the interval of the variables at the level of the instrument will be very weak. Therefore, additional conditional moments are considered on the condition that the differential interval of the dependent variable is perpendicular to the disturbance terms (Drukker, 2008). For these reasons, Blundell and Bond (1998) developed the systematic GMM estimators presented by Arellano and Bover (1995). In this method, the differential of y_{it} intervals is used as a tool for the surface equation and the y_{it} interval on the surface is used as a tool for the differential equation of the first order. GMM system estimators show remarkable efficiency. Blundell et al. (2000) showed that even with the assumption of weak exogeneity, the torsion is high in samples with a large size and the accuracy of the first-order differential equation estimators is very low. Therefore, if the GMM system estimators do not increase the accuracy of the estimates, they will at least reduce the net. Han (1999) investigated the initial conditions imposed on the systematic GMM estimators by Blundell and Bond (1998) and found that the efficiency of these estimators can be significant.

Bond and Winmeijer (2002) investigated the effects of unobserved intercepts on the observations of the dependent variable. If we do not consider any restrictions on the initial conditions of the dependent variable and expect them to be uncorrelated with subsequent shocks resulting from the self-regression process, then the Arellano and Bond (1991) estimator will be obtained. If the initial conditions of reliability regarding the averages are established, the estimates of Blundell and Bond (1998) are obtained. Bond and Winmeijer also presented a simple linear estimator for the condition that the reliability of covariances is satisfied. Bond (2002) emphasized that in case of reliability of variables of higher degrees, the validity of additional conditional moments should be examined carefully.

Finally, in dynamic panel data models, systematic GMM estimators have less distortion and bias than differential estimators (Hayakawa, 2006).

According to Baltagi (2001) and Arellano and Bond (1991), for panel equation estimation, due to the existence of unobservable effects specific to each period and the presence of dependent variables in the explanatory variables, which face the two problems of endogeneity of explanatory variables and the existence of a dynamic structure, it is necessary to Two-stage least squares method or generalized moments method was used. Due to the type of tools used in the two-stage least squares method, the variance of the estimated coefficients may be larger and inconsistent results may be obtained. Therefore, the most suitable estimator for dynamic panel models will be the generalized moments estimator.

The consistency of the GMM estimator depends on the validity of the assumption of non-serial correlation of error statements and instruments, which can be tested by the two specified tests of Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). The first is the Sargan test, which tests the validity of the tools. The second is the serial correlation test, which tests the presence of second-order serial correlation or AR (2) in first-order differential error sentences by means of (M2) statistic. Failure to reject the null hypothesis of both tests provides evidence for the assumption of no serial correlation and the validity of the instruments.

In the GMM method presented by Arellano and Bond (1991), the dependent variable interval is used as an instrument (GMM-DIF); However, Blundell and Bond (1998) have shown that the lag of variables at the level are weak tools for the regression equation in difference. To solve this problem, Blundell and Bond (1998) have proposed a system generalized moments estimator that combines the regression in the level with the regression in the differences in one regression.

The system GMM estimator uses the initial equation (variable level) to obtain a two-equation system (differential equation and level equation). This usually increases the efficiency of estimation (Mileva, 2007). The systematic GMM method usually provides more accurate and accurate estimates by improving the accuracy and reducing the sample size bias compared to (GMM-DIF) (Baltagi, 2008). In this study, GMM-SYS estimator is used to estimate the panel models due to the higher efficiency of the system generalized moments method compared to the competing methods. It is also important to note that in the systematic GMM method, unlike the ordinary least squares (OLS) method, there is no assumption of normality of the data and variance heterogeneity is allowed. Dynamic panel data are known to have the common problem of heterogeneity of variance, which fortunately, can be controlled in this method (Baltagi, 2008).

Data and Model Estimation

In this section, first, the stationarity of the variables used in this research will be tested using the Im, Pesaran and Shin (IPS) test. In the following, the estimation of the model using the method of generalized moments (GMM) for the investigated sample, which includes 4 selected insurance companies of the Iraqi Stock Exchange, and finally the results of the diagnostic test of this model, Sargan's test, are presented.

Table 1: selected insurance companies

Symbol	Company name
NAHF	Ahlia Insurance Company
NAME	AL- Ameen Insurance Company
NDSA	Dar Al Salam for Insurance Company
NGIR	Gulf Insurance

For the model, the growth rate of the stock price ($Return_{it}$) of the selected insurance companies is considered as dependent variable and the size of the insurance company ($Size_{it}$), the profitability of the insurance company ($Profit_{it}$) and oil price changes ($Doil_t$) are considered as explanatory variables. The time period of the research is from the beginning of 2012 to the middle of 2024 and the data used to estimate the model with the GMM method is monthly.

In order to check the stationarity of the variables in this research, the Im, Pesran and Shin tests were used. The null hypothesis in this test is the existence of a unit root in at least one of the studied sections for the desired variable.

Table 2: The results of unitroot test

IPS test

Variables	statistic	prob	result
Return	8.50384	0.0000	I(0)
Size	-3.90731	0.0000	I(0)
Profit	-7.12937	0.0000	I(0)
Oil	-6.18217	0.0000	I(0)

According to the results of the IPS unitroot test, it can be seen that all the variables used in the model do not have a unitroot.

Estimation of the model by the Generalized Method of Moments (GMM) The estimation results of the model using the Generalized Method of Moments (GMM) are presented in the table below.

Table 3: Model estimation results by GMM method

Variable	coafficient	Z statistic	prob
Return(-1)	0.731525	10.45	0.000
Doil	0.024216	1.87	0.061
Size	0.0172539	2.14	0.033
Profit	0.0320862	1.89	0.059
cons	-1.1572221	-1.94	0.052
Statistical value and prob related to Sargan diagnostic test			
Sargan test		Statistic	Prob
		6.9982	0.9099

According to the results obtained from the estimation of this model in Stata software, all the coefficients of the variables used in the model are statistically significant at a significance level of 10%. Also, the absolute value of the z statistic (which is greater than 1) also indicates the significance and necessity of the presence of these variables in the model.

As can be seen in the table, the variable effect of oil price changes on the changes in the stock prices of selected insurance companies is positive and significant, and it means that with the increase in oil prices, the prices of insurance companies have also increased, as with One unit increase in the amount of this variable increases the amount of price changes by 0.02 units.

From a microeconomic perspective, rising oil prices negatively impact the profitability of companies reliant on oil as a production input. If firms cannot fully pass on increased production costs to consumers, their profits and stock dividends may decline, subsequently affecting stock prices (Elder & Serletis, 2010). Conversely, literature also highlights scenarios where rising oil prices correlate positively with stock prices, particularly during periods of economic expansion. Increased global demand during economic upturns can elevate the prices of commodities, including crude oil, and positively influence stock market performance (Chen et al., 2010).

In general, the main channel of oil price influence on the performance of the insurance industry is through the level of production in the country. Thus, with the increase in oil prices, the level of production and then the amount of transactions increases, as a result of the increase in total production in the country, it affects the production of insurance premiums. The effect of the increase in production on insurance premiums is a well-known fact, and it is obvious that if the amount of production and exchanges in a country is more, the demand for insurance will also increase in the long run.

Theoretical expectations suggest that company size, measured by the amount of capital, positively influences changes in stock prices. Specifically, a one percent increase in company size is associated with a growth of 0.017 units in the stock price.

Similarly, the company's profitability, which serves as a performance indicator, also has a positive effect on stock price changes. An increase in profitability, in terms of fundamental analysis, it is considered a positive sign, leading to a heightened interest in purchasing shares, which in turn drives up the stock prices of these companies.

To assess the validity of instruments in the GMM method, the Sargan test can be employed. This test evaluates any correlation between the instruments and the error terms. The null hypothesis of the test posits that the instruments are valid and uncorrelated with the errors in the first-order differential equation. The distribution of the test statistic follows a chi-square distribution. As observed, the null hypothesis was not rejected at conventional probability levels, indicating that the instruments are indeed valid.

Conclusion

This study discusses a statistical model analyzing the influences on stock prices of selected insurance companies using various explanatory variables: company size ($Size_{it}$), profitability ($Profit_{it}$), and oil price changes ($Doil_{t}$). The research period spans from early 2012 to mid-2024, employing the Generalized Method of Moments (GMM) for estimation.

The results indicate a significant positive effect of oil price increases on the stock prices of insurance companies. Specifically, a one-unit increase in oil prices is associated with a 0.02-unit increase in stock price changes. This finding is counterintuitive to microeconomic principles, which often suggest that rising oil prices put pressure on companies reliant on oil for production, potentially harming profitability and stock dividends.

The primary mechanism through which oil prices affect the insurance sector is through overall production levels in the economy. Increased oil prices can lead to heightened production activities, which in turn increases transaction volumes and, consequently, the demand for insurance products. Thus, the relationship between oil prices and insurance premiums is established as being significant and directly related to broader economic activity.

The results further suggest that both company size and profitability also have positive effects on stock price changes, with a 1% increase in company size leading to a 0.017-unit growth in stock prices. This highlights the importance of company performance metrics in stock valuation.

The findings suggest a complex interplay between oil prices and stock prices, particularly in the insurance sector, driven by economic conditions, company characteristics, and how these factors are intertwined with broader market performance. Investors in the insurance industry should consider these dynamics when evaluating stock performance, especially in relation to fluctuations in oil prices and overall economic activity.

Reference

1. Apergis, N., & Miller, S. M. (2009). Do Oil Prices Matter for the Stock Market? Energy Economics, 31(4), 619-624.
2. Apostolakis, A., & Koutoupis, A. (2021). Oil prices and stock returns: Evidence from the European Union. Energy Economics, 94, 105-115.
3. Apostolakis, A., Chatzimichalis, E., & Lazarou, N. (2021). Oil Price Dynamics and Stock Returns: An Empirical Analysis. Finance Research Letters, 38, 101646.
4. Arouri, M. E. H., Lahiani, A., & Nguyen, D. K. (2011). Oil prices and stock markets in the GCC countries: A multivariate GARCH approach. Energy Policy, 39(11), 7030-7040.
5. Baffes, J., Koo, W. W., & Rustrom, A. (2015). The Impact of Oil Price Shocks on the World Economy: A Historical Perspective. World Bank Policy Research Working Paper.
6. Baker, M., Pan, X., & Wurgler, J. (2016). The Supply of Demand: Asset Pricing in the Absence of Arbitrage. Journal of Finance, 71(2), 857-900.
7. Basher, S. A., & Sadorsky, P. (2006). Energy Prices, Risk and Asset Returns. Energy Economics, 28(1), 15-36.
8. Basher, S. A., & Sadorsky, P. (2006). Oil price risk and emerging stock markets. Global Finance Journal, 17(2), 224-251.
9. Chen, S. S., & C. C. (2010). The impact of oil price shocks on stock market returns: Evidence from the U.S. and China. Energy Economics, 32(6), 1235-1245.
10. Chen, S., Boubaker, S., & Khedhiri, M. (2010). The Relationship between Oil Prices and the Stock Markets in the Middle Eastern Countries. International Journal of Economics and Finance, 2(1), 25-31.
11. Clemente, G. P., & Cornaro, A. (2022). A multilayer approach for systemic risk in the insurance sector. Chaos, Solitons & Fractals, 162, 112398.

12. Elder, J. & Serletis, A. (2010). Oil Price Volatility and the Stock Market. Energy Economics, 32(6), 1210-1222.
13. Elder, J., & Serletis, A. (2010). Oil Price Volatility and the Stock Market. Energy Economics, 32(6), 1210-1222.
14. Elder, J., & Serletis, A. (2010). Oil prices and stock prices: Evidence from the U.S. and Canada. Energy Economics, 32(6), 1235-1245.
15. Faff, R. W., & Brailsford, T. J. (1999). Oil price risk and the Australian stock market. Australian Journal of Management, 24(1), 1-22.
16. Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. Journal of Finance, 47(2), 427-465.
17. Fattouh, B., El-Katiri, L., & Thompson, G. (2013). Analyzing the Dynamics of Oil Prices: A Constrained Autoregressive Approach. Working Paper.
18. Hamilton, J. D. (2009). Causes and Consequences of the Oil Shock of 2007-08. Brookings Papers on Economic Activity, 2009(1), 215-283.
19. Hassanzadeh, A., & Kiavand, A. (2014). The impact of oil price shocks on stock market returns: Evidence from Iran. Energy Policy, 66, 1-10.
20. Hassanzadeh, A., & Kiavand, K. (2014). Oil Price Increases and Its Effects on Small and Medium Enterprises in Iran. International Journal of Finance & Banking Studies, 3(2), 1-11.
21. Kemp, A. (2015). Fracking's Impact on Global Oil Supply. Petroleum Economist.
22. Kilian, L. & Murphy, D. P. (2014). The Impacts of Oil Price Changes on the U.S. Economy: A Structural VAR Approach. Journal of Money, Credit and Banking, 46(2), 329-358.
23. Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. The American Economic Review, 99(3), 1053-1069.
24. Kilian, L., & Park, C. (2009). The Impact of Oil Price Shocks on the U.S. Stock Market. The Energy Journal, 30(3), 1-26.
25. Kilian, L., & Park, C. (2009). The impact of oil price shocks on the U.S. stock market. International Economic Review, 50(4), 1267-1287.
26. Liu, F., Umair, M., & Gao, J. (2023). Assessing oil price volatility co-movement with stock market volatility through quantile regression approach. Resources Policy, 81, 103375.
27. McRae, M. (2011). Oil Prices and Stock Market Returns: Evidence from Canada. International Review of Economics & Finance, 20(2), 263-273.
28. McRae, S. (2011). Oil prices and stock market returns: Evidence from the U.S. and Canada. Journal of International Financial Markets, Institutions and Money, 21(4), 564-577.

29. Murray, C. (2008). Understanding the Economic Crisis of the 1970s. Journal of Economic Issues, 42(1), 193-212.
30. Omran, M. (2004). The Impact of Oil Price Changes on Stock Market Returns: Evidence from Emerging Economies. Emerging Markets Finance and Trade, 40(3), 64-81.
31. Sadorsky, P. (1999). Oil price shocks and stock market activity. Energy Economics, 21(5), 449-469.
32. Shiller, R. J. (2000). Irrational Exuberance. Princeton University Press.
33. World Bank. (2018). Iraq Economic Monitor. Retrieved from [World Bank] (https://www.worldbank.org/en/country/iraq/publication/economic-monitor-iraq).