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Oil Price Implications for the Petroleum and Pharmaceutical Industry: the Quantile Regression Approach

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Abstract:
In the study, quantile regression (QR) is employed as the primary research tool, with ordinary least squares (OLS) regression used for comparison purposes. The motivation for this research stems from conflicting findings in existing literature regarding the spillover effects of Brent crude oil prices for the pharmaceutical industry. Findings from the QR analysis indicate that more substantial spillover effects occur in the tail quantiles, specifically during periods of economic crisis and prosperity. Recommendations for future research should focus on gaining a deeper understanding of the mechanisms underlying the differential responses of oil and pharmaceutical companies to oil price fluctuations, as well as identifying additional factors that may moderate these effects. In light of the study's findings, it is recommended to consider different regulatory approaches that could help reduce the sensitivity of oil companies to oil price oscillations. Additionally, support for business diversification strategies is advised to mitigate potential economic risks for both industries.

Keywords: oil shock spillover effect, oil and pharmaceutical industries, quantile regression

JEL Classification: E00, D00, G01

1. Introduction

The impact of crude oil prices on various financial assets is one of the most widely researched topics in the energy literature. Looking back on the past ten years, it is evident that there were significant ups and downs in crude oil price movements. Various factors, such as fluctuations in supply and demand, financial crises, wars and international political conflicts, affect these changes. Therefore, there is a significant tendency towards research that deals with the aforementioned factors of influence (Klein, 2018). Consequently, the escalating fluctuations in oil prices over the past years contributed to severe concerns among the key consumers, large corporations and policymakers due to the role that crude oil plays in the global economy (Wang and Wu, 2012; Baumeister and Peersman, 2013).

According to Caro et al. (2020), the COVID-19 pandemic inflicted a significant damage on the global economy. The major impact on social stability, politics, and countries' economies is noticeable, which has resulted in the slowdown of the workforce and the cancellation of services that are not needed. Valensisi (2020) dealt with the analysis of poverty, which increased because the influence of the pandemic, with the possibility of playing back the whole progress in poverty reduction made in the last decade. Besides, the additional shock on the oil market occurred because of the conflict between Russia and Ukraine (Akhtaruzzaman et al., 2022).

Despite numerous studies attempting to determine the impact of oil price fluctuations on stock markets, unanimous consensus or conclusion have not been reached. Research findings from various authors suggest that crude oil trade is widespread, and any oscillations in oil prices significantly affect movements in financial markets, especially stock markets (Hashmi et al., 2021; Jiang et al., 2020). Additionally, Ziadat et al. (2024) attempted to identify and confirm the positive impact of oil on financial markets attributed to the process of oil financialization. This occurs when investors consider oil just as a separate financial asset class rather than having a direct interest in the underlying commodity. On the other hand, research conducted by Zhu et al. (2024) suggests a negative relationship between oil prices and the stock market, which could provide significant insights for shaping and implementing economic policies and risk management practices. Chancharat and Sinlapates (2023) suggest a positive relationship between the crude oil market and the stock market while indicating low volatility of crude oil spillovers. Jin et al. (2023) assess volatility transmission from one market to another through complex channels, while the financial industry expresses significant concern over the substantial impact of risk spillovers from oil markets to stock markets, providing a rationale for investigating the potential asymmetric impact of oil price fluctuations on stock prices. The research goal of this study is to determine how Brent oil prices affect the stock prices of companies in the oil production and pharmaceutical sectors in the United States. Specifically, this research focuses on identifying differences in the sensitivity of these sectors to oil price changes and understanding the mechanisms through which these impacts are transmitted to stock markets.

According to the above-written, the main goal of this paper is to investigate the impact of Brent oil on the stock prices of companies from two very different sectors – oil production and pharmacy in the US. These two industries are the opposites when it comes to dependence on the price of oil, and the paper intends to examine how the price of oil affects companies that are highly oil-dependent and those that are not. The pharmaceutical industry is indirectly affected by changes in oil prices via raw material costs, transportation costs, packaging materials, and energy costs. Numerous papers found conflicting findings related to the pharmaceutical industry and oil. Thus, further investigation is needed, and this is the motive for this research. For instance, Alsalman et al. (2023) indicated that the oil price movements strongly affect the profits or losses of various companies, among which are the companies from the pharmaceutical industry. Sarwar et al. (2019) also confirmed a connection between the adverse effects of oil spills on the shares of companies, among which is the pharmaceutical industry. On the other hand, Chen et al. (2017) stated that there are insignificant estimates for predictors related to oil and that the pharmaceutical industry is not necessarily related to oil.

Conversely, top oil companies such as Chevron, Conoco Phillips and Exxon Mobil greatly influence global oil production. Considering their activities in different parts of the world, it is inevitable that their actions are subject to certain economic and political developments in the world market. If the movement of their shares is analysed, it can be seen how economic fluctuations, geopolitical events, or energy policies affect this market. All oil companies are very susceptible to oil price changes. Therefore, it is reasonable to assume that oil prices significantly affect the stock prices of oil companies more than those of pharmaceutical companies. In order to test this hypothesis, five companies from the oil and pharmaceutical sectors are selected.

Figure 1: Oil price dynamics (2017–2022)

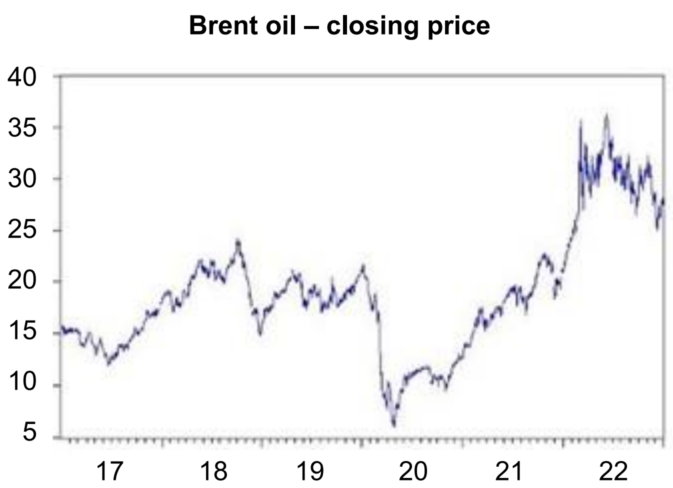


Figure 1 shows the movement of the price of Brent oil in the period from 2017 to 2022. As can be seen, a significant drop in oil prices happened during the pandemic, which confirms the conclusions reached by Shariff et al. (2020). In other words, immediately after the start of the pandemic, there was a significant drop in the price of oil by 30%. This relatively short period is selected because recent years are filled with extreme oil price movements, mainly due to the pandemic and the war in Ukraine.

The research is primarily focused on American companies. Several reasons justify this approach. First, the American market was the primary source of spillover effects to other markets. Second, COVID-19 spread in the United States following the crisis in China, Italy, and Korea, and it can be seen that economic policymakers in America possessed important information regarding the challenges brought by COVID-19 based on the experience of the mentioned countries. Finally, the US financial markets were among the worst affected by the COVID-19 crisis.

The primary research methodology used in this paper is the conditional quantile regression (QR) of Koenker and Bassett (1978), while the ordinary least square approach serves the purpose of comparison. The sample covers the COVID-19 pandemic, which has devastated national economies and corporate businesses. This means that analysed corporate time series are probably prone to outliers and extreme values. Classical QR is robust to outliers because it can capture skewed distribution and tail behaviour and deals with non-normality. Unlike other QR methods, such as robust QR or Bayesian QR, the classical QR of Koenker and Bassett (1978) is easy to implement and estimate, which is the main reason for choosing this method. Compared to the simple OLS regression, QR can provide distributional information, which means that it estimates the spillover effect under different market conditions, while OLS does not have this capability. In other words, QR provides insights into the entire conditional distribution of the dependent variable, which is particularly useful when the distribution is not symmetric or when there is heteroscedasticity.

To the best of our knowledge, none of the papers dealing with this topic has conducted research in this way. Therefore, this paper contributes to the existing literature in several ways. First, the research provides a deeper insight into the effects that oil shocks have on large companies from different industrial sectors – oil and little-studied pharmaceuticals. Furthermore, estimated quantile parameters provide the possibility of determining the dissimilar influence of oil shocks on companies' share prices when there are different economic conditions. Also, the research deals with the effect of increased oil price fluctuations during the COVID-19 pandemic, which is a unique opportunity to measure the extreme oil influence on companies' stock prices. These findings can be helpful for investors, policymakers, and company managers to adequately formulate their decisions in risk management strategy.

The paper's theoretical contribution lies in applying classical quantile regression of Koenker and Bassett (1978), enabling analysis of shock effects on stock prices under various economic conditions. This methodology is resilient to extreme values and distribution irregularities, crucial for time series susceptible to such fluctuations, such as oil prices during the COVID-19 pandemic. The practical contribution involves a deeper understanding of the impact of oil shocks on large companies across different industrial sectors, which are oil and pharmaceuticals. Estimating quantile parameters facilitates distinguishing the effects of these shocks on stock prices in different economic environments, which is essential for investment decision-makers, policymakers, and managers in formulating risk management strategies. Furthermore, this paper provides insight into the extreme impacts of oil price fluctuations during the COVID-19 pandemic on the U.S. market, serving as a basis for improved risk management and informed decision-making in turbulent economic times.

This paper is divided into multiple sections. An outline of the current research in this field follows the introduction. The research methodology is explained in section 3. The empirical data is presented in section 4. Research results are presented in the section 5.

2. The Review of Literature

This section provides a review of literature that researched connections between oil price and stocks, as well as papers that examined the impact of COVID-19 on the oil and stock markets.

Many studies have investigated the relationship between oil price and stock markets. Some studies suggest that stock market movements are influenced by oil price changes (Sadorsky, 2012; Jones and Kaul, 1996). These studies indicate a negative impact on stock market returns in response to a positive oil price shock. They provide evidence of the negative influence on stock market returns due to positive oil price shocks, although they use different samples and consider different countries. For example, Chang (2023) provides evidence of a positive impact on specific quantiles and a negative impact on others in the UK. Soriano and Torro (2022) studied COVID-19 and its implications on oil price behavior. They observed a negative relationship between the oil price market and the stock market. They argued that financial, security, and public health crises were evident in the previous decade, contributing to the decline in oil prices. In their study, Gao et al. (2023) stated that oil as a raw commodity is very important and affects various segments of the global economy and politics, with significant implications of oil prices effect on stock prices.

Also, Haliloglu et al. (2021) confirmed that oil is a crucial factor affecting the global economy. They conclude that crude oil is used by industrial sectors such as transportation and manufacturing and also accounts for a considerable portion of the world's energy consumption. Their research concludes that turbulence in the oil market greatly impacts the costs in sectors that are more energy-dependent on oil. Atukeren et al. (2021) suggested that fluctuations in oil prices affect world economic activity in various ways. When there is an increase in the price of oil, it is conditioned by moments of economic slowdown, as well as very pronounced levels of inflation. The price of oil can also be used as the leading indicator for predicting the trends in business activity and financial market.

In studies conducted by Malik and Ewing (2009), Aurori et al. (2011), and Conrad et al. (2014), the relationship between stock markets and crude oil markets was analyzed using the multivariate generalized autoregressive conditional heteroskedasticity model. These studies investigated the spillover effects and volatility transmission between stock and oil markets. Aurori (2011) states that there is a bidirectional spillover effect between the oil market and the US stock market. These works can be categorized as studies examining the dynamic correlation between stock and oil markets.

Furthermore, certain studies can be put into a specific category, namely those that use models to determine the interdependence between stock and oil markets. In their research, they employ wavelet analysis. For instance, Aloui et al. (2013) indicate a positive dependence between European countries' oil and stock markets. Aloui and Aïssa (2016) find that the relationship between stocks and oil prices oscillates and is not uniform, based on the crisis that occurred in 2008.

Benedetto et al. (2020) investigated the flow of information and its direction between the oil volatility index and the variance point of returns on the WTI and Brent markets. According to the results of Cao and Xie (2023), there is a pronounced dependence between the crude oil and crude energy futures markets, and the asymmetry occurs in the quantile. Thus, both positive and negative returns realized through crude oil futures have a time-varying asymmetry through the impact on clean energy. Their research analysed the relationship between crude oil and political stability. The period is from 2000 to 2020, covering 100 countries. They distinguished between different dependences on oil, both economic and energy-related. Using simultaneous quantile regression, they confirmed that dependence on oil can be dangerous for countries' internal stability. Ashraf (2020) discovered a direct correlation between the drop in stock prices and the number of confirmed deaths due to COVID-19. Baker et al. (2020a, 2020b) reveal that COVID-19 seriously impacts stock market volatility, surpassing the impact of all other diseases and pandemics in the previous period. Conducted research clearly shows that the global health crisis or the COVID-19 pandemic has a negative impact on the stock and energy markets. The COVID-19 pandemic has increased the degree of interdependence between oil and equity markets (Hung et al., 2021, Ali et al., 2022, Mensi et al., 2022). Previous studies have recognized significant correlation between the oil and stock markets during periods of financial, geopolitical and energy crises (Al-Fayoumi et al., 2023).

3. Research Methodology

Two methods are used in the paper: QR as the primary research tool and OLS regression as a complementary model. The OLS method estimates the conditional mean of the dependent variable based on the specified independent variables. The OLS technique is the most commonly used approach for parameter estimation. However, the efficiency of OLS decreases noticeably when applied to extreme values in the distributions or the context of detailed analysis. The parameters of the OLS model are derived by minimizing the objective loss function, which is the root mean square error. Econometrically speaking, the OLS estimates are considered efficient only when the error terms exhibit neither autocorrelation nor heteroscedasticity.

Given the shortcomings of the OLS method, the quantile regression method is applied as it overcomes the deficiencies of OLS. The concept of quantile regression is based on conditional quantile functions. Quantile regression is a statistical method used to estimate a dependent variable's conditional median or conditional quartile, given a set of independent factors. In the OLS context, the regression coefficients of the independent variables represent the magnitude of the effects resulting from a one-unit increase in the corresponding predictor variables. Similarly, the coefficients obtained from quantile regression represent the changes in a given quantile when the predictor variables experience a one-unit change. Quantiles and percentiles divide data samples into distinct categories (Maiti, 2021). The OLS model focuses on the conditional mean of the dependent variable. In contrast, applying the quantile regression model presents a more complete picture of the variability of the dependent variable in specific quantiles. When the disturbance moment is not normally distributed, applying quantile estimators permits a higher degree of efficiency than the OLS estimator. Referring to Chevapatrakul and Paez-Farrell (2014), if y is linearly dependent on x, then τ^{th} conditional quantile function of y is given as follows:

$$Q_y(\tau|x) = inf\{b|F_y(b|x) \geq \tau\} = \sum_k \beta_k(\tau)x_k = x'\beta(\tau), \tag{1}$$

where b is the element of the conditional distribution function of y. $F_y(b|x)$ denotes the conditional distribution function of y given x. Parameter $\beta(\tau)$ for $\tau \in (0.1)$ indicates the dependence relationship between vector x and the τ^{th} conditional quantile of y. x' is $n \times 1$ vector, containing constant and independent variables.

4. The Set of Data

This paper uses the daily closing prices of Brent oil and ten closing stock prices of the US companies from two distinct economic sectors (oil production and pharmaceuticals). The following oil companies were selected: Chevron Corporation, ConocoPhillips, ExxonMobil Corporation, Occidental Petroleum Corporation, and Phillips 66. On the other hand, selected farmaceutical companies are Aboot Laboratories, Amgen Inc., Bristol Myers Squibb Company, Gilead Sciences Inc. and Regeneron Pharmaceuticals. All selected companies are listed on the NYSE or NASDAQ stock exchanges. All daily data are transformed into logarithmic values by applying the subsequent formula:

$$r_{it} = 100\,x\ln(p_{it} / p_{it-1}) \tag{2}$$

In other words, every variable is modelled in QR as a growth rate. All time series of the selected companies are synchronized with Brent oil, making ten pairs. The study covers the period from January 2017 to December 2023, while data is recovered from the stooq.com website.

Table 1 shows descriptive statistics of the time series. Chevron Corporation shows the highest degree of riskiness and dispersion from the mean value. Also, the skewness value indicates that the distribution's tail is mainly extended to the left, i.e., negative asymmetry is present in most observed companies. A high value of kurtosis indicates the existence of extreme shocks. The Jarque-Bera test, calculated as in equation (3), suggests the non-normality of the observed time series. In other words, all the time series of the companies display high deviation from normality, primarily due to extreme values and outliers. This empirical characteristic of the time series justifies the usage of QR.

Table 1: Descriptive statistics

	Mean	St.dev.	Skew.	Kurt.	JB	DF-GLS
Panel A: Oil companies						
Chevron Corporation	−0.245	98.080	−0.087	9.460	2626.5	−19.265
Conocophilips	−0.038	37.080	−0.016	7.239	1068.8	−21.612
ExxonMobil Corporation	0.012	0.841	−0.176	8.979	2553.2	−4.870
Occidental Petroleum Corporation	0.001	1.670	−4.129	95.153	538242.0	−7.873
Phillips 66	−0.051	41.719	0.002	5.748	454.4	−24.354
Panel B: Pharmaceutical companies						
Aboot Laboratories	0.032	0.688	−0.238	9.511	2680.1	−6.908
Amgen inc	0.021	0.672	0.218	9.400	2588.1	−3.126
Bristol Myers Squibb Company	0.022	1.512	−1.071	11.928	5300.7	−40.229
Gilead Sciences inc	0.010	0.708	0.340	9.154	2411.0	−1.039
Regeneron Pharmaceuticals	0.021	0.859	0.367	8.597	2335.8	−22.957

Notes: JB stands for the Jarque-Bera coefficients of normality, DF-GLS is the Dickey-Fuller generalized least squares test with 10 lags assuming only constant, and 1% and 5% critical values are 2.566 and 1.941, respectively.

Source: author's calculation

On the other hand, the time series are stationary, meaning that the mean value of the data tends to be zero. Stationarity is tested by the Dickey-Fuller GLS test as in Elliott et al. (1996) in a two-step process. In the first step, the time series is estimated by generalized least squares, while in the second step, a normal Dickey-Fuller test is used to test for a unit root. DF-GLS test improves the power of a regular ADF test in cases when the autoregressive parameter is near to one. The test statistics are compared with the critical value, and if it is lower, then the null hypothesis can be rejected, which means that the time series is stationary.

$$JB = \frac{n}{6} \times \left[S^2 + \frac{(K-3)^2}{4} \right] \tag{3}$$

where S is skewness, K is kurtosis, and n is the number of observations.

Based on the descriptive statistics, it can be assumed that the COVID-19 pandemic has significantly affected the observed companies, and most companies have recorded a significant drop during that time. This is the reason why kurtosis values in Table 1 are very high. These results coincide with the findings of other authors. For example, Lee (2022) determined that COVID-19 significantly impacts stock price volatility in the banking sector and has a strong spillover effect on American economic and financial systems. Insaidoo et al. (2023) researched the cause of changes in the financial market in developing countries (Brazil, India, Kenya and South Africa), claiming that more profound financial market research is limited. However, they confirmed that the COVID-19 pandemic is the most significant cause of changes in the financial market.

4. Results of the Empirical Research

4.1 Results of the Least Square regression

The first step in assessing the influence of oil price on the selected stocks is the estimation of OLS regression; Table 1 shows the results. This approach evaluates the average effect of the regressor on the dependent variable, but it is a weak estimator because it is not very informative and sometimes produces biased results. According to the results, oil shocks spill over to all companies with very high statistical significance. This means that oil is an essential factor affecting stocks regardless of whether the sector is heavily dependent on oil or not. In addition, all OLS parameters are positive, which means that the dynamics of oil price and stocks are positively correlated.

Interestingly, the estimated OLS parameters of the pharmaceutical companies are from four to five times lower compared to oil companies, which is also in line with expectations. This is the case because pharmaceutical companies are not directly related to oil production, so a more substantial effect of oil on their stock prices is unlikely.

The OLS regression estimates only one parameter that indicates the average effect of oil on stocks, not considering different economic conditions that are undoubtedly present. Therefore, it is hard to believe that oil shocks equally affect stock prices in recession, normal conditions, and economic expansion. This is one reason why OLS is a poor and relatively naive method, which calls for a more elaborate model, such as QR.

Table 2: Least Square regression – Brent oil and companies from the oil and pharmaceutical industry

Company	Estimated parameters in OLS regression
Chevron Corporation	0.394 (0.016) ***
ConocoPhillips	0.565 (0.018) ***
ExxonMobil Corporation	0.451 (0.016) ***
Occidental Petroleum Corporation	0.890 (0.032) ***
Phillips 66	0.379 (0.019) ***
Aboot Laboratories	0.094 (0.016) ***
Amgen inc.	0.115 (0.015) ***
Bristol Myers Squibb Company	0.161(0.036) ***
Gilead Sciences inc	0.080 (0.016) ***
Regeneron Pharmaceuticals	0.072 (0.017) ***

Note: ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively; numbers in parentheses represent standard error

Source: author's calculation

4.2 Results obtained by the quantile regression model

This section analyses the results obtained via the estimated quantile parameters, shown in the interval from $\tau0.05$ to $\tau0.95$. Table 3 presents the estimated quantile parameters, while Figure 2 graphically displays these results. The application of quantiles provides an opportunity to inspect the effects of oil shocks under different economic conditions, i.e., in recession, stable economic mode, and when the economy grows. Seven quantiles are estimated, which portray a particular economic state. Specifically, the left tail quantiles, $\tau0.05$ and $\tau0.20$, indicate the state of recession, $\tau0.35$, $\tau0.5$ and $\tau0.65$ present the state of stable economic condition, while quantiles $\tau0.8$ and $\tau0.95$ denote the state of economic expansion.

Table 3 presents the quantile regression findings, where the impact of Brent oil on the share prices of ten companies from the oil and pharmaceutical industry is analysed. As can be seen, almost all estimated quantile parameters are highly statistically significant and in line with expectations and economic logic. Also, all parameters are positive, which means that oil and stock prices move in the same direction. It is interesting to notice that most plots in Figure 2 have the "U" shape. This means that oil shocks have the highest effect on the companies in recession and expansion, while in normal conditions, this effect is the lowest. In other words, when the world economy is in recession, global oil consumption decreases, which causes oil price drop. The same happens with the share of companies. In other words, negative global economic conditions affect the business of all companies to a greater or lesser extent, causing their stock prices to fall. On the other hand, during expansion, global oil consumption increases, which raises the price of oil. Additionally, favourable economic conditions positively affect companies, reflecting the rise of their stocks.

Table 3: Quantile regression results

Company	Estimated quantiles						
	0.05	0.20	0.35	0.50	0.65	0.80	0.95
Chevron	0.509 (0.508)	0.478*** (0.052)	0.428*** (0.034)	0.394*** (0.031)	0.386*** (0.030)	0.368*** (0.046)	0.022* (0.196)
Cono-cophilips	0.513 (0.357)	0.601** (0.050)	0.604*** (0.054)	0.585*** (0.047)	0.518*** (0.043)	0.497*** (0.058)	
ExxonMobil	0.551*** (0.022)	0.481*** (0.014)	0.463*** (0.021)	0.435*** (0.019)	0.438*** (0.028)	0.462*** (0.033)	0.486*** (0.034)
Occidental Petroleum	0.969*** (0.064)	0.758*** (0.061)	0.642*** (0.049)	0.624*** (0.046)	0.604*** (0.044)	0.728*** (0.043)	0.792*** (0.044)
Phillips 66	0.240* (0.149)	0.527*** (0.060)	0.416*** (0.027)	0.386*** (0.040)	0.424*** (0.042)	0.521*** (0.030)	0.813*** (0.229)
Aboot Laboratories	0.162*** (0.029)	0.124*** (0.036)	0.063*** (0.026)	0.043 (0.029)	0.043 (0.033)	0.050*** (0.020)	0.074*** (0.015)
Amgen inc.	0.197*** (0.038)	0.109*** (0.029)	0.062*** (0.025)	0.067*** (0.022)	0.071*** (0.023)	0.070*** (0.017)	0.144*** (0.024)
Bristol Myers Squibb	0.427*** (0.060)	0.202*** (0.048)	0.141*** (0.030)	0.096*** (0.039)	0.066 (0.044)	0.051 (0.042)	0.097 (0.084)
Gilead Sciences inc	0.140*** (0.039)	0.106*** (0.016)	0.068*** (0.027)	0.045** (0.020)	0.047*** (0.021)	0.035 (0.022)	0.030 (0.068)
Regeneron Pharmac.	0.140*** (0.023)	0.091*** (0.025)	0.096*** (0.037)	0.075*** (0.028)	0.049*** (0.030)	0.024 (0.027)	0.088* (0.053)

Note: ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively; numbers in parentheses represent standard error.

Source: author's calculation

For the Chevron Corporation, it can be noticed that oil does not influence the lowest quantile because $\tau0.05$ is insignificant. This means that Chevron is resilient to oil shocks when an extreme recession occurs. The highest effect is recorded on the $\tau0.20$ quantile with the amount of 0.478, meaning that a 1% drop in oil price causes a 0.478% drop in Chevron Corporation's stock price. As the quartiles increase, the oil's effect remains relatively high, which is expected since it is an oil company, but it slowly decreases. In the state of economic expansion, the effect of oil shocks on Chevron stocks is negligible.

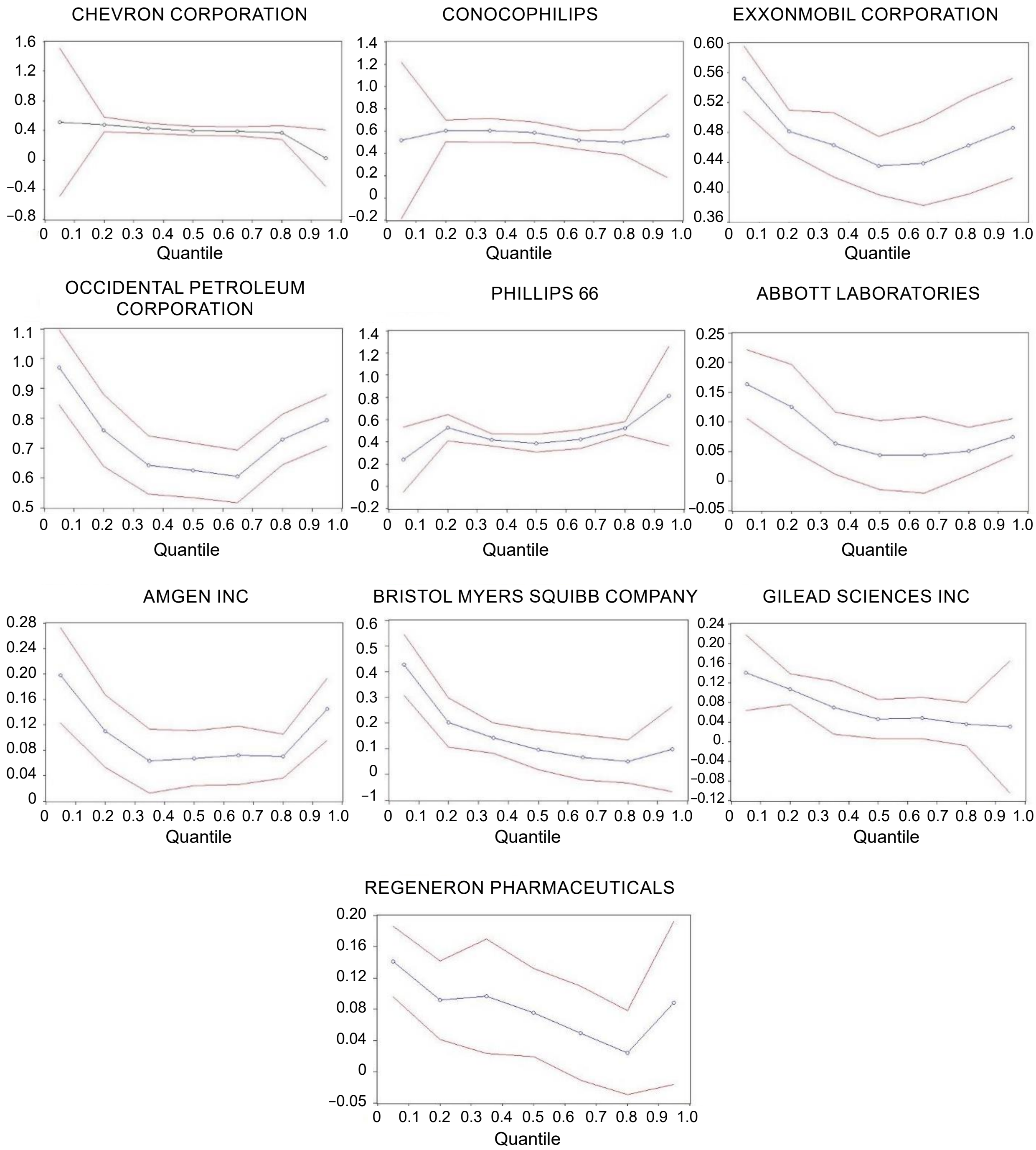
In the case of ConocoPhillips, the results are relatively similar to those of Chevron because the estimated parameter at the lowest quantile is not significant. The effect of oil shocks on ConocoPhillips is higher than on Chevron. At all observed quantiles, the effect of oil is higher in the case of ConocoPhillips vis-à-vis Chevron. Also, oil impacts the highest quantile of ConocoPhillips, but confidence intervals of the $\tau0.95$ quantile are wide, which means this parameter is unreliable.

On the other hand, in the case of Exxonmobile, all quantile parameters are relatively high and highly significant with relatively narrow confidence intervals. This means that all estimated quantile parameters are trustworthy. Besides, this indicates that oil shocks significantly impact Exxonmobile stocks even in extreme economic conditions, which differs from Chevron and ConocoPhillips. The highest quantile parameters are recorded at $\tau0.05$ and $\tau0.95$ quantile.

Occidental Petroleum is a corporation that exhibits the highest sensitivity to oil shocks because all estimated quantiles are very high. At the lowest quantile, the estimated parameter is 0.969, which means that oil shocks affect Occidental Petroleum almost one-to-one. During the economic boom, the estimated quantile was also very high (0.792). All these quantile parameters are highly statistically significant with narrow confidence levels, signalling of their reliability.

The last oil company from the sample is Phillips 66. All quantile parameters of Phillips 66 are statistically significant, but standard errors of the $\tau0.05$ and $\tau0.95$ are relatively high, which means that these parameters cannot be trusted much. Also, the low confidence level of these tail quantile parameters aligns with the previous assertion. Estimated parameters from $\tau0.20$ to $\tau0.80$ are relatively high, meaning that oil price significantly impacts this company. However, it is interesting to note that the median quantile is the lowest of all oil companies, which means that oil has the lowest effect on the Phillips 66 stock under normal economic conditions.

Figure 2: Graphic representation of the estimated quantiles



Source: author's processing

Analysing pharmaceutical companies, estimated quantile parameters are significantly lower than in the case of oil companies. In addition, more statistically insignificant quantile parameters are found aming the pharmaceutical companies than oil companies. This means that oil shocks are not an essential factor affecting stocks of the pharmaceutical sector, which is in line with expectations. As in the case of oil companies, the estimated quantile parameters form the "U" shape in most cases, which means that the effect is more substantial in extreme market conditions than normally. All confidence intervals are relatively narrow, meaning the estimated quantile parameters are reliable.

In particular, Aboot Laboratories reports five statistically significant quantile parameters, mainly around the distribution's tails, while the median quantile and $\tau 0.65$ quantile are insignificant. Besides, it should be noted that five out of seven parameters are very low, i.e., below 8%, which aligns with the assertion that oil shocks have a negligible effect on the pharmaceutal sector. The highest quantile parameter is found at the left tail of the distribution, amounting to 0.162. This indicates that Aboot Laboratories records a somewhat more substantial effect from oil in conditions of deep recession. However, this effect is significantly lower than that of oil companies.

In the case of Amgen Company, all quantile parameters are statistically significant but relatively low. The highest parameters are found at the left and right tail of the distribution, i.e. 0.197 and 0.144, respectively. This pharmaceutical company reports the highest tail parameters of all analysed companies from this sector. This means that the dynamics of oil under extreme market conditions coincide with the movement of Amgen stock prices more than in case of other pharmaceutical companies.

Bristol Myers Squibb records the highest impact from oil shocks, and the effect is recorded from $\tau 0.05$ to $\tau 0.50$ quantiles, which means that the spillover effect is stronger under the conditions of lower economic activity. The left tail quantile is very high (0.427), which indicates that this company is under the most considerable pressure from the oil market when the economy is in recession.

Gilead Sciences and Regeneron are the two pharmaceutical companies with the lowest effects from the oil market. In other words, although much of the estimated parameters are statistically significant, they are close to zero, which means that oil has a very modest effect on these two companies. According to the results, the most decisive impact is recorded on the left tail quantile, which is 0.140 for both companies.

The estimated results indicate that more intense effects are found in more energy-dependent industries. These results are in line with the number of existing papers. For instance, Yang et al. (2023) argued that the price of oil significantly affects companies from the oil industry compared to other industries. Chowdhury and Garg (2023) added that the price of oil affects stock returns in moments when there are highly volatile market conditions, which is in line with the estimated tail quantile parameters in this research. Umar et al. (2024) suggested that oil price fluctuations can be transmitted to companies that use oil, and state that their growth or decline will contribute to the growth or decline of costs in the company and thus, to the fluctuation of the stock market index. Wei et al. (2023) contended that shocks from the crude oil market affect stock prices through the expected discount rate and dividend. Additionally, Zhao et al. (2023) state that changes in oil prices are not consistent in all countries and all industries and further indicate that countries that are net importers and countries that are net exporters react differently to fluctuations in oil prices. An asymmetric effect is present in the obtained results, which highly coincides with the research by Xie et al. (2021).

5. Discussion

The results reveal that oil shocks have a significantly higher impact on oil companies than on the pharmaceutical sector, and this spillover effect is sensitive to market conditions. These results have several implications for companies and market participants investing in these stocks. For instance, oil companies are more subject to changes in oil prices, which directly affect their revenue and profitability and potentially lead to changes in the stock prices. Besides, the financial health of oil companies can be influenced by their debt level. Companies may accept more debt during high oil prices to fund expansion projects. If oil prices drop suddenly, highly leveraged companies may face challenges in servicing their debt, which negatively impacts their stock prices. The overall sentiment in the energy sector also plays a role. In other words, positive sentiment during high oil prices may attract more investors to the sector, boosting investments and cash flows, while negative sentiment during low oil prices can lead to a sell-off. As for the investors' point of view, the results indicate that there are both oil companies that are more and less sensitive to oil price changes. Investors who want to hedge against the oil price changes can invest in more resilient oil companies, such as Chevron. In the case of other companies, investors can hedge their positions by purchasing futures contracts.

On the other hand, the spillover effects of oil shocks on pharmaceutical companies are typically indirect, as the pharmaceutical industry is not tied to oil production directly. However, these companies are also subject to certain implications of oil price changes. First, pharmaceutical companies rely on various raw materials and chemicals in their manufacturing processes. Increasing production costs due to rising oil prices can indirectly affect pharmaceutical companies. Second, higher oil prices can lead to increased transportation costs. This may impact pharmaceutical companies' logistics and distribution expenses, potentially affecting profit margins. Third, if oil shocks lead to broader economic impacts, such as inflation or reduced consumer spending, pharmaceutical companies may experience changes in product demand. Investors in pharmaceutical companies can pay less attention to oil prices, as oil shocks have a very modest effect on their stocks. In other words, they do not need to hedge their positions due to changes in oil prices. These findings are supported by Al Janabi et al. (2010) and Apergis and Miller (2009). These authors indicate negligible or absent impact of oil prices on stock markets.

6. Conclusion

This paper thoroughly analyses the effects of Brent oil on the stock price of ten companies from two radically different industries – oil and pharmacy. During the research process, we used quantile regression and OLS method. Applying these two approaches ensures the robustness of the obtained results. Obtained results indicate limited possibilities of the OLS methodology, while quantile regression provides more complete findings.

The research results suggest that oil, as the most essential commodity in the world, affects the stock prices of various companies, which means that there are different implications for companies and stock investors. According to expectations and economic logic, the decrease in the price of Brent oil is the most pronounced among companies from the oil industry. The effect of oil price decline is visible during economic recession when the economy is experiencing a downturn. However, the results indicate that a significant spillover effect also exists in the state of economic prosperity. The estimated quantile parameters form "U" shape plot in this way. Finally, the research contributes to a deeper understanding of the different impacts of oil price changes on companies operating in different industrial sectors. The results can help the market participants to make sound and informed decisions and implement strategies that will help them to mitigate risks related to the various fluctuations that occur in the global oil market.

However, the research is limited by its focus on companies from only two industrial sectors, which restricts the generalizability of the findings. This highlights the need for further research that explores how fluctuations in Brent oil prices impact companies in various sectors, such as real estate, technology, and consumer goods. Such broader analysis would facilitate a better understanding of the oil price impacts across different industries and benefit policymakers in formulating strategies for economic sectors affected by oil market changes.

Additionally, it is crucial to consider the dissimilarity of conditions causing fluctuations in Brent oil prices, with them being often specific to the United States. Future research should involve more detailed analyses of factors such as US regulatory frameworks impacting the oil market and international economic policies related to oil prices. This would enhance the understanding of the mechanisms driving oil price fluctuations and their impact on company stock prices, crucial for informed policy decisions and financial market stability.

In summary, future research should continue to explore the broader implications of oil price changes across different sectors and analyze the factors shaping the oil market within the context of global and national economic policies. This would provide valuable insights into the complexity of the global oil market and facilitate the development of strategies for risk management and sustainable economic development.

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