

Yield and Volatility of Pharmaceutical Industry under the Russia-Ukraine Conflict: A Perspective of Changes in Oil Price

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Abstract. The Russian-Ukraine conflict has resulted in a series of impacts on the economy, one of which is rising energy prices. This paper studies the impact of oil price changes on pharmaceutical returns by employing time series methods to construct VAR and ARMA-GARCH models. This paper finds that an increase in either WTI or Brent futures creates a small negative net impact on pharmaceutical returns, and the time for this impact is only observable in the short run. The VAR model suggests that the WTI and Brent return's lagged value at period 5 presents a significant relation with the present value of the pharmaceutical returns. The ARMA-GARCH model locates a GARCH effect between past values of oil price changes and pharmaceutical returns/ However, it shows no sufficient evidence to support the claim that oil price changes contain any effect on pharmaceutical returns. The findings of this paper can serve as a reference for researchers and traders alike who are interested in understanding the effect of specific macroeconomic factors on the returns of the pharmaceutical industry.

Keywords: Russia-Ukraine conflict; pharmaceutical; oil prices.

1. Introduction

The Russian-Ukrainian conflict has created a large impact on many industries in the global economy. The outbreak of the war has heightened much political uncertainty amidst the global pandemic since 2021. One of the main consequences is rising oil prices due to supply shocks and mounting uncertainty over geopolitical factors. The price per barrel of oil has risen from around 80\$ to more than 100\$, reaching a maximum of around 110\$ since the outbreak of the Russian-Ukrainian war. Inflation has risen in major economies in the world as a response to increasing energy prices.

While the impact on many industries, especially the manufacturing sectors, has been extensively studied, little literatures study the effect of oil price increases on pharmaceutical companies. As the world is still living under the Covid era, this paper thinks it is beneficial to study if the changes in oil price will create shocks to pharmaceutical companies as it can provide insights into the connection between certain macroeconomic factors and the performance of pharmaceutical companies in this particular time. The effect will be studied under VAR and ARMA-GARCH models, this paper will also visualize it through impulse response graphs.

Few literatures have studied the time series of pharmaceutical returns. Yang and Zhou have studied the time series of pharmaceutical companies' returns in both developed and emerging countries and found that monetary supply, consumer price index, and industrial production, all important macroeconomic factors, have no significant impact on pharmaceutical returns [1]. More generally, some researchers point out the lack of evidence to identify specific macro variables that are responsible for the volatility of financial asset prices, or if any significant exogenous influences on prices could be observed [2].

Modeling time series data for oil prices calls for attention to the conditional distribution, concentrated volatility clustering, and high volatility. Gibson and Schwartz, Cortazar and Schwartz and Schwartz show that oil prices demonstrate volatility clustering as well as persistence, making the random walk model unfit when studying volatility in oil markets [3-5]. Cartea and Figueroa warned that the likelihood of extreme events taking place is much higher than the estimation provided by Gaussian distribution due to observation of the existence of fat tail in the energy market [6].

Agnolucci compared the forecasting capability between the GARCH-type model and the implied volatility model using daily returns of WTI and Brent crude oil and found that GARCH model performs better as it exhibits a highly persistent response to the shocks to the conditional variance [7].

This paper aims to understand the extent to which the change in oil prices affects the return in the pharmaceutical industry. In the process of establishing models, this paper takes special attention to reflecting the ‘volatility clustering effect’ of the changes in the oil price by examining the assumption of conditional homoskedasticity in the time series data.

The following parts of this paper are structured as follows: Part 2 outlines the research design which includes the description of data sources, explanation of unit root test and the VAR, ARMA-GARCH model specification; Part 3 presents the empirical results produced by the models, engaging in the order identification for VAR and ARMA models, as well as the analysis of the estimations from the Impulse Response Function and the ARMA-GARCH model; Part 5 discusses the findings of this paper and their implications

2. Research Design

2.1 Data Sources

Since this paper wishes to examine the how Russian-Ukrainian conflict has impacted the pharmaceutical returns in the scope of oil price changes, it is decided to collect data from November 1st, 2021, about three months before Russian troops entered Ukraine on the 24th of February in 2022. This paper mainly collected three sets of data: WTI oil futures, Brent oil futures, and the S P select pharmaceutical index. It should be noted that, due to the unalignment of the three parameters in terms of dates, this paper took out individual data points if respective entries from the other two data sets are missing.

This paper collected its data from the financial platform investing.com. It is one of the top three global financial websites in the world and it offers comprehensive information regarding the financial market.

This paper chooses the two most important benchmarks for global crude oil prices: Brent crude futures and WTI futures. Brent crude futures, more specifically known as the price of the ICE (International Exchange) Brent Crude Oil futures contract. It is originally a “physically and financially traded oil market based around the North Sea of Northwest Europe”. Since 2021, it has expanded and added crude oil blends from other oil fields. Brent has been viewed as an important “regional benchmark” for a “large number of light sweet crude oils produced in the North Sea” [8]. More importantly, it is usually referred to as a global benchmark for general global crude prices, and its active forward and derivative markets make its role more pertinent. West Texas Intermediate (WTI) is oil sourced “primarily from inland Texas and is one of the highest quality oils in the world that is easy to refine. It is regarded as a “light sweet crude oil that serves as one of the main global oil benchmarks” [9].

This paper chooses the S&P pharmaceuticals select industry index since it provides a comprehensive picture of the pharmaceutical portion of the S P market index. This index tracks stocks from major stock exchanges in the US. To avoid the heteroskedasticity, the “returns” shown in the following sections of this paper are taken natural logarithm, respectively.

2.2 Unit Root Test

In order to initiate the development of time series model, it is needed to check if the time series this paper intends to study follow stationarity. Assume, preliminarily, that the time series in question can be written in the form:

$$a_t = \varphi a_{t-1} + \varepsilon_t \quad (1)$$

Since $\mathbb{E}[x] = 0$, it follows:

$$\mathbb{E}[a_t] = \varphi \mathbb{E}[a_{t-1}] = \varphi^2 \mathbb{E}[a_{t-2}] = \dots = \varphi^t a_0 \quad (2)$$

Hence (1) as:

$$a_t = \varphi^t a_0 + \sum_{i=0}^{t-1} \varphi^i \varepsilon_{t-i} \quad (3)$$

The variance is:

$$Var(a_t) = \varsigma^2[\varphi^0 + \varphi^2 + \varphi^4 + \dots + \varphi^{2(t-1)}] \quad (4)$$

Now there are three cases,

When $|\varphi| < 1$:

$$\mathbb{E}[a_t] \xrightarrow{t \rightarrow \infty} 0 \quad (5)$$

$$Var(a_t) \xrightarrow{t \rightarrow \infty} \frac{\varsigma^2}{1 - \varphi^2} \quad (6)$$

When $|\varphi| > 1$:

$$\mathbb{E}[a_t] \xrightarrow{t \rightarrow \infty} \mp \infty \quad (7)$$

When $|\varphi| = 1$:

$$\mathbb{E}[a_t] = a_0 \quad (8)$$

$$Var(a_t) = t\varsigma^2 \quad (9)$$

While the first two cases demonstrate their stationary property, the third case can be deceptive to a rough graph inspection by eye. This is called a unit root and the test examines the existence of unit root by testing: $H_0: \varphi = 1$, and $H_1: \varphi \neq 1$

Table 1. ADF Test

Variables	t-statistic	p-value
Index		
WTI	-2.087	0.5532
Brent	-2.130	0.5293
Pharmaceutical index	-2.709	0.2324
Yield		
WTI	-10.509	0.000***
Brent	-10.135	0.000***
Biomedical index	-9.232	0.000***

From Table 1, it can be concluded that while the index of WTI, Brent, and pharmaceuticals are all non-stationary, the natural logarithms of their respective returns are all stationary.

2.3 Vector Auto-regressive Model

To accommodate a model where it regresses the lagged time effect of multiple variables in the time series model, this paper decides to employ a vector auto-regression (VAR) model. The VAR model generalizes the uni-variate auto-regressive model by including the lagged time value of multiple variables. Generally, the VAR model carries greater flexibility since it is not bounded by economic or financial theory. Additionally, VAR models, if stationary and satisfies the Ordinary Least Squares assumption, can be estimated asymptotically by OLS whose estimates are consistent and jointly normal in large samples. Consequently, the VAR model is applicable to conventional p and t-test and viable for joint hypothesis testing in a set of equations. (literary review on the methods) Christopher Sims proposed this model in 1980 to infer causality under structures of economy, known as structural vector auto-regression. (SVAR) Limited by the scope, this paper will not consider SVAR model as it requires particular assumptions drawn from specific economic theories.

$$\begin{bmatrix} x_{1,t} \\ x_{2,t} \end{bmatrix} = \beta_0 + \beta_1 \begin{bmatrix} x_{1,t-1} \\ x_{2,t-2} \end{bmatrix} + \beta_2 \begin{bmatrix} x_{1,t-1} \\ x_{2,t-2} \end{bmatrix} + \varepsilon \quad (10)$$

In equation (10), the error term ε captures the value that cannot be described by past values of the term x_1 and x_2 . The term ε shows the exogenous shocks to the system. Since this paper does not account for exogenous variables in our regression, this shock can be decomposed into two parts: the shock that is uncorrelated with the other variables in the system and the one that correlates with system variables.

2.4 ARMA-GARCH model Specification

The ARMA model is developed by Box and Jenkins in 1970 to perform forecasts for time-series data that is stationary. It consists of the auto-regressive (AR) model and moving average (MA) model.

The AR(p) model dwells on the assumption that future values could be predicted by past values. It chooses the most significant lag value at order p as the regressor to predict the value of the time series at time t. It is written as:

$$y_t = \phi_0 + \sum_{i=1}^p \phi_i y_{t-i} + \varepsilon_t \quad (11)$$

The MA(q) model assumes that a time series at time t can be predicted by the present and previous error term (stochastic term) in a linear fashion. It is written as:

$$y_t = c_0 + \sum_{i=1}^q \theta_i \varepsilon_{t-1} + \varepsilon_t \quad (12)$$

Combining the AR and MA models, produces the ARMA model which includes both the past value terms and the past stochastic terms.

$$y_t = \phi_0 + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{k=0}^l \omega_k \varepsilon_{t-k} + \varepsilon_t \quad (13)$$

Until now, this paper has assumed that the variance of our time series is constant and follows conditional homoskedasticity. Engel points out that the assumption of homoskedasticity in financial time series is unreasonable and might lead to inaccurate results [10]. To anticipate changing variance in our time series over different periods, this paper uses the Autoregressive Conditional Heteroskedasticity (ARCH) model developed by Engle in 1982 in order to better capture the volatility in oil prices. Consider a general linear regression model as:

$$y_t = x_t' \beta + \varepsilon_t \quad (14)$$

This paper defines the conditional variance for the error term $Var(\varepsilon_t | \varepsilon_{t-1}, \dots)$ as ε_t . To generalize, for ε_t^2 that depends on the pth order of the square of error terms:

$$\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_p \varepsilon_{t-p}^2 \quad (15)$$

Due to the non-negativity of σ_t^2 , this paper imposes $\alpha_i \in (0,1)$ for $i \in [0,p]$. It can be observed that for a ε_{t-1} that deviates largely from its expected value 0, its effect will be translated to a larger conditional variance of the ε_t^2 term, meaning that ε_t^2 would have a large deviation from its mean 0. The same logic applies to the case where ε_{t-1}^2 is smaller. Due to this property, the ARCH model can

perform volatility clustering: one period of large variation is likely to be followed by a large variation the next period.

For a large p , the ARCH(p) model will compromise the sample size to accommodate more regressors. Bollerslev proposed GARCH to reduce the number of regressors and improve the accuracy of variance predictions [10]. In addition to the ARCH model, GARCH model adds autoregression time series of the variance term ζ^2 . The general GARCH(p, q) model is specified as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \gamma_1 \sigma_{t-1}^2 + \cdots + \gamma_p \sigma_{t-p}^2 \quad (16)$$

To illustrate how GARCH model saves the number of regressors, this paper uses a GARCH (1,1) model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \zeta_{t-1}^2 \quad (17)$$

σ_{t-1}^2 can be rewritten into:

$$\sigma_{t-1}^2 = \alpha_0 + \alpha_1 \varepsilon_{t-2}^2 + \gamma_1 \zeta_{t-2}^2 \quad (18)$$

σ_t^2 and all past values can be rewritten recursively:

$$\sigma_t^2 = \alpha_0(1 + \gamma_1 + \gamma_1^2 + \dots) + \alpha_1(\varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-2}^2 + \gamma_1^2 \varepsilon_{t-3}^2 + \dots) \quad (19)$$

3. Empirical Results

3.1 VAR Identification

This paper resorts to the ratio likelihood test developed by Neyman and Pearson to realize this. It is wished to see the distance between the log-likelihood attained at the maximum likelihood of a parameter and the log-likelihood achieved with the null hypothesis being true:

$$LR = 2(\log L|\hat{\theta}_{ML}) - \log L(\theta_{H_0}) \quad (20)$$

And tests for: $H_0: \theta = \theta_{H_0}$, and $H_1: \theta > \theta_{H_0}$.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1264.88				2.6e-11*	-15.8727*	-16.0287*	-15.9943*
1	1271.03	12.313	9	0.0196	2.7e-11	-15.8369	-15.956	-15.8184
2	1277.92	13.763	9	0.131	3.0e-11	-15.8103	-15.8491	-15.6084
3	1280.34	4.8575	9	0.847	3.2e-11	-15.7276	-15.6835	-15.3396
4	1284.2	7.7099	9	0.564	3.1e-11	-15.6629	-15.5312	-15.0841
5	1293.99	19.574	9	0.021	3.4e-11	-15.6728	-15.4088	-14.8585
6	1296.68	5.3785	9	0.800	3.7e-11	-15.5934	-15.2542	-14.6008
7	1299.1	4.8491	9	0.847	4.0e-11	-15.5107	-15.1104	-14.0816
8	1301.44	4.6855	9	0.861	4.3e-11	-15.427	-14.9413	-13.8584
9	1305.76	8.6256	9	0.473	4.6e-11	-15.368	-14.8214	-13.6082
10	1310.21	8.9036	9	0.446	5.1e-11	-16.3108	-14.6743	-13.3492
11	1310.75	1.0846	9	0.999	5.4e-11	-15.1613	-14.5184	-13.1165
12	1316.33	11.153	9	0.265	5.8e-11	-15.1707	-14.3889	-12.923

From table 2 this paper selects lag 5 for our VAR model as it has achieved a significance with p-value below the 5% threshold.

Theoretically, a companion matrix should be created and its eigenvalues should be subsequently computed:

$$A = \begin{pmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I & 0 & \dots & 0 & 0 \\ 0 & I & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I & 0 \end{pmatrix} \quad (21)$$

The modulus of the complex eigenvalue $r + ci$ should be $\sqrt{r^2 + c^2}$. Lutekepohl has shown that the stability condition of VAR is satisfied if the modulus of each eigenvalue of A is less than 1 [11]. Stata helps us realize this in form of a unit circle with center at (0,0) and radius 1.

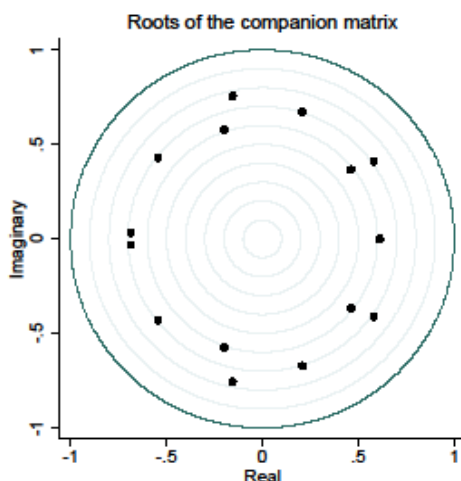


Figure 1. VAR stability

Figure 1 shows that all the roots of the companion matrix are within the circle, meaning less than 1. It can be concluded that our VAR model is stable.

3.2 Impulse and Response Functions

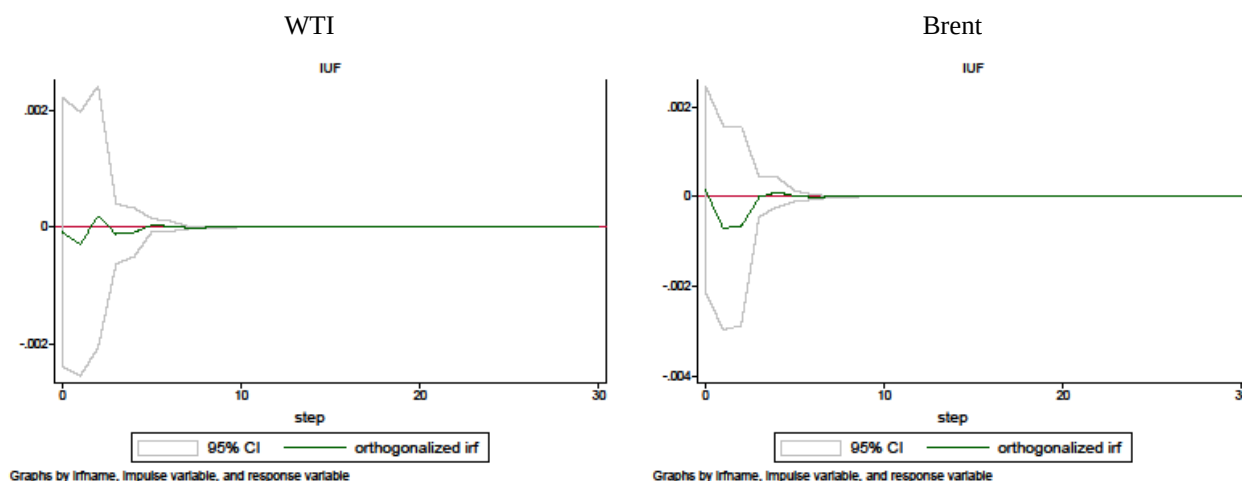


Figure 2. IRF for Brent and WTI in relation to the pharmaceutical index

Judging from the estimated results of the IRF, the increase in international oil prices creates a negative net effect on the return of the pharmaceutical index. More specifically, at the period $t=0$, a 1% increase in the WTI price produces a positive impact on the pharmaceutical returns in the future 1 period, reaching an extreme value at around -0.006%. The impact becomes positive in period 2 and then reverts to a much smaller negative value in period 3. The effect of this shock is shown to vanish completely after period 5.

For Brent, at the period $t=0$, the increase in its prices continues to generate a negative impact on the pharmaceutical returns: 1% increase creates a negative impact for the future two time periods and the effect completely wears out after period 5.

In terms of time, it can be concluded that the impact that international oil price produces on pharmaceutical returns is in the very immediate short run. The reasons will be explained in the later section.

3.3 ARMA Identification

This paper chooses the auto-correlation function for the MA process since it wants to identify which past value best correlates with the present value. Generally, the auto-correlation function can be written, for $h = 1, 2, 3$ as:

$$\frac{Cov(x_t, x_{t-1})}{Var(x_t)} \quad (22)$$

The plot for the result of the ACF function of the time series is as follows:

Graph 3 shows no lag orders which contain a significant correlation with its present value. Hence it is decided to drop the moving average term together.

This paper resorts to the partial auto-correlation function since the lag order of the AR term can be found at the sharp cutoff of the PACF function. To illustrate, the PACF of a 2-order lag time series is:

$$\frac{Cov(x_t, x_{t-2}|x_{t-1})}{\sqrt{Var(x_t|x_{t-1})Var(x_{t-2}|x_{t-1})}} \quad (23)$$

To draw the result of the PACF function with 95% confidence interval:

Graph 3 shows that the 17th lag order is the smallest lag order that has acquired a significant correlation with its present value, which proceeds to choose $p = 17$ for AR(p) model.

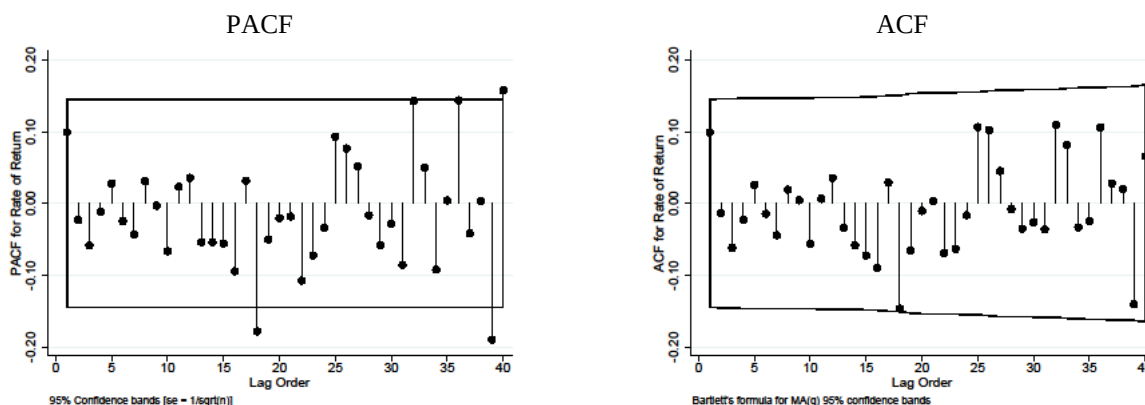


Figure 3. PACF and ACF graphs for pharmaceutical index

3.4 ARMA-GARCH Estimation

Based on the previous discussion of this paper, this paper decides to employ a ARMA (17,0) – GARCH (1,1) model to best study how the return of oil futures influences the return of the pharmaceutical index. This paper first checks the impact of WTI on the pharmaceutical index:

Table 3 shows that while there exists a significant GARCH effect between the return of the pharmaceutical index and that of WTI, there is not enough evidence to conclude that WTI has a significant impact on the volatility of the return of the pharmaceutical index.

In terms of Brent futures: there is a strong significance for a GARCH relation between Brent futures and pharmaceutical index returns. However, it cannot be concluded that the return of the Brent futures has a significant impact on that of the pharmaceutical index.

Table 3. ARMA-GARCH estimation results, variance equation

	(1)		(2)	
	Coef.	Std. err	Coef.	Std. err
WTI	-8.9616	10.2933		
Brent			-10.2200	10.3736
ARCH (-1)	0.1129	0.1084	0.1093	0.1019
GARCH (-1)	0.6460*	0.3659	0.6756**	0.4398
Constant	-9.7611***	1.3520	-9.8803***	1.3839

4. Discussion

This paper finds no significant relationship between past values of Brent futures, WTI futures, and the present value of the pharmaceutical index. While it is surmised that an increase in oil prices might create a shock to the pharmaceutical industry much in the same fashion as it has taken place in other industries, this paper found no strong evidence to support the claim.

While past values of the return for the pharmaceutical index are shown to create a significant impact on the return of the Brent and WTI futures, our VAR model shows no significant impact of the latter on the former. A close examination of the respective impulse response graphs provides a more detailed account: the increase in return for both WTI and Brent create a considerably small negative net effect on the return of the pharmaceutical index and their impact completely vanishes after period five. Comparatively, Brent return creates a greater negative impact on the return of pharmaceutical index in period one while WTI generates a greater positive impact on pharmaceutical index returns in period two. However, it should be noted that the maximum impact leveled by either of the oil futures is well below 0.1. Correcting for conditional heteroskedasticity, the ARMA-GARCH model also does not show a significant relationship between oil future returns and pharmaceutical index returns. A significant GARCH effect is presented. It is important to note that even such a small amount of impact might not be entirely caused by changes in oil prices since neither models account for any exogenous factors. This result corroborates with the research conducted by Yang and Zhou [1], which found no significant linear relationship between three of the major macroeconomic indicators: monetary supply (M2), CPI (consumer price index), industrial production, and the pharmaceutical returns. Since oil futures affect the pharmaceutical industry in more subtle ways, if any than the abovementioned macroeconomic indicators, this paper can conclude that there is no sufficient evidence to support the notion that oil price changes have a significant impact on pharmaceutical returns.

Reflecting on the premises that motivated this investigation, this paper might have over-generalized the impact of energy prices on the pharmaceutical industry by assuming a comparable pattern of price transmission mechanism vis a vis the manufacturing industry. It can be suggested that further attempts to study this subject could be carried out with attention to specifying the exogenous factors in relation to the ways in which pharmaceutical industry returns can be impacted by energy prices. The complex mechanism to which how returns of pharmaceutical companies are determined, as well as how they perceive energy price shocks on both the supply and demand end necessitates a more structural approach to the issue. To contextualize, current events such as the Covid-pandemic also have a considerable impact on the pharmaceutical returns. Thus, it is recommended that the impact of oil price on pharmaceutical returns be studied structurally in conjunction with exogenous factors.

5. Conclusion

Spurred by the introduction of increasing uncertainties in geopolitics and economics, the energy price has increased considerably since the outbreak of the Russian-Ukrainian conflict. This paper examines the time series data of the return of Brent and WTI prices and seeks to answer the question if oil price change does impact the return of pharmaceutical companies. The results do not present

any sufficient evidence to support the claim that changes in oil prices can affect pharmaceutical companies' returns.

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