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INFLUENCE OF OIL PRICE SHOCKS ON STOCK MARKET RETURNS

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ABSTRACT

This paper studies the influence of oil price shocks on stock market returns. The paper addresses the research problem of whether oil price shocks have a significant influence on American and European stock market returns. The aim of the paper is to investigate whether there is any difference in impacts caused by demand- and supply-side price shocks. The paper studies the supply-side 2014-2016 oil price shock and the demand-side 2020 oil price shock by applying Vector Autoregression (VAR) modeling and interpreting the results through Impulse Response Functions and variance decompositions. The composite daily return indexes for all companies listed on the New York Stock Exchange (NYSE) and the Euro STOXX 600, as well as the daily Brent crude oil prices were selected as the data sets for the study.

The author concludes that oil price shocks alone seem to not be sufficient enough for analysing what causes a decline in stock markets. Although the results of the VAR analysis reveal that there was a correlation between crude oil prices and stock market returns during the aforementioned price shocks, it was only slightly significant in 2020 and almost nonexistent from 2014 to 2016.

Keywords: oil prices, stock market returns, Vector Autoregression

INTRODUCTION

The importance of oil to the global economy is so vital that estimates of economic growth are typically accompanied with the caveat: the estimate is reliable, provided there is no oil shock. Because global energy markets are in high turbulence, it is essential to study the effects of oil price shocks on the macroeconomy.

The research problem tackled in this paper is whether oil price shocks have a significant impact on American and European stock market returns, with the specific aim of—if oil price shocks can be reliably used to predict stock market returns—investigating whether there is any difference in impacts caused by demand- and supply-side price shocks. In particular, this paper considers the impact on American and European markets of one significant supply-side shock, namely the 2014-2016 oil price shock during which the world saw one of the largest drops in oil prices since World War II, and one demand-side shock, specifically the 2020 oil price shock caused by the COVID-19 pandemic and an oil price war between Saudi Arabia and Russia. Thus, this paper aims to answer the following research questions:

1. Did oil price shocks in 2014-2016 and in 2020 have a negative impact on American and European stock market returns?
2. Do the impacts of oil price shocks on stock market returns differ significantly depending on if the shock comes from the demand or supply side?

Developing on previous studies which investigate the relationship between oil price and stock market returns, this paper uses Vector Autoregression (VAR) analysis performed in R to conduct an empirical investigation into the relationship between daily prices of Brent crude oil and daily total return indexes of NYSE composite and STOXX Europe 600 markets. The data selected covers the time periods of 2013-2017 and 2019-2021, in order to focus on the specific time periods of oil price shocks chosen to represent demand and supply shocks.

This paper is organized as follows. After the introduction, the first chapter focuses on an overview of theory and existing literature on the topic. The first part of the theory is background on the link between oil prices and stock market returns, followed by an explanation of how demand and supply factors influence oil prices, and including a short background of the specific price shocks which are investigated in this study. Finally, a more in-depth review of empirical studies on the subject is given, and hypotheses are developed based on the theoretical background. The second chapter introduces the data and methodology chosen for the study. Justification is given for both the selection of the data and VAR as an analytical method, and the process of building a VAR model is described in detail. Additionally, descriptions are given of methods for diagnosing whether the results of the VAR model are reliable and can be used to draw relevant conclusions. The third chapter focuses on the overall analysis performed. Specifically, it describes the processes of VAR estimation and diagnostics for models based on both time periods, and looks at impulse response functions and error variance decomposition derived from the two VAR models. Following this, the author provides more discussion on the results of the analysis, taking into consideration results achieved by past studies, and gives suggestions for how further studies could improve on the research done in this paper. The last chapter of the thesis presents a final summary of conclusions.

1. LITERATURE AND THEORETICAL REVIEW

1.1. Theoretical link between oil prices and stock market

Prior to three or four decades ago, the only thing economists truly understood about the oil market was its contribution to U.S. recessions, which was studied by Hamilton (1983). Since then, more extensive research has been conducted on the impact of oil price fluctuations on a variety of macroeconomic factors (see Jones and Kaul, 1996, Hamilton, 2003, Cunado and Perez, 2005, Lee and Chiu, 2011, Hamilton, 2014), because in today's world oil markets are closely interlinked with the macroeconomic and financial markets, displaying a pronounced financial characteristic. Oil markets are becoming more intertwined with other financial markets, such as the exchange rate market, stock market, and futures market, and have a more pronounced "financial premium." (Fan and Xu, 2011). Moreover, Kollias (2013) suggests that investors tend to be likely to equate rising oil prices with a thriving economy which demonstrates that increased oil prices may represent better business performance and have a commensurate influence on the stock market. For the reasons above, it is essential to comprehend the relationship between oil prices and the stock market.

When looking at the relationship between oil prices and stock market from a theoretical standpoint, the vast majority of the research follows the theoretical reasoning presented by Jones and Kaul (1996) and attempts to test the cash flow hypothesis, which claims that asset prices are determined by expected discounted cash flows (Fisher, 1930). The cash flow theory argues that the link between oil prices and stock returns can be negative or positive. As presented by Smyth and Narayan (2018), two channels suggest a negative relationship. First, because oil is a significant input for the majority of businesses, higher oil prices raise the cost of production, hence decreasing future cash flows, earnings, dividends, and stock returns. Second channel comes from an idea that an overestimation of expected inflation and an increase in nominal interest rates might result from higher oil prices. This will reduce earnings, dividends, and stock returns since interest rates are used to discount predicted future cash flows. A further third channel suggests the relationship can be both positive and negative. Through demand-side effects, oil price volatility can impact the effect of sensitivity of changes in oil prices on the risk premium component of the discount rate and on cash flow. Sensitivity to oil prices can have either a positive or negative influence on oil prices depending on the sign of the risk premium, which may vary significantly among enterprises and over time.

There are other theoretical standpoints on the relationship between oil prices and stock market. One being that oil-price shocks influence stock market returns or prices by influencing projected earnings (Jones et al., 2004). The theory that the value of stock prices equals the discounted expectation of future cash flows (dividends), which are in turn affected by macroeconomic events that may be influenced by oil shocks, is one justification for using the change in oil prices as a proxy for the change in key macroeconomic indicators. For example, the main economic variables in Gulf Cooperation Council (GCC) countries are affected by oil exports: earnings, government budget revenues and spending and aggregate demand. Correspondingly, oil price fluctuations should affect corporate output and earnings, domestic prices and stock market share prices in GCC countries.

1.2. Review of factors driving oil prices

The global oil market has seen substantial changes in the last few decades. Petroleum has grown into a global commodity as a result of increasing international commerce and the information technology revolution. Similarly, the crude oil price trajectory has changed in accordance with the historical structural changes of the oil market: starting off from being a regulated and integrated market until 1971, which then was replaced with the transitional period caused by the first and second oil shocks between 1973 and 1984, and finally to becoming a commodity and deregulated market (1986-present), where prices are determined based on expectations about supply-demand tightness (Mitchell, 2002). Kilian (2009) decomposes oil-price shocks into three categories using a structural VAR framework for the United States data: an oil-supply shock, an oil-demand shock driven by economic activity, and an oil-specific demand shock triggered by expectations of future changes in oil conditions. On the demand side, such expectations fluctuate based on changes in the global business cycle, which refers to aggregate demand shocks; and the uncertainty associated with unforeseen deficits in the levels of available supply relative to the anticipated levels of petroleum demand, which refers to precautionary demand shocks; (Kilian, 2009). When it comes to the supply side, the actual physical availability of crude oil and the uncertainty about future production capacity is what mainly impacts the market expectations (Fattouh, 2007). Collectively, these market imbalances correlate to an extensive history of oil price shocks that are believed to represent interruptions in oil production induced mostly by exogenous geopolitical events, such as wars, civil upheaval in OPEC states and others (Hamilton, 2009).

Demand shocks are helpful in explaining changes in oil prices. During the previous two decades, demand shocks in emerging and developed economies account for fifty to sixty percent of the changes in the real price of oil (Aastveit et al., 2014). Other empirical literature also actively demonstrates that demand shocks have a significant effect on oil price fluctuations (Bjornland, 2000; Dees et al., 2007; Fattouh, 2007; Kaufmann, 2011). Nevertheless, because there were no indices that capture shifts in the demand for industrial commodities, researchers have been facing a problem of quantifying the demand shocks. To tackle this Kilian (2009) constructs a new business cycle index that is intended to capture shifts in the global use of all industrial commodities and uses the index to examine its impact on the real price of oil and other fundamental indicators. He categorizes the primary determinants of the real price of oil as follows: (1) shocks to the current availability of oil, referred to as flow supply shocks; (2) shocks to the current demand for crude oil caused by fluctuations in the global business cycle, referred to as aggregate demand shocks; and (3) shocks caused by shifts in the precautionary demand for oil, referred to as precautionary demand shocks. The results of the study indicate that aggregate demand shocks tend to considerably increase oil prices and prove that the 2008 shock was demand-driven.

The 2020 oil price shock, which is studied in this paper, is an example of a demand shock. The global crude oil markets have experienced lackluster demand since March 2020. In order to minimize the spread of the new coronavirus (SARS-CoV-2), numerous governments around the globe have implemented virus containment measures, which have limited driving and various transportation services. Consequently, the rail, freight, and aviation industries were severely impacted, and the demand for gasoline, diesel, and jet fuel plummeted substantially. From the beginning of March to the beginning of April 2020, gasoline consumption decreased by 46.40 percent, which accounts for a decline from 9,449 to 5,065 thousand barrels per day; this was recognized as the greatest monthly decline in gasoline consumption in history. (EIA, as cited in Ma et al., 2021). As oil demand, which by definition is highly inelastic, faces stagnation, even small amounts of crude oil forced into the market result in a significant price drop, which was the case with all oil markets in March 2020: price of WTI futures, for instance, had been relatively stable since January 2019 trading between $50 and $60 per barrel, but once the pandemic was omnipresent worldwide, the price declined massively, falling from $50 per barrel to $30 per barrel in the period of only a month (Ma et al., 2021).

As regards to supply shocks, oil supply shocks account for a smaller fraction of real oil price variability in contrast to oil demand shocks (Baumeister and Peersman, 2013). For example, according to Kilian (2008), there is little evidence that the supply side of the oil market has been a significant influence on the real price of oil, nor did it play a major role during the oil price shocks of the 1970s and 1980s. Nevertheless, he emphasizes the necessity to identify observables that are likely to influence estimates of future oil supply availability and highlights the significance of capacity restrictions in crude oil production, which are deemed significant by his study. Killian's (2008b) findings make the following conclusions: (1) exogenous oil production shortfalls are of limited significance in explaining oil price changes during crisis periods; (2) of the episodes studied, only the 1980-81 oil price increases can be attributed to exogenous oil supply disruptions, albeit small by historical standards; and (3) the presence of capacity constraints in crude oil production amid large increases in oil demand has led to large oil price increases, especially in 1973, 1979, and 2004-05.

The 2014-16 oil price shock that is also chosen to be studied in this paper, is an example of a supply shock. During this period, oil prices experienced a sudden 70 percent drop from 2014-2016—one of the three largest drops in oil prices since World War II—, returning the prices to their historical averages. There is a general consensus that the decline in oil prices was due to supply-side factors. Arezki (2016) lists a number of concurring factors influencing oil price at the time, among them a decrease in shale production and removal of an oil export ban in the US, unexpectedly higher levels of output in countries such as Libya and Iraq, and a return of oil exports from Iran to international markets. Baumeister and Kilian (2016) identified four key causes of the 49-dollar decline in per-barrel price of Brent crude oil: an 11-dollar decline that was attributed to a global reduction in economic activity; a 16-dollar decline attributed to a mismatch between expected and actual oil production; a 9-dollar decline attributed to oil storage demand, and a 13-dollar decline attributed to further deterioration of the global economy. Another contributing factor to the drop in oil prices was the fact that it was preceded by such a prolonged term of rising oil prices; new technologies, the development of which was encouraged, during this time, were able to disrupt the global oil market as the price of extracting oil decreased and made it more realistic to sustain low oil prices for longer periods of time. A similarly impactful factor was a decision from OPEC to not cut back on oil production in late 2014 (Ellwanger et al., 2017); this supports the aforementioned empirical evidence by Baumeister and Kilian that a significant proportion of the initial price shock came about as the result of mismatched supply forecasting.

1.4. Review of empirical studies

Oil has had a significant influence in defining the economic and political development of industrialized economies throughout modern history. Numerous academics have studied the connections between oil price shocks and the macroeconomics of national economies during the past decades. Research on the relation of oil and macroeconomy has been greatly influenced by Hamilton's (1983) study of the impact of oil price shocks in US business cycles. According to Hamilton, who is often considered a pioneer in the study of effects of oil prices on macroeconomic indicators, a substantial spike in the price of crude petroleum preceded 7 of the 8 US post-World War II recessions. Hamilton suggested that in the absence of this prior spike in price, these recessions might have turned out to be less impactful or lasted for a different duration of time.

If, as proposed by Hamilton (1983), oil plays an essential role in the US and world economies, it can be anticipated that a direct correlation between changes of oil prices and changes in stock prices could be found, as stated by Huang et al (1996). Changes in the price of crude oil have always been regarded as one of the important factors for understanding fluctuations in stock prices. Despite that, economists are very much divided on the topic of the relationship between stock market returns and oil prices.

For instance, Kling (1985) suggests that increases in crude oil prices and stock market declines are very much related. Kling's investigation of the relationship between the S&P500, various major industries (among them the air transport, automobile and capital goods industries) and crude oil prices found that oil price shocks were followed by a decline of several months in select industries. In contrast, Chen et al. (1986) proposed that changes in monthly oil prices have no effect on asset prices. An empirical study done by Jones and Kaul (1996) focused on testing the reaction of advanced stock markets (Canada, UK, Japan, and US) to oil price shocks during the postwar period on the basis of the standard cash flow dividend valuation model. The regression analysis performed by Jones and Kaul showed that oil price shocks had adverse effects on real stock returns in all markets, and additionally caused excess volatility in the Japanese and UK stock markets. However, Huang et al. (1996), who used vector autoregressive (VAR) analysis to examine the relationship between prices of oil futures, stock returns and daily interest rates, discovered no negative relationship between stock returns and changes in the price of oil futures. Wei (2003), using a putty-clay investment model, suggested that an energy price shock in 1973-1974 could not have, by itself, had a significant enough effect to influence the 1974 decline in US stock prices. As summarized by Degiannakis et al. (2018), that the relationship between oil prices and stock markets is a time-varying correlation is a fairly recent consideration in the existing literature; a study by Filis et al. (2011) was one of the first studies to consider this, and found that demand-side shocks to oil prices in times of significant global change, such as those instigated by wars or financial crises, had a much greater influence on stock market prices when contrasted with supply-side shocks such as those caused by production cuts.

2. DATA AND METHODOLOGY

This chapter will first contain an overview of the data used in the later analysis and justification for its inclusion of the study. Then, explanation of and justification of Vector Autoregression as the selected analysis method will be given, as well as descriptions of further methods which are used to test the VAR model. The author chose to use the programming language R to conduct the analysis in this study due to its open-source nature making it “an ideal environment for reproducible econometric research” (Kleiber and Zeileis, 2008). The R code used can be found in the link in Appendix 1.

2.1. Data and descriptive statistics

Three sets of data were chosen for the purpose of this study: composite daily total return indices for all companies listed on the New York Stock Exchange (NYSE) and the Euro STOXX 600, and daily Brent crude oil price, from the period of 2013-2021. The data for NYSE (RIC ticker in EIKON: .NYA) and STOXX (RIC ticker in EIKON: .STOXX) was retrieved from the EIKON database, while data for Brent crude oil price was obtained from the U.S. Department of Energy, Energy Information Administration. The selection of which indices to use was based on examples of data selected for previous studies in the same field, such as research done by Chang et al. (2013), who analysed the impact of Brent and WTI oil prices on four stock market return indexes, including NYSE; and Fayyad and Daly (2011), who looked at the relationship between shocks to Brent crude oil price and the weighted equity market indices of stock markets in seven countries. Because one of the aims of this paper is to investigate whether specific oil price shocks (in 2014-2016 and in 2020) negatively impacted return indices for the aforementioned markets, the data was separated into two sets corresponding to these time periods (2013-2017 and 2019-2021), in order to look at each price shock in isolation.

The dataset was first compiled in Excel using an INDEX MATCH function to match the data for market return indexes to the oil price on corresponding days. Any day where a price or return index was missing was removed from the dataset. The data was then separated into two separate tables (for the periods 2013-2017 and 2019-2021 respectively), which were imported into R. After doing further cleaning of the data in R by formatting the date columns from text strings to proper dates, the data for oil prices and STOXX and NYSE indexes, for each of the two tables, was converted into a time series. Zeileis and Grothendieck (2005) and Kleiber and Zeileis (2008) have made note of the fact that the "ts" object class, which is contained in the baseline version of R and is typically used for representing time series data, is only suitable when the data contained is a regular series of annual, quarterly or monthly data, and when the data is not missing any values in the series. Because the data used in this paper is a daily series with missing dates, the "xts" object class from the xts package for R was used to represent the time series. Figures 1 and 2 show the visualisation of the time series data:

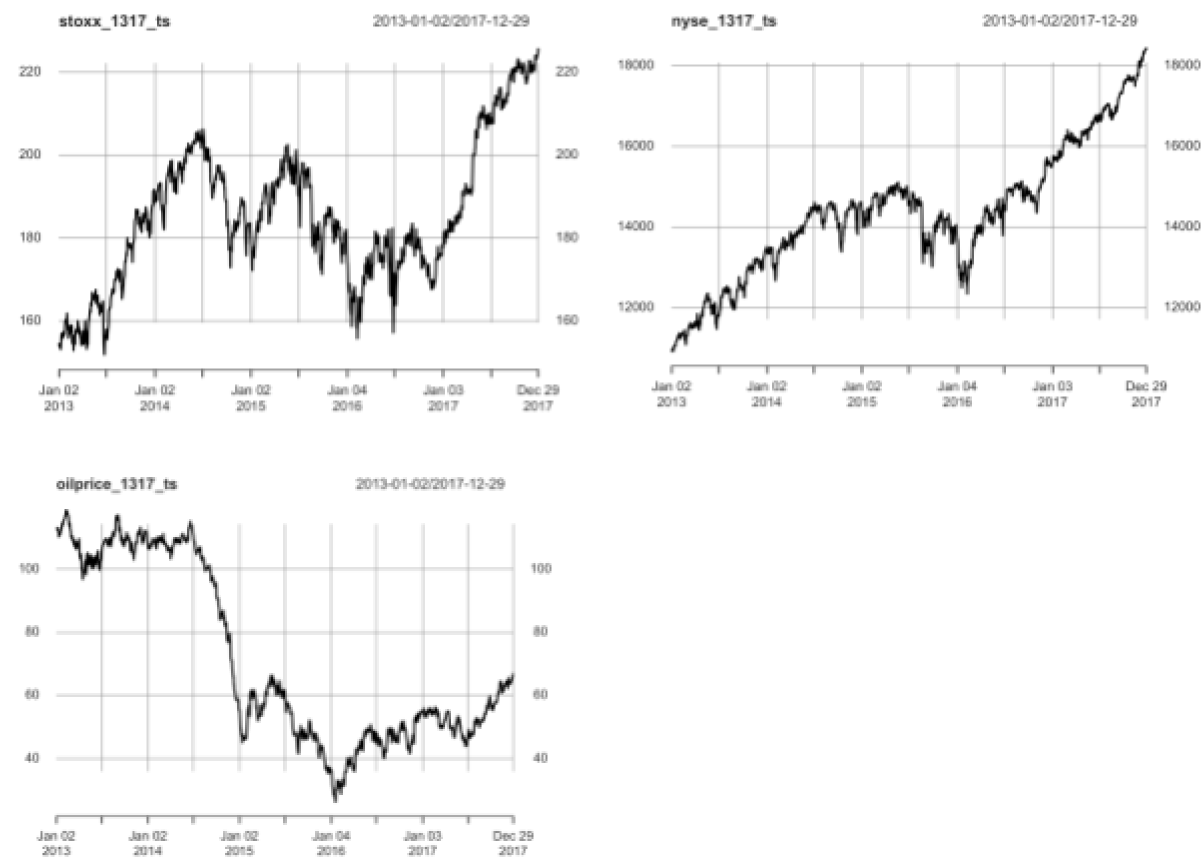


Figure 1. Time series data for 2013-2017.
Source: author's calculations

The time series of variables for 2013-2017 (Figure 2, above) shows that oil prices dropped drastically in early 2015, and again in early 2016 before starting to make a recovery; comparing with the drops in stock market returns, STOXX also suffered a drop in early 2015, while NYSE did not. Both stock markets seem to follow the trend of oil price slowly rising again before dropping in 2016 at the same time as the oil price did. In the time series of variables for 2019-2021 (Figure 3, below), the oil prices and stock market returns appear to very closely follow the same pattern; all of them experience a sharp drop around January 2020, and begin to steadily rise again until in early 2021 they reach the levels they were at before the drop.

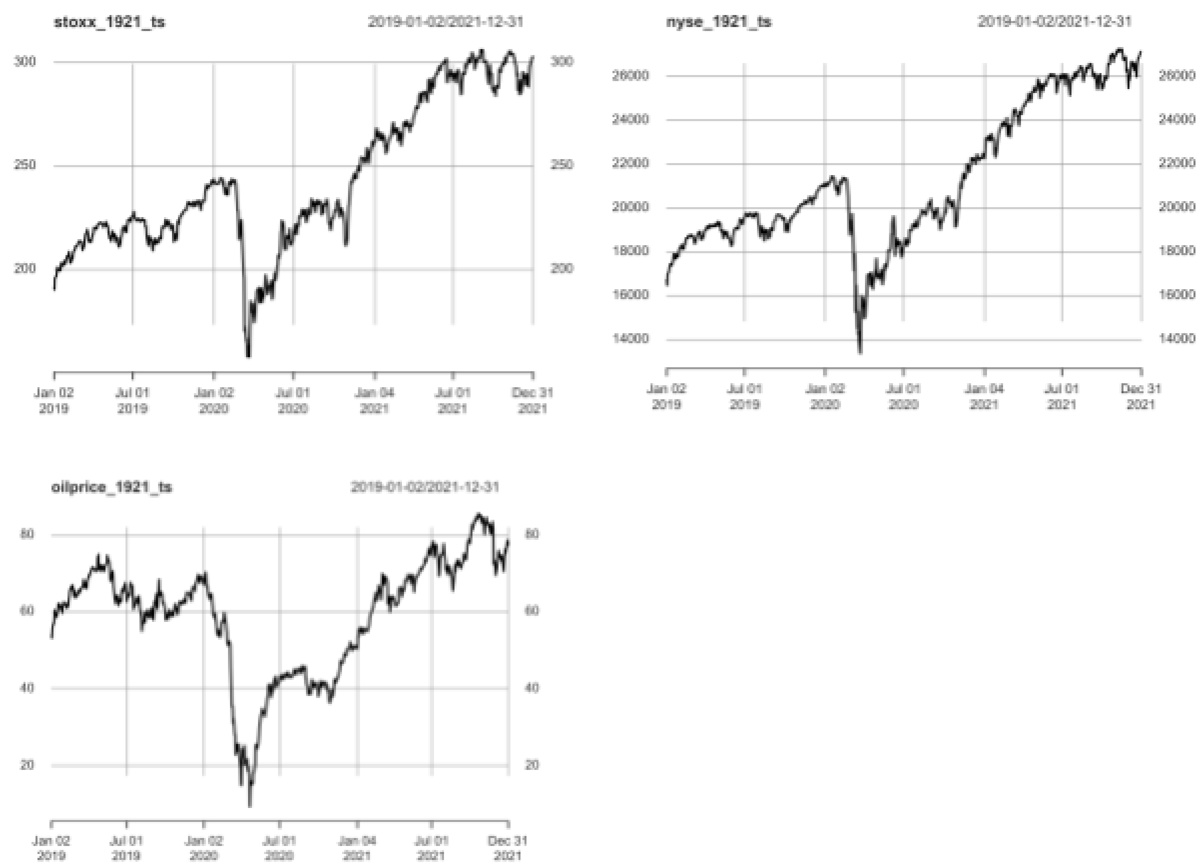


Figure 2. Time series data for 2019-2021.
Source: author’s calculations

Table 1 presents an overview of descriptive statistics of each variable in the dataset. Descriptive statistics were calculated using the pastecs package for R.

Table 1. Descriptive statistics for data used.

Sample period	Data	N	Max	Min	Median	Mean	Skewness	Kurtosis	Standard deviation
02-01-2013-29-12-2017	STOXX	1272	225.85	151.67	183.63	185.63	0.29	-0.41	16.87
	NYSE	1272	18451.85	10912.13	14376.29	14350.36	0.23	-0.19	1612.78
	Oil price	1272	118.9	26.01	57.7	71.39	0.4	-1.53	28.08
02-01-2019-31-12-2021	STOXX	765	306.55	157.33	231.29	242.73	0.31	-0.95	35.38
	NYSE	765	27281.79	13335.83	20096.84	21313.7	0.37	-1.02	3231.46
	Oil price	765	85.76	9.12	62.6	59.02	-0.82	0.28	15.12

Source: author's calculations

The data for both oil price and stock returns is slightly asymmetrical, due to the skewness values not being equal to zero. With the exception of oil price in 2019-2021, all data is skewed to the right. To check how much variability is in the dataset, the standard deviation can be compared to the mean. For both time periods, standard deviation has a lower value than the mean, which points to there not being much variability. The kurtosis values for data in 2013-2017 point to the data having a light-tailed distribution, which suggests there are not many outliers in the datasets. In 2019-2020, the only dataset with a positive kurtosis value, or heavy-tailed distribution, is the data for oil price, so it can be inferenced that there were more outlying values for oil prices in this time period.

In addition to the original data, logarithmically-differenced data was used for the actual estimation of the VAR model (further explanation for this can be found in section 2.2.). Figures 3 and 4 show the visualisation of the time series data after applying logarithmic differences.

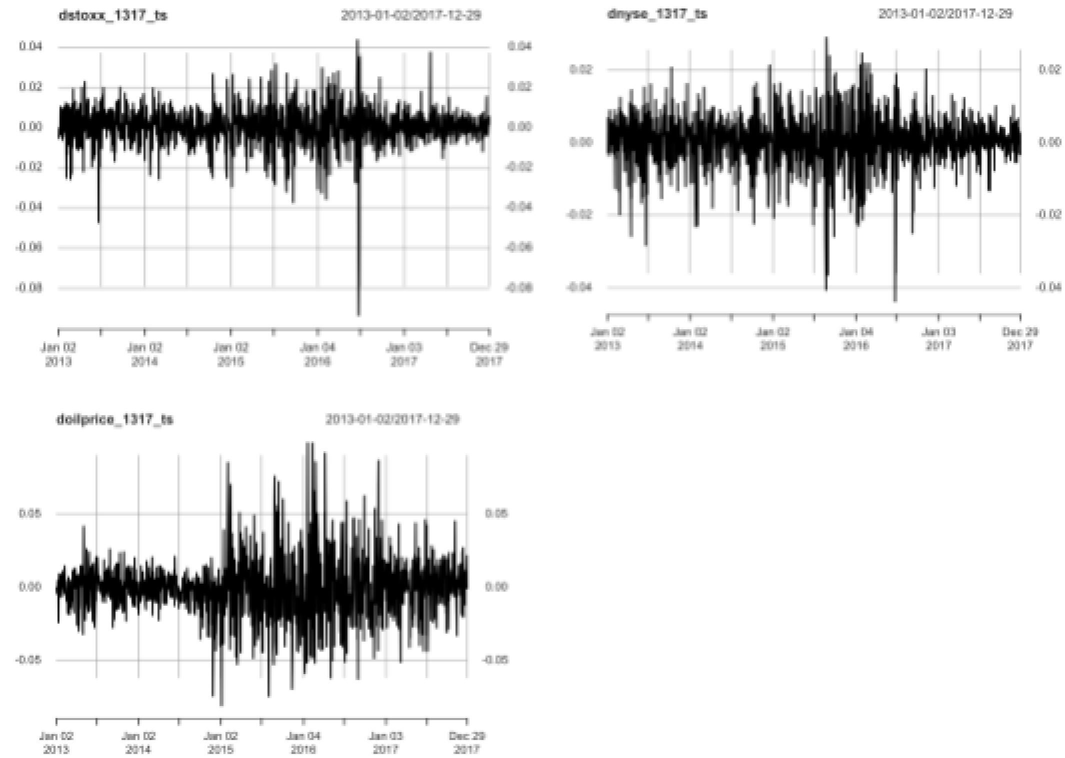


Figure 3. Stationary time series data for 2013-2017.
Source: author’s calculations

Looking at the stationary data for 2013-2017, it is clear that both STOXX and NYSE experienced a significant drop in returns in mid-2016, with NYSE experiencing an additional significant drop in mid-2015. The initial price drop of oil at the end of 2014 can also be seen clearly. The fluctuations in both stock markets and oil price appear to be more extreme, especially with significant outliers in oil price. In contrast, the stationary data for 2019-2021 has a much more contained fluctuation—although there are large drops in returns and oil prices in mid-2020, they appear to recover quickly and return to pre-drop levels of fluctuations by the end of 2020.

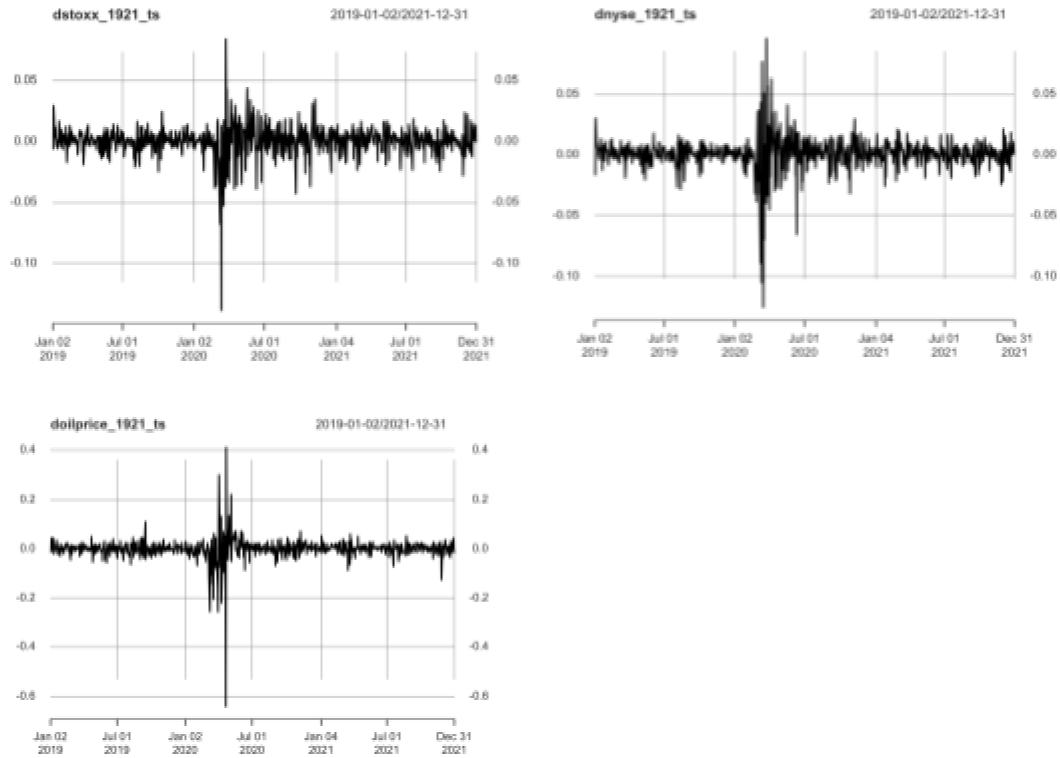


Figure 4. Stationary time series data for 2019-2021.
Source: author's calculations

The descriptive statistics for this data can be seen in Table 2 below:

Table 2. Descriptive statistics for logarithmically-differenced data

Sample period	Data	N	Max	Min	Median	Mean	Skewness	Kurtosis	Standard deviation
02-01-2013-29-12-2017	STOXX	1271	0.04	-0.09	0.00	0.00	-0.95	9.18	0.01
	NYSE	1271	0.02	-0.04	0.00	0.00	-0.59	2.99	0.01
	Oil price	1271	-0.08	0.10	0.00	-0.00	0.42	3.13	0.02
02-01-2019-31-12-2021	STOXX	764	0.08	-0.14	0.00	0.00	-1.93	23.65	0.01
	NYSE	764	0.10	-0.13	0.00	0.00	-1.48	20.37	0.01
	Oil price	764	0.41	-0.64	0.00	0.00	-3.10	70.58	0.04

Source: author's calculations

When looking at the characteristics of the logarithmically-differenced data compared to the original data, then several things can be noted: first, kurtosis values for all data increased significantly, and the data can be described as heaving a heavy-tailed distribution with more outlying values. The amount of variability in the data also increased, due to the values for standard deviation becoming slightly higher than the mean. Finally, the skewness shows that all data became skewed to the left rather than to the right.

2.2. Methodology

The type of analysis chosen for this study was Vector Autoregression (VAR) analysis, which is widely used in existing studies on the relations between oil prices and stock markets: take, for example, Scholtens and Yurtsever (2012), Fayyad and Daly (2011), and Papapetrou (2001). Because VAR allows for study of simultaneous interactions between time series (Huang et al., 1996) and sets no restrictions on the relationships of variables used (Abu Zarour, 2006), it is well-suited to analysing the unpredictability of oil price shocks. Specifically, the type of VAR analysis used in this study is a reduced form VAR, which uses separate linear equations, estimated using ordinary least squares (OLS) regression, to represent the variables in the analysis. The equations can be broken down into three main components: the past, or lagged values of a given variable, the past values of other variables in the model, and an uncorrelated error term (Stock & Watson, 2001). The standard equation for reduced form VAR, as can be seen in Floyd (2005) and further clarified in Hatemi-J (2003), can be expressed as Equation 1:

$$\mathrm{y}_t = \mathrm{b} + \mathrm{B}\ \mathrm{y}_{t-1} + \mathrm{u}_t$$

where

y_t – the time series variable represented by the equation,

b – a matrix of constant coefficients representing the intercept of the equation,

B – an unstandardised regression coefficient,

u_t – the uncorrelated error term.

The general process to adhere to when performing a VAR analysis can be seen in Figure 5 below – the first step is to specify the parameters of the VAR model, including the order of variables and the number of lags which should be used for estimation. According to Lütkepohl (2005), although the variable order cannot be determined by way of any statistical method, the first variable in the model should be “the only one with a potential immediate impact on all other variables”. If the variables are in the wrong order, the interpretation of the model may be completely different. Before selecting the lag order, a unit root test should first be used to test whether the data is stationary. Campbell and Perron (1991) suggest that the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981) is generally preferred for testing stationarity in time series data as opposed to the alternative Phillips-Perron test, as the Phillips-Perron statistic can be unreliable “when the data-generating process has a predominance of negative autocorrelations in first difference”. One drawback of the ADF test (as discussed by, for example, Campbell and Perron, 1991 and Hall, 1994) is that it requires the consideration of lags when calculating the test results, whereas the Phillips-Perron test does not. In R, the number of lags required is automatically calculated when the adf.test() function is run; this limitation of using an ADF test is still necessary to keep in mind, however, when considering the test output presented by R.

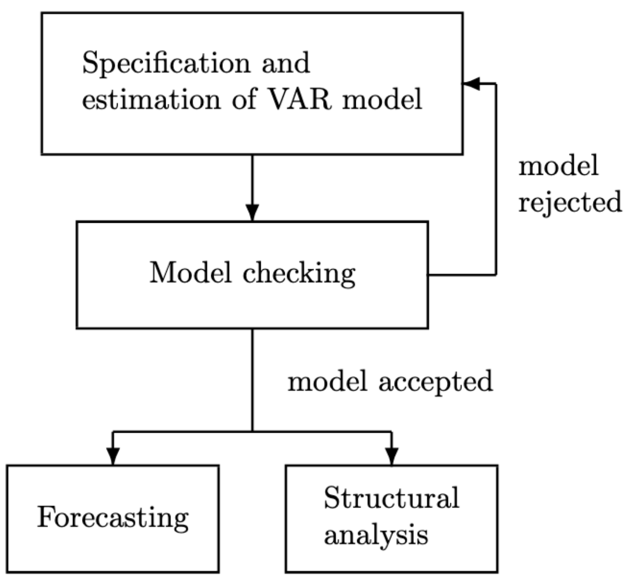


Figure 5. Process of VAR analysis.
Source: Lütkepohl (2005).

In order to determine if the data selected could indeed be used for a VAR model, an ADF test, where the null hypothesis is that the data is non-stationary, was performed on the original (non-logarithmically differenced) dataset. The breakdown of ADF test results for each dataset and variable can be seen in Appendix 2 (Table 1). According to the results of the initial ADF tests, the null hypothesis that the data was non-stationary could not be rejected. In an attempt to solve this, differences of logarithms were then applied to the data using the diff(log()) function in R. The ADF tests for the logarithmically differenced data produced statistically significant p-values (see Appendix 2, Table 2), which proved that the data was stationary and was suitable to be used for VAR analysis.

The next phase of preparing the VAR model, following the ADF tests, was to select the number of lags which should be used in the model. According to Lütkepohl (2005), the lowest Akaike Information criterion (AIC) value for each time series variable can be used to select the appropriate lag order. Although R gives three other possible information criteria which can be used to select lags—the Hannan-Quinn criterion (HQ), the Schwarz Information criterion (SC), and Akaike's Final Prediction Error (FPE)—it is not common practice to use more than one (Ivanov and Killian, 2005). The justification for choosing AIC over other information criteria is based on a study by Ivanov and Killian (2005), where the authors studied the accuracy of information criteria for monthly and quarterly VAR models and found that the AIC was more accurate for monthly data while the HQ was more accurate for quarterly data. Although the data used in this paper is daily, rather than quarterly or monthly, the conclusion drawn from Ivanov and Killian's study is that AIC would be best to use for data with a higher frequency. Therefore, it was decided to use AIC to determine the lag order. The formula used to calculate AIC, as devised by Akaike (1974) is as expressed in Equation 2:

$$\text{AIC} = (-2) \log(\text{maximum likelihood}) + 2k$$

where

k – the number of independently adjusted parameters in the model

Based on the AIC, the suggested number of lags for the data from 2013-2017 was 5, and for 2019-2021 10 lags. Two separate VAR models were then constructed, the results of which will be presented in the following chapter. The next step in the process of performing a VAR analysis (Figure 5) is to check the model after it has been estimated. The estimations of a regression modal can only lead to valid assumptions if the model satisfies the following criteria: “error terms are white noise, i.e. expected zero mean, no autocorrelations, constant variance, and normal distribution of errors.” (Hatemi-J, 2003). The presence of autocorrelation in a model can point to issues such as missing variables, in which case the estimates given would not be accurate. For this reason, it is ideal that autocorrelation is not present at all (Hatemi-J, 2003). Checking for autocorrelation can be done using a Portmanteau test, the two most well-known versions of which are the Box-Pierce test, first mentioned by Box and Pierce (1970), and the Ljung-Box test, developed by Ljung and Box (1978), which itself is an improved version of the Box-Pierce test and was chosen by the author as the method used to check for autocorrelation in this study. As elaborated on by Box and Pierce (1970), this kind of diagnostic check is necessary not only to judge the accuracy of interpretation of the model but to help identify ways in which the fit of the model could be improved. In this paper, residuals of the model were additionally tested for heteroscedasticity (volatility) – significant heteroscedasticity in a model can lead to errors in forecasting, due to the fact that it points to the presence of extreme outliers (Lütkepohl, 2005). Testing for heteroscedasticity of residuals in a regression model can be done using ARCH (Autoregressive Conditional Heteroscedastic) tests, a class of tests popularised by Robert Engle (1982) (Bollerslev, 2008). The most popular variation is the GARCH test, according to Kleiber and Zeileis (2008).

Referring again to Figure 5, if the model is accepted based on diagnostic checks then the next step is to proceed with forecasting and structural analysis. The relations between variables in VAR models can be interpreted through a series of impulse response functions, which are a series of matrices describing the response of a time series y_1 to a shock to an individual equation in the current period which is equivalent to one standard deviation (Floyd, 2005).

3. ANALYSIS

In this chapter, the process of estimating the VAR models for the selected time periods (2013-2017 and 2019-2021), on the basis of the methodology outlined in Chapter 2, is described. The author then comments on VAR model estimates, various diagnostics applied to the models, and results of impulse response functions and error variance decomposition. Finally, there is a brief discussion on the overall results of the analysis and what improvements could be made in future studies on the topic.

3.1. VAR estimation

Tables 3 and 4 below show the estimates of the VAR models for both selected time periods. Statistically significanct estimates are marked with codes according to their significance levels: *** (significance level of 0), ** (0.001), ** (0.01) and * (0.05). Looking at the coefficients of the equation *Oil.Price* for 2013-2017, a decrease in oil prices seems to have an initial negative impact on STOXX before the effect wears off, while it has the opposite effect on NYSE. However, the adjusted R-squared value shows that the data does not fit very well to the model—it is highest (0.089) for the equation *STOXX,* and lower for *NYSE* and *Oil.Price,* but overall suggests a low level of correlation for all equations. The critical value of F for this model is 1.67, based on 15 and 1250 degrees of freedom and a probability level of 0.05. Again, this shows that only the coefficients of *STOXX* can be reliably interpreted, as the F-statistic for *STOXX* is much higher than the critical value, while it is below the critical value for *NYSE* and only slightly higher for *Oil.Price*. The p-values for equations for *Oil.Price* and *NYSE* are also above a significance level of 0.05, making only the equation for *STOXX* statistically significant.

Table 3. VAR Model for 2013-2017

	Oil.Price		**NYSE**		**STOXX**	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Oil.Price (-1)	0.025	0.030	0.006	0.011	0.002	0.014
Oil.Price (-2)	0.018	0.030	0.016	0.011	0.011	0.014
Oil.Price (-3)	-0.014	0.030	-0.000	0.011	-0.001	0.014
Oil.Price (-4)	-0.002	0.030	-0.014	0.011	**-0.037	0.014
Oil.Price (-5)	0.005	0.030	0.006	0.011	-0.014	0.014
NYSE (-1)	**0.319	0.101	-0.050	0.038	***0.437	0.047
NYSE (-2)	*0.215	0.108	-0.058	0.041	0.097	0.050
NYSE (-3)	-0.072	0.109	0.013	0.041	*0.103	0.050
NYSE (-4)	-0.109	0.108	-0.005	0.041	0.062	0.050
NYSE (-5)	**-0.301	0.104	-0.019	0.039	0.080	0.048
STOXX (-1)	-0.144	0.082	0.030	0.031	***-0.208	0.038
STOXX (-2)	-0.106	0.083	-0.000	0.032	**-0.127	0.039
STOXX (-3)	0.134	0.084	-0.006	0.032	-0.059	0.039
STOXX (-4)	0.078	0.084	-0.039	0.032	**-0.127	0.039
STOXX (-5)	0.107	0.786	-0.039	0.030	***-0.125	0.036
const	-0.000	0.001	*0.000	0.000	0.000	0.000
F-statistic		1.88		1.2		9.26
P-value		0.212		0.261		<0.000
Adjusted R-squared		0.010		0.002		0.089

Source: author's calculations

For 2019-2021, a decrease in *Oil.Price* seems to have minimal negative impact on STOXX returns, while it has a more immediate negative impact on NYSE returns until the fifth lag. Here the adjusted R-squared values are higher than in the 2013-2017 model, although still not high enough to prove that there is high correlation between variables. The critical value of F is 1.47, based on 30 and 723 degrees of freedom and a probability level of 0.05. Here the F-statistics for all equations are higher than the critical value, which suggests that results are statistically significant. The p-values for all equations are also below a significance level of 0.05.

Table 4. VAR model for 2019-2021

	Oil.Price		NYSE		STOXX	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Oil.Price (-1)	-0.045	0.040	0.001	0.011	*-0.021	0.010
Oil.Price (-2)	*-0.083	0.039	*0.026	0.011	*0.025	0.010
Oil.Price (-3)	0.019	0.039	***0.050	0.011	**0.032	0.010
Oil.Price (-4)	0.041	0.039	-0.008	0.011	-0.001	0.010
Oil.Price (-5)	0.055	0.039	0.003	0.011	-0.002	0.010
Oil.Price (-6)	0.067	0.039	**-0.030	0.011	*-0.022	0.010
Oil.Price (-7)	**-0.116	0.039	***-0.038	0.011	-0.020	0.010
Oil.Price (-8)	*0.100	0.039	0.011	0.011	-0.007	0.010
Oil.Price (-9)	0.062	0.039	0.018	0.011	0.045	0.010
Oil.Price (-10)	***-0.218	0.040	0.000	0.011	***-0.004	0.010
NYSE (-1)	*-0.050	0.205	**-0.175	0.059	***0.395	0.054
NYSE (-2)	*-0.514	0.235	*-0.167	0.067	0.005	0.062
NYSE (-3)	***-0.857	0.235	***-0.258	0.068	-0.110	0.062
NYSE (-4)	**-0.781	0.237	***-0.307	0.068	*-0.147	0.062
NYSE (-5)	-0.426	0.237	-0.073	0.068	0.105	0.062
NYSE (-6)	0.053	0.238	**-0.207	0.068	*-0.129	0.063
NYSE (-7)	**0.679	0.237	**0.209	0.068	***0.238	0.062
NYSE (-8)	0.194	0.239	0.008	0.068	0.073	0.063
NYSE (-9)	*-0.541	0.230	**0.210	0.066	*0.145	0.060
NYSE (-10)	0.201	0.212	0.031	0.061	0.025	0.056
STOXX (-1)	*0.500	0.221	0.031	0.063	***-0.214	0.058
STOXX (-2)	**0.596	0.224	***0.348	0.064	*0.118	0.059
STOXX (-3)	**0.622	0.227	***0.231	0.065	0.057	0.060
STOXX (-4)	***0.970	0.229	***0.325	0.066	**0.198	0.060
STOXX (-5)	0.218	0.231	0.120	0.066	-0.028	0.061
STOXX (-6)	-0.001	0.231	0.127	0.066	-0.015	0.061
STOXX (-7)	0.340	0.233	-0.039	0.067	*-0.121	0.061
STOXX (-8)	-0.092	0.232	-0.063	0.067	**-0.163	0.061
STOXX (-9)	0.401	0.226	**-0.199	0.065	**-0.187	0.060
STOXX (-10)	0.398	0.203	0.024	0.058	0.025	0.053
const	-0.000	0.002	0.000	0.000	0.000	0.000

F-statistic	5.17	10.3	9.18
P-value	<0.000	<0.000	<0.000
Adjusted R-squared	0.143	0.269	0.246

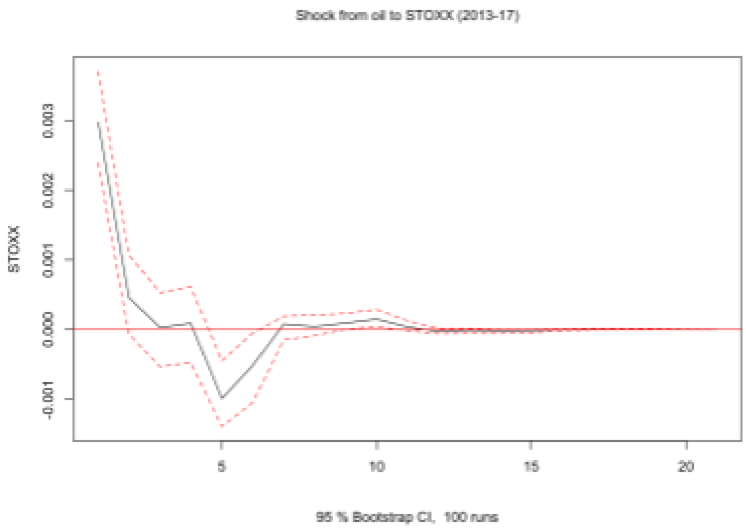
Source: author's calculations

Both models were run through a series of diagnostic tests following their estimation; the first was a test for serial correlation, done with an asymptotic Portmanteau test. If the p-value of the Portmanteau test is lower than 0.05, then there is serial correlation in the model; however, the 2013-2017 model had a p-value of 0.1 in the Portmanteau test, meaning this problem was avoided. Other tests done were an ARCH test for heteroscedasticity, a normality test to check if residuals were normally distributed, and an OLS-CUSUM test for stability; the OLS-CUSUM test showed that the model was stable (see Appendix 3, Figure 1), but it failed the ARCH and normality tests, meaning that the model contained heteroscedasticity and residuals are not normally distributed. The model for 2019-2021, unfortunately, failed not only the ARCH and normality tests, but also the Portmanteau test, meaning that the model had serial correlation, was heteroscedastic and had residuals which were not normally distributed. Like the model for 2013-2017, however, it was stable according to an OLS-CUSUM test (see Appendix 2, Figure 2).

A Ljung-Box test was also performed to check if the individual variables contained serial correlation. In the case of the model for 2013-2017, the data for STOXX had a p-value of <0.000, meaning that serial correlation was present; NYSE and oil price, however, had p-values of 0.08 and 0.3, respectively, which meant the null hypothesis of the Ljung-Box test that there is no serial correlation could not be rejected. For the 2019-2021 model, all individual variables also contained serial correlation according to the Ljung-Box test: tests on STOXX, NYSE and oil price returned p-values of <0.000 for all variables.

3.2. Impulse response functions

Next, impulse response functions were visualised for both VAR models to examine the impacts of oil shocks on STOXX and NYSE return indexes. Figure 6 shows the impulse responses for 2013-2017:



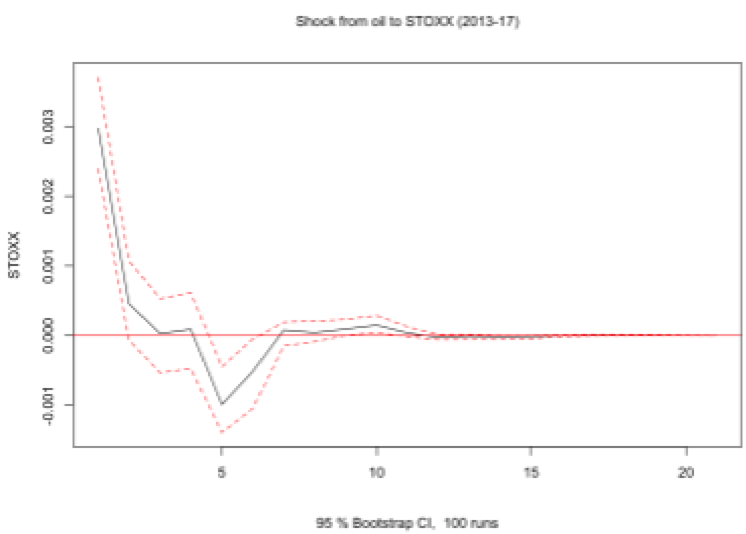


Figure 6. Impulse response functions for 2013-2017 VAR model.
Source: author’s calculations

According to the impulse response functions, the impact of the oil price on STOXX and NYSE decreases to 0 quite fast as time goes on, meaning that the oil price shock in this time period had a minimal impact on the stock markets.

The impulse response functions for the 2019-2021 model can be seen in Figure 7 below:

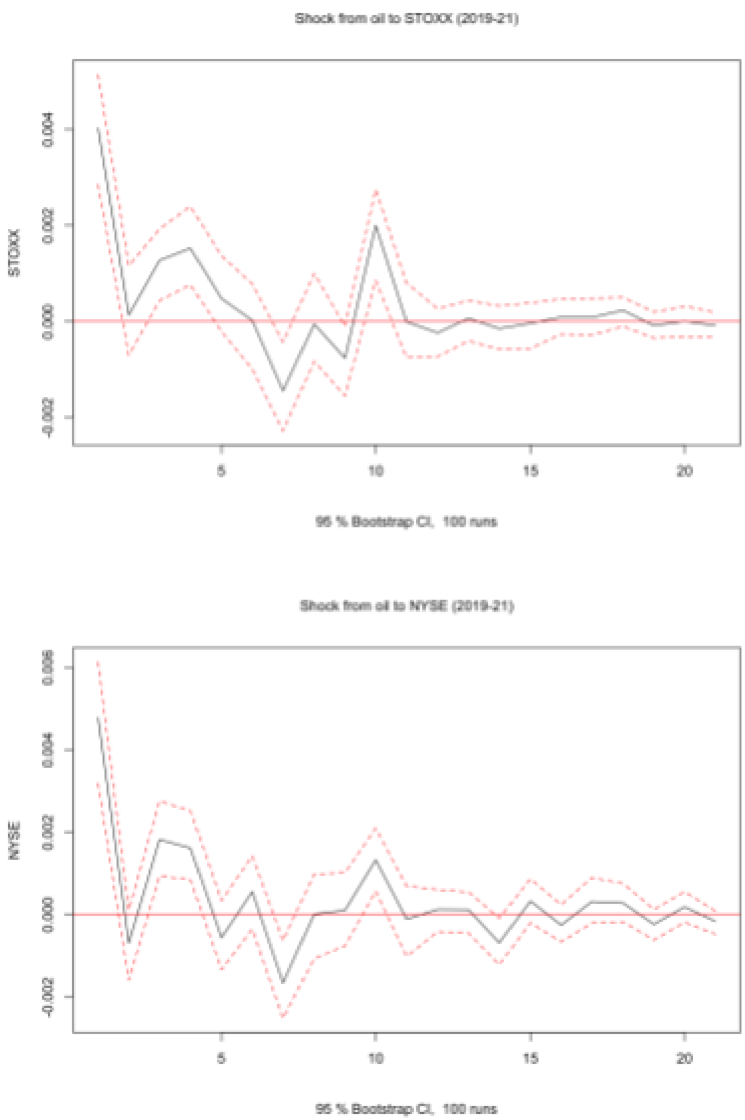


Figure 7. Impulse response functions for 2019-2021 VAR model.
Source: author's calculations

According to the impulse response functions, there is a much stronger impact of oil price shock on the stock markets in this time period.

3.3. Error variance decomposition

Forecast error variance decomposition (FEVD) shows the effect a shock to one variable has on itself as well as other variables in the model. It is important to note that the order of variables in the model also has an influence on the results of FEVD (Wichmann et al., 2019). Using the fevd() function in R to forecast for 5 periods ahead, the error variance decomposition was calculated for both VAR models, which were ordered as 1) Oil.Price, 2) NYSE and 3) STOXX. The results of FEVD can be seen in Tables 5 and 6 below:

Table 5. Error variance decomposition for 2013-2017 VAR model

	Oil.Price			***NYSE***			***STOXX***		
n periods ahead	**Oil.Price**	**NYSE**	**STOXX**	**Oil.Price**	**NYSE**	**STOXX**	**Oil.Price**	**NYSE**	**STOXX**
1	1.000	0.000	0.000	0.097	0.903	0.000	0.103	0.351	0.546
2	0.992	0.006	0.002	0.097	0.902	0.001	0.098	0.371	0.531
3	0.990	0.007	0.003	0.098	0.901	0.001	0.098	0.371	0.531
4	0.987	0.007	0.006	0.098	0.901	0.001	0.098	0.371	0.531
5	0.987	0.007	0.006	0.100	0.898	0.002	0.107	0.366	0.527

Source: author’s calculations

According to the results, a shock to oil price had a relatively equal impact on returns for STOXX and NYSE from 2013-2017 (Table 5). It is of note that NYSE returns also influenced STOXX returns more than oil price did, though STOXX had less influence on NYSE than oil. Looking at the time period 2019-2021 (Table 6), similar results can be observed – NYSE returns had a greater impact on STOXX returns than oil did, while STOXX barely influenced NYSE at all.

Table 6. Error variance decomposition for 2019-2021 VAR model

	Oil.Price			***NYSE***			***STOXX***		
n periods ahead	**Oil.Price**	**NYSE**	**STOXX**	**Oil.Price**	**NYSE**	**Oil**	**Oil.Price**	**NYSE**	**STOXX**
1	1.000	0.000	0.000	0.141	0.859	0.000	0.114	0.493	0.393
2	0.998	0.002	0.000	0.137	0.862	0.001	0.106	0.496	0.397
3	0.990	0.002	0.008	0.144	0.806	0.050	0.111	0.483	0.406

4	0.986	0.003	0.011	0.160	0.791	0.049	0.133	0.470	0.397
5	0.981	0.004	0.015	0.158	0.772	0.070	0.131	0.466	0.403

Source: author's calculations

Before making any conclusions on this, however, it was also necessary to test if the error variance decomposition in this case was sensitive to the order of variables in the model. In order to do so, reverse variants of both models, ordered as 1) STOXX, 2) NYSE and 3) Oil.Price were also built and tested for FEVD. The results of this can be seen in Tables 7:

Table 7. Error variance decomposition for 2013-2017 reverse VAR model

	STOXX			***NYSE***			***Oil.Price***		
n periods ahead	**STOXX**	**NYSE**	**Oil**	**STOXX**	**NYSE**	**Oil**	**STOXX**	**NYSE**	**Oil**
1	1.000	0.000	0.000	0.439	0.561	0.000	0.103	0.018	0.879
2	0.933	0.067	0.000	0.439	0.561	0.000	0.103	0.026	0.871
3	0.933	0.067	0.001	0.438	0.560	0.002	0.102	0.028	0.87
4	0.932	0.067	0.001	0.438	0.560	0.002	0.104	0.029	0.867
5	0.928	0.066	0.006	0.440	0.557	0.003	0.104	0.029	0.867

Source: author's calculations

In the reverse FEVD for 2013-2017 (Table 7), oil had barely any impact at all on STOXX and NYSE returns. Looking at the impact of shocks in the equations for STOXX and NYSE, the returns of the two stock markets had a greater influence on each other than oil prices, did, especially looking at the impact of STOXX on NYSE returns.

Table 8. Error variance decomposition for 2019-2021 reverse VAR model

	STOXX			***NYSE***			***Oil.Price***		
n periods ahead	**STOXX**	**NYSE**	**Oil.Price**	**STOXX**	**NYSE**	**Oil.Price**	**STOXX**	**NYSE**	**Oil.Price**
1	1.000	0.000	0.000	0.605	0.395	0.000	0.114	0.032	0.854
2	0.930	0.069	0.001	0.609	0.390	0.001	0.115	0.034	0.851
3	0.921	0.074	0.005	0.641	0.355	0.004	0.113	0.042	0.844
4	0.893	0.075	0.032	0.622	0.346	0.032	0.113	0.045	0.842

5	0.881	0.087	0.033	0.609	0.358	0.033	0.118	0.045	0.836

Source: author's calculations

Looking at the reverse FEVD for 2019-2021 (Table 8), similar conclusions can be drawn as for the reverse of the 2013-2017 model – shocks to oil price influenced stock markets less than stock markets influenced each other. According to Brooks (2019), the fact that the results of variance decomposition are sensitive to variable order points to the residuals of the equations having a higher correlation.

3.4. Discussion

According to the results of the author's analysis, oil prices did not have a great impact on STOXX and NYSE returns during the chosen time periods of 2013-2017 and 2019-2021. There is still, however, low reliability of the VAR model used for both instances, so it could be the case that VAR is not the most suitable method which could be used for analysing this data. When looking at forecasts of how oil prices affect stock market returns, impulse response functions showed that any impact of oil price shocks does not last for a very long time. The forecast error variance decomposition also helped to draw conclusions that oil price shocks do not significantly affect stock returns.

The analysis in this paper leads the author to draw similar conclusions as those made by Chang et al. (2013), Apergis and Miller (2009), and Cunado and Perez (2014), which found low correlations between oil price shocks and stock market returns. Chang et al. (2013), for example, note that "the conditional shocks were correlated only in the same market, and not across markets", while Cunado and Perez (2014) suggest that an oil price shock alone can not be expected to have any significant impact on stock markets, and it is instead crucial to take into account the underlying cause of the shock.

Based on the current analysis, a suggestion for further research would be to investigate the impacts of oil prices on a wider variety of stock market return indexes; due to the fact that return indexes for only two stock markets were used in this paper, there was little opportunity to investigate whether a country being a major oil producer plays a role in how oil prices impact its stock market, as this paper lacks sufficient samples for comparison. In addition to a greater variety of return indexes, there is room to add nuance to the definition of oil price shocks, such as making a distinction between supply- and demand-side shocks. Deeper analysis could also be done to account for other factors which had the potential to impact stock markets during the proposed time periods; the Russia-Saudi Arabia oil price war, for instance, also took place during the COVID-19 pandemic, which makes it difficult to claim that the stock market during this time period was significantly influenced by oil price shocks alone.

CONCLUSION

To recapitulate the original aim of this paper, the author sought to investigate 1) whether oil price shocks in 2014-2016 and in 2020 had a negative impact on American and European stock market returns; and 2) whether the impacts of oil price shocks on stock market returns differ significantly depending on if the shock comes from the demand or the supply side, using data for NYSE and STOXX returns and Brent crude oil prices. The VAR model showed that there was some correlation between crude oil prices and stock market returns during these time periods, but only the model for 2020 (overall time period of 2019-21) showed statistical significance, while for the model for 2014-2016 (time period of 2013-17), only the equation for STOXX was statistically significant. The models also did not hold up well to diagnostic tests; both models were heteroscedastic and did not have normal distribution of residuals, while the model for 2019-21 had serial correlation. This suggests that either VAR may not be the most optimal method to use for this type of data, or that additional variables should be included in the equations.

When looking at impulse response functions, then they showed results that would be expected from seeing the VAR models. During 2013-17, oil price shocks could only be forecasted to have a very minimal impact on stock market returns before they stopped affecting them at all, while the impact of price shocks lasted for a much longer time after the shock in 2019-21. Error variance decomposition was also performed to further check the impact of an oil price shock on stock market returns, and showed that it did not have a large impact at all, and the impact of oil price shocks on both stock markets was similar for both time periods.

One important conclusion that can be drawn from this paper, and which is in line with findings of previous authors, is that oil price shocks alone seem to not be sufficient enough for analysing what causes a decline in stock markets; it is likely that stock market returns are more responsive to other exogenous factors, including the circumstances surrounding the oil price shocks. Therefore, it is suggested that future research would control for these factors, examine how a wider selection of global stock markets responds to oil price shocks, and examine responses of these stock markets to a more diverse selection of oil price shocks that separates them into demand- and supply-side shocks.

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APPENDICES

Appendix 1. Link to code used

https://drive.google.com/drive/folders/1zC_22-be5ZzioQQd5JvtBKYkCd1I-UG_?usp=sharing

Appendix 2. Results of ADF tests

Table 1. ADF test results by variable.

	2013-2017			**2019-2021**		
	Oil price	**NYSE**	**STOXX**	**Oil price**	**NYSE**	**STOXX**
ADF statistic	-0.7	-2	-2	-2	-2	-2
Lag order	10	10	10	9	9	9
p-value	0.8	0.7	0.8	0.5	0.5	0.8

Source: author's calculations

Table 2. ADF test results by variable, after logarithmic differences were applied to the data.

	2013-2017			2019-2021		
	Oil price	NYSE	STOXX	Oil price	NYSE	STOXX
ADF statistic	-10	-12	-12	-10	-12	-8
Lag order	10	10	10	10	10	9
p-value	0.01	0.01	0.01	0.01	0.01	0.01

Source: author's calculations

Appendix 3. Results of OLS-CUSUM tests

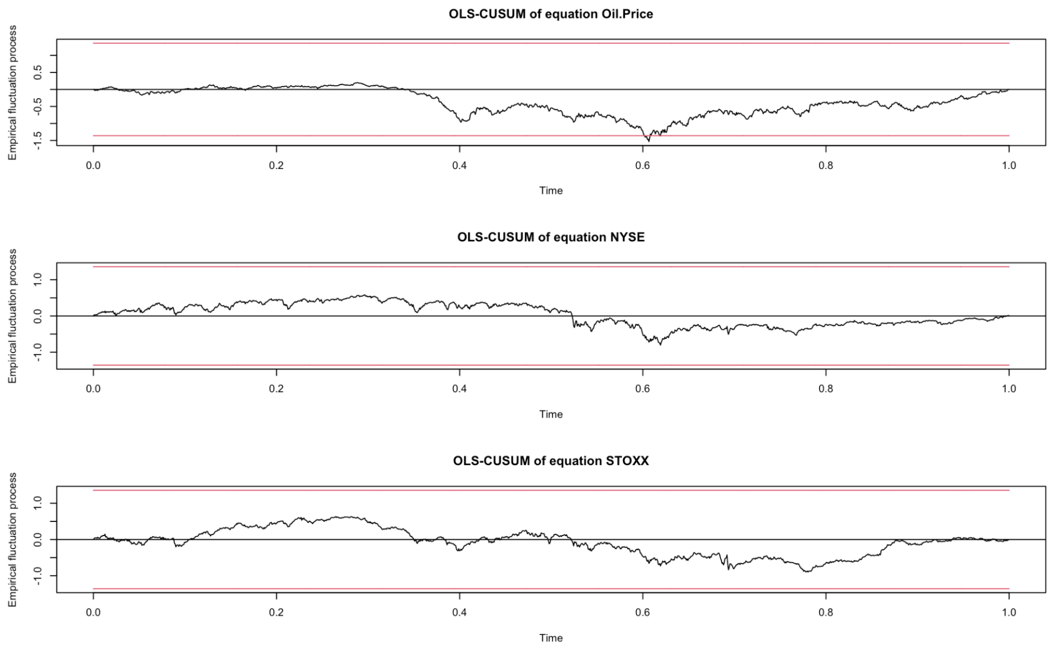

Figure 1. OLS-CUSUM test of the VAR model for 2013-2017. Source: author's calculations

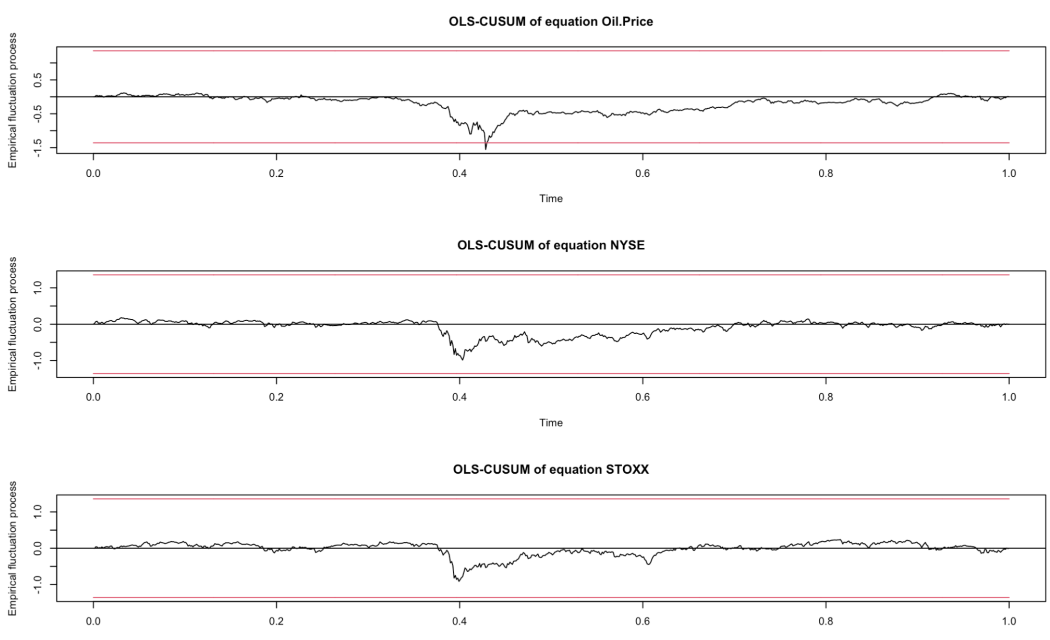

Figure 2. OLS-CUSUM test of the VAR model for 2019-2021. Source: author's calculations

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