Department of Environment, Land and Infrastructure Engineering
Master of Science in Petroleum Engineering

The Relationship Between Crude Oil Prices and Renewable Energy

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Abstract

Today's most used energy sources are Crude Oil, Gas, and Coal, which are the main reason for increasing CO_2 and pollution in the atmosphere. In recent years, Climate change, Environment, Energy Security Issues, and the development of new technologies caused an enhanced focus on emissions and clean energy usage. These issues have been addressed through various international agreements, and different countries are putting some obligations on their industry to reduce the emission of greenhouse gasses.

In order to decrease the dependency on fossil energies, investment and study on Renewable Energies have increased during the last years. Due to this continuous increase in using renewable energies, understanding their performance's effective parameters is very important. We expect that the Price of Crude Oil as one of the primary sources of energy and competitor of Clean Energies in different industries like transportation fuels, electricity, etc., has a significant influence on various aspects of Renewable Energies.

This thesis aims to analyse the relationship between renewable energy stocks and the price of crude oil. In order to determine this relationship, I used a time-series approaches Vector Autoregressive Model (VAR), Vector Error Correction Model (VECM), and Structural Vector Autoregressive Model (SVAR). Besides, by conducting Impulse Response Test, I can analyse Renewable Energies Stocks' response to the different positive and negative oil price shocks and investigate whether these responses are asymmetric or symmetric. In the end, by comparing these models in two periods before the Covid-19 pandemic and post-pandemic, I looked at the effect of the global pandemic and the financial crisis caused by it on the relationship of oil price and renewable energies sectors.

Sub-sectors of renewable energy are almost unaffected by shocks in Oil Prices. The results of my analysis indicate that the Global Covid-19 Pandemic has changed the under-consideration relationships. Furthermore, based on my findings, Crude oil is a net receiver of shocks from renewable energies. Also, the shock in Crude Oil Prices will mainly affect the Biofuel Index and its effect on other assets is not significant or dies out soon.

Acknowledgements

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1) Introduction

Continuous GDP growth and worldwide expansion of economies have raised the energy demand; Thus, fossil fuels (e.g., coal, natural gas, oil) as the primary sources of energy experienced a high demand period in the last decade. These non-renewable sources, which provide 80% of the world's energy supply, are one of the leading causes of greenhouse gas emissions. An enhanced concern related to CO2 emissions that jeopardized the sustainability of ecosystems, renewable energy production and consumption has experienced rapid growth, especially after the establishment of the Kyoto Protocol and also the European Union Emissions Trading System (EU-ETS). According to the limitation and goals defined in these agreements, the energy transition plans of the countries are proceeding faster; for example, in the United States of America, the consumption of renewable energy sources has increased by 12% in 2020; and during 2020 in comparison with 2019, the production capacity of renewable energies increased for 50%.

During the COVID-19 global pandemic, the world energy consumption dropped dramatically and put ahead the 30 years emission reduction projects for 2.5 years. But it was temporary, and soon the increasing consumption trend will be back; Therefore, reducing energy consumption is not the solution. Transition to clean (or renewable) energy has become the heart of focus to solve the problems of energy scarcity and climate change. That's why the policy-makers and investors shifted their attention towards the development of renewable energies.

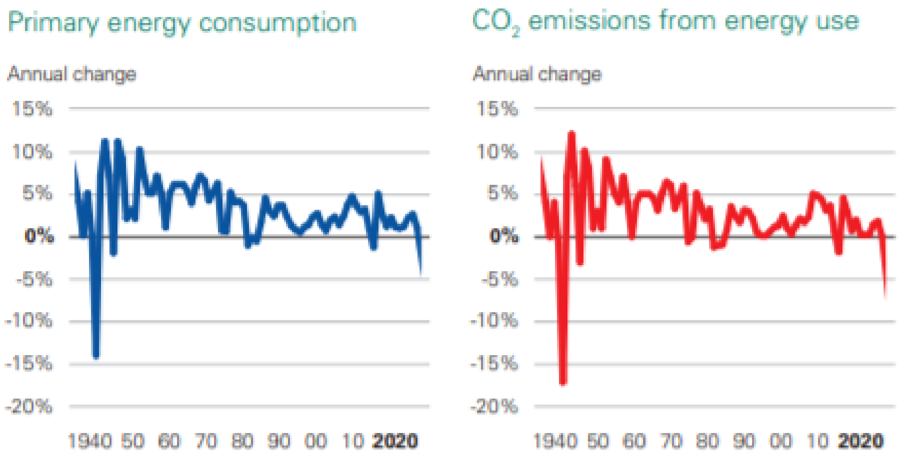

Figure 1: The Global Annual Energy Consumption Change [Left], and The Global Annual CO2 Emissions Change from Energy Use [Right]

(Source:BP – Statistical Review of World Energy 2021)

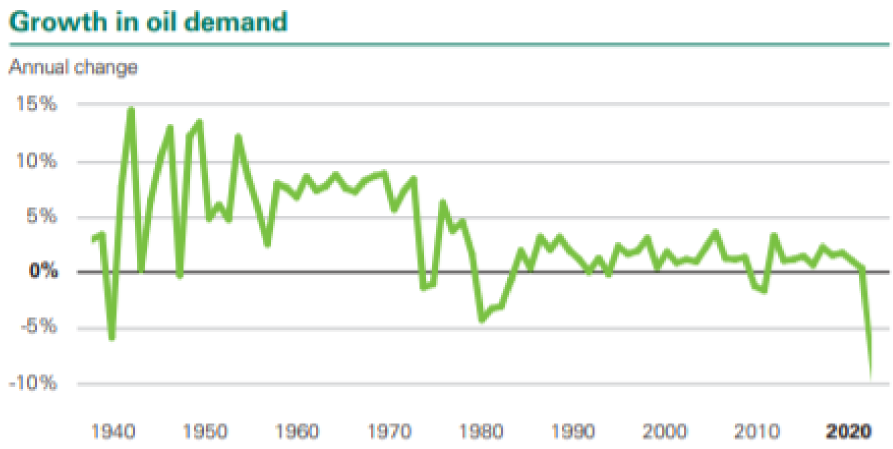

Figure 2: The Annual Change in Global Crude Oil Demand
(Source:BP – Statistical Review of World Energy 2021)

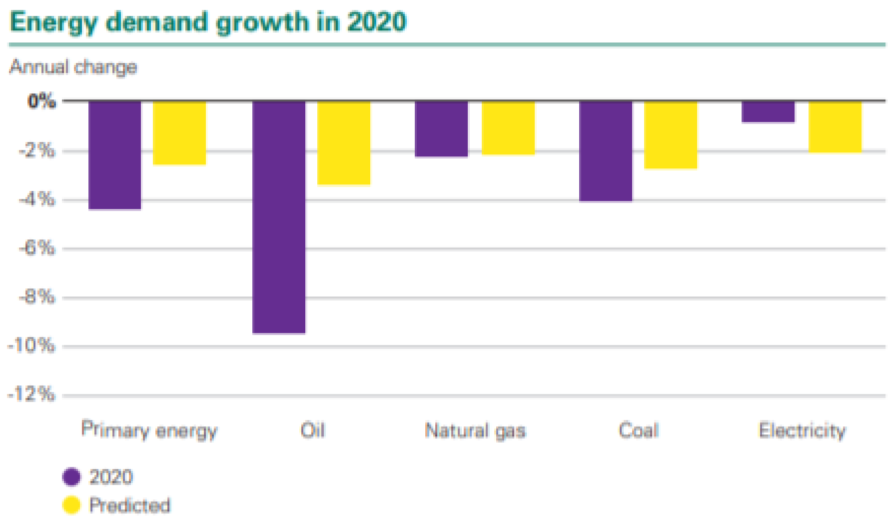

Figure 3: The Actual and Predicted Growth in Global Energy Demand
(Source:BP – Statistical Review of World Energy 2021)

Figures 1, and 2 show the dramatic changes in energy demand and consumption because of the Covid-19 pandemic during 2020. From figure 1, we can understand that world energy demand has fallen by 4.5%, and as a consequence, global carbon emissions decreased 6.3% compared to 2019. The expected growth in energy demand is shown in figure 3; as shown in this figure, almost in all sub-sectors of the energy, the reduction in the demand is more than expected.

The reduction in oil demand (Figure 2) caused a decline in crude oil price. The price of WTI oil decreased by approximately 20% in the two months following the start of the COVID-19 epidemic in Wuhan city. It can be a motivation for policy-makers and investors to promote the development of renewable energy sectors. Figure 4 reveals the increment of global investment in renewable energies for different countries. As it can be interpreted from the chart, the annual investment has an upward trend, and total investment in 2020 was 2% higher than in 2019.

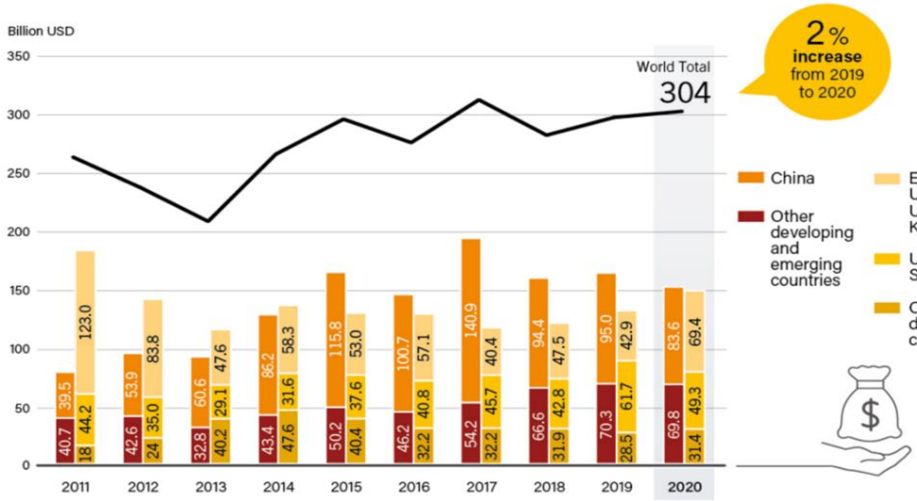

Figure 4: Annual Investment on Development of Renewable Energies

(Source: BloombergNEF)

By promoting subsidies, policymakers can influence the development of renewable energies. Figure 5 shows the subsidies on different sub-sectors of energy by governments. According to this chart, the policymakers' mid-term and long-term plan is to increase the subsidies on alternative energies and simultaneously decrease it for fossil energy; in this way, people have more desire to use clean energies instead of non-renewable energies. By applying these policies, governments try to reach their long-term goal of making Renewable energies the main source of energy by 2050 (Figure 6).

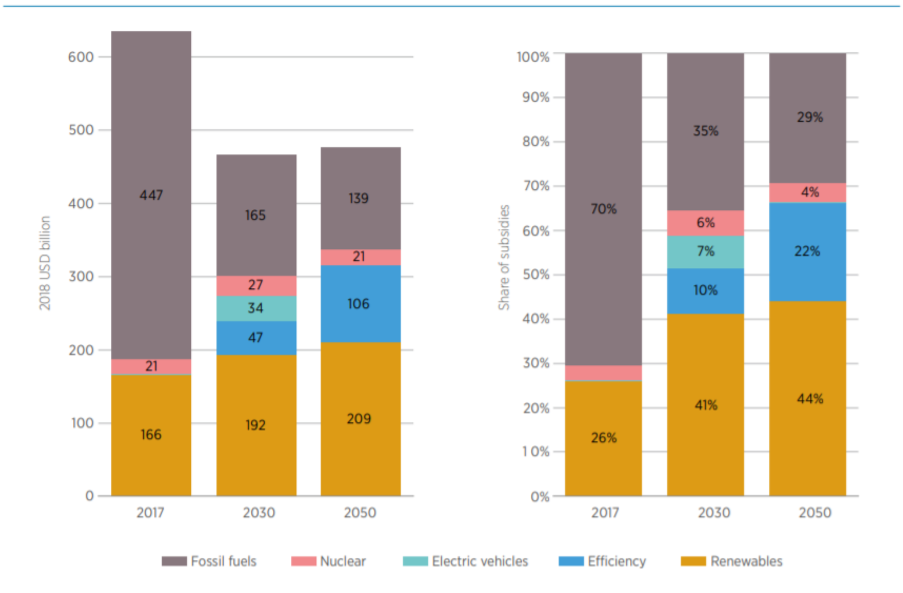

Figure 5: Comparison of Annual Subsidies on the Sub-Sectors of Energy

(Source: International Renewable Energy Agency – IRENA 2020)

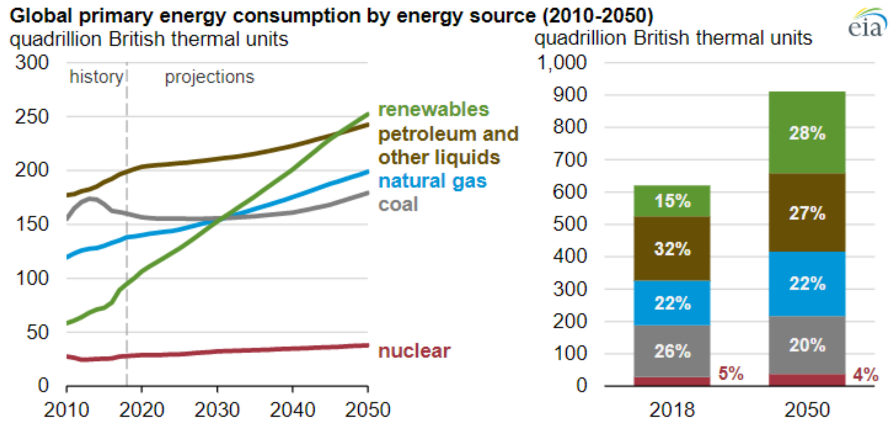

Figure 6: Outlook of Global Energy Sources

(Source: U.S. Energy Information Administration, International Energy Outlook 2019)

The renewable energy sector has been snowballing to become one of the most active segments of the energy industry. Worldwide, many countries have invested in renewable energy sources (Bhattacharya et al., 2016), and global use of renewables is also anticipated to expand rapidly in the coming years. According to the International Renewable Energy Agency (IRENA) projections, it is estimated that renewable energy sources may constitute at least 60 percent of several countries' total final energy consumption by 2050. For instance, In the European Union (EU), the share could expand from around 17 percent to above 70 percent.

The question that comes to mind is, how Crude Oil and Renewable Energies stocks can be related?

Even though governments can influence renewable energies development through strategies and policy regulations, the renewable energy stock market cannot be assumed isolated from the fossil energy market. In other words, the fluctuations of each market probably affect the other one, especially it will affect the amount of investment on them and their returns in capital markets.

By considering the energy market structure and energy demand, it can be understood that there is a substitution relationship between fossil energy and renewable energy. For example, when the crude oil prices rise, its demand decreases, and the investors spend more money on developing the renewable energy sector, which increases the stock prices of renewable energy companies. On the other hand, if the price of developing renewable energy is high, it will increase the demand for crude oil and investment.

In general, we would expect to see a negative relationship between fossil energy prices and renewable energy stock prices. Given the strategic importance of crude oil in the international energy market, existing studies focus on analysing how much global oil price changes, as a representative of fossil energy prices, influence the returns of renewable energy stocks. The conclusions are, however, still inconsistent.

Oil price movements are the most crucial factor in defining renewable energy stocks prices and the return opportunities of renewable energy companies (Reboredo, 2015). Higher oil prices particularly encourage policymakers and investors to promote energy transition, which affects renewable energy companies' rentability (Kumar et al., 2012). Therefore, understanding the interactions between the two primary energy sources is vital for both investors and policymakers to support the transition process from fossil energy to clean energy simultaneously by increasing their profit. For this reason, exploring the impacts of oil prices on the renewable energy sector is of great interest to economists.

During past decades enhanced focus on Clean Energies, motivated researchers in Energy Economics and Market to study the characteristics of this fast-growing sector. Therefore, a number of studies have been published which the broad objective of them is to understand the effect of crude oil prices movement and its shock on investment in the renewable energy sector and also the stock prices of this sector (i.e., Henriques and Sadorsky, 2008, Kumar et al., 2012, Sadorsky, 2012, Managi and Okimoto, 2013, Reboredo et al., 2017, and more recently Ike et al. (2020) and Murshed and Tanha (2020)).

In this thesis, by using econometric techniques of former researches, I will study the effect of shocks in crude oil prices on different sub-sectors of renewable energy to understand whether this effect is similar in every sub-sector or not. Furthers, by comparing the relationship between oil prices and renewable energy sectors prices in two periods of Jan 2009 to Dec 2019 and Jun 2020 to Sep 2021, I will show the influence of the Covid-19 pandemic on this relationship. It should be mentioned that since the pandemic is not completely finished and the data sample is small, my finding may change in the future, but I will analyze my results to the best of my knowledge.

In the second chapter, I provided a summary of the previous research related to my thesis topic. Chapter 3 explains the methods and models I used, and chapter 4 is about the data and indices I chose. The statistical results of my models are shown in chapter 5, and finally, chapter 6 is the conclusion of my analysis.

2) Former Researches

According to the rapid growth of renewable energy consumption and production, researchers have employed several econometric methods to analyse the interdependence between this sector and other financial market sectors. In recent years, because of the great importance of the Oil & Gas industry as the most prominent energy sector, various research has used a wide array of methodologies to investigate the relationship between crude oil prices and renewable energies. In this section, I will provide a summary of the findings of these researches.

Henriques and Sadorsky (2008) first started to study this relationship by using a four-variable VAR model to understand the dynamic relationships between alternative energy stock prices, technology stock prices, oil prices, and interest rates. They found that even though both technology stock prices and oil prices affect alternative energy stock prices, the influence of a shock in the stock price of technology on alternative energy stocks is much more significant than the shocks of oil prices. Trück & Inchaupse (2008), used a dynamic multi-factor setting based on a state-space model with time-varying coefficients to extend the research of Henriques & Sadorsky (2007). Their result shows that sharp increases in oil have little influence on investments in renewable energy markets and that the Wilderhill New Energy index seems to be more influenced by the Standard & Poor’s 500 Index and technology stocks than the crude oil price.

Kumar and Managi (2012) also believed that investors consider the clean energy and technology companies as similar assets, like Henriques and Sadorsky. But, by using a VAR framework to explore the relationship between clean energy stock prices, the stock prices of technology companies, oil prices and prices for carbon allowances, they showed that increasing oil prices have a significant positive impact on clean energy stock prices. At the same time, Broadstock et al. (2012) explored the effect of international oil prices on Chinese energy-related stock price returns. They used time-varying conditional correlation and asset pricing models. They studied the response of three sub-indices for fossil fuels, electricity, and the new energy sector, to international oil price shocks and reported that after the global financial crisis in 2008, the oil price changes is a significant factor in energy-related stock price movements.

Managi and Okimoto (2013) supported the findings of Henriques and Sadorsky (2008) and Kumar et al. (2012) about the similarity of clean energy stock prices and technology stock prices. Based on the model used by Henriques and Sadorsky (2008) and their parameters, Managi and Okimoto considered a Markov-switching model in order to explore possible structural effects among oil prices, technology stock prices, and clean energy stock prices. Their findings exhibit a positive relationship between oil prices and clean energy prices after the structural change in the market in late 2007.

Roberdo, in his first paper, 2015, used copulas to study the structural dependency between the oil and renewable energy market and estimated the conditional Value-at-Risk (Co-Var). He stated that oil prices have a time-varying and symmetric tail dependence with renewable energy indices, and its movements contribute around 30% to the fluctuations of the risk in renewable energy companies. Two years later, Reboredo et al. (2017), using continuous and discrete wavelets and linear and non-linear Granger Causality tests, studied the causal link between oil prices and renewable energy returns for the data from 2006 to 2015. Their result indicates that the dependency between two variables is more potent in the long term. Furthermore, they found a non-linear causality running from renewable energy indices to oil prices, but the causality in the opposite way depends on the size of the time scale and is not fixed.

Kyritsis and Serletis (2017) explored the influences of both oil price shocks, and the uncertainty about crude prices, on the stock returns of renewable energy and technology firms. They found that the effect of oil price uncertainty, stock returns of renewable energy and technology firms, is insignificant and shock in oil price is not influential on stock returns.

Ahmad et al. (2018) studied the optimal hedging ratios between clean energy equities and various other financial instruments such as oil, bonds, gold, VIX, and carbon prices. For estimating the time-varying optimal hedge ratios, they applied three different kinds of multivariate GARCH models (DCC, ADCC and GO-GARCH). The results suggest that crude oil after the VIX is the best asset to hedge clean energy equities.

Imran Hussain Shah et al. (2018) studied the relationship between renewable energy investment and oil prices for 3 countries with different strategies in Oil & Gas industry (Norway and the UK being oil-exporters, and the USA as an importer). Using VAR model, they found that a shock in oil price strongly explains the investment and movements of the renewable energy sector. Most recently, Murshed and Tanha (2020) and Ike et al. (2020) tried to find evidence of this relationship in different countries. Murshed and Tanha (2020) studied the non-linear link between renewable energy consumption and crude oil prices for four net oil-importing countries in South Asia (Bangladesh, India, Pakistan and Sri Lanka) over the period 1990–2018. They found that only when the crude oil prices are higher than an expected threshold of 135 $ per barrel, renewable energy consumption will be accelerated. Similarly, Ike et al. (2020) used data on G-7 countries and found a one-way causality from renewable energies to oil prices.

While most of the above studies provided important insight into the oil-clean energy stocks relationship, their primary focus has been on this relationship at the aggregate level. The use of aggregate stock indices makes it challenging to analyze the responses to oil prices from various sub-sectors within the clean energy sector. In this thesis, I tried to provide a better vision in this field by considering different indices for sub-sectors of renewable energies.

3) Statistical Theories and Methods

In order to quantify economic relationships accurately, certain features of the data should be examined. Understanding these characteristics helps us in model-building. In this chapter, the basic information and knowledge required to clarify the model and conclusion have been provided.

3.1 Vector Autoregression

Since Christopher A. Sims (1980) developed the concept of Vector Autoregressive models (VAR), this approach is known as a relatively simple and effective way to quantify connection in the time series data. All the variables included in the VAR model are assumed to be jointly endogenous; the VAR model gives a multivariate approach that explains all of these variables by their previous values and the lagged value of all other variables.

The simplest VAR model is Bivariate Vector Autoregression. This model only consists of two variables y_{1t} and y_{2t}. Thus, in a Bivariate VAR of order P (VAR(p)), each variable depends on its lagged value and the lagged values of other component up to P periods and error terms. The mathematical explanation of this model is:

$$y_{1t} = \beta_{10} + \beta_{11}y_{1t-1} \dots + \beta_{1p}y_{1t-p} + \alpha_{11}y_{2t-1} \dots + \alpha_{1p}y_{2t-p} + u_{1t}$$
$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} \dots + \beta_{2p}y_{2t-p} + \alpha_{21}y_{1t-1} \dots + \alpha_{2p}y_{1t-p} + u_{2t}$$

One of the advantages of VAR modeling is “Flexibility”, as we can understand from the equations, the model can be extended to a multivariant model, which instead of having only two variables in the system, we can have any number of components which is necessary for our model. Each of these variables has an equation and they affect each other. For ease of explanation, I describe the Bivariate VAR of the first order (VAR (1)), so each variable depends only upon the immediately previous values of y_{1t} and y_{2t}:

$$y_{1t} = \beta_{10} + \beta_{11}y_{1t-1} + \alpha_{11}y_{2t-1} + u_{1t}$$
$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} + \alpha_{21}y_{1t-1} + u_{2t}$$

We can write these equations in another form by putting the terms into matrices and vectors:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \alpha_{11} \\ \alpha_{21} & \beta_{21} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Or

$$y_t = \beta_0 + \beta_1 y_{t-1} + u_t$$

No contemporaneous terms are included in this VAR model; therefore, we can use the Ordinary Least Square method for estimating it.

3.1.1 Requirements of the VAR model

Obtaining trustable and credible results from the VAR is subject to the satisfaction of some statistical properties:

- The expected value of the error term must be zero, E (u_t)=0.
- Time series in the VAR model must be Stationary.
- No serial correlation.

3.1.2 Stationarity

When discussing modeling a time series process, it is vital to make sure our data are stationary to avoid the problem of spurious regression. Simply, stationarity means statistical properties of the process do not change over time. There are two important forms of stationarity:

3.1.2.1 Strict Stationary

A time series is called strict stationarity or strong-sense stationarity when its joint probability distribution is unaffected by change of time origin. It means that mean and variance of the data are constant during all period. Having these properties, makes time series to fluctuates around its mean with a constant range and has the tendency for returning to its mean value.

3.1.2.2 Weak Stationarity

A weak stationary or covariance stationary process should have:

- Same mean value at all time ($E(y_t) = \mu$),
- Same variance at all time ($E(y_t - \mu)(y_t - \mu) = \sigma^2 < \infty$)
- its autocovariance depends only on the time difference between observations ($E\big(y_{t_1} - \mu\big)\big(y_{t_2} - \mu\big) = \gamma_{t_2 - t_1} \quad \forall t_1, t_2$).

In the third assumption, autocovariance reveals the dependency of a variable on its previous values. Since the value of autocovariance depends on the unit of measurements, it is more convenient to normalize it by dividing by the variance and obtaining the term autocorrelation, which I used in this thesis.

For our purpose, satisfying the weak stationarity condition is sufficient, so I refer to it as stationarity in this research.

Accomplishing all the stationarity requirements is very uncommon when working with economic time series, especially when they are in their original unit of measurement. These time series that their mean value cannot be regarded as constant and have a time-changing variance are called non-stationary. Non-stationary time series have the tendency to exhibit an unpredictable upward and downward movement, which is known as the Random Walk.

Detecting whether the data are stationary or not is one of the most crucial steps of our analysis because if we treat non-stationary series like stationary ones, the results of our model will be unreliable and spurious. In the case of inappropriate modeling, it is possible that after regressing one non-stationary variable on another one we obtain a high R2 even though they are completely unrelated. This situation is called "Spurious Regression". The solution to this problem is transforming data to become stationary. The method that I used to transform time series from non-stationary to stationary is "Differencing the Data". For this purpose, I determined the order of integration of each time series which makes them stationary.

It is worth mentioning that there is an exception, "Cointegration of two non-stationary time series". Cointegration occurs when two non-stationary time series with the same order of integration follow a similar path during the time, and their combined trend can be stationary. I will discuss the concept of cointegration and its effect on our decision on modeling later.

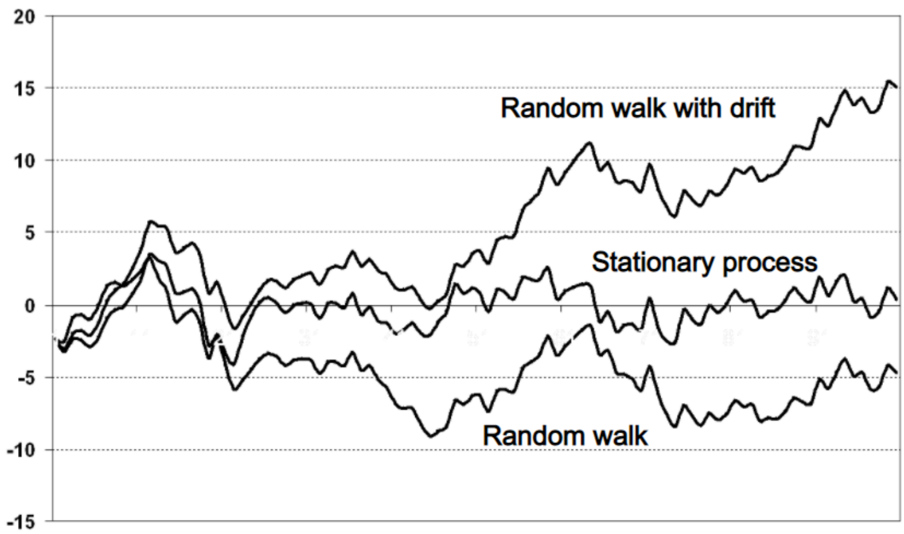

Figure 7: Graphical Comparison of Random Walk and Stationary Time Series

(Source: Investopedia.com)

3.1.3 Stationarity Test

As shown in figure 7, the most basic method for stationarity determination is the graphical analysis of plotted data. This method gives us an expectation from our data. However, conducting a statistical test to reveal the stationarity condition of the data is inevitable.

The necessity of detecting the stationarity condition of data, several statistical tests have been developed as more rigorous approaches. These tests rely on the presence of unit root, which shows our data is non-stationary. In order to obtain a more accurate result, in this research, I used a modification of the initial Dickey-Fuller test, Augmented Dickey-Fuller. This method has higher sensitivity than the normal DF test, which decreases the possibility of the wrong acceptation of the null hypothesis (having unit root) against the alternative hypothesis of stationary time series.

3.1.3.1 Dickey-Fuller Test

This test is the most common unit root test. In practice, the general equation that has been considered for testing the Y_t as a time series is:

$$d(Y_t) = \delta Y_{t-1} + u_t$$

The null hypothesis H_0: δ=0. If we cannot reject the null hypothesis, we conclude that the time series is non-stationarity. In this case, we should find the order of integration of our series, which is equal to the number of times that the time series must be differenced to become stationary. The order of integration is shown by I(d), which means the time series under consideration will be stationary after being differenced d times.

Before going further through the basic of the test, I should mention that the critical values of the t-statistic for the DF test does not follow the usual t-statistics and is calculated by the Monte Carlo method.

In this test, three equations are used to analyze the time series:

- Random Walk

$$d(Y_t) = \delta Y_{t-1} + u_t$$

- Random Walk with Drift

$$d(Y_t) = \delta Y_{t-1} + c + u_t$$

- Random Walk with Drift and Stochastic Trend

$$d(Y_t) = \delta Y_{t-1} + c + \gamma T + u_t$$

Same as the general equation, the null hypothesis for these equations is H_0: δ=0, which means the variable has a unit root, I(0). The alternative hypothesis H_A: δ<1, which is true if the time series is stationary, I(0). If we cannot reject the null hypothesis, the test must be repeated by different hypothesises, $(H_0): Y_t \sim I(2)$ and $(H_A): Y_t \sim I(1)$. In this case, if we reject the null hypothesis, our data are integrated of the first order; otherwise, we increase the order of integration for both null and alternative hypothesis until we are able to reject the null hypothesis and find the order of integration which makes the time series stationary.

One assumption of the Dickey-Fuller test is that the error term (u_t) is White Noise. It means that the error terms are not autocorrelated. If this assumption is not valid for the data, it can lead us to a false rejection of the null hypothesis. The Augmented Dickey-Fuller test (ADF) is the solution to this problem.

3.1.3.2 Augmented Dickey-Fuller test

The test is based on the influence of $d(Y_{t-k})$ as well as Y_{t-1} on the prediction of change in Y_t. Therefore, the term $d(Y_{t-k})$ is added to the equation of this test to make sure that the error term is not autocorrelated.

$$\mathrm{d}(y_t) = c + \gamma T + \delta y_{t-1} + \lambda_1 \mathrm{d}(y_{t-1}) + \cdots + \lambda_{p-1} \mathrm{d}(y_{t-p+1}) + u_t$$

The next step is finding lag length P in order to apply the test. The basic approach for finding P is the examination of t-values for each coefficient, but in this research, I relied on using different information criteria, which will be explained in the following paragraph.

3.1.4 VAR Lag Length Selection

As Konishi & Kitagawa (2008) state, "The majority of the problems in statistical inference can be considered to be problems related to statistical modeling". Since the accuracy of our model depends on using the optimal number of lags in all of the tests, proper Lag Order Selection is critical. Being unable to remove all of the autocorrelations and increment the standard error of coefficients are respectively the result of including too few and too many lags in the model, which makes the results biased and reduces the model's power.

Several information criteria can be used for model selection to determine the lag length of the VAR models, with smaller values of the information criterion being preferred. Each information criteria calculate two terms in order to find the optimal number of lags:

- The first factor is a function of the residual sum of squares.

- The second one applies some penalties for the loss of degrees of freedom from adding an independent variable.

By adding a new variable, the residual sum of squares will decrease but simultaneously, the second factor, penalty, increases. Thus, two factors influence information criteria in two opposite ways after adding a new variable. The difference between information criteria is the method they use to calculate penalty terms and how restrict it is.

According to the rule of thumb (Schwert 1989), the information criteria value will be calculated by $p_{max} = \left[12 * \left(\frac{T}{100}\right)^{\frac{1}{4}}\right]$ for each $p < p_{max}$ to $p = 0$. The goal is to find the number of independent variables which minimize this value. In this equation, T is the number of observations, and P is the number of lags.

The most popular information criteria are Akaike's (1994) information criterion (AIC), Schwarz's (1978) Bayesian information criterion (*SBIC*), and the Hannan--Quinn criterion (*HQIC*). Since having a similar number of lags in each equation is beneficial, I used the multivariate versions of these information criteria. Their definition is:

- Multivariate Akaike's Information Criterion:

$$MAIC = \log[\hat{\Sigma}]\frac{2pr}{T}$$

- Multivariate Schwarz's Bayesian Information Criterion:

$$MSBIC = \log[\hat{\Sigma}] + \frac{p}{T}\ln T$$

- Multivariate Hannan—Quinn Information criterion:

$$HQIC = \log[\hat{\Sigma}] + \frac{2p'}{T}\log(\log(T))$$

Here T is the number of observations, $\hat{\Sigma}$ is the variance-covariance matrix of the residuals, and $p' = k^2 p + k$ is the total number of regressors in all equations. In this formula, K represents the number of equations, and P is the number of lags.

Normally, all of these criteria will suggest the same number of lags, but a question arises: *Which criterion should be preferred if they suggest different model orders?* To find the solution to this problem, researchers compared these information criteria by various methods. Endres (2005) paid attention to the penalty term and size of the data sample. He stated that MSBIC is more restricted in adding lag than MAIC and is better for large data samples. At the same time, Ivanov & Kilian found out that the time series frequency is an important factor in choosing the preferable information criterion. They declared that for monthly and Quarterly time series, MAIC and MHQIC would give the best results, respectively. In this thesis, most of the time, all of the information criteria provided the same number of lags, but on the occasion that they were different since I used the monthly data, I relied on Ivanov & Kilian research, MAIC and MHQIC are the chosen criteria.

3.1.5 Cointegration

Two variables are cointegrated if both are integrated of the first order I(1), and there is at least one linear relationship between them that is stationary I(0). The cointegrated variables have a long-term relationship, and both of them exhibit a similar long-run path. Existing cointegration will invalidate the VAR model, and instead of it, the Vector Error Correction Model (VECM) should be used.

The two most used tests for testing the cointegration are Engle-Granger 2-Step test and Johansen's test. According to previous research, since Johansen's test treats all the variables as endogenous and tests the data for more than one cointegration relationship, I used it in this thesis.

3.1.5.1 Cointegration Test: Johansen's Test

This approach was proposed by Søren Johansen (1988) and tests the cointegration between the g number of variables with K lags in a VAR model. The simple formula for this model can be written as:

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} \dots + \beta_k y_{t-k} + u_t$$

Applying this test necessitates the converting of this VAR model to the VEC model:

In this formula $\Pi = \left(\sum_{i=1}^{k} \beta_i\right) - I_g$ and $\Gamma_i = \left(\sum_{j=1}^{i} \beta_j\right) - I_g$. All of the g variables in VAR are used in their first differenced form, and the coefficients of the k-1 lags of the dependent variables are shown by Γ matrix.

The purpose of this test is to calculate Π which represents the long-run coefficients of the model. In equilibrium condition, all of the Δy_{t-i} are zero, and the expected value of error term u_t is zero, thus $\Pi y_{t-k} = 0$.

The cointegration between variables will be tested by looking at the rank of Π via its eigenvalues. Determination of the rank of the matrix is according to the number of its eigenvalues (characteristic root), which is not zero.

This approach uses two statistics:

- $\lambda_{\text{trace}}(r) = -T\sum_{i=r+1}^{g} \ln\left(1-\hat{\lambda}_i\right)$
- $\lambda_{max}(r, r+1) = -T\ln\left(1-\hat{\lambda}_{t+1}\right)$

In these formulas, r is the number of cointegrations that are assumed in the null hypothesis; the $\hat{\lambda}_i$ is the estimated value for the i^{th} ordered eigenvalue from the matrix. The larger $\hat{\lambda}_i$ makes $\ln\left(1-\hat{\lambda}_i\right)$ more negative. Thus, the test statistic will increase. Each eigenvalue that is significantly different from zero is the sign of the existence of a cointegration vector.

λ_{trace} is a method to test the null hypothesis, which indicates that the number of cointegration vectors is less than or equal to "r" against the alternative hypothesis that this number is more than "r". While λ_{max} tests the null hypothesis of "r" cointegration vectors against "r+1" vectors as the alternative hypothesis. It should be mentioned that the distribution of the test statistic for these statistics is non-standard, and Johansen and Juselius (1990) provide critical values for them. These critical values depend on the value of "$g - r$", the number of non-stationary variables, and whether constants are included in each of the equations or not.

Johansen's test process starts by testing H0: r = 0, Π has no rank (no cointegration). If the test statistic is not greater than the critical value, the null hypothesis will be accepted, and the test is complete. In contrast, by rejecting this null hypothesis, another test should be conducted where the null hypothesis is: having one cointegration (H0: r=1). The increment of the "r" value and repeating the test continue until we are unable to reject the null hypothesis, so the rank of Π which indicates the number of cointegration vectors is examined. It should be noted that Π can not be full rank (r=g) because it shows that all the original variables are stationary.

When the rank of Π is zero, it means that there is no cointegration. Therefore, Δy_t depends only on Δy_{t-i} not on y_{t-1} so that there is no long-run relationship between the elements of y_{t-1}. In case of $1 < \text{rank}(\Pi) = r < g$, there are r cointegration vectors and Π can be defined as:

$$\Pi = \alpha\beta'$$

Where β is the matrix which indicates the cointegrating vectors and α gives the amount of them in the VEC model. These two are called "adjustment parameters". For example, in my models, which g=2 if there is one cointegration, we can write the like:

$$\Pi = \begin{pmatrix}\alpha_{11}\\ \alpha_{12}\end{pmatrix}\begin{pmatrix}\beta_{11} & \beta_{12}\end{pmatrix}\begin{pmatrix}y_1\\ y_2\end{pmatrix}_{t-k}$$

Can also be written:

$$\Pi = \binom{\alpha_{11}}{\alpha_{12}} (\beta_{11}y_1 + \beta_{12}y_2)_{t-k}$$

Using this equation, writing the separate equations for each variable of Δy_t will be possible. The normalized equation for Δy_1 will be:

$$\alpha_{11}\left(y_1 + \frac{\beta_{12}}{\beta_{11}}y_2\right)_{t-k}$$

3.1.6 Autocorrelation

One of the concerns for dealing with time series is autocorrelation. If the value of the error in one period is related to the value of the error in another period, it means that our regression suffers from autocorrelation.

In order to analyse the residuals to test for autocorrelation, one method is the graphical inspection of residuals. According to the pattern of error terms in each graph, it is possible to understand the existence of autocorrelation and its type.

In case of no autocorrelation: Cov $(\varepsilon_r, \varepsilon_s) = 0$ or Corr $(\varepsilon_t, \varepsilon_s) = 0$ for all $t \neq s$. Residuals are randomly scattered across the time axis. (Figure 8)

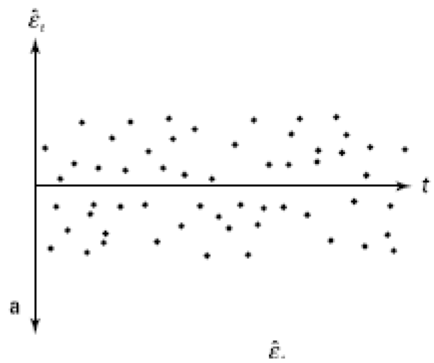

Figure 8: No Autocorrelation

(Source: Brooks, C. (2008). Introductory Econometrics Finance)

Positive Autocorrelation occurs when the value of a residual ε_t has the tendency of following the sign of its previous error term, ε_{t-1}. On this occasion, the plot of residuals usually is cyclical and doesn't cross the time axis very frequently. (Figure 9) And it will be expressed as: Cor $(\varepsilon_r, \varepsilon_s) > 0$ for all $t \neq s$.

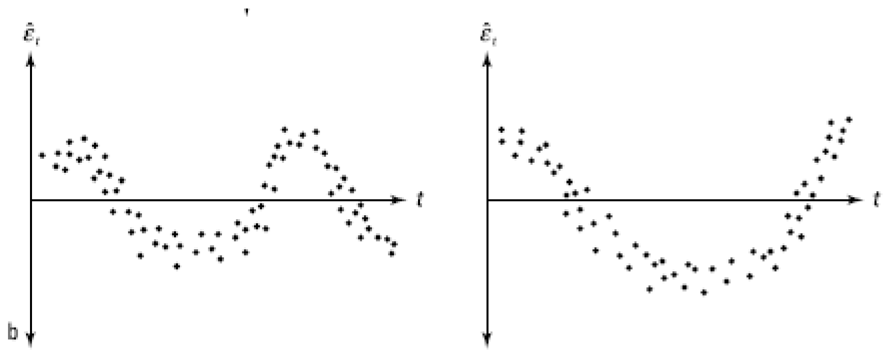

Figure 9: Positive Autocorrelation

(Source: Brooks, C. (2008). Introductory Econometrics Finance)

On the other hand, if a time series suffer from negative autocorrelation, an error of a given sign, ε_{t-1}, usually will be followed by an error of the opposite sign, ε_t. The graph of the residuals of this time series crosses the time axis very often. (Figure 10) So most positive errors tend to be followed or preceded by negative errors and vice versa.

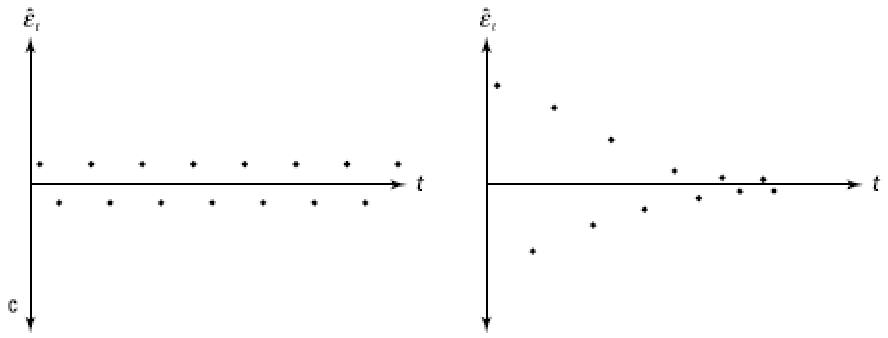

Figure 10: Negative Autocorrelation

(Source: Brooks, C. (2008). Introductory Econometrics Finance)

Even though the graphical analysis is very helpful, but it should be used as a complement to a statistical test. In this research, I performed the Lagrange Multiplier (LM) test based on the Johansen (1995) method to test the time series for autocorrelation.

3.1.6.1 Autocorrelation Test: Lagrange Multiplier

LM-Test was developed by Trevor S. Breusch (1978) and Leslie G. Godfrey (1978). With this test, investigation of the relationship between and several of its lagged values is possible simultaneously. Furthermore, since the LM test examines the autocorrelation up to the r^{th} order, it is better than other methods like Durbin—Watson test, which only measures the first-order autocorrelation.

The models of errors to be tested for autocorrelation can be written as:

$$u_t = p_1 u_{t-1} + p_2 u_{t-2} \ldots + p_r u_{t-r} + v_1, \quad v \sim N(0, \sigma_v^2)$$

For the hypothesis testing, H_0: no autocorrelation, which according to the equation can be represented:

$$H_0: p_1 = 0, p_2 = 0, \dots p_r = 0$$

And the alternative hypothesis is:

$$H_1: p_1 \neq 0, p_2 \neq 0, \dots p_r \neq 0$$

It should be noted that the test statistic for this method is x^2 distributed with p degrees of freedom. If the test statistics value is more than the critical value of the Chi-Squared x^2, the null hypothesis will be rejected, and the time series has autocorrelation.

3.1.7 Stability Test

If VAR is unstable, the impact of the shocks will never die out (rather will explode); thus, it is necessary to test the stability of the model. The method I used for the stability test in this thesis relies on analysing the eigenvalues of the model. If the roots of the companion matrix are lower than one, inside the unit circle, it implies that the model is stable; otherwise, the modification should be applied to the model or data.

3.1.8 Impulse Response Function

Performing Granger-causality reveals whether a variable in the model will impact other variables or not. However, finding the sign of this impact with this method is not possible. Essentially, the question that arises here is how a shock that appears at a certain point of time in one variable is processed in the system and which impact it has over time not only for this particular variable but also for the other variables of the system. In order to answer this question, I used: the impulse response function.

In this method, a unit shock to the error term will be applied, and when it enters the VAR model, the IRF allows us to trace out the time path of the shock on the variables. Since my models are VAR with two variables, I provided a further explanation with one example for a better understanding based on my models.

If we assume a 2-variable model, with a single lag, we can write this VAR model as:

$$y_{1t} = \beta_{11} y_{1t-1} + \alpha_{11} y_{2t-1} + u_{1t}$$
$$y_{2t} = \beta_{21} y_{2t-1} + \alpha_{21} y_{1t-1} + u_{2t}$$

Also, can be written as:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{11} & \alpha_{11} \\ \alpha_{21} & \beta_{21} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$
$$y_t = \beta_1 y_{t-1} + u_t$$

If

$$\beta_1 = \begin{pmatrix} 0.5 & 0.3 \\ 0 & 0.2 \end{pmatrix}$$

Without any shock, at t = 0

$$y_0 = u_0 = \begin{pmatrix} u_{10} \\ u_{20} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

And at t =1

$$y_1 = \beta_1 y_0 + u_1 = \begin{pmatrix} 0.5 & 0.3 \\ 0 & 0.2 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \end{pmatrix} + \begin{pmatrix} u_{11} \\ u_{21} \end{pmatrix} = \begin{pmatrix} u_{11} \\ u_{21} \end{pmatrix}$$

Now, if a unit shock will be applied at t=0, we can analyze its effect:

$$y_0 = \begin{pmatrix} y_{10} \\ y_{20} \end{pmatrix} = \begin{pmatrix} u_{10} \\ u_{20} \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

The effect of the shock at t =1:

$$y_1 = \beta_1 y_0 + u_1 = \begin{pmatrix} 0.5 & 0.3 \\ 0 & 0.2 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} + \begin{pmatrix} u_{11} \\ u_{21} \end{pmatrix} = \boxed{\begin{pmatrix} 0.8 \\ 0 \end{pmatrix}} + \begin{pmatrix} u_{11} \\ u_{21} \end{pmatrix}$$

The matrix in blue rectangular indicates the effect of a unit shock at t=0 on y_{1t}. It will thus be possible to plot the impulse response functions of y_{1t} and y_{2t} to a unit shock in y_{1t}. The same procedure will be applied for the shock in y_{2t}. It can be understood that in a system of 2 variables, there are four impulse response functions, the effect of the shock of each variable on itself and the other one.

Since IRFs are constructed using the estimated coefficients, and each coefficient is estimated imprecisely, the impulse responses also contain an error. The solution is to represent confidence intervals around the impulse responses that allow for the parameter uncertainty inherent in the estimation process. In the results chapter, the IRFs results are shown with a 95 percent confidence interval.

3.2 Vector Error Correction Model

Dealing with non-stationary variables that are cointegrated, we must use a restricted VAR model called Vector Error Correction Model or VECM.

The VEC restricts the long-run behaviour of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is called the *error correction term*, since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments.

In the simplest form of Vector Error Correction, there are two non-stationary but cointegrated variables. Their cointegration relationship can be written as:

$$y_{2,t} = \beta y_{1,t}$$

The VEC Model for these variables is expressed like:

$$\Delta y_{1,t} = \alpha_1 \left(y_{2,t-1} - \beta y_{1,t-1} \right) + \varepsilon_{1,t}$$
$$\Delta y_{2,t} = \alpha_2 \left(y_{2,t-1} - \beta y_{1,t-1} \right) + \varepsilon_{2,t}$$

In these equations, the $y_{2,t-1} - \beta y_{1,t-1}$ is called Error Correction term, which is equal to zero in long-run equilibrium. If two variables are deviating from their equilibrium, each one tries to restore it partially. In this case, the Error Correction Term is different from zero, and the term α_i indicates the speed of adjustment for each variable.

In the case of multiple variables, there is a vector of error-correction terms of length equal to the number of cointegrating vectors among the series.

4) Data Material

Financial data often differ from macroeconomic data regarding their frequency, accuracy, seasonality, and other properties. Accurate quantification of economic relationships depends not only on econometric model-building skills but also on the quality of the data used for analysis. Thus, the data must be derived from a reliable collection process. In my thesis, I used data in two periods; the first is from January 2009 until the end of 2019, and the second is from June 2020 until September 2021. In this chapter I will explain the reasons of choosing each index.

4.1 Renewable Energies

4.1.1 Alternative Energies

The WilderHill New Energy Global Innovation Index (NEX) comprises companies whose innovative technologies and services focus on generating and using clean energy, lower CO2- renewables, conservation, and efficiency. The index has been active from December 2000, and from 2006 is known as the best of its kind.

The index is mainly composed of 125 companies worldwide focused on wind, solar, biofuels, hydro, wave and tidal, geothermal, and other relevant renewable energy businesses, as well as energy conversion, storage, conservation, efficiency, materials, pollution control, emerging hydrogen and fuel cells.

To be included in the index, companies should meet some requirements like:

- At least 10 percent of each company’s market value is derived from the activities in Alternative Energies.
- They should be listed on at least one of the big international or national exchange markets.
- Their market capitalization for each 3-month should have an average of 100m USD.
- At least 250000 shares of this company should have been traded in the last six months.

4.1.2 Biofuels

The launch date of the S&P GSCI Biofuel Index (SPGSBF) is July 2007. It provides a benchmark for investment in the biofuels sector and as a measure of performance of this commodity over time.

The difference between this index and other ones is that this index pays attention to the biofuel industry contracts to track the performance of Biofuels. Thus, the eligibility criteria will be applied to the contracts, and there is no limit on the number of contracts, just:

- The contract must be denominated in U.S. dollars.
- The contract must have specific determined terms, like volume, time of delivery and its method, price, payment method, the penalty for delay or cancelation, and the expiry date.
- The commodity in the contract should meet some requirements like the average amount of trade and the annual average price.

4.1.3 Solar Energy

The Ardour Solar Energy Index, SOLRX, was launched in January 2005 and includes 27 companies from all around the world that are principally engaged in the solar energy sectors like Photovoltaics, Solar Thermal, Solar Lighting.

Some of SOLRX selection criteria for companies are:

- The company must derive 66% or more of its annual revenues from its participation in the solar energy sector.
- The company must be traded on at least one recognized stock exchange in the Americas, Europe, Middle East & Africa (EMEA), and Asia/Pacific.
- The company must have a minimum capitalization of 100 m USD and a minimum average daily trading volume greater than 1 m USD.

4.1.4 Wind Energy

The ISE Global Wind Energy Index (GWE) began in December 2005 and is designed to track the companies active in the wind energy industry based on analysis of the products and services offered by those companies.

The number of companies in this index is not fixed; thus, every stock in the wind industry that meets the index's eligibility requirements can be included in it. Some requirements are:

- The market capitalization of the company must be at least 100 m USD.
- The daily trading volume of the company should be at least 500 thousand USD for the last three months.
- Before being included in the index, it should be traded at least for three months in one recognized stock exchange.

According to the weighting method (quintile-based modified capitalization-weighted), which is used in this index, it does not let the large companies' stocks dominate the index.

4.2 Crude Oil

Between a considerable number of benchmarks for crude oil prices, West Texas Intermediate (WTI) and ICE Brent crude (Brent) are the most important ones with the most influences.

WTI is the leading benchmark of crude oil in the United States of America, and it refers to oil extracted from wells in the U.S. and sent via pipeline to Cushing, Oklahoma. On the other hand, the Brent is more worldwide, and almost two-thirds of all crude contracts around the world are referenced by it. Brent is used to pricing 15 different fields in the North Sea like the Forties, Oseberg, Ekofisk, and fields in Africa and the Middle East.

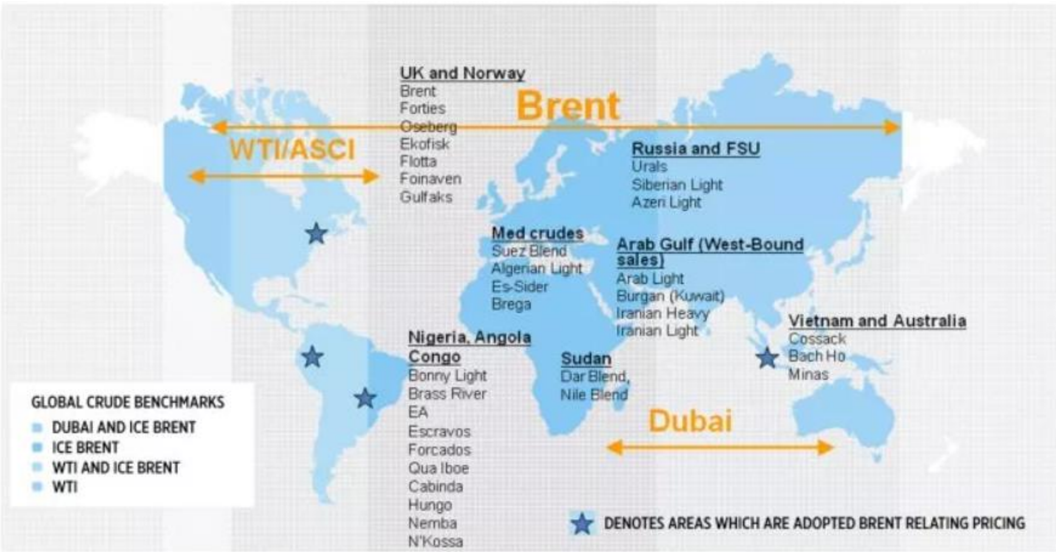

Figure 11: The Benchmark which is used in different countries
(Source: Intercontinental Exchange (ICE))

In order to analyze the crude oil price, I used the futures price of these benchmarks for several reasons. First of all, after the oil crisis at the end of the 1970s, the buyers paid more attention to finding a way to minimize the risk of sudden fluctuation in oil price, and they started to use crude oil futures contracts in which they could lock the price several month or years before buying it. Furthermore, previous researchers like Sadorsky (2001) and Scholtens & Wang (2008) stated that future prices are a better reflection of real oil price because despite of the spot prices, it is not affected by short-term supply-demand shocks. Also, before them, Gurcan(1998) and Crowder and Hamed (1993) believed that spot prices can be manipulated by big Oil & Gas companies.

The prices according to these benchmarks are highly correlated, and choosing just one of them may damage the results of the analysis. In order to robust my model, I used the average prices of these benchmarks.

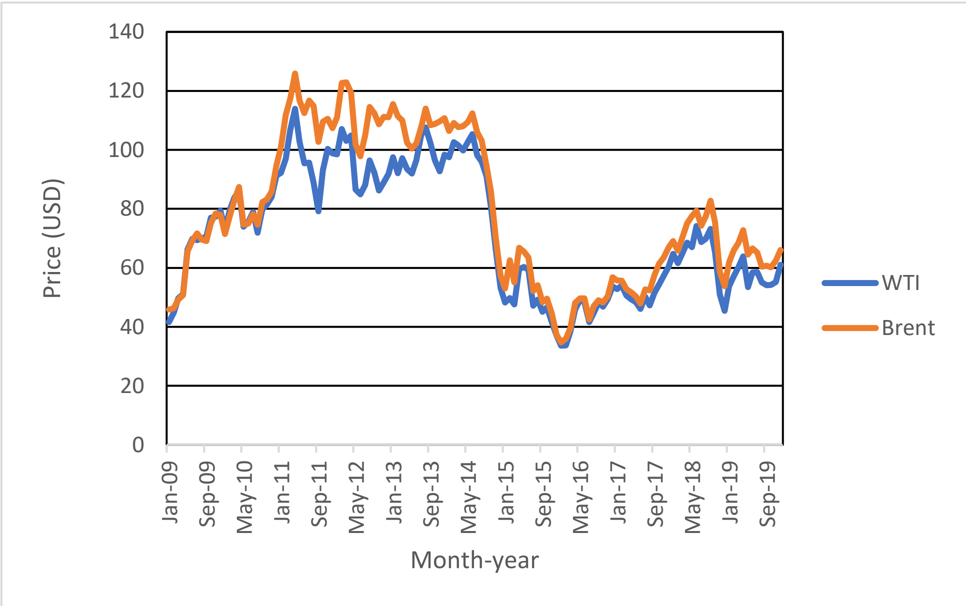

Figure 12: Annual WTI and Brent crude oil price

4.3 Descriptive Statistics of Data Sample

	OILPRICE	NEXINDEX	BIOFUELIND	SOLARINDEX	WINDINDEX
Mean	4.273083	5.187159	4.881101	6.479812	4.863657
Median	4.272313	5.221976	4.805843	6.294951	4.918979
Maximum	4.786741	5.516167	5.405736	7.714512	5.205324
Minimum	3.531641	4.665230	4.578518	5.568157	4.206184
Std. Dev.	0.319690	0.186346	0.231544	0.631635	0.240873
Skewness	-0.198073	-0.881893	0.672314	0.612223	-0.941310
Kurtosis	1.896999	3.422393	2.168371	2.016690	3.105678
Jarque-Bera	7.554484	18.09145	13.74797	13.56392	19.55485
Probability	0.022886	0.000118	0.001034	0.001134	0.000057
Sum	564.0469	684.7049	644.3054	855.3352	642.0028
Sum Sq. Dev.	13.38844	4.548930	7.023246	52.26420	7.600602
Observations	132	132	132	132	132

Table 1: Descriptive Statistics of The Data during the First Period, 2009-2019

	LOGOIL	LOGNEX	LOGBIO	LOGSOLAR	LOGWIND
Mean	4.008880	6.035163	4.923586	6.975533	5.523877
Median	4.053160	6.130155	4.984014	7.110260	5.589808
Maximum	4.327900	6.344811	5.162097	7.341597	5.685279
Minimum	3.600731	5.498110	4.589142	6.135764	5.178012
Std. Dev.	0.255718	0.243921	0.205569	0.349000	0.143933
Skewness	-0.175847	-0.874620	-0.389376	-1.270512	-1.053781
Kurtosis	1.506099	2.687146	1.656734	3.480624	3.040586
Jarque-Bera	1.570287	2.105148	1.607211	4.458535	2.962308
Probability	0.456054	0.349038	0.447712	0.107607	0.227375
Sum	64.14207	96.56261	78.77738	111.6085	88.38204
Sum Sq. Dev.	0.980877	0.892464	0.633882	1.827014	0.310749
Observations	16	16	16	16	16

Table 2: Descriptive Statistics of The Data during the Second Period, 2020-2021

5) Statistical Validity of my Models

In order to avoid the misleading results arising from using the wrong model, I will analyse the stochastic properties of the series that I used in this research. Investigating these properties helps me to understand whether any modification in my Vector Autoregressive Models is necessary or not. Ignoring this process will lead us to a statistically invalid model; thus, the conclusion would not be valuable. All of the tests have been described in previous chapters, and here I will only represent the discussion of the results.

5.1 Unit Root Tests

From the graphical analysis, it can be understood that all of the time series in both periods contain a unit root and are non-stationary in their level. As mentioned before, it is prevalent to have non-stationary data when dealing with financial time series.

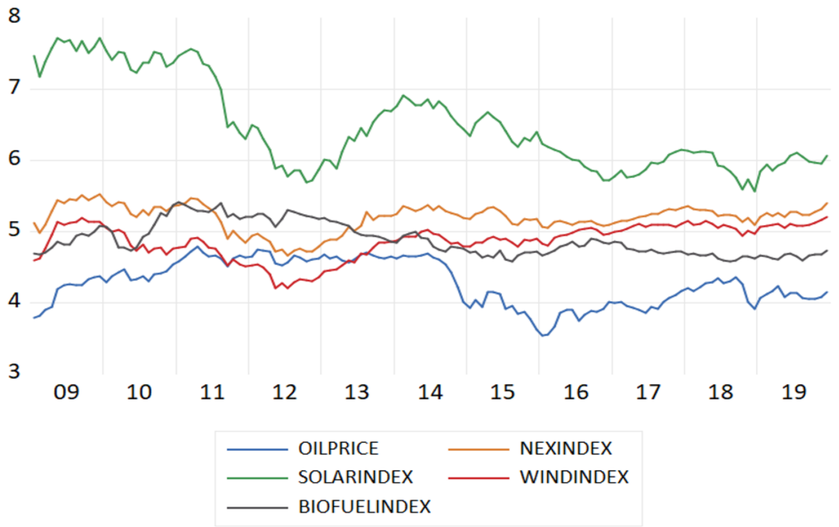

Figure 13: Natural Logarithm of Data during the first period, 2009-2019

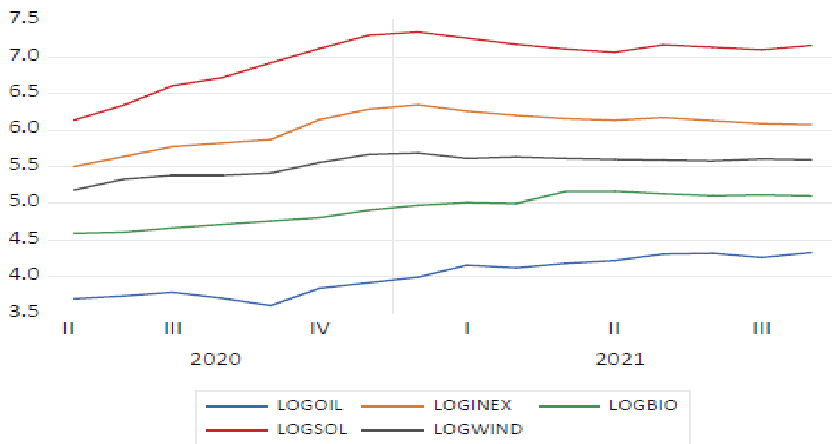

Figure 14: Natural Logarithm of Data during the second period, 2020-2021

Determination of order of integration is impossible with graphical analysis; therefore, I must conduct unit root tests for further analysis. To interpret the results of this test, I rely on five percentile rejection regions. One feature of the ADF test is that it reveals whether trend and drift are significant in describing the value of each observation or not. To examine this, I conducted the test for all three equations mentioned in the Stationary Test section and chose the most significant model.

The test results from the augmented Dickey-Fuller test can be found in the following tables. From the tables, I could confirm my suspicion of non-stationary time series for both periods.

Augmented Dickey-Fuller Unit Root Test on OILPRICE

Null Hypothesis: OILPRICE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.759107	0.2152
Test critical values:	1% level	-4.029595	
	5% level	-3.444487	
	10% level	-3.147063	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OILPRICE)
Method: Least Squares
Date: 10/18/21 Time: 15:01
Sample (adjusted): 2009M02 2019M12
Included observations: 131 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OILPRICE(-1)	-0.068210	0.024722	-2.759107	0.0066
C	0.326433	0.112971	2.889522	0.0045
@TREND("2009M01")	-0.000486	0.000209	-2.325730	0.0216

R-squared	0.065628	Mean dependent var	0.002842
Adjusted R-squared	0.051029	S.D. dependent var	0.082080
S.E. of regression	0.079958	Akaike info criterion	-2.191989
Sum squared resid	0.818345	Schwarz criterion	-2.126145
Log likelihood	146.5753	Hannan-Quinn criter.	-2.165234
F-statistic	4.495220	Durbin-Watson stat	1.645418
Prob(F-statistic)	0.012980		

Augmented Dickey-Fuller Unit Root Test on OIL

Null Hypothesis: OIL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.353582	0.3847
Test critical values:	1% level	-4.728363	
	5% level	-3.759743	
	10% level	-3.324976	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 15

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OIL)
Method: Least Squares
Date: 11/02/21 Time: 17:31
Sample (adjusted): 2020M07 2021M09
Included observations: 15 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OIL(-1)	-0.587905	0.249791	-2.353582	0.0365
C	20.91973	8.411109	2.487155	0.0286
@TREND("2020M06")	1.759615	0.757006	2.324441	0.0385

R-squared	0.319157	Mean dependent var	2.371667
Adjusted R-squared	0.205683	S.D. dependent var	4.524006
S.E. of regression	4.031995	Akaike info criterion	5.803256
Sum squared resid	195.0838	Schwarz criterion	5.944866
Log likelihood	-40.52442	Hannan-Quinn criter.	5.801748
F-statistic	2.812606	Durbin-Watson stat	1.898483
Prob(F-statistic)	0.099605		

Table 3: Augmented Dickey Fuller test on level for Oil Price, the left one is for period 2009-2019 and the right one for period 2020-2021

Augmented Dickey-Fuller Unit Root Test on NEXINDEX

Null Hypothesis: NEXINDEX has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.982482	0.2943
Test critical values:	1% level	-3.480818	
	5% level	-2.883579	
	10% level	-2.578601	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NEXINDEX)
Method: Least Squares
Date: 10/18/21 Time: 16:39
Sample (adjusted): 2009M02 2019M12
Included observations: 131 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NEXINDEX(-1)	-0.063407	0.031984	-1.982482	0.0496
C	0.330976	0.165958	1.994338	0.0482

R-squared	0.029566	Mean dependent var	0.002178
Adjusted R-squared	0.022043	S.D. dependent var	0.068628
S.E. of regression	0.067867	Akaike info criterion	-2.527381
Sum squared resid	0.594167	Schwarz criterion	-2.483485
Log likelihood	167.5435	Hannan-Quinn criter.	-2.509544
F-statistic	3.930234	Durbin-Watson stat	1.907551
Prob(F-statistic)	0.049550		

Augmented Dickey-Fuller Unit Root Test on NEX

Null Hypothesis: NEX has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.251203	0.1988
Test critical values:	1% level	-4.004425	
	5% level	-3.098896	
	10% level	-2.690439	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 14

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NEX)
Method: Least Squares
Date: 11/02/21 Time: 17:36
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NEX(-1)	-0.236971	0.105264	-2.251203	0.0458
D(NEX(-1))	0.476851	0.211163	2.258208	0.0452
C	108.9659	47.76092	2.281486	0.0434

R-squared	0.513963	Mean dependent var	10.93500
Adjusted R-squared	0.425593	S.D. dependent var	42.91625
S.E. of regression	32.52607	Akaike info criterion	9.989370
Sum squared resid	11637.40	Schwarz criterion	10.12631
Log likelihood	-66.92559	Hannan-Quinn criter.	9.976694
F-statistic	5.816017	Durbin-Watson stat	1.900039
Prob(F-statistic)	0.018909		

Table 4: Augmented Dickey Fuller test on level for NEX Index, the left one is for period 2009-2019 and the right one for period 2020-2021

Augmented Dickey-Fuller Unit Root Test on BIOFUELINDEX

Null Hypothesis: BIOFUELINDEX has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.830165	0.1893
Test critical values:	1% level	-4.029595	
	5% level	-3.444487	
	10% level	-3.147063	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BIOFUELINDEX)
Method: Least Squares
Date: 10/18/21 Time: 16:44
Sample (adjusted): 2009M02 2019M12
Included observations: 131 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BIOFUELINDEX(-1)	-0.082277	0.029072	-2.830165	0.0054
C	0.431713	0.149890	2.880206	0.0047
@TREND("2009M01")	-0.000450	0.000178	-2.533086	0.0125

R-squared	0.064685	Mean dependent var	0.000304
Adjusted R-squared	0.050071	S.D. dependent var	0.060098
S.E. of regression	0.058575	Akaike info criterion	-2.814399
Sum squared resid	0.439165	Schwarz criterion	-2.748555
Log likelihood	187.3431	Hannan-Quinn criter.	-2.787644
F-statistic	4.426146	Durbin-Watson stat	1.775278
Prob(F-statistic)	0.013845		

Augmented Dickey-Fuller Unit Root Test on BIO

Null Hypothesis: BIO has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.778006	0.9757
Test critical values:	1% level	-2.728252	
	5% level	-1.966270	
	10% level	-1.605026	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 15

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BIO)
Method: Least Squares
Date: 11/02/21 Time: 17:44
Sample (adjusted): 2020M07 2021M09
Included observations: 15 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BIO(-1)	0.026708	0.015021	1.778006	0.0971

R-squared	-0.081614	Mean dependent var	4.354667
Adjusted R-squared	-0.081614	S.D. dependent var	7.896373
S.E. of regression	8.212280	Akaike info criterion	7.113479
Sum squared resid	944.1815	Schwarz criterion	7.160682
Log likelihood	-52.35109	Hannan-Quinn criter.	7.112976
Durbin-Watson stat	1.851249		

Table 5: Augmented Dickey Fuller test on level for Biofuel Index, the left one is for period 2009-2019 and the right one for period 2020-2021

Augmented Dickey-Fuller Unit Root Test on SOLARINDEX

Null Hypothesis: SOLARINDEX has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.670846	0.7587
Test critical values:	1% level	-4.029595	
	5% level	-3.444487	
	10% level	-3.147063	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SOLARINDEX)
Method: Least Squares
Date: 10/18/21 Time: 15:47
Sample (adjusted): 2009M02 2019M12
Included observations: 131 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SOLARINDEX(-1)	-0.047032	0.028148	-1.670846	0.0972
C	0.322389	0.208249	1.548090	0.1241
@TREND("2009M01")	-0.000427	0.000469	-0.909013	0.3651

R-squared	0.024916	Mean dependent var	-0.010679
Adjusted R-squared	0.009680	S.D. dependent var	0.123779
S.E. of regression	0.123179	Akaike info criterion	-1.327728
Sum squared resid	1.942141	Schwarz criterion	-1.261883
Log likelihood	89.96616	Hannan-Quinn criter.	-1.300972
F-statistic	1.635366	Durbin-Watson stat	1.882138
Prob(F-statistic)	0.198926		

Augmented Dickey-Fuller Unit Root Test on SOLAR

Null Hypothesis: SOLAR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.611760	0.1138
Test critical values:	1% level	-4.004425	
	5% level	-3.098896	
	10% level	-2.690439	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 14

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SOLAR)
Method: Least Squares
Date: 11/02/21 Time: 16:35
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SOLAR(-1)	-0.230415	0.088222	-2.611760	0.0242
D(SOLAR(-1))	0.475175	0.194001	2.449348	0.0323
C	293.1556	107.9189	2.716445	0.0201

R-squared	0.606947	Mean dependent var	51.06519
Adjusted R-squared	0.535483	S.D. dependent var	127.7509
S.E. of regression	87.06927	Akaike info criterion	11.95869
Sum squared resid	83391.64	Schwarz criterion	12.09564
Log likelihood	-80.71086	Hannan-Quinn criter.	11.94602
F-statistic	8.493018	Durbin-Watson stat	1.904705
Prob(F-statistic)	0.005881		

Table 6: Augmented Dickey Fuller test on level for Solar Index, the left one is for period 2009-2019 and the right one for period 2020-2021

Augmented Dickey-Fuller Unit Root Test on WINDINDEX

Null Hypothesis: WINDINDEX has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.372905	0.5938
Test critical values:	1% level	-3.480818	
	5% level	-2.883579	
	10% level	-2.578601	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(WINDINDEX)
Method: Least Squares
Date: 11/11/21 Time: 17:51
Sample (adjusted): 2009M02 2019M12
Included observations: 131 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
WINDINDEX(-1)	-0.031505	0.022948	-1.372905	0.1722
C	0.157816	0.111685	1.413046	0.1601

R-squared	0.014401	Mean dependent var	0.004668
Adjusted R-squared	0.006761	S.D. dependent var	0.062987
S.E. of regression	0.062774	Akaike info criterion	-2.683415
Sum squared resid	0.508328	Schwarz criterion	-2.639519
Log likelihood	177.7637	Hannan-Quinn criter.	-2.665578
F-statistic	1.884869	Durbin-Watson stat	1.794770
Prob(F-statistic)	0.172164		

Augmented Dickey-Fuller Unit Root Test on WIND

Null Hypothesis: WIND has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.199988	0.9326
Test critical values:	1% level	-2.728252	
	5% level	-1.966270	
	10% level	-1.605026	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 15

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(WIND)
Method: Least Squares
Date: 11/02/21 Time: 17:33
Sample (adjusted): 2020M07 2021M09
Included observations: 15 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
WIND(-1)	0.019007	0.015839	1.199988	0.2501

R-squared	-0.063317	Mean dependent var	6.069333
Adjusted R-squared	-0.063317	S.D. dependent var	15.11804
S.E. of regression	15.58931	Akaike info criterion	8.395388
Sum squared resid	3402.372	Schwarz criterion	8.442592
Log likelihood	-61.96541	Hannan-Quinn criter.	8.394885
Durbin-Watson stat	1.109101		

Table 7: Augmented Dickey Fuller test on level for Wind Index, the left one is for period 2009-2019 and the right one for period 2020-2021

As to why all of the time series were found non-stationary, the next step is to determine the order of integration for each observation by rerunning the test for higher orders. Repeating the test using differenced variables reveals that all of the considered time series are integrated of the first order I(1) because I could reject the null hypothesis of having a unit root for them. The results of the ADF test for the first differenced series for both periods are shown below.

Augmented Dickey-Fuller Unit Root Test on D(OILPRICE)

Null Hypothesis: D(OILPRICE) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.486353	0.0000
Test critical values:	1% level	-2.582872	
	5% level	-1.943304	
	10% level	-1.615087	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OILPRICE,2)
Method: Least Squares
Date: 10/18/21 Time: 15:06
Sample (adjusted): 2009M03 2019M12
Included observations: 130 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(OILPRICE(-1))	-0.824391	0.086903	-9.486353	0.0000

R-squared	0.410930	Mean dependent var	0.000289
Adjusted R-squared	0.410930	S.D. dependent var	0.105666
S.E. of regression	0.081099	Akaike info criterion	-2.178622
Sum squared resid	0.848446	Schwarz criterion	-2.156564
Log likelihood	142.6104	Hannan-Quinn criter.	-2.169659
Durbin-Watson stat	1.998949		

Augmented Dickey-Fuller Unit Root Test on D(OIL)

Null Hypothesis: D(OIL) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.199998	0.0037
Test critical values:	1% level	-2.740613	
	5% level	-1.968430	
	10% level	-1.604392	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 14

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OIL,2)
Method: Least Squares
Date: 11/02/21 Time: 17:32
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(OIL(-1))	-0.913174	0.285367	-3.199998	0.0070

R-squared	0.439887	Mean dependent var	0.247143
Adjusted R-squared	0.439887	S.D. dependent var	7.088000
S.E. of regression	5.304709	Akaike info criterion	6.243816
Sum squared resid	365.8192	Schwarz criterion	6.289463
Log likelihood	-42.70671	Hannan-Quinn criter.	6.239591
Durbin-Watson stat	1.943425		

Table 8: Augmented dickey fuller test on Differenced Oil Price, the left one is for period 2009-2019 and the right one for period 2020-2021

Augmented Dickey-Fuller Unit Root Test on D(NEXINDEX)

Null Hypothesis: D(NEXINDEX) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.53588	0.0000
Test critical values:	1% level	-2.582872	
	5% level	-1.943304	
	10% level	-1.615087	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NEXINDEX,2)
Method: Least Squares
Date: 10/18/21 Time: 16:41
Sample (adjusted): 2009M03 2019M12
Included observations: 130 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(NEXINDEX(-1))	-1.007068	0.087299	-11.53588	0.0000

R-squared	0.507620	Mean dependent var	0.001722
Adjusted R-squared	0.507620	S.D. dependent var	0.096763
S.E. of regression	0.067899	Akaike info criterion	-2.533942
Sum squared resid	0.594717	Schwarz criterion	-2.511885
Log likelihood	165.7063	Hannan-Quinn criter.	-2.524980
Durbin-Watson stat	1.920698		

Augmented Dickey-Fuller Unit Root Test on D(NEX)

Null Hypothesis: D(NEX) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.976380	0.0492
Test critical values:	1% level	-2.740613	
	5% level	-1.968430	
	10% level	-1.604392	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 14

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NEX,2)
Method: Least Squares
Date: 11/02/21 Time: 17:43
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(NEX(-1))	-0.438202	0.221719	-1.976380	0.0697

R-squared	0.226628	Mean dependent var	-3.016429
Adjusted R-squared	0.226628	S.D. dependent var	41.29967
S.E. of regression	36.31957	Akaike info criterion	10.09134
Sum squared resid	17148.45	Schwarz criterion	10.13699
Log likelihood	-69.63938	Hannan-Quinn criter.	10.08711
Durbin-Watson stat	1.806001		

Table 9: Augmented dickey fuller test on Differenced NEX Index, the left one is for period 2009-2019 and the right one for period 2020-2021

Augmented Dickey-Fuller Unit Root Test on D(BIOFUELINDEX)

Null Hypothesis: D(BIOFUELINDEX) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.27615	0.0000
Test critical values:	1% level	-2.582872	
	5% level	-1.943304	
	10% level	-1.615087	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BIOFUELINDEX,2)
Method: Least Squares
Date: 10/18/21 Time: 16:48
Sample (adjusted): 2009M03 2019M12
Included observations: 130 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(BIOFUELINDEX(-1))	-0.902704	0.087845	-10.27615	0.0000

R-squared	0.450111	Mean dependent var	0.000421
Adjusted R-squared	0.450111	S.D. dependent var	0.080972
S.E. of regression	0.060044	Akaike info criterion	-2.779807
Sum squared resid	0.465085	Schwarz criterion	-2.757749
Log likelihood	181.6875	Hannan-Quinn criter.	-2.770844
Durbin-Watson stat	1.988194		

Augmented Dickey-Fuller Unit Root Test on D(BIO)

Null Hypothesis: D(BIO) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.751540	0.0098
Test critical values:	1% level	-2.740613	
	5% level	-1.968430	
	10% level	-1.604392	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 14

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BIO,2)
Method: Least Squares
Date: 11/02/21 Time: 17:44
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(BIO(-1))	-0.737428	0.268006	-2.751540	0.0165

R-squared	0.367621	Mean dependent var	-0.284286
Adjusted R-squared	0.367621	S.D. dependent var	11.43744
S.E. of regression	9.095311	Akaike info criterion	7.322144
Sum squared resid	1075.421	Schwarz criterion	7.367791
Log likelihood	-50.25501	Hannan-Quinn criter.	7.317919
Durbin-Watson stat	2.052943		

Table 10: Augmented dickey fuller test on Differenced of Biofuel Index, the left one is for period 2009-2019 and the right one for period 2020-2021

Augmented Dickey-Fuller Unit Root Test on D(SOLARINDEX)

Null Hypothesis: D(SOLARINDEX) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.29523	0.0000
Test critical values:	1% level	-2.582872	
	5% level	-1.943304	
	10% level	-1.615087	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SOLARINDEX,2)
Method: Least Squares
Date: 10/18/21 Time: 15:48
Sample (adjusted): 2009M03 2019M12
Included observations: 130 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SOLARINDEX(-1))	-0.977512	0.086542	-11.29523	0.0000

R-squared	0.497087	Mean dependent var	0.002974
Adjusted R-squared	0.497087	S.D. dependent var	0.172375
S.E. of regression	0.122242	Akaike info criterion	-1.357968
Sum squared resid	1.927656	Schwarz criterion	-1.335910
Log likelihood	89.26794	Hannan-Quinn criter.	-1.349005
Durbin-Watson stat	1.915588		

Augmented Dickey-Fuller Unit Root Test on D(SOLAR)

Null Hypothesis: D(SOLAR) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.874821	0.0078
Test critical values:	1% level	-2.740613	
	5% level	-1.968430	
	10% level	-1.604392	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 14

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SOLAR,2)
Method: Least Squares
Date: 11/12/21 Time: 07:15
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SOLAR(-1))	-0.344202	0.205515	-1.674821	0.1178

R-squared	0.177169	Mean dependent var	-2.128936
Adjusted R-squared	0.177169	S.D. dependent var	114.1767
S.E. of regression	103.5697	Akaike info criterion	12.18712
Sum squared resid	139447.0	Schwarz criterion	12.23276
Log likelihood	-84.30982	Hannan-Quinn criter.	12.18289
Durbin-Watson stat	1.717253		

Table 11: Augmented dickey fuller test on Differenced of Solar Index, the left one is for period 2009-2019 and the right one for period 2020-2021

Augmented Dickey-Fuller Unit Root Test on D(WINDINDEX)

Null Hypothesis: D(WINDINDEX) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.36150	0.0000
Test critical values:	1% level	-2.582872	
	5% level	-1.943304	
	10% level	-1.615087	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(WINDINDEX,2)
Method: Least Squares
Date: 10/18/21 Time: 15:27
Sample (adjusted): 2009M03 2019M12
Included observations: 130 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(WINDINDEX(-1))	-0.910251	0.087849	-10.36150	0.0000

R-squared	0.454221	Mean dependent var	0.000190
Adjusted R-squared	0.454221	S.D. dependent var	0.085427
S.E. of regression	0.063111	Akaike info criterion	-2.680186
Sum squared resid	0.513804	Schwarz criterion	-2.658128
Log likelihood	175.2121	Hannan-Quinn criter.	-2.671223
Durbin-Watson stat	1.993411		

Augmented Dickey-Fuller Unit Root Test on D(WIND)

Null Hypothesis: D(WIND) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.723058	0.0104
Test critical values:	1% level	-2.740613	
	5% level	-1.968430	
	10% level	-1.604392	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 14

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(WIND,2)
Method: Least Squares
Date: 11/02/21 Time: 17:35
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(WIND(-1))	-0.598221	0.219687	-2.723058	0.0174

R-squared	0.350759	Mean dependent var	-2.247857
Adjusted R-squared	0.350759	S.D. dependent var	16.67883
S.E. of regression	13.43906	Akaike info criterion	8.102956
Sum squared resid	2347.907	Schwarz criterion	8.148603
Log likelihood	-55.72069	Hannan-Quinn criter.	8.098731
Durbin-Watson stat	1.756861		

Table 12: Augmented dickey fuller test on Differenced of Wind Index, the left one is for period 2009-2019 and the right one for period 2020-2021

From the graphical point of view, figures below show the change in the time series before and after being differenced for one time. It can be seen that now the time series are stationary and fluctuate around zero with constant variance.

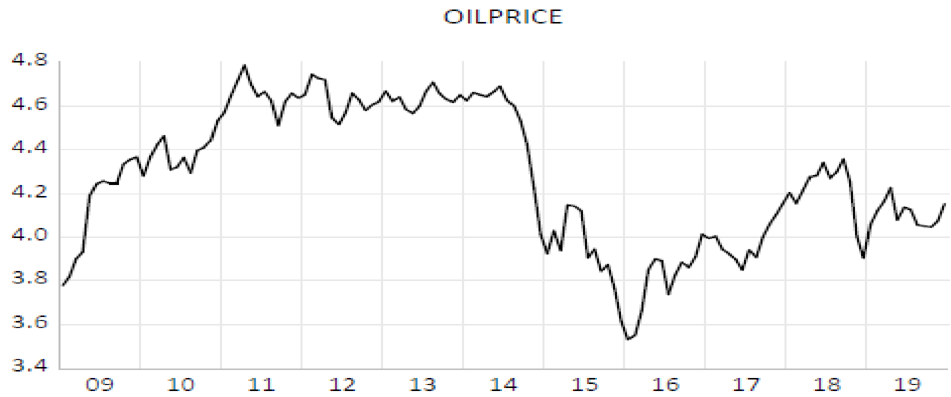

Figure 15: Natural Logarithm of Oil Price during first period

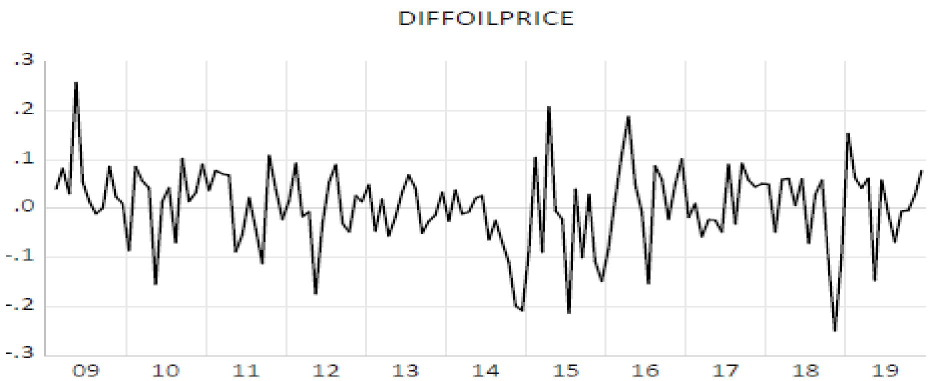

Figure 16: First differenced of Oil Price during first period

5.2 Lag Length & Cointegration

Transforming time series to stationary successfully, I must determine the optimal number of lags in my Vector Autoregressive Models. For this purpose, I used the information criteria approach. According to previous studies for monthly data, the best information criteria is MAIC, so I used it to find the maximum lag number in my model. Also, for more accuracy, I checked the value of HQIC as a supplementary criterion that gives the most trustable results. The optimal number of lags for modeling renewable energy prices vs. oil prices is presented below.

Optimal number of lags for **VAR** and **VECM**		
	Oil Price	D(Oil Price)
D(NEX Index)	-	1
D(Solar Index)	-	1
D(Wind Index)	-	1
Biofuel index	2	-

Optimal number of lags for **VAR** and **VECM**		
	Oil Price	D(Oil Price)
D(NEX)	-	1
Solar	1	-
D(Wind)	-	1
D(Bio)	-	1

Table 13: Optimal Number of lags, the left table for period 2009-2019 and the right one for period 2020-2021

Conducting Johansen's test revealed that in both periods, for one occasion, I should use the Vector Error Correction Model instead of VAR because two I(1) time series (biofuel and oil in the first period, Solar and oil in the second period) are cointegrated. Since in the VECM model stationarity is not essential, the optimal number of lags is chosen by variables on their level, and differencing is not needed.

The results of Lag Length detection and Johansen's test for Cointegration from the software are shown in the appendix.

5.3 Autocorrelation

Estimating the number of lags by minimizing the information criteria can make the VAR and VECM models invalid because it increases the probability of having autocorrelation. In my research, LM test results say the models don't exhibit autocorrelation; therefore, the optimal number of lags is as same as before. In the case of having autocorrelation, the number of lags should be increased until autocorrelation disappears.

VAR Residual Serial Correlation LM Tests
Date: 11/05/21 Time: 18:28
Sample: 2009M01 2019M12
Included observations: 131

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	5.985398	4	0.2002	1.508300	(4, 250.0)	0.2002
2	0.701668	4	0.9511	0.174962	(4, 250.0)	0.9511
3	8.417550	4	0.0774	2.131546	(4, 250.0)	0.0774

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	5.985398	4	0.2002	1.508300	(4, 250.0)	0.2002
2	6.581083	8	0.5824	0.823559	(8, 246.0)	0.5825
3	14.38265	12	0.2769	1.209155	(12, 242.0)	0.2771

*Edgeworth expansion corrected likelihood ratio statistic.

VAR Residual Serial Correlation LM Tests
Date: 11/08/21 Time: 11:06
Sample: 2020M06 2021M09
Included observations: 15

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.335182	4	0.8554	0.327603	(4, 18.0)	0.8558
2	2.579607	4	0.6304	0.654377	(4, 18.0)	0.6313

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.335182	4	0.8554	0.327603	(4, 18.0)	0.8558
2	6.030065	8	0.6439	0.745092	(8, 14.0)	0.6533

*Edgeworth expansion corrected likelihood ratio statistic.

Table 14: The LM test results for autocorrelation NEX Index and Oil Price, the left table is for period 2009-2019 and the right one for period 2020-2021

VEC Residual Serial Correlation LM Tests
Date: 11/12/21 Time: 09:31
Sample: 2009M01 2019M12
Included observations: 129

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.554784	4	0.8169	0.388334	(4, 240.0)	0.8169
2	3.198174	4	0.5252	0.801532	(4, 240.0)	0.5252
3	1.929181	4	0.7488	0.482221	(4, 240.0)	0.7488

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.554784	4	0.8169	0.388334	(4, 240.0)	0.8169
2	11.32378	8	0.1840	1.431345	(8, 236.0)	0.1841
3	15.45125	12	0.2177	1.302435	(12, 232.0)	0.2179

*Edgeworth expansion corrected likelihood ratio statistic.

VAR Residual Serial Correlation LM Tests
Date: 11/12/21 Time: 09:38
Sample: 2020M06 2021M09
Included observations: 15

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.774391	4	0.7772	0.440499	(4, 18.0)	0.7777
2	3.021747	4	0.5542	0.775728	(4, 18.0)	0.5552

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.774391	4	0.7772	0.440499	(4, 18.0)	0.7777
2	6.759750	8	0.5628	0.854519	(8, 14.0)	0.5736

*Edgeworth expansion corrected likelihood ratio statistic.

Table 15: The LM test results for autocorrelation Biofuel Index and Oil Price, the left table is for period 2009-2019 and the right one for period 2020-2021

VAR Residual Serial Correlation LM Tests
Date: 11/05/21 Time: 18:44
Sample: 2009M01 2019M12
Included observations: 130

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	3.356291	4	0.5001	0.841398	(4, 244.0)	0.5001
2	2.876010	4	0.5788	0.720287	(4, 244.0)	0.5788
3	3.748346	4	0.4411	0.940437	(4, 244.0)	0.4411

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	3.356291	4	0.5001	0.841398	(4, 244.0)	0.5001
2	8.410692	8	0.3944	1.056536	(8, 240.0)	0.3945
3	10.75875	12	0.5497	0.897854	(12, 236.0)	0.5499

*Edgeworth expansion corrected likelihood ratio statistic.

VEC Residual Serial Correlation LM Tests
Date: 11/12/21 Time: 09:46
Sample: 2020M06 2021M09
Included observations: 14

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	6.855392	4	0.1437	2.027795	(4, 14.0)	0.1456
2	5.242933	4	0.2633	1.464397	(4, 14.0)	0.2654

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	6.855392	4	0.1437	2.027795	(4, 14.0)	0.1456
2	10.29924	8	0.2446	1.510448	(8, 10.0)	0.2658

*Edgeworth expansion corrected likelihood ratio statistic.

Table 16: The LM test results for autocorrelation Solar Index and Oil Price, the left table is for period 2009-2019 and the right one for period 2020-2021

VAR Residual Serial Correlation LM Tests
Date: 11/12/21 Time: 09:45
Sample: 2009M01 2019M12
Included observations: 130

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.238937	4	0.3746	1.064514	(4, 248.0)	0.3746
2	2.434393	4	0.6564	0.609127	(4, 248.0)	0.6564
3	7.952493	4	0.0933	2.012099	(4, 248.0)	0.0933

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.238937	4	0.3746	1.064514	(4, 248.0)	0.3746
2	12.30647	8	0.1380	1.558119	(8, 244.0)	0.1381
3	21.83635	12	0.0394	1.864410	(12, 240.0)	0.0395

*Edgeworth expansion corrected likelihood ratio statistic.

VAR Residual Serial Correlation LM Tests
Date: 11/12/21 Time: 09:47
Sample: 2020M06 2021M09
Included observations: 15

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	2.988972	4	0.5597	0.766635	(4, 18.0)	0.5607
2	4.320107	4	0.3644	1.148847	(4, 18.0)	0.3657

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	2.988972	4	0.5597	0.766635	(4, 18.0)	0.5607
2	12.05515	8	0.1488	1.806376	(8, 14.0)	0.1592

*Edgeworth expansion corrected likelihood ratio statistic.

Table 17: The LM test results for autocorrelation Wind Index and Oil Price, the left table is for period 2009-2019 and the right one for period 2020-2021

5.4 Stability

Calculating eigenvalues of my models and the fact that all of them are less than 1, confirms that my models are stable. The figures show the result of Inverse Root calculation of the models.

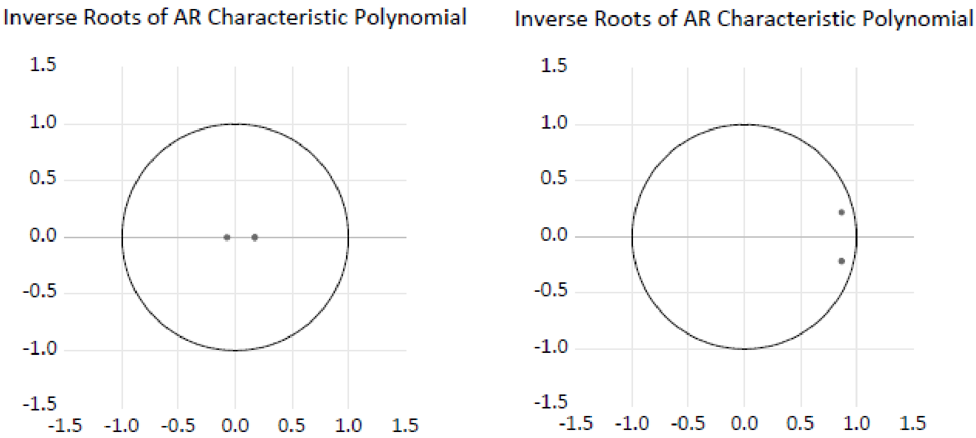

Figure 17: Stability test of NEX Index- Oil Price model, the left figure is for period 2009-2019 and the right one for period 2020-2021

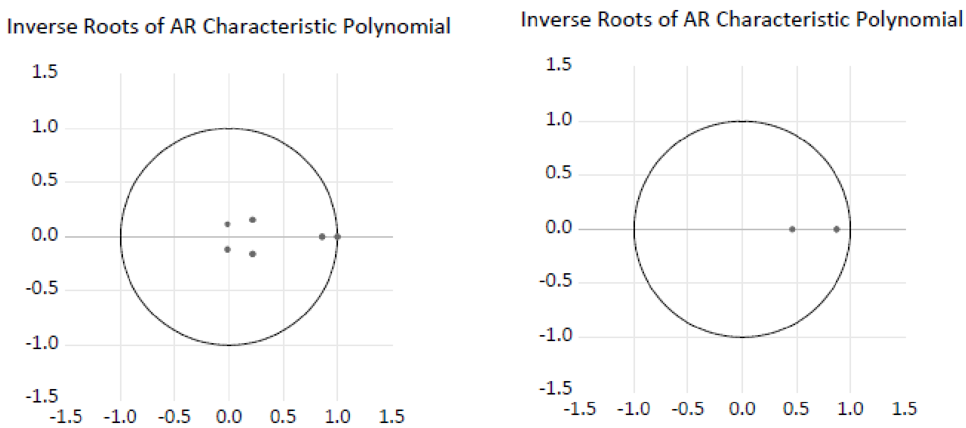

Figure 18: Stability test of Biofuel Index- Oil Price model, the left figure is for period 2009-2019 and the right one for period 2020-2021

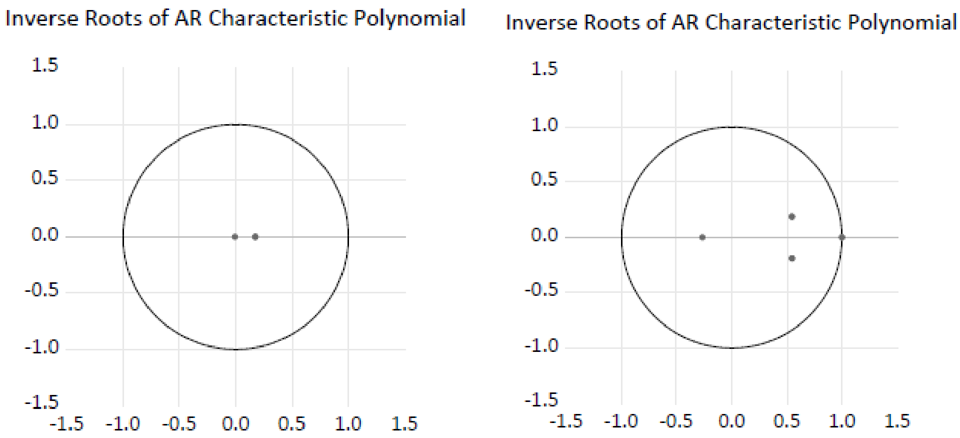

Figure 19: Stability test of Solar Index- Oil Price model, the left figure is for period 2009-2019 and the right one for period 2020-2021

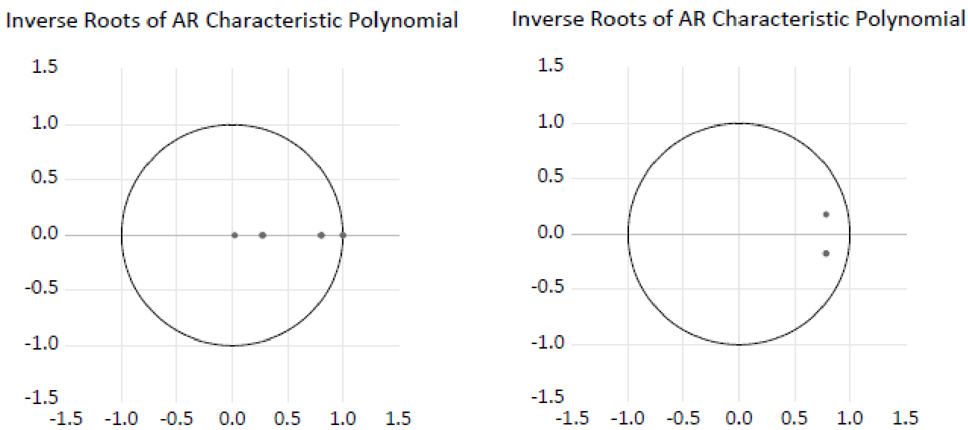

Figure 20: Stability test of Wind Index- Oil Price model, the left figure is for period 2009-2019 and the right one for period 2020-2021

5.5 Granger Causality & Impulse Response Functions

Understanding the relationship between the variables using these functions is necessary; first, Granger Causality reveals whether the relationship exists. Then, using the Impulse Response function allows me to determine the sign of this relationship and how long a shock in one variable will affect the other one.

The impulse response functions, which are presented in the figures, measure the response of the dependent variable to a positive shock in one of the independent variables. The solid line tracks the response in time in these figures, and two dashed lines represent the 95 percent confidence interval.

The results of both functions are shown below. It is worth mentioning that no granger causality test is performed on the occasions when time series are cointegrated.

5.5.1 Results of Granger Causality Test

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 11/12/21 Time: 10:14
Sample: 2009M01 2019M12
Included observations: 130

Dependent variable: DIFFNEXINDEX

Excluded	Chi-sq	df	Prob.
DIFFOILPRICE	0.981015	1	0.3219
All	0.981015	1	0.3219

Dependent variable: DIFFOILPRICE

Excluded	Chi-sq	df	Prob.
DIFFNEXINDEX	0.258334	1	0.6113
All	0.258334	1	0.6113

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 11/12/21 Time: 10:17
Sample: 2020M06 2021M09
Included observations: 14

Dependent variable: DIFFLOGNEX

Excluded	Chi-sq	df	Prob.
DIFFLOGOIL	4.245147	1	0.0394
All	4.245147	1	0.0394

Dependent variable: DIFFLOGOIL

Excluded	Chi-sq	df	Prob.
DIFFLOGNEX	0.401013	1	0.5266
All	0.401013	1	0.5266

Table 18: Granger Causality test result for NEX Index-Oil Price Model, the left figure is for period 2009-2019 and the right one for period 2020-2021

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 11/12/21 Time: 10:21
Sample: 2020M06 2021M09
Included observations: 14

Dependent variable: DIFFLOGBIO

Excluded	Chi-sq	df	Prob.
DIFFLOGOIL	0.030672	1	0.8610
All	0.030672	1	0.8610

Dependent variable: DIFFLOGOIL

Excluded	Chi-sq	df	Prob.
DIFFLOGBIO	0.234829	1	0.6280
All	0.234829	1	0.6280

Table 19: Granger Causality test result for Biofuel Index-Oil Price Model, for period 2020-2021

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 11/12/21 Time: 10:25
Sample: 2009M01 2019M12
Included observations: 130

Dependent variable: DIFFSOLARINDEX

Excluded	Chi-sq	df	Prob.
DIFFOILPRICE	0.310373	1	0.5775
All	0.310373	1	0.5775

Dependent variable: DIFFOILPRICE

Excluded	Chi-sq	df	Prob.
DIFFSOLARINDEX	0.096031	1	0.7566
All	0.096031	1	0.7566

Table 20: Granger Causality test result for Solar Index-Oil Price Model, for period 2009-2019

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 11/12/21 Time: 10:28
Sample: 2009M01 2019M12
Included observations: 130

Dependent variable: DIFFWINDINDEX

Excluded	Chi-sq	df	Prob.
DIFFOILPRICE	0.039633	1	0.8422
All	0.039633	1	0.8422

Dependent variable: DIFFOILPRICE

Excluded	Chi-sq	df	Prob.
DIFFWINDINDEX	0.998350	1	0.3177
All	0.998350	1	0.3177

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 11/12/21 Time: 10:30
Sample: 2020M06 2021M09
Included observations: 14

Dependent variable: DIFFLOGWIND

Excluded	Chi-sq	df	Prob.
DIFFLOGOIL	0.102870	1	0.7484
All	0.102870	1	0.7484

Dependent variable: DIFFLOGOIL

Excluded	Chi-sq	df	Prob.
DIFFLOGWIND	0.986967	1	0.3205
All	0.986967	1	0.3205

Table 21: Granger Causality test result for Wind Index-Oil Price Model the left figure is for period 2009-2019 and the right one for period 2020-2021

5.5.2 Results of Impulse Response Functions

Since the IRF results are of great importance in my research, I will write an explanation for each graph and a comparison for understanding the effect of the Covid-19 Pandemic.

5.5.2.1 NEX Index – Crude Oil Prices Model

In the first period, a shock in Oil Price has a limited positive significant effect on the NEX index, but in the period after the pandemic, its impact is negative and more substantial and lasts longer than the previous one.

Contrarily, a positive shock in NEX Index will significantly increase the Oil Price for a short period because the shock dies out quickly.

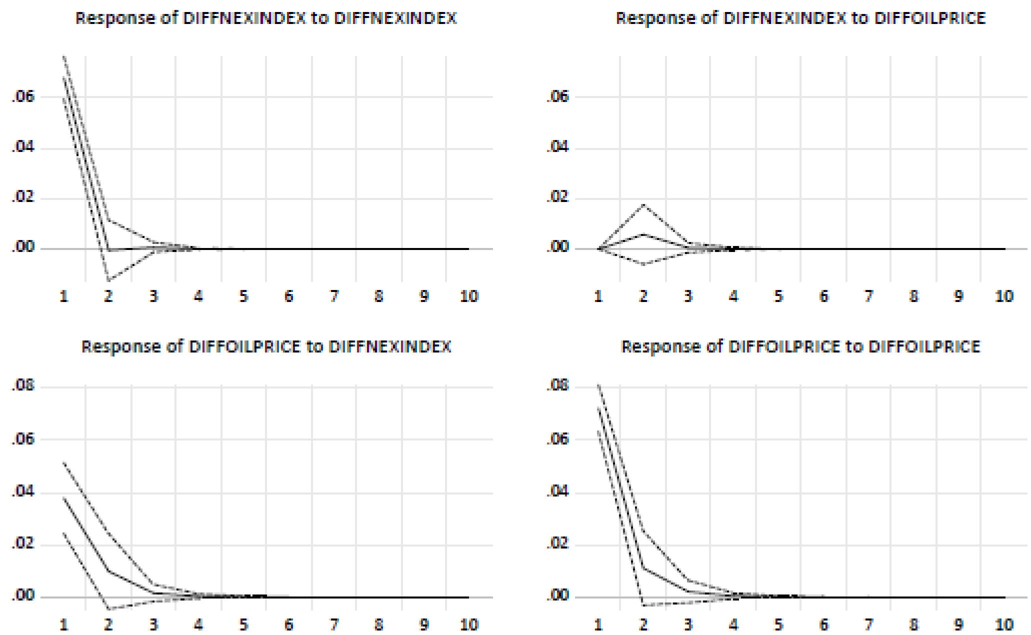

Figure 21: The IRF results for NEX Index - Crude Oil Price Model during the first period

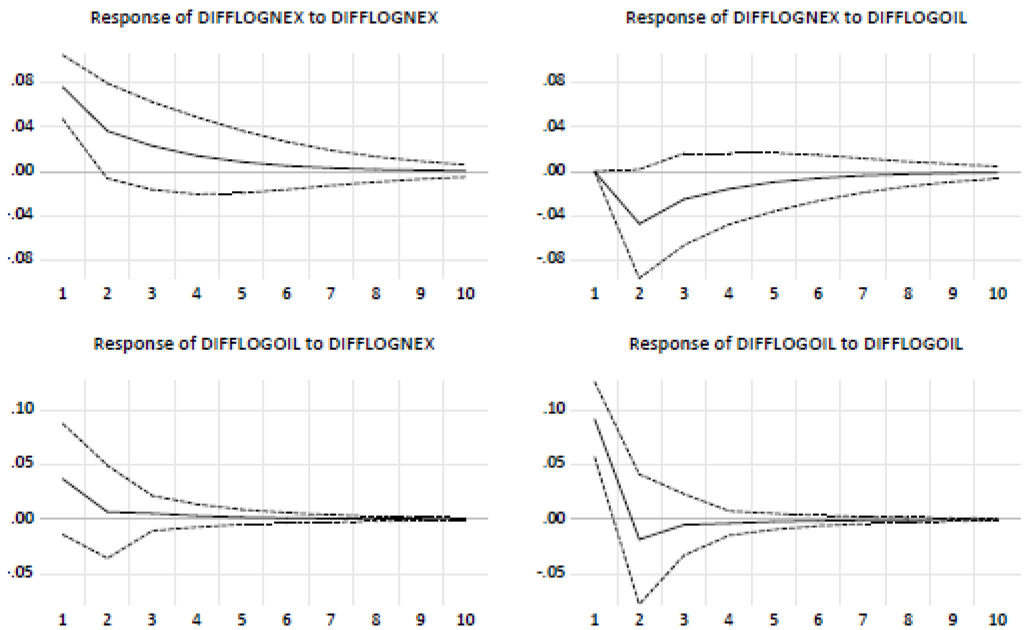

Figure 22: The IRF results for NEX Index - Crude Oil Price Model during the second period

5.5.2.2 Biofuel Index – Crude Oil Price Model

Using stationary data is not required in the VECM, so the shock of each variable has a lasting effect on the other one. A shock in Oil Price has an immediate negative impact on Biofuel; even though this effect by time will decrease at a low speed but still the long-term effect of an Oil Price shock is negative. On the contrary, a shock in Biofuel Index has a permanent positive impact on the oil prices.

In the second period, since we performed a VAR model, the structure of the graphs is different, and the same shocks have limited effects. Approximately a shock in Oil Price will not affect the Biofuel Index; on the other hand, a positive shock in the biofuel index has a minor positive effect on the oil prices, which diminishes immediately.

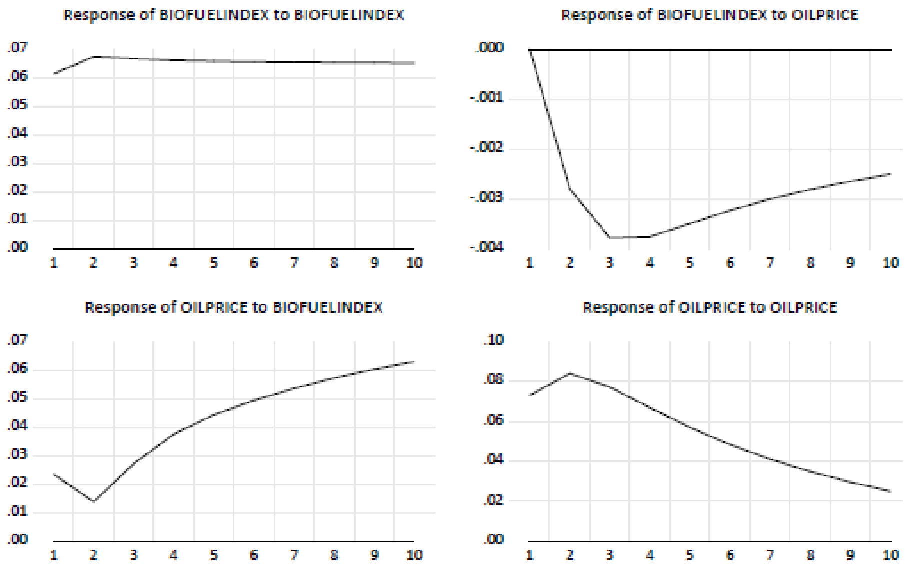

Figure 23: The IRF results for Biofuel Index - Crude Oil Price Model during the first period

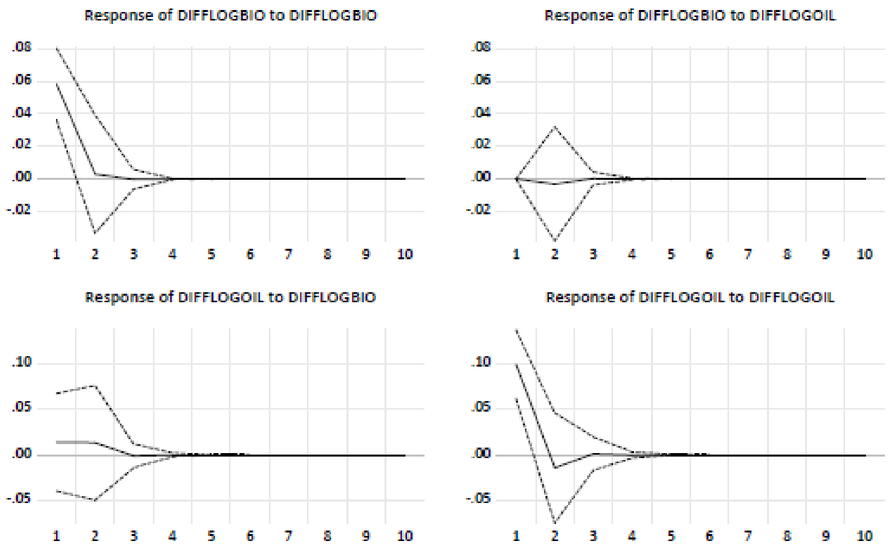

Figure 24: The IRF results for Biofuel Index - Crude Oil Price Model during the second period

5.5.2.3 Solar Index – Crude Oil Price Model

In the first period, the effect of both variables on each other is almost similar. A positive shock in one of them has a small positive impact on the other one, which quickly dies.

However, in the second period, a positive shock in Oil Price has a permanently negative effect on Solar Index. This effect stays constant for a short period and after that decreases gradually, but the long-term effect is still negative. On the other hand, a positive shock in Solar Index has a positive effect on Oil Price and increases it for a long time.

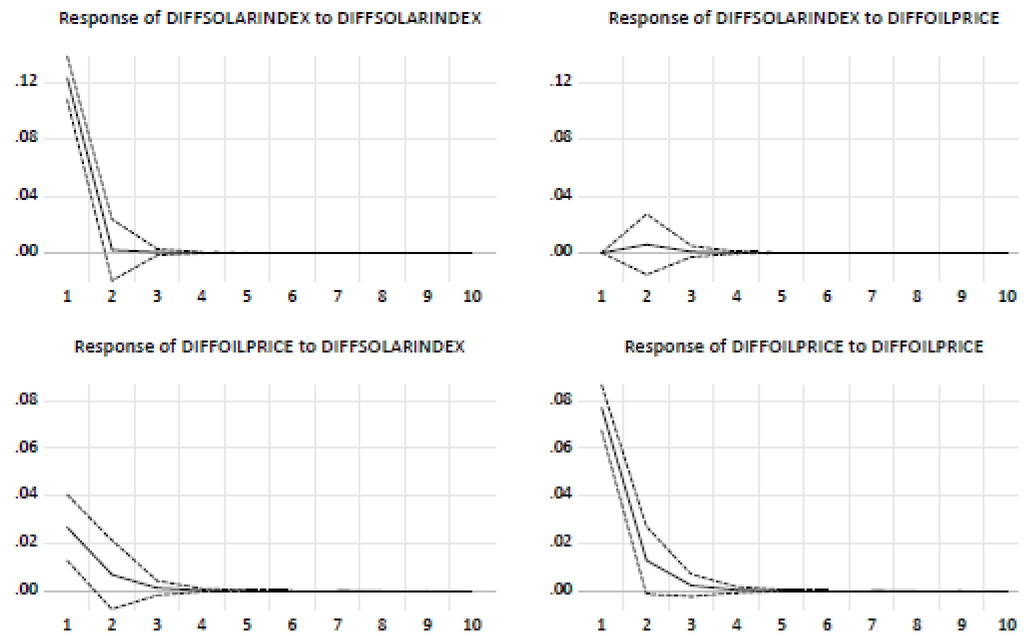

Figure 25: The IRF results for Solar Index - Crude Oil Price Model during the first period

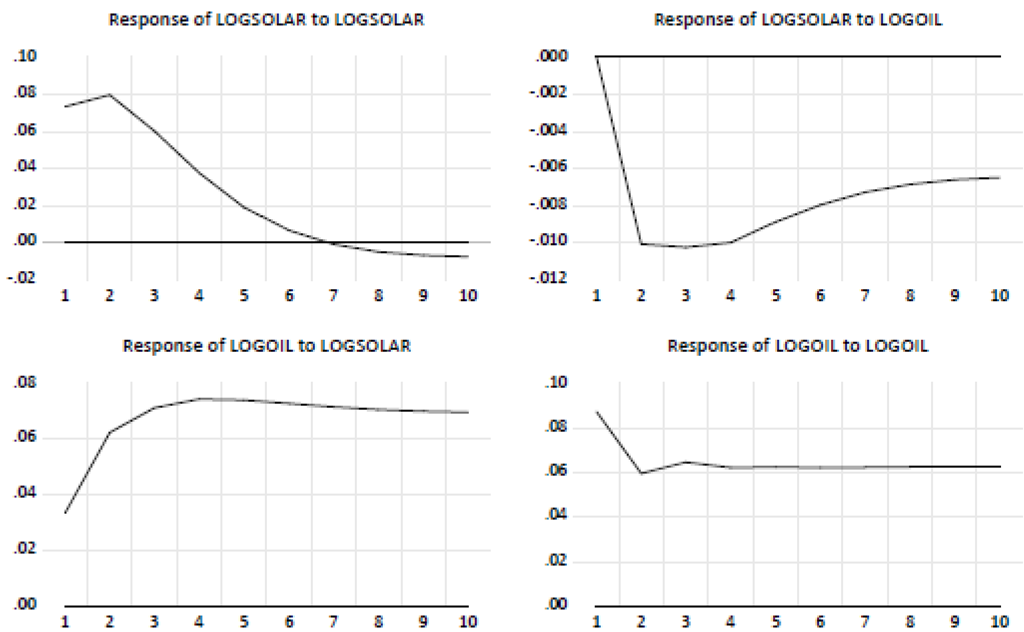

Figure 26: The IRF results for Solar Index - Crude Oil Price Model during the second period

5.5.2.4 Wind Index – Crude Oil Price Model

A shock in Oil Price has an insignificant positive effect on Wind Index in the first period and a negligible negative impact in the second period. From these results, I conclude that shocks in Oil Price will not cause any movement in Wind Index.

However, a shock in Wind Index in both periods increases the Oil Price for a short time, yet this effect is significant according to the IRF.

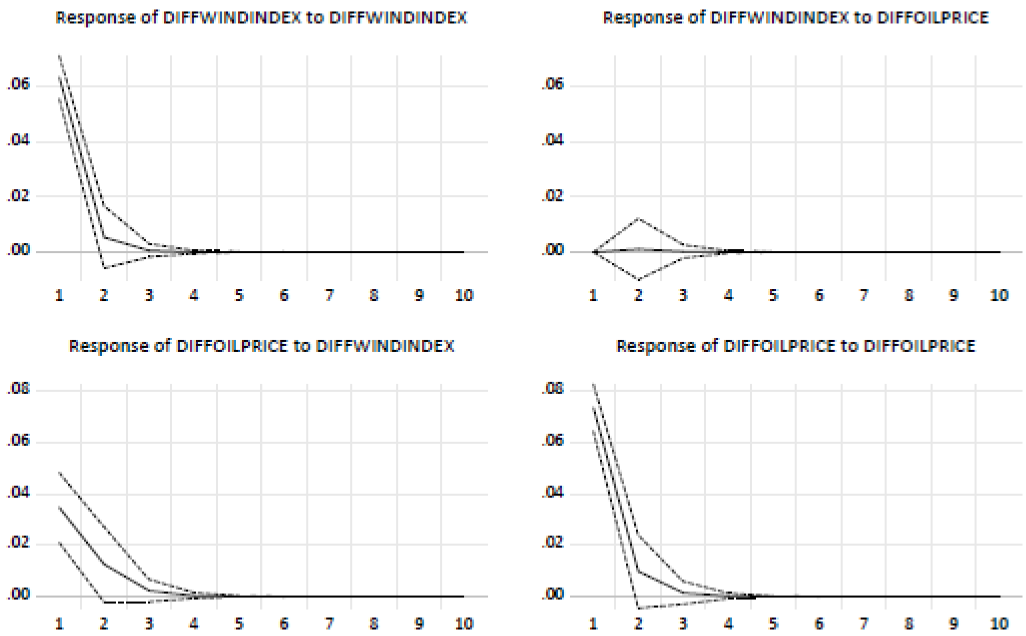

Figure 27: The IRF results for Wind Index - Crude Oil Price Model during the first period

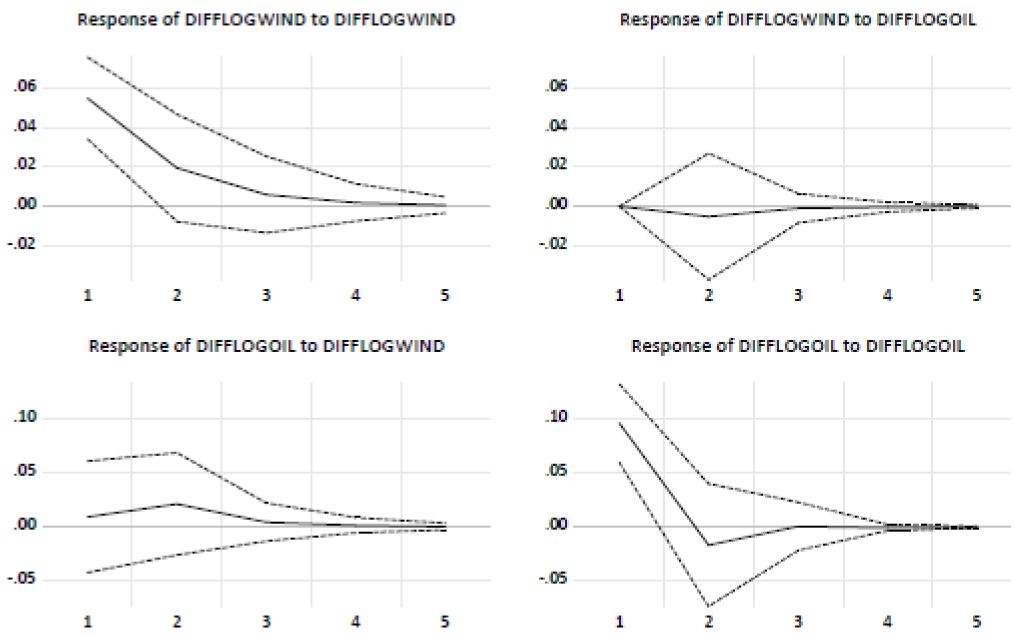

Figure 28: The IRF results for Wind Index - Crude Oil Price Model during the second period

6) Discussion & Conclusion

6.1 Discussion

In this section, I will provide empirical evidence for my economic statistical analysis, even though it is very common that the statistical results are not explained by economic phenomena.

Based on the statistical analysis, it can be concluded that oil price shocks have a significant effect only on the Biofuel Index. This behaviour can be explained by how these assets are connected and the macroeconomic factors that affect especially the renewable energy sub-sectors.

The independency of NEX, Wind, and Solar indices from oil price fluctuations may be caused by the fact that the investment in renewable energies has increased a lot in recent years. The large investment and development of the technology have reduced energy production costs from renewable resources. Therefore, renewables can compete successfully with crude oil, even when the oil price is low. On the other hand, since the main product of Solar and Wind energies is electricity and their share of production has increased in recent years (29% of global electricity production), and the fact that oil is not one of the primary sources of electricity generation, it could be expected that oil price shocks don't affect these assets significantly. However, that small influence can be explained by the effects of oil price on the two primary non-renewable sources of electricity generation, which are coal and gas. Thus, the nonsignificant influence of oil is because of its indirect effect on electricity production. Also, crude oil can compete with electricity in the transportation sector (0.3% of transportation fuel is from renewable electricity). However, since electric cars are more expensive than combustion engine cars and the amount of transportation fuel from electricity energy is not high, they can still not be considered a substitution for each other. It is probable that in the near future, according to the development of technology, the share of electric cars will increase and compete with fossil fuel-based cars.

Furthermore, developing countries, especially China and India, experienced rapid economic growth, which caused a rise in energy demand, but under different global pressures for environmental pollution reduction, simultaneously they have developed their renewable energy industry.

The surprising result from my statistical model is the positive influence of the NEX, SOLRX, and GWE indices shocks on the oil price. This result was unexpected since the share of crude oil in global energy production is much more than renewables, and it is unlikely that their fluctuation can affect the crude oil prices. The cause of this result can be the requirement of fossil energies to develop the technology and equipment in the renewable energy sector. It implies that more investment and expansion of this sector can increase the oil demand and consequently its price for short time.

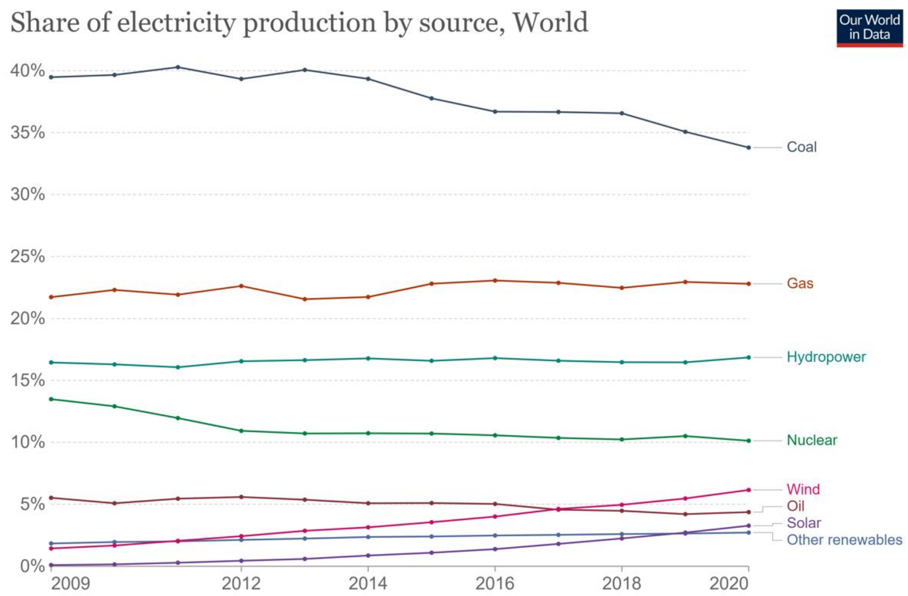

Figure 29: Annual share of different sources in Electricity Production
(Source: BP Statistical Review of World Energy & Ember)

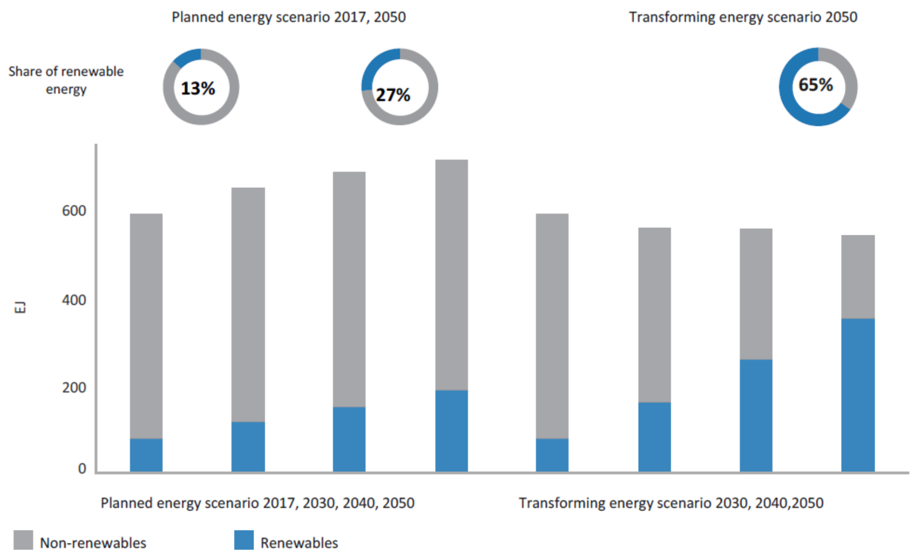

Figure 30: Planned share of Renewable Energies in future of Energy Production
(Source: Global Renewables Outlook: Energy transformation 2050, IRENA 2020)

Cointegration between biofuel and crude oil can be clearly explained. Both of these assets exhibit the movement of the commodities which their main product is the transportation fuels. Also, indirectly they compete as sources of heating. Biofuels and fossil fuels are the main sources of transportation fuel production, the global share of Biofuels is 3.1%; therefore, a positive shock in crude oil prices, increases the incentives of using biofuel between people and from the other side pushes the governments to increase the subsides on biofuel which makes biofuel a stronger competitor for gasoline. In the opposite way, when biofuel prices increase, the demand for traditional fossil fuels increases, which can increase the price of crude oil. So, the long-run relationship between these assets exhibited from the model is totally in line with economic theories.

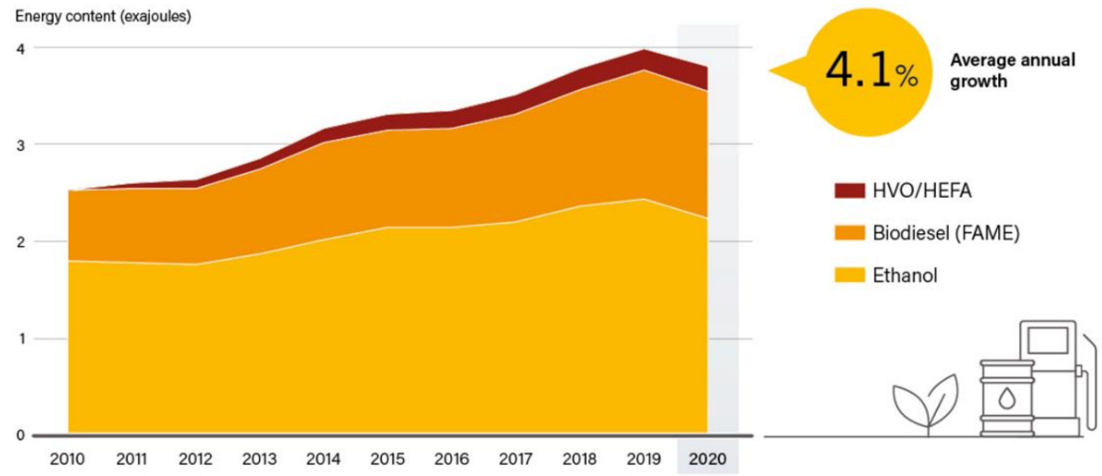

Figure 31: Global annual production of Biofuels

(Source: International Energy Agency- IEA)

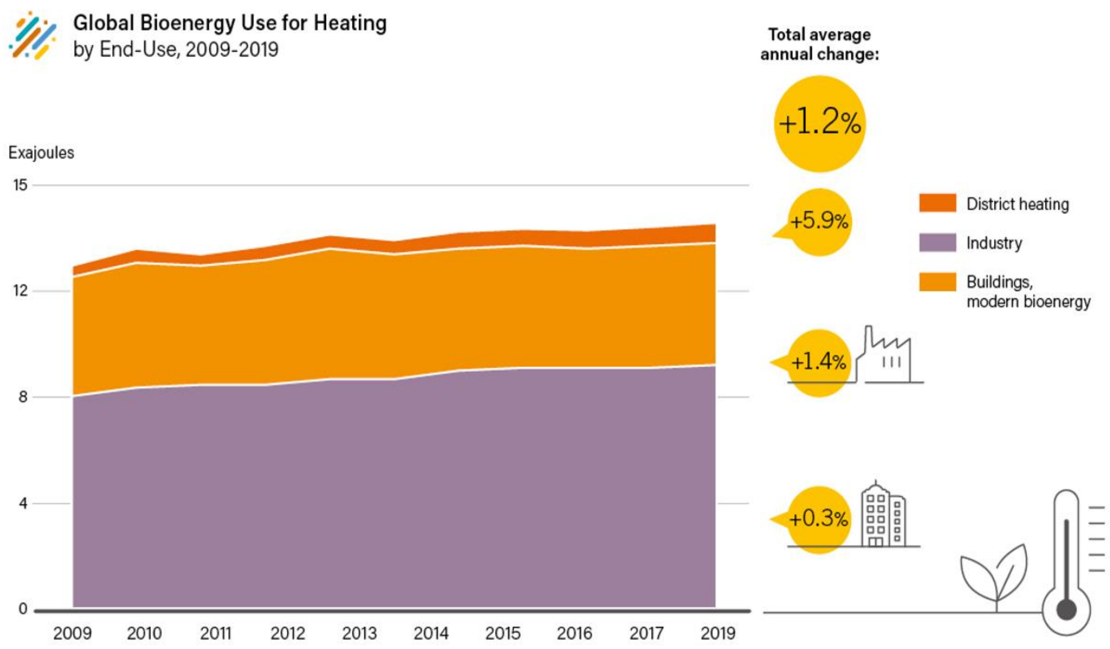

Figure 32: Global Bioenergy use for heating

(Source: International Energy Agency- IEA)

Performing the statistical analysis on the data for a short time after the Covid-19 Pandemic makes the economic explanation of the results difficult. Looking at the results of the model, I understood that the pandemic has changed the relationships under consideration. The Global GDP growth was negatively affected by the pandemic, and a drastic decline in crude oil prices happened in this period; after a while, crude oil prices started to increase again. According to the huge economic loss during the pandemic, when the situation is going back to normal, the government and investors don't have the previous incentives for promoting the development of the renewable energy sectors. This behaviour which will last for a short time can explain the statistical results of my methods for the influence of crude oil prices on renewable energy sub-sectors. The only explanation for the vice versa effect can be the return of crude oil prices to the upward trend. In general, by using this data, I could reach the purpose of my research, understanding whether pandemic can affect the relationships under consideration or not. Nonetheless, it would be better to repeat these tests in the future with a broader range of data to understand the effect of crude oil prices properly.

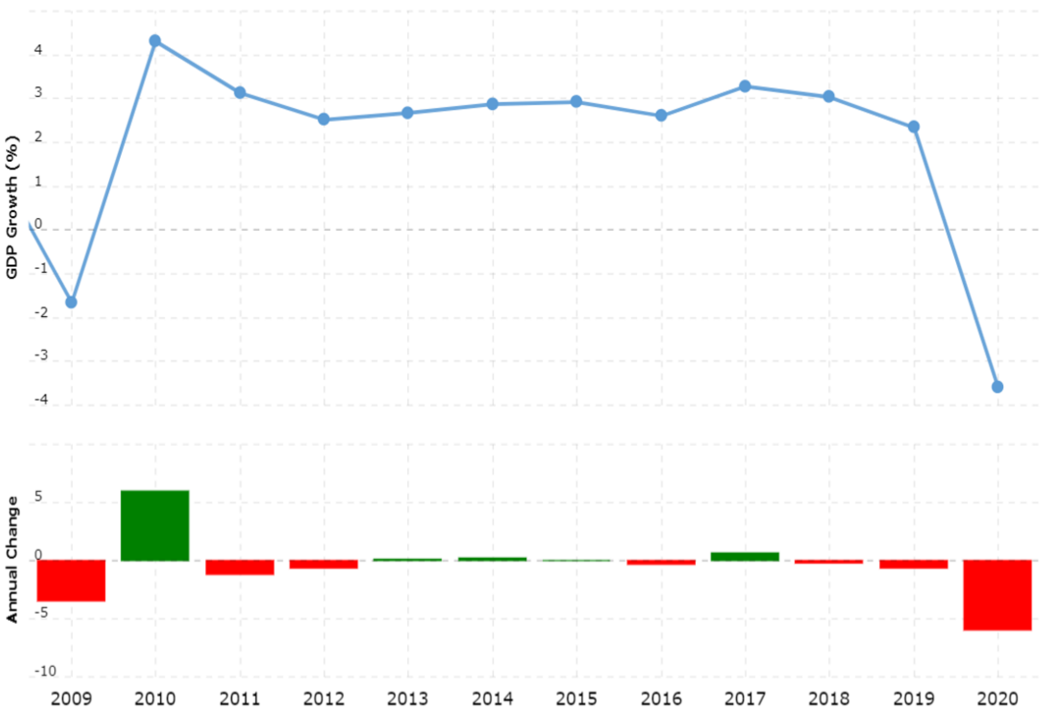

Figure 33: Global GDP Growth Percentage

(Source: World Bank)

6.2 Conclusion

In my thesis, I first tried to explore the relationship between crude oil prices and the renewable energy sub-sectors prices, and whether the influence of shock in crude oil prices is similar for all the sub-sectors. Furthermore, according to the importance of the recent financial crisis due to the Global Covid-19 Pandemic, I studied the changes caused by the pandemic on these relationships by using data in two periods that have covered a turbulent time in the world economy. To perform my analysis, I used two econometrics models, VAR and VECM models, and interpreted their results statistically and according to the economic theories.

My findings indicate that crude oil is a net receiver of shocks from renewable energy assets, and the opposite way interaction, on most of the occasions, reveals that the effect of crude oil prices shock on other assets or is either not significant or dies out soon.

In accordance with my first goal in this research, my conclusion will be based on my models in the first period. Therefore, I conclude that Alternative Energies, Solar and Wind Power indices exhibit the same response to a shock in crude oil prices. However, because its market structure is very similar to crude oil, the Biofuel index is cointegrated with crude oil prices. Thus, they have a long-term relationship, and their effects on each other last for a long time. Therefore, in general, crude oil prices have a different impact on the sub-sectors of Renewable Energy.

Comparing the results from my statistical models for two sample periods reveals that the Global Covid-19 Pandemic caused a change in the interaction of renewable energy assets and crude oil prices. As mentioned before, it is highly recommended to perform the analysis with more sample data to have a better insight into this change.

Even though the purpose of my thesis was to emphasize on the statistical results, for better understanding, I tried to explain them based on different financial theories and market movements.

By analysing the results of this thesis, not only policy-makers can design their policies to support the energy transition process by means of fiscal policy, but investors can improve their hedging strategies for maximizing the profits from their portfolios as well.

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Appendix

Appendix 1: Lag Length Detection

First Period:

VAR Lag Order Selection Criteria
Endogenous variables: NEXINDEX OILPRICE
Exogenous variables: C
Date: 11/12/21 Time: 11:55
Sample: 2009M01 2019M12
Included observations: 124

Lag	LogL	LR	FPE	AIC	SC	HQ
0	0.182966	NA	0.003530	0.029307	0.074795	0.047785
1	317.8519	619.9667	2.24e-05*	-5.029869*	-4.893403*	-4.974433*
2	320.4663	5.018111	2.29e-05	-5.007521	-4.780079	-4.915129
3	320.9882	0.984869	2.43e-05	-4.951423	-4.633004	-4.822074
4	327.1360	11.40318*	2.34e-05	-4.986065	-4.576669	-4.819759
5	329.1651	3.698244	2.42e-05	-4.954277	-4.453904	-4.751014
6	329.8738	1.269625	2.55e-05	-4.901190	-4.309840	-4.660970
7	331.1513	2.245979	2.67e-05	-4.857279	-4.174953	-4.580102
8	331.9831	1.435560	2.81e-05	-4.806179	-4.032876	-4.492045

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 22: Lag Length of NEX Index - Crude Oil Prices Model

VAR Lag Order Selection Criteria
Endogenous variables: BIOFUELINDEX OILPRICE
Exogenous variables: C
Date: 11/12/21 Time: 11:55
Sample: 2009M01 2019M12
Included observations: 124

Lag	LogL	LR	FPE	AIC	SC	HQ
0	11.65617	NA	0.002934	-0.155745	-0.110256	-0.137266
1	319.6149	601.0162	2.18e-05	-5.058305	-4.921839*	-5.002869
2	328.0698	16.22794*	2.03e-05*	-5.130158*	-4.902716	-5.037765*
3	329.4341	2.574683	2.12e-05	-5.087647	-4.769228	-4.958298
4	330.7826	2.501160	2.21e-05	-5.044880	-4.635485	-4.878574
5	331.9951	2.209816	2.31e-05	-4.999920	-4.499548	-4.796657
6	332.2824	0.514466	2.46e-05	-4.940039	-4.348690	-4.699819
7	335.0098	4.794840	2.51e-05	-4.919512	-4.237186	-4.642335
8	335.9637	1.646255	2.64e-05	-4.870382	-4.097079	-4.556248

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 23: Lag Length of Biofuel Index - Crude Oil Prices Model

VAR Lag Order Selection Criteria
Endogenous variables: SOLARINDEX OILPRICE
Exogenous variables: C
Date: 11/12/21 Time: 11:56
Sample: 2009M01 2019M12
Included observations: 124

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-133.0979	NA	0.030296	2.178998	2.224486	2.197476
1	233.2589	714.9865*	8.77e-05*	-3.665465*	-3.529000*	-3.610030*
2	235.1751	3.677957	9.07e-05	-3.631857	-3.404414	-3.539464
3	236.3590	2.234195	9.50e-05	-3.586436	-3.268017	-3.457087
4	238.6844	4.313172	9.76e-05	-3.559426	-3.150030	-3.393120
5	239.6747	1.804828	0.000102	-3.510882	-3.010509	-3.307619
6	240.7665	1.954811	0.000107	-3.463976	-2.872627	-3.223756
7	241.6685	1.585693	0.000113	-3.414008	-2.731682	-3.136831
8	243.6231	3.373228	0.000117	-3.381017	-2.607714	-3.066883

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 24:Lag Length of Solar Index - Crude Oil Prices Model

VAR Lag Order Selection Criteria
Endogenous variables: WINDINDEX OILPRICE
Exogenous variables: C
Date: 11/12/21 Time: 11:56
Sample: 2009M01 2019M12
Included observations: 124

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-13.27520	NA	0.004386	0.246374	0.291863	0.264853
1	327.1182	664.3162	1.93e-05*	-5.179327*	-5.042861*	-5.123891*
2	329.6184	4.798678	1.98e-05	-5.155135	-4.927693	-5.062743
3	330.5177	1.696998	2.08e-05	-5.105124	-4.786705	-4.975774
4	336.8803	11.80161*	2.00e-05	-5.143230	-4.733834	-4.976924
5	338.6372	3.202169	2.08e-05	-5.107052	-4.606679	-4.903789
6	339.3970	1.360244	2.19e-05	-5.054790	-4.463441	-4.814570
7	339.8946	0.874900	2.32e-05	-4.998301	-4.315974	-4.721124
8	341.8851	3.435157	2.40e-05	-4.965889	-4.192586	-4.651755

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 25: Lag Length of Wind Index - Crude Oil Prices Model

Second Period

VAR Lag Order Selection Criteria
Endogenous variables: LOGNEX LOGOIL
Exogenous variables: C
Date: 11/12/21 Time: 04:27
Sample: 2020M06 2021M09
Included observations: 14

Lag	LogL	LR	FPE	AIC	SC	HQ
0	8.072917	NA	0.001440	-0.867560	-0.776266	-0.876011
1	38.28596	47.47763*	3.45e-05*	-4.612279*	-4.338398*	-4.637632*
2	39.97836	2.175954	5.06e-05	-4.282623	-3.826154	-4.324878

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 26: Lag Length of NEX Index - Crude Oil Prices Model, Second Period

VAR Lag Order Selection Criteria
Endogenous variables: LOGBIO LOGOIL
Exogenous variables: C
Date: 11/08/21 Time: 11:38
Sample: 2020M06 2021M09
Included observations: 14

Lag	LogL	LR	FPE	AIC	SC	HQ
0	19.68766	NA	0.000274	-2.526808	-2.435514	-2.535259
1	41.90065	34.90613*	2.06e-05*	-5.128664*	-4.854783*	-5.154017*
2	43.22091	1.697478	3.18e-05	-4.745845	-4.289375	-4.788099

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 27: Lag Length of Biofuel Index - Crude Oil Prices Model, Second Period

VAR Lag Order Selection Criteria
Endogenous variables: LOGSOLAR LOGOIL
Exogenous variables: C
Date: 11/02/21 Time: 18:19
Sample: 2020M06 2021M09
Included observations: 14

Lag	LogL	LR	FPE	AIC	SC	HQ
0	5.477977	NA	0.002087	-0.496854	-0.405560	-0.505305
1	35.84773	47.72390*	4.89e-05*	-4.263962*	-3.990080*	-4.289315*
2	36.72222	1.124340	8.05e-05	-3.817460	-3.360990	-3.859715

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 28: Lag Length of Solar Index - Crude Oil Prices Model, Second Period

VAR Lag Order Selection Criteria
Endogenous variables: LOGWIND LOGOIL
Exogenous variables: C
Date: 11/02/21 Time: 18:33
Sample: 2020M06 2021M09
Included observations: 14

Lag	LogL	LR	FPE	AIC	SC	HQ
0	17.19763	NA	0.000391	-2.171090	-2.079796	-2.179541
1	41.30989	37.89070*	2.24e-05*	-5.044271*	-4.770389*	-5.069623*
2	43.13740	2.349652	3.22e-05	-4.733914	-4.277445	-4.776169

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 29: Lag Length of Wind Index - Crude Oil Prices Model, Second Period

Appendix 2: Cointegration Test Result

First Period

Johansen Cointegration Test

Date: 11/12/21 Time: 11:37
Sample (adjusted): 2009M03 2019M12
Included observations: 130 after adjustments
Trend assumption: No deterministic trend (restricted constant)
Series: NEXINDEX OILPRICE
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.077206	11.93712	20.26184	0.4544
At most 1	0.011409	1.491651	9.164546	0.8749

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.077206	10.44547	15.89210	0.2955
At most 1	0.011409	1.491651	9.164546	0.8749

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

NEXINDEX	OILPRICE	C
-4.048949	-2.401940	31.43500
3.685156	-2.079652	-10.24418

Unrestricted Adjustment Coefficients (alpha):

D(NEXINDEX)	0.018392	-0.001341
D(OILPRICE)	0.013930	0.006755

1 Cointegrating Equation(s): Log likelihood 329.9605

Normalized cointegrating coefficients (standard error in parentheses)

NEXINDEX	OILPRICE	C
1.000000	0.593226	-7.763744
	(0.23999)	(1.02927)

Adjustment coefficients (standard error in parentheses)

D(NEXINDEX)	-0.074468
	(0.02329)
D(OILPRICE)	-0.056403
	(0.02856)

Table 30: Johansen's Test for NEX Index - Crude Oil Prices Model

Johansen Cointegration Test

Date: 11/12/21 Time: 11:36
Sample (adjusted): 2009M03 2019M12
Included observations: 130 after adjustments
Trend assumption: No deterministic trend
Series: BIOFUELINDEX OILPRICE
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.105467	14.49152	12.32090	0.0213
At most 1	1.98E-05	0.002579	4.129906	0.9653

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.105467	14.48894	11.22480	0.0129
At most 1	1.98E-05	0.002579	4.129906	0.9653

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

BIOFUELIND	OILPRICE
-4.006206	4.552582
-0.147100	0.400612

Unrestricted Adjustment Coefficients (alpha):

D(BIOFUELIN	-0.003286	-0.000262
D(OILPRICE)	-0.025767	-4.21E-05

1 Cointegrating Equation(s): Log likelihood 338.5857

Normalized cointegrating coefficients (standard error in parentheses)

BIOFUELIND	OILPRICE
1.000000	-1.136382
	(0.01505)

Adjustment coefficients (standard error in parentheses)

D(BIOFUELIN	0.013166
	(0.02121)
D(OILPRICE)	0.103226
	(0.02689)

Table 31: Johansen's Test for Biofuel Index - Crude Oil Prices Model

Johansen Cointegration Test

Date: 11/12/21 Time: 11:38
Sample (adjusted): 2009M03 2019M12
Included observations: 130 after adjustments
Trend assumption: No deterministic trend (restricted constant)
Series: SOLARINDEX OILPRICE
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.047123	9.979320	20.26184	0.6419
At most 1	0.028092	3.704291	9.164546	0.4579

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.047123	6.275029	15.89210	0.7565
At most 1	0.028092	3.704291	9.164546	0.4579

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

SOLARINDEX	OILPRICE	C
1.165523	-2.841113	4.857219
0.928121	1.716702	-12.91470

Unrestricted Adjustment Coefficients (alpha):

D(SOLARIND	0.000266	-0.020388
D(OILPRICE)	0.016646	-0.004248

1 Cointegrating Equation(s): Log likelihood 242.3656

Normalized cointegrating coefficients (standard error in parentheses)

SOLARINDEX	OILPRICE	C
1.000000	-2.437630	4.167417
	(1.08330)	(4.64471)

Adjustment coefficients (standard error in parentheses)

D(SOLARIND	0.000310
	(0.01258)
D(OILPRICE)	0.019401
	(0.00817)

Table 32: Johansen's Test for Solar Index - Crude Oil Prices Model

Johansen Cointegration Test

Date: 11/12/21 Time: 11:40
Sample (adjusted): 2009M03 2019M12
Included observations: 130 after adjustments
Trend assumption: No deterministic trend (restricted constant)
Series: WINDINDEX OILPRICE
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.110406	16.02391	20.26184	0.1733
At most 1	0.006251	0.815133	9.164546	0.9725

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.110406	15.20878	15.89210	0.0637
At most 1	0.006251	0.815133	9.164546	0.9725

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

WINDINDEX	OILPRICE	C
-3.838171	-3.386017	33.33732
2.701424	-1.495623	-6.990256

Unrestricted Adjustment Coefficients (alpha):

D(WINDINDEX)	0.020466	-0.000991
D(OILPRICE)	0.015991	0.005098

1 Cointegrating Equation(s): Log likelihood 339.0088

Normalized cointegrating coefficients (standard error in parentheses)

WINDINDEX	OILPRICE	C
1.000000	0.882195	-8.685731
	(0.20926)	(0.89796)

Adjustment coefficients (standard error in parentheses)

D(WINDINDEX)	-0.078554
	(0.02024)
D(OILPRICE)	-0.061378
	(0.02686)

Table 33: Johansen's Test for Wind Index - Crude Oil Prices Model

Second Period

Johansen Cointegration Test

Date: 11/12/21 Time: 11:29
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: LOGNEX LOGOIL
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.709403	24.75267	25.87211	0.0684
At most 1	0.412706	7.451223	12.51798	0.2998

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.709403	17.30144	19.38704	0.0979
At most 1	0.412706	7.451223	12.51798	0.2998

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LOGNEX	LOGOIL	@TREND(20M07)
6.057987	13.73436	-0.655570
-3.376287	12.85501	-0.591865

Unrestricted Adjustment Coefficients (alpha):

D(LOGNEX)	-0.052286	-0.016945
D(LOGOIL)	0.001399	-0.056423

1 Cointegrating Equation(s): Log likelihood 41.77278

Normalized cointegrating coefficients (standard error in parentheses)

LOGNEX	LOGOIL	@TREND(20M07)
1.000000	2.267150	-0.108216
	(0.59877)	(0.02996)

Adjustment coefficients (standard error in parentheses)

D(LOGNEX)	-0.316745
	(0.08163)
D(LOGOIL)	0.008476
	(0.16826)

Table 34: Johansen's Test for NEX Index - Crude Oil Prices Model, Second Period

Johansen Cointegration Test

Date: 11/08/21 Time: 11:38
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments
Trend assumption: Quadratic deterministic trend
Series: LOGBIO LOGOIL
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.533576	10.89438	18.39771	0.3983
At most 1	0.015391	0.217143	3.841465	0.6412

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.533576	10.67724	17.14769	0.3378
At most 1	0.015391	0.217143	3.841465	0.6412

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LOGBIO	LOGOIL
-15.20258	15.39964
19.46187	4.788429

Unrestricted Adjustment Coefficients (alpha):

D(LOGBIO)	-0.002096	-0.005559
D(LOGOIL)	-0.064095	-0.001326

1 Cointegrating Equation(s): Log likelihood 43.25779

Normalized cointegrating coefficients (standard error in parentheses)

LOGBIO	LOGOIL
1.000000	-1.012962
	(0.30921)

Adjustment coefficients (standard error in parentheses)

D(LOGBIO)	0.031861
	(0.22731)
D(LOGOIL)	0.974410
	(0.30847)

Table 35: Johansen's Test for Biofuel Index - Crude Oil Prices Model, Second Period

Johansen Cointegration Test

Date: 11/08/21 Time: 10:47
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: LOGSOLAR LOGOIL
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.777508	28.12667	25.87211	0.0258
At most 1	0.397209	7.086597	12.51798	0.3356

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.777508	21.04008	19.38704	0.0286
At most 1	0.397209	7.086597	12.51798	0.3356

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LOGSOLAR	LOGOIL	@TREND(20M07)
5.605038	14.27734	-0.757125
-1.761632	12.73694	-0.594158

Unrestricted Adjustment Coefficients (alpha):

D(LOGSOLAR)	-0.068689	-0.000343
D(LOGOIL)	0.002380	-0.056056

1 Cointegrating Equation(s): Log likelihood 40.39606

Normalized cointegrating coefficients (standard error in parentheses)

LOGSOLAR	LOGOIL	@TREND(20M07)
1.000000	2.547233	-0.135079
	(0.49693)	(0.02597)

Adjustment coefficients (standard error in parentheses)

D(LOGSOLAR)	-0.385006
	(0.06514)
D(LOGOIL)	0.013343
	(0.15767)

Table 36: Johansen's Test for Solar Index - Crude Oil Prices Model, Second Period

Johansen Cointegration Test

Date: 11/02/21 Time: 18:33
Sample (adjusted): 2020M08 2021M09
Included observations: 14 after adjustments
Trend assumption: Linear deterministic trend
Series: LOGWIND LOGOIL
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.503129	12.18936	15.49471	0.1481
At most 1	0.157384	2.397415	3.841465	0.1215

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.503129	9.791943	14.26460	0.2259
At most 1	0.157384	2.397415	3.841465	0.1215

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LOGWIND	LOGOIL
-11.86180	1.636079
5.625236	-6.787835

Unrestricted Adjustment Coefficients (alpha):

D(LOGWIND)	0.019504	0.015957
D(LOGOIL)	-0.046525	0.021863

1 Cointegrating Equation(s): Log likelihood 41.93869

Normalized cointegrating coefficients (standard error in parentheses)

LOGWIND	LOGOIL
1.000000	-0.137928
	(0.14391)

Adjustment coefficients (standard error in parentheses)

D(LOGWIND)	-0.231348
	(0.16748)
D(LOGOIL)	0.551869
	(0.26983)

Table 37: Johansen's Test for Wind Index - Crude Oil Prices Model, Second Period