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RENEWABLE ENERGY STOCK PERFORMANCE IN THE FACE OF ENERGY CRISIS: A STUDY OF THE EUROPEAN MARKET

Bachelor's thesis

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has not been previously presented for grading.

The document length is 9707 words from the introduction to the end of the conclusion.

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TABLE OF CONTENTS

ABSTRACT

This paper examines the impact of the energy crisis towards renewable energy companies' stock performance. The paper analyses the research problem of the energy crisis that has had an impact and what kind, on European companies' stock performance, especially in the renewable energy sector. The study examines the pre and after-times of the global energy crisis. The paper investigates the pre-crisis period of 2018-2021 and post-crisis time 2022-2023 by applying Vector autoregressions (VAR) models and diagnostics drawn from it. The author also compares the cumulative returns of the indices, to find more information on the period of interest. The sample consists of the European renewable stock index and European crude oil spot price index and Europe total returns index.

Conclusions made by the author imply that changes in crude oil prices in the pre or post-energy crisis period do not have a significant impact on renewable energy stock returns in Europe. Crude oil price shocks seem to have more effect on Europe's total stock returns and renewables stock returns in the post-crisis period, but not in a significant matter. Renewables have performed slightly better in a significant matter than the market in the face of the energy crisis, but it has been more volatile throughout the period. This results in renewables not being better than the market in the face of the energy crisis.

Keywords: renewable energy, energy crisis, stock returns, crude oil prices

INTRODUCTION

The price and supply of energy is an important variable in the global economy and fluctuations in both of these variables can provide serious unreliability on the economy. Governments are forced to continue to push towards renewable energy sources and the impacts of energy price fluctuations on renewable energy stock performances is important knowledge for investors and governments. This is because energy crises are not one-of-a-kind, but reappearing events.

The research problem that this paper is tackling is if the recent energy crisis has had an impact on European renewable energy companies' stock performance and to what extent. This paper assesses the pre and post-energy crisis events to find the correlation between the crisis events and changes in the performance of stocks and also by seeing if energy price is an estimator for renewables. The energy crisis of 2021-2023 was caused by multiple variables such as the rapid economic bounce back from COVID-19 pandemic and the Russian attack war, which shot energy prices through the roof and sped up the demand for the transition towards renewable energy solutions. Thus, this paper seeks to answer the following research questions:

1. What is the relationship between rising energy prices and the performance of European renewable energy company stocks?
2. Do European renewable energy stocks outperform overall market returns in the face of energy crisis events in 2022-2023?

This paper constructs an empirical analysis by using different indices to measure the relationship between renewable energy stock prices which were taken as an index, energy prices where crude oil spot price is used as an estimator, total stock returns in Europe and energy stock prices. To construct an empirical investigation regression analysis is run with the indices chosen to highlight the existing or non-existing changes because of Energy crisis events after 2021. Crude oil has been chosen to illustrate energy prices for the paper. All of the indices that are chosen for this particular study are taken from Refinitiv Eikon and those are Refinitiv Europe Renewable Energy Price Return Index, ICE Europe Brent Crude Electronic Energy Future, and Refinitiv Europe Total

Return Index. The data which this paper covers is for the period of 5 years and 2 months dating from January 2018 to March of 2023. This period is chosen to get data from pre and post-crisis times, to see if the crisis has had an impact. Other than renewable energy stocks the paper also seeks to get knowledge on, if there are any differences in the impacts on renewables and Europe's total stock markets.

The organization of the paper goes as follows. The first chapter after the introduction focuses on existing literature and theory on the topic. First, the basics of energy and the economy, renewable energy and the recent energy crisis in Europe are discussed. In the first part, there is also a brief overview of theoretical standpoints that are necessary to know to understand the characteristics and aims of the paper more thoroughly. At the end of the first part, a review of the existing literature and studies is done more in-depth, to see how the topic has been studied earlier. The second chapter begins with a presentation of the data and methodology which are also justified for the specific paper. The usage of the method of VAR analysis is introduced and described more thoroughly. The third chapter will give out an analysis that is performed with the data and chosen methods, with a variety of diagnostics backing up the results. The third chapter also provides challenges which could be addressed in upcoming studies on the same subject. Finally, the last part of the paper will give out conclusions and a summary of the paper.

1. ENERGY SECTOR AND RENEWABLE ENERGY

In this section firstly the author will provide a theoretical overview of the topic with the help of existing literature already conducted. Secondly, an overview of the topic from the perspective of existing studies is gone through, as existing results and methodology are introduced.

1.1. Overview of energy and its impacts on the economy.

Energy is one of the main components of quality of life. It is used for all people's doings from industries to heating and lighting individuals' homes. Fossil fuels account for climate, environmental and health impacts, but still, those have to be used in today's world to achieve prosperous economies. (Balázs, 2023) The energy sector has great impacts on economies, which have been studied by different authors. Salim *et al*., (2014) have found that there is a two-way relationship between GDP and energy consumption in the short-run, which would then lead to a conclusion that there is a linkage between energy consumption and the countries' economic well-being and growth. The linkages have been found to work in the long run also, as Apergis & Payne (2012) have found out, there is also a two-way relationship between conventional energy, renewable energy and GDP, both in the short- and long run.

When talking about the energy sector as a whole one thing that cannot be set aside is that energy was employing around 41 million people, and if end uses are accounted there are 20 million more. In Europe, the number of employees has been around 7,5 million in 2019. Employment is not going to fall as new projects and implementations are introduced all the time, since the transition towards green energy solutions is demanded and introduced more widely. The share of employment in green energy solutions has been increasing at a stable rate and it has also proven to be a resilient sector resulting from insights from the Covid-19 pandemic. (IEA, 2022) These facts tell much regarding the importance of the energy sector to economies.

1.2. Theoretical relationship between energy prices and the stock market

Dating back four decades, the linkages of energy prices and stock markets were narrow and the basic assumption was that the energy, more specifically oil markets had some role in the U.S. recessions (Hamilton, 1983). The first assumption made by literature has been that oil prices have a significant and negative reflection on stock returns, as the costs of production are higher when the price of oil is higher. The differences between oil markets and stock markets have since been investigated broadly, with different kinds of variables and methods. (see, Jones & Kaul, 1996; Papapetrou, 2001; El Hedi Arouri & Nguyen, 2010)

There is a variety of perspectives regarding theoretical standpoints. Most of the studies reporting the relationship between oil prices and stock markets rely on the point that higher oil prices result in a decrease in stock returns. (see, Sadorsky 1999, 2008) This is mostly based on the rationale by Jones and Kaul (1993)

1.3. Renewable energy

Renewable energy (RE) has various definitions, but in simplicity, it is the type of energy that comes from natural sources that replenish continuously. There are different types of energy used for heating and electricity that are considered renewable such as solar, ocean, wind, hydropower, biomass and geothermal energy. Also, biofuels and hydrogen that are extracted from renewable sources are considered RE. (El Bassam, 2021)

Energy use has been increasing as a result of many factors. In a broad picture, energy tells about economic and societal development, which then results in increased energy usage. (Lu *et al*, 2016) It can be seen in many ways that alternative sources of energy are considered more nowadays and for example, in the 21st century variety of different renewable, sustainable and clean energy indices are available in stock exchanges. The interest can also be seen as many economical studies are conducted relating to renewable energy markets. (Kazemilari *et al*. 2017) Renewable energy is widely discussed in today's world and especially in Europe because of the EU's ambitious climate targets of net-zero greenhouse gas emissions by 2050. This is seen as an urgent challenge but comes with the opportunity for a better future for all. (European Commission, 2023) The development of the renewable energy sector will be even faster than expected, because of the energy crisis sparked by Russia's invasion to Ukraine. It is forecasted, that there will be an acceleration of 85% in renewables and that renewables will elucidate over 90% of the global capacity expansion of electricity in the same period. By 2027 it is forecasted, that renewables will become the largest source of electricity in the global power mix. (International Energy Agency, 2022)

The renewable energy sources discussed in this thesis are defined as those that are not finite and can be replenished at a rate that is equal to or greater than the rate of consumption

1.4. Recent energy crisis

The energy crisis referred to in this thesis relates to the one that started in 2021 resulting from various factors. What is seen as the major cause that started the rise of energy prices is the major rebound from the plunge in energy usage resulting from the global COVID-19 pandemic. The bounceback from the crisis was the strongest in 80 years. The acceleration of energy prices was seeing all-time highs. (IEA, 2021) Import prices of energy doubled in the second quarter of 2021, which affected Europe's energy prices heavily on the producer and consumer side since Europe imports much of its energy. (European Council, 2022) As mentioned earlier, Europe has been heavily dependent on energy imports, which then resulted in the global energy crisis that was sparked by Russia's invasion to Ukraine. European gas supplies were damaged in an unseen manner as its biggest supplier Russia could not be concidered as an option anymore. (IEA, 2023)

The recent energy crisis will undoubtfully have an impact on the economy of Europe, and this paper will try to enlighten, what kind of results is seen in the renewable energy stocks because of the situation. As the crisis is in many ways one of a kind and also recent, the impact on it renewable energy stocks have not been brought up yet.

1.5. Review of literature

The previous literature on the relationship between renewable energy and energy prices is dated to the previous few decades as the topic of renewables is still relatively fresh. It can be seen, that in the previous years, there is an exponential rise in the amounts of studies conducted, which are trying to explain indeed the changes in renewable stocks because of energy prices. The author will in this part go through the results and characteristics, which have been drawn concerning the relationship between renewable energy stocks and energy prices. Based on the overall results of the studies it is seen that the significance of the relationship between energy and renewable energy stock performance is depending on the period of the sample.

Papers studying the impact of overall energy markets on stocks and even more in detail searching for linkages in energy prices and alternative energy stocks have come up. (see Oberndorfer, 2009; Henriques & Sadorsky, 2008; Beijsterveldt, 2019; Reboredo & Ugolini, 2018; Liu *et al*., 2022) There are also reports showing that oil prices have a positive correlation with energy stocks. The correlation is seen to be more significant after the financial crisis of 2008. (Broadstock *et al*., 2012) The positive relationship between energy prices and renewable energy stocks has also come up in other studies for example (Reboredo & Ugolini, 2018) There is not one clear opinion about the relationship between energy prices and renewable energy stock performance, and thus it is important to study the relationship more, as the topic is more spoken in the times of war and recent European energy crisis. As stated earlier, older studies tend to rely on the statement that oil prices don't have a positive impact on stock markets. This can also be a false statement, as renewables can be seen as substitutes for new possibilities when energy prices are rising.

Henriques and Sadorsky (2008) have used vector autoregression (VAR) to investigate if there is a relationship between oil prices and alternative stock prices in the U.S. They have chosen the WilderHill Clean Energy Index (ECO) as it was the first benchmark index for alternative energy companies. The other three components of the VAR model were: Area Technology Index, U.S. West Texas Intermediate crude oil futures prices, and interest rate. The VAR estimation was made using ten lags and Model fit tests proved that the model is indeed good for VAR. The authors ran the Granger causality test using the LA-VAR Wald test introduced by Toda and Yamamoto (1995), which showed that past oil prices, interest rates and stock prices all have explained the alternative stock prices in history. The study shows that oil prices have little significant impact on alternative energy stock prices. It also implies that oil prices are not that important, as technology stocks have a bigger influence on the stock prices of alternatives. This idea fights the past assumptions made that oil would be a more important variable to stock prices.

Kumar *et al*. (2012) continued o the basis of Henrique and Sadorsky (2008) to compute VAR to find a relationship between oil and alternative energy stocks. They extend the VAR model from 4-variable to 5-variable lag-augmented, which also adds to the list of carbon markets. All the other indices are the same as in Sadorsky´s and Henriques´ models. Also as a difference to the previous study, the authors use weekly data rather than daily. Authors confirm as in the previous study, that variations of the three indices used are explained by the past movements of oil prices. There is also specially mentioned that there is a positive relationship between oil prices and alternative energy stocks, as those would work as substitutes. The fifth variable was carbon market price returns, which did not act as a factor in alternative stock prices.

Managi and Okimoto (2013) have tried to examine the same problem with Henriques and Sadorsky (2008) and Kumar *et al*. (2012) for the sample period of January 3rd of 2001 to February 24th of 2010. They have aimed to consider structural changes to understand the relationship between oil prices, clean energy stock prices and technology stock prices even more. The authors also want to examine if the changes in the data will affect the relationship, as previous literature has not been able to find evidence of a positive effect on clean energy stock prices and oil prices. To further the study from Henriques and Sadorskys' (2008) paper, the authors use Markov-switching (MS) framework. The usage of the MS framework provides effective tools for investigating economic system, which has possible structural changes and asymmetric effects. The authors believe that there are structural breaks regarding oil prices in the economy. The study indeed did find structural changes in the market, as oil prices surged and the U.S. economy fell into a recession at the end of 2007. The main conclusion and new insights into the research problem were, that there was a positive relationship between oil prices and clean energy companies mainly after structural breaks, such as recession.

A previous study by Reboredo & Ugolini (2018) has compiled data on the impact of the price movements of fossil fuels towards clean energy stock returns with a multivariate vine-copula dependence setup. The period of the study is 2009-2016 using daily data. In this study, they extend their previous study (Reboredo & Ugolini, 2016) from a bivariate to a multivariate setup. This way the aim is to find the connections between returns and different energy classes. The study shows that in the EU extreme and moderate downward fluctuations in electricity prices harm renewable energy stock returns. Electricity is said to be the main driver of the ERIX index. With fossil energy, the impact is the opposite, if the price goes up, the returns of renewables are increasing. The main conclusions are that green investors should pay attention to oil and electricity price fluctuations, as those are the main contributors to upside and downside risk for renewable stock returns. Found in the study, the symmetric tail dependence suggests that investors should use risk strategy for both short and long positions. Also, there is seen to be positive dependence between the returns of renewables and most of the energy prices.

2. DATA AND METHODOLOGY

The chapter on data and methodology first gives an overview and brief discussion of why the data used is chosen and justified with the paper. The paper uses VAR analysis as its statistical method, and the method is explained more in-depth in the next part of this section. This part will also justify the usage of VAR for this specific data. Also adding to the VAR model, simple statistics are discussed as a method for correlation and straight impact of energy prices towards renewables. For the VAR analysis, data is first handled in Excel and exported to the R-Studio platform, where it is possible to construct the model and the analysis. For the other statistics, the same data that is used in, the previous step is used to draw correlations between the variables during different times.

2.1. Data and descriptive statistics

In total four datasets have been chosen for this paper in order to get analysis that gives information regarding the research problem of energy crisis' impact on renewable stocks. The two datasets not including energy price and renewable energy stock performance are helping to estimate the performance of renewables compared to total market returns in Europe and all of the energy sector in Europe. Datasets that are used in this study are: ICE Europe Brent Crude Electronic Energy Future (Ric ticker in EIKON: LCOc1), Refinitiv Europe Renewable Energy-502010 Price Return Index (RIC ticker in EIKON: .TRXFLDEUPUE21), and Refinitiv Europe Total Return Index (RIC Ticker in EIKON: .TRXFLDEUTU), were taken out as total weekly return indexes. Because the study aims to evaluate the impact of energy prices towards renewable energy stock performance, the sample contains pre (2018-2022) and post (2022-2023) crisis events. This way it is possible to conclude how the crisis has impacted if at all the dynamics of renewable stock performance. The selection of indices was chosen, as previous studies, such as (Henriques & Sadorsky, 2008) use index returns as their datasets.

The dataset was first constructed in Excel using the exported data from Refinitiv Eikon financial database. After exporting the data, it was gone through in case of missing values or dates, with the VLOOKUP function and exact match setting, so there would be no misleading or blank data rows.

After the cleaning of the data, it was ready to be exported to R-Studio, where all of the graphs and analyses were constructed. As the data was imported to R, the descriptive statistics (Table 1) and time series of all the variables were conducted to see the overall patterns and statistics throughout the interest. To conduct further analysis with a chosen method other types of graphs were also constructed with R, such as the time series with logarithmic differences to continue with VAR regression (Figure 3). The way of doing the illustrations in R helps the author and reader to go through the visualisations clearly without getting confused with graph models and processes. The code used in R to construct the needed visualizations and analysis are presented in Appendix 1 The overall time series of all variables are visualized in Figure 1 and Figure 2 as original values and logarithmically differentiated respectively.

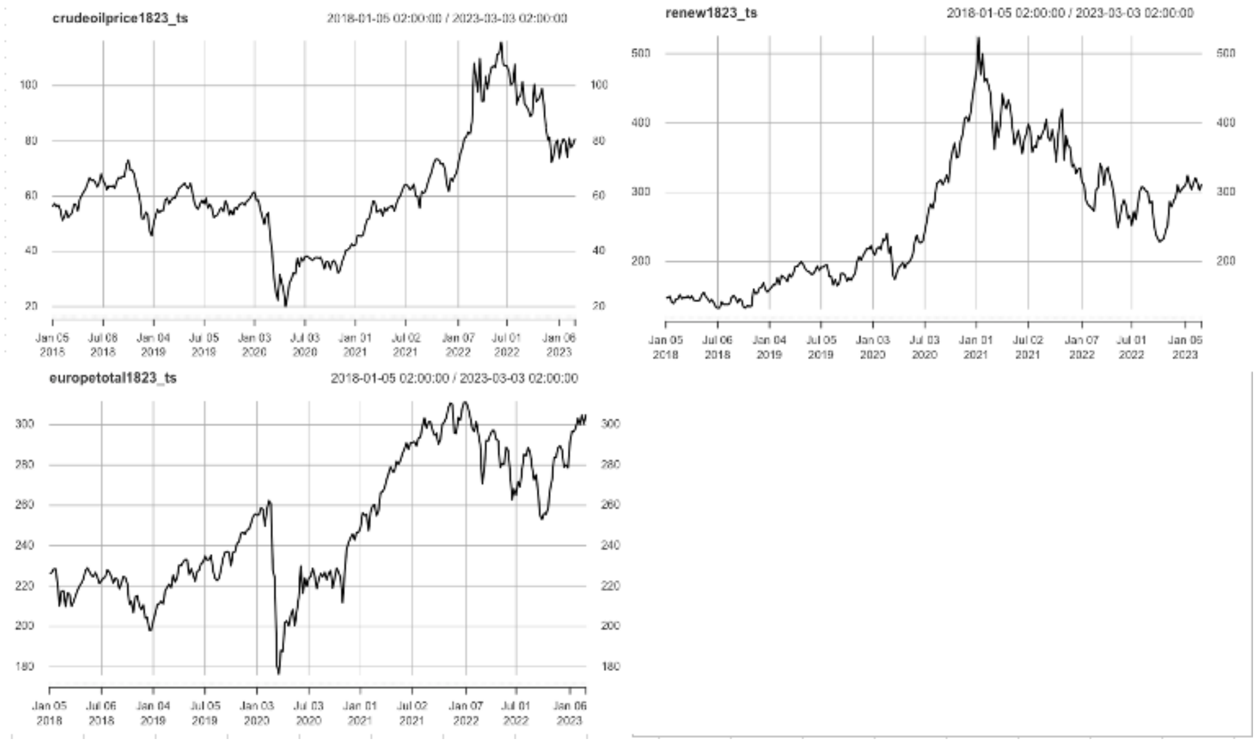

Figure 1. Time series data for 2018-2023
Source: author’s calculations

The visualization of the time series in Figure 1 shows the development of the indices of European renewable energy companies (renew1823_ts), Crude Oil prices in Europe (crudeoilprice_1823), and Europe total returns (europetotal1823_ts) in the studied period. In the figure, it can be seen, that renewables have not been impacted by the COVID-19 pandemic in the same way that other variables have and renewables have also risen significantly from March 2020 to January 2021. Resulting of the fast recovery from the pandemic, all of the indices started climbing rapidly before the market had seen another drop in the fourth quarter of 2020, where it seems that renewables have not been impacted by it at all. One thing that the author wants to point out from Figure 1 is that in February 2022 when the war in Ukraine started, Europe's total markets have seen a drop in renewables as crude oil rocketed upwards. Because of many factors, like the Russias and Ukraine tensions and the rapid recovery from the pandemic, it can be seen that the markets have been volatile. Also, because of the same reason, in the meantime, energy prices have been increasing rapidly from 2021 and rocketed in 2022, when the peak was met.

Table 1. Descriptive statistics of crude oil price, renewables returns and Europe total returns for 1/2018-3/2023

Data	n	mean	sd	median	min	max	skew	kurtosis	Se
Crude Oil Price	270	62,67	19,87	59,20	19,82	116,03	0,59	0,11	1,21
Renewables returns	270	259,99	95,66	241,8	132,12	524,58	0,45	-0,9	5,82
Europe Total returns	270	250,13	33,45	242,5	176,13	311,46	0,23	-1,24	2,04

Source: author's calculations

Descriptive statistics of the original variables for the sample period are computed with R using the package "psych" and function "describe()" (table above). All of the variables that are studied have moderate skewness, with the energy sector being the only one which is negatively skewed. This means that all but one variable has most of its values lying on the left side of the distribution. Crude Oil has the highest skewness of all variables (0,59), which is still far away from high. All of the variables are platykurtic with Kurtosis values smaller than 3, which tells that there are fewer outliers in the dataset than in a normal distribution. The standard deviation of the variables can be used to see how is the variability in the dataset. Renewables are seen to have the highest standard deviation among the variables (95,66), whereas crude oil prices have the lowest (19,87). This tells that renewables returns have the highest volatility in the period of interest.

To compute and run VAR analysis, logarithmically-differenced data was also compiled because of the criteria of the method (specified in methodology section 2.2). After the logarithmic differences had been added to the original time series data, the illustration of the time series data (Figure 2), changed as one can see below. The visualizations give a more thorough understanding of the changes in the returns during the sample period.

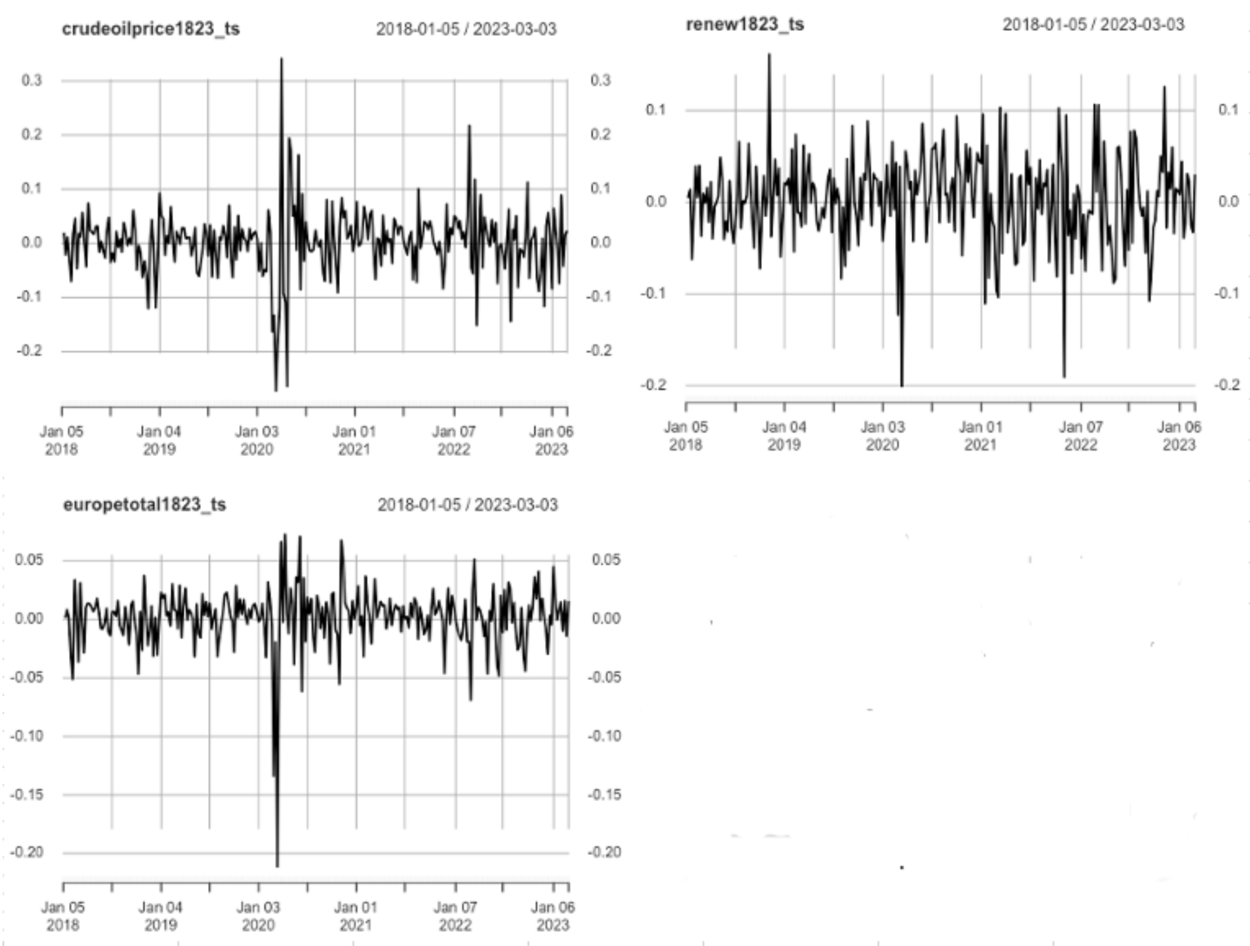

Figure 2. Logarithmically Differentiated Time Series data for 2018-2023
Source: Author’s calculations

What can be seen from the logarithmically-differenced data is that all of the variables have seen a significant drop in the first quarter of 2020, mainly because of the COVID-19 pandemic. Crude oil and renewables are seen to be more volatile and exposed to significant up and downsides in the sample period and especially after the large drop in 2020. Crude oil has seen a great rise in prices at the beginning of 2022 it can be seen from the illustration that renewables have also spiked upwards. The total indexes have both seen bigger drop than rise in the period of the crude oil hike. The total indexes have been handling the drops better than crude oil and renewables, this is wide because those are indeed estimators of larger groups.

2.2. Methodology

The method that this paper is going to use to execute the analysis is vector autoregression (VAR). VARs were founded by Christopher A. Sims (1980), and the framework brought out an efficient way of forecasting, describing, structural inference and policy analysis. This framework suits the authors' intentions well as it can fit data and make reasonable estimations of causal connections. (Stock & Watson, 2001) In the VAR model there is no need for determining which are endogenous or explanatory variables, as all of the variables depend on the lagged values of all chosen variables. This creates a way how to capture the properties and dynamics of the data. (Brooks, 2019) The fitting of VAR can also be justified for this paper, as many previous studies using similar datasets and variables have used it also such as Kumar et. al 2012, Managi & Okimoto, 2013 and Henriques & Sadorsky, 2008. The VAR is estimated with ordinary least regression (OLS). This type of VAR is also called reduced form VAR, where every variable is a function of its past values and the past values of other chosen variables. The construction of the equation can be seen below. The equation for reduced from VAR is expressed by (Floyd, 2005) as follows in Equation 1:

$$y_t = b + B\, y_{t-1} + u_t$$

where

y_t- Time series variable

b - a matrix of constant coefficients representing the intercept of the equation

B - an Unstandardised regression coefficient

u_t- error term

The process of performing VAR analysis begins with a choice of the order for variables and the lag length. Choosing the lag length is an essential part of the VAR analysis. If the lag length chosen is too large, it can result in a decrease in degrees of freedom and a rise in standard error in coefficients that are estimated in the analysis. On the other hand, if the length of the lag is too small, it may not capture the characteristics of the data. The choice of lag length should be considered with care to obtain unbiased analysis as per Toda and Yamamoto (1995) The order of the variables cannot be calculated by any statistical method that would give the correct answer, but it should still be considered to get unbiased answers. Based on Lüthkepol (2005), the first variable would have to be the one that could potentially have an immediate impact on the other variables. The wrong order of the variables can result in totally different outcomes, so this one should also be thought about carefully.

To continue the analysis of VAR, the author has to prove that the data is stationary. This can be done with the augmented Dickey-Fuler (ADF) test by Dickey and Fuller (1981). The ADF test can be run in R by function adf.test() in the "tseries" package. The function counts the required lags automatically. When the ADF test was done with the original data, it was seen that the hypothesis of non-stationary data could not be rejected, as the p-values of the ADF test were not statistically significant. To reject the hypothesis of non-stationarity, logarithmic differences had to be applied to the original data. This was conducted in R using function diff(log()). After the planting of logarithmic differences, the p-values of ADF tests proved to be significant, resulting in the capability of rejecting the null hypothesis of non-stationarity. This means that all of the p-values in the new adf tests were significant. The ADF test results can be found in Appendix 2. After the usage of logarithmic differences, data was stationary, and the author was able to continue with the VAR analysis.

The next step with the VAR analysis is the lag selection, which can be computed in many ways in R, which include the Schwarz Information criterion (SC), Akaike Information Criterion (AIC), Akaike´s Final Prediction Error (FPE) and Hannah-Quinn error. When selecting lags, it does not give any value to the analysis and normally only one of these criteria is used to select the lags according to Ivanov and Killian (2005). The AIC was chosen as the method for this paper, as Ivanov and Killian (2005) have shown that if the timeframe is more frequent, AIC is better than HQ. Also what Khim-Sen Liew (2004) has studied is that for a smaller sample than 120 AIC performs better than HQ. These two standpoints justify that the usage of AIC would indeed be suitable for the author going forward with VAR analysis. The equation used to calculate the AIC is formed by Akaike (1974) as follows in Equation 2:

$$AIC = (-2)\log(\max. likelihood) + 2k$$

Where

k – the number of independently adjusted parameters in the model

When conducting the lag selection, all of the criterion types gave the same lag length which was 1 for the original data (2018-2023) and 10 for the energy crisis event period (2022-2023). After the lag selection was done, the author was able to construct VAR models in R, which are presented in the upcoming chapter in Table 2 and Table 3. The var model shows the variables and the model characteristics with given lag lengths, which are 8 for the period 2018-2022 and 10 for 2022-2023 in this paper. The estimated model has to be justified so, it would meet the criteria of error terms being white noise. This means that i.e.t there should be zero mean, constant variance, normal distributions for error and lastly no autocorrelations, as discussed by Hatemi (2004). To check the autocorrelation of the model, the Portmanteau test is run with the Ljung-Box test introduced by Ljung and Box (1978). The Ljung-Box test is seen as an improved version of the same kind of test introduced by Box and Pierce (1970), which also implies that to recognise the areas where it would be possible to make the models fit better it is crucial to make these kind of diagnostics for the model. To analyse the model in more depth Impulse response analysis is conducted. After concluding that the model is ok to use and does not contain autocorrelation, Impulse Response analysis is made. Impulse Response Analysis describes the transformation of the variables in the face of the shock of one or more variables. (Mohr, 2020) In this paper the impact of shock in Crude Oil prices in other variables plays an important role in the VAR analysis, and for that reason, Impulse Response Analysis fits the model well. For the final diagnostics forecast error variance decomposition (FEVD).

The VAR model is done for two time periods, the first being the pre-energy crisis period of 2018-2022 and the second one beginning from 2022 until 2023. This is done as the author is interested to see the difference in the characteristics and results of the models, between a longer period, and the period when the oil prices have hiked drastically and the energy crisis has sparked. In total all the same steps are gone through with both datasets to be able to compare.

After the VAR models are conducted, the author seeks to get information on the comparison of the performance of Europe´s total returns and renewables returns in Europe. This is done by firstly conducting a t-Test: Paired Two Sample for Means in Excel. This way the author can get knowledge on the significance of the difference of the returns in the periods of interest. After this comparison between the cumulative returns is done in order to see the characteristics of the returns in the pre-and post-crisis time in a clear illustration, where conclusions could be drawn.

3. ANALYSIS

In the third chapter of the thesis, the author will go through the estimates and analysis conducted as brought up in Chapter 2. The VAR model is estimated with the weekly data of the pre-crisis period of 2018 to 2022 and for the energy crisis event period of 2022-2023. The outcomes of the VAR model are stated and discussed by the author before going further down to conclusions regarding the overall analysis and the study. In the end, the author will also provide some suggestions for improvements for future studies of the subject.

3.1. VAR model estimation

Below in Table 2 is illustrated the VAR model for the pre-crisis period of 2018-2022. Here, the significant estimates are marked as follows: * (significance level of 0.05), ** (significance level of 0,01), ***(significance level of 0).

The price of crude oil is the only one which is significant from the three variables as can be seen from the F-statistic of 4.12 and the p-value. This is mostly due to its relationship in the model with the ETR. At a high statistical significance level, the change in crude oil price is due to a change in ETR in the first two lags as the estimates of ETR lags 1 and two are significant in the crude oils equation. Europe Totals past values are seen to be more important than the other variables to predict the present value of crude oil price. Overall, the independent variables can be said to explain 27.3% of the change in crude oil price. The equation of RER and ETR is not statistically significant, and the variability in the variables is not well explained by other variables as can be seen from adjusted R-squared values of -0.0108 for RER and 0.0145 for ETR. When looking at the P-values of the equations, a conclusion can be made that the equation of Crude Oil is the only one with statistical significance.

Table 2. VAR model for 1/2018-1/2022

	Crude Oil Price (CUP)		Renewables returns (RER)		Europe Total Returns (ETR)	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	St. Error
CUP (L1)	-0.043	0.084	-0.082	0.078	0.021	0.042
CUP (L2)	-0.137	0.084	0.041	0.078	0.020	0.042
CUP (L3)	**-0.212****	0.081	-0.065	0.075	0.001	0.041
CUP (L4)	0.149	0.082	0.045	0.076	0.066	0.041
CUP (L5)	0.001	0.078	-0.029	0.072	0.047	0.039
CUP (L6)	**-0.189***	0.077	-0.083	0.072	-0.075	0.039
CUP (L7)	**0.196***	0.077	0.086	0.071	**0.091***	0.039
CUP (L8)	**-0.241****	0.075	0.070	0.069	0.005	0.038
RER (L1)	-0.137	0.095	**-0.197***	0.200	-0.067	0.048
RER (L2)	-0.141	0.096	0.010	0.089	-0.022	0.048
RER (L3)	-0.063	0.096	-0.025	0.089	-0.017	0.048
RER (L4)	0.081	0.095	0.165	0.088	-0.025	0.048
RER (L5)	0.006	0.096	-0.048	0.089	-0.023	0.048
RER (L6)	0.035	0.095	-0.010	0.088	-0.048	0.048
RER (L7)	-0.004	0.095	0.041	0.088	0.028	0.048
RER (L8)	0.002	0.095	-0.092	0.088	-0.023	0.048
ETR (L1)	**1.075*****	0.198	**0.438***	0.183	0.076	0.099
ETR (L2)	**0.598****	0.217	0.079	0.200	0.085	0.109
ETR (L3)	- 0.030	0.217	0.044	0.201	-0.061	0.109
ETR (L4)	0.082	0.208	-0.286	0.192	**-0.210***	0.104
ETR (L5)	0.153	0.195	0.079	0.180	-0.109	0.098
ETR (L6)	**0.678*****	0.198	0.239	0.183	0.108	0.099
ETR (L7)	-0.108	0.204	0.124	0.188	-0.092	0.102
ETR (L8)	**0.423***	0.201	-0.164	0.186	-0.028	0.101
Const.	-0.002	0.004	0.004	0.004	0.003	0.002
F statistic		4.12		0.911		1.12
P- Value		0.0000000201		0.587		0.324
Adjusted R-squared		0.273		-0.0108		0.0145

Source: author´s calculation

The estimation of the model was followed by different diagnostics such as serial correlation, heteroscedasticity, and normality test. The serial correlation was tested with the asymptotic Portmanteau test in R with the function "serial. test()". As the p-value of the test was smaller than 0.05 the model failed this test and there was serial correlation included. The model also failed the normality and heteroscedasticity test, which was unfortunate. The only test that the model passed was the OLS-CUSUM test, where the corresponding lines stayed inside the critical borders. The OLS-CUSUM results can be seen in Appendix 2.

The model for the energy crisis period of January 2022 to March 2023 can be seen in Table 3 below. The VAR model for the period 2022-2023 shows that renewables and Europe total returns do not work as a significant estimator for crude oil, except for one (ETR L3) of the coefficients that is on significant levels. This could also be because the shock to crude oil prices resulting from Russia's war with Ukraine was unpredictable, and the demand and supply of crude oil did not follow its regular path. The equation for crude oil overall shows that the data does not fit the model well, as the predictor variables only account for a small proportion of 20,1% variance (adjusted R-squared of 0,201), and p-value, as well as f-statistics, implicate that the model is not significant. From the output of the renewables equation, it can be said that the lagged Europe total retune has significant positive effects on renewables returns with a significance level of 95% or better. Crude oil on the other hand does not act as a good predictor for renewables for this period with only one significant estimate in the ninth lag. The F-statistic of 1.89 and p-value of 0.0708, which can be interpreted as significant with a significance level of 90%, also suggest better outcomes for this period than for 2018-2023. The adjusted R-squared for renewables shows the highest explanation in variability for all equations in the two models, with 0.347 as a mark. The crude oil price and renewables do not act as a good predictor for Europe's total returns as the F-statistic, p-value and adjusted R-squared are worst across the model.

Table 3. VAR model for 1/2022-3/2023

	Crude Oil Price (CUP)		Renewables returns (RER)		Europe Total Returns (ETR)	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	St. Error
CUP (L1)	**-0.531***	0.199	0.088	0.149	0.042	0.082
CUP (L2)	-0.314	0.184	-0.044	0.138	0.064	0.076
CUP (L3)	0.039	0.192	-0.090	0.144	0.131	0.079
CUP (L4)	0.168	0.194	-0.247	0.147	-0.035	0.080
CUP (L5)	0.095	0.206	-0.252	0.154	-0.036	0.085
CUP (L6)	0.267	0.206	-0.322	0.154	**-0.223***	0.085
CUP (L7)	-0.067	0.209	-0.006	0.157	-0.117	0.086
CUP (L8)	-0.006	0.195	-0.004	0.146	-0.105	0.080
CUP (L9)	-0.282	0.188	**0.325***	0.141	0.086	0.077
CUP(L10)	-0.033	0.175	-0.007	0.131	0.046	0.072
RER (L1)	0.273	0.267	-0.391	0.200	-0.013	0.110
RER (L2)	-0.044	0.245	**-0.442***	0.184	-0.106	0.101
RER (L3)	0.199	0.232	-0.216	0.174	-0.019	0.096
RER (L4)	- 0.090	0.243	-0.111	0.182	-0.104	0.099
RER (L5)	- 0.283	0.219	0.009	0.165	0.068	0.090
RER (L6)	- 0.046	0.231	-0.132	0.173	0.049	0.095
RER (L7)	0.354	0.240	-0.046	0.180	0.140	0.099
RER (L8)	0.187	0.236	**-0.824*****	0.177	**-0.209***	0.097
RER (L9)	0.341	0.238	0.183	0.179	0.108	0.098
RER (L10)	0.460	0.245	**-0.791*****	0.184	**-0.304****	0.101
ETR (L1)	-0.492	0.640	**1.676****	0.480	0.303	0.264
ETR (L2)	- 0.222	0.528	0.807	0.396	0.063	0.217
ETR (L3)	**- 1.261***	0.561	**0.921***	0.421	0.055	0.231

ETR (L4)	-0.040	0.588	0.504	0.441	0.302	0.242
ETR (L5)	0.314	0.489	-0.156	0.367	-0.159	0.202
ETR (L6)	-0.461	0.511	0.212	0.383	-0.056	0.210
ETR (L7)	-0.038	0.527	-0.535	0.395	**-0.537***	0.217
ETR (L8)	-0.025	0.536	**1.126***	0.402	0.237	0.221
ETR (L9)	-0.375	0.552	-0.116	0.414	-0.337	0.228
ETR (L10)	-1.076	0.584	**1.659****	0.438	0.383	0.240
Const.	-0.00882	0.00789	-0.00288	0.0059	0.00057	0.00325
F statistic		1.42		1.89		1.1
P- Value		0.209		0.0708		0.42
Adjusted R-squared		0.201		0.347		0.0562

Source: author´s calculation

The Portmanteau test for the second model implicated an extremely small p-value, resulting in a conclusion that there is a serial correlation in the model. The second model failed the serial correlation test as did the first one. The P- value of 1 with test statistic 246, with 360 degrees of freedom implies that there is also conditional heteroscedasticity in the model. Different from the first model, the second model of post-crisis events passed all the normality tests. the OLS-CUSUM test for the model of 2022-2023 which can be seen in Appendix 2 shows that the model was stable and did not interfere with the critical lines. The second model seems more suitable than the first one, thus not still fully significant.

To get more insights into the models. The author compiles more diagnostics in the following chapters.

3.2. Impulse Response Analysis

Impulse response analysis was the next step in the analysis of the effects of Crude Oil shocks on Renewables and Europe's total returns. By conducting the model, the author seeks to find information related to the shock in energy prices namely the crude oil spot prices to renewables and Europe's total returns. This gives a broader understanding related to possible changes in chosen variables related to shocks in a specific timeframe. The impulse response was conducted in R using function if () with 30 periods. The analysis of the response was likewise conducted for the pre-crisis period and the post-crisis period. The outcomes of impulse response are shown and interpreted below in Figures 3 and 4.

Figure 3 (below) shows the results of the impulse response from crude oil to renewables and Europe's total for the pre-crisis period, where the y-axis illustrates the percentage change and the x-axis illustrates time. Shocks in crude oil are seen to have a very similar impact on both variables when considering the period of 2018-2022. As one can see from the graph, both variables have a quick positive initial reaction towards the shock in crude oil. The movements in the renewables curve seem to be more volatile. After the tenth period, the volatility caused by the shock in crude oil prices has been worn off by both variables. There is a minimal difference in the responses, as the response of Europe total is a bit bigger, but still not even close to significant levels.

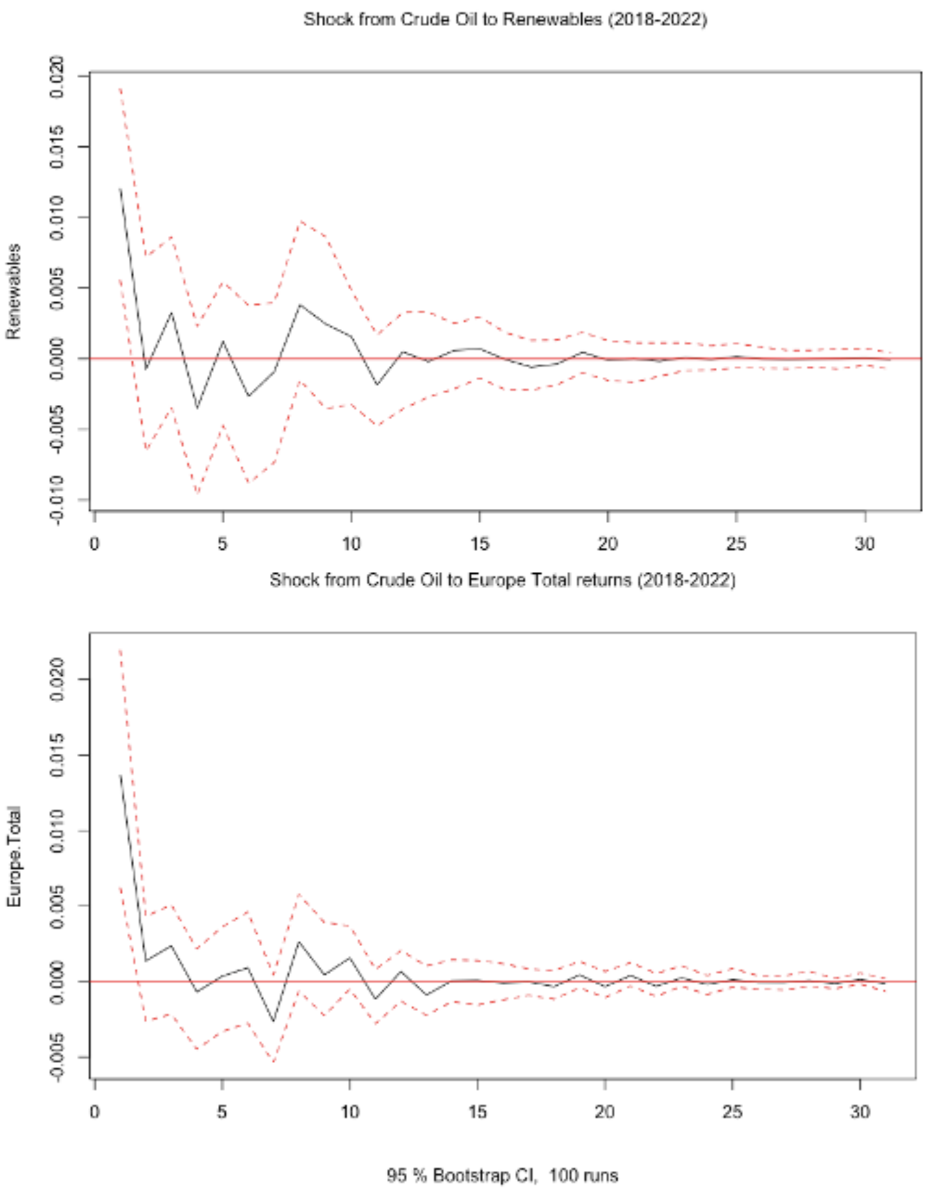

Figure 3. Impulse Response Curve 2018-2022
Source: author’s calculations

The second figure illustrates that again, the initial shock to the variables is positive. However, there is a difference in the impulse responses of renewables and Europe's total returns. The effect of crude oil price shocks is seen to have a longer effect on both variables when compared to Figure 3. One thing to keep in mind is that even though the responses are not the same, the impulse curves are not moving in significant levels as those are moving inside the red curves in both illustrations.

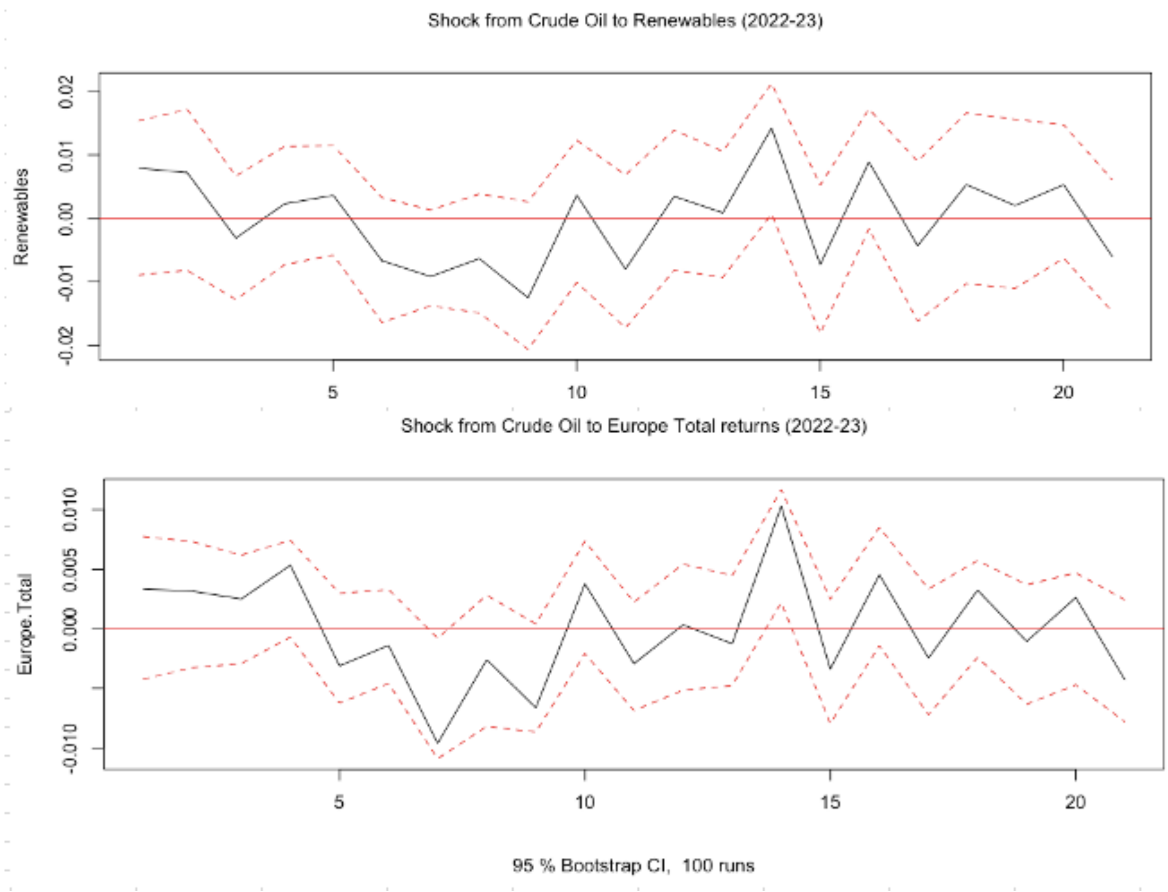

Figure 4. Impulse Response Curve 2022-2023
Source: author’s calculations

The movements from the tenth period are very similar between Europe's total returns and renewables. There is some difference in the initial shock, which seems to be more positive for renewables before the negative drop in the third period. The overall curves show that the effect of oil price shock has been much more impactful for both variables in the period of energy crisis events, and the effects do not wear off quickly, as they do in the overall period of 2018-2023.

3.3. Forecast error variance decomposition (FEVD)

FEVD is another type of calculation drawn to see the impact of shock between the variables in the model. FEVD is computed in R simply by using the function find (), where the model is inserted and only the forecasted periods ahead are added. For these models, the author has used forecasted periods of 5. The results of the forecast error variance decomposition test are shown below in Tables 4 and 5.

Table 4. Error variance composition for the VAR model of 2018-2022

	Crude oil price (CUP)			**Renewables (RER)**			**Europe's total return (ETR)**		
n periods ahead	**CUP**	**RER**	**ETR**	**CUP**	**RER**	**ETR**	**CUP**	**RER**	**ETR**
1	1.000	0.000	0.000	0.0599	0.940	0.000	0.263	0.167	0.570
2	0.856	0.00776	0.136	0.0577	0.911	0.0308	0.262	0.172	0.566
3	0.823	0.00899	0.168	0.0616	0.907	0.0313	0.267	0.170	0.563
4	0.823	0.01453	0.163	0.0660	0.903	0.0311	0.266	0.173	0.561
5	0.820	0.01655	0.163	0.0648	0.887	0.0484	0.256	0.182	0.562

Source: author´s calculation

What can be drawn from Table 4 (above) representing the period of 2018-2022 is that crude oil prices and renewables are stable on their own, as RER accounts for at least 88.7% of the variance itself and crude oil price 82% respectively. For CUP, for the three first periods, the proportions are changing, and the ETR seems to account more for the variance. It seems that RER does not attribute changes more than 1.65% although its proportion rises along the periods. For the RER equation, neither CUP nor ETR are accounting for over 6.48%, which is the highest value resulting from CUP in the fifth period ahead. This indicates that neither CUP nor ETR is accounting for the variance of RER in a mentionable manner. ETR seems to be most affected by other variables as CUP is seen to affect 25.6%-26.7% and RER 16.7%-18.2% from its variance. The proportion of

ETR´s impact on variance is only 56.1%-57%, which is the lowest among the equations and implies that other variables affect ETR quite much.

For the FEVD model of the 2022-2023 model (Table 5 below), notable changes are occurring, as RER seems to be much more affected by other variables than previously. For the other two variables, there is not that big of a change happening.

Table 5. Error variance composition for VAR model of 2022-2023

	Crude oil price (cup)			**Renewables (RER)**			**Europe's total return (ETR)**		
n periods ahead	**CUP**	**RER**	**ETR**	**CUP**	**RER**	**ETR**	**CUP**	**RER**	**ETR**
1	1.000	0.000	0.000	0.0392	0.961	0.000	0.0231	0.382	0.595
2	0.977	0.00439	0.0187	0.0457	0.633	0.321	0.0397	0.371	0.589
3	0.957	0.01582	0.0275	0.0471	0.606	0.347	0.0501	0.370	0.580
4	0.835	0.02795	0.1373	0.0481	0.593	0.359	0.0964	0.351	0.552
5	0.816	0.02740	0.1568	0.0525	0.589	0.359	0.1107	0.344	0.545

Source: author´s calculation

In Table 5 above the VAR model with the period of 2022-2023 is conducted. For CUP in the first period ahead it accounts for 100% of FEV itself, but in the following periods, the proportion of Ren and ETR are rising until the last lag, where ETR accounts for 15.68% and REN 2.74%. RER accounts for 96.1 % itself and CUP for 3.92% in the first period ahead. However, the proportion change drastically after the first lag as ETR is attributed to 32.1% in the second lag and 35.9% in the last lag. CUP does not seem to change much between the lag staying inside the range of 3.92%-5.25%. For ETR the proportion of impact on itself stays around the same in all periods. The further the model goes, ETR seems to be affected by other variables. RER seems to impact 38.2% in the first period, as CUP did 2.31% at the same time, but in the last period CUP already accounts for 11.07% as REN accounts for 34.4%. All the variables are affected by each other's in further periods and CUP seems to be the most stable one of these three, as its variance is the most influenced by its shocks in all periods. There are a variety of factors which cause the difference in the FEVDs. The change in the economic situation can be cause resulting in a case where the RER is not stable on its own anymore but is impacted by changes in other variables more. This could be happening because RER has seen positive returns on its own in the pre-energy crisis period, where the other variables have suffered more from losses. This would result in RER accounting for its variance earlier, whereas in the period of 2022-2023 RER has seen very market-like conditions. This also results in the incapability to be stable on its own and to be impacted by other variables more.

3.4. Comparing the performance of Europe's total returns and renewables returns

In this section, the author uses a t-test and calculations of cumulative returns to get information related to the performance of renewables returns and Europe's total returns in pre- and post-crisis periods.

3.4.1. T-test of the returns

The author compiled a t-test for the pre-and post-crisis periods to find differences in the returns performance of renewables and Europe's total returns. Below in Tables 6 and 7 are illustrated the results of the t-Test for paired two sample for means. The t-Test is done in Excel and the aim is to see if there is a statistically significant difference in the returns.

Table 6. t-Test: Paired Two Sample for Means for period 1/2018-12/2021

	Renewables	Europe Total
Mean	251,47	240,15
Variance	11284,41	944,19
Observations	209	209
Pearson Correlation	0,710	
Hypothesized Mean Difference	0	
df	208	
t Stat	1,879	
P(T<=t) one-tail	0,031	
t Critical one-tail	1,652	
P(T<=t) two-tail	0,062	
t Critical two-tail	1,971	

Source: author´s calculation

Table 6 (above) is the paired t-Test results for the pre-crisis period of 1/2018 to 12/2021. Renewables 251,47 mean of the returns is higher than Europe's total returns mean of 240,15. The variance of renewables is much higher, which has been the case in various of the metrics in this paper, implicating that there is more volatility in renewables. As the t Stat of 1,879 states, the difference of the means is not statistically significant at a 5% level of significance. The t-Test of the pre-crisis period concludes that the renewables returns are higher than renewables, but there is no certainty that this is not due to chance as the difference is not statistically significant.

Table 7. t-Test: Paired Two Sample for Means for period 1/2022-3/2023

	Renewables	Europe Total
Mean	289,92	284,75
Variance	808,27	217,89
Observations	62	62
Pearson Correlation	0,750	
Hypothesized Mean Difference	0	
df	61	
t Stat	2,043	
P(T<=t) one-tail	0,023	
t Critical one-tail	1,670	
P(T<=t) two-tail	0,045	
t Critical two-tail	2,000	

Source: author´s calculation

Table 7 (above) shows the results of the t-Test of the post-crisis period. The renewables are seen to have a small advantage on the mean, implicating that the average returns have been slightly higher. The variance of renewables is much higher which can be seen in Figure 2 also. With the significance level of 5%, it can be concluded that the difference in the mean returns is statistically significant as the t-statistic is 2.04. This can lead to a conclusion that can be said with high confidence that the difference between the two variables is not due to chance. What can also be drawn is that the difference is not big, and the volatility of renewables is much higher.

3.4.2. Cumulative returns

In Figure 5 (below), the author has computed cumulative returns of Europe's total returns and renewables returns to find information related to the second research question. Cumulative returns are computed for both pre-crisis and post-crisis periods to understand the characteristics of the returns more in-depth. The cumulative returns are calculated in Excel and formatted as a graph, to give out understandable illustration of the two periods and the variables.

In the first graph, it is seen that renewables (in green) have clearly outperformed Europe's total returns (in black) after the major shock in the first quarter of 2020. After a long hike from March 2020 until January 2021 renewables cumulative returns have been very volatile, whereas ETR has gained returns in a stable manner. In the pre-crisis period from 2018, renewables cumulative returns are up 107%, as Europe's total returns are up only around 39%. This could be due to the rise in the need for electricity among individuals, as people stayed more at home and household consumption of energy was rising. The demand side can be the major key when discussing the long rise of renewables between 2020-2021. The Europe total returns consist logically of all industries, which is one of the main reasons why the bounce of the cumulative returns has been much slower than the industry of renewables.

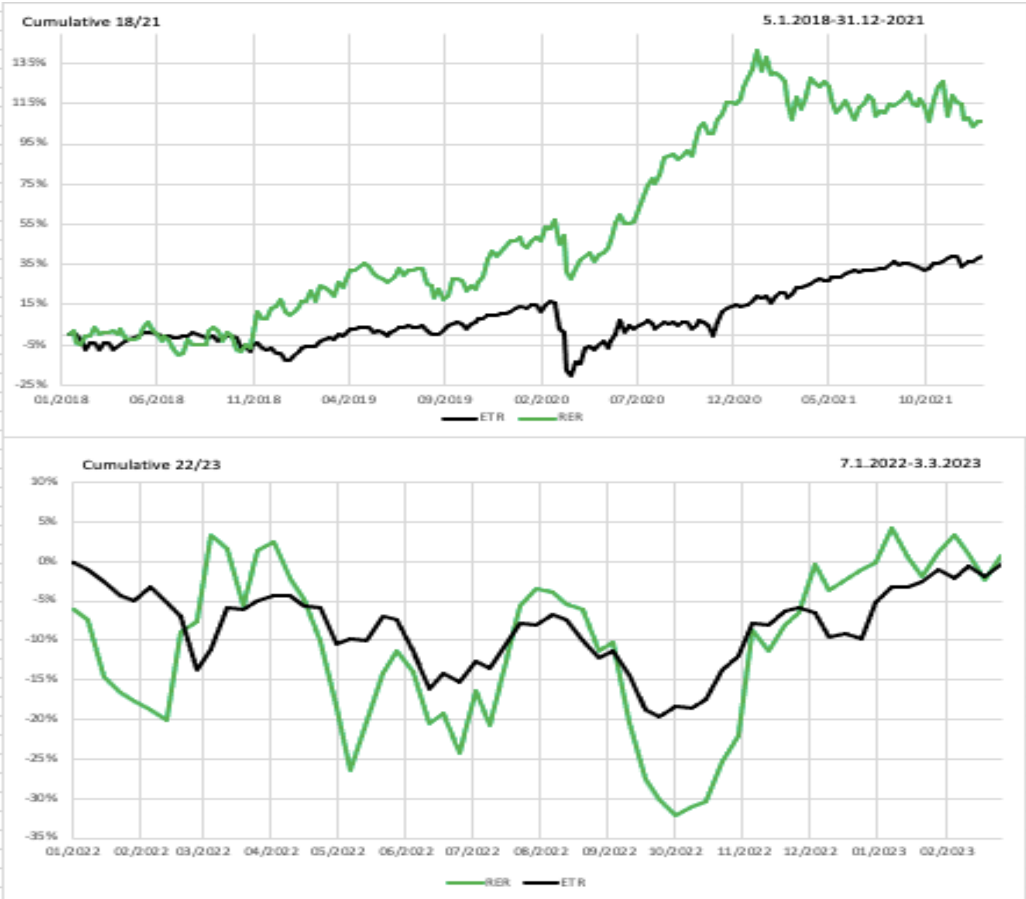

Figure 5. Cumulative returns for Europe total returns and renewables returns in the pre-and post-crisis period.
Source: author’s calculations

The second graph from Figure 5 illustrates the post-crisis period of 2022-2023. Here the dynamics of the variables have changed drastically. During the energy crisis events, neither of the indices gained many positive cumulative returns. The cumulative returns from 2022 to 2023 have been on the negative side most of the time before coming towards a positive break at the end of 2022, where the crude oil prices (as seen in Figure 1) have dropped from the highest point. The cumulative returns of the renewables have been very volatile and have seen bigger ups and downs than Europe's total returns. After all the cumulative returns signify, that renewables have not been performing better than Europe's total returns in the face of the energy crisis and that it has been more unpredictable.

3.5. Discussion of analysis

Looking at the overall results of the analysis conducted by the author, there is no evidence of crude oil prices affecting the returns of the renewables in Europe in the pre (2018-2023) nor the post (2022-2023) period of energy crisis events. The fact that beginning of the war and the consequences of it resulted in unpredictable market conditions, especially for energy prices. This developed a scheme where crude oil price did not follow its regular path, which can be the reason why it did not have any significant relationship with other variables in the models. Some implications of the relationship between renewables and oil can be seen in the impulse responses and forecast error variance in the direction that crude oil would account for more change in the concentrated period versus the overall period. What is seen from the models and diagnostics is that if there is some serious relationship between these variables it is between Europe's total returns and renewables, as seen in the VAR and FEVD diagnostics. The FEVD model indicates that, in the pre-crisis period, renewables are the most stable variable and other variables are not affecting its variance. However, in the post-crisis period, Europe's total returns seem to affect 32.1% to 35.9 % of the changes in the renewables returns. Crude oil seems to impact these variables more and result in more volatility in the variables in the post-crisis period, but what is notable is that it seems that the data does not fit the VAR models too well. The results cannot be taken as certainty, as the significance levels of most of the diagnostics were not sufficient.

The comparison with the t-Test showed, that renewables have been performing better in both periods. For the pre-crisis period of 2018 until the end of 2021, the difference is bigger, but it is not statistically significant. On the other hand, in the post-crisis period, the difference is statistically significant, and renewables are seen to perform better. The cumulative returns suggest that renewables have not been able to perform at much better levels than Europe's total returns in the face of the energy crisis. When looking at Figure 5 it is clear that in the long run, renewables have been gaining more cumulative returns than the market, but this is not the case in the post-crisis period. Renewables and Europe's total returns cumulative gains are very close to the same levels between 2022 and 2023. Both, the t-Test, and the cumulative returns suggest that renewables returns have been much more volatile than Europe's total returns. Because of the unpredictability, renewables cannot be seen as a superior alternative for investors in the face of an energy crisis, when looking at these results.

Perhaps some other methods or variables should be introduced to this data to find the real relationships between the shocks in the variables. Also, the usage of more precise data changing from weekly to daily could result in more accurate results and analytics. To find more meaningful results the author would suggest using several oil price shocks, as those are not once occurring events. This would help to find the characteristics that would play a role across the price shocks and would give more in-depth insights.

The author did find some same features as Inchauspe *et al*. (2015) that the relationship between energy price and renewables is higher after price shock in energy, although this paper was not able to prove it in a statistically significant manner. The author found similarities with Henriques and Sadorsky (2008) as well as Kyritsis and Serletis (2019) as they have found out in their research, that there is no significant relationship between oil prices and renewable energy stocks. The same results that those previous studies have found with technology stock is found with Europe's total return, which implies that there is more relationship between renewables and other stocks rather than with energy prices.

CONCLUSION

This paper had a few objectives the author was seeking to answer. The problems were stated in the beginning as follows: 1. What is the relationship between rising energy prices and the performance of European renewable energy companies stocks? 2. Do European renewable energy stocks outperform overall market return in the face of energy crisis events in 2021-2022? Two VAR models were constructed for the analysis. The VAR model for the pre-crisis period of 2018-2022 did not show any significance towards the relationships between the crude oil price and renewables returns in Europe, and the additional diagnostics also implied, that the data was not fitting the model well. The model failed the tests of serial correlation, normality and heteroscedasticity. The second model which was done during the period of high energy price hikes and energy crisis events, did bring up some significance. Though it seemed that the relationship was between renewables returns and the Europe total returns rather than with crude oil prices. The overall results were mostly not significant and thus not too reliable estimations were made.

The impulse review is done after the diagnostics gave also differing figures for the two models. The period 2018-2022 models impulse responses were showing that both renewables returns and Europe total returns had a quick initial positive shock to oil price shocks, but the reaction was worn off very quickly and did not move significantly. On the other hand, the concentrated period for energy crisis events showed that the impact lasted much longer and did not wear off. Neither of the impulse responses gave out significant changes, because of price shocks in oil. The forecast error variance decomposition implied that the renewables had a very low impact from other variables in the first model, whereas in the second model, more of those variances were explained by other variables, mostly by Europe's total returns. Europe's total returns showed that renewables and crude oil both had more effect on it in the post-crisis period model. What should be pointed out is that crude oil did not have close to any impact towards renewables in either of the models.

The comparison of the cumulative returns of renewables and Europe's total returns suggested, that renewables have not been performing better than the market in the face of the energy crisis. Renewables are seen to be a more unstable and thus worse alternative for Europe's total returns.

To conclude, the energy price shock of 2022-2023 did not have any significant impact on renewables. The Europe total returns are seen to be more impacted by other variables than renewables in these models. This is also found to be the truth in many previous studies. For future studies it is suggested that more variables and more frequent data could be used to find the real relationships and the data would fit the model better. Also, several shocks could be addressed in the same paper to find reappearing characteristics in the relationships. Finally, some different models could be used to attack the problem from different perspectives.

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APPENDICES

Appendix 1: R codes

R-Code for 2018-2023 time series and descriptive statistics:
https://drive.google.com/file/d/1qMdiWSjowLCLxeb75XWtJeZgITh3PahG/view?usp=sharing

R-Code for VAR model and diagnostics model 2018-2022:
https://drive.google.com/file/d/1YJgGOKBvyyq-h3CNut3M-592XjtjDf9o/view?usp=sharing

R-Code for VAR model and diagnostics 2022-2023:
https://drive.google.com/file/d/1NW-SS6W4I_LwwBgWg_dmvWY07TTFaHr_/view?usp=sharing

Appendix 2: ADF test results

Table 1: ADF test results for period 1/2018-12/2021

18-22	Original Time Series			Logarithmically differentiated time series		
	Crude Oil Price	Renewables	Europe Total Returns	Crude Oil Price	Renewables	Europe Total Returns
Lag order	5	5	5	5	5	5
p-value	0,6402	0,6534	0,7113	0,01	0,01	0,01
ADF-stat	-1,82	-1,85	-1,68	-5,0984	-6,3109	-6,23

Table 2: ADF test result for period 1/2022-3/2023

22-23	Original Time Series			Logarithmically differentiated time series		
	Crude Oil Price	Renewables	Europe Total Returns	Crude Oil Price	Renewables	Europe Total Returns
Lag order	3	3	3	3	3	3
p-value	0,3	0,4	0,7	0,05	0,04	0,02
ADF-stat	-3,00	-3,00	-2,00	-3	-4	-4,00

Appendix 3 OLS-CUSUM test results

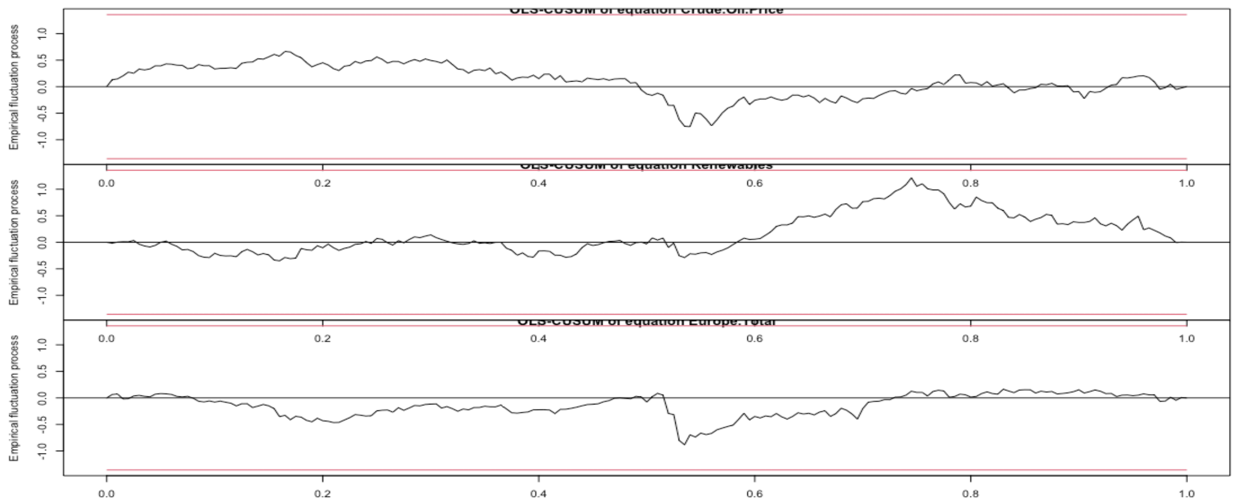

Figure 1. OLS-CUSUM test of the 2018-2022 VAR model.

Source: author´s calculations

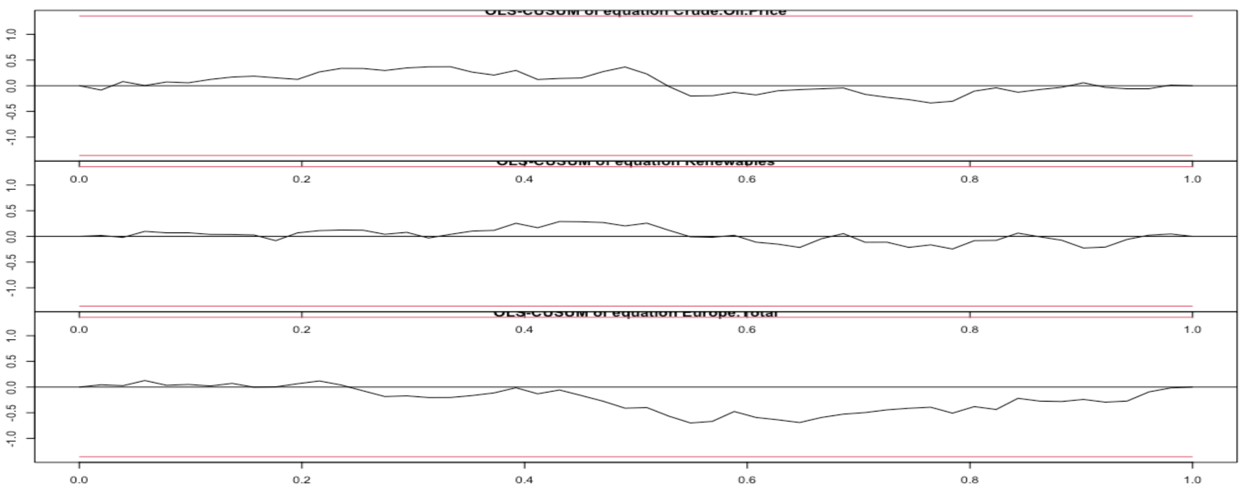

Figure 2. OLS-CUSUM test of the 2022-2023 VAR model.

Source: author’s calculations

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