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Crude Oil Price Shocks and European Stock Markets during the COVID-19 Period

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Abstract: This paper investigates the interrelations between stock returns and crude oil prices for European oil-importing/exporting countries. A vector autoregression (VAR) model is applied to estimate the significance of stock market responses to changes in oil prices during the pandemic period 2019–2021. A Granger causality test is applied to find the direction and the intensity of the relation between crude oil and the indices of the European stock markets. The findings of this paper hold with or without the COVID-19 pandemic episode and reveal the interaction between the European stock markets and the crude oil prices. The results indicate that in steady periods, before the COVID-19 outbreak and after the announcement of vaccinations, there is no interdependence between crude oil and stock prices, whereas in high volatility periods, the causality from stock markets to oil prices increases and both oil-exporting and -importing countries are equally influenced. These findings have implications both for investors and fund managers.

Keywords: crude oil; stock market; VAR models; COVID-19

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Citation: Katsampoxakis, I.; Christopoulos, A.; Kalantonis, P.; Nastas, V. Crude Oil Price Shocks and European Stock Markets during the COVID-19 Period. *Energies* **2022**, *15*, 4090. https://doi.org/10.3390/en15114090

Academic Editors: Štefan Bojnec and Nuno Carlos Leitão

Received: 20 April 2022
Accepted: 31 May 2022
Published: 2 June 2022

1. Introduction

The highly contagious spread of the coronavirus (COVID-19) has severely affected the global economy. This was the third time in a decade that the global economy was facing a serious challenge. The first was in 2007–2008 with the subprime mortgage crisis in the US and the second in 2010 with the sovereign debt crisis in Europe. Both crises also affected the banking system worldwide, which further harmed the real economy by freezing lending. The pandemic crisis, though, had unprecedented causes and affected the world economy in two dimensions. The first was the health dimension expressed with big numbers of deaths and infected people, reinforced by the persistent and continuous mutations of the COVID-19 virus. The second was the economic dimension that was due to the lock-down policies and the increased uncertainty worldwide resulting in decreasing consumption and consequently in decreasing demand for energy and a drop in energy prices.

Usually, uncertainty affects almost every sector of an economy in the short term or in the long term but mostly it affects the financial sector, which makes corporate financing difficult and the cost of capital high. Of course a situation like this, unavoidably will affect the state financing too (Ref. [1]).

The maintaining of such problems for a long period brings fear for a global economic downturn, with implications for production costs and corporate profits, employment, growth rates, and deviation from macroeconomic policies stimulating growth and social prosperity (Ref. [2]).

The announcement, though, for the massive supply of the vaccines reduces to some extent the systemic risk of the economies worldwide.

In this paper, we investigate the relationship between oil and stock indices by examining the impact of the pandemic and the response of the economies after the announcement that vaccines authorized for emergency use. In our analysis, we focus on countries that are key exporters and importers of energy. The rest of the paper is organized as follows. The literature review is presented in Section 2 and the data, assumptions, and methodology are presented in Section 3. The empirical results are presented and discussed in Section 4 and finally, in Section 5, we present the conclusions with a brief discussion of future work.

2. Literature Review

The effects of COVID-19 worldwide were the core interest of research after 2019. In several cases these studies provide useful conclusions for the relationship between financial markets and the energy sector. The effects of the pandemic are expected to be in the center of academic interest even in the next years.

Ref. [3] use a Johansen VEC model to examine the existence of a dynamic relationship and the properties of the causality between the prices of crude oil and the energy index of India in the short run and the long run. They find a long-run relationship between these two variables, whereas causality results show that Indian stock prices are significantly influenced by movement of international crude oil prices, at least in the short run.

The aim of Ref. [4] is to investigate the relationship between stock returns and oil prices for oil countries separately. They apply a panel Granger causality test to show that when oil prices collapsed because of the COVID-19 pandemic, there was an increase in the interdependence between oil and stock prices. Although they find that both the oil-exporting and oil-importing countries were affected in the same way, the impact was higher for exporting countries.

Ref. [5] study the effect of natural gas prices on the stock markets of three leading natural-gas-exporting countries, namely Russia, Norway, and Qatar. They use monthly data for natural gas prices and the stock exchange market index for these three countries for the period 2005 to 2013. They apply Granger causality and find the existence of a two-way relationship between natural gas prices and stock exchanges in Russia at a significance of 10% and in Norway at a 5% significance level, whereas they find no causality relationship with Qatar. On the other hand, they show that natural gas price shock does not have significant impact on any of the three stock exchanges.

Ref. [6] investigate the impact of oil-market shocks on stock prices in major oil exporting countries and examine the implications on domestic and international investors. They find speculative shocks impact on stock returns in Canada, Russia, Kuwait, and the UAE and they show a significant impact of oil-demand shocks on stock returns in Canada, Norway, Russia, Kuwait, Saudi Arabia, and the UAE. In addition, oil-supply shocks cannot affect Mexico stock returns, whereas they affect the stock returns in the UK, Kuwait, and the UAE.

Ref. [7] evaluate the dynamic relationship between oil price shocks and stock market returns in specific oil-importing countries of the MENA region for the period 2005–2018. They apply VAR models, Granger causality tests, and other techniques using weekly data to point to a causality relation from oil prices to stock market returns for the examined countries Egypt, Morocco, and Jordan.

Ref. [8] apply a cross-country analysis between the United States and China to investigate for volatility spillovers between their stock markets and natural gas, crude oil, and gold markets. They find that crude oil yields a negative return spillover for the US stock market but a positive return for the Chinese stock market. In the case of gold, though, we find the strongest volatility spillover effect for the stock markets of both countries. In the case of the US stock market, they find a positive volatility spillover effect and on the Chinese stock market they find a negative effect. They also find a dynamic nature of the spillover effect, where the return spillover is mainly found in the short term and the volatility spillover in the long term.

Ref. [9] research how the prices of crude oil influence the stock markets in nine Middle Eastern countries in the period 2001–2015 by using daily data. They aim to find a possible dynamic relationship by examining the effect of crude oil prices on stock market capitalization in these countries. They apply a VAR and a VECM and impulse response function and find the existence of a dynamic long-run linkage between oil prices and seven countries of the sample, whereas a long-run relationship between oil prices and stock markets exists only in three countries. They also find a short-run causality from oil prices to the stock markets for two countries and verify a positive relationship between oil prices and stock market value for most countries.

Ref. [10] investigate the interrelation between natural gas and the exchange rate of the BRICS countries (Brazil, Russia, India, China, and South Africa) in terms of time and frequency. They aim to value the variation effect in one variable that comes from the value of other variables for different frequencies for the period August 2010 to June 2019. They find that BRICS's exchange rates are hardly influenced by natural gas prices, which provides important information for policymakers in oil-dependent countries.

Ref. [11] aim to explore the dynamic effects that oil shocks have on the exchange rates for oil importer and exporter countries. They apply a structural vector autoregressive model to find that the impacts from oil supply shocks are more significant on the exchange rates of exporters than of importers. However, except from Japan and the UK, countries are in general more sensitive to oil demand shocks, ending with the appreciation of their exchange rates. According to their findings, such spill-over effects were strengthened after the crisis of 2007–2008, providing useful tools for periods of oil shocks to avoid exchange rate risks.

Ref. [12] examines the link between natural gas prices, crude oil prices, gold prices, exchange rates, and the stock market index in Indian context using weekly data for the period 1997 to 2019. They find that gold, stock market, and natural gas has an asymmetric effect on crude oil in the long run, whereas crude oil has an asymmetric effect on natural gas in the short run. They also find no impact of the exchange rate on crude oil and natural gas prices, whereas gold significantly affects both natural gas and crude oil in the short run and in the long run.

Ref. [13] apply a multivariate GARCH methodology investigating risk transmission and hedging strategies between natural gas market and stock markets. For the crisis periods they find Granger causality from natural gas to the Chinese stock markets as these markets are exposed to extreme weather conditions, governmental policies, and financial crisis.

Ref. [14] investigate the period before and after the oil price crash of 2014 to examine the systemic risk between WTI crude oil futures, New York Harbor gasoline futures, Henry Hub natural gas futures, and specific stock markets in the MENA region. In the short term, they find both negative and positive dependence of energy with MENA stock markets for the period before and after the oil crash. In addition, dependence is higher in the long term and after the oil crash and, therefore, expected loss is more significant after the crash in the long term. Finally, energy price shocks affect mainly the stock markets of oil-exporting MENA countries instead of the importing ones.

Ref. [15] examines the time-varying transmission between oil price shocks and the stock market in Turkey for the period 1988 to 2018. He applies a VAR model, using monthly WTI spot crude oil prices, world crude oil production data, the Kilian index to measure the global real economic activity, and BIST data. The results of this study verify the consistency of such TVP-VAR models in capturing the time-varying nature of oil price shocks.

Ref. [16] find that global oil and natural gas reserves are not equally distributed and, therefore, some countries are exporters and some are importers. Ukraine imports 90% of its oil and natural gas needs. They use monthly data to investigate the period 2008–2019 and find the effects of price changes in oil and natural gas on the returns of the Ukrainian Stock Exchange index. The causality test shows that a change in oil prices of USD 1 causes a change in the stock index of 0.56, whereas a change in natural gas price of USD 1 causes a change in the stock index of 0.31. Ref. [17] examine how oil price volatility responds to the

COVID-19 pandemic and stock market volatility. They use a panel model with daily data to examine the relationship between oil price volatility and the announcements for COVID-19 infections and deaths. Their findings imply that oil volatility is significantly affected by COVID-19 deaths. According to the conclusions, COVID-19 is a new risk component existing on top of economic and market uncertainty.

The main purpose of such studies is to provide the necessary information for policy makers to act effectively in similar cases, preventing negative effects.

In our paper, we extend this scope by studying the period before and after the announcement of the COVID-19 vaccines.

3. Methodology

In our analysis, we aim to examine the relationship between stock indices and the price of crude oil for countries where crude oil is an essential factor for their economy, either as an import or export country for oil and natural gas. In our study, we use a sample of four countries. Two of them are net oil importers and the other two are net oil and natural gas exporters. In particular, we examine the RTS index of Russia and OBX index for Norway as oil-exporting countries and CAC 40 Index of France and DAX for Germany as oil-importing countries.

In our analysis, we apply the natural logarithm of the daily closing prices in the primary stock indices of the countries of our sample and the daily closing prices of Brent crude oil. The examined period spans from the 1 January 2019 to the 9 November 2021, divided into three sub-periods.

The first sub-period (pre-COVID 19 period) starts from the 1 January 2019 until the 6 March 2020, covering the steady period from before the crash of oil prices until the outbreak of COVID-19. The second sub-period (pre-vaccine period) spans from the 9 March 2020 until the 9 November 2020, covering a volatile period, with either lockdowns or restrictions and uncertainty in the global economy. This period ends with the announcement of the approval of a vaccine for trial with an optimistic 90% (https://www.pfizer.com/news/press-release/press-release-detail/pfizer-and-biontech-announce-vaccine-candidate-against, accessed on 4 February 2022) effectiveness against infection. The third sub-period (post-vaccine period) is covering the period after the announcement of a vaccine until one year later. The distinction of the examined period into three sub-periods allows us to analyze the effects of the pandemic, taking into consideration the economic conditions for each period.

The data for the stock market indices and the crude oil prices are collected from Investing.com and in the case of non-stationary variables, we apply stationary first logarithmic differences.

Thus, we apply VAR models, as proposed by Ref. [18], to investigate possible interrelationships between crude oil and European stock market indices. Generally, VAR models are used for short-term estimates and for the analysis of dynamic effects on the variables, which are typically treated as being a priori endogenous as a function of p-lagged values of all the endogenous variables in the system. The Granger causality test assumes vector autoregressive models for two stationary time-series, X_t and Y_t:

$$X_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{p} \gamma_j X_{t-j} + \varepsilon_t \tag{1}$$

where α indicates a constant term, β_i represents a coefficient that quantifies the extent to which Y_{t-i} explains X_t, γ_j presents an autoregressive coefficient that quantifies the extent to which X_{t-j} explains X_t, ε_t presents Gaussian white noise, and finally p denotes the largest lag order obtained from the relevant information criteria.

The null hypothesis, which is "Y_t does not Granger cause X_t", is defined as follows:

$$H_0 : \beta_1 = \beta_2 = \ldots = \beta_p = 0 \tag{2}$$

The VAR model is applied to capture the dynamic relations between multiple time series whereas Johansen's methodology estimates whether cointegration exists and the number of the cointegration relationships. Trace and maximum eigenvalue testing examine whether cointegrated vectors exist between the time series as described by Ref. [19].

In a VAR system, impulse response functions measure the effect of a shock to an endogenous variable on itself or on another endogenous variable through the dynamic structure of the VAR (Ref. [20]).The impulse response function identifies the effect that a random shock in a given moment has to an endogenous variable in a finite time horizon. Usually, the shocks are expressed in terms of standard deviations. Generalized impulses as described by Ref. [21] construct an orthogonal set of innovations that is not determined by the VAR ordering. In contrast with impulse response functions for structural models, generalized impulse responses do not need identifying structural shocks.

4. Empirical Results

Figure 1 represents the evolution, in real terms, of the closing values for the selected variables throughout the selected sample.

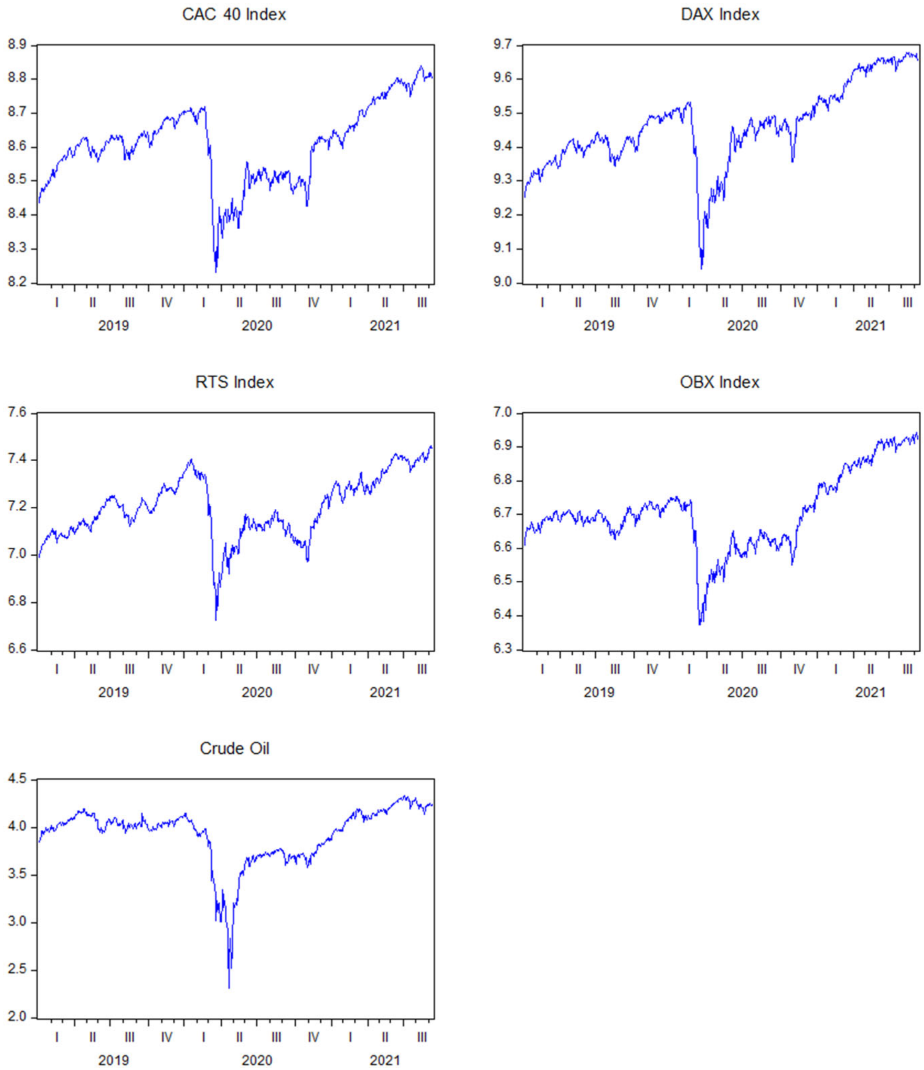

Figure 1. Price history (2019–2021).

The augmented Dickey–Fuller (ADF) unit root test is applied to test for the stationarity of the selected variables. We find that all variables during the three periods are non-stationary in levels, according to the results presented in Tables A1–A3 of Appendix A. This is the reason that differenced variables that are stationary according to the ADF test are used. Furthermore, the descriptive statistics for the five variables during the overall study period from 2019 to 2021 are also presented: the mean, the median, the standard deviation, the skewness, the kurtosis, and the Jarque–Bera statistic with its related probability. As presented in Table 1, the average daily returns of the selected variables are 0.0633% for the CAC 40 index, 0.0652% for the DAX index, 0.0899% for the RTS index, 0.0588% for the OBX index, and 0.1134% for Brent crude oil. Between these five variables, it is evident that crude oil offers the highest average return on a daily basis. Regarding stock indices, the RTS index offers the highest average daily return. Additionally, both the maximum and minimum values are the highest and the lowest for crude oil, whereas, regarding stock indices, the DAX offers the highest maximum value and the CAC 40 the lowest value. Table 1 also provides information about the skewness and kurtosis values of the selected time-series. The Jarque–Bera probability value is 0.00000 for all time-series, indicating that null hypothesis for normality is rejected for all the variables concluding that the examined series are non-normal. Finally, to examine the presence of multicollinearity, we compute the VIF statistics for the entire period of our study. The results of the VIF statistics, presented in Table 2, show that multicollinearity is not a problem for our analysis as the results of both the individual VIFs and the mean VIF are below the accepted benchmark of 10. In such cases, as Refs. [3,4] suggest, a standard VAR analysis can be applied on the time-series.

Table 1. Descriptive Statistics for Stock Indices and Crude Oil Returns (2019–2021).

	CAC 40 Index	DAX Index	RTS Index	OBX Index	Brent Crude Oil
Mean	0.000633	0.000652	0.000899	0.000558	0.001134
Median	0.001234	0.001047	0.001668	0.000226	0.002108
Maximum	0.080561	0.104143	0.088251	0.052368	0.319634
Minimum	−0.130983	−0.130549	−0.116844	−0.088648	−0.417711
Std. Dev.	0.014008	0.014186	0.016990	0.012343	0.042527
Skewness	−1.236120	−0.899376	−1.059246	−0.747675	−0.954746
Kurtosis	19.59565	20.45250	13.17504	9.518193	32.94220
Jarque-Bera	7366.641	8054.763	2826.509	1170.250	23554.75
Probability	0.000000	0.000000	0.000000	0.000000	0.000000

Table 2. Results of Multicollinearity Test.

Variables	VIF	Mean VIF
CAC Index	9.06	
DAX Index	8.47	
RTS Index	2.05	4.64
OBX Index	2.39	
Brent Crude Oil	1.22	

The Granger causality test has been applied to examine causality between the selected time-series for the three sub-periods and the results are presented in Table 3 and graphically in Figures 2–4. It is shown that crude oil does not Granger-cause the CAC 40 index and DAX index, the stock indices from oil-importing countries (France and Germany), for any of the three sub-periods. On the other hand, it is shown that the CAC 40 index and DAX index Granger-cause oil during the COVID-19 outbreak. In addition, the CAC 40 index exhibits the same behavior during the period after the invention of the vaccine. Regarding oil-exporting countries, the same results are presented for Russia and crude oil related to Granger causality from crude oil to the RTS Index. In particular, crude oil does not Granger-cause the RTS index, for any of the sub-periods, whereas it is noticeable that the RTS index Granger-causes crude oil during the period after the creation of the vaccine. Last but not least, regarding the OBX index of Norway and crude oil, we can see a two-way Granger causality during the period before the COVID-19 outbreak but there is no causality during the high-volatile period. Finally, it is shown that the OBX index Granger-causes crude oil during the period after the development of a vaccine. Regarding the Granger causality tests, the results for the three sub-periods are presented on Table 3.

Table 3. Granger Causality Test.

Null Hypothesis (H_0)	Pre-COVID-19 Period	Pre-Vaccine Period	Post-Vaccine Period
	p-Value	*p*-Value	*p*-Value
DAX $\nrightarrow$ OIL	0.0537	**0.0135** *	0.0552
CAC40 $\nrightarrow$ OIL	0.0051	**0.0045** *	**0.0103** *
OBX $\nrightarrow$ OIL	**0.0109** *	0.0720	**0.0239** *
RTS $\nrightarrow$ OIL	0.3958	0.1418	**0.0001** *
OIL $\nrightarrow$ DAX	0.1915	0.1504	0.9372
OIL $\nrightarrow$ CAC40	0.0889	0.1272	0.4973
OIL $\nrightarrow$ OBX	**0.0343** *	0.0702	0.2346
OIL $\nrightarrow$ RTS	0.0744	0.4219	0.3935

The notation "A $\nrightarrow$ B" denotes the null hypothesis that "A does not Granger-cause B", * indicates significance at the 5% level.

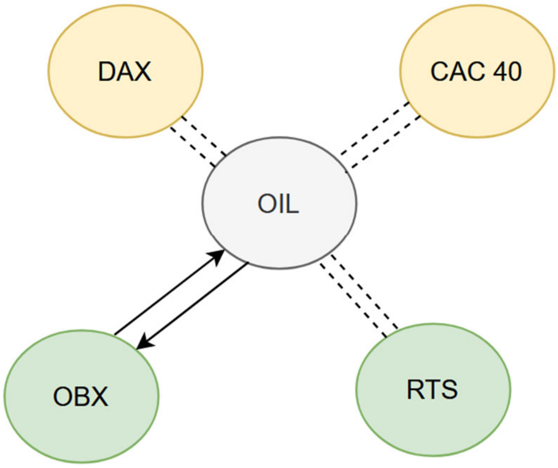

Figure 2. Granger causality results (pre-COVID-19 period).

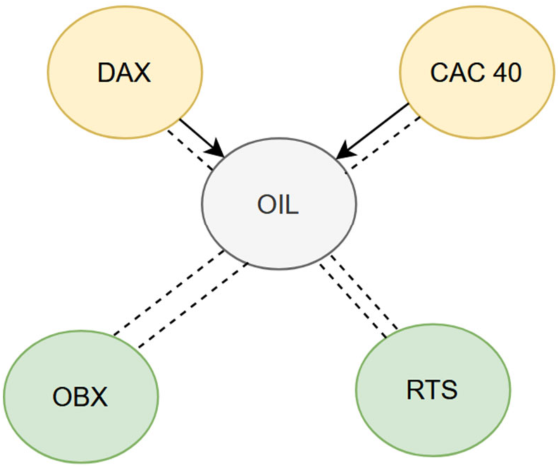

Figure 3. Granger causality results (pre-vaccine period).

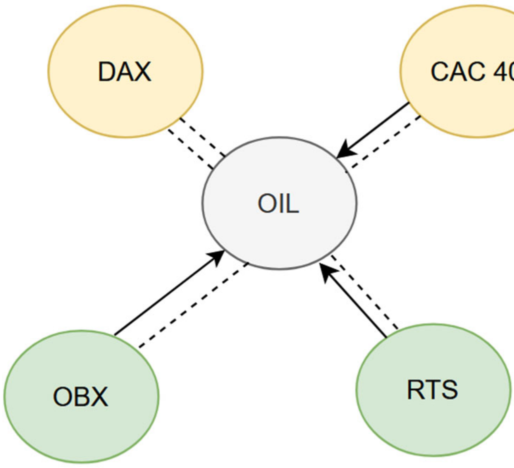

Figure 4. Granger causality results (post-vaccine period).

In addition, Johansen's methodology is applied for our selected time-series to examine the possible existence of cointegrating equations between them. Tables 4–9 test the null hypothesis for no existence of a cointegrating equation between the selected time-series. The results for the trace and maximum eigenvalue tests for the selected sub-periods show that the null hypothesis for the non-existence of a cointegrating equation between the selected time-series cannot be rejected at a 5% significance level.

Table 4. Trace statistic—Johansen cointegration method (pre-COVID-19 period).

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value 5%	Prob.
None	0.076821	52.71405	69.81889	0.5178
At most 1	0.062318	32.41136	47.85613	0.5894
At most 2	0.042048	16.06792	29.79707	0.7075
At most 3	0.012681	5.156586	15.49471	0.7920
At most 4	0.007511	1.914962	3.841466	0.1664

Table 5. Max eigenvalue—Johansen cointegration method (pre-COVID-19 period).

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Critical Value 5%	Prob.
None	0.076821	20.30269	33.87687	0.7353
At most 1	0.062318	16.34345	27.58434	0.6365
At most 2	0.042048	10.91133	21.13162	0.6562
At most 3	0.012681	3.241625	14.26460	0.9293
At most 4	0.007511	1.914962	3.841466	0.1664

More specifically, as we present in Tables 4 and 5, for the pre-COVID-19 period, the *p*-values of trace test and max-eigen test are both greater than 0.05 and therefore the null hypothesis cannot be rejected in the first step. Therefore, the results imply that there exists no long-run relationship between the variables.

Moreover, as is presented in Tables 6 and 7, for the second sub-period, the pre-vaccine period, the *p*-values of the relevant tests are both greater than the critical value in the first step. Thus, the H_0 cannot be rejected, which means that there are no cointegrating equations.

Table 6. Trace statistic—Johansen cointegration method (pre-vaccine period).

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value 5%	Prob.
None	0.183311	68.12198	76.97277	0.1953
At most 1	0.112459	38.15251	54.07904	0.5647
At most 2	0.062520	20.49598	35.19275	0.6951
At most 3	0.044188	10.94105	20.26184	0.5478
At most 4	0.028323	4.252295	9.164546	0.3758

Table 7. Max eigenvalue—Johansen cointegration method (pre-vaccine period).

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Critical Value 5%	Prob.
None	0.183311	29.96947	34.80587	0.1688
At most 1	0.112459	17.65653	28.58808	0.6050
At most 2	0.062520	9.554931	22.29962	0.8681
At most 3	0.044188	6.688754	15.89210	0.7073
At most 4	0.028323	4.252295	9.164546	0.3758

Table 8. Trace statistic—Johansen cointegration method (post-vaccine period).

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value 5%	Prob.
None	0.105372	64.06980	76.97277	0.3188
At most 1	0.065524	38.34862	54.07904	0.5546
At most 2	0.051791	22.69393	35.19275	0.5488
At most 3	0.026650	10.40923	20.26184	0.5996
At most 4	0.017888	4.169533	9.164546	0.3875

Table 9. Max eigenvalue—Johansen cointegration method (post-vaccine period).

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Critical Value 5%	Prob.
None	0.105372	25.72118	34.80587	0.3969
At most 1	0.065524	15.65469	28.58808	0.7691
At most 2	0.051791	12.28470	22.29962	0.6269
At most 3	0.026650	6.239701	15.89210	0.7606
At most 4	0.017888	4.169533	9.164546	0.3875

Finally, similar results are concluded also for the third period of research, the post–vaccine period. Results for this period are presented in Tables 8 and 9.

As we use sub-periods to distinguish before and after the vaccine, the Granger results present notable differences. For this reason, we highlight these periods to study the generalized impulse response functions. More specifically, as is shown from the results of Table 3, during the pre-vaccine period the DAX and CAC40, which are indices of oil-importing countries, Granger cause crude oil. Contrarily, during the post-vaccine period we saw that with the exception of the CAC40 index, the OBX and RTS, which are indices of oil-exporting countries, Granger cause oil. For this reason, we focus on the responses of both crude oil and stock indices before and after the development of a vaccine. Having this in mind, we should not only apply Granger to examine if a variable causes another one, but also if a shock in one variable can affect each variable separately.

The response of the selected variable, indicated in logged first differences, to a positive one standard deviation shock in each of our explanatory variables is also assessed. The impulse response function confirms the dynamic response of this shock on the volatility variable at a 95% confidence interval. Hence, one period refers to one trading day, as is shown on the x-axis, whereas the y-axis presents the logged first difference of the dependent variable. The impulse corresponds to a one standard deviation shock on the residuals that are affected by the shock, which in this case is an innovation. The solid line corresponds to the response, and the dashed lines indicate a 95% confidence interval of the response. All variables are log converted and in the following graphic presentations, we are looking for significance in the impact of each variable's shock for the three sub-periods, including the pre-vaccine and the post-vaccine period, and the significant impact is present when the confidence interval does not include the zero value. The impulse response converges to zero as time passes, straight after period 10 in all impulse response functions. Figures 5–8 present the estimated generalized impulse response functions for the pre-vaccine period, which is characterized as a highly volatile period, and for the post-vaccine period.

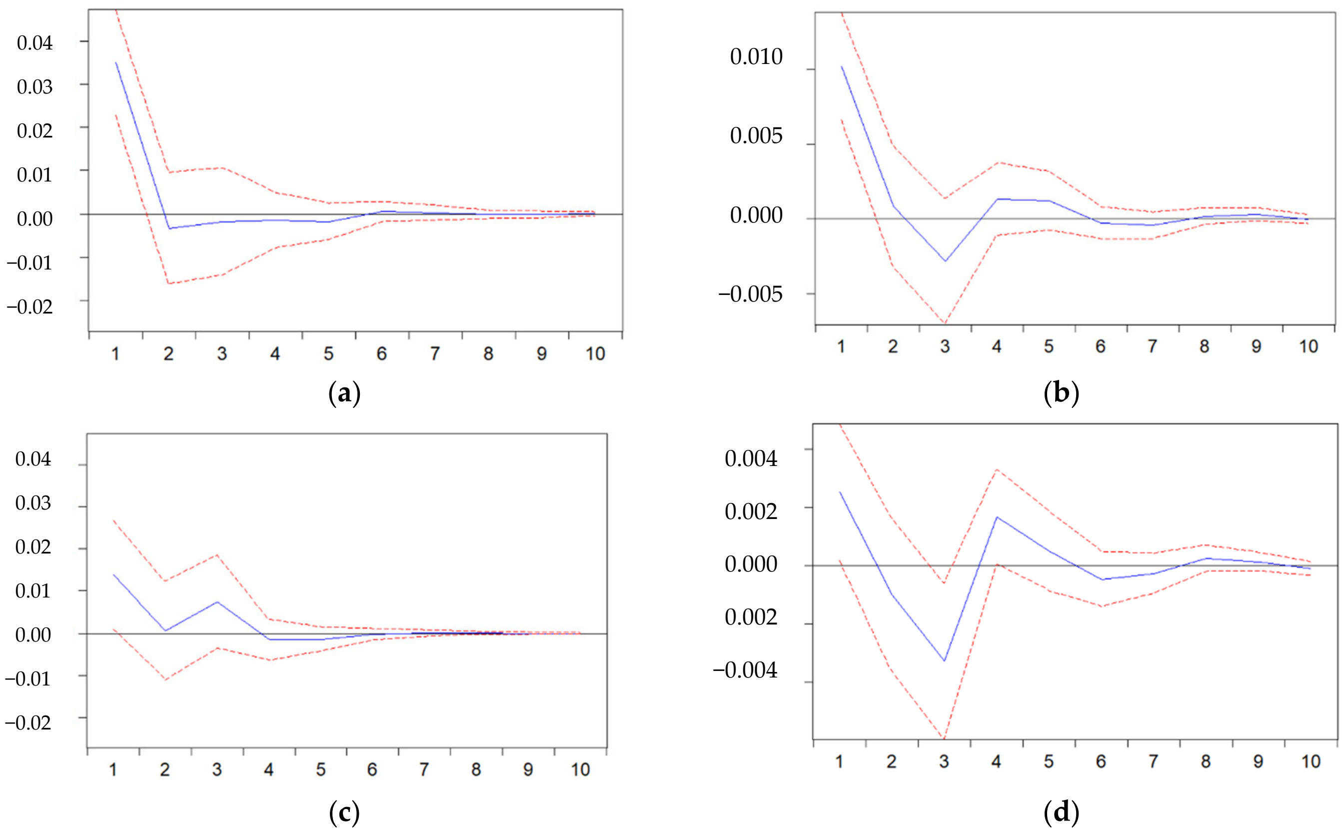

Figure 5. Generalized impulse response functions (pre-vaccine period for oil-exporting countries). (**a**) Response of oil to the RTS index. It is shown that when the RTS index price is shocked by one standard deviation shock, oil prices positively respond 1 day after the shock. (**b**) Response of the RTS index to oil. It is shown that when the OBX index price is shocked by one standard deviation shock, oil prices positively respond 1 day after the shock. (**c**) Response of the OBX index to oil. It is shown that when the oil price is shocked by one standard deviation shock, the RTS index price positively responds 1 day after the shock. (**d**) Response of the OBX index to oil. It is shown that when the oil price is shocked by one standard deviation shock, the OBX index price positively, negatively, and positively responds 1, 3, and 4 days, respectively, after the shocks.

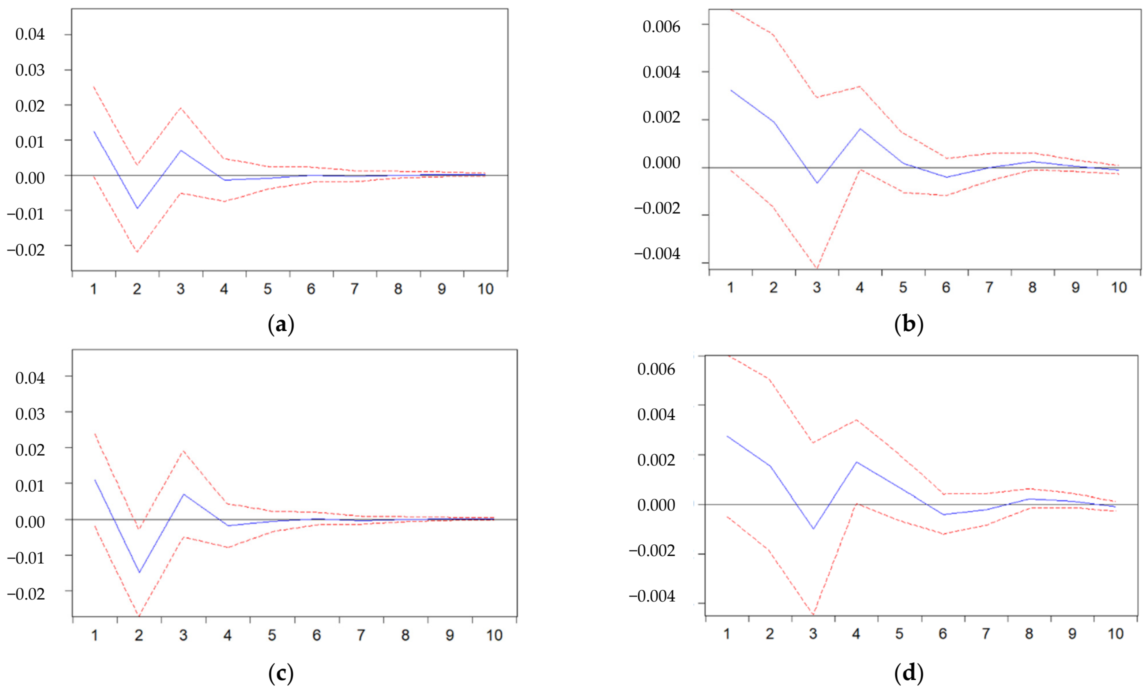

Figure 6. Generalized impulse response functions (pre-vaccine period for oil-importing countries). (**a**) Response of oil to the DAX index. It is shown that when the DAX index price is shocked by one standard deviation shock, the oil price positively responds 1 day after the shock. (**b**) Response of the DAX index to oil. It is shown that when oil price is shocked by one standard deviation shock, the DAX index price positively responds 1 and 4 days after the shocks. (**c**) Response of oil to the CAC40 index. It is shown that when the CAC 40 index price is shocked by one standard deviation shock, oil price negatively responds 2 days after the shocks. (**d**) Response of the CAC 40 index to oil. It is shown that when the oil price is shocked by one standard deviation shock, the CAC 40 index price positively responds 4 days after the shock.

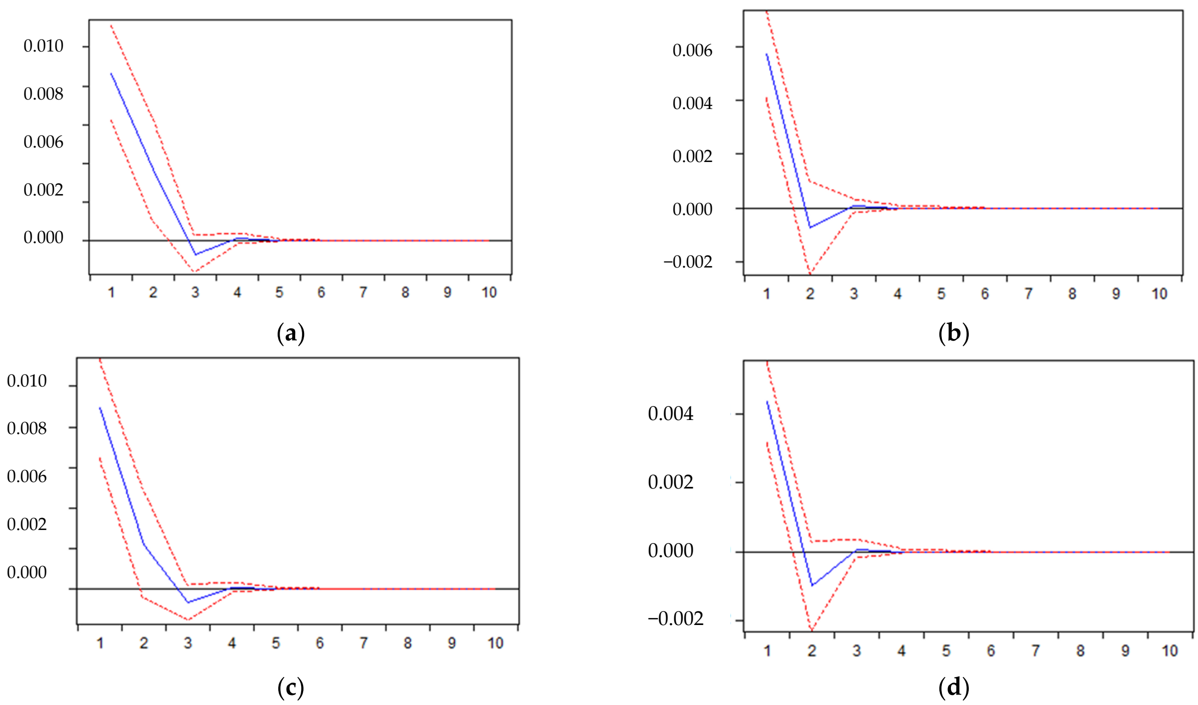

Figure 7. Generalized impulse response functions (post-vaccine period for oil-exporting countries). (**a**) Response of oil to the RTS index. It is shown that when the RTS index price is shocked by one

standard deviation shock, the oil price positively responds 1 day after the shock. (**b**) Response of oil to the RTS index. It is shown that when the OBX index price is shocked by one standard deviation shock, the oil price positively responds 1 day after the shock. (**c**) Response of the OBX index to oil. It is shown that when the oil price is shocked by one standard deviation shock, the RTS index price positively responds 1 day after the shock. (**d**) Response of the OBX index to oil. It is shown that when the oil price is shocked by one standard deviation shock, the OBX index price positively responds 1 day after the shock.

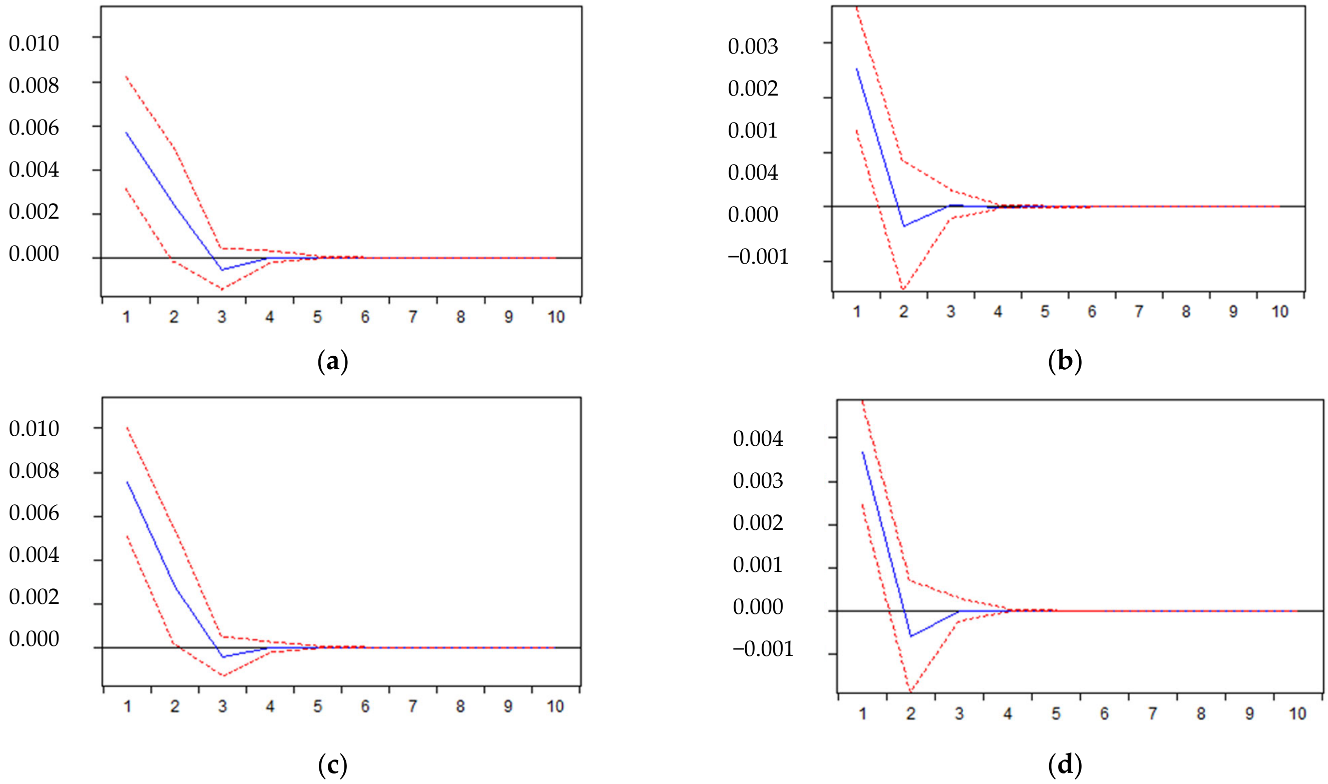

Figure 8. Generalized impulse response functions (post-vaccine period for oil-importing countries). (**a**) Response of oil to the DAX index. It is shown that when the DAX index price is shocked by one standard deviation shock, the oil price positively responds 1 day after the shock. (**b**) Response of the DAX index to oil. It is shown that when the oil price is shocked by one standard deviation shock, the DAX index price positively responds 1 day after the shock. (**c**) Response of oil to the CAC40 index. It is shown that when the CAC 40 index price is shocked by one standard deviation shock, the oil price positively responds 1 day after the shock. (**d**) Response of the CAC 40 index to oil. It is shown that when the oil price is shocked by one standard deviation shock, the CAC 40 index price positively responds 1 day after the shock.

The dynamics of the impulse responses show that during the volatile period changes in stock prices become more sensitive to oil price changes and vice versa. Our empirical results are in line with previous studies. Refs. [2,4] find a non-existence of long-run equilibrium relationships between variables, but because of COVID-19 the interdependence between Brent crude oil and the stock market for both oil-importing and oil-exporting countries is increasing in the short term.

5. Conclusions

In this paper we focus on the investigation of the impact of the dynamic time-frequency interrelationship between crude oil prices and the four primary stock markets of four European states. Two of them, Russia and Norway, are oil-exporting countries and the other two, Germany and France, are oil-importing countries. In our analysis, we employ a standard VAR approach by testing Granger causality and applying impulse response functions.

The examination period is between 2019 and 2021, separated into three sub-periods. The first sub-period is the pre-COVID-19 period from the 1 January 2019 until the 6 March 2020 and the second period is the COVID-19 period starting on the 9 March 2020 until the announcement of vaccine creation on the 9 November 2020. As expected, the second sub-period is the most volatile period of our analysis. Finally, the third sub-period refers to the period after the announcement of the vaccine.

This is a novel study that examines the influence of the COVID-19 pandemic on the returns of crude oil prices on four major stock markets in Europe, separating the sample not only before and after COVID-19, but also during the pandemic. Therefore, the findings of this work are significant for policy makers and managers. Overall, the current evidence reveals that in contrast with the pre-COVID-19 period, the dynamic linkages are more remarkable during the COVID-19 period and especially during the pre-vaccine period. Even more notable are the findings for evidence on time-frequency linkages between crude oil and the four primary European stock markets, which can provide critical suggestions for portfolio managers, investors, and governments. There are some potential limitations, though, in the applied methodology with reference to the size of the sample for the three sub-periods. However, an avenue for future work has opened where the data and the periods can be widened and other techniques like Copula transformation on the selected variables can be applied.

Author Contributions: Conceptualization, I.K., A.C. and P.K.; methodology, I.K. and V.N.; software, V.N.; validation, I.K., A.C., P.K. and V.N.; formal analysis I.K. and V.N.; investigation, I.K.; resources, V.N.; data curation, V.N.; writing—original draft preparation, I.K., A.C., P.K. and V.N.; writing—review and editing, I.K., A.C., P.K. and V.N.; visualization, I.K. and V.N.; supervision, I.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments: The authors are grateful to the anonymous reviewers for providing constructive comments to enhance the quality of this paper.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Augmented Dickey–Fuller Test Results (Pre-COVID Period).

	Level 1st Difference			
Variables	***t*-Statistic**	***p*-Value**	***t*-Statistic**	***p*-Value**
RTS Index	−2.129509	0.2333	−14.26042	0.0000
CAC 40 Index	−2.424626	0.1358	−14.77705	0.0000
DAX Index	−2.201090	0.2064	−14.96951	0.0000
OBX Index	−2.429706	0.1345	−12.45357	0.0000
Crude Oil	−1.818801	0.3710	−16.63828	0.0000

Table A2. Augmented Dickey–Fuller Test Results (Pre-Vaccine Period).

	Level 1st Difference			
Variables	***t*-Statistic**	***p*-Value**	***t*-Statistic**	***p*-Value**
RTS Index	−2.011460	0.2818	−10.53422	0.0000
CAC 40 Index	−2.406441	0.1415	−12.98634	0.0000
DAX Index	−1.281578	0.6378	−13.25490	0.0000
OBX Index	−1.814752	0.3724	−13.47877	0.0000
Crude Oil	−1.830313	0.3649	−12.40659	0.0000

Table A3. Augmented Dickey–Fuller Test Results (Post-Vaccine Period).

	Level 1st Difference			
Variables	***t*-Statistic**	***p*-Value**	***t*-Statistic**	***p*-Value**
RTS Index	−1.951080	0.3086	−15.41962	0.0000
CAC Index	−2.358557	0.1547	−17.15347	0.0000
DAX Index	−2.495903	0.1176	−18.83141	0.0000
OBX Index	−2.641558	0.0860	−16.54574	0.0000
Crude Oil	−2.568971	0.1008	−17.29031	0.0000

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