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The Impact of COVID-19 on the Relationship between Non-Renewable Energy and Saudi Stock Market Sectors Using Wavelet Coherence Approach and Neural Networks

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Abstract: In this study, we examine the impact of COVID-19 on the relationship between non-renewable energy and Saudi stock market sectors for the period 11 January 2017–22 January 2022. We apply wavelet coherence and Radial Basis Function Neural Network (RBFNN) models. Our results provide evidence that COVID-19 led to an increase in the strength of the relationship between oil as a main non-renewable energy source and Saudi stock market sectors and affected the nature and direction of this relationship. The relationships between oil and commercial and professional services, materials, banks, energy, and transportation sectors are the most affected. Our results will help hedge funds, mutual funds, and individual investors, forecast the direction of Saudi stock market sectors and the use of oil for hedging or diversification during periods of uncertainty and crisis. It will also help decision and policymakers in Saudi Arabia to make the necessary decisions and actions to maintain the stability of the stock market sectors during these periods.

Keywords: wavelet coherence; neural network; Saudi stock market; non-renewable energy; oil

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1. Introduction

The World Health Organization declared COVID-19 a global pandemic in March 2020 [1], after which many countries announced several measures that affected economic activities worldwide [2]. The pandemic has spread more than SARS and Ebola, raising the number of COVID-19 cases in July 2021 to almost 180 million and 4 million COVID-19 deaths worldwide [3]. The impact of this pandemic on financial markets was more severe than the impact of the 2008 global financial crisis [4]. Meanwhile, oil is the most prominent energy source in the non-renewable energy market as well as being the most traded commodity in the world [5]. With economic activity halted during lockdowns in almost all industrial economies, global oil demand has fallen sharply, causing its price to drop significantly [6]. For example, the West Texas Intermediate (WTI) future contracts price fell from $65 on 8 January 2020 to a negative price on 20 April 2020, posting its biggest drop in history. Stock markets also fell sharply, for example, the S&P 500 index decreased by 34% over the period 19 February 2020 to 23 March 2020. The Saudi stock index (TASI) decreased by 24% over the same period [7]. Saudi Arabia holds 16.9% of the world's oil reserves and produced 13.33% of the world's oil production in 2020 [8]. It also has the largest gross domestic product among Arab countries, as well as the largest market capitalization and the largest average market capitalization of companies listed on Arab stock markets in 2020 [9]. Oil is important for investors as it is a component of their asset portfolios, in addition to providing valuable information to predict the prices of various financial assets due to its high volatility [6]. Theoretically, there are many channels connecting oil to the stock market, for example, stock valuation, monetary, output, fiscal and uncertainty channels [10].

Meanwhile, there are many empirical studies whose results suggested a relationship between oil and the stock market, including studies that suggested a relationship between oil and the US stock market [10–14], while other studies suggested a relationship between oil and European stock markets [15–17]. In the same vein, the results of other literature suggested the existence of a relationship between oil on the one hand and the stock markets of oil exporting and importing countries [18–20] and the stock market of Japan and Hong Kong [21] on the other hand. In the same context, on a smaller scale, the literature suggested a relationship between the oil and electricity utility sector in the United States and Europe [22], and the clean energy sector [23]. At the same time, the results of other empirical studies indicated that there is a relationship between oil and the Saudi stock market [11,23–28]. In a more detailed context, other studies provided evidence of a relationship between oil and sectors of the Saudi stock market [29–31].

What motivated us to study the impact of COVID-19 on the relationship between oil as a primary non-renewable energy source and the Saudi stock market sectors is that studying the relationship between oil and the stock sectors of the largest Arab economy in periods of uncertainty, including COVID-19, will be of great benefit to a large segment of investors in helping them make decisions about the allocation of their financial resources to build their investment portfolios. The results of our study will be helpful in identifying to what extent oil can be used in diversification or hedging when investing in shares of Saudi stock sectors. Surprisingly, to the best of our knowledge, there is a dearth in the literature that studies this relationship during COVID-19. Furthermore, our study has several contributions to the current literature: First, we used daily observations to capture a more detailed picture than those captured by Jouini [30], who used weekly observations, and those captured by Hamdan and Hamdan [32], who used monthly observations. Second, we used neural networks to confirm the results of the wavelet coherence model. Neural networks belong to the machine learning family, which is a completely different technique from the wavelet coherence model, which belongs to the classical analysis family. When we achieve similar results across models belonging to different analysis families, one of which is powered by artificial intelligence, this will indicate the accuracy of our results. To the best of our knowledge, none of the previous empirical studies used neural networks to study this relationship in the Saudi stock market. Third, we use oil CFDs that are traded around the clock to reflect a fresh picture of the impact of COVID-19 on oil prices, in addition to the fact that there are common trading hours between them and the Saudi market on Monday, Tuesday, Wednesday, and Thursday. Fourth, we investigated the relationship between oil and twenty sectors of the Saudi stock market, while the literature deals with this relationship by examining five sectors [30], twelve sectors [32], and fifteen sectors [31]. Consequently, we have studied the relationship between oil and some sectors that have not been studied before, such as software and services, food and beverages, diversified financials, pharma, biotech, and life science and healthcare equipment and services.

Using wavelet coherence and the RBF network, we captured two streams of results: The first stream provides us with the nature of the relationship between oil and the twenty sectors of the stock market in general during the period from January 2017 to January 2022. Our results suggest that the strongest relationship was between oil and energy, materials, utilities, transportation, banks, and telecommunication services sectors. While the weakest relationship was between oil and real estate management and development, diversified financials, and media and entertainment sectors. These results support the fiscal channel proposed by Degiannakis et al. [10] as a theoretical transmission mechanism between oil and stock market returns. The second stream provides us with the impact of COVID-19 on the relationship between oil and Saudi stock market sectors. Our results show a noticeable change in the relationship between oil and all sectors, as the relationship between oil and market sectors became stronger and either oil or sector-led these relationships compare to the period before COVID-19. Our results will help investment and hedge funds and individual investors determine how to use oil as a tool to predict the direction of stocks in Saudi stock sectors. It will also help them determine to what extent oil can be used in diversification or hedging against different sectors in the Saudi stock market during periods of uncertainty and crisis that negatively affect oil prices and increase their volatility. It will also help policymakers and decision-makers in the Saudi stock market make the necessary decisions during these periods to maintain the stability of the Saudi stock sectors.

The remainder of our work is constructed as follows: Section 2 reviews the literature. Section 3 explains our dataset and methodology. Section 4 presents and discusses our results while Section 5 concludes our work.

2. Literature Review

2.1. Theoretical Transmission Channels between Oil Prices and Stock Market

Many theoretical channels explain the mechanism of the relationship between oil and the stock market [10]. The first channel appears through the stock valuation process, which illustrates the relationship between stocks and oil through the economic theory that suggests that the value of stocks is their expected discounted cash flow [33]. The cash flows of stocks are affected by the price of oil, and the direction of this influence depends on the relationship of the company that issued those shares to oil. This company may be a producer or consumer of oil, which will affect its revenues or costs, and this will eventually affect its cash flows and, therefore, the evaluation of its shares by investors, which will affect its prices [34–37]. The effect of the second channel comes from the impact of oil prices on inflation rates, which in turn affect the interest rate, and both affect the discount rate that is used to discount the expected cash flows in order to evaluate stocks [10]. As rising oil prices lead to higher production costs, resulting in higher prices for goods and services, leading to higher inflation rates, this leads central banks to raise interest rates (see [38–40]). An increase in the interest rate leads to higher borrowing costs and an increase in the discount rate used in stock valuation, negatively impacting the stock market [10]. The third channel is related to oil-exporting countries. These countries finance their infrastructure with oil revenues [41]; there is also a direct relationship between the income of these countries from oil exports and their short- and long-term government expenditure [42]. Rising oil prices will cause an increase in government spending, which in turn will cause an increase in corporate cash flows, which will cause their share prices to rise. The exact opposite will happen when oil prices fall, as it will lead to a decrease in government spending, then a decrease in corporate cash flows, and then a decrease in share prices. The fourth channel proposed by Brown and Yücel [43] indicates that the increase in oil prices suggests a shortage of energy, which is the main input for production. Thus, productivity growth slows, then wages fall, and unemployment rates rise. This is followed by a decline in the GDP growth rate, which will lead to a new wave of rising unemployment rates, and then a further decline in the GDP growth rate, which will negatively affect the stock market.

2.2. The Relationship between Oil and Stock Markets around the World

Many studies have examined the effect of oil on stock markets. Sadorsky's [11] results showed that oil prices and their volatility play an important role in influencing the performance of the US stock market. Finta et al. [12] also concluded that the fluctuation in oil prices is transmitted to the US stock market, especially during the common trading hours between the two markets. In the same vein, Park and Ratti's [13] results, using a multivariate VAR analysis, suggest that oil price shocks affect the returns of stock markets in the USA and 13 European markets in the same month or within one month over 1986–2005. In the same context, using the Autoregressive Conditional Jump Intensity (ARJI) model over the period January 1992 to November 2006, Chiou and Lee's [14] results suggested a negative significant statistically effect of oil prices on stock returns in the US stock market. Statistical significance appears only in cases of significant fluctuations in the spot oil market and the futures market. Rahman [15] supported earlier studies when he studied the impact of volatility in oil prices on US stock market returns, where he found evidence that the increasing volatility in oil prices negatively affects US stock returns. When Jammazi and Aloui [16] studied the effect of oil price shocks on the stock markets of Britain, France, and Japan using wavelet analysis and the Markov Switching Vector Autoregressive (MS-VAR) approach during the period January 1989 to December 2007, they found that there was no effect on the stock markets during depression periods, except in Japan, and the inverse relationship was clearer before 1999. Arouri [17] was interested in studying the link between oil and stock sectors in Europe, and his results suggested that there is a significant link between the change in oil prices and the stock sectors of most European stock markets, in addition to the nature and the sensitivity of the reaction of stock market returns to the change in oil prices differs from one sector to another. On the other hand, in the G-7 countries, Lee et al. [18] studied the relationship between oil and stock markets during the period between January 1991 and May 2005. They found that oil price shocks did not have a significant effect on each of the stock indices of these countries. Furthermore, they found that the change in stock prices in Germany, the UK, and the US lead to a change in oil prices. The study by Wang et al. [44] included a study of the relationship between oil and stock markets in oil-exporting and oil-importing countries using structural VAR analysis during the period January 1999 to December 2011. Their results suggested that the stock market's response to shocks in the oil market depends on whether the country is an exporter or importer of oil, the extent to which oil is important to the country's economy, and the impact is greater in the exporting countries than in the oil importing countries. In the same vein, Basher et al. [19] studied the impact of oil market shocks on the stock markets of various oil-exporting countries during the period from January 1974 to August 2015 using a multi-factor Markov-switching framework. Their results suggested that the oil market shocks had a significant effect on the stock markets of Canada, Norway, Russia, Kuwait, and the United Arab Emirates, and the only country whose stock market was not affected by the shocks of the oil market in Mexico. In the same context, Jiang and Yoon [20] concluded that there is a direct and time-varying relationship between oil revenues and the stock markets of five oil-exporting and importing countries represented in China, India, Japan, Russia, and Canada, where Russia's stock market was the most closely related and China the least, and the correlation was strong and significant after the global financial crisis of 2008–2011. The relationship between oil and the stock markets of the US, Japan, Hong Kong, China, and South Korea was studied by Ding et al. [21] during the period from January 1996 to October 2012. They found that the Japanese stock market and Hong Kong affects WTI returns, just as all stock markets affect Dubai crude oil returns except the Chinese stock market, conversely, Dubai crude affects all stock markets except the US market. On a small scale, Zhang et al. [22] studied the Spillover of volatility and returns between oil and electricity utility sector indices in Europe and North America during the period August 2009 to August 2019. Their results suggested that spillover is higher in Europe than in North America. Overall, there is a significant oil impact on the electricity stocks sector in North America and Europe. On the same narrow scale, Ref. [23] studied the impact of oil on clean energy stock indices before and during the VOVID-19 pandemic, and their results indicated that there is a causal relationship between oil returns and clean energy stock index returns during normal market conditions, but this relationship does not exist during difficult market periods.

2.3. The Relationship between Oil and the Saudi Stock Market

The relationship between oil and the Saudi stock market has drawn the attention of many researchers. Hammoudeh and Aleisa [24] studied the effect of oil on the stock markets of the Gulf Cooperation Council (GCC) countries during the period from December 1994 to December 2001. Their results suggested that there is a two-way causal relationship between the Saudi stock market and oil. Maghyereh and Al-Kandari [25] studied the relationship between oil and the GCC stock markets during the period from January 1996 to December 2003 using nonlinear cointegration analysis. They concluded that oil prices affect the GCC stock indices, including the Saudi stock market. Arouri and Rault [26] followed suit when they studied the long-term relationship between oil and GCC stock markets during the period from January 1996 to December 2007 using recent bootstrap panel cointegration techniques and seemingly unrelated regression (SUR) methods. Their results indicated evidence of a relationship between oil and GCC stock markets, while the increase in oil prices leads to a positive effect on stock prices in these markets except Saudi Arabia. In the same context, Boubaker and Sghaier [27] investigated the dependence structure between daily oil price changes and stock market returns in GCC countries during the period between January 2005 and February 2013. Their results suggested that there is evidence of positive and asymmetric dependence between oil price changes and GCC stock market returns, including the Saudi stock market. In another context, Alqahtani et al. [28] investigated the dynamics of the co-movement of GCC stock markets with the uncertainty associated with oil prices during the period from 2007 to 2018 using an ARMA-DCC-EGARCH and time-varying Student-t copula models. They concluded that the uncertainty in the oil markets negatively affects the returns of the GCC markets, and it was found that the Saudi stock market was affected by the volatility in oil prices at an average level. Cheikh et al. [29] examined this relationship during the period from January 2005 to December 2019. Their results suggested that the Saudi stock market is sensitive only to negative deviations in oil prices, and this sensitivity increases in large changes in oil prices more than in small ones. With a focus on intraday volatility spillover effects between oil and the Saudi stock market, Finta et al. [12] discovered that volatility in oil prices during common trading hours between oil and the US stock market has little impact on the Saudi stock market, while there is an indirectly significant transfer of volatility from the oil market to the Saudi stock market.

Some articles focused on the relationship between oil and Saudi stock market sectors. Jouini [30] used weekly observations from January 2007 to September 2011 to investigate the relationship between the price of oil and five market sectors, namely communications and IT, industrial investment, insurance, energy and utilities, and banks and financial services, using the VAR-GARCH. The author concluded that there is evidence of the transmission of returns and fluctuations between oil and Saudi stock market sectors, where the transmission of returns is from oil to some market sectors, while the transmission of fluctuations is bidirectional between oil and market sectors. On a larger scale with the same spirit, Mensi [31] used weekly observations during the period between January 2007 and February 2017 to test the co-movement between oil and fifteen sectors of the Saudi stock market using the wavelet method. His results indicated the existence of co-movement between oil and Saudi stock market sectors over time through different frequencies. This joint movement intensified after the global financial crisis of 2008. Among the fifteen sectors, the petrochemical sector was the most affected by the increase in oil prices, while the tourism and hotel sector was the least affected. The sectors that were not affected by the drop in oil prices after mid-2014 were the banking, food and agriculture industries, telecommunications, media and publishing, and hospitality and tourism. Likewise, on a smaller scale, Hamdan and Hamdan [32] tested the long-term relationship between oil and the Saudi stock market in general, and then the relationship between oil and twelve of its sectors. Using monthly observations from 2007 to 2016, the authors found that the Saudi stock market is highly sensitive to high and low oil prices. At the sector level, the authors noted that the oil and gas sector and the industrial sector interact inversely with oil prices in the case of high oil prices, while the oil and gas sector interacts directly with oil in the case of low oil prices.

After the previous review of the literature, it was found that there are theoretical channels that explain the relationship between oil and the stock market, among them, which shows that the nature of the relationship between the two depends on whether the issuing company of stocks is a consumer or an oil producer, while other channels explain the inverse relationship between oil and the stock market and the latter clarifies the positive relationship between them. At the level of applied studies which investigated the relationship of oil with stock markets around the world, these studies showed that there is a relationship between oil and the US stock market [11,12,14,15]. These studies also suggested a relationship between oil and a number of European stock markets [13,17], oil-exporting and oil-importing countries stock markets [20,44], in contrast, other studies have suggested that oil does not affect the British and French stock markets during periods of depression. In the same context, some studies have also indicated that oil does not affect the G7 stock markets [18] and Mexico stock market. Regarding the relationship of oil with certain stock market sectors, these studies showed that there is a relationship between oil on the one hand and electricity utility sector indices in Europe and North America [22] and clean energy stock indices [23] on the other hand. As for the studies that addressed the relationship between oil and the Saudi stock market, their results suggested the existence of a relationship between oil and the Saudi stock market [23,24,26–28,31], other studies have shown that the impact of oil on the Saudi stock market is weak [12], and in a different context, studies have shown that oil does not affect the Saudi stock market [26]. In a closer context, studies dealing with the relationship between oil and stock sectors in the Saudi market suggested that the strength of the oil impact varies by sector [30]. Other studies have suggested that some sectors in the market are not affected by oil [31], some sectors have a direct relationship with oil, and others that have an inverse relationship [32].

The difference is in the nature of the impact of oil on the stock market in theory and the difference in the results of empirical research on the nature of this impact on stock markets around the world, especially in the Saudi stock market with its various sectors. Pointing out that the world has become a small village, in addition to the evidence presented by Zimmermann et al. [45], suggests that the level of globalization of countries affects the speed of transmission of COVID-19, which in turn led to a lockdown in most countries of the world, negatively affecting oil prices. What Ehnts and Paetz [46] suggest about the shortcomings that COVID-19 showed in Europe, in addition to the fact that, as far as we know, the literature did not investigate the relationship between oil and the twenty sectors of the Saudi stock market during the COVID-19 pandemic, all this motivated us to study the impact of COVID-19 on the relationship between oil and the twenty sectors of the Saudi stock market.

3. Experimental Data and Methodology

3.1. Experimental Data

Unlike most studies that have been applied to the Saudi market sectors, our data include daily observations covering the period from 11 January 2017 to 27 January 2022. Our choice of daily observations was due to the large movement that was taking place in global markets around the clock with each new news flow about the pandemic. In order for our models to capture the details of the relationship between non-renewable energy and Saudi stock market sectors, we choose CFDs rather than spot market historical data for both West Texas Intermediate (USOIL) and Brent crude oil (UKOIL) as proxies for non-renewable energy, such as oil is the most important non-renewable energy resource and, at the same time, the most traded commodity in the world. Our dataset is 1263 observations for USOIL, UKOIL, and twenty Saudi stock sectors indices, except for the software and services sector, which was added to the Saudi stock market sectors as of 24 April 2019, whose observations amount to 689 observations. We obtained the dataset from TradingView [47]. We ran the wavelet coherence model for the entire study period, but the RBFNN model ran into two sub-periods, the first before COVID-19 from 11 January 2017 to 20 January 2020, and the other from 21 January 2022 to 27 January 2022, where the start of COVID-19 was determined in our study based on the start of the Saudi stock market index (TASI), USOIL, and UKOIL response to the pandemic, which is shown in Figure 1. Symbols for Saudi stock sectors indices are shown in Table 1.

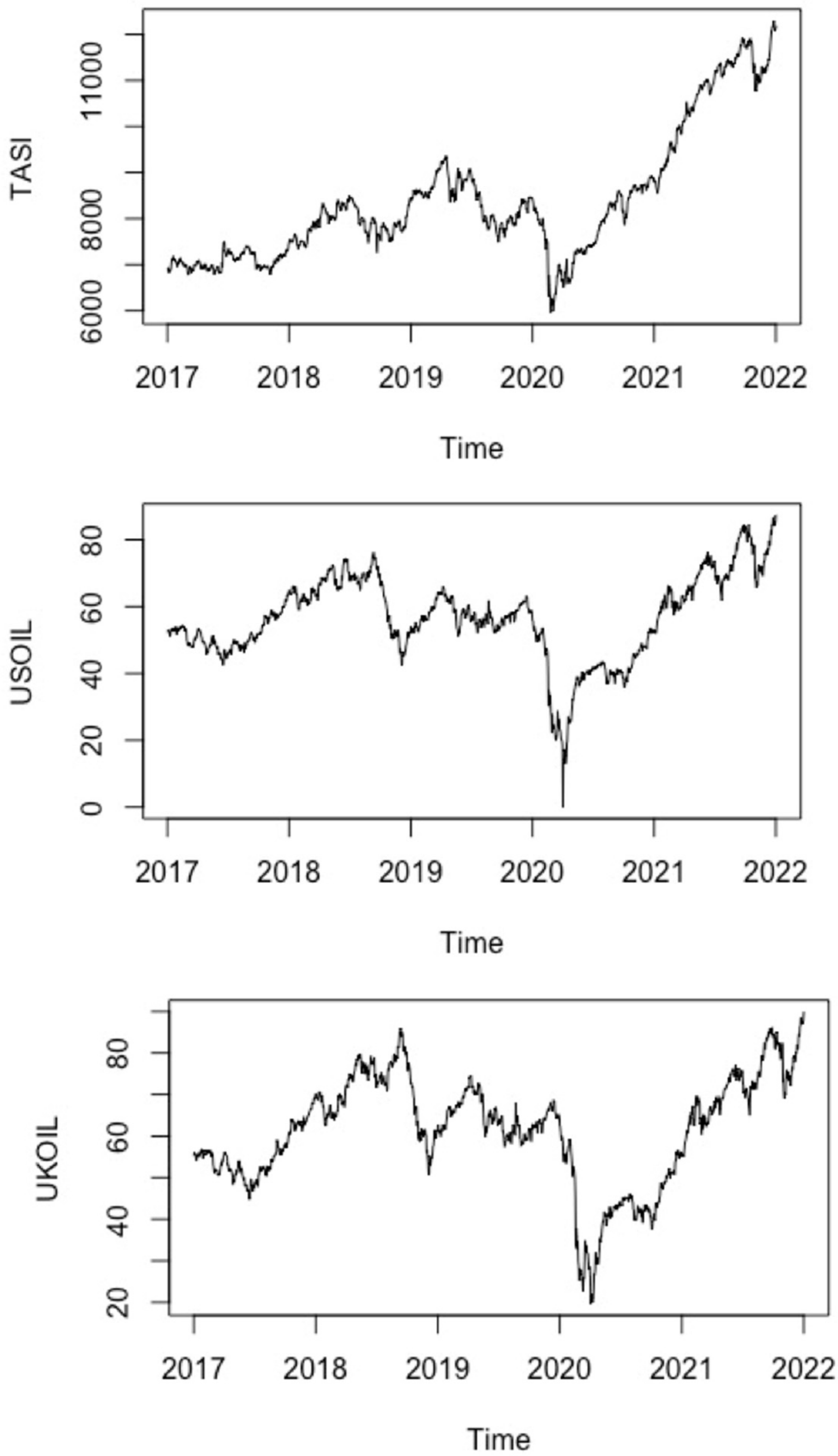


Figure 1. TASI, USOIL, and UKOIL during the study period.

3.2. Methodology

In building our models, R and DTREG software is used, and two different models are employed. The first model is traditional namely wavelet coherence, and the second one are machine learning models, namely Radial Basis Function Neural Network (RBFNN).

Table 1. Symbols for Saudi stock sectors indices.

Stock Sector Index	Symbol
Utilities	TUTI
Telecommunication services	TTSI
Banks	TBNI
Insurance	TISI
Real estate management and development	TRMI
Software and services	TSSI
Diversified financials	TDFI
Pharma, biotech, and life science	TPBI
Healthcare equipment and services	THEI
Food and beverages	TFBI
Food and staples retailing	TFSI
Retailing	TRLI
Media and entertainment	TMDI
Consumer services	TCSI
Consumer durables and apparel	TDAI
Transportation	TTNI
Commercial and professional services	TCPI
Capital goods	TCGI
Materials	TMTI
Energy	TENI

3.2.1. Wavelet Coherence

To achieve our goal of identifying the impact of COVID-19 on the relationship between the oil and Saudi stock market sectors, we used the wavelet coherency approach presented by Grinsted et al. [48] as it will present an analysis that includes the strength, type, direction, and significance of the relationship between the variables. The heat maps produced by the wavelet coherence model will allow us to track the relationship between oil and sectors of the Saudi stock market over time. These maps show the strength, type, direction, and significance of the relationship over time, which will allow us to identify the impact of COVID-19 on this relationship as well as track the change in this influence over the period of the pandemic. Waves decompose the time series of variables into time-based scales and then present the change that occurs between these parts based on the scales. The mother wave produces small waves since it is a function of the series of observations o and scale z as

$$\psi_{\tau,z}(o) = \frac{1}{\sqrt{z}}\psi\left(\frac{o-\tau}{z}\right), \quad (1)$$

where $\frac{1}{\sqrt{z}}$ is normalization factor; z is scale; $\frac{1}{\sqrt{z}}$ is time position. Previous empirical studies used many types of wavelets to deconstruct time series. We will use the Morlet wavelet which gives the best results for time series of oil and stock markets [49]. Grinsted et al. [48] indicated that the Morlet wavelet Fourier period is almost equal to the scale used

$$\psi^M(o) = \frac{1}{\pi^{1/4}} e^{i\omega_0 o} e^{-o^2/2}, \quad (2)$$

where ω_0 is the wavelet central frequency. Discrete-time series continuous wavelet transforms w_a

$$w_a(\tau, z) = \int_{-\infty}^{+\infty} x(o)\psi^*_{\tau,z}(o)do = \frac{1}{\sqrt{z}} \int_{-\infty}^{+\infty} x(o)\psi^*\left(\frac{o-\tau}{z}\right)do, \quad (3)$$

where $*$ represents the complex conjugate. Variance is accessed through

$$\|x\|^2 = \frac{1}{C_\psi} \int_0^\infty \left[\int_{-\infty}^{+\infty} \left|W_a(\tau, z)^2\right| d\tau\right] \frac{dz}{z^2}, \quad (4)$$

cross wavelet power $\left|W_a(\tau,z)^2\right|$ defined by Torrence and Compo [50] as two-time series $a(o)$ and $b(o)$ with the continuous transforms $W_a(\tau,z)$ and $W_b(\tau,z)$ as

$$W_{ab}(\tau,z) = W_{ab}(\tau,z) \cdot W_b^*(\tau,z), \tag{5}$$

in the time-frequency area, the high common power between the series showed by cross-wavelet power. The squared coherence of the wavelet is

$$R^2(\tau,Z) = \frac{\left|Z\left(z^{-1}W_{ab}(\tau,z)\right)\right|^2}{Z\left(z^{-1}|Z(W_a(\tau,z))|^2\right) \cdot Z\left(z^{-1}|W_b(\tau,z)|^2\right)}, \tag{6}$$

where $Z(.)$ and R^2 are the smoothing operator and the wavelet squared coherency, respectively. The difference of the phase is

$$\phi_{ab} = \tan^{-1}\frac{\Im\{W_{ab}(\tau,Z)\}}{\Re\{W_{ab}(\tau,Z)\}}, \phi_{ab}[-\pi,\pi], \tag{7}$$

where $\Re$ and $\Im$ represent the smooth power spectrum real part and imaginary, respectively.

3.2.2. Radial Basis Function Neural Network

We chose RBFNN to confirm our results because it belongs to the machine learning family, which is a completely different technique from the wavelet coherence model, which belongs to the classical analysis family. When we achieve similar results across models belonging to different analysis families, one of which is powered by artificial intelligence, this will indicate the accuracy of our results. RBFNN is characterized by its ability to predict the dependent variable with high accuracy when there are negative and positive values in the independent variables. This is consistent with the nature of the variables in our study. The idea of using RBFNN to confirm the results of the wavelet coherence model is to use the forecast error to deduce the strength of the relationship between oil and the Saudi stock market sectors before and during COVID-19. The radial basis function neural network consists of three layers: the input layer which contains two independent variables in our model, which are USOIL and UKOIL, the hidden layer in which each neuron applies the radial basis function, and the output layer, which is the expected values of the independent variable in our model, which are the index values of each of the sectors of the Saudi stock market as shown in Figure 2 (See for example, Heddam [51,52]).

The hidden layer neurons of RBFNN in comprise Gaussian transfer functions whose outputs are inversely proportional to the distance from the center to the neuron [51,52]. The RBFNN Gaussian function is the following

$$\varphi_i(x) = \exp\left(-\frac{\|x-\mu_i\|^2}{2\sigma_i^2}\right) i = 1,2,\ \ldots,\ N, \tag{8}$$

where σ_i^2 represent the hidden neuro spread. The RBFNN output is given by

$$\gamma_i = \sum_{j=1}^{N} w_{ij}\varphi_i(x) + B_2, \tag{9}$$

where B_2 is the bias, N represents the hidden layer neurons number, and w_{ij} is a weighted connection between the radial basis function neuron and the output neuron.

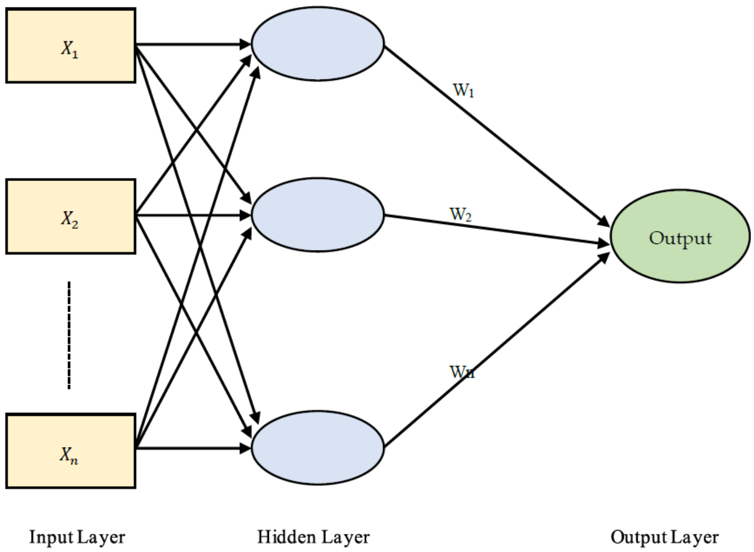


Figure 2. The architecture of a Radial Basis Function Neural Network. Note: The configuration of the RBFNN is in three layers. The first layer is the input layer where one neuron is assigned to each independent variable.This layer provides the values of the variables to the next layer. The second layer is the hidden layer whose optimal number of neurons is determined by training. Each neuron consists of a radial basis function which is positioned in multiple dimensions based on the independent variables. Its position and spread are determined by the training process. This layer transfers its output to the next layer. The last layer is the summation layer which receives the hidden layer values multiplied by their weight and then adds the weighted values and presents it as an output of the network. This network uses the training algorithm developed by Chen et al. [53]. This algorithm can determine the right time to stop adding cells by monitoring the prediction error, and thus stop when it starts to increase. The weights in the hidden and summation layer are calculated using ridge regression with a sophisticated procedure developed by Orr [54], which minimizes the error generalized cross-validation error [51].

4. Results and Discussion

4.1. USOIL and Saudi Stock Sectors Wavelet Coherence Results

To investigate the impact of COVID-19 on the relationship between USOIL and the Saudi stock market sectors, we run a wavelet coherence model for oil with each of the market sectors separately. Wavelet coherence heatmaps are in Figures 3 and 4. The straight up (↑) implies that Oil is leading and the down (↓) arrows imply that the stock sector is leading. The ↗ and ↙ arrows mean that the sector index leads oil, whereas the ↘ and ↖ arrows indicate that oil leads the Stock sector. Black lines indicate a significant relationship at 5%. The cooler the color (blue), the lower the strength of the relationship between the two variables, conversely, the warmer the color (red), the stronger the relationship. The arrows pointing to the right indicate the positive relationship between oil and stock indices, while the arrows pointing to the left indicate the inverse relationship between them [55]. Our results can be summarized across three scenarios as follows:

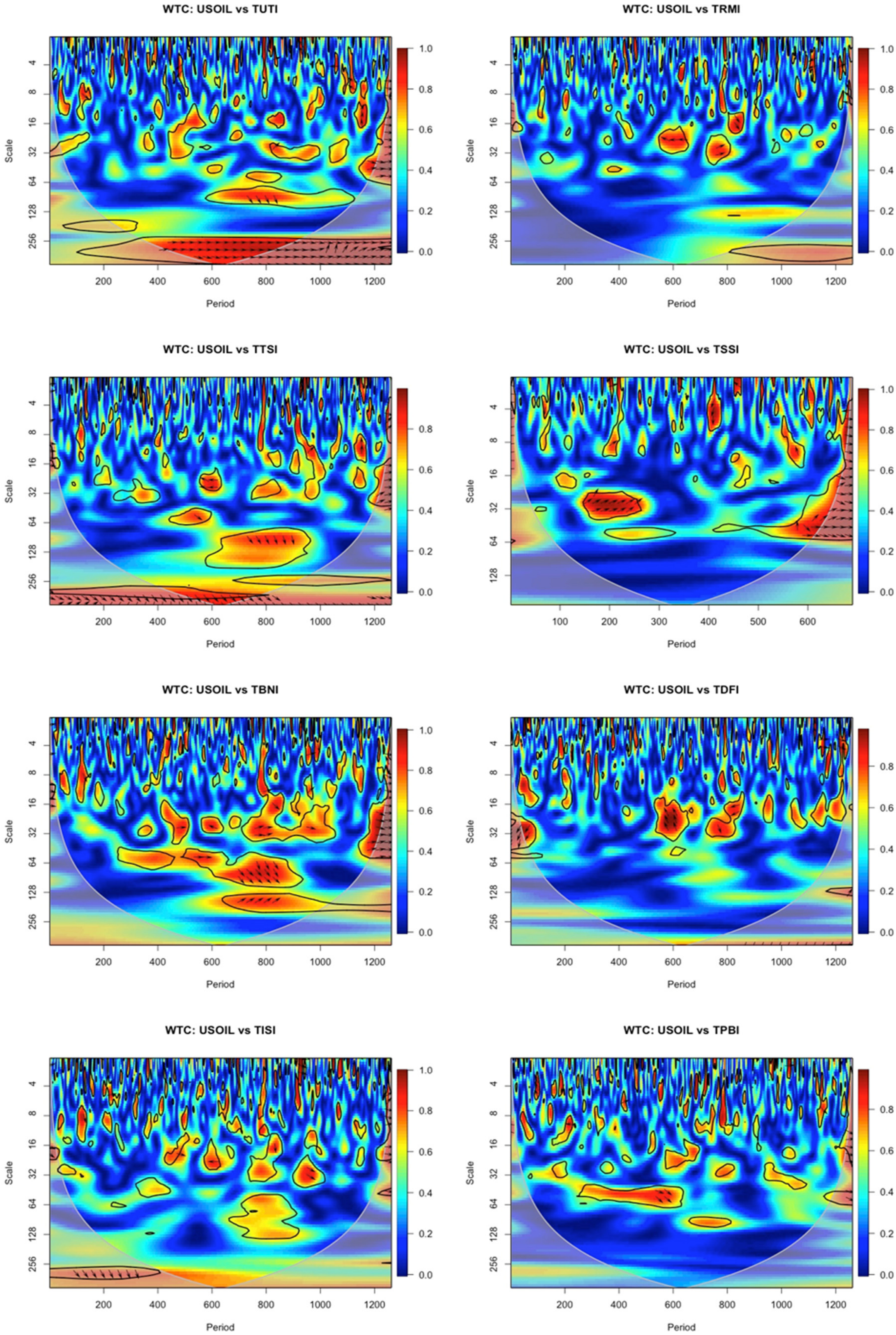


Figure 3. *Cont.*

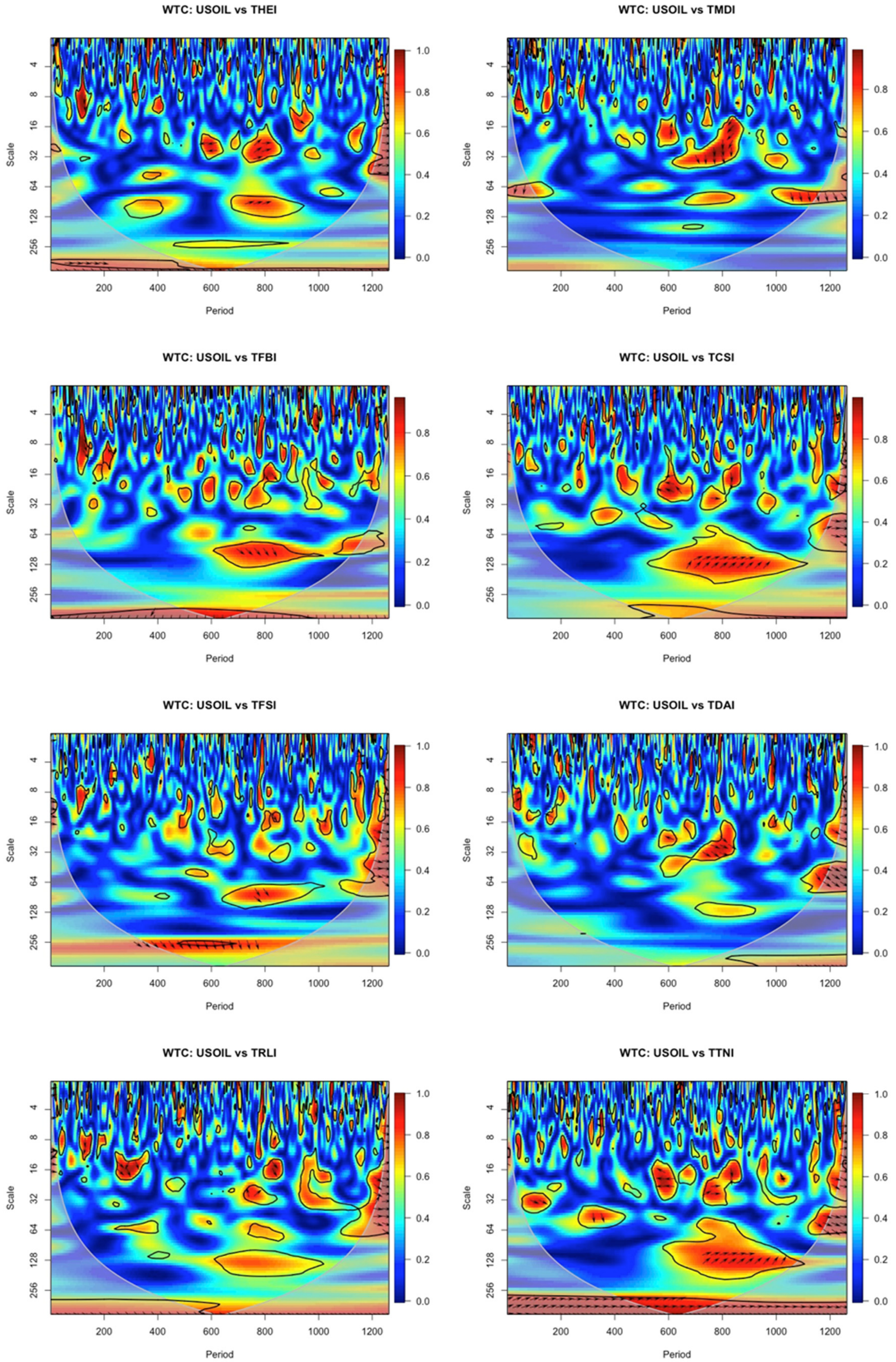


Figure 3. *Cont.*

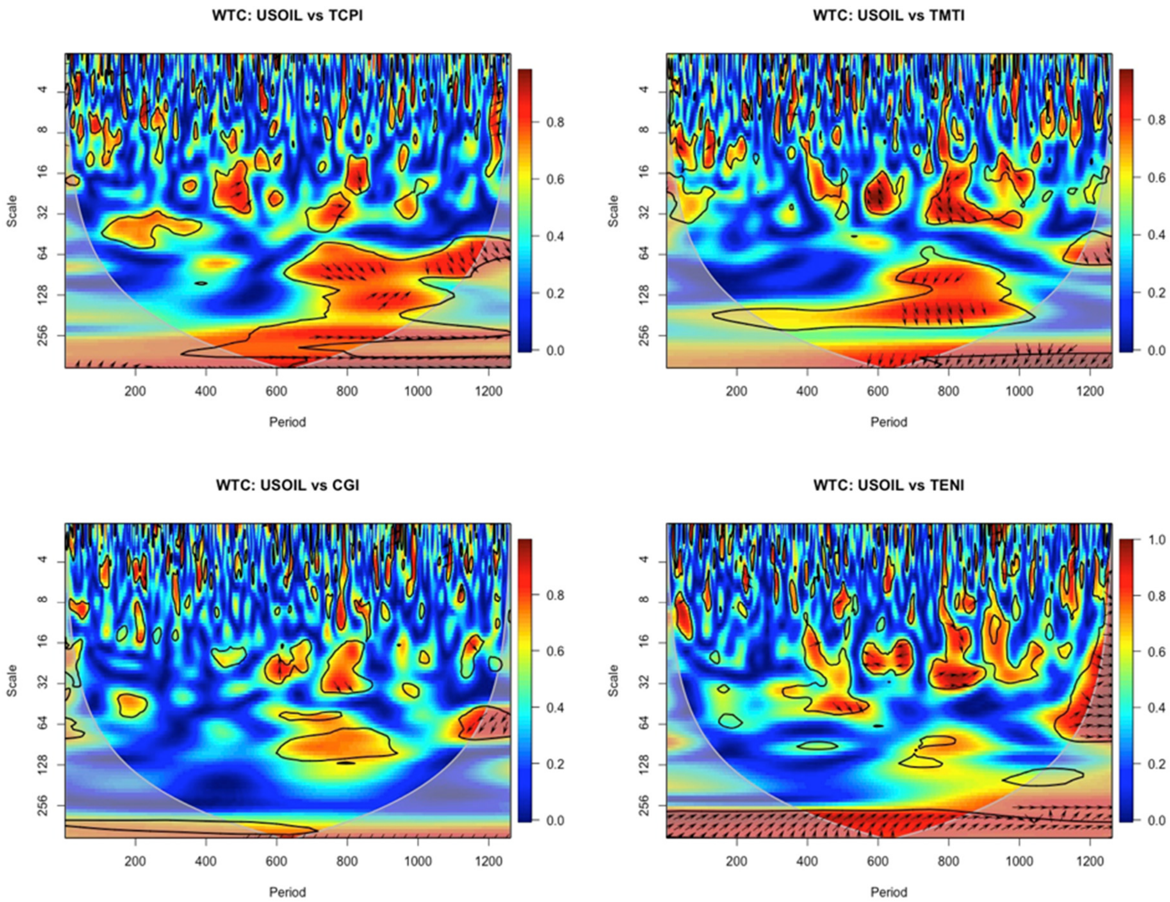


Figure 3. USOIL and Saudi stock market sectors wavelet coherence results.

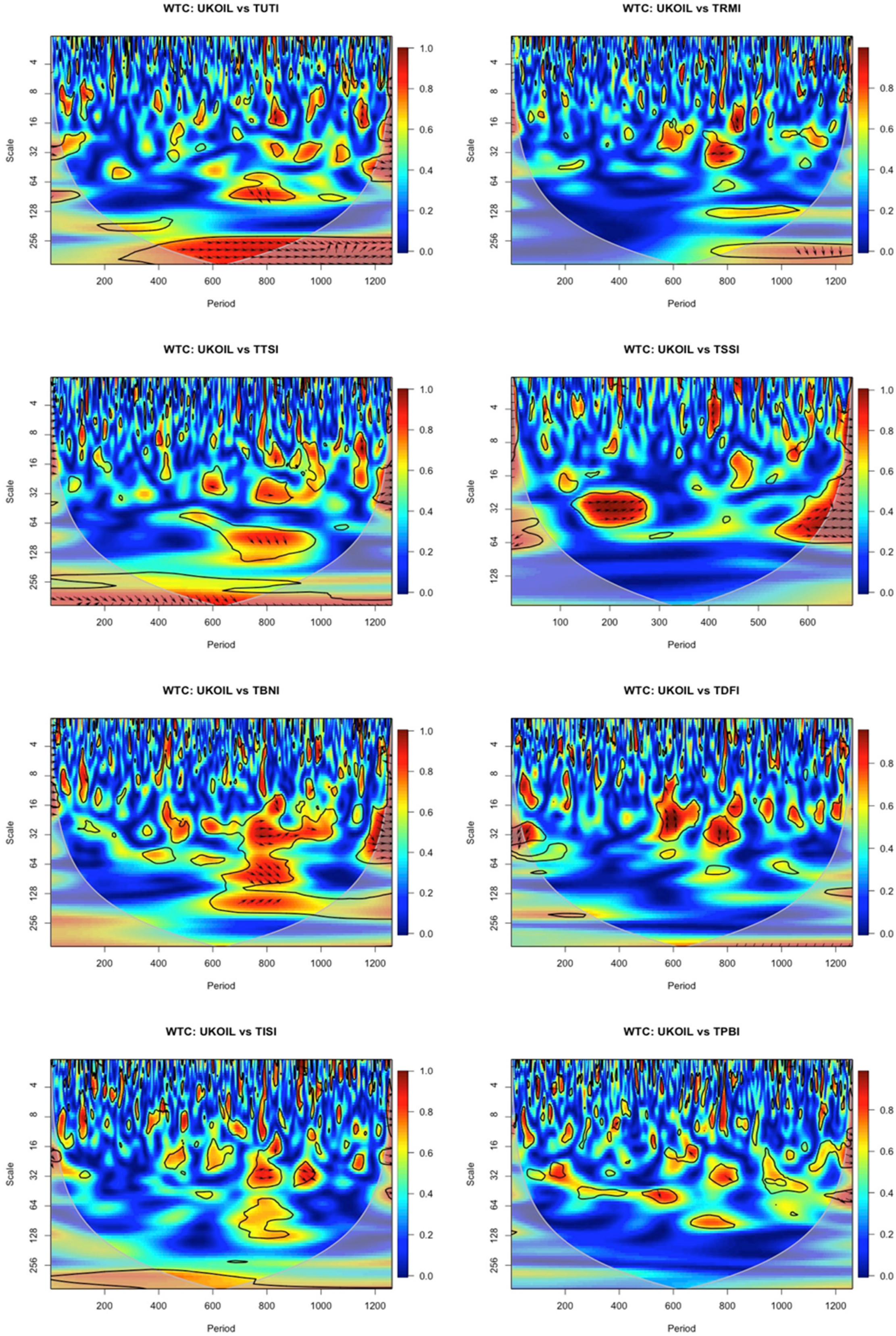
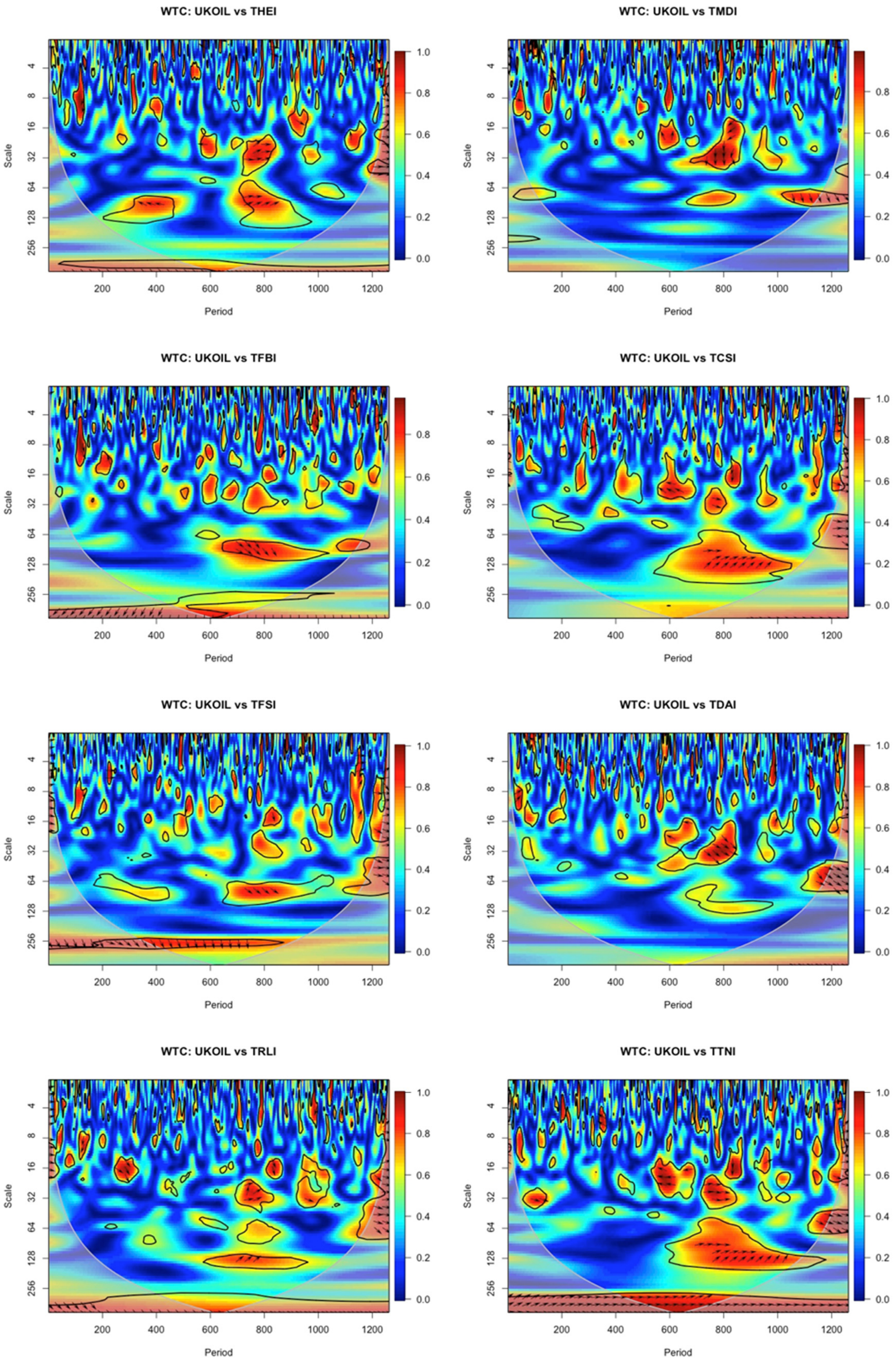


Figure 4. *Cont.*



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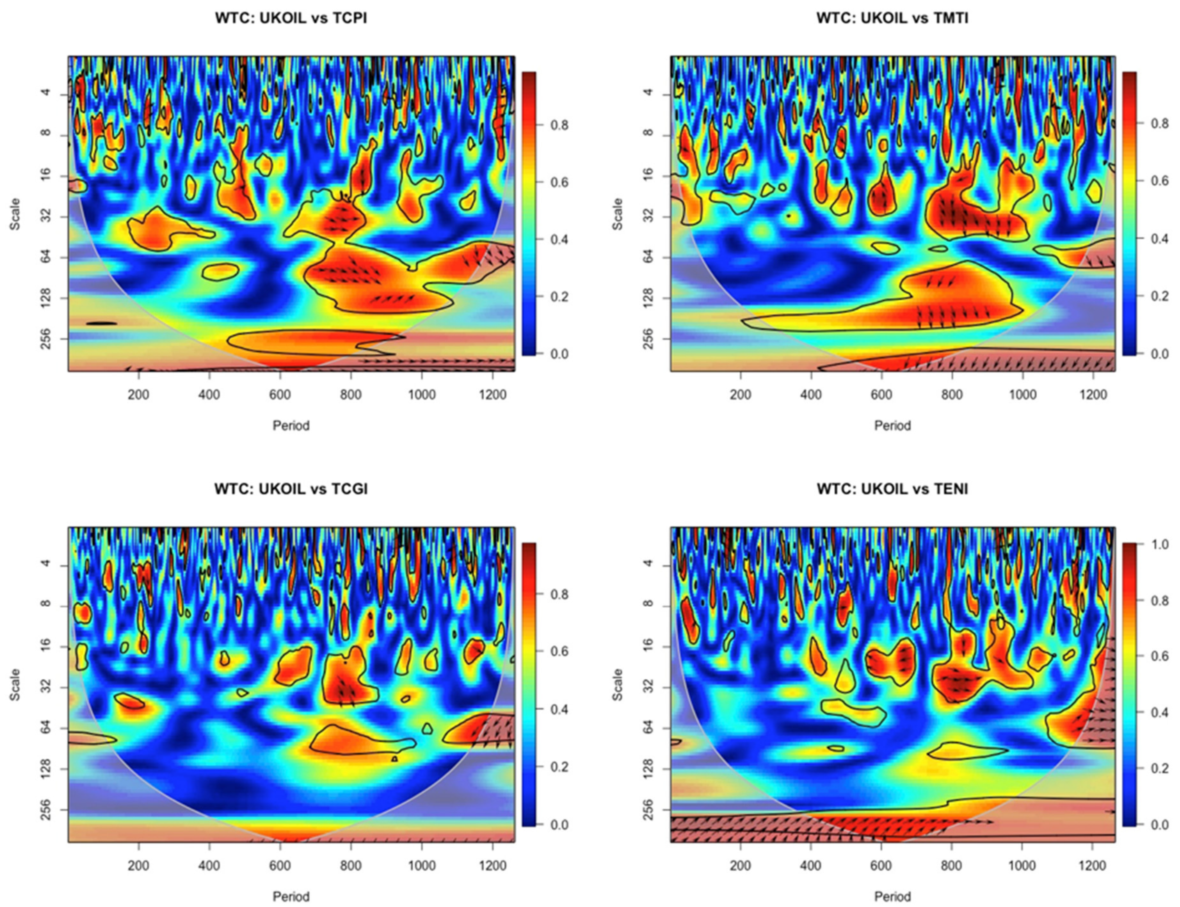

Figure 4. UKOIL and Saudi stock market sectors wavelet coherence results.

4.1.1. The Relationship between USOIL and Saudi Stock Market Sectors throughout the Entire Study Period

Figure 3 shows the results of the running wavelet coherence model for USOIL and the twenty sectors of the Saudi stock market. Figure 3 suggests that, overall, there is a significant relationship between oil and all sectors of the Saudi stock market whose strength (frequency) varies over time over the study period from January 2017 to January 2022. These results are an extension and support of the results that Jouini [30] reached using the VAR-GARCH model over the period January 2007 to September 2011, which suggests evidence of the impact of oil in some sectors of the market. It is also in line with Mensi [31] results using the wavelet approach during the period from January 2007 to February 2017, which summarized that there is a relationship between oil and the fifteen sectors of the Saudi stock market at that time. In addition, it supports the results suggested by Hamdan and Hamdan [32] regarding the energy, materials, and building and construction sectors using the Markov switching technique in the period from 2007 to 2017. The strongest relationship was between oil and energy, materials, utilities, transportation, banks, and telecommunication services sectors, while the weakest relationship was between oil and real estate management and development, diversified financials, and media and entertainment sectors. The relationship between USOIL and the energy sector is direct most of the time, led by USOIL sometimes and led by the sector index most of the time, but this happens at intervals. In the same context, we find that the relationship between USOIL and the materials sector is inverse most of the time. The leader in it is the sector index, while it is led by USOIL when it is positive. Perhaps the reason for this is the ability of investment fund managers to predict oil prices and exit the sector's shares in the face of oil price rises and enter the sector's shares before its price fell. In terms of the direct relationship led by USOIL, may be the result of practices by non-specialized private investors who enter shares in the sector with optimism due to the rise in oil prices or leave shares in the sector for fear of falling oil prices. Along the same lines as the energy sector, Figure 3 suggests a direct relationship between USOIL and the utilities, transportation, banks, and telecommunication services sectors, in which the leader is USOIL. Perhaps the reason behind this is that the rise in oil prices leads to an increase in public revenue from oil exports, which may indicate an increase in public spending, which in turn leads to an increase in people's income and then to an increase in their spending on goods and services, which leads to an increase in the profits of these sectors and a rise in their share prices. These results support the fiscal channel which was proposed by Degiannakis et al. [10] to clarify the mechanism of the impact of oil on the stock market. Our results also indicate that there is a direct relationship between USOIL and the commercial and professional services sector, but alternately led by USOIL and the sector index. The reason for this may be that investment funds entered the shares of this sector based on their expectations about the price of oil.

4.1.2. The Impact of COVID-19 on the Relationship between USOIL and Saudi Stock Market Sectors

Figure 3 suggests that the relationships most affected by COVID-19 are the relationship between USOIL and the commercial and professional services sector, where the strength of the relationship increased significantly during COVID-19. This is shown by the large dark red area at lower frequencies than those which appeared before COVID-19, indicating a strong direct relationship led by USOIL. Most of the time, it is marked by a short period led by the sector index. The reason for the increase in the strength of the relationship may be the severity of the impact of the historical fall in oil prices during that period, bringing the price of its futures contracts to a negative number, and the correlation of this sector with the general economic situation in Saudi Arabia, which is related to the return of its oil exports, as this Sector includes companies that provide logistics services and human resources services, in addition to providing support services to airlines [56] that stopped operating during that period. The relationship between USOIL and the materials sector comes second, as the relationship during COVID-19 turned into a more powerful oil-led positive relationship in the first two months of the pandemic, while a less strong inverse relationship prevailed, led by the sector index throughout the COVID-19 period at very high frequencies, which may explain the inverse relationship in the presence of cement, steel, and petrochemical companies that consume large amounts of energy and some oil derivatives, whose profits increase with the fall in oil prices and its profits decrease with the increase in oil prices. These results support the stock valuation channel which was proposed by Degiannakis et al. [10] to clarify the mechanism of the impact of oil on the stock market. While the positive relationship during the first two months, which is consistent with what is suggested by Jouini's [30] findings regarding the petrochemical sector, may be a result of the panic that prevailed in the global markets and the collapse of oil prices to historic levels.

The relationship in third place is the relationship between USOIL and the banking sector, which has become a more robust and direct relationship led by oil most of the time. The reason for this may be the decline in the operations volume of banks during that period. Therefore, the expectation of a decrease in profits, in addition to the state of panic that invaded the markets during that period. Suddenly, the relationship between USOIL and the energy sector ranked fourth, as the strength of the positive relationship increased, but the leader in the relationship unexpectedly became the indicator of the sector. This sector includes Saudi Aramco, the world's largest oil producer, as well as refining and distribution companies, and Saudi Arabia's largest shipping company.

The Saudi government owns 94.18% of Saudi Aramco, the Public Investment Fund owns 4% of Saudi Aramco and 22.55% of the largest shipping company [57]. In addition to the attractiveness of this sector for the institutional investor, this may be the reason for the sector's leadership in the relationship, since experts in these parties can predict the direction of oil with high accuracy and then make decisions to enter or exit the sector based on these expectations, which moves the index before oil. These results contradict the results of Hamdan and Hamdan [32], which suggest that the oil and gas sector interacts inversely with oil prices in the event of an increase in oil prices. The reason for the difference in results may be that they used monthly observations, while we used daily observations, in addition to the difference in the study period. While we find that the impact of COVID-19 on the relationship between USOIL and the transportation sector ranks fifth to become a direct and more powerful relationship led by the sector after it was an inverse relationship led by USOIL at times or the sector index at other times before COVID-19, we see that the reason for the change in the nature of the relationship during COVID-19 due to the complete lockdown that swept the country in parallel with the general lockdown in most countries in the world, which led to a decrease in the demand for oil and the demand for transport services, which caused a decrease in both. The sixth place affected by COVID-19 was occupied by the relationship between USOIL and the customer services sector, as the relationship turned from a moderate simultaneous relationship before COVID-19 to a strong direct relationship led by oil during COVID-19 led by oil. The reason for the change in the relationship due to COVID-19 may be that both oil and the companies of this sector were affected by the decrease in demand for oil and the products of the sector companies which operates in the field of tourism, hospitality, education, training and entertainment [58], and then the opposite occurred when the impact of the pandemic was removed. These results contradict Mensi's [31] findings, which suggested that the tourism and hospitality sector was not affected by the mid-2014 oil price crash. The conflicting results may be due to our use of daily observations in addition to using oil CFDs that trade around the clock, including Saudi stock market trading hours. While Mensi [31] used weekly observations in addition to spot market oil prices whose working hours differ from the working hours of the Saudi stock market. The next relationship that was affected by COVID-19 is the relationship between USOIL and the telecommunications services sector, as it has become a stronger direct relationship, oil-led at times and simultaneous at others. The explanation for this may be the panic that gripped the markets as a result of the uncertainty that prevailed in the financial markets. Next is the relationship between USOIL and the media and entertainment sector, which turned from a stronger inverse relationship at the beginning of the pandemic to become a direct relationship led by oil in the last period of the pandemic.

The reason for the strength of the inverse relationship at the start of the pandemic may be the increased demand for the products of companies in the sector, and the positive relationship in the recent period of the pandemic may be caused by the interaction of stocks of the sector with the rise that occurred in the Saudi stock market in general. This was followed in the same vein by the relationship between USOIL and the healthcare equipment and services sector, which became a stronger direct relationship led by the sector only in the first three months of the pandemic. Likewise, the relationship between oil and the software and services sector has been affected. While Figure 3 suggests that the relationships that were slightly affected are the relationship between USOIL and the real estate management and development, insurance and pharma, biotech and lifestyle sectors. The reason why these relationships were not significantly affected by COVID-19 may be that the demand for their products during the pandemic was not significantly affected. Our results go in the direction of the results of the literature that dealt with the relationship between oil and the Saudi stock market [23,24,26].

4.2. Additional Analysis Using UKOIL

To ensure the accuracy of our main analysis results, we run a wavelet coherence model that uses UKOIL data as another proxy of non-renewable energy. Figure 4 suggests results very similar to the results suggested by our main analysis, confirming the accuracy of the results.

4.3. Robustness Analysis

To confirm the accuracy of our results more closely, we run the RBFNN model using US oil and UK oil as independent variables, and each Saudi stock market sector index as the dependent variable. Figure 5, Tables 2–4 suggest very similar results to the results of our primary and additional analyses, confirming the accuracy of our results.

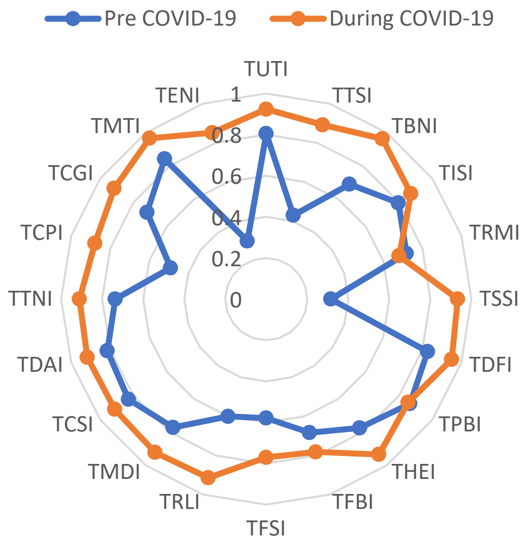

Figure 5. Oil and Saudi stock sectors proportion of variance explained by RBF network model pre and during COVID-19.

Table 2. Entire study period oil and Saudi stock sectors RBFNN parameters and results.

Stock Sector	Neurons Number	Min. R	Max. R	Max. λ	Min. λ	R^2	MAPE
TUTI	28	0.01	2053.51	0.03598	6.71059	0.74612	6.9225404
TTSI	100	0.01	87,061.7	0.00154	9.71237	0.51898	11.250193
TBNI	100	0.01	1028.51	0.00133	9.63528	0.73200	11.514796
TISI	64	0.01	3073.96	0.00144	9.85014	0.73561	6.8458073
TRMI	96	0.01	5611.12	0.01128	9.6831	0.53596	9.7370187
TSSI	92	0.01	812.215	0.01042	9.4689	0.94486	15.378037
TDFI	83	0.01	2631.7	0.00154	9.40929	0.85036	8.6979566
TPBI	88	0.01	10,098.7	0.00144	9.83449	0.80802	6.600101
THEI	89	0.01	1209.76	0.00113	9.35244	0.85141	7.6887315
TFBI	53	0.01	15,161.8	0.00774	9.83449	0.70145	5.8172327
TFSI	40	0.01	2901.86	0.00106	9.51137	0.62209	12.240706
TRLI	100	0.01	886.494	0.00154	9.96173	0.68137	9.8910692
TMDI	100	0.01	4667.57	0.00155	9.77451	0.86416	13.67636
TCSI	93	0.01	17,593.2	0.00154	9.96106	0.82301	5.0179009
TDAI	65	0.01	16,966.3	0.00154	9.42349	0.79083	10.349934
TTNI	81	0.01	1068.91	0.00154	9.75851	0.80913	5.7427778
TCPI	78	0.01	960.504	0.00106	9.83449	0.73750	2.7066831
TCGI	100	0.01	3272.51	0.00249	9.75851	0.79643	10.464229
TMTI	55	0.01	923.031	0.00154	9.87185	0.85161	5.109887
TENI	100	0.01	806.482	0.0035	9.71237	0.56116	5.4715945

Table 3. Pre-COVID-19 oil and Saudi stock sectors RBFNN parameters and results.

Stock Sector	Neurons Number	Min. R	Max. R	Max. λ	Min. λ	R^2	MAPE
TUTI	58	0.01	592.361	0.00485	8.87923	0.80511	4.5383858
TTSI	45	0.01	564.073	0.00154	6.51411	0.42839	8.5320564
TBNI	65	0.01	3111.09	0.00154	9.83449	0.69073	7.7555082
TISI	63	0.01	823.748	0.00774	9.87185	0.79652	3.2807765
TRMI	59	0.01	598.739	0.00444	9.85816	0.71869	6.8177898
TSSI	8	0.01	590.891	0.04107	7.50911	0.31557	4.651889
TDFI	59	0.01	5958.29	0.00485	9.78059	0.82746	4.2622335
TPBI	53	0.01	614.374	0.01077	9.69531	0.86633	3.3296659
THEI	79	0.01	2389.06	0.00249	9.50746	0.77553	4.5244775
TFBI	38	0.01	429.345	0.01042	9.1263	0.68367	5.2657034
TFSI	41	0.01	597.929	0.06803	9.50746	0.57914	4.5664314
TRLI	64	0.01	7485.57	0.01077	9.50746	0.60030	5.7059172
TMDI	39	0.01	624.073	0.00425	9.29268	0.77243	11.561854
TCSI	44	0.01	799.19	0.01027	9.36281	0.83015	3.7904233
TDAI	84	0.01	9557.05	0.00144	9.96525	0.81465	4.1337266
TTNI	61	0.01	598.242	0.01092	9.04996	0.73624	2.8444954
TCPI	48	0.01	9416.92	0.01028	9.51347	0.48993	2.4092531
TCGI	63	0.01	4404.94	0.01078	9.29268	0.71811	3.3502931
TMTI	78	0.01	1356.81	0.00686	9.77451	0.84281	2.3283973
TENI	8	0.01	528.976	2.49891	6.47411	0.29711	5.5889289

Table 4. During COVID-19, oil and Saudi stock sectors RBF network parameters and results.

Stock Sector	Neurons Number	Min. R	Max. R	Max. λ	Min. λ	R^2	MAPE
TUTI	44	0.01	22561.5	0.04546	7.86835	0.92417	4.5597721
TTSI	36	0.01	820.876	0.01095	7.65818	0.89121	3.1011354
TBNI	45	0.01	586.518	0.01095	9.76457	0.96386	3.4044754
TISI	46	0.01	1056.69	0.00312	9.51137	0.87227	4.7872269
TRMI	6	0.01	903.727	0.46024	5.18997	0.68133	5.3999148
TSSI	24	0.01	1273.71	0.00155	9.24398	0.93379	13.613964
TDFI	34	0.01	8088.65	0.01913	9.1263	0.95071	6.4217171
TPBI	40	0.01	898.74	0.00154	9.51137	0.85531	6.32463
THEI	36	0.01	616.881	0.00412	8.87365	0.93479	5.826658
TFBI	41	0.01	568.988	0.00133	8.83	0.78248	3.7379601
TFSI	31	0.01	581.657	0.0027	6.71059	0.77075	5.0380033
TRLI	52	0.01	1004.38	0.00706	9.75851	0.91479	4.1357413
TMDI	16	0.01	443.34	0.00444	8.96491	0.92245	8.7081687
TCSI	24	0.01	584.187	0.00521	9.41963	0.91267	3.8737875
TDAI	29	0.01	623.906	0.00155	9.50746	0.91758	7.8037005
TTNI	14	0.01	920.786	0.05033	5.94811	0.91064	5.0999203
TCPI	30	0.01	594.703	0.00154	9.63528	0.87819	2.4467219
TCGI	13	0.01	441.43	0.00155	7.61547	0.91639	8.5132016
TMTI	31	0.01	1566.64	0.01204	8.5496	0.96736	3.3658887
TENI	43	0.01	15,219.2	0.00154	9.50746	0.85116	1.7128421

5. Conclusions

In this study, we investigate the impact of COVID-19 on the relationship between oil as one of the main sources of non-renewable energy on the one hand and the twenty sectors of the Saudi stock market on the other hand. We apply two models to analyse our data: The first is the wavelet coherence model that can capture the nature, strength, and direction of the relationship between time series over time, and the other is a machine learning model namely RBFNN, where this model can determine the extent to which oil is able to predict each of the Saudi stock sectors. The impact of COVID-19 is recognized by the different abilities of the RBFNN model to predict Saudi market sectors indices before and during COVID-19.

Our main results can be divided into five pillars. The first pillar: There is a relationship between oil and all sectors of the Saudi stock market whose strength varies over time. This result is consistent with Mensi [31], which suggests the existence of a relationship between oil and some sectors of the Saudi stock market. The second pillar: The strongest relationships during the study period, in general, were the relationships between oil on the one hand and energy, materials, utilities, transportation, banks, and telecommunication services sectors on the other hand. The relationship between oil and the energy sector is direct most of the time, led by oil sometimes and led by the sector index most of the time, while our results suggest a direct relationship between oil and the utilities, transportation, banks, and telecommunication services sectors, in which the leader is oil. These results contradict Mensi's [31] findings, which suggest that banks were not affected by oil after 2014. The third pillar: The weakest relationship during the study period, in general, was between oil and real estate management and development, diversified financials, and media and entertainment sectors. The fourth pillar: Our results here provide the impact of COVID-19 on the relationship between oil and Saudi stock market sectors. As our results showed a noticeable change in the relationship between oil and all sectors, as the relationship between oil and market sectors became stronger and either oil or sector-led, these relationships after they were simultaneous relationships before COVID-19. The most affected relationships are the relationships between oil and the commercial and professional services sector which has become a stronger and more direct relationship led by oil; the materials sector, which turned into a more powerful oil-led positive relationship in the first two months of the pandemic, while a less strong inverse relationship emerged during the rest of COVID-19 period; banks sector, which has become a more robust and direct relationship led by oil most of the time; the energy sector, as the strength of the positive relationship increased, but the leader in the relationship unexpectedly became the indicator of the sector; the transportation sector, which became a direct and more powerful relationship led by the sector after it was an inverse relationship led by oil at times or the sector index at other times before COVID-19; the customer services sector, as the relationship turned from a moderate simultaneous relationship before COVID-19 to a strong direct relationship led by oil during COVID-19; the telecommunications services sector, as it has become a stronger direct relationship, oil-led at times and simultaneous at others; the media and entertainment sector which turned from a stronger inverse relationship at the beginning of the pandemic to become a direct relationship led by oil in the last period of the pandemic; the healthcare equipment and services sector, which became a stronger direct relationship led by the sector only in the first three months of the pandemic and the software and services sector which affected like the previous sector. The fifth pillar: Our results also suggest that the relationships that were slightly affected by COVID-19 are the relationship between oil and the real estate management and development, insurance and pharma, biotech and lifestyle sectors. The reason why these relationships were not significantly affected by COVID-19 may be that the demand for their products during the pandemic was not significantly affected. Our results go in the direction of the results of the literature that dealt with the relationship between oil and the Saudi stock market [24,25,27] and support the fiscal channel proposed by Degiannakis et al. [10] as a theoretical transmission mechanism between oil and stock market returns.

Our results have several contributions to the current literature. First, our results were extracted with two models, one of which is traditional and the other belongs to the family of artificial intelligence. Second, we studied the relationship between oil and sectors that the previous literature had not studied, which are software and services, food and beverages, diversified financials, pharma, biotech, and life science and healthcare equipment and services. Third, our results provided evidence supporting the theoretical transmission mechanism between oil and stock market returns during periods of uncertainty and crisis in the largest Arab stock market.

Our results have important implications for investors and policymakers. First, during periods of uncertainty and high volatility in the financial markets, our results will help hedge funds, mutual funds, and individual investors to predict the direction of Saudi stock sector indices based on the movement of oil prices and help them determine the extent to which oil can be used in their portfolios to hedge or diversify. Second, our results will help the Saudi Capital Market Authority, decision-makers and policymakers to take the necessary measures and decisions to maintain the stability of the Saudi Arabian stock market sectors during periods of crisis and uncertainty that negatively affect oil prices.

Future studies may focus on clean energy's relationship with stock markets in oil exporting and importing countries before and during COVID-19, the mediating role of oil on the relationship between carbon emissions and Saudi stock market sectors, and investigating the impact of COVID-19 on the relationship between oil and cryptocurrencies.

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