Examining the spillover effects of volatile oil prices on Iran’s stock market using wavelet-based multivariate GARCH model

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Abstract
Fluctuations in the oil market can significantly influence various sectors of the economy, such as the stock markets of countries that rely heavily on oil revenues. Oil prices are one of the key influential external factors affecting the stock exchange index of oil-dependent Iran. This paper investigates the spillover effects of oil prices on Iran’s stock exchange index weekly from March 2009 to March 2020. Using a time-series wavelet decomposition approach, a series of OPEC oil prices and Iran’s total stock market index were decomposed into various time scales (4 levels) to analyze oil market spillover into the stock market using the multivariate GARCH TBEKK model. The results confirmed that volatility spillover from the oil to the stock market occurred in all the time scales (short, medium, and long term). However, the spillover in the long term is more pronounced than over the short, demonstrating that stock market volatility is strongly influenced by long-term exogenous oil price fluctuations. Hence, oil market shocks are one of the influential factors affecting stock market turbulence in Iran.

Keywords Volatility Spillover · Stock Market · Oil Prices · Wavelet Transformation · Multivariate GARCH Model

JEL Classification C32 · C51 · G12 · Q34

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1 Introduction

The oil market is one of the main markets in the world, usually impacting other markets. In other words, oil price fluctuations cause upheavals in other markets, including the stock market, though the reverse is not typically true. As a major oil-exporting country, Iran’s political, economic, and other sectors are significantly affected by oil price fluctuations. This is due to oil revenues as a principal component of the government budget indirectly affecting other economic activities.

For oil-importing countries, oil price shocks negatively impact economic activities. Increases in oil prices lead to higher production costs since oil is one of the most critical factors of production (Backus and Crucini 2000; Arouri et al. 2011). The transfer of these higher costs to consumers increases consumer expenditures and, eventually, leads to a reduction in demand. Lower consumption will result in lower production and, consequently, higher unemployment (Lardic and Mignon 2006). Stock markets react negatively to any rise in crude oil prices resulting in a decline in the stock exchange index in these countries (Sadorsky 1999).

Empirical studies have shown the negative relationship between oil prices and stock market returns based on the fact that oil prices are assumed as a risk factor for the stock market (Jones and Kaul (1996)). Researchers such as Filis et al. (2011), Chen (2010), Miller and Ratti (2009), and O’Neill et al. (2008) have provided evidence proving this negative relationship, although, for oil-exporting countries, there seems to be a direct relationship between oil price shocks and stock market efficiency (Arouri and Rault 2010).

Many scholars argue that oil prices indirectly affect the stock market, and macroeconomic indicators confirm this relationship. Bjørnland (2000) believes that an increase in oil prices and, consequently, an increase in the income of oil-exporting countries will positively affect their economic performance. Increased incomes are expected to lead to higher spending and investment and the injection of financial resources into the economy, which, in turn, will increase production and reduce unemployment. Hence, stock markets tend to react positively to such events. The spilling over of oil market price fluctuations into the stock market can vary depending on the length of time (short, medium, and long term). Also, the intensity of fluctuations or shocks from the oil market on stock markets varies over the various time scales.

Given these issues and the lack of research on this matter in Iran, the current paper explores the volatility spillover effects between the oil and stock markets over different time frames. It investigates the issue over the short, medium, and long-term periods (different frequencies) via wavelet transformation, followed by an examination of volatility spillover in each time scale. The main advantage of this method is that spillover effects are studied in different time scales, and that volatility spillover is investigated thoroughly and in detail in each time scale.

The subsequent sections are organized as follows: First, the literature review is presented, followed by the methodology used in the model, the definitions of variables, and the various method stages. Then, the model’s estimations and analysis
of the findings are presented. Finally, the results obtained are reported together with their policy implications.

2 Literature Review

Malik and Hammoudeh (2007) investigated shock and volatility transmission mechanisms using the daily price data of stock markets in Saudi Arabia, Kuwait, and Bahrain, and crude oil global markets as well as the US equity market in 1994–2001 using the multivariate GARCH and BEKK models. The results of their study show that oil market fluctuations are transferred to equity markets in the Gulf, especially Saudi Arabia. In addition, shocks in US equity markets also indirectly affect the volatility of Gulf equity markets.

Park and Ratti (2008) examined the effects of oil price shocks on stock markets in the US and 13 European countries for the 1986–2005 periods using the Vector Auto-Regressive (VAR) model and found that the shocks significantly depressed stock returns in the European markets. Also, oil price shocks in comparison to interest rates, have a greater impact on the variability of stock returns in the United States and other countries.

Ewing and Malik (2010) explored volatility spillover between oil and (selective) stock markets from 1993–2008 using the bivariate GARCH model. The results showed that there are structural breaks in oil price volatility spillover and that oil price shocks have a stronger initial effect but disappear faster than previously thought.

Filis et al. (2011) investigated time-varying correlations between the stock market and oil prices for Canada, Mexico, and Brazil as exporter countries and the US, Germany, and the Netherlands as importers using the DCC-GARCH-GJR model for 1987–2009. They found no difference in the dynamic correlation between oil and stock prices for both groups of countries. Also, supply-side oil price shocks did not affect the relationship between stocks and oil markets although the demand-side equation showed a greater impact on the correlation between the two sets of prices.

Arouri et al. (2011) examined oil price fluctuation spillovers and stock markets in Gulf Cooperation Council (GCC) countries from June 2005 to February 2010 using the VAR-GARCH model and found significant spillover effects between the two.

Awartani and Maghyereh (2013) studied the dynamic volatility spillover effect between oil and stock markets in GCC countries in 2004–2012. They found an asymmetric bi-directional volatility spillover effects between the two markets with the oil markets being more likely to impact other markets in terms of returns and fluctuations.

Chang et al. (2013) investigated volatility spillovers between financial and crude oil markets based on the daily returns of the FTSE100, NYSE, Dow Jones, and S&P 500 markets as well as the spot, forward, and future daily prices of BRENT and WTI crude oil from 2 January 1998 to 4 November 2009. Their results indicated little evidence of volatility spillover between the two markets.

Ewing and Malik (2016) studied oil price fluctuations and stock market prices of the United States in terms of structural failure from 1 July 1996 to the end of
June 2013 using mono- and bivariate GARCH. They determined that structural failures were endogenous and concluded that there were no fluctuation spillovers between oil prices and stock markets. However, by including structural failure in the model, intensive fluctuation spillovers can be observed.

Huang et al. (2015) examined the multi-scale dynamic relationship between crude oil prices and the stock market in China using wavelet analysis and the VAR vector autoregressive model. Their evidence suggests a two-way Granger causality relationship between many stock market index sectors (except for health, water, electricity, and consumption) and crude oil prices in the short, medium, and long terms. They found that the effects of crude oil price shocks on different sectors varied across different time horizons.

Khalfaoui et al. (2015) investigated the relationship between the crude oil market (WTI) and stock markets of the G-7 countries over different time horizons by combining multivariate GARCH model and wavelet analysis. The results showed substantial spillover between the two markets as well as time-varying correlations for different market pairs.

Aimer (2016) investigated the conditional correlation and spillover fluctuations between oil price shocks and stock market indices in Middle East countries during 2000–2015 using multivariate GARCH models (BEKK-GARCH and DCC-GARCH). The results show significant spillover effects from Texas oil prices (WTI) on the stock indices of both oil exporting and importing countries. The results also show that the dynamic correlation between the two factors is not different in both types of economies.

Mamipour and Feli (2017) investigated the effects of oil price spillovers on the returns of 37 selected industries in the Tehran Stock Exchange using the variance decomposition analysis proposed by Diebold and Yilmaz (2012) within the framework of a generalized VAR model. Separating the oil markets into high and low volatility regimes using the Markov switching model, they found less effects of oil-market volatility on the stock market in the low volatility regime.

Ping et al. (2018) explored the dynamic conditional correlation (DCC) between fuel oil spot prices and future and energy stock markets in China compared to the US. They found that the volatility spillover between the three markets in China to be less than in the US. In addition, they found a bidirectional effect of volatility spillovers between fuel oil spot and futures as well as fuel oil spot and energy stock markets, while the effects of the energy stock market on the fuel oil futures market was one-sided.

Botshekan and Mohseni (2018) examined the dynamic conditional correlation and volatility spillover among returns of crude oil price and stock index by Baba, Engel, Kroner, and Kraft (BEKK), Dynamic Conditional Correlation (DCC), Constant Conditional Correlation (CCC), and multivariate GARCH model. They found a conditional correlation of volatility-spillover effects of the oil price on the stock index.

Karimi et al. (2018) investigated the spillover effect of oil on Tehran Stock exchange markets by Multivariate GARCH models. They indicated a relationship between the oil market and the stock market before and after oil sanctions. Based
on the results, Iran is clearly dependent on oil, and its effects on various financial markets, including stock exchanges, are observed.

Khalfaoui et al. (2019) studied the volatility spillover between the oil and stock markets of oil-importing and exporting countries using symmetric and asymmetric versions of DCC and correlated DCC (cDCC) models. In general, the results showed that lagged oil price shocks affect oil-importing countries and that there was no significant interdependence between the stock markets of both groups of countries.

Cevik et al. (2021) surveyed the volatility spillover effects between crude oil prices and stock market returns in Saudi Arabia using the APARCH operation and found a one-way causality relationship between the two factors.

Karimi et al. (2020) evaluated the symmetric and asymmetric dynamic conditional correlations between volatilities of oil prices and stock markets in the Persian Gulf region by Dynamic Conditional Correlation (DCC) and Asymmetric Dynamic Conditional Correlation (ADCC) models. The results suggested an asymmetric dynamic conditional correlation between Iran and Dubai stock markets and a symmetric dynamic conditional correlation between Saudi Arabia stock market and OPEC crude oil prices. Additionally, based on the results, a symmetric dynamic conditional correlation between Qatar and Dubai stock markets and an asymmetric dynamic conditional correlation between the Saudi stock market and Brent crude oil were detected.

Mensi et al. (2022) examined volatility spillovers between the US stock market (S&P500 index) and both oil and gold before and during the global health crisis (GHC), i.e., the COVID-19 pandemic. The results revealed negative (positive) conditional correlations between the S&P500 and gold (oil). The time-varying conditional correlations between markets were higher during the COVID-19 pandemic. Additionally, gold offers more diversification gains than oil does during the pandemic. More expensive hedging is perceived during a pandemic compared to before. For all sub-periods examined in this study, oil offers higher hedging effectiveness (HE) than gold. For both oil and gold, HE was detected lower during the COVID-19 outbreak.

A literature review of empirical studies on the volatility spillover between the oil market and Iran’s stock market indicated that several studies had covered this subject. The most noticeable studies include Mamipour and Feli (2017), Fotros and Hoshidari (2017), Karimi et al. (2018), Botshekan and Mohseni (2018), Karimi et al. (2020), and Tehrani et al. (2021). These studies attempted to examine the relationship between the oil market and Iran’s Stock Market, mostly focusing on prosperity and recession periods, pre- and post-sanction periods, and various stock markets. The results demonstrated a significant relationship between oil and stock markets. However, they ignored volatility-spillover effects of the oil market on Iran’s stock market in various time scales (short, medium, and long-term), while such spillovers may vary at different periods, and investor awareness of this issue can affect their behaviour in the financial markets. Thus, this study aims to examine the volatility-spillover effect of the oil market on the stock market at various time scales.

Therefore, through wavelet transform, data on oil prices and the total stock market index are analyzed at different time scales. In this process, variables are decomposed into different time scales, and the volatility spillover between the two markets...
is studied using the GARCH-TBEKK approach. Moreover, another innovative aspect of this research is using a lower-triangular matrix (TBEKK model) employed for modeling the variance–covariance equation. The oil prices are treated as endogenous in the BEKK model, while in the triangular BEKK model, they are treated as exogenous. In other words, it is assumed that there are no spillover effects from Iran’s stock market into the oil market, though the reverse is possible. This method leads to more accurate results regarding the spillover analysis by considering just one side that truly happens in the economy. Hence, the treatment of oil prices as an exogenous variable to study its spillover effects on Iran’s stock market in different time scales represents a contribution of this paper.

3 Methodology

First, the time series were decomposed using wavelet transform and their fluctuations or noises extracted at different levels. Then volatility spillovers in the two markets were examined using the GARCH-TBEKK model.

3.1 Wavelet Transform

Some properties of time series were not visible in the time domain and can be visualized by transferring them to other domains. Wavelet transform is a useful tool in which wave-shaped functions decompose a time series into a series of coefficients. This group of functions is created by moving a basic wavelet function called the mother wavelet or by analyzing the wavelet (Mallat 1999). The wavelet has two pairs of functions: the father wavelet (as an Approximation function) symbolized with \( A \) and the mother wavelet (as a Detail function) presented as the symbol \( D \). Moving the basic wavelet function or the analyzer creates the wavelet function. Each set of wavelet coefficients presents a part of the time series on a different scale. The ability of wavelets in using the time series and their scales allows them to simultaneously focus on the time and frequency domains. The most important issue in using wavelet transform is the selection of a basic function of the wavelet, that is, the mother or analyzer wavelet.

Wavelet functions are generally classified into two i.e., continuous and discrete wavelet functions. The Haar wavelet is considered a discrete wavelet function. Since economic data are discrete, the Haar wavelet function is used in this study. An example of a Haar wavelet expansion is shown in Fig. 1.

The approximation of any discrete function or time series using the wavelet functions is as follows:

\[
f(t) = \sum_k s_{J,k} \phi_{J,k}(t) + \sum_k d_{J,k} \psi_{J,k}(t) + \sum_k d_{J-1,k} \psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k} \psi_{1,k}(t)
\]

where \( j \) represents the number of analysis levels or scales and \( K \) is the amount of movement in time at each level.

The wavelet coefficient is obtained by the following relations:
where $S_{J,k}$ is the $j^{th}$ level smoothness and $d_{J,k}$ is the $j^{th}$ level detail (Crowley (2007)).

The mother wavelet function has two conditions. The first is the acceptability condition for which the function must follow the following relation (Struzik 2001):

$$S_{J,k} \approx \int \phi_{J,k}(t)f(t)d(t)$$

$$d_{J,k} \approx \int \Psi_{J,k}(t)f(t)d(t)$$

where $S_{J,k}$ is the $j^{th}$ level smoothness and $d_{J,k}$ is the $j^{th}$ level detail (Crowley (2007)).

The mother wavelet function has two conditions. The first is the acceptability condition for which the function must follow the following relation (Struzik 2001):

$$C_{\psi} = \int_{0}^{+\infty} \frac{[\Psi(f)]^2}{|f|} df$$

where $f$ represents frequency and $\Psi(f)$ is the mother wavelet. This condition indicates that the mean of the wavelet function is zero. In fact, it can be seen that $\Psi(0) = 0$. Otherwise, the integral in the above relation would be infinite in zero frequency.
The energy of the wavelet function should be considered unit as a second condition

$$\int_{-\infty}^{+\infty} |\psi(t)|^2 dt = 1$$  \(6\)

Continuous Wavelet Transform (CWT) is a function of two variables \(u\) and \(s\), and is calculated from the multiplication of the desired function in the wavelet function and the integration of the product (Gençay et al. 2001). By considering that the desired function \(x(t)\) is time dependent function, the wavelet transform is as follows:

$$W(u, s) = \int_{-\infty}^{+\infty} x(t)\psi_{u,s}(t)dt$$  \(7\)

where, \(\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)\) is the elementary wavelet function extended to \(s\), and displaced with the value of \(u\) on the time axis. The resulting coefficients are a function of the two \(s\) (scale) and \(u\) (the amount of displacement in time), while the main function only depends on the time.

If the wavelet function used in the analysis satisfies the mother wavelet acceptance condition, the original time series can be reconstructed by inverting the operations on the coefficients using the following formula:

$$X(t) = \frac{1}{c_{\psi}} \int_{0}^{\infty} \int_{-\infty}^{\infty} W(u, s)\psi_{u,s}(t)du ds$$  \(8\)

In this study, the series of OPEC oil prices and stock prices in Iran were decomposed using the Haar wavelet into four levels representing 2 to 4, 4 to 8, 8 to 16, and 16 to 32 weeks.

### 3.2 Modeling Volatility Spillover Effects

In this study, the volatility spillover between oil prices and total stock price index over the period 2009–2020 is estimated using weekly data and by applying a bivariate VAR-GARCH-TBEKK model.

Multivariate GARCH (1,1) is typically presented as follows:

$$R_t = X_t\theta + \epsilon_t, \quad \epsilon_t|\epsilon_{t-1} \sim N(0, h_t)h_t = a_0 + a_1, \quad \epsilon_{t-1}^2 + \beta h_{t-1}$$  \(9\)

where \(X_t\) is the explanatory variables vector, \(\theta\) is the coefficient vector, \(\epsilon_t\) is the residual with normal distribution, and \(h_t\) is the conditional variance vector.
The Multivariate GARCH Model employed in this study is generalized as follows:

Mean equation:

\[
R_t(i) = \begin{bmatrix} R_{s,t}(i) \\ R_{0,t}(i) \end{bmatrix} = \begin{bmatrix} \mu_s(i) \\ \mu_0(i) \end{bmatrix} + \begin{bmatrix} \varphi_{11} & \varphi_{12} \\ \varphi_{21} & \varphi_{22} \end{bmatrix} \begin{bmatrix} R_{s,t-1}(i) \\ R_{0,t-1}(i) \end{bmatrix} + \begin{bmatrix} \varepsilon_{s,t}(i) \\ \varepsilon_{0,t}(i) \end{bmatrix}
\tag{10}
\]

Variance–covariance equation related to BEKK:

\[
C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}, \quad A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}
\tag{11}
\]

where \( R_t(i) \) is a 2 × 1 vector of stock and oil price variables for wavelet scale \( i \), \( \varepsilon_t(i) \) and \( \mu_0(i) \) are related to \( \mu(i) \). Thus, \( \mu(i) \) is a 2 × 1 vector that represents long-term coefficients.

\( \varepsilon_t(i) \): Random error vector at time \( t \) for scale \( i \)

\( H_t(i) \): Conditional matrix–vector (2 × 2) in scale \( i \)

C: constant coefficients matrix

A: conditional residuals coefficients matrix (ARCH effects)

B: conditional covariance coefficients matrix (GARCH effects)

The non-diagonal elements of matrices \( A \) and \( B \) \((a_{12}, a_{21}, b_{12}, b_{21})\) reflect the spillover transmission of fluctuations between oil and stock markets.

A lower-triangular matrix is employed for modeling the variance–covariance equation in this study. In other words, it is assumed that there is no fluctuation spillover from the stock market into the oil market though the reverse is possible. This method is called the TBEKK. Hence, the conditional variance–covariance matrix is specified by the TBEKK(1,1) method, as follows:

\[
\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix}
\tag{12}
\]

Equation 10 represents how fluctuations and shocks transfer between markets at various scales.

Finally, the effect of the oil price spillover on the stock market index is tested by the null hypothesis \( H_0 : b_{21} = a_{21} = 0 \). If the null hypothesis isn’t rejected, the conditional variance of the oil price and the stock market indexes is calculated only with their lagged values, and all non-diagonal elements of the variance–covariance matrix will be zero. If the null hypothesis is rejected, it can be concluded that oil price fluctuations will spillover into the stock market.

### 3.3 Data

This study analyze fluctuations in OPEC oil prices and the Tehran Stock Market Index from 25 March 2009 to 11 March 2020 using weekly data within the framework of the wavelet transform analysis and multivariate GARCH model.
4 Model Estimation and Data Analysis

4.1 Wavelet Transform and Data Decomposing

Following the selection of the Haar wavelet as the mother wavelet, the signal decomposes into approximation and detail signals where, at each level of the decomposition, the approximate signal can be decomposed again using the mother wavelet. In addition to achieving an approximate signal at a higher level this allows more detail signals to be obtained. The approximate and detail signals of order i are shown as $A_i$ and $D_i$ symbols, respectively. The sum of $A_i$ and $D_i$ reconstructs the original signal again with $n$ determining the level of decomposition of the wavelet transform. This relationship is expressed by Eq. 11.

$$S_t = A_n + D_1 + D_2 + \cdots + D_n$$

(13)

In this study, wavelet transform is used in analysing the data for different time horizons before estimating. As shown in Fig. 2, using the Haar wavelet transform, the same time series formed by the weekly OPEC oil prices and Iran’s stock market index was decomposed up to four levels. The results of this decomposition are the 5 categories of coefficients; one of which belongs to the fourth level of decomposition ($A_4$) and represents the general process of data without details. The other four groups comprising the first ($D_1$), second ($D_2$), third ($D_3$), and fourth ($D_4$) levels of decomposition indicate data with frequency levels of the time series as the noise series. The five new time series with specific characteristics are considered the outputs of this process so that the relationship between them and the original signal can be defined by Eq. 12.

$$S_t = A_4 + D_4 + D_3 + D_2 + D_1$$

(14)

The results of the wavelet transform for the OPEC oil prices and stock market index variables are shown in Figs. 3 and 4, respectively.

In Figs. 3 and 4, $S$ represents the original time series subdivided into its approximations ($A$), and the noises ($D$) in each approximation. The basic idea behind wavelets is scale-based analysis. The wavelet scale is such that the first
to fourth levels of decomposition represent 2 to 4, 4 to 8, 8 to 16, and 16 to 32 weeks, respectively. Subsequently, as the main time series are decomposed from the bottom to top levels, the scales move from the short to the long terms.

Fig. 3 Wavelet decomposition of the oil price

Fig. 4 Wavelet decomposition of the stock market index
4.2 Descriptive Statistics

Following analysis of the data, the noise series or details (D) of both variables are modelled for each level. Since the variables used in the VAR model need to be stationary, the Augmented Dicky-Fuller (ADF) test is used for the unit root test of the variables. The results of the unit root tests indicate that all variables are stationary at the different levels (Table 1).

4.3 VAR-GARCH-TBEKK Model Estimation

Following the decomposition of the oil and stock price variables into four levels, the results of the estimation of the VAR-GARCH model are evaluated and analyzed for each level. As pointed earlier, the results of the model for the first level are indicative of the spillovers of oil price fluctuations on the stock market over the short period (2–4 weeks) and higher level estimate fluctuation spillovers over the very long period (16–32 weeks). The model estimation results for the D1 to D4 scales are shown in Tables 2 and 3, respectively.

The results of the mean equation and conditional covariance equation estimation for the D1- D2, and D3- D4 decomposition stages are presented in Tables 2 and 3, respectively. For the mean equation, the vector autoregressive model order 1 (VAR (1)) is used. The results of the mean equation show that oil price fluctuations and stock prices are significantly correlated over the very long time scale (16–32 weeks). In Table 2 and 3, the results of the covariance-variance equation are estimated, including matrices A and B, which represent the effects of the ARCH and GARCH variables, respectively.

The diagonal parameters in matrix A indicate ARCH effects of their own past shocks on their conditional variance. All the estimated diagonal parameters of matrix A (a11, a22) are significant in all time scales. The diagonal parameters

| Table 1 | Descriptive statistics for wavelet components |
|---------|---------------------------------------------|
|         | DO1  | DO2  | DO3   | DO4   | DS1   | DS2    | DS3   | DS     |
| Mean    | 0.000| 0.000| 3.13E-18| 0.066| 0.000| 0.000| 0.000| -2.26E-13|
| Median  | 0.000| 0.000| 0.000| 0.064| 0.000| 0.000| 0.000| -1.36E-11|
| Maximum | 22.355| 13.132| 7.941| 12.76| 22.820| 24.543.75| 39.564.88| 20.990.62|
| Minimum | -22.355| -13.132| -7.941| -12.76| -22.820| -24.543.75| -39.564.88| -20.990.62|
| Std. Dev| 1.867| 2.03| 2.636| 4.102| 2726.810| 3637.19| 6544.163| 6158.359|
| Skewness| 0.000| 0.000| 5.07E-18| -0.027| 0.000| 0.000| 9.84E-17| -6.82E-17|
| Kurtosis| 73.39| 14.434| 3.669| 4.568| 39.401| 25.794| 22.406| 8.185|
| Jarque–Bera | 117.262.8| 3094.502| 10.594| 58.291| 31.360.11| 12.297.18| 8913.575| 636.455|
| Probability| 0.000| 0.000| 0.005| 0.000| 0.000| 0.000| 0.000| 0.000|
| Observations| 568| 568| 568| 568| 568| 568| 568| 568|
| ADF     | -14.156***| -8.360***| -8.403***| -5.990***| -20.951***| -6.441***| -6.282***| -6.976***|

*** Significant at the 1% level.
in matrix B (b11, b22) measure the effects of their own past volatility on their conditional variance (GARCH effects). The results suggest that b11 is significant in all time scales, but b22 is insignificant in short-term scales (D1 and D2) while significant in long-term scales (D3 and D4).

The non-diagonal parameters of matrices A and B capture transmissions across markets. As mentioned earlier, the volatility spillover effects of Iran’s stock market on oil markets are assumed to be zero in the TBEKK model. Thus, the parameters of a21 and b21 represent volatility spillover from OPEC oil price to Iran’s stock market index. All the estimated parameters of a21 and b21, except b21 in a very short-term scale (D1), are significant in all time scales. The significant coefficients of a21 and b21 indicate volatility spillovers from the OPEC oil market to Iran’s stock market in the short, medium, and long terms. In other words, the momentum in the oil price leads to stock market volatility. The results of simultaneous and general spillover of oil prices on stock prices were tested with the Wald test and are presented in Table 4. In order to examine the volatility-spillover effects of the oil market on the stock market, the null hypothesis of $H_0 : b_{21} = a_{21} = 0$ needs to be tested. If the null hypothesis is rejected, it can be concluded that oil price fluctuations will spill over into the stock market. The results are consistent with the studies done by Fotros and Hoshidari (2017), Mamipour and Feli (2017), Karimi et al. (2018), Botshekan and Mohseni (2018), Karimi et al. (2020).

### Table 2 Results of VAR-GARCH–TBEKK model for scales D1 and D2

| Variable (D1)          | Variable (D2)          |
|------------------------|------------------------|
| Mean Model(DS1)        | Mean Model(DS2)        |
| Constant               | -22.0518 (26.3022)     | Constant               | -93.1099 (20.4576) * |
| DS1_{t-1}              | -0.4112 (0.0497) *     | DS2_{t-1}              | 0.0833 (0.0326) *    |
| DO1_{t-1}              | -2.3685 (10.2602)      | DO2_{t-1}              | 2.7516 (6.8184)      |
| Mean Model(DO1)        | Mean Model(DO2)        |
| Constant               | 0.0666 (0.0339) **     | Constant               | 0.1143 (0.0470) *    |
| DS1_{t-1}              | -0.00004 (0.00002) **  | DS1_{t-1}              | 0.00001 (0.0000) *** |
| DO1_{t-1}              | -0.1060 (0.0342) *     | DO1_{t-1}              | 0.0655 (0.0307) **   |

Conditional variance–covariance equations

|             | Variable (D1)          | Variable (D2)          |
|-------------|------------------------|------------------------|
| C(1,1)      | 333.9813 (20.3449) *   | C(1,1)                 | 248.6327 (24.0156) * |
| C(2,1)      | -0.0108 (0.1025)       | C(2,1)                 | 0.2031 (0.0925) **   |
| C(2,2)      | 0.8761 (0.0382) *      | C(2,2)                 | 0.9674 (0.0494) *    |
| a(1,1)      | 0.5971 (0.0506) *      | a(1,1)                 | 0.8875 (0.0525) *    |
| a(2,1)      | -0.00004 (0.00003) *** | a(2,1)                 | -0.00002 (0.00001) **|
| a(2,2)      | 1.0198 (0.0562) *      | a(2,2)                 | 0.8738 (0.0559) *    |
| b(1,1)      | 0.8099 (0.0207) *      | b(1,1)                 | 0.6402 (0.0206) *    |
| b(2,1)      | -0.00003 (0.00003)     | b(2,1)                 | 0.00003 (0.00001) ** |
| b(2,2)      | -0.0354 (0.0536)       | b(2,2)                 | -0.0634 (0.0960)     |

The standard errors of coefficients are presented in parentheses. *, **, *** is presented significant at 1%, 5%, and 10% levels respectively.
The results demonstrate that oil price volatility is transmitted to Iran’s stock market in all time scales. Consequently, stock price fluctuations are affected by exogenous oil prices in both the short and long term.

A comparison of the results of the Wald test at different time scales (levels) shows that although the null hypothesis is rejected at all levels and the stock market is affected by oil price shocks, their significance levels are different. That is, the oil price fluctuations over the long-term (D4) are more significant than for the short-term (D1), indicating that long-term oil price volatility spillover on stock market fluctuations is more dominant.

Following the analysis of the results, it can be argued that, first, according to the capital asset pricing model, the asset prices at any point in time are equal to

| Table 3 | Results of VAR-GARCH–TBEKK model for scales D3 and D4 |
|---------|--------------------------------------------------|
| Variable (D3) | Variable (D4) |
| Mean Model(DS3) | Mean Model(DS4) |
| Constant | -39.4558 (24.3267) *** |
| DS3t-1 | 0.3464 (0.0311) * |
| DO3t-1 | 5.4162 (7.1586) |
| Mean Model(DO3) | Mean Model(DO4) |
| Constant | 0.0220 (0.0472) |
| DS3t-1 | -0.000004 (0.000005) |
| DO3t-1 | 0.2921 (0.0264) * |

Conditional variance–covariance equations

| C(1,1) | 202.7700 (22.0986) * |
| C(2,1) | 0.1232 (0.1099) |
| C(2,2) | 0.7140 (0.0437)* |
| a(1,1) | 0.5855 (0.0338) * |
| a(2,1) | 0.000001 (0.000008) ** |
| a(2,2) | 0.8141 (0.0452) * |
| b(1,1) | 0.8494 (0.0136) * |
| b(2,1) | -0.00002 (0.000005) * |
| b(2,2) | 0.5081 (0.0445) * |

| Table 4 | Wald test results of OPEC oil price volatility spillover to the Iran stock market |
|---------|--------------------------------------------------------------------------------|
| Hypothesis | Restrictions | Level | Chi-Squared | P-value | Result |
| There is not oil price volatility spillover on stock market | a(2,1)=b(2,1)=0 | 1 | 7.035 | 0.029 | Reject |
| | | 2 | 9.663 | 0.007 | Reject |
| | | 3 | 21.117 | 0.00002 | Reject |
| | | 4 | 30.508 | 0.0000 | reject |

The standard errors of coefficients are presented in parentheses. *, **, *** is presented significant at 1%, 5%, and 10% levels respectively.
the present value of the expected future cash flows of that asset. This cash flow is clearly influenced by macroeconomic variables such as oil price fluctuations. Thus, it is obvious that the stock market absorbs information about the consequences of oil shocks and reflects it on stock prices (Bjørnland 2009). Secondly, Iran is one of the world’s largest oil producers, where the government earns oil revenues, and its monetary and fiscal policies are fully affected by the oil market shocks. Therefore, Iran’s macroeconomic variables, such as budget revenues, government investment, inflation, and economic growth, are highly dependent on oil price fluctuations. Furthermore, the way oil revenues are managed in Iran requires oil shocks to be transmitted directly to macroeconomic variables (Mamipour et al. 2021). As a result, the oil price volatility spillover on the stock market occurs both in the short and long run. And given that the impact of oil shocks on macroeconomic variables is more visible in the long run, the spillover effect of oil price on the stock market is more meaningful in the long run.

5 Conclusion

The complex structures of today’s economies cause losses in one sector or one country to spread rapidly to other sectors or other countries. Experimental evidence demonstrates that markets are not disconnected and that their operations do not take place in isolation. Accordingly, fluctuations in the various asset markets are strongly correlated. Identifying the structure of the relationships between markets in a situation where shocks in one market can create significant volatility in another is of particular importance for authorities and investors. The authorities, for instance, can initiate measures to avoid or mitigate any political and security consequences of events in financial markets, while shareholders and investors can opt for more diversified low-risk portfolios to secure appropriate profits and preserve their capital.

The present paper examined the spillover of oil price fluctuations on the stock market using the wavelet transform and multivariate GARCH analysis methods. These methods allow such spillover fluctuations to be examined at different time scales in both the short and long term. Based on the wavelet transform, the findings revealed that fluctuations from oil to stock markets occurred at all levels. However, due to significant coefficients of transmissions across markets, the volatility spillover effects from the oil market to Iran’s stock market are more pronounced in the long term compared to the short. Overall, the results indicate the enormous impact that global oil markets have on Iran’s stock market. Consequently, as a country with abundant oil resources, Iran is always affected by external oil prices shocks and impulses in the world market. Any movements or fluctuations in oil markets are transmitted to the stock market leading to its volatility as well as increased risks for investors. Oil shock transmissions to the stock market are more pronounced over the long term and tend to deter less risk-tolerant investors. They also impact other financial sectors such as the currency markets and real assets, including gold.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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