Petroleum Business Review, Vol. 6, No. 3, pp. 41–54, July 2022

The Impact of Iranian Oil Sanctions on The Oil Market Volatility Spillover Network

Habib Ansari Samani[a*] and Samaneh Bagheri[b]

[a] *Assistant Professor, Faculty of Economics, Management and Accounting, Yazd University, Yazd, Iran, Email: ha.ansarisa@gmail.com*

[b] *Ph.D. Student, Faculty of Economics, Management and Accounting, Yazd University, Yazd, Iran, Email: samabagheri90@yahoo.com*

ARTICLE INFO

Keywords:
Iranian oil sanction
Complex network
Oil market
Diebold–Yilmaz spillover index

Received: 20 August 2021
Revised: 05 December 2021
Accepted: 02 January 2022

How To Cite:

Habib Ansari Samani, Samaneh Bagheri; (The Impact of Iranian Oil Sanctions on the Oil Market Volatility Spillover Network; *Vol. 6, No. 3, pp. 40–54, July 2022*

DOI:10.22050/pbr.2022.300673.1219

ABSTRACT

This study examines the effect of sanctions on Iran's oil on the international oil market network for the first time with complex network analysis (CAN) using Diebold–Yilmaz and Arch indices from 1991.01 to 2019.12. The analysis was performed in two periods before and after the sanctions, and the results were compared. The results show that the Iranian oil market in both networks before and after the sanction is one of the influential nodes in the oil network. The volatility spillover of the Iranian oil market in the oil network market has increased after the sanctions. Further, the volatility spillover from other oil markets increases after the sanction. Nevertheless, the sanction has not significantly impacted the oil market network. The Iranian oil market volatility is received before the sanction in the network, but its role changes after the sanction, becoming a sender node.

1. Introduction

Oil is a strategic and vital commodity and a raw material for industrialized countries, and it is an influential market for all their financial markets. Oil and gas connect Iran to the international community and their regional and global market. This connection has become particularly important during the sanctions, which shows that changes in these sectors have affected domestic affairs and determined the country's international situation.

In the years following the victory of the Islamic Revolution and the US embassy incident on November 4, 1979, and the Iranian government's support for some regional developments as well as its nuclear program, Iran formally faced trade and economic sanctions from the United States and European countries. Of course, these sanctions have been accompanied by ups and downs over 43 years. For example, in 2012, the purchase of Iranian oil was banned and had many effects, including currency shocks, on Iran's connection. However, on December 17, 2015, some of these sanctions were lifted. Furthermore, following the

* Corresponding Author

withdrawal of the United States from the Joint Comprehensive Plan of Action, significantly since November 5, 2016, sanctions have intensified.

US government officials have called sanctions against Iran the most burdensome and most crippling in the history of human civilization. However, the question is how much these sanctions have affected Iran and the world's economy. Because Iran produces about 14% of the world's oil and ranks third, these sanctions can hurt global markets and other economies. Various studies show that sanctions, in addition to the sanctioning and sanctioned country, negatively affect other countries and markets. Numerous studies have been conducted in this field, and some believe that the side effects of sanctions on the global economy are significant (Moeeni. 2021; Sanandaji, 2018; Simonov, 2015; Yang et al., 2004).

One of the goals of international sanctions has been to stop Iran's nuclear activities by putting pressure on the government by reducing its sources of income, especially oil revenues. Since Iran's role in the global oil market is essential, the Iranian oil sanctions have caused changes in the world oil market. This study examines whether Iranian oil sanctions have changed the transmission network of fluctuations in the global oil market. It seeks to answer whether the Iranian oil sanction has affected the international oil market. Has there been a change? How has the change in the oil market network been? Furthermore, what does this change mean?

Hence, the complex network analysis method with Diebold and Yilmaz index (2012) and ARCH model, which in various research in financial markets (Memon and Yao, 2019; Gao et al., 2017; Kang and Lee, 2019) and recently in energy markets (Liu et al. 2020) has been used. The data for the period before and after the oil sanction on Iran, i.e., 1991.01 to 2019.12, are related to the two periods before the intensification of oil sanctions: 1991.01 to 2012.3 and after the 2012.03 sanctions. Sanctions appear to have made Iranian oil more influential than the global oil market.

2. Theoretical background and literature review

Financial spillover is when disturbances are transmitted from one market to another. Financial spillover can cause financial stress and seriously damage the country's economy. The mechanism of fiscal spillover can be explained through the effects of spillovers and financial crises caused by the behavior of governments, investors, and borrowers (Noroozifar et al., 2019). Fiscal spillover is an increase in the interrelationship of markets, defined as a shock to a country or a group of countries (Forbes and Rigobon, 2002). The countries that boycott Iran's oil consider the removal of the oil sanctions on Iran, the deprivation of Iran from oil revenues, and a way to force it to resolve its nuclear ambiguities. These sanctions include sanctions on buyers and tanker insurance or banking sanctions and are a way to dissuade customers (Fredrick, 2008). The studies of Shaffer (2012), Geng et al. (2014), Nagayama and Horita (2014), Zhong et al. (2014), Chen et al. (2016), Kaya and Eren (2016), Due et al. (2017), Sun et al. (2017), Fracasso et al. (2018), Chen et al. (2018), Woroniuk et al. (2019), Semanour et al. (2020) and Peng et al. (2021) have focused on the network method.

The following studies can be mentioned among the studies that have examined the energy market network.

Woroniuk et al. (2019) examined the European gas market, commercial hubs, and price formation from a network perspective from 2016 to 2018. The results of this study indicate that the natural gas trade in Europe is developing in the short term. Still, each hub has unique features that provide a different rate of development and integration.

Semanour et al. (2021) studied the global liquefied natural gas network and the maritime transport landscape using a complex network from 2013 to 2017. This study shows that analyzing the transportation pattern is vital for optimizing trade strategies between countries and ensuring energy imports and exports. Closer trade relations characterize the liquefied natural gas transmission network. The global liquefied natural gas network is linked to three nearby trade zones.

From the studies that have used the complex network method, Rahimi Baghi and Arab Salehi Nasrabadi (2018) investigated systemic risk in the financial system using the Granger casualty network.

Raei et al. (2010) studied the analysis of the Tehran Stock Exchange market using complex networks based on the threshold method. Dastkhan and Shams Gharniyeh (2017) reviewed and compared assessment indicators in financial networks in the Tehran Stock Exchange by complex network analysis (can).

Chowdhuri et al. (2019) examined network changes in financial system communication as an Asian experience. They concluded that the financial markets of countries weekend after the financial crisis and that many financial markets were connected through financial markets established with global markets.

The studies that examined the oil market during financial crises can be found in Ebrahimi et al. (2016), which examined the price regimes of the two major indicators of the global oil market before and after the financial crisis: an application of the Markov switching approach. Mollic and Asefa (2013) examined oil prices and stock markets using the Garch and MGARCH-DCC methods. The results indicated that oil prices and exchange rates had a negative effect on stock returns before the financial crisis, but this effect has been positive since 2009.

Lahmiri (2016) studied the turmoil in the crude oil markets during the international financial crises before and after 2008 with the Lyapunov test. The results showed no price turmoil in both crude oil markets before and after the financial crisis. Further, there was a post-financial crisis in both the Brent and West Texas fluctuation. Karunanayake et al. (2010) examined the effect of stock market returns and fluctuation on each other in four countries: Australia, the United States, the United Kingdom, and Singapore. Using the multivariate Garch approach, they confirmed the one-way effect of returns from the United Kingdom stock markets to the Singapore and Australian markets and the effects of joint fluctuations in all four markets. Fry-Mckibbin and Hsiao (2015) also examined the turbulence caused by their 2008 global crises from the United States banking sector to the stock market and global banking sector. Their results showed turbulence spread from the United States banking sector to other sectors.

As a review of the research background shows, in oil market studies, no research has examined the network of these markets. So far, few studies have examined the effect of Iran's oil sanctions on oil markets. This study, for the first time, examines the network of oil markets and compares these markets before and after the Iranian oil sanctions

3. Data and methods

3.1. Complex network

A network is a set of vertices or nodes, and the connections are called edges (Baggio 2008). Nodes can be an individual, a group, an organization, and a country. The connections between nodes are examined in network analysis, and these connections can be directional and without direction or weighted. One of the simplest types of networks is the directional dual communication network, which only indicates the presence or absence of communication between nodes. If the network is directional, it is called an arc; if it is directionless, it is called an edge (Hogan 2007). In a weighted communication network mode, the weight indicates the amount, frequency, or intensity of communication (Wasserman et al., 1994; Garton et al., 1999; Scott, 1991). A complex network consists of several nodes and hubs (nodes with a high degree of connection) connected by edges. This approach considers market complex relationships as a network. The network $G=(V,E)$ consists of nodes and edges. $V=(1,2, \dots, N)$ includes the node, and E is composed of edges and shows the relations of spillovers between markets; i and j show the nodes in the network, and e_{ij} indicates the connection between nodes i and j (Zhang et al., 2020). The CNA approach in our study is based on Diebold–Yilmaz (2014, 2015), and VAR analysis and causality are based on Billio et al. (2012).

3.2. Diebold–Yilmaz spillover index

The AR (p) model is as follows:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t \qquad (1)$$

where y is a vector in time, c is a fixed vector, u is a k × 1 vector, a vector of the error term per unit of time, and A is a matrix of K × K coefficients. Equation (1) can be written as Equation (2).

$$Y_t = c + A_1 Y_{t-1} + U_t \qquad (2)$$

A is a matrix with $K_p \times K_p$, and C, Y, and U are $K_p \times 1$ matrixes.

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2 & \cdots & \mathbf{A}_{p-1} & \mathbf{A}_p \\ \mathbf{I}_K & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_K & \mathbf{0} & \mathbf{0} & \\ \vdots & \ddots & \vdots & \vdots & \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I}_K & \mathbf{0} \end{bmatrix}, \quad Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_P \end{bmatrix}, C = \begin{bmatrix} c \\ 0 \\ \vdots \\ 0 \end{bmatrix} U = \begin{bmatrix} U_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

After the estimation, analysis of variance shows how much each variable explains the other variables. The average squared error is shown below.

$$\text{MSE}[y_{it}(H)] = \sum_{j=0}^{H-1} \sum_{k=1}^{k} (e_i' \theta_j e_k)^2 \qquad (3)$$

where e_i is the most critical column of I_K and $\theta_j = P\emptyset_j$ P is a bottom triangle matrix.

Analysis of variance-covariance can be expressed in Equation (4).

$$\Omega_u = E(u_t u_t'),\ \phi_j = JA^jJ' \qquad (4)$$

where $J = [Ik, 0....0]$, and k is represented by Equation (5) (Zhang et al. 2017).

$$\theta_{ik,H} = \sum_{j=0}^{H-1} (e_i' \theta_j e_k)^2 / \mathrm{MSE}[y_{it}(H)] \qquad (5)$$

All research variables are estimated according to Zhang et al. (2020) and Chowdhuri et al. (2019), as Ln $[pt/\mathrm{pt} - 1] \times 100$. According to Zhang (2017), the Diebold–Yilmaz index is used for spillover between oil markets.

This study investigates Iran's oil sanctions effect on the international oil market networks from 1991.01 to 2019.12 before and after the Iranian oil sanctions. Because oil sanctions were imposed on Iran's oil in 2012.2, we split monthly data into two periods: 1991.01 to 2012.02 and 2012.3 to 2019.12. Complex network nodes include Iran, Oman, Norway, West Texas, Brent, Saudi Arabia, UAE, Nigeria, Egypt, Libya, Mexico, Russia, Indonesia, Algeria, and Malaysia. The monthly data are obtained from the OPEC website. In this study, Gephi, Pajek, and Eviews software were used.

4. Results

4.1. Complexity network with Diebold–Yilmaz spillover index

Table 1: The volatility spillover matrix before the Iranian oil sanction based on the relationship between the financial markets of Diebold and Yilmaz (2009)

	Iran	Algeria	Angola	brent	Egypt	Indonesia	Libya	Malaysia	Mexico	Nigeria	Norway	Oman	Russia	Saudi Arab	United Arab emirate	WTI
Iran	7.0	6.2	6.2	6.4	6	5.1	6.3	5.8	6.3	6.2	6.3	6.7	6.6	6.4	6.5	5.9
Algeria	6.2	6.8	6.6	6.7	6.5	4.9	6.7	5.7	6.4	6.7	6.7	6.2	6.2	5.8	6	5.9
Angola	6.2	6.6	6.8	6.7	6.5	5.1	6.6	5.6	6.4	6.6	6.6	6.2	6.2	6	6.1	5.9
brent	6.2	6.6	6.6	6.7	6.5	4.9	6.7	5.6	6.4	6.6	6.7	6.2	6.2	6	6.1	5.9
Egypt	6.1	6.7	6.6	6.7	7	4.7	6.7	5.4	6.4	6.7	6.7	6.2	6.2	6	6.1	5.8
Indonesia	6.4	6	6.2	6.1	5.7	8	6	6.7	6.1	5.9	6	6.5	6.4	6.1	6.3	5.7
Libya	6.2	6.7	6.6	6.7	6.5	4.9	6.8	5.6	6.5	6.6	6.7	6.2	6.2	5.9	6.1	5.9
Malaysia	6.4	6.3	6.3	6.3	5.9	6	6.3	7.4	6.2	6.2	6.2	6.4	6.3	6	6.2	5.8
Mexico	6.2	6.5	6.5	6.5	6.3	4.9	6.5	5.6	6.9	6.4	6.5	6.3	6.2	6.1	6.1	6.5
Nigeria	6.2	6.7	6.7	6.7	6.5	4.8	6.7	5.6	6.4	6.8	6.7	6.2	6.2	5.9	6.1	5.9
Norway	6.2	6.7	6.6	6.7	6.5	4.8	6.7	5.6	6.4	6.7	6.8	6.2	6.2	5.9	6.1	5.9
Oman	6.5	6.1	6.2	6.3	6.1	5	6.2	5.6	6.2	6.1	6.2	7	6.9	6.7	6.9	5.8
Russia	6.5	6.2	6.2	6.3	6.1	5	6.2	5.7	6.2	6.1	6.2	7	7	6.7	6.8	5.8
Saudi Arabia	6.5	6	6.2	6.2	6	4.9	6.1	5.4	6.2	6	6.1	7	6.9	7.3	7.1	5.8
United Arab Emirates	6.5	6.1	6.2	6.3	6.1	5	6.2	5.5	6.2	6.1	6.2	7.1	7	6.9	7.1	5.8
WTI	6.3	6.4	6.3	6.4	6.1	4.9	6.4	5.6	7	6.2	6.4	6.3	6.3	6.1	6.1	7.3

Table 2: The volatility spillover matrix after the Iranian oil sanction based on the relationship between Diebold and Yilmaz financial markets (2009)

	Iran	Algeria	Angola	Brent	Egypt	Indonesia	Libya	Malaysia	Mexico	Nigeria	Norway	Oman	Russia	Saudi Arab	United Arab Emirates	WTI
Iran	6.6	6.4	6.5	6.4	6.5	5.3	6.4	6.4	5.8	6.5	6.4	6.3	6.4	6.1	6.3	5.7
Algeria	6.4	6.5	6.5	6.5	6.5	5.4	6.5	6.4	5.9	6.5	6.5	6.2	6.3	6	6.2	5.7
Angola	6.4	6.4	6.6	6.4	6.4	5.3	6.4	6.4	5.9	6.5	6.4	6.3	6.4	6	6.3	5.7
Brent	6.4	6.5	6.5	6.5	6.4	5.3	6.5	6.4	5.9	6.5	6.5	6.3	6.3	6	6.3	5.8
Egypt	6.5	6.4	6.5	6.4	6.5	5.3	6.4	6.3	5.9	6.4	6.4	6.3	6.4	6.1	6.3	5.7
Indonesia	6.2	6.3	6.4	6.3	6.3	7.2	6.4	6.2	5.9	6.3	6.3	6.1	6.2	5.8	6.1	6
Libya	6.4	6.5	6.5	6.5	6.4	5.4	6.5	6.3	5.9	6.5	6.5	6.3	6.3	6	6.2	5.8
Malaysia	6.5	6.5	6.5	6.4	6.4	5.3	6.4	6.5	5.9	6.5	6.4	6.3	6.4	6	6.2	5.8
Mexico	6.3	6.3	6.4	6.3	6.3	5.4	6.4	6.3	6.7	6.4	6.3	6.2	6.3	5.9	6.2	6.3
Nigeria	6.4	6.5	6.6	6.5	6.4	5.3	6.5	6.4	5.9	6.6	6.5	6.3	6.3	6	6.3	5.7
Norway	6.4	6.5	6.5	6.5	6.4	5.3	6.5	6.4	5.8	6.5	6.5	6.2	6.3	6	6.2	5.7
Oman	6.4	6.3	6.4	6.4	6.4	5.2	6.4	6.3	5.8	6.4	6.3	6.6	6.6	6.4	6.6	5.6
Russia	6.4	6.3	6.5	6.4	6.4	5.3	6.4	6.3	5.8	6.4	6.3	6.5	6.7	6.3	6.5	5.7
Saudi Arabia	6.4	6.3	6.4	6.4	6.4	5.1	6.3	6.2	5.7	6.3	6.3	6.7	6.6	6.7	6.7	5.5
United Arab Emirates	6.4	6.3	6.4	6.4	6.4	5.2	6.4	6.3	5.7	6.4	6.3	6.6	6.6	6.4	6.6	5.6
WTI	6.3	6.3	6.3	6.3	6.3	5.5	6.3	6.2	6.4	6.3	6.2	6.1	6.3	5.8	6.1	7.2

Comparing Tables 1 and 2 for the Diebold and Yilmaz indices shows an intensification in fluctuations transferred from Iran to other markets after the sanctions. Further, there is an increase in transmitted fluctuations to Iran for most oil markets except for Mexico, Oman, Russia, Saudi Arabia, UAE, and WTI. These results are also confirmed in Tables 3 and 4.

Table 3: Average net directional spillover in oil markets before the oil sanction

Oil market	Spillover from other oil markets	Spillover to other oil markets	Average net directional spillover
The period before the Iranian oil sanction			
	From others	**To others**	
Iran	93	94.7	–1.7
Algeria	93.2	95.8	–2.6
Angola	93.2	95.9	–2.7
Brent	93.3	97.2	–3.9
Egypt	93	93.3	–0.3

Oil market	Spillover from other oil markets	Spillover to other oil markets	Average net directional spillover
Indonesia	92	74.8	17.2
Libya	93.2	96.2	–3
Malesia	92.6	85.1	7.5
Mexico	93.1	95.2	–2.1
Nigeria	93.2	94.9	–1.7
Norway	93.2	96.3	–3.1
Oman	93	96.7	–3.7
Russia	93	95.9	–2.9
Saudi Arabia	92.7	92.4	0.3
United Arab Emirates	92.9	94.6	–1.7
WTI	92.7	88.4	4.3

According to Table 3, volatility receivers in international oil markets are Iran, Algeria, Angola, Brent, Egypt, Libya, Mexico, Nigeria, Norway, Oman, Russia, and the United Arab Emirates. The volatility transmitters are Indonesia, Malaysia, Saudi Arabia, and West Texas.

Table 4: Average net directional spillover in oil markets after the oil sanction

Oil market	Spillover from other oil markets	Spillover to other oil markets	Average net directional spillover
The period after the Iranian oil sanction			
	From others	**To others**	
Iran	**93.4**	**96**	**2.6**
Algeria	93.5	95.8	2.3
Angola	93.4	96.9	3.5
Brent	93.5	96.2	2.7
Egypt	93.5	95.8	2.3
Indonesia	92.8	79.6	–13.2
Libya	93.5	96.1	2.6
Malaysia	93.5	94.7	1.2
Mexico	93.3	88.1	–5.2
Nigeria	93.4	96.6	3.2
Norway	93.5	95.5	2
Oman	93.4	94.7	1.3
Russia	93.3	95.8	2.5
Saudi Arabia	93.3	90.9	–2.4
United Arab Emirates	93.4	94.4	1
WTI	92.8	86.3	–6.5

Petroleum Business Review, Vol. 6, No. 3, pp. 41–54, July 2022

A comparison of the results of directional transmission in the oil market before and after the Iranian sanctions shows that the sanctions have changed the status of the fluctuation sender or receiver in all markets. The only exceptions were Malaysia (the sender of the fluctuations before and after the sanctions) and Mexico (the sender of the fluctuations before and after the sanctions). Other markets have changed their status from sender to receiver and from receiver to sender. This shows that the sanctions against Iran have significantly impacted the transmission of fluctuations in the oil market. A transmitter of volatility before the embargo period, Iran has become a recipient of volatility during the embargo period. This has happened to Algeria, Angola, Brent, Egypt, Libya, Nigeria, Norway, Oman, Russia, and the United States. The opposite is Saudi Arabia and Indonesian WTI markets that were formerly recipients and became the sender of the volatility after the sanctions.

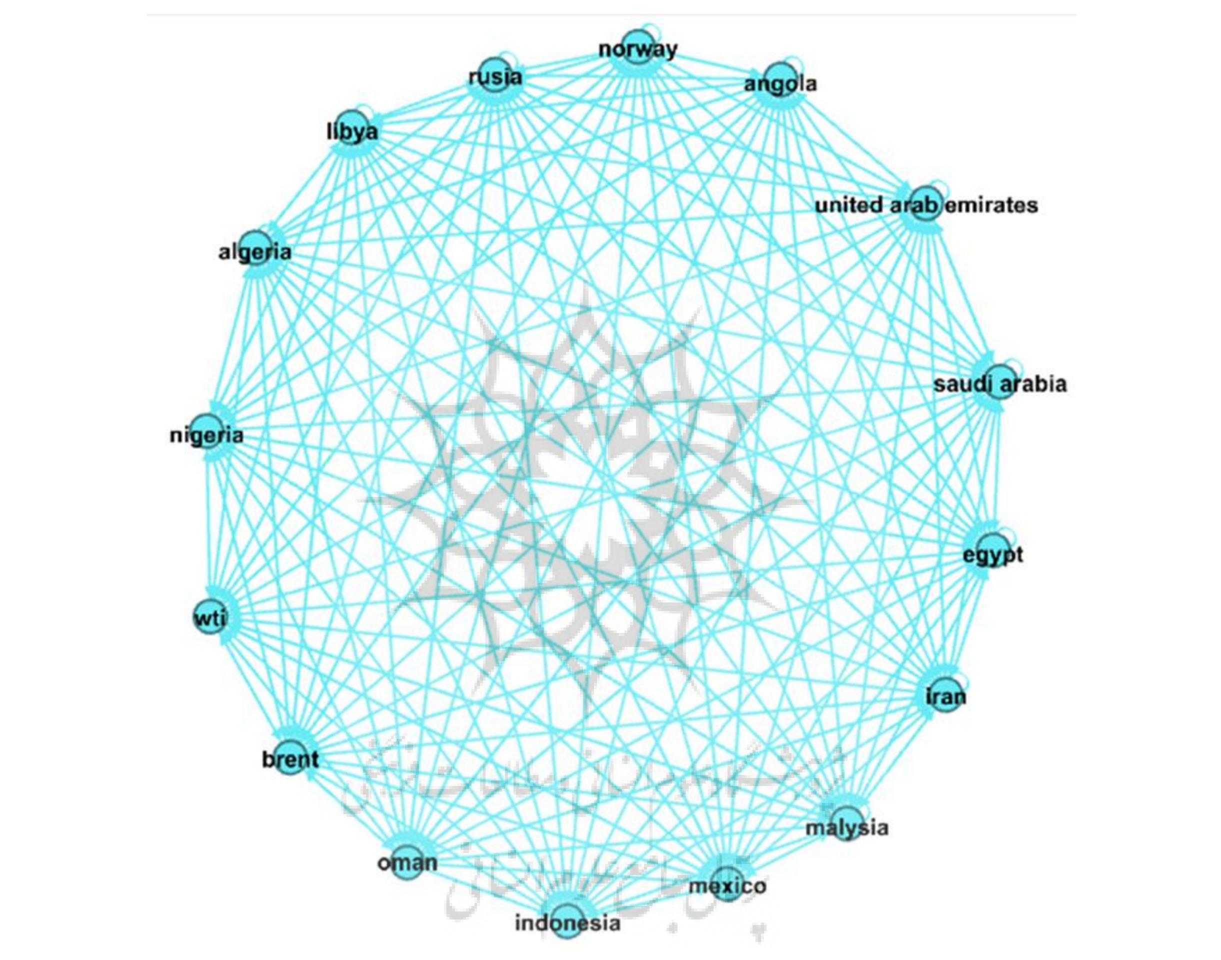

Figure 1: The complex network of oil markets before the Iranian sanction

Table 5: The complex network of the oil market before the Iranian oil sanctions

Label	Weighted degree	Weighted out-degree	Weighted indegree
Russia	203.9	103	100.9
Oman	200.9	103.7	97.2
Saudi Arabia	200.4	99.8	100.6
Norway	203.4	103	100.4
United Arab Emirates	197.3	101.7	95.6
Nigeria	203.1	101.9	101.2
WIT	197.2	95.6	101.6

Label	Weighted degree	Weighted out-degree	Weighted indegree
Iran	200.5	100.6	99.9
Mexico	203.9	102.2	101.7
Algeria	199	98.8	100.2
Malaysia	200	101.2	98.8
Angola	202.5	101.8	100.7
Libya	201.7	103.1	98.6
Brent	204	103.2	100.8
Indonesia	179.5	79.1	100.4
Egypt	200.7	100.3	100.4

Based on the change in the in-degree and out-degree indices, in Table 5, the most affected oil markets are WTI, Mexico, Nigeria, and Russia Brent; the least affected markets are United Arab Emirates, Oman, Libya, and Malaysia. Oman, Brent, Libya, Norway, and Russia are the most affected markets. Furthermore, the least affected markets are Indonesia, WTI, Algeria, Saudi Arabia, and Egypt.

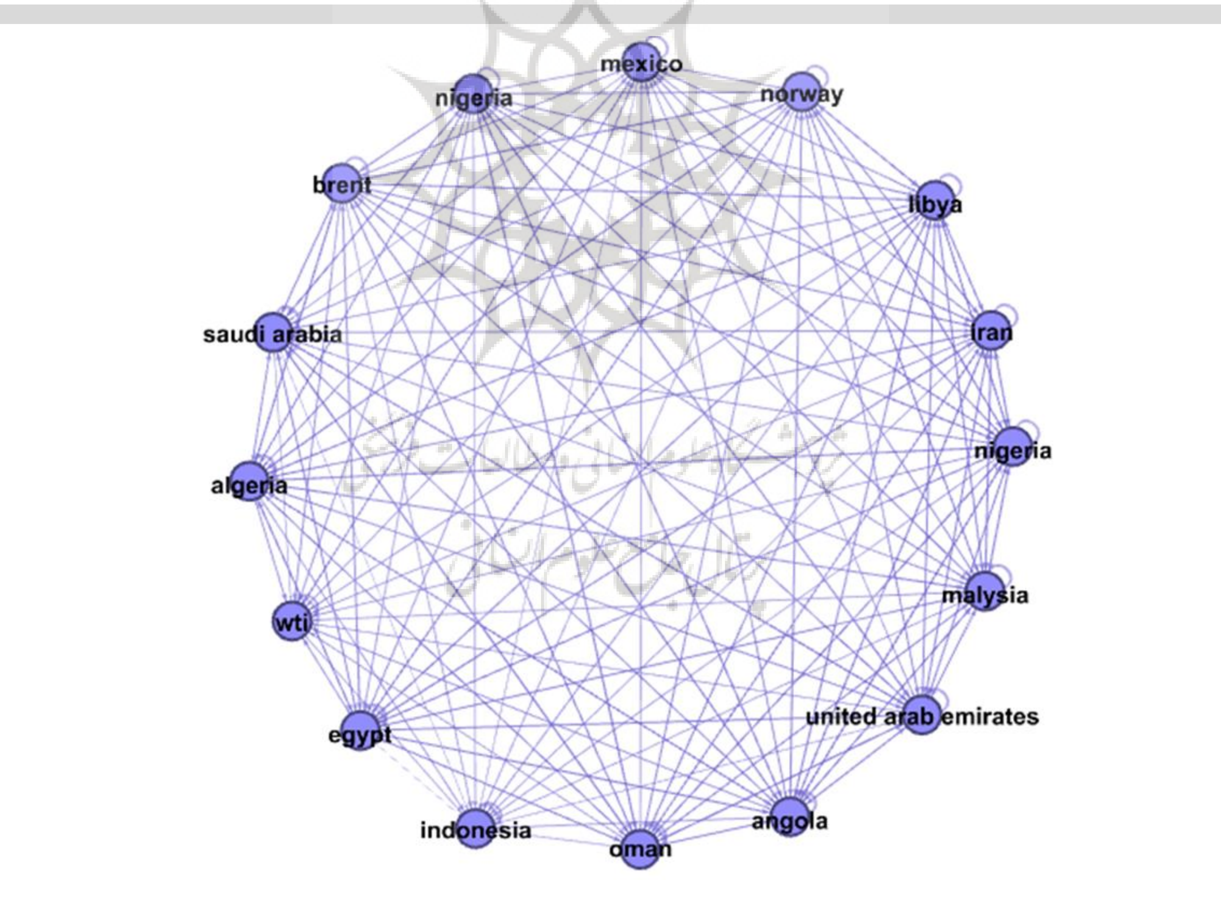

Figure 2: The complex network of oil markets after the Iranian oil sanctions

The most significant increase in inflows and outflows is related to the United Arab Emirates and Libya. The most significant decrease in inflows is also related to Nigeria, Indonesia, and Mexico. The most significant decrease in the output flow is related to Mexico, Saudi Arabia, and WTI, and the highest increase in output is related to Indonesia, Algeria, and Iran. The most significant decrease in the degree of relations is related to Mexico, followed by WTI and Saudi Arabia. The most significant increase in the overall degree is related to Indonesia, the United Arab Emirates, and Algeria. As the results show, Iran has not changed much in the degree of entry or exit or, overall, after the sanctions, indicating that the sanctions have not been able to change Iran's position in the world oil network regarding risk conditions. However, the results show that Iran has become a more influential node after the sanction. Sanctions have made Iran the most effective node in the network. Table 6 shows the characteristics of the oil markets after the Iranian oil sanction.

Table 6: The complex network of the international oil market after the Iranian oil sanction

Label	Weighted degree	Weighted out-degree	Weighted indegree
Nigeria	201.6	102.4	**99.2**
Oman	201.4	101.3	**100.1**
Saudi Arabia	197.5	97.5	**100**
Norway	201.7	102	**99.7**
United Arab Emirates	201.1	101.1	**100**
Nigeria	203.2	103	**100.2**
WTI	193.4	93.5	**99.9**
Iran	**202.4**	**102.4**	**100**
Mexico	194.9	94.9	**100**
Algeria	202.3	102.3	**100**
Malaysia	200.8	100.8	**100**
Angola	203.2	103.5	**99.7**
Libya	202.7	102.7	**100**
Brent	202.2	102.6	**99.6**
Indonesia	185.8	86.8	**99**
Egypt	200.2	100.4	**99.8**

The Libyan market has the most negligible influence in this network, and Malaysia and the Angola oil market will have the least impact on their complex network. After the sanction on Iranian oil, the centrality of proximity has increased, and the weight of the node has decreased.

Table 7: Comparison of complex networks before and after oil sanctions

Network properties	After the sanction	Before the sanction
Average degree	32	**32**
Average weighted degree	38.44	**35.173**
Graph density	1.06	**1.06**
Average path length	1	**1**
Average clustering coefficient	0.94	**0.94**

The proximity centrality index measures the number of steps it takes to move its fit from one node to another in the network. A node with a high proximity centrality can communicate faster with other nodes. The average of the shortest path length indicates the average of the closest path that both nodes in the network can communicate with each other. In the international oil network, before the sanction, Saudi Arabia was less affected than other nodes of the network, and the UAE was less influential than the other nodes.

The clustering coefficient measures the number of nodes that tend to fit together in a cluster. In other words, it is used to investigate the close relationship of nodes in the oil network. This index also has a value between zero and one and indicates correlations or coherence in the networks. The higher the value of the clustering coefficient, the closer the neighbors of a node are to each other. The average clustering coefficient in each network is high. Therefore, it shows the high cohesion of both networks. According to Table 7, the average path length, network density, average clustering coefficient, and average path length in the network before and after the sanctions on the Iranian oil market have not changed. Due to the reduction of the Iranian oil market volatility spillover in the second network, the average weight of the network has decreased in the second network.

4.2. Complexity network with ARCH method

Table 8: The network before the Iranian oil sanction

	In degree	Out degree	Degree	Weighted in degree	Weighted out-degree	Weighted degree	Closeness centrality	Betweenness centrality
Iran	5	7	12	1.45	0.95	2.4	0.65	12.30
Saudi Arabia	7	5	12	1.52	0.98	2.5	0.57	8.75
Algeria	7	9	16	2.73	2.64	5.37	0.71	22.07
Angola	9	5	14	1.5	0.77	2.27	0.6	16.86
Brent	5	5	10	1.3	2.47	3.77	0.57	9.80
Egypt	8	9	17	2.46	2.34	4.8	0.71	17.42
Indonesia	2	6	8	0.8	1.14	1.94	0.5	2.55
Malaysia	6	5	11	1.59	2.08	3.67	0.57	11.79
Mexico	6	6	12	1.76	2.44	4.2	0.6	4.29
Nigeria	5	4	9	1.45	0.87	2.32	0.53	6.59
Norway	4	3	7	0.98	0.82	2.32	0.53	2.79
Oman	9	10	19	2.89	3.72	6.61	33.22	0.75
Russia	2	3	5	0.95	0.84	1.79	1.08	0.51
United Arab Emirates	6	5	11	2.3	1.51	3.81	0.57	8.75
WTI	6	5	11	1.74	1.45	3.19	0.55	3.14

According to Table 6 in the network before the oil sanction, Iran's influence on seven edges has a weight of 1.45, and Iran's impressiveness weight with five input edges was 0.95.

Table 9: The network after the Iranian oil sanction

	In degree	Out degree	Degree	Weighted in degree	Weighted out-degree	Weighted Degree	Betweenness Centrality	Closeness Centrality
Iran	3	4	7	1.06	1.44	2.5	0.51	6.73
Saudi Arabia	4	6	10	2.66	3.19	5.85	0.6	15.51
Algeria	4	5	9	1.08	1.81	2.89	0.57	10.07
Angola	4	4	8	0.91	1.07	1.98	0.5	4.9
Brent	4	5	9	0.98	5.16	6.14	0.51	16.31

	In degree	Out degree	Degree	Weighted in degree	Weighted out-degree	Weighted Degree	Betweenness Centrality	Closeness Centrality
Egypt	7	7	14	2.8	1.66	4.46	0.62	33.07
Indonesia	3	4	7	1.37	2	3.37	0.53	5.25
Malaysia	6	4	10	2.15	0.85	3	0.55	19.79
Mexico	1	3	4	0.53	0.7	1.23	0.46	2.5
Nigeria	6	4	10	1.38	1.92	3.3	0.5	10.68
Norway	7	5	12	6.49	0.81	7.3	0.55	26.33
Oman	5	4	9	1.09	1.46	2.55	0.5	7.41
Russia	7	6	13	1.66	1.91	3.57	0.57	26.14
United Arab Emirates	6	6	12	1.31	1.99	3.3	0.57	15.20
WTI	3	3	6	1.27	1.98	3.25	0.42	15.86
Libya	2	2	4	1.93	0.72	2.65	0.45	1.11

After the oil sanction on the Iranian oil market, the effectiveness nodes were increased from 0.95 to 1.44, but the number of input edges decreased to 4 output edges. The Iranian oil impressiveness was also reduced to 3 input edges with a weight of 1.06. The complex network based on ARCH shows that the impact of Iranian oil in the oil market network has increased after the Iranian oil sanction, but its impressiveness has decreased.

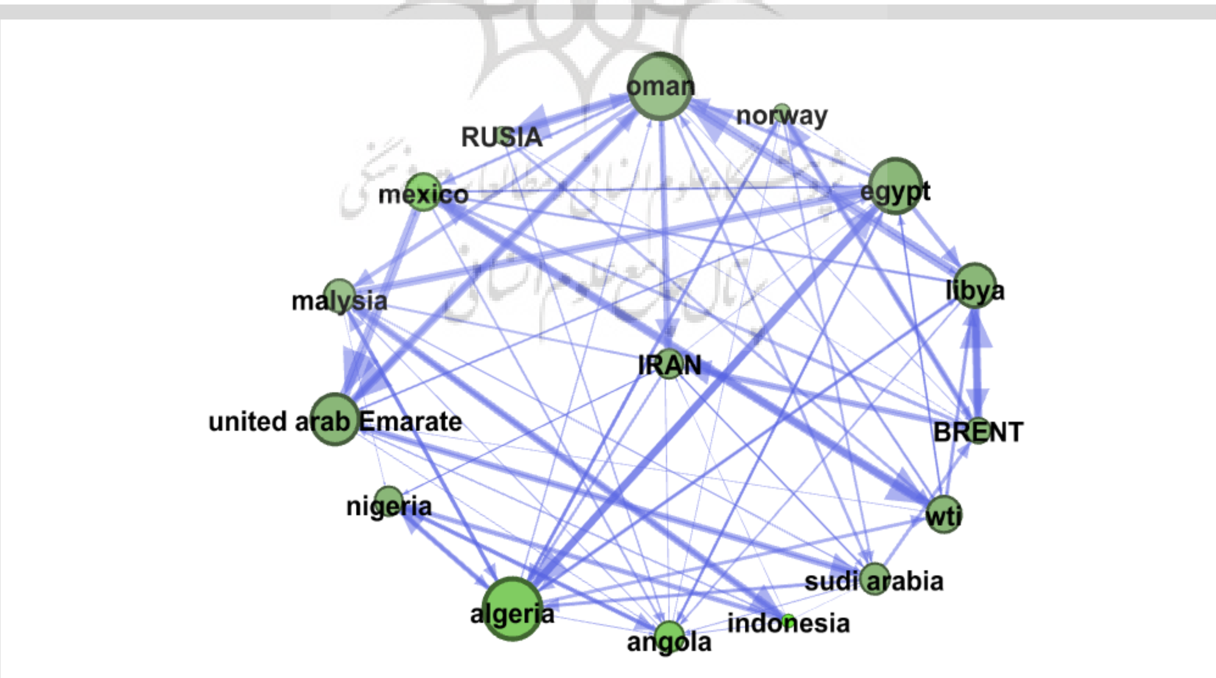

Figure 3: The network before the sanction

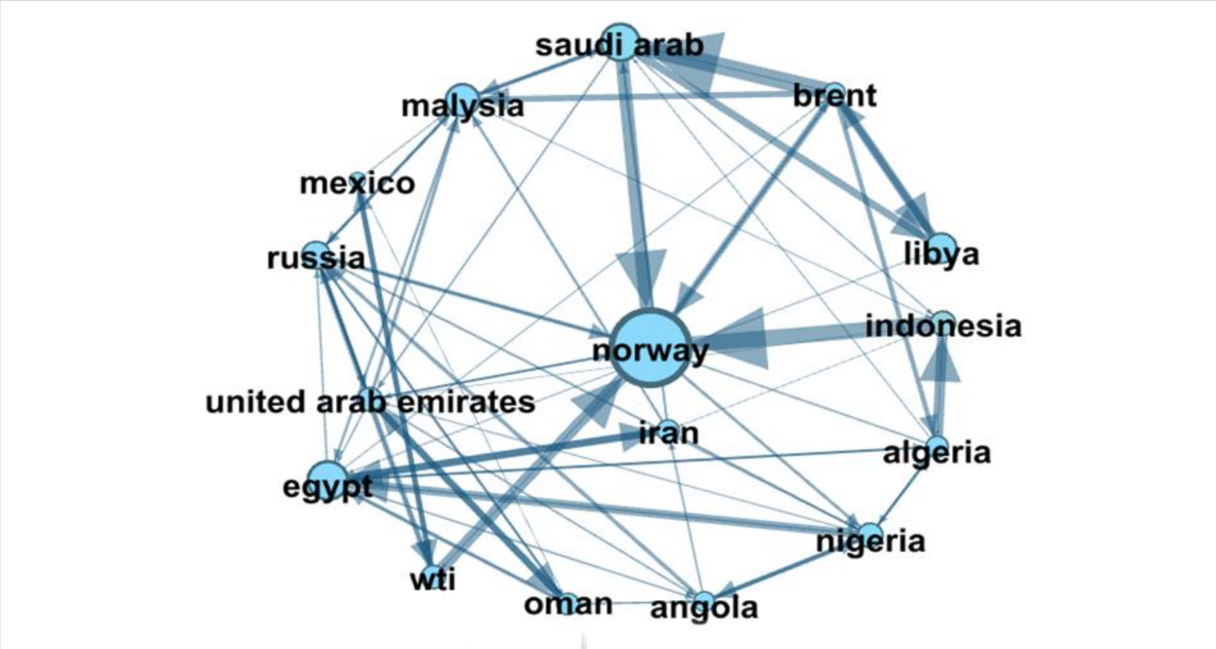

Figure 4: The network after the sanction

Table 10: The comparison of the network with the ARCH method

	Network of oil markets before the sanctions	Network of oil markets before the sanctions
Average degree	5.81	**4.5**
Average weighted degree	1.71	**1.79**
Graph density	0.38	**0.3**
Average path length	1.67	**1.90**

According to Table 10, in the oil market network, in the network after the Iranian oil sanction, the average edge weight, network density, average network length, and average network path length decreased, which indicates a crisis in the network, implying that a fluctuation in times of financial crisis spreads faster and more directly in oil markets. The connection between financial markets and the spillover network is reduced during a financial crisis, and sanctions on the Iranian oil market have acted as a crisis in the network.

5. Conclusions

The oil market is affected by other markets, and spillover in this market is significant for the sellers and buyers of this strategic commodity. In many oil-selling countries, such as Iran, the budget depends on oil revenues, and turbulence in this market is vital for these oil-dependence countries. The United States and Europe oil sanctions began in 2012 to reduce oil revenues against Iran over its nuclear activities. This study analyzed and compared the international oil market network with a complex network approach for two periods: after and before Iranian oil sanctions, 1991.01 to 2012.02 and 2012.3 to 2019.12.

According to the results, Iranian oil sanctions did not affect oil networks. Iran's oil market has become more vulnerable since the sanctions. Moreover, after the sanction, his role changed from a volatile receiver to a volatile transmitter in the oil market. Despite Iran's significant influence in the oil market, the sanction has not significantly impacted the network of oil markets.

The complex network based on ARCH shows that the impact of Iranian oil in the oil market network has increased after the Iranian oil sanction, but its impressiveness has decreased.

Based on the Diebold–Yilmaz complex network, the average path length, network density, average clustering coefficient, and average path length in the network did not change after the sanctions. The average weight of the network decreased in the second network, which has been due to the reduction of the volatility spillover of the Iranian oil market in the second network.

Based on a complex network of the ARCH method, in the network after the Iranian oil sanction, the average edge weight, network density, average network length, and average network path length have decreased, which indicates a crisis in the network, implying that a fluctuation in times of financial crisis spreads faster and more directly in oil markets. The connection between financial markets and the spillover network is reduced during a financial crisis, and sanctions on the Iranian oil market have acted as a crisis in the network.

References

Baggio, R. (2007). Network analysis of a tourism destination. School of Tourism, the University of Queensland, Australia.

Billio, M., Getmansky, M., Lo, A. W., Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics, 104, 535–559.

Chen, Z., An, H., An, F., Guan, Q., and Hao, X. (2018). Structural risk evaluation of global gas trade by a network-based dynamics simulation model, Energy .159: 457–471.

Chowdhury, B, Dungy, M, Kangogo, M, Abu Sayeed, M, Volkov, V (2019). The Changing Network of Market Linlage: The Asian Experience, International Review of Financial Analysis, 64:71–92.

Dastkhan, H, Shams Gharneh, N. (2017). Systemic Risk Measures in Financial Markets: Identifying the Systemically Important Companies in TSE. Journal of risk modeling and financial Engineering.1 (2): 1–21.

Dastkhan, H., and Shams Gharneh, N. (2017). Systemic risk measures in financial markets: identifying the systemically important companies in TSE. Journal of Risk Modeling and Financial Engineering, 2(1), 1–21.

Diebold, F. X., and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, 182, 119–134.

Diebold, F. X., and Yilmaz, K. (2015). Trans-Atlantic equity volatility connectedness: European Financial Institutions, and US 2004–2014. Journal of Financial Econometrics, 14, 81–127.

Diebold, F.X., Yilmaz, K., (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119, 158–171.

Du R., Dong G., Tian, L., Wang Y., Liu Y., Wang M., and Fang, G. (2016). A Complex Network Perspective on Features and Evolution of World Crude Oil Trade", Energy Procedia, 104: 221–226.

Du R., Wang Y., Dong G., Tian L., Liu Y., Wang M., and Fang, G. (2017). A Complex Network Perspective on Interrelations and Evolution Features of International Oil Trade, 2002–2013, 196: 142–151.

Dudlák, T. (2018). After the sanctions: Policy challenges in the transition to a new political economy of the Iranian oil and gas sectors. Energy Policy. 121:464–475.

Ebrahimi, M, Babaei agh Esmaili, M. Kafili, V., (2017), Investigate price regimes of two prime index in the world oil market (Brent and WTI) before and after the financial crisis: Evidence from the Markov regime-switching model. Quantitative Economics. 13(3): 57–83.

Ebrahimi, M., Babaei Agh Esmaili, M., and Kafili, V. (2016). Investigate price regimes of two prime index in the world oil market (Brent and WTI) before and after the financial crisis: Evidence from the Markov regime switching model. Quarterly Journal of Quantitative Economics, 13(3), 57–83.

Forbes, K., and Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market co-movements, The Journal of Finance, 57(5): 2223–61.

Fracasso, A., Hien, T., Nguyen, T., and Schiavo, E. (2018). The Evolution of Oil Trade: A Complex Network Approach, Retrieved from: https://doi.org/10.1017/nws.2018.6.

Fry-McKibbin, R.A., and Hsiao, C.Y. (2015). Extremal dependence tests for contagion, Econometric Reviews, Published online: November 25, 2015: 1–24.

Kagan, Frederick W. (2008). Iranian Influence. Washington DC: American Enterprise Institute.pp.12–32.

Karunanayake, I., and Valadkhani, An O'Brien, M. (2010). Modeling Australian stock market volatility: A multivariate GARCH approach, University of Wollongong, Economics, Working Paper Series.

Kaya, S, S., and Eren, E. (2016). Complex Network Approach to International Trade of Fossil Fuel, International Science Index, Economics and Management Engineering 10(1):52–60.

Kuzubaş,T, Ömercikoğlu,I and Burak, S.(2014). Network centrality measures and systemic risk: An application to the Turkish financial crisis. Physica A.405:203-2015.

Lahmiri, S. (2016). A Study on Chaos in Crude Oil Markets Before and After 2008 International Financial Crisis, Physica A: Statistical Mechanics and its Applications, 466:389–395.

Mollick, A. V and Asefa, T A. (2013).US Stock Returns and Oil Prices: The Tale from Daily Data and the 2008–2009 Financial Crisis. Energy Economics, 36:1–18.

Nowrouzifar, T, Fattahi, S, Sohaili, K. (2019). The Impact of Economic Sanctions on the Amount of Dependence between Oil and Financial Market (Extremal Dependence Approach). Economical Modelling, 1(45):1–17.

Nowrouzifar, Tahereh, Shahram Fattahi, and Kiomars Sohaili (2019). "The Impact of Economic Sanctions on the Amount of Dependence between Oil and Financial Market (Extremal Dependence Approach)." Economic Modeling 13.45: 1–17.

Rahimi Baghi, Ali, Mehdi Arab Salehi, and Mohammad Vaez Barzani. (2019). "Assessing the Systemic Risk in the Financial System of Iran using Granger Causality Network Method." Financial Research Journal 21.1:121–142.

Semanur, S., Huseyin, T., and Halil, O. (2020). An Alternative View to The Global Coal Trade: Complex Network Approach, Studies in Business and Economics no. 15(1): 270–288.

Woroniuk, D., Karam, A., and Jamasb, T. (2019). European Gas Markets, Trading Hubs, and Price Formation: A Network Perspective, Cambridge Working Papers in Economics, 1–38.

Woroniuk, D., Karam, A., and Jamasb, T. (2019). European Gas Markets, Trading Hubs, and Price Formation: A Network Perspective, Cambridge Working Papers in Economics, 1–38.

Zhang, D. (2017). Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. Energy Economics.62: 323–333.

Zhang, W, Zhuang, X, and Lu, Y. (2020). Spatial spillover effects and risk contagion around G20 stock markets based on volatility network. North American Journal of Economics and Finance.

Zhong, W., An, H., Gao, X., and Sun, X. (2014). The Evolution of Communities in The International Oil Trade Network, Physica A: Statistical Mechanics and Its Applications, No. 213, 1–19.