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A Dynamic Network Comparison Analysis of Crude Oil Trade: Evidence from Eastern Europe and Eurasia

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Abstract: *This article characterizes a dynamic crude oil trade network of Eastern Europe and Eurasia using the network connectedness measure of Diebold and Yilmaz (2014, 2015) and asymmetric reaction of crude oil bilateral trade flow in response to the positive and negative changes of its key determinants using the nonlinear panel ARDL model. Results indicate the existence of large and time-varying spillovers with a considerable explanatory power among the crude oil trade flow volatility of Iran, Russia, US and Saudi Arabia in Eastern Europe and Eurasia crude oil trade network. The findings also show that crude oil trade flow of Eastern Europe and Eurasia experiences net volatility transmission to Iran, Russia and US respectively, whereas it is a net volatility receiver from Saudi Arabia. Also based on gravity models, the analysis confirms the existence of impact, reaction and adjustment asymmetry through different magnitude among network participants.*

***Keywords*:** Crude Oil Trade; Dynamic Network Connectedness Measure; Gravity Model; Nonlinear Panel ARDL Model

***JEL Classification*:** C22, F13, Q370, Q43, Q47, Q370, C320

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Introduction

"Most of the Central European countries depend on imported energy. The former Soviet Union, and specifically Russia, was the only well positioned energy supplier with monopoly power at the closed COMECON[1] markets so that the Eastern European energy dependence was augmenting the impact of the Soviet political and military presence in the region. As usual for communist ideology, this monopolistic position was dressed in different, impressive 'socialist' co-operation and integration schemes meant to provide some economic substance to the otherwise empty COMECON shell. As related to the energy, these included the construction of a pipeline called 'Drujba' (Friendship) to transport Russian crude oil to East European refineries, etc. All these infrastructural projects had the purpose of sustaining the East European dependence on Russian energy and technology transfers, and also, at a political level, to give the impression that Russia, by offering its energy resources at discounted prices, is subsidizing its East European affiliates" (Balabanov 1998). It is also noted that regional and international crude oil trade play an important role in connecting crude oil producers with crude oil consumers, since there is an imbalance in the distribution of crude oil resources and crude oil consuming areas in the world (Dong et al. 2016). In addition, the international crude oil trade attracts the world's attention due to crude oil's large share of energy consumption and because most of crude oil-exporting countries have a high degree of political instability. Thus, energy security and competition, due to emerging economies in the international crude oil trade, are the main concerns of crude oil-importing countries. Therefore, features of the global crude oil trade are becoming increasingly important to understand (Managi & Kitamura, 2017). Moreover, as an important factor affecting economic development, people's living and economic stability, global crude oil trade patterns are increasingly concerned by researchers and policy makers. Additionally, the possible nonlinearity in crude oil bilateral trade flow is driven, according to Jammazi et al. (2014), "by successive episodes of economic and financial crisis, black swan events, geopolitical tensions, structural changes in business cycle, and heterogeneous economic agents." The authors also added, "the asymmetries can arise from the differences in the fundamental factors that determine the dynamics of markets under consideration". Although the world crude oil trade flow has drawn some attention from researchers such as Yazdani & Pirpour (2018), Ji et al. (2018), Managi & Kitamura (2017) and Babri et al. (2015), we do not find any study, considering the dynamic volatility spillovers and connectedness of crude oil trade network and analysis of asymmetric reaction of crude oil bilateral trade flow through a gravity model. By focusing on how time varying volatility spillovers and nonlinearity in regional and global crude oil trade network responses contribute to the overall economy, the energy sector can make an important contribution to the recovery from the global downturn and reach to the economic stability as well (Energy Vision Update

2012, World Economic Forum). Accordingly, for portfolio and risk management using the connectedness measure and non-linear panel auto regressive distributed lag (NPARDL) method, we construct the crude oil network structure of Eastern Europe and Eurasia and study the following research questions:

1. What is the spillover level among the crude oil trade flow volatilities of Iran, Russia, US and Saudi Arabia in Eastern Europe and Eurasia crude oil trade network (net pairwise spillover, net total spillover and spillover index)? Does their network total spillover change over time?
2. How crude oil bilateral trade flow of Eastern Europe and Eurasia reacts to the increasing and decreasing changes of its main determinants (the existence of impact, reaction and adjustment asymmetry)?

Literature Review

An et al. (2018) investigate the dependency network of the international oil trade by focusing on its changes after the oil price drop and show that the global oil trade relationships changed considerably after 2014. Managi and Kitamura (2017) examine the international crude oil trade and the international petroleum trade through positional and role analysis revealing the restrictions on trade partner selection due to geographical resistance forces neighboring oil-importing countries to choose similar oil-exporting countries and the diversification in petroleum exporting countries reduces the supply disruption risk for importing countries. Dong et al (2016) find the oil trade network follows power-law distribution. Moreover, countries with high centrality are also with high degree. Yazdani and Pirpour (2018) use the Poisson pseudo-maximum-likelihood method, the Malmquist index and panel data method as well and conclude the gross domestic product (GDP) per capita, the difference of proven crude oil reserves, the access to sea, and the intra-industry trade (IIT) have positive effects on the bilateral trade flow, while the effects of transportation costs and economic sanctions are negative. Also, the impact of IIT on the bilateral trade productivity is positive. Babri et al. (2017) extend the traditional gravity model on coal, iron ore and oil seaborne trade flow and demonstrate that the proposed construction results in a significantly better fit for the observed data. Accordingly, based on OPEC country groupings during 1980–2018, the first contribution of this paper is to identify the Eastern Europe and Eurasia's dynamic crude oil trade network to perform the rolling-window analysis using the Diebold and Yilmaz (DY) methodology (2014, 2015) and distinguish the dynamic volatility spillovers and connectedness of crude oil trade flow (An et al, 2018) among Eastern Europe and Eurasia crude oil markets of Iran, Russia, US and Saudi Arabia which is implicitly also linked to the idea of stress testing (Diebold & Yilmaz, 2014). As the second contribution and for following the features of systemic risk spillovers and effective policymaking, this research aims to analyze the existence of impact, reaction and adjustment asymmetry of crude oil bilateral trade flow in response to the positive and negative changes of its key determinants, based on gravity theory using the nonlinear panel auto regressive distributed lag (NPARDL) method during 1980–2018. We therefore, set up Russia, US and Saudi Arabia in accordance with Onur Tas et al. (2018). Moreover, Saudi Arabia, Russia and Iran experience the first, second and fourth world crude oil net exporters respectively, whereas US is currently considered as the biggest world crude oil producer and has the largest world proven crude oil reserves as well (IEA, 2019). Furthermore, the crude oil export of US maybe close to Saudi Arabia's in 2024 (OPEC, 2018). Thus, this study may lead to make new research results for scholars and policy makers.

Theoretical Framework, Estimation Methods and Data Description

Theoretical Framework and Estimation Methods

The theoretical framework and estimation methods of this paper are presented in two separate sections in order to address the distinct but interrelated research questions examined empirically in this paper.

Dynamic Volatility Spillovers and Connectedness of Crude Oil Trade Network

We implement the methodology developed by Diebold and Yilmaz (2014, 2015) to calculate the dynamic volatility spillovers and connectedness measure of crude oil trade network (Diebold & Yilmaz, 2009; Onur Tas et al. 2018; Dong et al. 2016; Zhou et al. 2009; Lue & Zhou 2011). This measure provides us the direction and magnitude of the effect of changes in crude oil trade flow of a country on other countries. DY (2015) build the connectedness measure using the variance decomposition matrix of a vector-autoregressive (VAR) model of crude oil trade flow cycle. We construct a VAR model using the yearly data of crude oil trade flow (An et al, 2018) by each country. The highest connectedness measure score is 100 since we derive $d_{ij}(H)$ using the variance decomposition matrix. As stated by DY (2015), this approach is intentionally nonstructural and remains agnostic on how connectedness arises for a wide range of possible underlying under minimal assumptions. There are $N^2 - N$ separate pairwise directional connectedness measures. Moreover, moving average coefficients is of utmost importance in understanding the dynamic links between variables. These coefficients allow dividing the H-step-ahead forecast error variances of each variable into parts attributable to the various system shocks. We follow DY (2015) and implement the generalized orthogonalization approach of Koop et al. (1996) and Pesaran and Shin (1998) when estimating the parameters of the VAR and calculating variance decompositions but not the traditional method using Cholesky-decomposition. Cholesky-decomposition urges the user to order variables upon the importance of the impact on other variables. This approach is independent of the ordering of variables and accounts for correlated shocks. Accordingly, the forecast error variance decomposition (FEVD) for H-step ahead or variable j's contribution to the H-period-ahead generalized error variance of variable i is as follows:

$$d_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\acute{e}_i A_h \sum e_j \right)^2}{\sum_{h=0}^{H-1} (\acute{e}_i A_h \sum A'_h e_j)}, \tag{1}$$

where σ_{ij} is the standard deviation of ε_j, $\sum$ is the covariance matrix of shock vector in the non-orthogonalized VAR, and e_i is the selection vector with ith element unity and zeros elsewhere. $d_{ij}(H)$ is the fraction of the H-step-ahead error variance of i from shocks to j. In the matrix, diagonals and off-diagonals present own contributions (variable i to itself) and pairwise-contributions (variable i to variable j), respectively. However, row sums in generalized variance decomposition matrices are not necessarily equal to 1 and thus each entry is normalized by the row sum. DY (2015) defines the pairwise directional connectedness from j to i using $C_{i \leftarrow j}(H) = d_{ij}(H)$. Accordingly, we calculate the total directional connectedness to obtain concise crude oil trade flow coordination measures. The total connectedness from others to i is:

$$C_{i \leftarrow o}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{d_{ij}}(H)}{\sum_{i,j=1}^{N} \widetilde{d_{ij}}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{d_{ij}}(H)}{N} \times 100 \tag{2}$$

The total connectedness from i to others is:

$$C_{o \leftarrow i}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{d_{ij}}(H)}{\sum_{i,j=1}^{N} \widetilde{d_{ij}}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{d_{ij}}(H)}{N} \times 100 \tag{3}$$

in order to examine whether one variable is a net receiver or transmitter of shocks, the net spillover effects are calculated as:

$$C_i^{net}(H) = C_{o \leftarrow i}(H) - C_{i \leftarrow o}(H) \tag{4}$$

Finally, We calculate the total connectedness, C, to study the total coordination level in the network:

$$C(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{d_{ij}}(H)}{\sum_{i,j=1}^{N} \widetilde{d_{ij}}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{d_{ij}}(H)}{N} \times 100 \tag{5}$$

Where: $d_{ii}(H)$ is the main diagonal elements or own variance shares, $d_{ij}(H)$ is off-diagonal elements or cross variance shares of FEVD. Spillover index shows the average contribution of spillovers from shocks to all variables to the total forecast error variance. Alternatively, the spillover index gives the degree of the connectedness of the J-variables system. The main advantage of spillover analysis is that the directional spillovers can be easily calculated. In brief, the net pairwise spillover identifies the country that plays the dominant role in information transmission between two countries. We calculate the total directional connectedness to obtain concise crude oil trade flow coordination measures. The net total directional connectedness indicates the country that plays the dominant role in information transmission between countries and spillover index measures the total information flow among all markets under consideration. However, it is of no surprise that each market's explanatory power on itself FEV is highest (Antonakakis et al., 2016).

The symmetric Reaction of Crude Oil Bilateral Trade Network to Its Key Determinants: A Gravity Model Approach

One of the most popular international trade models, extensively has been used to formulate trade flow between countries, is the gravity model of trade, which was firstly introduced by Tinbergen (1962) and Poyhonen (1963). In this study, we have used the specification of the gravity model shown in the following equation (Yazdani & Pirpour, 2018):

$$T_{ijt} = \alpha_0 + \alpha_1 Y_{it} + \alpha_2 Y_{jt} + \alpha_3 \tau_{ijt} + \alpha_4 ORD_{ijt} + \varepsilon_{ij} \tag{6}$$

where T_{ijt} is the bilateral trade flow (the sum of exports and imports) of crude oil between countries i and j at time t in constant 2005 price. Y_{it} and Y_{jt} are the GDP per capita of countries i and j at time t in constant 2005 price, respectively. τ_{ijt} is the transportation costs between countries i and j at time t in constant 2005 price. ORD_{ijt} is the proven crude oil reserves difference between countries i and j at time t. As previously noted, we construct the Shin et al. (2014) nonlinear ARDL model in panel form which is also a nonlinear representation of the dynamic heterogeneous panel data model that is suitable for large T panels to follow whether crude oil trade flow is directly asymmetric proportional to positive and negative changes of GDP per capita in both exporting and importing countries[2] and the difference of proven crude oil reserves as well, while the effects of increasing and decreasing components of transportation costs are negative[3], as crude oil reserves are unequally located in the world. We adopt this approach for the following reasons. First, it allows us to capture asymmetries nonlinearly. Second, it accounts for inherent heterogeneity effect in the data. Thirdly, it is more appropriate when there is presence of unit root or mixed order of integration of not more than I(1). Another important advantage of this procedure is that estimation is possible even when the explanatory variables are endogenous indicating there is no need for any causality tests in NPARDL method (Shin et al., 2014). Unlike the symmetric case, this version of the panel ARDL, referred to as nonlinear panel ARDL, allows for asymmetric response of dependent variable to the increasing and decreasing of independent variables. In other words, under this scenario, positive and negative changes are not expected to have identical impacts on endogenous variable. The asymmetry in the relation between the dependent variable and each of the independent variables refers to the asymmetry in the impact of negative and positive changes of 1% in each of the independent variable on the crude oil bilateral trade flow as the dependent variable in both signs and magnitude. Further, the asymmetric short- and long term specification of crude oil bilateral trade flow in response to the positive and negative changes of the explanatory variables are specified as shown in Equation (7).

$$\begin{aligned}\Delta Y_{it} &= a_i + \beta_{0i} Y_{i,t-1} + \beta_{1i} X^{+}_{1,t-1} + \beta_{2i} X^{-}_{1,t-1} + \beta_{3i} X^{+}_{2,t-1} + \beta_{4i} X^{-}_{2,t-1} + \ldots + \\ &\beta_{(n-1)i} X^{+}_{n,t-1} + \beta_{ni} X^{-}_{n,t-1} + \sum\nolimits_{j=1}^{m} \lambda_{ij} \Delta Y_{i,t-j} + \sum\nolimits_{j=0}^{n} \left(\gamma^{+}_{ij} \Delta X^{+}_{1,t-j} + \gamma^{-}_{ij} \Delta X^{-}_{1,t-j} \right) + \\ &\sum\nolimits_{j=0}^{p} \left(\theta^{+}_{ij} \Delta X^{+}_{2,t-j} + \theta^{-}_{ij} \Delta X^{-}_{2,t-j} \right) + \ldots + \sum\nolimits_{j=0}^{q} \left(\delta^{+}_{ij} \Delta X^{+}_{n,t-j} + \delta^{-}_{ij} \Delta X^{-}_{n,t-j} \right) + \mu_i + U_{it}\end{aligned} \tag{7}$$

Where m, n, p and q represent the lag orders. In accordance with the nature of the suggested independent variables in the gravity equations of mentioned models in this paper, GDP per capita of countries i and j at time t and the transportation costs between countries i and j at time t are considered as the dynamic regressors, whereas the proven crude oil reserves difference between countries i and j at time t acts as the fixed regressor of non-linear panel ARDL models. $\left(\alpha_{1i} = \frac{\beta_{1i}}{\beta_{0i}}, \alpha_{3i} = \frac{\beta_{3i}}{\beta_{0i}}, \ldots, \alpha_{(n-1)i} = \frac{\beta_{(n-1)i}}{\beta_{0i}} \right)$ and $\left(\alpha_{2i} = \frac{\beta_{2i}}{\beta_{0i}}, \alpha_{4i} = \frac{\beta_{4i}}{\beta_{0i}}, \ldots, \alpha_{ni} = \frac{\beta_{ni}}{\beta_{0i}} \right)$ capture the aforementioned long term impacts of increases and decreases of the explanatory variables. Furthermore, $\left(\sum\nolimits_{j=1}^{n} \gamma^{+}_{ij}, \sum\nolimits_{j=1}^{p} \theta^{+}_{ij}, \ldots, \sum\nolimits_{j=1}^{q} \delta^{+}_{ij} \right)$ and $\left(\sum\nolimits_{j=1}^{n} \gamma^{-}_{ij}, \sum\nolimits_{j=1}^{p} \theta^{-}_{ij}, \ldots, \sum\nolimits_{j=1}^{q} \delta^{-}_{ij} \right)$ capture the short term impacts on crude oil bilateral trade flow of the positive and negative changes in the determinants respectively. Moreover, ε_t is an iid process with zero mean and constant variance. For each independent variable iv_{it}, increases (iv^{+}_{it}) and decreases (iv^{-}_{it}) are specified as follows:

$$iv^{+}_{it} = \begin{Bmatrix} \Delta iv_{it} & \textit{if } \Delta iv_{it} > 0 \\ 0 & \textit{otherwise} \end{Bmatrix}, \tag{8}$$

$$iv_{it}^{-} = \begin{cases} \Delta iv_{it} & if\ \Delta iv_{it} > 0 \\ 0 & otherwise \end{cases} \tag{9}$$

Then, we proceed following Katrakilidis and Trachanas (2012) and Ibrahim (2015) to determine the final specification of the nonlinear panel ARDL model. However, the nonlinear panel ARDL model in fact admits three general forms of asymmetry: (i) long term or reaction asymmetry; (ii) impact asymmetry, associated with the inequality of the coefficients on the contemporaneous first differences of independent variables; (iii) adjustment asymmetry, captured by the patterns of adjustment from initial equilibrium to the new equilibrium following an economic perturbation (i.e. the dynamic multipliers). Adjustment asymmetry derives from the interaction of impact and reaction asymmetries in conjunction with the error correction coefficient (Shin et al., 2014).

Data Description

This study uses natural logarithm of annual data during 1980–2018. The annual data of the crude oil trade flow and proven crude oil reserves difference from EIA[4], crude oil bilateral trade flow are gathered from the IRICA and United Nations Statistics Division, the GDP per capita from the World Bank, some of the transportation costs from the ESCAP and the rest of them calculated by the authors, based on Novy (2013) approach[5], the proven crude oil reserves difference from EIA and calculated by the authors, based on Yazdani and Pirpour (2018).

Empirical Results

Dynamic Volatility Spillovers and Connectedness of Crude Oil Trade Network

The results of the dynamic spillovers and connectedness among crude oil trade flow of Iran, Russia, US and Saudi Arabia in Eastern Europe and Eurasia Countries including, Russia, Kazakhstan, Poland, Belarus, Romania, Czech Republic, Hungary, Azerbaijan and other countries of Eastern Europe and Eurasia are presented at tables 1-4. We estimate a VAR(1) model as selected by the Schwarz criteria[6]. Based on DY (2015), the rolling windows and forecast horizon are set as 17 and 1 respectively. Furthermore, we conclude that there is a unilateral volatility transmission when the sign of net spillover is positive and greater than one and of course the opposite around. Moreover, there would be a bidirectional spillover with the results lower than one in absolute value. Table 1 presents the matrix of directional spillovers among crude oil trade flows, directional spillovers from each crude oil trade flow to all other crude oil trade flows (“Contribution To others”) and directional spillovers from all other crude oil trade flows to each crude oil trade flow ("From others"). Based on the results, Belarus is the largest transmitter and receiver of spillover effects from other countries, while Russia is the lowest transmitter and receiver of spillover effects from other countries. Findings also reveal that Russia, Czech Republic, Iran, Azerbaijan and Kazakhstan experience (-21.1), (-19.4), (-16.4), (-14.8) and (-4.3) percent of net total spillover in crude oil trade flow respectively, showing they are net volatility receiver from Eastern Europe and Eurasia's crude oil trade network, whereas Belarus, Poland, Hungary and Romania experience net uncertainty transmission to the network with (27.4), (13.7), (11.0) and (3.6) percent respectively.

Table 1: Dynamic Volatility Spillovers and Connectedness of Iran-Eastern Europe and Eurasia Crude Oil Trade Network

	Russia	**Iran**	**Kazakh-stan**	**Poland**	**Belarus**	**Romania**	**Czech**	**Hungary**	**Azer-baijan**	**Other Countries**	**From Others**
Russia	37.4	0.8	1.3	13.2	1.9	2.6	10.4	15.2	0.2	17.0	62.6
Iran	0.6	31.4	6.9	12.4	14.8	21.6	1.2	3.7	1.8	5.5	68.6
Kazakhstan	1.0	6.2	28.1	4.6	12.8	16.9	1.3	6.2	18.4	4.7	71.9
Poland	7.8	8.8	3.6	22.2	11.5	5.0	6.0	16.8	1.1	17.0	77.8
Belarus	1.0	9.4	9.1	10.3	19.9	13.2	5.8	9.2	9.0	13.0	80.1
Romania	1.8	17.5	15.3	5.8	16.9	25.5	1.2	2.6	8.1	5.3	74.5
Czech	10.1	1.3	1.6	9.9	10.7	1.7	36.6	10.0	5.0	12.9	63.4
Hungary	9.3	2.7	5.1	17.4	10.5	2.4	6.3	22.9	5.5	17.9	77.1
Azerbaijan	0.2	1.8	21.2	1.7	14.7	10.3	4.4	7.8	32.4	5.6	67.6
Other Countries	9.6	3.7	3.5	16.2	13.7	4.4	7.5	16.5	3.6	21.1	78.9
Contribution to others	41.5	52.2	67.6	91.5	107.5	78.1	44.0	88.1	52.8	99.0	722.4
Contribution including own	78.9	83.7	95.7	113.7	127.5	103.6	80.6	111.0	85.2	120.1	1000
Net Total Spillover	-21.1	-16.4	-4.3	13.7	27.4	3.6	-19.4	11.0	-14.8	20.1	SOI: 72.2%

Source: Authors Calculations

The spillover index (SOI) reaches 72.2%, indicating a sizable degree of connectedness, explanatory power or the share of each country's contribution in volatility transmission among Iran-Eastern Europe and Eurasia crude oil trade network during the sample period, which needs high degree of concentration for reasoning volatility transmission inside the network. Table 2 presents the matrix of dynamic volatility spillovers and connectedness of Russia-Eastern Europe and Eurasia crude oil trade network. Based on the results, Hungary and Romania are the largest transmitter and receiver of total spillover effects from other countries respectively, while Russia is the fewest transmitter and receiver of spillover effects from other countries.

Table 2: Dynamic Volatility Spillovers and Connectedness of Russia-Eastern Europe and Eurasia Crude Oil Trade Network

	Russia	**Kazakh-stan**	**Poland**	**Belarus**	**Romania**	**Czech**	**Hungary**	**Azer-baijan**	**Other Countries**	**From Others**
Russia	47.9	1.0	15.7	1.4	1.1	3.5	8.3	0.1	21.1	52.1
Kazakhstan	0.7	31.6	6.1	20.1	25.6	10.6	4.5	0.4	0.4	68.4
Poland	11.1	6.6	34.0	17.1	6.6	0.0	3.9	0.0	20.6	66.0
Belarus	0.9	19.7	15.5	30.9	21.6	2.8	0.4	0.0	8.3	69.1
Romania	0.6	21.9	5.2	18.9	27.0	13.4	8.8	4.0	0.0	73.0
Czech	2.1	9.6	0.0	2.6	14.3	28.9	20.6	15.6	6.3	71.1
Hungary	4.8	4.0	3.3	0.3	9.2	20.0	28.1	16.3	14.1	71.9
Azerbaijan	0.1	0.5	0.0	0.0	6.0	21.8	23.4	40.4	8.0	59.6
Other Countries	13.6	0.4	18.7	8.2	0.0	6.7	15.5	6.1	30.8	69.2
Contribution to others	33.9	63.6	64.5	68.6	84.5	78.8	85.3	42.3	78.8	600.3
Contribution including own	81.8	95.3	98.6	99.5	111.5	107.7	113.4	82.7	109.6	900.1
Net Total Spillover	-18.2	-4.8	-1.5	-0.5	11.5	7.7	13.4	-17.3	9.6	SOI: 66.7%

Source: Authors Calculations

Findings also indicate that Russia, Azerbaijan, Kazakhstan and Poland expose (-18.2), (-17.3), (-4.8), and (-1.5) percent of net total spillover in crude oil trade flow respectively, mentioning they are net uncertainty receiver from Eastern Europe and Eurasia's crude oil trade network and a bilateral spillover for Belarus (-0.5), while Hungary, Romania and Czech Republic capture net volatility transmission to the network with (13.4), (11.5) and (7.7) percent respectively. Also, the explanatory power of the complex is 66.7%, which exhibits 23.3% of the dynamic volatilities in crude oil trade flow come from outside of Russia-Eastern Europe and Eurasia crude oil trade network. This result illustrates that these countries are strongly linked with each other.

Table 3: Dynamic Volatility Spillovers and Connectedness of US-Eastern Europe and Eurasia Crude Oil Trade Network

	US	**Russia**	**Kazakh-stan**	**Poland**	**Belarus**	**Romania**	**Czech**	**Hungary**	**Azer-baijan**	**Other Countries**	**From Others**
Us	30.6	4.2	1.3	1.3	4.6	0.2	18.6	14.8	20.0	4.5	69.4
Russia	4.4	32.3	3.3	17.8	12.7	10.9	0.2	3.2	0.8	14.5	67.7
Kazakhstan	1.7	4.0	39.4	4.8	6.0	0.2	9.2	12.1	14.1	8.5	60.6
Poland	1.1	13.7	3.0	24.8	13.5	6.7	5.6	13.0	0.4	18.3	75.2
Belarus	3.3	8.6	3.4	11.9	21.9	9.3	9.9	9.9	4.4	17.3	78.1
Romania	0.2	14.0	0.2	11.1	17.6	41.4	3.1	0.3	1.1	11.0	58.6
Czech	14.7	0.1	5.6	5.5	10.9	1.8	24.2	13.4	14.1	9.7	75.8
Hungary	10.4	2.1	6.6	11.3	9.7	0.1	12.0	21.5	11.5	14.8	78.5
Azerbaijan	18.2	0.7	9.9	0.5	5.6	0.7	16.2	14.8	27.8	5.5	72.2
Other Countries	3.0	9.2	4.4	15.1	16.2	5.4	8.2	14.0	4.1	20.4	79.6
Contribution to others	56.9	56.6	37.7	79.3	96.7	35.3	82.9	95.7	70.5	104.1	715.7
Contribution including own	87.5	88.9	77.1	104.1	118.6	76.8	107.1	117.1	98.3	124.6	1000.1
Net Total Spillover	-12.5	-11.1	-22.9	4.1	18.6	-23.3	7.1	17.2	-1.7	24.5	SOI: 71.6%

Source: Authors Calculations

Based on Table 3, Belarus and Hungary act as the largest transmitter and receiver of spillover effects from other countries respectively, while Romania is the smallest transmitter and receiver of spillover effects from other countries. Results also pinpoint that Romania, Kazakhstan, US, Russia, and Azerbaijan observe (-23.3), (-22.9), (-12.5), (-11.1) and (-1.7) percent of net total spillover in crude oil trade flow respectively, denoting they contribute as net uncertainty receivers from Eastern Europe and Eurasia's crude oil trade network. While Belarus, Hungary, Czech Republic and Poland capture net volatility transmission to the network with (18.6), (17.2), (7.1) and (4.1) percent respectively. As strongly linked with each other, the degree of integration owns a spread 71.6% of the dynamic volatilities in crude oil trade flow come from inside of US-Eastern Europe and Eurasia crude oil trade network during the sample period.

Table 4: Dynamic Volatility Spillovers and Connectedness of Saudi Arabia-Eastern Europe and Eurasia Crude Oil Trade Network

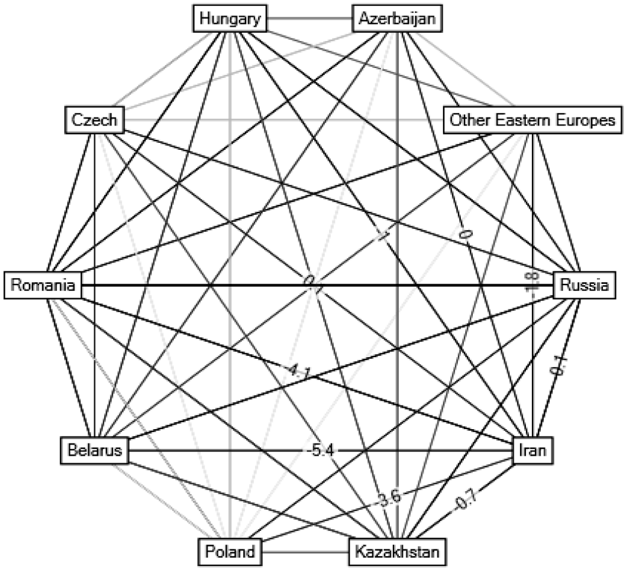
	Saudi	**Russia**	**Kazakh-stan**	**Poland**	**Belarus**	**Romania**	**Czech**	**Hungary**	**Azer-baijan**	**Other Countries**	**From Others**
Saudi	19.8	4.5	13.9	11.8	0.5	9.4	10.9	12.9	3.4	12.8	80.2
Russia	6.9	30.6	14.6	11.8	2.3	11.4	4.5	5.5	0.1	12.4	69.4
Kazakhstan	14.3	9.7	20.3	11.3	0.9	11.3	8.1	9.9	1.0	13.3	79.7
Poland	15.3	9.9	14.3	25.8	2.2	7.7	6.2	8.1	0.0	10.3	74.2
Belarus	1.5	4.4	2.6	5.1	59.6	16.9	0.8	8.1	0.2	0.8	40.4
Romania	8.7	6.8	10.1	5.4	5.2	18.2	11.5	15.6	7.0	11.7	81.8
Czech	10.9	2.9	7.9	4.8	0.3	12.5	19.8	15.7	11.8	13.4	80.2
Hungary	11.3	3.1	8.5	5.5	2.4	15.0	13.8	17.5	10.1	12.8	82.5
Azerbaijan	5.6	0.1	1.5	0.1	0.1	12.5	19.3	18.8	32.6	9.4	67.4
Other Countries	11.9	7.4	11.9	7.3	0.3	11.8	12.4	13.4	5.3	18.3	81.7
Contribution to others	86.4	48.7	85.4	63.1	14.0	108.4	87.6	108.1	38.8	97.0	737.4
Contribution including own	106.3	79.3	105.7	88.9	73.6	126.6	107.4	125.5	71.3	115.3	999.9
Net Total Spillover	6.2	-20.7	5.7	-11.1	-26.4	26.6	7.4	25.6	-28.6	15.3	SOI: 73.7%

Source: Authors Calculations

In accordance with Table 4, Romania and Hungary are found as the highest transmitter and receiver of spillover effects from other countries respectively, while Belarus as the lowest transmitter and receiver of spillover effects from other countries. Additionally, Romania, Hungary, Czech Republic, Saudi Arabia and Kazakhstan are net volatility transmitter to Eastern Europe and Eurasia crude oil trade network with (26.6), (25.6), (7.4), (6.2) and (5.7) percent of net total spillover in crude oil trade flow respectively, while Azerbaijan, Belarus, Russia and Poland act a net uncertainty receiver from the network with (-28.6), (-26.4), (-20.7) and (-11.1) percent respectively. Moreover, the share of each country's contribution in volatility transmission in Saudi Arabia -Eastern Europe and Eurasia crude oil trade network reaches 73.7% during the sample period, which shows the great complexity in the crude oil trade flow volatilities of mentioned countries.

To better visualize the structure of connectedness, the direction and the strength of spillovers between the Iran, Russia, US, Saudi Arabia and Eastern Europe and Eurasia crude oil trade flows, Figures. 1-4, provide the network of pairwise return connectedness. Based on Fig. 1, Belarus is the largest net volatility transmitter (unilateral spillover) to Iran, followed by Romania, Poland and Hungary; whereas Iran experiences a bidirectional spillover with Kazakhstan, Russia and Czech Republic. It is worthy of note that no evidence of unidirectional or bidirectional spillover exists between Iran and Azerbaijan, suggesting potential diversification benefits.

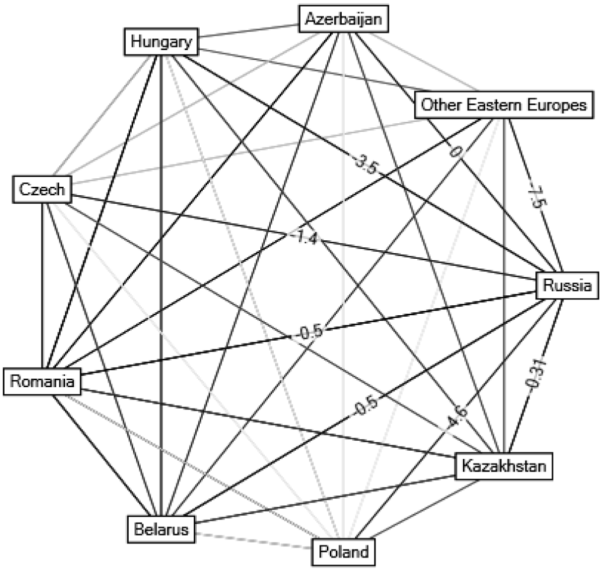
Figure 1: Net Pairwise Volatility Spillovers of Iran-Eastern Europe and Eurasia Crude Oil Trade Network



Source: Authors Calculations

Moreover and in accordance with Fig. 2, Poland shows the greatest net volatility transmission (unilateral spillover), to Russia followed by Hungary and Czech Republic; whereas Russia faces a bidirectional spillover with Kazakhstan, Belarus and Romania. Findings also express no evidence of unidirectional or bidirectional spillover between Russia and Azerbaijan, suggesting potential diversification benefits.

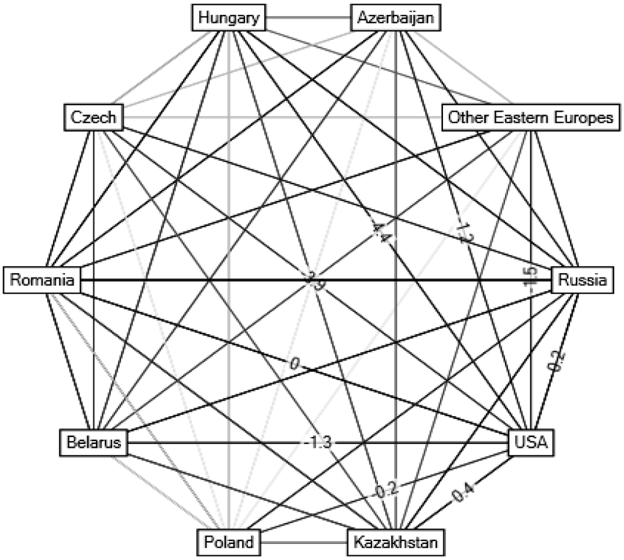
Figure 2: Net Pairwise Volatility Spillovers of Russia-Eastern Europe and Eurasia Crude Oil Trade Network



Source: Authors Calculations

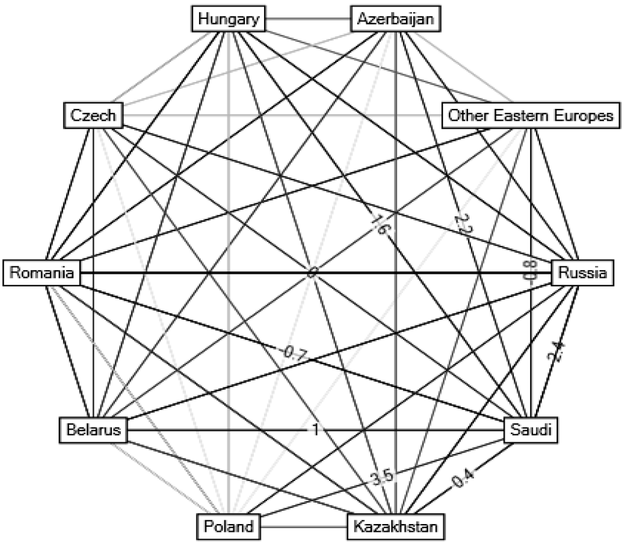
Compatible with Fig. 3, Hungary transmits the largest net volatility (unilateral spillover) to US followed by Czech Republic, Belarus and Azerbaijan; whereas US displays a bidirectional spillover with Kazakhstan, Poland and Russia. There is also no evidence of unidirectional or bidirectional spillover between US and Romania, suggesting potential diversification benefits. Finally and based on Fig. 4, Poland has the highest unilateral volatility spillover from Saudi Arabia followed by Russia, Azerbaijan, Hungary and Belarus; whereas Saudi Arabia experiences a bidirectional spillover with Romania and Kazakhstan. Findings also indicate no evidence of unidirectional or bidirectional spillover between Saudi Arabia and Czech Republic, suggesting potential diversification benefits. We also examine how network strength of major crude oil exporting countries changes over time. We specifically analyze the impact of Iran, Russia, US and Saudi Arabia on Eastern Europe and Eurasia crude oil trade network.

Figure 3: Net Pairwise Volatility Spillovers of US-Eastern Europe and Eurasia Crude Oil Trade Network



Source: Authors Calculations

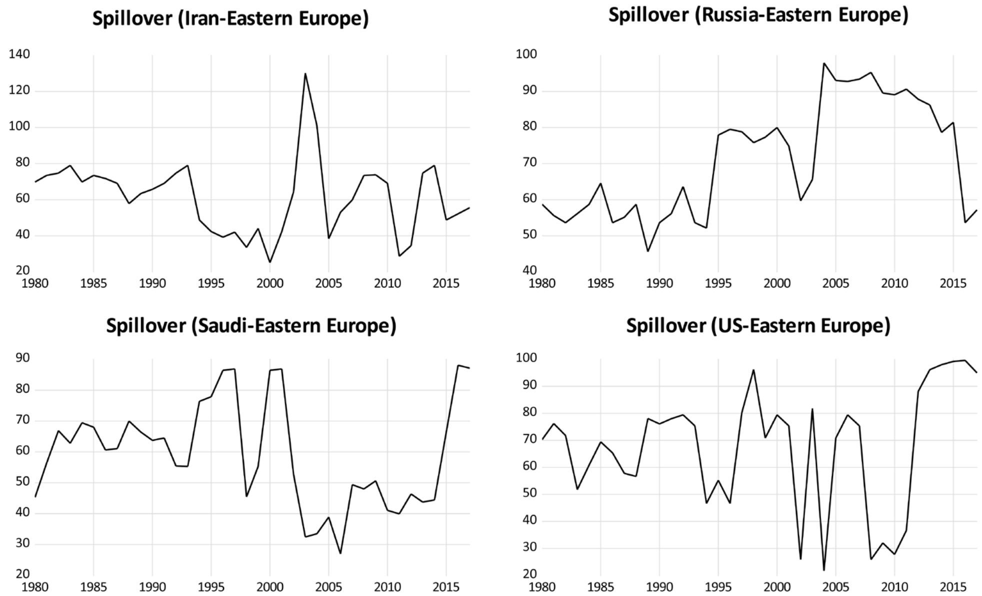
Figure 4: Net Pairwise Volatility Spillovers of Saudi-Eastern Europe and Eurasia Crude Oil Trade Network



Source: Authors Calculations

Based on figure 5, Iran, Russia, US and Saudi Arabia experience time varying spillover index with the highest (lowest) levels of 130.1 (25.7), 98.5 (46.1), 100.4 (22.1) and 88.1 (27.2) respectively over time.

Figure 5: Time-Varying Network Strength of Iran, Russia, Saudi Arabia and the US



Source: Authors Calculations

The symmetric Reaction of Crude Oil Bilateral Trade Network to its Key Determinants: A Gravity Model Approach

Unit Root Tests

In particular, increasing and decreasing changes of real GDP per capita for exporting and importing countries are respectively presented as (GDPI_POS), (GDPI_NEG), (GDPJ_POS) and (GDPJ_NEG). We also show the positive and negative changes of transportation cost as (TC_POS) and (TC_NEG) and proven crude oil reserves difference with (ORD). Hence, the outcomes of the (Levin, Lin & Chu), (ADF) and (Pesaran & Shin) panel unit root tests indicate, that the different series are integrated with an order of 0 or 1, no series is I(2)[7].

Cointegration Tests, Diagnostic Tests and Nonlinear Panel ARDL Model Coefficients

Table 5 presents the result of Wald test for cointegration advanced by Pesaran et al. (2001) and Shin et al. (2014). In fact, We show F-statistics and Chi-Square statistics which are significant at the 1% and 5% level. Based on the results, the mentioned variables in all gravity models move together in the long term. Moreover, the results of the estimated NPARDL cointegration or dynamic error correction term (ECT) of the proposed models associated with the asymmetric long term cointegration are reported at table 7 as well.

Table 5: Nonlinear Panel ARDL Cointegration Tests Results

Nonlinear Panel ARDL Cointegration Results							
Iran		Russia		US		Saudi Arabia	
F-Stat	Chi-Sq	F-Stat	Chi-Sq	F-Stat	Chi-Sq	F-Stat	Chi-Sq
(41)***	(246)***	(23.2)***	(139)***	(36.3)***	(218)***	(38)***	(233)***

(Note): ***, **, * denotes 1%, 5% and 10% level of statistical significance, respectively
Source: Authors Calculations

Furthermore, based on table 6 and in accordance with the results of Normality test, We can conclude that the proposed models have a normal distribution at 1% and 5% significance level. Also, the diagnostics tests indicate the presence of no cross-section dependence (Pesaran CD test of Pesaran (2004)), no serial correlation (Wooldridge test) and homoscedasticity (Modified Wald test). In addition, the stability of the models is tested by conducting CUSUM and CUSUM Squares tests. In accordance with the results, both tests reveal the stability of the models coefficients since the estimated models lie within the 5% significance line for CUSUM and CUSUM Squares tests. Finally, the Root Mean Square Error Test (RMSE) results determine that all considered nonlinear panel ARDL models fit economic indicators and well predicted as well[8].

Table 6: Nonlinear Panel ARDL Diagnostic Tests Results

Nonlinear Panel ARDL Diagnostic Tests Results							
Jarque-Bera				Cross-Section Dependence			
Iran	Russia	US	Saudi Arabia	Iran	Russia	US	Saudi Arabia
(1.39)**	(2.96)**	(1.23)**	(5.63)***	(29.31)**	(39.62)***	(23.21)**	(36.79)***
Serial Correlation				Heteroskedasticity			
Iran	Russia	US	Saudi Arabia	Iran	Russia	US	Saudi Arabia
(33.19)***	(35.87)***	(41.58)***	(42.22)***	(59.76)***	(53.87)***	(54.65)***	(57.02)***

(Note): ***, **, * denotes 1%, 5% and 10% level of statistical significance, respectively
Source: Authors Calculations

After passing the adequacy of the dynamic specification based on various diagnostic statistics, in accordance with equation (7), investigating the short- and long term relations between the crude oil bilateral trade flow and the explanatory variables of the gravity models for Eastern Europe and Eurasia crude oil bilateral trade network are presented at table 7.

Table 7: The NPARDL Estimation Results

Dynamic NPARDL Results								**COINTEQ**
Variable	D(GDPI_ POS)	D(GDPI_ NEG)	D(GDPJ_ POS)	D(GDPJ_ NEG)	D(TC_ POS)	D(TC_ NEG)	(ORD)	(ECT)
Iran	(2.28)**	(2.10)**	(0.57)***	(1.43)**	(-0.10)***	(-0.41)***	(0.009)***	(-0.62)***
Russia	(0.52)**	(1.49)***	(0.16)**	(0.67)***	(-0.06)***	(-0.1)***	(1.13)***	(-0.32)***
US	(1.29)***	(0.4)**	(0.05)**	(0.15)***	(-0.16)***	(-0.11)***	(0.007)***	(-0.53)***
Saudi Arabia	(0.98)**	(0.91)***	(0.66)**	(5.78)***	(-0.19)***	(-0.54)**	(0.11)**	(-0.48)***

Long Term Results						
Variable	(GDPI_POS)	(GDPI_NEG)	(GDPJ_POS)	(GDPJ_NEG)	(TC_POS)	(TC_NEG)
Iran	(1.2)**	(4.7)***	(0.16)***	(0.82)***	(-0.12)***	(-1.14)***
Russia	(1.16)***	(1.66)***	(0.13)***	(1.15)***	(-0.6)***	(-0.39)***
US	(1.16) **	(6.21)***	(0.02)**	(0.0004)***	(-0.16)***	(-1.65)***
Saudi Arabia	(0.58)***	(2.32)**	(0.3)**	(0.1)***	(-0.43)***	(-0.57)***

Notes): ***, **, * denotes 1%, 5% and 10% level of statistical significance, respectively
Source: Authors Calculations

Based on the dynamic nonlinear and long term estimated parameters provided at table 7, the estimated short- and long term coefficients of the independent variables for Iran, Russia, US and Saudi Arabia in Eastern Europe and Eurasia crude oil bilateral trade network are highly significant at 1% and 5% significant levels. In particular, positive and negative changes of real GDP per capita for both origin and destination countries present positive coefficients, that is compatible with Niu (2017) and Silva and Tenreyro (2006), whereas consistent with Bougheas et al. (1999), we see the opposite results for transportation cost. Moreover, relying on the Heckscher-Ohlin theory the results indicate the existence of positive relationship between proven crude oil reserves difference and crude oil bilateral trade flow. The findings also show the impact and reaction asymmetry for both positive and negative changes in the main determinants of Eastern Europe and Eurasia crude oil bilateral trade network. Additionally, the statistically significant negative coefficient of error correction term indicates the existence of asymmetric cointegration for the proposed models. Finally, it can be detected mixed magnitude short- and long term effects of positive and negative changes of independent variables on crude oil bilateral trade flow. However, the statistical significance of the short- and long term estimated parameters of the nonlinear panel ARDL models in fact indicate long term or reaction asymmetry and impact asymmetry, associated with the inequality of the coefficients on the contemporaneous first differences of independent variables (Shin et al. 2014). Also, Table 8 summarizes the Wald test results (Chi-Sq Statistics) of short term asymmetry (impact asymmetry) and long term asymmetry (reaction asymmetry) in the Gravity Models.

Table 8: Short- and Long Term Asymmetry Wald Tests

Variable	**GDPI**		**GDPJ**		**TC**	
Asymmetry	Short Term	Long Term	Short Term	Long Term	Short Term	Long Term
Iran	(35.2)***	(30.8)***	(15.7)***	(19.8)***	(43.1)***	(46)***
Russia	(8.6)**	(7.7)**	(19.3)***	(18.7)***	(2.4)**	(3)**
US	(41.1)***	(48.4)***	(3.8)**	(3.2)**	(24.2)***	(20.5)***
Saudi Arabia	(4.7)**	(5.4)**	(9.6)***	(10.7)***	(8.7)***	(9.5)***

Notes): ***, **, * denotes 1%, 5% and 10% level of statistical significance, respectively
Source: Authors Calculations

Based on table 8, the results of the Wald test show the rejection of the null hypothesis of significant short- and long term symmetry for the positive and negative changes in all independent variables. Consequently, the findings of the proposed models confirm the presence of significantly asymmetric responses of crude oil bilateral trade flow to both positive and negative changes in all explanatory variables, which maybe also verified by the plots of the cumulative dynamic multipliers. Moreover, the results of comparison effectiveness for Iran, Russia, US and Saudi Arabia crude oil bilateral trade flow in Eastern Europe and Eurasia crude oil bilateral trade network are presented at table 9.

Table 9: The NPARDL Comparing Coefficients across Gravity Models

Dynamic NPARDL							
Iran		Russia		US		Saudi Arabia	
Highest	Lowest	Highest	Lowest	Highest	Lowest	Highest	Lowest
D(GDPI_POS)	D(TC_POS)	D(GDPI_NEG)	D(TC_POS)	D(GDPJ_NEG)	D(TC_POS)	D(GDPJ_NEG)	D(TC_POS)
Long Term NPARDL							
Iran		Russia		US		Saudi Arabia	
Highest	Lowest	Highest	Lowest	Highest	Lowest	Highest	Lowest
(GDPI_NEG)	(TC_POS)	(GDPI_NEG)	(GDPJ_POS)	(GDPI_NEG)	(GDPJ_NEG)	(GDPI_NEG)	(GDPJ_NEG)

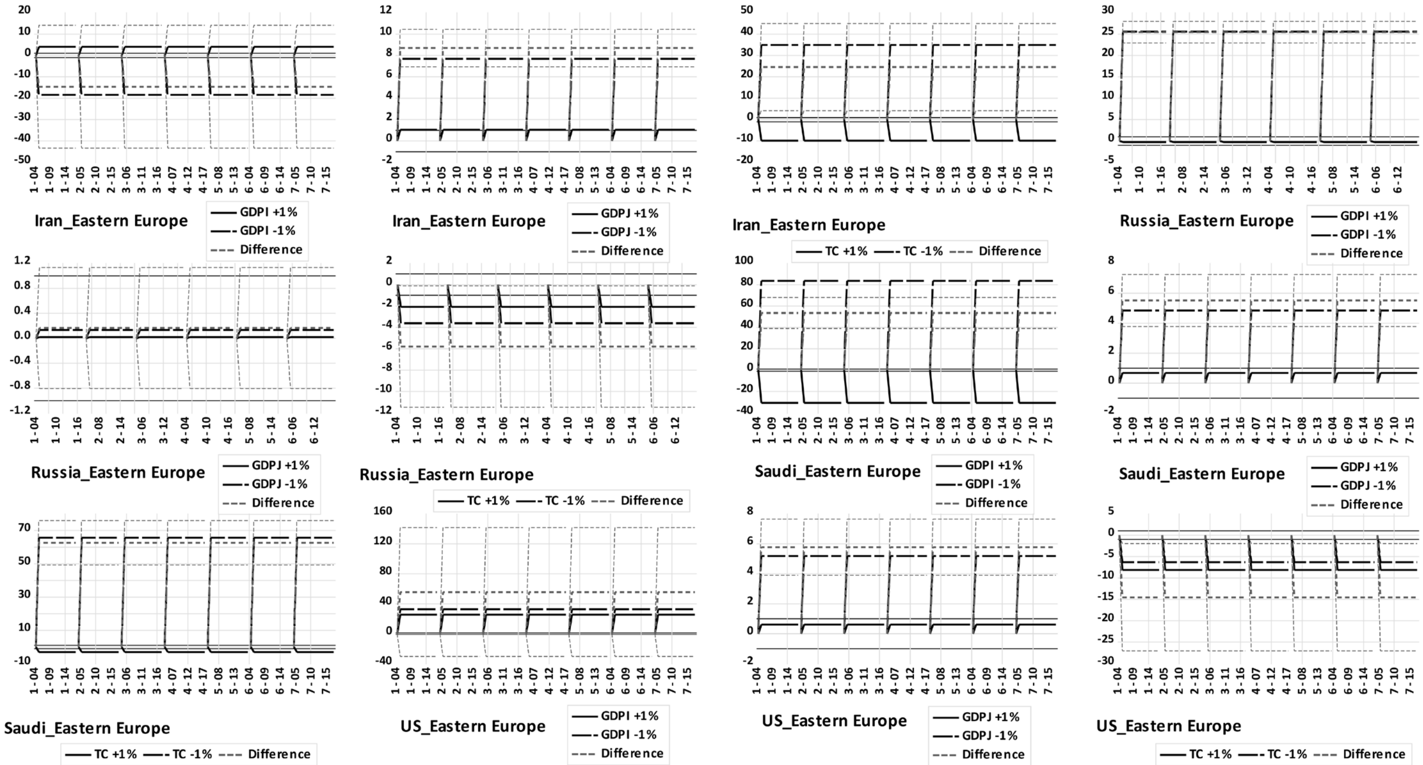
Source: Authors Calculations

According to table 9, in short term Iran needs to focus more on increases of its GDP per capita as the main factor of Eastern Europe and Eurasia crude oil bilateral trade network, while facing the lowest effectiveness in the positive changes of crude oil transportation cost. In addition, the long term comparison result is the same as the short term for crude oil transportation cost with the concerns of the highest effectiveness in the negative changes of Iran's GDP per capita. Moreover, focusing on GDP per capita in Russia is the most important element in the in both short- and long term Russia- Eastern Europe and Eurasia crude oil bilateral trade network, whereas the crude oil transportation cost and GDP per capita of destinations show the lowest effectiveness magnitude in short- and long term, respectively. Furthermore, the negative changes in GDP per capita of the destination areas play the most important role in both US and Saudi Arabia short term crude oil bilateral trade network, while the greatest long term effectiveness is related to the positive changes in GDP per capita of US and Suadi Arabia. Additionally, the increases of crude oil transportation cost and decreases of GDP per capita in both US and Saudi Arabia's crude oil bilateral trade network destination countries indicate the lowest magnitude in short- and long term respectively. To sum up, the different outcomes in the highest and lowest effectiveness on crude oil bilateral trade flow maybe due to the different and specific features of origin and destination countries in their crude oil bilateral trade network, requiring their own specific policies in short- and long term.

Cumulative Dynamic Multipliers

According to figure 6, plots of non-linear panel ARDL cumulative dynamic multipliers of the proposed models display the adjustment asymmetry or dynamic effects of positive and negative changes in GDP per capita of origin and destination countries and transportation cost, captured by the patterns of adjustment from initial equilibrium to the new equilibrium. Based on the results, an asymmetric response of crude oil bilateral trade flow to one percent positive and negative changes of GDP per capita of both origin (Iran, Russia, US and Saudi Arabia) and destinations and transportation cost for the gravity models is detected. It is also provided a particularly significant reaction of the dependent variable in response to one percent positive and negative changes in all independent variables with a time deferred impact for the proposed gravity models. To sum up, the plots of the cumulative dynamic multipliers of the suggested models confirm the presence of significantly short- and long term adjustment asymmetry (dynamic effects) of crude oil bilateral trade flow to both positive and negative changes in all explanatory variables. The results also show that the crude oil bilateral trade flow experiences mixed sensitivity to positive and negative changes in GDP per capita of origin and destination countries and transportation cost as well for the gravity models of Eastern Europe and Eurasia.

Figure 6: Cumulative Dynamic Multipliers of Eastern Europe & Eurasia Crude Oil Bilateral Trade Network



Source: Authors Calculations

Conclusion and Policy Implication

This study contributes to the growing empirical literature on the crude oil trade network by quantifying for the first time a dynamic crude oil trade network of Eastern Europe and Eurasia using the network connectedness measure of DY (2014, 2015) and the existence of asymmetric reaction of crude oil bilateral trade flow in response to the positive and negative changes of its main determinants using the nonlinear panel auto regressive distributed lag model during 1980–2018. Overall, it is interesting to know that crude oil trade flows exhibit relatively diverse levels of integration and that, consequently, shocks to one crude oil trade flow induce large spillovers to the other segments in a way that would raise diversification possibilities. In fact, countries may benefit from some evidence of week integration in some cases to improve their portfolio diversification by exploiting the findings on how crude oil trade flows influence one another. As the results of volatility connectedness, policy makers and financial participants can assist dynamic volatility spillovers and connectedness in building volatility-hedging strategies and consistently managing risk via measures such as value-at-risk. Additionally, in order to increase the crude oil bilateral trade among the origin countries including Iran, Russia, US and Saudi Arabia and destination countries in Eastern Europe and Eurasia crude oil bilateral trade network, the growth of GDP per capita of both exporting and importing countries through using the suitable investments at unused capacities in the economies and reducing the transportation costs by investing in the domestic and international maritime transportation infrastructures in active crude oil trade participants should be mentioned. Moreover, main crude oil exporting countries maybe better consider the effective factors such as consumers' preferences regarding crude oil quality differentiation and economies of scale in crude oil industry as well. Consequently, focusing on dynamic volatility spillovers and connectedness of crude oil trade flow and how nonlinearity in crude oil bilateral trade flow responses contribute to the overall economy substantially help financial participants, energy policy-makers and governments to monitor the largest risk contributors across crude oil trade network and make different decisions within different timescales when there are shocks to energy sectors which can make an important contribution to the recovery from the global downturn and economic instability as well. From the perspective of investors, our results construct a risk network that protects their positions from the financial distress of other markets. For policymakers, identifying the market's dynamic ranking of systemic risk contributions is critical. When a crisis occurs in the crude oil trade network, policymakers can know the largest risk contributors and the markets that are most connected to them, thereby allowing them to, for example, control the degree of openness in their own market. Finally, the results of this study contribute to monitoring risk across crude oil trade network and managing overall risk more effectively.

NOTES

[1] COMECON is the Western acronym for the Council of Mutual Economic Assistance embracing Bulgaria, Czechoslovakia, Hungary, Poland, Romania and the Former Soviet Union (FSU)
[2] Niu (2017) and Silva and Tenreyro (2006)
[3] Bougheas et al. (1999)
[4] Energy Information Administration
[5] For details, see Novy (2013)
[6] We examine the stationary of crude oil trade flow data for each country by employing Augmented Dickey-Fuller and Phillips-Perron unit root test. The test results will be available in the case of request. Both tests conclude that the cyclical components of crude oil trade flow that we use in the VAR analysis do not have a unit root.
[7] The details of descriptive statistics and unit root tests will be available in the case of request.
[8] The figures of CUSUM, CUSUM Squares and Root Mean Square Error tests will be available in the case of request.

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