American University Kyiv

THE EFFECT OF RUSSIAN WAR IN UKRAINE ON THE OIL MARKETS
(ВПЛИВ РОСІЙСЬКОЇ ВІЙНИ В УКРАЇНІ НА НАФТОВІ РИНКИ)

by **Oleksandr Donchenko**

Presented in Partial Fulfillment of the Requirements for
the Degree Master in Global Management

2024

APPROVED BY:

Roman Sheremeta, Ph.D., Faculty Mentor

Acknowledgments

I want to extend my heartfelt appreciation to everyone who has made this academic journey possible. First and foremost, among them, is my advisor, Dr. Roman Sheremeta. His positive attitude, patience, vast knowledge, encouragement and mentorship have been instrumental in shaping this work.

I am grateful to the members of my research committee, Ph.D., Dr. Habil. Hanna Shvindina, and Dr. Yuriy Bots. Their constructive feedback and thoughtful suggestions have significantly enhanced the depth and quality of this study.

Special thanks to all my classmates at American University Kyiv for their collaborative efforts, meaningful discussions and fun. Our collective contributions, knowledge sharing and meaningful interactions have not only enriched the learning experience, but also created a vibrant academic community.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

ln	Natural logarithm.
stat.	Statistic.
t., i.	Trend and intercept.
WTI	West Texas Intermediate.
US	The United States of America.
USD	The dollar of the United States of America.
bln	Billion.
mln	Million.
mb/d	Millions of barrels per a day.
y/y	Year-on-year.
VAR	Vector auto-regression model.
GDP	The gross domestic product of a country.
i. e.,	That is.
e.g.,	For example.
p.p.	Percentage points.
et al.	And others.

ABSTRACT

The intensification of the Russian war in Ukraine has been eroding global markets, disrupting established trade routes, and contributing to the inflation of food and energy prices worldwide. Since 2014, the war has exerted unbearable costs for Ukraine, and the brutal unprovoked escalation in February 2022 caused even more burden through the intolerable loss of lives, the unprecedented migration crisis, the substantial budget deficit, and economic downturn. The Russian government has been predominantly financed through the export of fossil fuels. Therefore, it's of the highest strategic importance for Ukraine to influence the aggressor's ability to finance the war through the unification of international efforts.

In this capstone project, we try to understand the effect of the Russian war escalation in Ukraine on energy markets. The analysis focuses on revealing the interdependencies among Russian oil spot, WTI and Brent futures prices. The series covers the period from July 12, 2018, to October 4, 2023.

To summarize, our findings reveal the post-February 2022 change in the price mechanism of the international oil markets. In the aftermath of large-scale military operation, Russia has lost its strategic position in terms of the "influence" on the oil futures markets, and the direction of "causality" has been lost or reshuffled towards Russian traders. These results underscore the importance of international sanctions limiting the aggressor's ability to continue the war. Considering the broader context, the implications of this research fortify Ukraine's communication strategy in lobbying to limit Russia's prospect on energy markets.

Keywords: *oil, futures, spot, price, causality, pre-escalation, post-escalation, Russia, Ukraine.*

1. INTRODUCTION

Since 2014, Russia has been undermining the international community through its unprovoked brutal invasion of Ukraine, resulting in the annexation of the Crimea and control over the Eastern Donbas (Gurvich & Prilepskiy, 2018; Marples, 2022). In response, Ukraine's allies led by the US, implemented measures to limit Russian energy companies' access to financial resources and technology (Gould-Davies, 2018; Brown, 2020; Aslund & Snegovaya, 2021).

Both, Ukraine and Russia, play pivotal roles in international commodity markets. Russia stands as the third-biggest producer and the second-largest crude oil exporter (IEA, 2022). Ukraine ranked among the top-five global wheat exporters and secured the third position in corn exports (USDA, 2023). In February 2022, the Russian full-scale escalation of the war against Ukraine prompted developed countries to impose new sanctions, aiming to curb trade and weaken the financial strength of the aggressor. The escalating war led to disruptions, causing a surge in prices, particularly in the energy sector during the first quarter of 2022 (WBG, 2022).

The implementation of sanctions against Russia has caused a wide discussion within the international community of economists and politicians. The disruption of the international oil market became one of the motives of Saudi Arabia to increase the crude oil exports from 6.6 mb/d in 2020 to 7.4 in 2022 (FRED, 2023) with a remaining trend in 2023 (Roussanoglou, 2023). In the last decade the US became one of the largest oil products exporters and steadily increased its presence on the international market from 3.2 in 2020 to 3.6 mb/d in 2022, expanding in 2023 (EIA, 2023). Russia increased crude oil export from 4.6 in 2020 to 4.7 mb/d in 2022 (CEIC, 2023). The trend is in line with the global crude oil demand upward movement in the aftermath of the Covid-2019 pandemic. The international demand for oil in 2022 stood at the level of 99.57 mb/d and is estimated to reach 101.7-101.9 in 2023 (IEA, 2023; Statista, 2023). The supply of oil amounted to 93.9 in 2022 (Statista, 2023a) and estimated at the level of 101.9 mb/d in 2023 (IEA, 2023). The community of major exporters remains positive with expectation of oil demand increasing by 2.2 mb/d in 2024 (Sengupta, 2023). With favorable conditions for major oil producers in 2023 and similar business incentives in 2024, Russia expands its trade with leading importers through seaborn crude oil export, China and India, while the EU share decreased from a quarter to only 2% y/y, (Dodonov et al., 2023).

Based on the existing literature it's known that Russia's aggression against Ukraine has affected the poorest people suffering from hunger worldwide, the sanctions implied by mostly North-Atlantic and European nations have influenced Russian ability to finance the war against Ukraine. However, there is not enough evidence supporting Russia's incapability to impose any effect on the energy market through the pricing mechanism.

There are several theoretical pillars of this research. The economic theory, as articulated by Working (1949), regarding commodity reserves coupled with the efficient market hypothesis discussed by Fama (1970), delineates how prices on spot and futures markets respond to an innovation, either political, military or other structural alterations. Additionally, within the realm of international relations, this analysis adds to our understanding of possible communications strategies regarding the common effort aimed at collectively restraining Russia's prospect on the oil market. This perspective is viewed through the lenses of realism, Morgenthau (1948), and constructivism as discussed by Sørensen et al. (2022).

The main idea of the research is to study whether Russia does continue to maintain direct influence on energy markets. Therefore, the research question is whether the spot price of Russia's Urals blend, North Sea's Brent and WTI oil futures are linked by "causality" either one or another direction. There are two outcomes of the study: H_0 – no causality running from Russia's Urals oil spot price either to North Sea's Brent or the US WTI futures, H_1 – otherwise. Rejecting H_0 will strongly support Ukraine's position demanding new solutions against Russia on the international oil market.

Ukraine encountered the unprecedented challenges of the defense war against Russia. However, there is an important question of public management in international affairs. In particular, The President of Ukraine, The Ministry of International Affairs as well as the Parliament Committee on International Policy have met the urgent demand for evidence-based facts regarding the outcomes of the already implemented measures, but also new possible solutions to fight Russia in the international economy domain. Results of the analysis are important in shaping Ukraine's argumentation against Russia in international communications. The empirically proven evidence about Russia's backed influence on international energy markets will support Ukraine's position in negotiations and navigate public management decisions in international lobbying for the development of new packages of sanctions. To underscore these claims, we turn to the economic theories pivoting trading strategies in commodities markets during periods of heightened uncertainty or policy innovations.

The analysis required for the research includes following steps: check the price series for the order of integration, set up a vector-autoregression model, check for serial correlation to remove it in the model to test the Granger "causality", conduct post-estimation tests to check the robustness of results.

2. LITERATURE REVIEW

The ruthless escalation of the war by Russia against Ukraine in February 2022 triggered significant disruption on the international energy market as developed countries implemented sanctions to limit the aggressor's revenue. In its essence, the portfolio of sanctions functions as both, a discount for Russian oil and a partial ban on imports. Researchers have capitalized on this theme, arguing whether sanctions are effective. Yet, available knowledge reveals a scarcity of evidence concerning the post-escalation functional connection between the Urals oil spot, the WTI, and the Brent futures markets.

It’s rather quite challenging to exaggerate the importance of oil exports for Russia’s economy; a 1% change in oil price constitutes 0.44% of Russia's GDP growth, Ito (2012). Tuzova and Qayum (2016) affirmed the significance of the oil for Russia, with an estimated decrease of the GDP on average by almost one-fifth. The estimated effect of sanctions in the period from 2014 until the end of 2017 is USD 280 bln, Gurvich and Prilepskiy (2015).

However, the first round of sanctions in the aftermath of 2014 proved insufficient in diminishing Russia’s power on the global oil market. The Urals oil blend retained its impact on the international market being a reliable indicator for predicting Brent price, but not vice-versa, Hajko and Neubauer (2015). Thus, Russian companies would be expected to maintain its position on the global energy market.

Research on sanctions against Russia lacks consensus. Girardone (2022) contends that sanctions imposed on the Russian financial sector post-2014 have not caused losses for banks, instead, they claimed record profits, furthermore the author avers that limiting energy trade might cause significant disruption of value chains in Europe and the US, but also increase the price of products and services. In contrast, Yudaruddin and Lesmana (2023) note a negative response from all the known Western banking organizations to Putin's aggression in Ukraine. Besides, the spillover effects of Russia's escalation in Ukraine on 24 February 2022 have been evident in the EU, the US, and Ukraine, but also in Russia itself, where food price inflation appears to be highly correlated with the Euro area countries, Ozili (2022).

Intriguing, Russia’s economy faced differentiated effects of sanctions for varied economic actors. Huynh et al. (2023) suggests that companies heavily bound with the Kremlin appeared to be prepared for the invasion of the Crimea, but also later wider aggression, and so were not affected by sanctions that much as non-energy companies. The sanctions do not appear to impact economic performance of Russian firms persistently, while management discovers strategies to tackle those, Gaur et al. (2023).

As Russia continues its brutal aggression, the war against Ukraine may cause 3-7% annual decrease of Russia’s economy if major importers would shut down trade with Russia, Hosoe (2023). Simola (2023) found that sanctions are neither unprecedented nor insignificant with notable effect on targeted sectors. Although there is evidence for sanctions violations, it's reported that oil export of Russia declined by USD 15.6 bln with overall drop by USD 39.8 bln and the contribution of lower prices for the oil - USD 4.2 bln, Hilgenstock et al. (2023).

The perfect market concept assumes that prices provide accurate signals, reflecting all available information, Fama (1970). This is of paramount importance for commodity traders in the frame of price discovery mechanism to differentiate goods and instruments as prices setters or takers. There is large body of literature investigating the causality direction and its changes among futures and spot. Bekiros and Diks (2008) described persistent bi-directional causality between futures and spot markets of WTI. Interesting results by Kaufmann and Ullman (2009) shows how causality goes from spot for Dubai-Fateh, extending its influence to other spot and futures markets. Nevertheless, the evidence exhibits variability, pointing to diverse outcomes resulting from market innovations, especially in unique circumstances.

The global oil market significantly influenced by the level of available reserves, Ahmadi et al. (2020), shaping trading and hedging decisions of companies, but also actions of governments. Abosedra and Radchenko (2002) suggests that traders are incentivized to increase oil inventories when the price is expected to increase and the other way around. The notable case study recorded in April of 2020 when prices for oil declined to minimum levels, while futures went negative, with abnormally increased reserves due to the 2019 post-covid demand shock, Bourghelle et al. (2021). Reverse happened after February 2022. Therefore, participation in futures markets is helpful to reduce the risk due to unpredictable events. Pindyck (2004) reviews the importance of storage levels in the context of derivatives markets, describing volatility as externally caused variable. Later analysis by Knittel and Pindyck (2016) supports the idea of the storage influence on the spot and futures prices, marking that speculation has rather no impact on oil. Dvir and Rogoff (2014) has found the co-integration between oil inventories and real prices being characterized with mirroring under inflexibly and divergence with responsive supply.

In that regard, the "peak oil" theory well explains motivations of governments to maintain "spare capacity" of available commodity for being able to limit unpredictable shocks, Gholz and Press (2010). Moreover, it's rather intriguing how global policy players diversified their actions on the constructivism in cooperation, Ukraine's allies, and realism in benefiting from Russian war, China, India and Turkey. The major difference between the two domains of thought in the context of international policy tensions is that the Western block of countries acts first based on the demands of citizens uniting around support to Ukraine and then pragmatic constraints aiming to minimize own economic loss from sanctions against Russia. In contrast, the Eastern block is rather motivated by real short-term benefits, but not voters call. This research focuses on the question whether Russia still imposes an effect on the international energy markets through pricing mechanisms and study of WTI, Brent futures prices, and Urals spot prices.

3. RESEARCH DATA

The disruption caused by the Russian war with Ukraine in international supply chains has been the driving force behind the upward price trend observed across various commodities, including energy (Ihle et al., 2022). The analysis concentrates on three key variables: the spot price of the Russian Urals blend, the January 2024 futures for WTI (the US oil), and the February 2024 futures for Brent (North Sea oil), sourced from FML (2023a, 2023b, 2023c). All series are denominated in the US dollars per barrel. Notably, the Urals and WTI series were obtained without missing values. However, the Brent series exhibited ninety missed observations within the sample, which comprised 1348 data points spanning a time period of 1910 days from July 12, 2018, to October 4, 2023. Throughout the analyzed period, there were 546 weekends and 16 days for which data was not provided. Handling missing values, imputation for the Brent series is carried out using arbitrary values calculated with the Amelia package for R, developed by Honaker et al. (2011). Following the imputation procedure, the series were configured for subsequent transformations. The daily price dataset underwent a transformation into weekly-average series, a method employed to mitigate potential challenges associated with serial correlation and outliers, exemplified by the negative price observed for WTI on April 20, 2020.

The summary metrics for daily and weekly-average levels suggest that there is no significant difference between both samples, as indicated by the mean, median, standard deviation, kurtosis, and skewness values (refer to the Table 1). Subsequently, the weekly-average levels were transformed with a natural logarithm. The conversion of prices into a smaller frequency resulted in a reduced sample size of 277 points, comprising 186 observations in the pre- and 91 in the post-escalation period.

Table 1. Descriptive statistics for the analyzed series

	Type	Mean	SE	Median	SD	Kurtosis	Skewness	Sample
Daily	Urals	64,3	0,4	65,2	15,5	1,1	-0,6	
	WTI	66,6	0,5	66,5	20,1	0,5	0,1	1348
	Imp. Brent	71,6	0,5	71,8	19,7	0,1	0,1	
Weekly avg.	Urals	64,1	0,93	65,1	15,5	1,1	-0,6	
	WTI	66,3	1,20	66,1	20,0	0,2	0,1	
	Imp. Brent	71,4	1,18	71,6	19,6	0,1	0,1	277
Weekly avg.	*ln* Urals	4,1	0,02	4,2	0,3	7,1	-2,2	
	ln WTI	4,1	0,02	4,2	0,4	12,0	-2,2	
	ln Imp. Brent	4,2	0,02	4,3	0,3	1,5	-0,9	

Source: Data adapted from FML (2023a, 2023b, 2023c)

Table 2. Comparative analysis of weekly averaged series ratios pre- vs. post-February 2022

Series	Urals	WTI	Imp. Brent
Pre. - February 2022	60,0	56,0	61,3
Post. - February 2022	72,5	87,1	91,6
% change	21%	56%	50%

Source: Data adapted from FML (2023a, 2023b, 2023c)

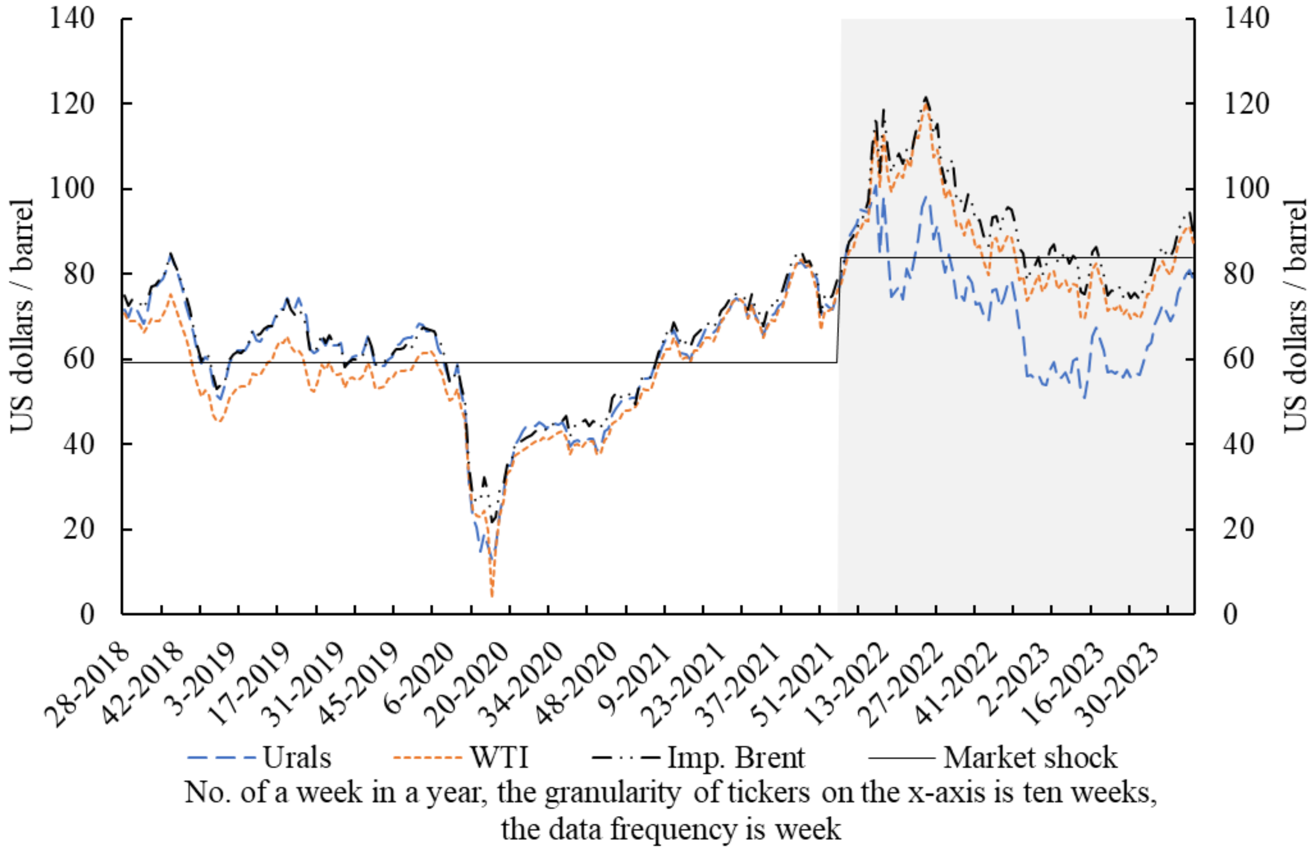


Figure 1. Weekly averages: Urals spot, WTI, and Brent futures prices

Source: Data adapted from FML (2023a, 2023b, 2023c)

The analysis expands beyond retrospective examination, integrating the outcomes of the market price mechanism after the intervention on February 24, 2022. In the light of the war escalation, oil and futures prices demonstrated a pronounced signal of the shock (refer to the Figure 1). The next section of the study delves into the effect on the oil spot and futures prices, with WTI and Brent markets experiencing a markable spike with over 50% rise, whereas the Urals only 21% increase (refer to the Table 2).

4. RESEARCH METHODOLOGY

The analysis commences by testing variables for a unit root to deduce the order of integration. Then, if one of the series is integrated with I(1), while others are stationary at levels, it highlights that the particular variable first-difference transform is investigated against a unit root presence and represents the maximum order of integration. KPSS Kwiatkowski et al. (1991), ADF Dickey and Fuller (1979), and DFGLS Elliott (1996) tests are used to analyze series for stationarity. The KPSS test is designed to detect the trend-stationarity, while ADF and DFGLS identify series with a unit root, i.e., non-stationarity.

Sims (1980) proposed the vector-autoregressive model. The modelling approach utilizes either level or log-transformed variables. The bivariate model specification is based on the following equations 1 and 2, Gujarati (2003). To fit the model the lag length j is selected based on criteria suggested by Akaike (1974), Schwarz (1978), Hannan and Quinn (1979). The model is verified with the Residual Serial Correlation LM Test, Breusch (1978) and Godfrey (1978). If there is a sign of autocorrelation, the j order of lag might be increased. The model is also verified if kurtosis and skewness of residuals distribution signal normality with the Bera and Jarque (1981). The stability of the model verified with inverse roots of the characteristic polynomial. Glaister (1984) suggests that the model should be stable meaning that disturbance of residuals decays with time as close as possible to zero.

$$M_{1t} = \alpha \ + \sum_{j=1}^{k} \beta_j \, M_{t-j} + \sum_{j=1}^{k} \gamma_j \, R_{t-j} \ + \ \mu_{1t}, eq. 1$$

$$R_{2t} = \alpha' \ + \sum_{j=1}^{k} \theta_j \, M_{t-j} + \sum_{j=1}^{k} \varphi_j \, R_{t-j} \ + \ \mu_{2t}, eq. 2$$

We proceed the analysis of causality with the Toda-Yamamoto (1995) methodology through addition of an exogenous lag of both variables in the bivariate models. The final step is to utilize the Block Exogeneity Wald test to check for the presence and direction of causality. The augmented model with exogenous lags of variables then checked for goodness-of-fit using serial correlation, the stability, residuals normality tests. The algorithm is motivated by its robust methodology against presence of cointegration as well as level of integration among variables Toda-Yamamoto (1995). It’s assumed that non-normality is allowed in time series analysis as well as heteroscedasticity is acceptable in the context of the research purpose Barker & Shaw (2015). The serial-correlation has to be avoided as well as non-stability of the model with characteristic polynomial roots outside of the unit circle. In writing this capstone project the following software was used: IHS Markit (2024), Microsoft Corporation (2024).

5. RESULTS AND DISCUSSION

The aim of the analysis is to answer the question - how is the Russian aggression towards Ukraine associated with the global oil market? To investigate the “causality” and its direction among Russian Urals price series and international prices for oil futures, the bivariate vector-autoregressive models estimated augmenting an additional exogenous lag d_{max}, following the Toda-Yamamoto (1995) procedure.

The pair of hypotheses to test is: H_0 Russian oil price Urals is not helpful in prediction of the US oil futures price series WTI after February 2022 and H_0 Russian oil price does not “cause” the North Sea oil futures price Brent in the aftermath of the wider aggression. To elaborate on the research question, models are estimated for the time periods before the large-scale escalation and after.

The analysis of time series confirms that the largest order of the integration among three series is I(1) as all variables are stationary when transformed with the first difference.

Table 3. Testing series for the unit-root and the order of integration

Test stat. $_{t., i.}$	KPSS, LM-Stat.		ADF, t-Stat.		DFGLS, t-Stat.	
Series	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
Urals	0.19	0.05***	-2.15	-7.01***	-1.74	-6.21***
WTI	0.22	0.07***	-2.21	-6.15***	-1.47	-7.32***
Imp. Brent	0.24	0.08***	-1.94	-15.62***	-1.44	-4.5***
ln Urals	0.19	0.03***	-2.36	-7.16***	-1.99	-6.83***
ln WTI	0.22	0.03***	-2.8	-15.09***	-2.21	-14.96***
ln Imp. Brent	0.25	0.06***	-2.80	-13.41***	-2.22	-4.55***

Sample: 277 weekly averaged observations

The unit root and stationarity tests already indicate that the maximum order of integration is I(1) and so d_{max} is 1. Therefore, for the pre-escalation period for the VAR model of Urals and WTI prices, the $j + d_{max} = 8$, as the $j = 7$ based on the AIC, FPE and LR (refer to the Table 4). The model verified for the serial correlation with the LM test (refer to the Table B1), and the stability (refer to the Figure B1).

The model for the post-escalation period tested for $j = 8$ and $j + d_{max} = 9$, the variables of Urals and WTI are used in *ln*-transform of levels to tackle the issue of serial correlation.

The suggested j is different considering varied criterions. The LR is selected arbitrarily to mitigate the serial correlation issue in the model, but also to achieve the model stability for the Toda-Yamamoto Granger-causality testing.

Table 4. The j-lag criterions for Urals and WTI series

Pre-escalation, in levels	LR, lag 7 23.09	FPE, lag 7 14.47*	AIC, lag 7 8.35*	SC, lag 2 8.66*	HQ, lag 3 8.54*
Post-escalation, in *ln*-levels	LR, lag 8 11.62*	FPE, lag 4 1.59e-06*	AIC, lag 4 -7.68*	SC, lag 1 -7.49*	HQ, lag 1 -7.59*

Table 5. Toda-Yamamoto Granger-Causality Block-Exogeneity Wald tests Urals – WTI

H_0 hypothesis	Chi-sq	df	Prob	Causality
Pre-escalation				
WTI does not cause Urals	14.6	7	0.04	WTI → Urals
Urals does not cause WTI	22.4	7	0.002	WTI ← Urals
Post-escalation				
ln WTI does not cause *ln* Urals	18.0	8	0.03	WTI → Urals
ln Urals does not cause *ln* WTI	10.7	8	0.22	WTI ↚ Urals

The analysis of "causality" between oil and futures prices in pre- and post-intervention of Russia towards Ukraine reveals that Urals oil in the pre-war period affected through price signaling WTI futures market. Although, there is mutual Granger "causality" found before February 2022 (refer to the Table 5), Russia has lost its strategic influence on WTI.

With the similar approach the series for Urals spot and Brent futures prices analysed. The lag j = 7 for the model selected based on the AIC, FPE and LR criterions for the pre-escalation period. As the test for the price series suggests the $d_{max} = 1$, thus the $j + d_{max} = 8$ for the pre-escalation VAR model of Urals and Brent price series. To analyse the post-escalation dynamics of Urals and Brent oil prices were *ln*-transformed in order to mitigate serial correlation and persuade the stability of the system.

The post-escalation period model tested for the lag-selection criterions for j-lag. Most of the criterions suggest to go with max j = 2. However, it was not enough to mitigate the serial correlation issue as well as the stability problem. The lag is selected arbitrarily so that j = 11. The test for the "causality" suggests no connection between Urals and Brent prices compared to the pre-intervention period.

The outcome of the modelling for the Urals-Brent pair is that in the pre-escalating period Urals prices were observed to be useful for prediction of Brent prices and not vice-versa, e. i., there was one-directional Granger "causality" (refer to the Table 7). This implies a sign of larger price-signaling power of Russian oil traders on the global market compared to other market actors, e.g., speculators, hedging companies. The situation changed over the Russian full-scale escalation in February 2022, suggesting Russia's weaker position on the market.

Table 6. The j-lag criterions for Urals and Brent

Pre-escalation, in levels	LR, lag 7 11.90*	FPE, lag 7 7.36*	AIC, lag 7 7.67*	SC, lag 2 7.93*	HQ, lag 3 7.81*
Post-escalation, in *ln*-levels	LR, lag 2 14.46*	FPE, lag 2 1.28e-06*	AIC, lag 2 -7.89*	SC, lag 1 -7.65*	HQ, lag 2 -7.78*

Table 7. Toda-Yamamoto Granger-Causality Block-Exogeneity Wald tests Urals – Brent

H_0 hypothesis	Chi-sq	df	Prob	Causality
Pre-escalation				
Brent does not cause Urals	10.9	7	0.14	Brent ↛ Urals
Urals does not cause Brent	16.2	7	0.02	Brent ← Urals
Post-escalation: log-transform				
ln Brent does not cause *ln* Urals	15.8	12	0.20	Brent ↛ Urals
ln Urals does not cause *ln* Brent	13.6	12	0.33	Brent ↚ Urals

The analysis reveals that Urals oil in the pre-war period affected through price mechanism both, WTI and Brent futures markets. As a consequence of the Russian war against Ukraine and later western sanctions Russian oil companies faced incompatible price levels. Russia has lost its strategic influence on WTI and Brent blends, at least in the period of the analysis.

These findings have direct implications for the Office of the President of Ukraine, the Ministry of International Relations of Ukraine, and the Parliamentary Group of cooperation between deputies from other countries. The study furnishes additional arguments to Ukraine about effectiveness of sanctions against Russian oil exporting companies. The results reinforce Ukraine's communication strategy – the one among many other strategic management assignments of highest priority in the context of Russia's continuing war in Ukraine. Russia has lost its ability to "cause" the Brent and WTI futures prices and actually remain "influenced" by the price formation mechanism of WTI futures market.

With the Russian war escalation against Ukraine in February 2022, the international community has been challenged with disrupted supply chains of energy commodities. The results indicate "lower utility" of Russian oil in planning the stable price-volume assumptions while developing mid- and long-term commercial cooperation. The Granger "causality" applied to investigate whether two variables are linearly described with co-dependency, unidirectional bound or neither. The analysis highlights "stronger position" of Russian oil traders on international markets through its effect on the WTI and Brent futures in the pre-escalation period and marks the absence of functional "pricing influence" in the post-escalation period. Alzahrani et al. (2014) argued about no dominance of "causality" direction from futures to spot markets and vice-versa either in pre- or post-crisis time. Notably, in analyzed scenario Russian oil spot price in the post-escalation period appears to be “caused” by the WTI futures pricing mechanism, implying the effect on the Russian energy market. Therefore, the international unified effort in limiting Russia’s oil export revenues is associated with the much weaker pricing power of the aggressor on the US oil futures market. It is of particular relevance for management. The implication is that oil trading companies should carefully monitor the market and anticipate Russian exporters behavior influenced by the US oil futures market.

While the study provides valuable insights about prices “causality” direction among spot and futures oil markets in the light of market disruption caused by the war, there are several limitations to be considered. The data was prepared in the Fall of 2023 and represents unequal sizes of subsamples for pre- and post-escalation periods. Thus, the challenge due to historical events on the international oil market delt with careful imputations as well as transformations of series. Nonetheless, its recognized that with larger post-escalation subsamples the testing results could be adjusted. Especially, if adding additional context of the global energy market or considering different functional settings of the pricing mechanism. Russia reshuffled its energy trade towards China, India and Turkey. Moreover, the unique characteristic of the Russian oil trade with its gray commercial fleet, may introduce non-linear form of “causality”, motivating researchers to elaborate more on these dynamics in the future studies.

To elaborate on the initial research question of this study, scholars and analysts could contribute more with adding better data samples, expanding the context of the study with more variables or try test different functional forms of the pricing mechanism. Additionally, there are interesting questions which could be answered later on, for example: a. Is the Russian oil spot price integrated with the WTI, Brent and other futures markets? b. How the integration changed in the pre- and post-escalation periods? c. If present, what kind of price-transmission mechanism exists between spot and derivatives markets?

6. THEORETICAL IMPLICATIONS

The research looks specifically at the price mechanism of the international oil market during the major global geopolitical disturbances caused by the largest war in Europe since the World War II. It's observed that spot price for Urals oil has increased post—February 2022 with a smaller rate on average, comparing to the WTI and the Brent futures. This could be explained by the bundle of factors. First and foremost, the sanctions design with the partial import ban as well as the price limit for Russian oil. In the second place, the structural change in the Russian exports later on being redirected towards markets of China, India and Turkey eager for discounts. Motivated by the general hypothesis – the Russian oil spot price doesn't Granger causes the WTI and the Brent futures, we can't reject it in the post-February 2022 period. Simultaneously, the H_0 is rejected for the pre-escalation time, contributing nuanced evidence to the understanding of the price discovery mechanism in the oil markets, driven by powers of extracting, processing and other companies. As the Russian oil spot price found to be "caused" by the WTI futures markets, the managerial implications of it lies in the domain of economic theory of the storage and the efficient market hypothesis.

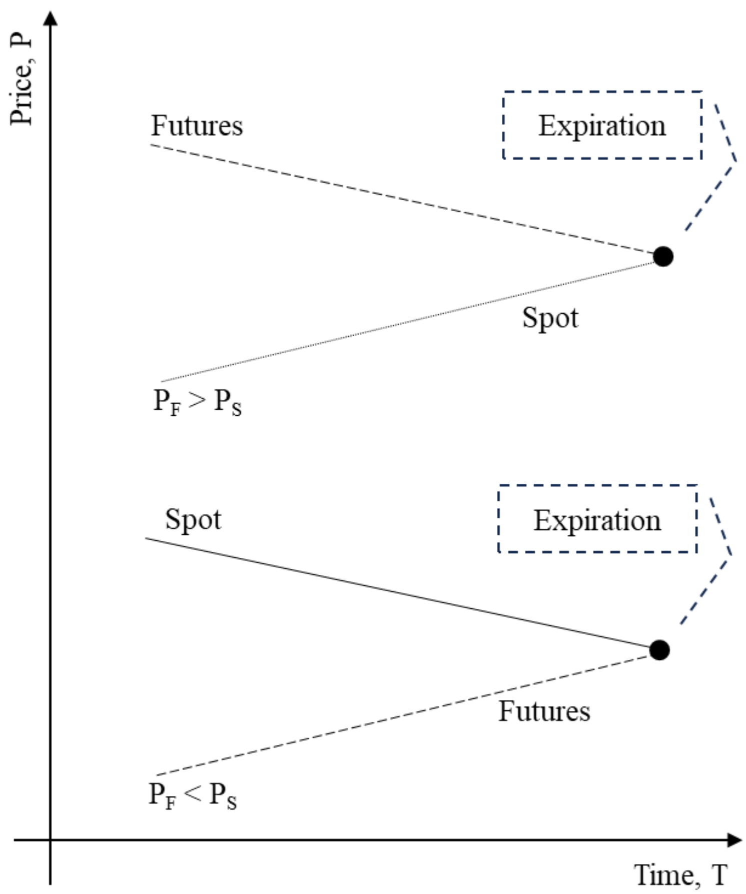


Figure 2. The theoretical trading strategy

Commodities markets are influenced by storage levels, i.e., available goods in the market (Brooks et al., 2013; Miljkovic and Goetz, 2020). In its essence, the simplified idea incentivizes refineries to boost purchases when available commodity is low and vice versa (Hanieh, 2021). In such periods markets described by higher than spot futures prices, the contango (Juvenal and Petrella, 2015), as expectation drives spot price up, as with increasing demand supply should adjust. In the case of supply disruptions, delay in fulfillment of storage amplify demand, shifting spot above futures price, the backwardation (Litzenberger and Rabinowitz, 1995), with conceptualized shortages in short-term and expected increase of supplies supported by higher prices (refer to the Figure 2). This implies that trading managers and analysts should closely monitor the WTI relative to reserves and extraction of the crude oil. This theoretic setting provides useful insights for planning operational business of companies. As in the case of contango, traders will be expected to buy crude oil and short futures contracts to secure favorable prices. The short-term demand for oil characterized by much steeper slope than supply, leading to the higher shortage. Otherwise, in the backwardation regime, market actors would be expected to sell the oil in the excess simultaneously taking long-term position in futures to secure more favorable prices later on. In short-term the slope of oil supply is expected to be much steeper than demand, driving the spot price down.

As the price of Urals oil described with strong positive correlation in pre-February 2022 with WTI and Brent futures, and about 10-15 p.p. less in the post-escalation period, in accordance with the efficient market hypothesis the spot price is expected to mirror the futures, given the “causality” direction.

Zooming out from the micro-level, obtained results advance our comprehension of the international relations through theories of constructivism and realism. Recognizing Russia’s heavy dependance on global energy markets, in particular oil, there is an important implication for the design of sanctions. The theory of storage provides a concept of decision mechanism for policymakers, helping to understand when to increase oil supplies to diminish the aggressor’s revenue from exports. In the wider scope of global affairs, the geopolitical shifts towards Eastern countries like China, India and Turkey demonstrate a strategic utilization of realism, allowing trade with a nation that has unjustly invaded the neighbor. The restructuring of discounted exports by Russia towards Eastern countries has reshaped international dynamics, with India emerging as a major exporter of petrol to the EU. Contrastingly, Ukraine and its allies align referring to the constructivism, emphasizing unifying values are common principles, rules of law regarding the international borders, human rights as well as security. However, the realism strongly imputed into the practice. As Ukraine’s allies are not ready to completely ban trade with Russia, political influence among Eastern countries is limited, economic ties are rather strong between major actors in global politics, the theory of realism advocates for sanctions as a strategic instrument, providing time to recalibrate economic policies and defense supply chains.

REFERENCES

Abosedra, S., & Radchenko, S. (2002). Oil stock management and futures prices: An empirical analysis. J. Energy & Dev., 28, 173. Retrieved from: https://www.jstor.org/stable/24809253.

Ahmadi, M., Bashiri Behmiri, N., & Manera, M. (2020). The theory of storage in the crude oil futures market, the role of financial conditions. Journal of Futures Markets, 40(7), 1160-1175. Retrieved from: https://onlinelibrary.wiley.com/doi/abs/10.1002/fut.22113.

Akaike, H. (1974). A new look at the statistical model identification. IEEE transactions on automatic control, 19(6), 716-723. Retrieved from: https://ieeexplore.ieee.org/abstract/document/1100705.

Alzahrani, M., Masih, M., & Al-Titi, O. (2014). Linear and non-linear Granger causality between oil spot and futures prices: A wavelet-based test. Journal of International Money and Finance, 48, 175-201. Retrieved from: https://doi.org/10.1016/j.jimonfin.2014.07.001.

Åslund, A., & Snegovaya, M. (2021). The impact of Western sanctions on Russia and how they can be made even more effective. Atlantic Council, 3. Retrieved from: https://www.atlanticcouncil.org/wp-content/uploads/2021/05/The-impact-of-Western-sanctions-on-Russia-and-how-they-can-be-made-even-more-effective-5.2.pdf.

Barker, L. E., & Shaw, K. M. (2015). Best (but oft-forgotten) practices: checking assumptions concerning regression residuals. The American journal of clinical nutrition, 102(3), 533-539. Retrieved from: https://doi.org/10.3945/ajcn.115.113498.

Bekiros, S. D., & Diks, C. G. (2008). The relationship between crude oil spot and futures prices: Cointegration, linear and nonlinear causality. Energy Economics, 30(5), 2673-2685. Retrieved from: https://doi.org/10.1016/j.eneco.2008.03.006.

Bera, A. K., & Jarque, C. M. (1981). Efficient tests for normality, homoscedasticity and serial independence of regression residuals: Monte Carlo evidence. Economics letters, 7(4), 313-318. Retrieved from: https://doi.org/10.1016/0165-1765(81)90035-5.

Bourghelle, D., Jawadi, F., & Rozin, P. (2021). Oil price volatility in the context of Covid-19. International Economics, 167, 39-49. Retrieved from: https://doi.org/10.1016/j.inteco.2021.05.001.

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. Australian economic papers, 17(31), 334-355. Retrieved from: https://doi.org/10.1111/j.1467-8454.1978.tb00635.x.

Brown, P. (2020). Oil market effects from US economic sanctions: Iran, Russia, Venezuela (Vol. 3, pp. 154-196). Washington, DC, USA: Congressional Research Service. Retrieved from: https://www.everycrsreport.com/files/20200205_R46213_7bb76e54df206bce64dd8b2f4b4c8543148720df.pdf.

Brooks, C., Prokopczuk, M., & Wu, Y. (2013). Commodity futures prices: More evidence on forecast power, risk premia and the theory of storage. The Quarterly Review of Economics and Finance, 53(1), 73-85. Retrieved from: https://doi.org/10.1016/j.qref.2013.01.003.

CEIC. (2023). Russia Crude Oil: Exports. www.ceicdata.com. Retrieved from: https://www.ceicdata.com/en/indicator/russia/crude-oil-exports.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American statistical association, 74(366a), 427-431. Retrieved from: https://doi.org/10.1080/01621459.1979.10482531.

Dvir, E., & Rogoff, K. (2014). Demand effects and speculation in oil markets: Theory and evidence. Journal of International Money and Finance, 42, 113-128. Retrieved from: https://www.sciencedirect.com/science/article/abs/pii/S0261560613001095.

EIA. (2023). Petroleum & Other Liquids. U.S. Energy Information System. Retrieved from: https://www.eia.gov/dnav/pet/pet_move_exp_dc_NUS-Z00_mbblpd_m.htm.

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient Tests for an Autoregressive Unit Root. Econometrica, 64(4), 813–836. https://doi.org/10.2307/2171846. Retrieved from:

https://www.jstor.org/stable/2171846.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The journal of Finance, 25(2), 383-417. Retrieved from: https://www.jstor.org/stable/2325486?read-now=1.

FML (2023a). Brent Oil Futures - Feb 24 (LCOG4). Fusion Media Limited. Investing.com. Retrieved from: https://www.investing.com/commodities/brent-oil-historical-data.

FML (2023b). Crude Oil Urals Europe CFR Spot. Fusion Media Limited. Investing.com. Retrieved from: https://www.investing.com/commodities/crude-oil-urals-spot-futures-historical-data.

FML (2023c). Crude Oil WTI Futures - Jan 24 (CLF4). Fusion Media Limited Investing.com. Retrieved from: https://www.investing.com/commodities/crude-oil-historical-data.

FRED. (2023). FRED Economic Data | St. Louis FED. Crude Oil Exports for Saudi Arabia. Retrieved from: https://fred.stlouisfed.org/series/SAUNXGOCMBD.

Gaur, A., Settles, A., & Väätänen, J. (2023). Do Economic Sanctions Work? Evidence from the Russia-Ukraine Conflict. Journal of Management Studies. Retrieved from: https://onlinelibrary.wiley.com/doi/full/10.1111/joms.12933.

Gholz, E., & Press, D. G. (2010). Protecting "the prize": oil and the US national interest. Security Studies, 19(3), 453-485. Retrieved from: https://www.tandfonline.com/doi/abs/10.1080/09636412.2010.505865.

Girardone, C. (2022). Russian sanctions and the banking sector. British Journal of Management, 33(4), 1683-1688. Retrieved from: https://onlinelibrary.wiley.com/doi/full/10.1111/1467-8551.12656.

Glaister, S. (1984), Mathematical Methods for Economists, 3rd edn, Blackwell, Oxford. In Chaiechi, T., Pryce, J., & Bhati, A. (2015). Research Note: Macroeconomic Impacts of the Tourism Industry and the Contemporaneous Feedback Effect—An Australian Case Study. Tourism Economics, 21(3), 685-696. Retrieved from: https://doi.org/10.5367/te.2013.0364.

Godfrey, L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. Econometrica: Journal of the Econometric Society, 1293-1301. Retrieved from: https://doi.org/10.2307/1913829.

Gould-Davies, N. (2018). Economic effects and political impacts: Assessing Western sanctions on Russia (No. 8/2018). BOFIT Policy Brief. Retrieved from: https://www.econstor.eu/bitstream/10419/251680/1/bpb1808.pdf.

Gujarati D. N. (2003). Basic Econometrics. 4th ed. McGraw-Hill. Page 849.

Gurvich, E., & Prilepskiy, I. (2015). The impact of financial sanctions on the Russian economy. Russian journal of economics, 1(4), 359-385. Retrieved from: https://www.sciencedirect.com/science/article/pii/S2405473916000039.

Gurvich, E., & Prilepskiy, I. (2018). Western sanctions and Russian responses: Effects after three years. In The Russian economy under Putin (pp. 30-47). Routledge. Retrieved from: https://books.google.com.ua/books?hl=en&lr=&id=omE-PEAAAQBAJ&oi=fnd&pg=PA30&dq=western+sanctions+against+russia&ots=t3ahcr-vuH6&sig=m1b7il-CU1N4iIsQKCCjlH-9ZAk&redir_esc=y#v=onepage&q=western%20sanctions%20against%20russia&f=false.

Hanieh, A. (2021). COVID-19 and global oil markets. Canadian Journal of Development Studies/Revue canadienne d'études du développement, 42(1-2), 101-108. Redrived from: https://doi.org/10.1080/02255189.2020.1821614.

Hajko, V., & Neubauer, J. (2015). The causal relationships between Brent and Urals oil price benchmarks. In 18th International Scientific Conference "Enterprise and the Competitive Environment," March (pp. 5-6). Retrieved from: https://www.researchgate.net/publication/284154160_The_causal_relationships_between_Brent_and_Urals_oil_price_benchmarks.

Hannan, E. J., & Quinn, B. G. (1979). The determination of the order of an autoregression. Journal of the Royal Statistical Society: Series B (Methodological), 41(2), 190-195. Retrieved from:

https://rss.onlinelibrary.wiley.com/doi/abs/10.1111/j.2517-6161.1979.tb01072.x.

Hilgenstock, B., Ribakova, E., Shapoval, N., Babina, T., Itskhoki, O., & Mironov, M. (2023). Russian Oil Exports Under International Sanctions. Available at SSRN. Retrieved from: https://ssrn.com/abstract=4430053.

Honaker, J., King, G., & Blackwell, M. (2011). Amelia II: A program for missing data. Journal of statistical software, 45, 1-47. Retrieved from: https://www.jstatsoft.org/article/view/v045i07.

Hosoe, N. (2023). The cost of war: Impact of sanctions on Russia following the invasion of Ukraine. Journal of Policy Modeling, 45(2), 305-319. Retrieved from: https://doi.org/10.1016/j.jpolmod.2023.04.001.

Huynh, L. D. T., Hoang, K., & Ongena, S. (2023). The impact of foreign sanctions on firm performance in Russia. Swiss Finance Institute Research Paper, (23-115). Retrieved from: http://dx.doi.org/10.2139/ssrn.4645442.

IEA. (2022). Russian supplies to global energy markets. IEA. Paris. Redrived from: https://www.iea.org/reports/russian-supplies-to-global-energy-markets.

IEA. (2023). Oil Market Report - December 2023. Retrieved from: https://www.iea.org/reports/oil-market-report-december-2023.

Ihle, R., Bar-Nahum, Z., Nivievskyi, O., & Rubin, O. D. (2022). Russia's invasion of Ukraine increased the synchronisation of global commodity prices. Australian Journal of Agricultural and Resource Economics, 66(4), 775-796. Retrieved from: https://doi.org/10.1111/1467-8489.12496.

IHS Markit. (2024), EViews 12 Student Version Lite (Student Edition – Sep 20 2023) [Computer Software]. HIS Global Inc. www.eviews.com. Retrieved from: https://cdn1.eviews.com/EViews12SVInstaller%2864-bit%29.exe.

Ito, K. (2012). The impact of oil price volatility on the macroeconomy in Russia. The Annals of Regional Science, 48, 695-702. Retrieved from: https://doi.org/10.1007/s00168-010-0417-1**.**

Juvenal, L., Petrella, I. (2015). Speculation in the oil market. Journal of Applied Econometrics, 30(4), 621–649. Retrieved from: https://www.jstor.org/stable/26609050.

Kaufmann, R. K., & Ullman, B. (2009). Oil prices, speculation, and fundamentals: Interpreting causal relations among spot and futures prices. Energy Economics, 31(4), 550-558. Retrieved from: https://doi.org/10.1016/j.eneco.2009.01.013.

Knittel, C. R., & Pindyck, R. S. (2016). The simple economics of commodity price speculation. American Economic Journal: Macroeconomics, 8(2), 85-110. Retrieved from: https://www.aeaweb.org/articles?id=10.1257/mac.20140033.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. Journal of econometrics, 54(1-3), 159-178. Retrieved from: https://www.sciencedirect.com/science/article/abs/pii/030440769290104Y.

Litzenberger, R. H., & Rabinowitz, N. (1995). Backwardation in Oil Futures Markets: Theory and Empirical Evidence. The Journal of Finance, 50(5), 1517–1545. Retrieved from: https://doi.org/10.2307/2329325.

Marples, D. R. (2022). Russia's war goals in Ukraine. *Canadian Slavonic Papers*, *64*(2-3), 207-219. Retrieved from: https://doi.org/10.1080/00085006.2022.2107837.

Microsoft Corporation (2024). Microsoft 365 Excel (16.0.17321.42305) [Computer Software]. Microsoft Corporation. https://www.microsoft365.com/. Redrived from: https://www.microsoft365.com/launch/excel?auth=2**.**

Miljkovic, D., & Goetz, C. (2020). The effects of futures markets on oil spot price volatility in regional US markets. Applied Energy, 273, 115288. Retrieved from: https://doi.org/10.1016/j.apenergy.2020.115288.

Morgenthau, H. (1948). Politics Among Nations: The struggle for power and peace. New York, Alfred Kopf. In Duguri, U. S., Hassan, I., & Ibrahim, Y. K. (2022). International Relations, Realism, and

Liberalism: A Theoretical Review. International Journal of Social and Humanities Extension (IJSHE), 1-6. Retrieved from: http://www.ijshe.info/index.php/ijshe/article/view/18.

Ozili, P. K. (2022). Global economic consequence of Russian invasion of Ukraine. Available at SSRN 4064770. Retrieved from: https://ssrn.com/abstract=4064770.

Pindyck, R. S. (2004). Volatility and commodity price dynamics. Journal of Futures Markets: Futures, Options, and Other Derivative Products, 24(11), 1029-1047. Retrieved from: https://onlinelibrary.wiley.com/doi/abs/10.1002/fut.20120.

Roussanoglou, N. (2023). Saudi Arabia Crude Oil Exports Keep Rising in 2023. Hellenic Shipping News. Retrieved from: https://www.hellenicshippingnews.com/saudi-arabia-crude-oil-exports-keep-rising-in-2023.

Schwarz, G. (1978). Estimating the dimension of a model. The annals of statistics, 461-464. Redrived from: https://www.jstor.org/stable/2958889.

Sengupta, C. (2023). OPEC maintains bullish oil demand forecast for 2024. Retrieved from: https://www.energyconnects.com/opinion/features/2023/december/opec-maintains-bullish-oil-demand-forecast-for-2024/.

Simola, H. (2023). What the literature says about the effects of sanctions on Russia. Retrieved from: https://publications.bof.fi/handle/10024/52716.

Sims, C. A. (1980). Macroeconomics and reality. Econometrica: journal of the Econometric Society, 1-48. Retrieved from: https://doi.org/10.2307/1912017.

Sørensen, G., Møller, J., & Jackson, R. H. (2022). Introduction to international relations: theories and approaches. Oxford university press. Retrieved from: books.google.com.

Statista. (2023). Demand for crude oil worldwide from 2005 to 2022, with a forecast for 2023 (in million barrels per day) [OPEC]. Retrieved from: https://www.statista.com/statistics/271823/global-crude-oil-demand/.

Statista. (2023a). Oil production worldwide from 1998 to 2022 (in 1,000 barrels per day). Retrieved from: https://www.statista.com/statistics/265203/global-oil-production-in-barrels-per-day/.

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. Journal of econometrics, 66(1-2), 225-250. Retrieved from: https://www.sciencedirect.com/science/article/abs/pii/0304407694016168.

Tuzova, Y., & Qayum, F. (2016). Global oil glut and sanctions: The impact on Putin's Russia. Energy Policy, 90, 140-151. Retrieved from: https://www.sciencedirect.com/science/article/abs/pii/S0301421515302214.

USDA. (2023). World Agricultural Supply and Demand Estimates. www.usda.gov. Retrieved from: https://www.usda.gov/oce/commodity/wasde/wasde1123.pdf.

WBG. (2022). Commodity Markets Outlook, April 2022: The Impact of the War in Ukraine on Commodity Markets. openknowledge.worldbank.org. Retrieved from: https://openknowledge.worldbank.org/server/api/core/bitstreams/da0196b9-6f9c-5d28-b77c-31a936d5098f/content.

Working, H. (1949). The theory of price of storage. The American economic review, 39(6), 1254-1262. Retrieved from: https://www.jstor.org/stable/1816601.

Yudaruddin, R., & Lesmana, D. (2023). Banking sector's reaction during the Russian invasion of Ukraine: who reacted the most?. Journal of Economic Studies. Retrieved from: https://www.emerald.com/insight/content/doi/10.1108/JES-04-2023-0206/full/html.

APPENDIX A.

Table A1. Testing series for the unit-root and the order of integration in pre-escalation period

Test stat. t., i.	KPSS, LM-Stat.		ADF, t-Stat.		DFGLS, t-Stat.	
Series	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
Urals	0.31	0.04***	-2.05	-6.48***	-1.91	-6.29***
WTI	0.33	0.04***	-1.73	-10.54***	-1.33	-10.36***
Imp. Brent	0.34	0.05***	-1.44	-10.69***	-1.26	-10.08***
ln Urals	0.27	0.03***	-2.12	-5.74***	-1.98	-5.71***
ln WTI	0.28	0.04***	-2.39	-12.41***	-2.13	-12.44***
ln Imp. Brent	0.31	0.05***	-2.19	-4.55**	-2.03	-4.37***

Sample: 1-186 weekly averaged observations

Table A2. Testing series for the unit-root and the order of integration in post-escalation period

Test stat. t., i.	KPSS, LM-Stat.		ADF, t-Stat.		DFGLS, t-Stat.	
Series	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
Urals	0.22	0.09***	0.38	-5.65***	-1.34	-1.45
WTI	0.15**	0.16**	-0.85	-3.24*	-2.23	-0.97
Imp. Brent	0.14*	0.15**	-2.9	-3.8**	-1.73	-1.20
ln Urals	0.22	0.09***	-1.58	-5.08***	-1.73	-1.50
ln WTI	0.16**	0.17**	-0.69	-3.18*	-2.17	-0.83
ln Imp. Brent	0.15*	0.16**	-2.87	-7.13***	-1.65	-0.97

Sample: 187-277 weekly averaged observations

Table A3. The correlations between spot and futures prices in the pre-escalation period

Pre-February 2022			
	Urals	WTI	Imp. Brent
Urals	1,00		
WTI	0,97	1,00	
Imp. Brent	0,99	0,98	1,00

Sample: 1-186 weekly averaged observations

Table A4. The correlations between spot and futures prices in the post-escalation period

Post-February 2022			
	Urals	WTI	Imp. Brent
Urals	1,00		
WTI	0,86	1,00	
Imp. Brent	0,84	0,99	1,00

Sample: 187-277 weekly averaged observations

APPENDIX B.

Table B1. Pre-escalating VAR model in levels Urals-WTI Serial correlation LM Test

Conventional model with j lags

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.696241	4	0.3199	1.179006	(4, 320.0)	0.3199
2	7.144508	4	0.1284	1.800525	(4, 320.0)	0.1284
3	2.842773	4	0.5845	0.711626	(4, 320.0)	0.5845
4	2.588890	4	0.6288	0.647815	(4, 320.0)	0.6288
5	6.171483	4	0.1867	1.552945	(4, 320.0)	0.1867
6	8.187977	4	0.0849	2.066866	(4, 320.0)	0.0849
7	7.808968	4	0.0988	1.970026	(4, 320.0)	0.0988
8	2.859339	4	0.5816	0.715791	(4, 320.0)	0.5816

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.696241	4	0.3199	1.179006	(4, 320.0)	0.3199
2	11.84025	8	0.1585	1.493661	(8, 316.0)	0.1585
3	14.31875	12	0.2808	1.201336	(12, 312.0)	0.2809
4	15.36418	16	0.4981	0.962197	(16, 308.0)	0.4984
5	22.05252	20	0.3377	1.109549	(20, 304.0)	0.3381
6	30.59256	24	0.1659	1.292114	(24, 300.0)	0.1664
7	35.39134	28	0.1588	1.282864	(28, 296.0)	0.1595
8	43.64101	32	0.0823	1.393872	(32, 292.0)	0.0830

*Edgeworth expansion corrected likelihood ratio statistic.

Augmented model j+d_{max}

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	5.605101	4	0.2306	1.409328	(4, 314.0)	0.2306
2	4.199667	4	0.3797	1.053591	(4, 314.0)	0.3797
3	0.412779	4	0.9814	0.102935	(4, 314.0)	0.9814
4	3.340454	4	0.5025	0.836892	(4, 314.0)	0.5026
5	1.749047	4	0.7818	0.437086	(4, 314.0)	0.7818
6	6.127819	4	0.1898	1.542042	(4, 314.0)	0.1898
7	2.759367	4	0.5989	0.690673	(4, 314.0)	0.5989
8	5.164962	4	0.2708	1.297752	(4, 314.0)	0.2708
9	4.842764	4	0.3038	1.216172	(4, 314.0)	0.3038

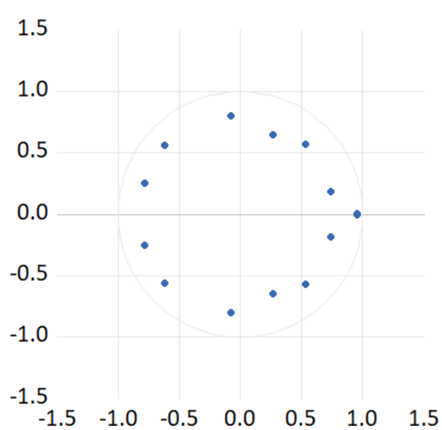
Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	5.605101	4	0.2306	1.409328	(4, 314.0)	0.2306
2	7.722355	8	0.4611	0.967934	(8, 310.0)	0.4611
3	9.012527	12	0.7019	0.749781	(12, 306.0)	0.7019
4	12.22240	16	0.7285	0.761557	(16, 302.0)	0.7287
5	13.84421	20	0.8383	0.687298	(20, 298.0)	0.8385
6	22.09026	24	0.5739	0.920152	(24, 294.0)	0.5745
7	24.15836	28	0.6731	0.859594	(28, 290.0)	0.6740
8	33.13680	32	0.4115	1.040124	(32, 286.0)	0.4130
9	34.57342	36	0.5364	0.960215	(36, 282.0)	0.5383

*Edgeworth expansion corrected likelihood ratio statistic.

Conventional model with j lags	Augmented model j+d^{max}

Inverse Roots of AR Characteristics Polynomial



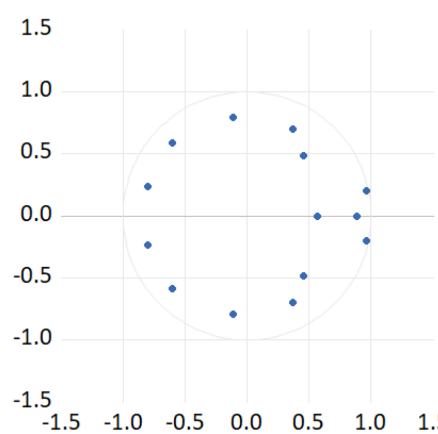


Figure B1. Pre-escalating VAR model in levels Urals-WTI AR roots test for stability

Table B2. Post-escalating VAR model in ln-levels Urals-WTI Serial correlation LM Test

Conventional model with j lags

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	5.086110	4	0.2786	1.285166	(4, 144.0)	0.2786
2	5.833189	4	0.2120	1.477765	(4, 144.0)	0.2120
3	3.456503	4	0.4845	0.868477	(4, 144.0)	0.4845
4	6.714413	4	0.1518	1.706226	(4, 144.0)	0.1518
5	5.315451	4	0.2564	1.344185	(4, 144.0)	0.2565
6	4.298724	4	0.3671	1.083247	(4, 144.0)	0.3671
7	3.129529	4	0.5364	0.785432	(4, 144.0)	0.5364
8	2.107366	4	0.7160	0.527029	(4, 144.0)	0.7160
9	4.246744	4	0.3736	1.069956	(4, 144.0)	0.3737

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	5.086110	4	0.2786	1.285166	(4, 144.0)	0.2786
2	10.06991	8	0.2602	1.276758	(8, 140.0)	0.2603
3	15.63039	12	0.2088	1.328625	(12, 136.0)	0.2092
4	18.14663	16	0.3154	1.150515	(16, 132.0)	0.3165
5	24.89207	20	0.2056	1.275181	(20, 128.0)	0.2074
6	33.20972	24	0.0997	1.440968	(24, 124.0)	0.1018
7	36.73123	28	0.1249	1.363192	(28, 120.0)	0.1284
8	40.30637	32	0.1488	1.305974	(32, 116.0)	0.1543
9	44.03521	36	0.1681	1.265778	(36, 112.0)	0.1762

Augmented model j+d_{max}

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.571258	4	0.3342	1.153304	(4, 140.0)	0.3342
2	2.985637	4	0.5602	0.749018	(4, 140.0)	0.5603
3	9.581759	4	0.0481	2.461128	(4, 140.0)	0.0481
4	8.660750	4	0.0702	2.217230	(4, 140.0)	0.0702
5	2.614559	4	0.6242	0.655059	(4, 140.0)	0.6243
6	5.342622	4	0.2539	1.351628	(4, 140.0)	0.2539
7	5.170522	4	0.2702	1.307286	(4, 140.0)	0.2703
8	5.232880	4	0.2642	1.323346	(4, 140.0)	0.2642
9	4.263131	4	0.3716	1.074384	(4, 140.0)	0.3716

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.571258	4	0.3342	1.153304	(4, 140.0)	0.3342
2	8.552696	8	0.3814	1.078864	(8, 136.0)	0.3816
3	16.32629	12	0.1767	1.392176	(12, 132.0)	0.1772
4	18.93857	16	0.2719	1.204820	(16, 128.0)	0.2730
5	23.73869	20	0.2540	1.211521	(20, 124.0)	0.2561
6	27.70048	24	0.2729	1.177366	(24, 120.0)	0.2764
7	32.22904	28	0.2653	1.175813	(28, 116.0)	0.2705
8	36.62822	32	0.2626	1.170070	(32, 112.0)	0.2702
9	39.90375	36	0.3007	1.128203	(36, 108.0)	0.3116

*Edgeworth expansion corrected likelihood ratio statistic.

Conventional model with j lags	Augmented model j+d^{max}

Inverse Roots of AR Characteristics Polynomial

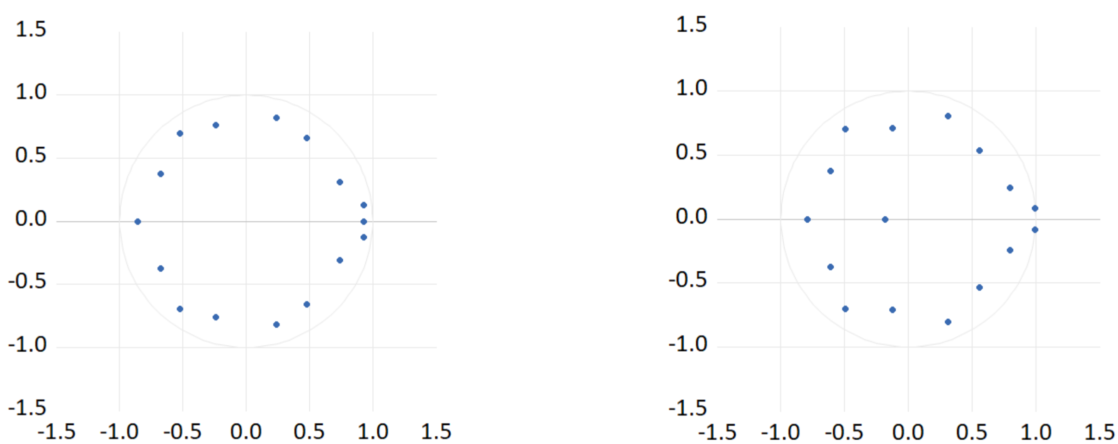


Figure B2. Post-escalating VAR model in ln-levels Urals-WTI AR roots test for stability

Table B3. Pre-escalating VAR model in levels Urals-Brent Serial correlation LM Test

Conventional model with j lags

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.670351	4	0.3228	1.172459	(4, 320.0)	0.3228
2	4.585482	4	0.3325	1.151001	(4, 320.0)	0.3325
3	1.999454	4	0.7359	0.499861	(4, 320.0)	0.7359
4	0.415664	4	0.9812	0.103659	(4, 320.0)	0.9812
5	1.146347	4	0.8869	0.286205	(4, 320.0)	0.8869
6	0.605406	4	0.9625	0.151022	(4, 320.0)	0.9625
7	2.491476	4	0.6462	0.623345	(4, 320.0)	0.6462
8	1.499724	4	0.8267	0.374637	(4, 320.0)	0.8267

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.670351	4	0.3228	1.172459	(4, 320.0)	0.3228
2	7.044264	8	0.5319	0.881954	(8, 316.0)	0.5319
3	8.054556	12	0.7809	0.669090	(12, 312.0)	0.7809
4	8.687897	16	0.9257	0.538316	(16, 308.0)	0.9258
5	9.785538	20	0.9719	0.482715	(20, 304.0)	0.9719
6	11.01233	24	0.9889	0.450548	(24, 300.0)	0.9890
7	19.11919	28	0.8944	0.674761	(28, 296.0)	0.8948
8	23.86806	32	0.8492	0.737740	(32, 292.0)	0.8498

*Edgeworth expansion corrected likelihood ratio statistic.

Augmented model j+d_{max}

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.013798	4	0.9077	0.253052	(4, 314.0)	0.9077
2	1.797832	4	0.7729	0.449312	(4, 314.0)	0.7729
3	0.945831	4	0.9179	0.236061	(4, 314.0)	0.9179
4	2.606576	4	0.6257	0.652270	(4, 314.0)	0.6257
5	2.017329	4	0.7326	0.504344	(4, 314.0)	0.7326
6	3.295744	4	0.5096	0.825632	(4, 314.0)	0.5096
7	6.761239	4	0.1491	1.703157	(4, 314.0)	0.1491
8	1.326815	4	0.8568	0.331348	(4, 314.0)	0.8568

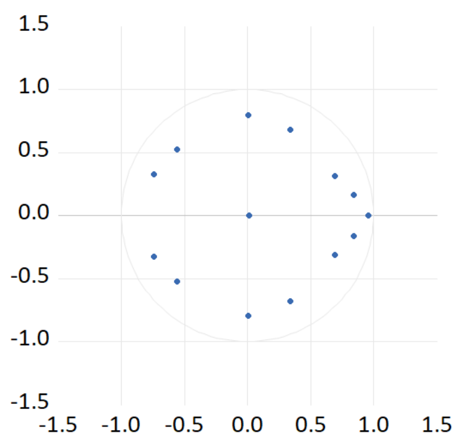
Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.013798	4	0.9077	0.253052	(4, 314.0)	0.9077
2	2.489907	8	0.9622	0.309485	(8, 310.0)	0.9622
3	3.753002	12	0.9875	0.309586	(12, 306.0)	0.9875
4	6.649765	16	0.9794	0.410597	(16, 302.0)	0.9795
5	10.03526	20	0.9675	0.495101	(20, 298.0)	0.9676
6	11.36377	24	0.9862	0.465023	(24, 294.0)	0.9862
7	18.89365	28	0.9014	0.666383	(28, 290.0)	0.9017
8	22.40787	32	0.8961	0.690742	(32, 286.0)	0.8966

*Edgeworth expansion corrected likelihood ratio statistic.

Conventional model with j lags | Augmented model j+d^{max}

Inverse Roots of AR Characteristics Polynomial



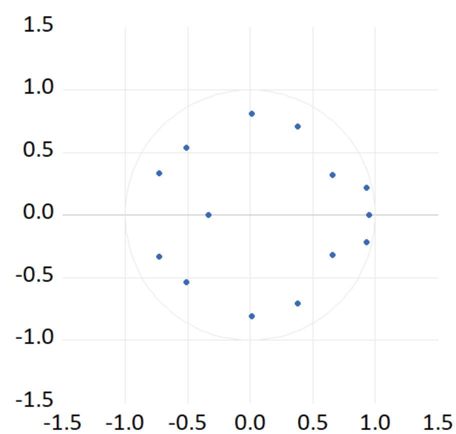


Figure B3. Pre-escalating VAR model in levels Urals-Brent AR roots test for stability

Table B4. Post-escalating VAR model in ln-levels Urals-Brent Serial correlation LM Test

Conventional model with j lags

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.230710	4	0.3757	1.066878	(4, 128.0)	0.3757
2	3.490006	4	0.4794	0.877555	(4, 128.0)	0.4794
3	7.109027	4	0.1302	1.812976	(4, 128.0)	0.1303
4	7.213700	4	0.1250	1.840424	(4, 128.0)	0.1250
5	2.482353	4	0.6478	0.621740	(4, 128.0)	0.6478
6	5.533769	4	0.2368	1.402587	(4, 128.0)	0.2368
7	4.727775	4	0.3164	1.194537	(4, 128.0)	0.3164
8	5.569869	4	0.2337	1.411935	(4, 128.0)	0.2337
9	1.663468	4	0.7973	0.415315	(4, 128.0)	0.7974
10	3.550080	4	0.4703	0.892869	(4, 128.0)	0.4703
11	1.695443	4	0.7915	0.423351	(4, 128.0)	0.7916
12	3.240942	4	0.5183	0.814139	(4, 128.0)	0.5184
13	6.957967	4	0.1381	1.773404	(4, 128.0)	0.1382

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.230710	4	0.3757	1.066878	(4, 128.0)	0.3757
2	7.624475	8	0.4710	0.959046	(8, 124.0)	0.4712
3	10.64035	12	0.5600	0.888508	(12, 120.0)	0.5606
4	16.74121	16	0.4025	1.057086	(16, 116.0)	0.4040
5	21.13754	20	0.3891	1.068914	(20, 112.0)	0.3918
6	26.07899	24	0.3492	1.102587	(24, 108.0)	0.3536
7	30.73300	28	0.3291	1.115787	(28, 104.0)	0.3358
8	35.91577	32	0.2900	1.145562	(32, 100.0)	0.2995
9	38.79330	36	0.3449	1.092258	(36, 96.0)	0.3587
10	45.59833	40	0.2506	1.168440	(40, 92.0)	0.2677
11	48.50208	44	0.2963	1.120897	(44, 88.0)	0.3202
12	60.88510	48	0.1003	1.341435	(48, 84.0)	0.1190
13	64.70902	52	0.1110	1.310798	(52, 80.0)	0.1364

*Edgeworth expansion corrected likelihood ratio statistic.

Augmented model j+d_{max}

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	2.865429	4	0.5806	0.718834	(4, 124.0)	0.5806
2	1.746239	4	0.7823	0.436106	(4, 124.0)	0.7823
3	11.23959	4	0.0240	2.916578	(4, 124.0)	0.0240
4	7.452426	4	0.1138	1.904407	(4, 124.0)	0.1138
5	2.363611	4	0.6692	0.591753	(4, 124.0)	0.6692
6	4.277163	4	0.3698	1.079093	(4, 124.0)	0.3698
7	2.941668	4	0.5676	0.738186	(4, 124.0)	0.5677
8	6.294720	4	0.1782	1.601065	(4, 124.0)	0.1782
9	3.855291	4	0.4259	0.971009	(4, 124.0)	0.4260
10	2.681311	4	0.6125	0.672148	(4, 124.0)	0.6125
11	2.991790	4	0.5592	0.750915	(4, 124.0)	0.5592
12	2.148664	4	0.7084	0.537475	(4, 124.0)	0.7085
13	6.988249	4	0.1365	1.782446	(4, 124.0)	0.1365

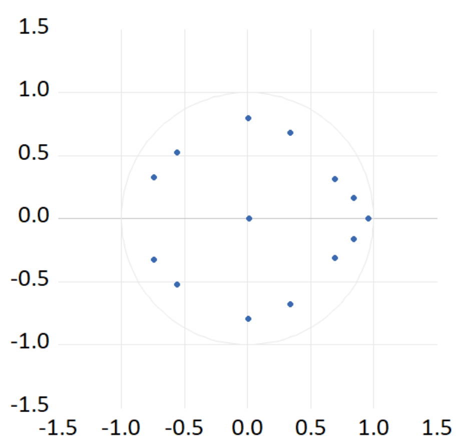
Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	2.865429	4	0.5806	0.718834	(4, 124.0)	0.5806
2	4.593671	8	0.8000	0.570796	(8, 120.0)	0.8001
3	16.26458	12	0.1794	1.390752	(12, 116.0)	0.1800
4	18.76987	16	0.2808	1.195950	(16, 112.0)	0.2823
5	24.14729	20	0.2360	1.237836	(20, 108.0)	0.2386
6	24.97144	24	0.4073	1.050927	(24, 104.0)	0.4121
7	26.69475	28	0.5349	0.951693	(28, 100.0)	0.5420
8	29.93636	32	0.5713	0.928702	(32, 96.0)	0.5813
9	39.82896	36	0.3036	1.127243	(36, 92.0)	0.3180
10	47.58746	40	0.1912	1.232195	(40, 88.0)	0.2077
11	51.37902	44	0.2071	1.205043	(44, 84.0)	0.2297
12	58.20373	48	0.1486	1.265995	(48, 80.0)	0.1738
13	65.70708	52	0.0959	1.339681	(52, 76.0)	0.1212

*Edgeworth expansion corrected likelihood ratio statistic.

Conventional model with j lags	Augmented model j+d^{max}

Inverse Roots of AR Characteristics Polynomial



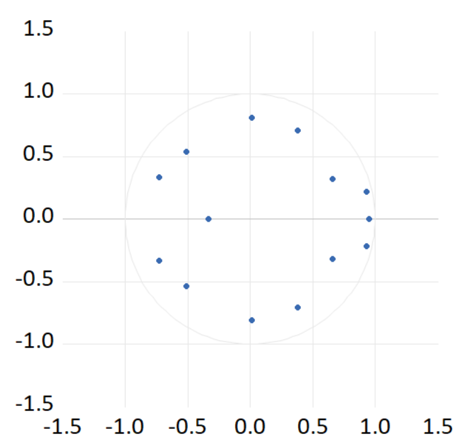


Figure B4. Post-escalating VAR model in ln-levels Urals-Brent AR roots test for stability