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JOURNAL OF SMART ECONOMIC GROWTH

www.jseg.ro ISSN: 2537-141X Volume 7, Number 1, Year 2022

Ho Do Natural Gas and Oil Prices Affect Industrial Production in G 7 Countrices during the Russian-Ukrainian war : Based on Panel NARDL Approach

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Abstract: *paper applies days data from 2021:M1-2022:M6, in G7 Countrices, namely US, UK, Japan, Italy, France, Canada, Germany to examines the long-run, examines the asymmetrics impact of Natural Gas and Oil Prices on Industrial Production in Times of Russia-Ukraine war. We use the Panel Data Nardl approach by (Shin et al., 2014) and asymmetrical Granger Causility test by (Hatemi-j, 2012).The results of this study reveal that there is a non-linear connection among the variables in the long run. As the empirical results of the Panel-NARDL model estimation shows that the response of Industrial Production to positive oil shocks is greater than the negative shocks. Other result the response of Industrial Production to negative Natural Gas shocks is greater than the positive shocks. According to Hatemi-J (2012), there is a bi-directional causality running from positive shocks and negative shocks to the oil price and natural Gas price to Industrial Production.*

JEL classification: Q43, O55, N17, C33.

Key words: Oil price shocks, Natural Gaz price shocks, Industrial production

1. Introduction

In times of the Russia-Ukraine war, this paper looks at the to econometrically investigates the symmetric or asymmetric impact of the Natural Gas and Oil Prices shocks on industrial production for the G7 countries, specifically the US, UK, Japan, Italy, France, Canada, and Germany. Industrial production indexes are one of the leading indicators of gross domestic product, which reflects a country's overall economic performance. In other words, changes in industrial production indicate a contracting or expanding economy, and the G7 member countries with the highest industrial production are also the ones that are closest to China. Russia depends on Ukraine for the transit of its gas to Europe, so given the growing global significance of the G7 economies, understanding how their economic policies are affected by extreme events like the war between the Ukraine and Russia is crucial for policymakers around the world in their search for resilient policies to limit negative international shock spillovers. Accordingly, the conflict between Russia and Ukraine will cause an energy crisis in several G7 nations, including the US, UK, and Japan, as well as in European nations like France, Germany, and Italy. As a result, fluctuations in the price of oil and natural gas—two essential inputs for industrial production—have an impact on the entire economy. Understanding oil price shocks and natural gas price fluctuations is crucial not only because. Not only for energy policy makers, but also for managing energy resource portfolios and hedging against anomalous price fluctuations during crises, understanding of oil price shocks and natural gas prices is crucial.

A brief survey of the literature is given in Section 2.The model specification, data, and methods are described in Section 3.In Section 4, the empirical findings are covered.The research paper is concluded in Section 5.

2.Literature Review

Empirical research by Balke et al. (2002), Kilian & Vigfusson (2009), and Dirk Jan & Roger (2014) show that energy price shocks have a long-term negative impact on economic growth. Furthermore, these studies demonstrate that one of the most important markers of the nation's GDP and economic expansion is industrial production. The whole industrial production therefore heavily depends on variations in oil prices. when changes in the level of industrial production cause the economy to decline or expand. (Farhan & al., 2017) take into account the relationship between Pakistan's industrial production and fluctuations in oil prices. With the use of a VAR model, the authors chose the years 2000 to 2015. This study demonstrates that fluctuations in the price of oil had some detrimental effects on Pakistan's industrial production. It is advised to predict oil prices in the future so that precautions can be taken and the influence on industrial production levels can be managed.

According to (Herrera & al, 2011), the impact of oil price shocks on industrial production in the United States was studied using econometrics. The findings indicate that industries that use a lot of energy in their production or that make products that use a lot of energy are clearly linked to energy price shocks. (Rebeca, 2007) used a Vector Autoregression (VAR) model to examine the effects of oil price shocks on the output of the major manufacturing industries in six OECD countries from 1975 to 1998. The findings of this study confirm that the responses to an oil price shock by industrial output vary across the four European Monetary Union (EMU) countries under consideration (France, Germany, Italy, and Spain). Korhan et al. (2015), focusing on the Turkish economy, discovered that oil price shocks were a significant factor in almost all US recessions from 1961 to 2012. He concludes that changes in oil prices Granger-caused changes in Turkey's GDP. Furthermore, the industrial sector's reliance on imported crude oil makes the country vulnerable to changes in oil prices.Given the relationship between oil prices and industrial production, it can be argued that hedging against oil price uncertainty is critical for Turkey to have sustainable and stable industrial production in the short and medium term.

The relationship between oil and natural gas prices and industrial production was studied from 1968 to 2018. (Abbas, 2020). The authors employ unit roots, ARDL bounds, and VECM Granger causality as empirical strategies. According to Abbas et al. (2020), crude oil has a positive demand and natural gas has a negative supply link with industrial production in the short term. Long term, there is an asymmetric link between natural gas, crude oil, and industrial production in the United States. (Ylmaz, 2014) use panel regression to determine the significant effect of changes in oil and natural gas prices on industrial production in the 18 Eurozone member countries from January 2001 to September 2013. According to (Lutz et al, 2011), increases in energy prices have a greater impact on energy importing countries due to wealth transfer to exporting countries, resulting in a decrease in the purchasing power of industries. In the same vein, (Debojyoti et al., 2018) used the maximum overlap discrete wavelet transform (MODWT)-based quantile regression (QR) analysis to investigate the relationship between US economic growth and crude oil prices, using the Industrial Production Index and West Texas Intermediate crude oil spot prices as proxies, from January 1986 to June 2017. According to the study's findings, a QR analysis based on MODWT provides evidence of a supply-driven link between crude oil prices and economic growth in the short run. However, in the medium to long run, a demand-driven relationship exists between crude oil prices and economic growth.

The results of this studies make it clear that no study have been conducted to investigate the asymmetric or asymmetric impact of the natural gas and oil price shocks on industrial production in the context of the panel data NARDL technique with asymmetrical Granger Causality. We contribute to the existing literature by analyzing the impact of Natural Gas and Oil Price Shocks on Industrial Production in G 7 Countries during the Russian-Ukrainian War using Shin's nonlinear approach to cointegration of the NARDL method (2014).This study also differs from previous studies on Natural Gas and Oil Price Shocks and oil price shocks in that it considers the effects of both positive and negative oil price shocks on industrial production.

3.Methods and Materials

3.1 Data Set

In this paper, we modeling the investigates the symmetric or asymmetric impact of the Natural Gas and Oil Prices on Industrial Production for G7 Countries in Times of Russia-Ukraine war.. Therefore we use Industrial Production as the dependent variable in our study. We use oil price, Natural Gas Price as independent variables. A 18 monthly data for all variables is taken into consideration from 2021:M1-2022:M6. Definitions and sources for all variables can be found in the Table 01.

Table 01 : Variable Definition

Variable	Description	Source
Industrial Production Index (IPI)	The industrial production index (abbreviated IPI and also known as the industrial output index or the industrial volume index) is a business cycle indicator that measures monthly changes in industry's price-adjusted output.	The Federal Reserve Board (FRB) publishes
Oil Price (OP)	CrudeOil Price ($/barrel).	“NYMEX-New York Mercantile Exchange”.
Natural Gas Price (NGP)	Natural Gas Price ($/barrel).	“NYMEX-New York Mercantile Exchange”.

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JOURNAL OF SMART ECONOMIC GROWTH

www.jseg.ro ISSN: 2537-141X Volume 7, Number 1, Year 2022

3.2.Method

The model is based on the literature review to explore the connection that exists between independent variables Natural Gas and Oil Prices and Industrial Production Index is combination of theoretical and empirical, The functional form of the model is presented by Equation 01:

$$IPI = f(OP, NGP)\ldots\ldots\ldots\ \ldots\ldots\ldots\ldots\ \ldots.(01)$$

To reduce the variation and in duce stationary in the variance-covariance matrix, the natural logarithmic form (Ln) is applied to all the variables. The log linear (1) equation to examine the long run relationship between variables is given as follow:

$$LIPI_t = LOP_t^+ + LOP_t^- + LNGP_t^+ + LNGP_t^- \ldots\ldots\ldots\ \ldots\ldots\ldots\ldots\ \ldots(02)$$

For the long-term estimation and c_ointegration of equation (2), we follow the following steps :

3.2.1.Unit root tests

The first step is to check the stationarity of the variables to ensure that no variable is integrated of order two. In this context, testing for unit roots in heterogeneous panels has received a lot of attention during the last ten years. See, for instance, Im et al. (1995, 2003), Levin et al. (2002), Maddala and Wu (1999), Choi (2001), Hadri (2000), Bowman D (unpublished 1999), and Shin and Snell (2002). Baltagi and Kao (2000) offer a preliminary analysis. However, this body of literature made the assumption that each time series in the panel had an independent cross-sectional distribution. Although it was acknowledged that this was a somewhat restrictive assumption, especially in the setting of cross-country (region) regressions, it was believed that demeaning the series cross-sectionally before applying the panel unit root test could help to partially resolve the issue (see Im et al., 1995). The pair-wise cross-section covariances of the error components varied throughout the various series, therefore it was obvious that cross-section de-meaning could not be applied generally. In order to address this weakness, Chang (2002), Choi (2002), Phillips and Sul (2003), Bai and Ng (2004), Breitung and Das (2005), Choi and Chue (2007), Moon and Perron (2004), and Smith et al. suggested new panel unit root tests in the literature (2004). For this study we have chosen the four kinds of unit root tests Levin and Lin (1992, 1993), Im, Pesaran and Shin

(1997, 2002, 2003),ADF-Fisher Chi-square and PP-Fisher Chi-square, Hadri (2000), Breitung and Das (2005) .They are frequently used in the literature on econometrics.

3.2.2.Co-integration test:

The Third step of our empirical work involves investigating the long-run relationship between COVID-19 Pandemic and the geopolitical risk, economic policy uncertainty, using the panel co-integration technique due to (Kao, 1999) and (Pedroni, 2004).

According to the (Pedroni, 2004) the cross-sectional units have to be independent, otherwise their size properties would be misleading. Introduces seven panel co-integration statistics based on both homogeneity and heterogeneity assumptions. Assuming a panel of N countries T observations and regressors (X_m) the co integration test follows the equation :

$$y_{it} = \alpha_i + \lambda_{it} + \sum_{j=1}^{m} \beta_{j,it} x_{j,it} + \varepsilon_{it} \text{.......... .(03)}$$

Where y_{it} and x_{it} are assumed to be integrated of oeder one in levels i, e I(1). The seven statistics can be divided into tow sets. The first one consists of four panel statistics (the panel variance-statistics, the panel ρ-statistics, the panel PP-statistics, the panel ADF-statistics). The second set consists of three group panel statistics (the group ρ-statistics, the group PP-statistics, the group ADF-statistics). Under the null hypothesis all seven tests indicate the absence of c-ointegration $H_0: \rho i = 0 \forall i$ whereas the alternative hypothesise is given by $H_0: \rho < 1 \forall i$; where ρ_i is the autoregressive term of the estimated residual under H_1.

In addition, The (Kao, 1999) test follows the same approach as the Pedroni test but is based on the assumption of homogeneity across panels with

$$x_{it} = \alpha_i y_{it\beta} + \varepsilon_{it} \text{.......... ....(04)}$$

Where i=1……N; t = 1…..T; α_i = individual constant term, β = slope parameter and ω_i= stationary distribution ; X_{it} and Y_{it} are integrated processes of order I(1) for all i and (Kao, 1999) derives tow (DF and ADF) types of panel cointegration tests both tests can be calculated from :

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JOURNAL OF SMART ECONOMIC GROWTH

www.jseg.ro ISSN: 2537-141X Volume 7, Number 1, Year 2022

$$\overline{\omega}_{it} = \rho\overline{\omega}_{it-1} + V_{it} \quad \text{and} \quad \overline{\omega}_{it} = \rho\overline{\omega}_{it-1} + \sum_{j=1}^{\rho} \theta_j \Delta\overline{\omega}_{it-j} + V_{it} \text{.......... ..(05)}$$

Where $\overline{\omega}_{\text{it-1}}$ is obtained from the equation (01), the null hypothesis is $H_0: \rho = 1$ no cointegration, while the alternative hypothesis is $H_1: \rho < 1$. According to Kao Residual co-integration Test (Kao, 1999), the hypothesis of zero non-cointegration is rejected and the existence of a long-term relationship between researches variables.

3.2.3 Estimation of Panel non-linear ARDL

Next step is to estimate the Panel NARDL model, according to Shin et al. (2014) the Panel NARDL approach is that it reveals differences in the responses to positive and negative changes. The main advantages of Panel NARDL model is that, one can examine the non-linear integration relationship between variables in the model with the ability to estimate both short and long-runeffects. So it is superiorto Panel ARDL if the topic and data is appropriate to the methodology. This methodology employs partial sum decompositions to implement nonlinearity by examining the possible asymmetric effects in the long and short-run,we introduce the following long-term asymmetric regression :

$$y_t = \beta^+ x_t + \beta^- x_t + \mu_t \text{.......... ....(06)}$$

$$\Delta x_t = v_t \text{.......... ....(07)}$$

$$x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} \max(\Delta x_j, 0), x_t^- = \sum_{j=1}^{\wedge t} \Delta x_j^- = \sum_{j=1}^{t} \min(\Delta x_j, 0) \text{.......(08)}$$

$$Z_t = \beta_0^+ Y_t^+ + \beta_0^- Y_t^- + \beta_1^+ X_t^+ + \beta_1^- X_t^- \text{.......... ....(09)}$$

Where y_t and x_t are scalar I(1) variables and x_t is decomposed as $x_t = x_0 + x_t^+ + x_t^-$ where x_t^+ and x_t^- are partial sum processes of positive and negative changes in x_t. Z_t is stationary then y_t and x_t. On based on the division of the independent variable x and after entering both X_t^+ and X_t^-,

Although the model was developed for time series, we decomposed the real oil price abd natural Gaz price into increase and decrease for all countries and adopted it for all cross-sections. The advantage of this model is that it examined both the long-run and short-run asymmetric effects of real oil price on growth. The Panel NARDL decomposes oil price and natural Gaz price into negative and positive changes. Non-linear Panel NARDL model can be represented as two model,

$$\text{Model01}: \Delta IPI_t = \mu + \rho IPI_{t-1} + \theta^{+} OP^{+}_{t-1} + \theta^{-} OP^{-}_{t-1} + \sum_{j=1}^{p-1} \alpha_j \Delta IPI_{t-j}$$

$$+ \sum_{j=0}^{q-1} (\Pi^{+}_j \Delta OP^{+}_{t-j} + \Pi^{-}_j \Delta OP^{-}_{t-j}) + \varepsilon_t \text{.......... ....}(10)$$

$$= \Delta y_t = \rho (IPI_{t-1} + (\theta^{+}/\rho\rho) O^{+}_{t-1} + (\theta^{-}/\rho\rho) O^{-}_{t-1}) + \sum_{j=1}^{p-1} \alpha_j \Delta IPI_{t-j}$$

$$+ \sum_{j=0}^{q-1} (\Pi^{+}_j \Delta OP^{+}_{t-j} + \Pi^{-}_j \Delta OP^{-}_{t-j}) + \varepsilon_t \text{.......... ....}(11)$$

$$\text{Model02}: \Delta IPI_t = \mu + \rho IPI_{t-1} + \theta^{+} NGP^{+}_{t-1} + \theta^{-} NGP^{-}_{t-1} + \sum_{j=1}^{p-1} \alpha_j \Delta IPI_{t-j}$$

$$+ \sum_{j=0}^{q-1} (\Pi^{+}_j \Delta NGP^{+}_{t-j} + \Pi^{-}_j \Delta NGP^{-}_{t-j}) + \varepsilon_t \text{.......... ....}(12)$$

$$= \Delta y_t = \rho (IPI_{t-1} + (\theta^{+}/\rho\rho) NG^{+}_{t-1} + (\theta^{-}/\rho\rho) NG^{-}_{t-1}) + \sum_{j=1}^{p-1} \alpha_j \Delta IPI_{t-j}$$

$$+ \sum_{j=0}^{q-1} (\Pi^{+}_j \Delta NGP^{+}_{t-j} + \Pi^{-}_j \Delta NGP^{-}_{t-j}) + \varepsilon_t \text{.......... ....}(13)$$

Whereθ^{+} and θ^{-} ρ represents the transactions in the long term, and π_j^{+}, π_j^{-} and $\alpha_j$represents the transactions in the short term. Equations 06 and 08 demonstrate how the approach intended by decompose Industrial Production Indexes and Natural Gas and Oil Price Fluctuations into their respective positive and negative Industrial Production Indexes (Shin et al., 2014). The following methods are used to separate variations in natural gas and oil prices and industrial production into positive and negative signs. Theoretically, actual oil price and natural gas are defined as follows:

$$OP^{+}_{it} = \sum_{j=1}^{t} \Delta OP^{+}_{j} = \sum_{j=1}^{t} \max(\Delta OP_{ij}, 0), OP^{-}_{it} = \sum_{j=1}^{\wedge t} \Delta x^{-}_{j} = \sum_{j=1}^{t} \min(\Delta OP_{ij}, 0) \text{.......}(14)$$

$$NGP^{+}_{it} = \sum_{j=1}^{t} \Delta NGP^{+}_{ij} = \sum_{j=1}^{t} \max(\Delta NGP_{ij}, 0), NGP^{-}_{it} = \sum_{j=1}^{\wedge t} \Delta NGP^{-}_{ij} = \sum_{j=1}^{t} \min(\Delta NGP_{ij}, 0) \text{.......}(15)$$

Symmetry test using the Wald test, where the nullhypothesisistested, whichis the symmetry of the relationshipbetween the two variables as shown in equation 16, in contrast to the alternative hypothesisthat states that the relationshipbetween the two variables is not asymmetric, as in equation No. 17.

$$(\beta^{+} = -\theta^{+} / \rho) = (\beta^{-} = -\theta^{-} / \rho) \text{......... ....}(16)$$

$$(\beta^{+} = -\theta^{+} / \rho) \neq (\beta^{-} = -\theta^{-} / \rho) \text{......... ....}(17)$$

3.2.4.Panel asymmetric Granger Causality test

Finally, the asymmetric panel causality test established by Hatemi-J (2012) utilized to demonstrate the causal links between Natural Gas and Oil Prices and Industrial Production. Because the Granger causality test is based on the assumption that positive shocks have a causal effect that is equal in absolute magnitude to that of negative shocks. As a result, the Granger causality method does not ignore the possibility of asymmetric causal effects (Hatemi-J 2012). According to Hatemi-J (2012), tests for causality should be conducted using cumulative sums of the positive and negative components of the underlying variables in order to allow for asymmetry. In this method, the integration of variables like x1 and x2 is assumed to be of the first degree, and the equivalent solution found by the recursive method is as follows:

$$x_{1,t} = x_{1,t-1} + \varepsilon_{1,t} = x_{1,0} \cdot + \sum_{j=1}^{t} \varepsilon_{1,j} \text{.......... ....} (18)$$

$$x_{2,t} = x_{2,t-1} + \varepsilon_{2,t} = x_{2,0} + \sum_{j=1}^{t} \varepsilon_{2,j} \text{.......... ....}(19)$$

Hatemi-J (2011) constructed the cumulative sums of the shocks, which are represented by the letters x_{1t}^{+}; x_{1t}^{-}; x_{2t}^{+} x_{2t}^{-} as follows.

$$x_{1t}^{+} = x_{1,0}^{+} + \varepsilon_{1,j}^{+} = x_{1,0} + \sum_{j=1}^{t} \varepsilon_{1,j}^{+} \text{.......... ....}(20)$$

$$x_{2,t}^{+} = x_{2,0}^{+} + \varepsilon_{2,j}^{+} = x_{2,0} + \sum_{j=1}^{t} \varepsilon_{2,j}^{+} \text{.......... ....}(21)$$

$$x_{1t}^{-} = x_{1,0}^{-} + \varepsilon_{1,j}^{-} = x_{1,0} + \sum_{j=1}^{t} \varepsilon_{1,j}^{-} \text{.......... ....}(22)$$

$$x_{2,t}^{-} = x_{2,0}^{-} + \varepsilon_{2,j}^{-} = x_{2,0} + \sum_{j=1}^{t} \varepsilon_{2,j}^{-} \text{.......... ....}(23)$$

The panel causality test by Hatemi-J (2011) is carried out in a vector autoregressive seemingly unrelated regression model of order k. When both factors are broken down into positive shocks, as shown in equation (24) and negative shocks as shown in equation (25)

$$\begin{bmatrix} x_{1,t}^{+} \\ x_{2,t}^{+} \end{bmatrix} = \begin{bmatrix} \beta_{i,0} \\ \gamma_{i,0} \end{bmatrix} + \begin{bmatrix} \sum_{r=1}^{k} \beta_{1,r} & \sum_{r=1}^{k} \beta_{2,r} \\ \sum_{r=1}^{k} \gamma_{1,r} & \sum_{r=1}^{k} \gamma_{2,r} \end{bmatrix} \cdot \begin{bmatrix} x_{1,t-r}^{+} \\ x_{2,t-r}^{+} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,j}^{+} \\ \varepsilon_{2,j}^{+} \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots(24)$$

$$\begin{bmatrix} x_{1,t}^{-} \\ x_{2,t}^{-} \end{bmatrix} = \begin{bmatrix} \beta_{i,0} \\ \gamma_{i,0} \end{bmatrix} + \begin{bmatrix} \sum_{r=1}^{k} \beta_{1,r} & \sum_{r=1}^{k} \beta_{2,r} \\ \sum_{r=1}^{k} \gamma_{1,r} & \sum_{r=1}^{k} \gamma_{2,r} \end{bmatrix} \cdot \begin{bmatrix} x_{1,t-r}^{-} \\ x_{2,t-r}^{-} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,j}^{-} \\ \varepsilon_{2,j}^{-} \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots(25)$$

When one is positive and other is negative as shown in equation (26), When one is negative and other is positive as shown in equation (27),

$$\begin{bmatrix} x_{1,t}^{+} \\ x_{2,t}^{-} \end{bmatrix} = \begin{bmatrix} \beta_{i,0} \\ \gamma_{i,0} \end{bmatrix} + \begin{bmatrix} \sum_{r=1}^{k} \beta_{1,r} & \sum_{r=1}^{k} \beta_{2,r} \\ \sum_{r=1}^{k} \gamma_{1,r} & \sum_{r=1}^{k} \gamma_{2,r} \end{bmatrix} \cdot \begin{bmatrix} x_{1,t-r}^{+} \\ x_{2,t-r}^{-} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,j}^{+} \\ \varepsilon_{2,j}^{-} \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots(26)$$

$$\begin{bmatrix} x_{1,t}^{-} \\ x_{2,t}^{+} \end{bmatrix} = \begin{bmatrix} \beta_{i,0} \\ \gamma_{i,0} \end{bmatrix} + \begin{bmatrix} \sum_{r=1}^{k} \beta_{1,r} & \sum_{r=1}^{k} \beta_{2,r} \\ \sum_{r=1}^{k} \gamma_{1,r} & \sum_{r=1}^{k} \gamma_{2,r} \end{bmatrix} \cdot \begin{bmatrix} x_{1,t-r}^{-} \\ x_{2,t-r}^{+} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,j}^{-} \\ \varepsilon_{2,j}^{+} \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots(27)$$

4.Results and Discussions

4.1 Result of Descriptive Statistics

The summary statistics of the variables used for the analysis are presented in the Table 02; the mean for Industrial Production (IPI) is 0.41 with standard deviation of 0.25 While the corresponding values for mean and standard deviation for oil price (OP), Natural Gas (NGP), are 0.36 and 0.57 respectively. The statistic of Skewness reveals that Industrial Production (IPI), are skewed to right while oil price (OP), Natural Gas (NGP), has the left side skewness.

Table 02 : Descriptive Statistics

Variables	IPI	OP	NGP
Mean	0.41	0.54	0.47
Median	0.43	0.17	0.57
Maximum	0.89	0.91	0.73
Minimum	0.11	0.18	0.52
Std. Dev.	0.25	0.36	0.57
Skewness	0.14	-0.12	-1.10
Kurtosis	0.21	0.74	0.37

4.2 Result of Unit Root Test:

We start by applying the IPS, LLC, ADF, PP, Hadri, Breitung; panel unit root tests to each individual series, in order to conclude whether the series are stationary or not. Table 3; shows the test of stationary result, from the table we see that Natural Gas price (NGP) and Oil price (OP) is stationary at level I(0) and variable Industrial Production (IPI) are non stationary at level but stationary at 1erdifference I(1) with 5% significance level. As all the variables are found to have the order of I(0) and I(1), we choose to employ Panel-NARDL test in order to determine the long-run co-integration between Industrial Production (IPI) and select variables for G7 Countries. In these case, the long-term relationship between the research variables is examined by Pedroni and Kao Residual Co-integration Test (1999).

JOURNAL OF SMART ECONOMIC GROWTH
www.jseg.ro ISSN: 2537-141X Volume 7, Number 1, Year 2022

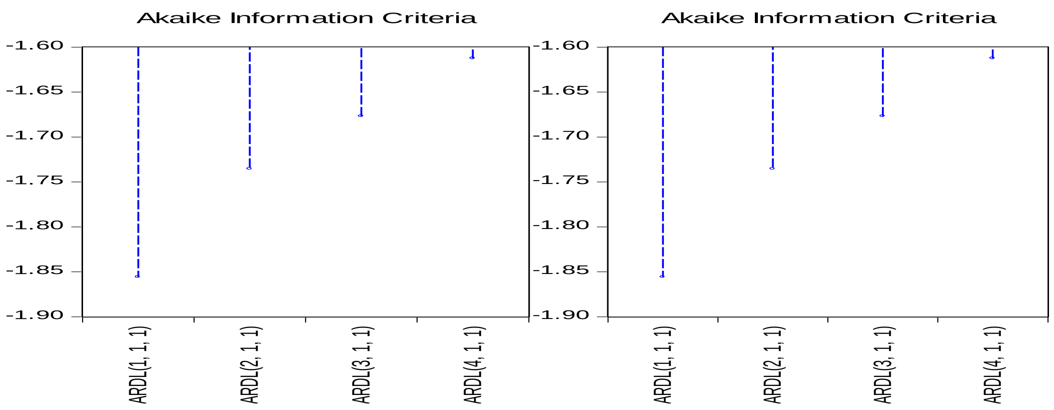
Table 03 Panel Unit Root Tests

Variables	Statistics	Values	Order of integration
LIPI	LLC	−6.44***	I(1)
	IPS	-4.56***	I(1)
	ADF	-7.37***	I(1)
LOP	Hadri	-15.96***	I(1)
	Breitung	-18.47***	I(1)
	LLC	−5.98***	I(0)
	IPS	-5.67***	I(0)
	ADF	-4.94***	I(0)
LNGP	Hadri	-8.57***	I(0)
	Breitung	-13.17***	I(0)
	LLC	−5.49***	I(0)
	IPS	-4.04***	I(0)
	ADF	-6.29***	I(0)
	Hadri	-14.57***	I(0)
	Breitung	-12.37***	I(0)

***significant at the 5 per cent level

The second step was the estimation of a basic panel-ARDL model that explains Industrial Production (IPI) and its determinants. are achievable. The first step is to determine the optimal delay and Panel NARDL pattern form. As seen in Fig. 01, Schwartz's lowest criterion is related to Panel NARDL(1, 1, 1) Therefore, the optimal pattern is Panel NARDL(1, 1, 1) in model 01 and 02, respectively.

Figure ° 01. Selection optimal model NARDL according to Schwarz criterion in Model 01 and Model 02



4.3. Results of co-integration test:

The Third step of our empirical work involves investigating the long-run relationship between Gas and Oil Prices and Industrial Production, using the panel co-integration technique due to (Kao, 1999) and (Pedroni, 2004).

In table 4 and table indicates that the four panel statistics among the four statistics used of the within- dimension, discard the no co integration null hypothesis and approve the variables co integration. The null hypothesis is further discarded by two out of the three between-dimension staistics, namely the PP-statistic and the ADF-staistic, which further confirms the existence of co integration among variables. To conclude, six out of seven tests confirm the long-term variables co integration in model 01 and 02, respectively.

Table 04 Results of Pedroni cointegration test

	Model 01 $LIPI_t = f(LOP_t^+, LOP_t^-)$				**Model 02** $LIPI_t = f(LNGP_t^+, LNGP_t^-)$			
Within dimension	Statistic	Prob.	Weighted statistic	Prob	Statistic	Prob.	Weighted statistic	Prob
Panel v-Statistic	-5.325^{**}	0.0000	-5.634^{*}	0.0340	-6.369^{**}	0.0000	-4.287^{*}	0.0000
Panel rho-Statistic	-6.152^{**}	0.0000	-5.075^{**}	0.0000	-5.294^{**}	0.0000	-5.456^{**}	0.0000
Panel PP-Statistic	-5.201^{**}	0.0000	-5.201^{**}	0.0000	-5.384^{*}	0.0427	-4.698^{**}	0.0235
Panel ADF-Statistic	-5.264^{**}	0.0000	-5.302^{**}	0.0000	-5.369^{**}	0.0000	-4.195^{*}	0.0247
Between-dimension								
Group rho-Statistic	0.230	-	0.5326	-	0.398	-	0.4718	-
Group PP-Statistic	-4.140^{**}	-	0.0000	-	-5.448^{*}	-	0.0452	-
Group ADF-Statistic	-4.406^{*}	-	0.0152	-	-4.587^{**}	-	0.0000	-

Note: **, * imply significance level at the 1%, 5% level respectively

According to Kao Residual co-integration Test (Kao, 1999), the hypothesis of zero non-cointegration is rejected and the existence of a long-term relationship between researches variables is confirmed (Table 05). In these case We reject the null hypothesis and accept the alternative hypothesis that there is a common integration between the variables of the study. These results allow us to estimate the error model of the Panel ardl (long-term equilibrium speed) in model 01 and 02, respectively.

Table 05 Results of KAO cointegration test

	Model 01 $LIPI_t = f(LOP_t^+, LOP_t^-)$		**Model 02** $LIPI_t = f(LNGP_t^+, LNGP_t^-)$	
	Statistic	**Prob.**	**Statistic**	**Prob.**
ADF test	-4.325***	0.0000	-5.325***	0.0000

***significant at the 5 per cent level

4.4.Results of Nonlinear model (Panel-NARDL)

In Table 06; demonstrates the nonlinear impacts of real oil prices and Natural Gas price on Industrial Production using two models; the first one includes effective oil prices shocks as an exogenous variable, the second model contains Natural Gas price shocks as an exogenous variable. In both models, we introduce Natural Gas and oil price shocks to check their effects on Industrial Production.

Empirical results of the Panel-NARDL process indicate that in model one we estimate that only positive oil shock which has a significant influence in the Industrial Production, and the negative oil shocks do not have any short-run effect. In this context, we can say that in the first model 1% increase in real oil price leads to an increase of 0.264% of Industrial Production (at the 1% level). From model 02, we estimate that only negative Natural Gas price shock which has a significant influence in the total Industrial Production, and the positive Natural Gas price shocks do not have any long-run effect. In this context, we can say that in the second model 1% increase in real Natural Gas price leads to an decrease of 0.136% of Industrial Production (at the 1% level).

Additionally, shows the Short run coefficient of Panel-NARDL model, with the table 09; we can see that the sign of lagged error correction representation (ecmt-1) is negative and statistically significant in both models. which provides the existence of cointegration evidence. (ecmt-1) is highly significant (at 1%) where 21.6% (16.5%) of the short-run deviation in model 01 (model 02) from equilibrium is regulated Monthly to restore the equilibrium in this relationship.

Table 06 Estimated long-run and short-run coefficients

Variables	**ECM form with $\Delta LIPI_t$ as on endogenous variable**					
	Model 01 ; $LIPI_t = f(LOP_t^+, LOP_t^-)$			**Model 02 ;** $LIPI_t = f(LNGP_t^+, LNGP_t^-)$		
	Coefficient	**t-statistic**	**Prob**	**Coefficient**	**t-statistic**	**Prob**
	Short Run Equation					
$\Delta LIPI_{t-1}$	0.035684	0.203684	0.0000	0.156820	0.478952	0.0000
ΔLOP_t^+	0.014752	0.265321	0.0000	-	-	-
ΔLOP_{t-1}^+	-0.001528	-0.203487	0.0000	-	-	-
$\Delta LNGP_t$	-	-	-	-0.012634	-0.258951	0.0000
$\Delta LNGP_{t-1}$	-	-	-	-0.036985	-0.048756	0.0000
ECT_{t-1}	-0.426024	-0.250147	0.0000	-0.436985	-0.156234	0.0000
Long Run Equation						
LOP_t^+	0.264795	0.154260	0.0000	-	-	-
LOP_t^-	0.001534	0.047851	0.0000	-	-	-
$LNGP_t^+$	-	-	-	0.004156	0.005795	0.0000
$LNGP_t^-$	-	-	-	0.236702	0.136564	0.0000
Constant	11.822562	0.325614	0.0000	9.3256981	0.478652	0.0000

4.5.Results of Panel asymmetric Granger Causality test

Table 07; confirms, there is a bi-directional causality running from positive shocks and negative shocks to the oil price to wards positive shocks to Industrial Production, and there is a bi-directional causality running from positive shocks and negative shocks to the Industrial Production to wards positive shocks to oil price. In addition, there is a bi-directional causality running from positive shocks and negative shocks to the Natural Gas price to wards negative shocks to Industrial Production, and there is a bi-directional causality running from positive shocks and negative shocks to the Industrial Production to wards negative shocks to Natural Gas.

Table 07 Panel Asymmetric Granger Causality test

The panel causality test by Hatemi-J (2012)	Model 01 $LIPI_t = f(LOP_t^+, LOP_t^-)$		Model 02 $LIPI_t = f(LNGP_t^+, LNGP_t^-)$	
	Null hypothesis			
	Statistic	Prob.	Statistic	Prob.
OP does not Granger Cause IPI	1.524*	0.0003	-	-
IPI does not Granger Cause OP	0.387**	0.0423	-	-
NGP does not Granger Cause IPI	-	-	0.165**	0.0356
IPI does not Granger Cause NGP	-	-	0.527**	0.0198

Note:**, * imply significance level at the 1%, 5% level respectively

5.Discussion of Results:

In this paper, we modeling the investigates the symmetric or asymmetric impact of the Natural Gas and Oil Prices on Industrial Production in G7 countrise in Times of Russia-Ukraine war, by utilizing non linear panel ARDL and asymmetrical Granger Causality test.

The panel ARDL 's findings indicate a large positive association between crude oil and industrial production and a considerable negative relationship between natural gas and industrial production. Table 06 shows substantial positive and negative relationships between the prices of crude oil and natural gas. However, the price of natural gas shows considerable positive and negative relationships. It demonstrates that, in the short term, rising crude oil prices have a favorable (demand-driven) effect on industrial production in the G7 countries. In contrast, the price of replacement natural gas is negatively correlated with industrial production in the G7 countries (supply-driven).

It indicates that the industrial production of the G7 countries is not affected by the rise in the price of crude oil. The economy will grow more quickly if natural gas prices are reduced, and the industrial production of the G7 countries will be less affected by the price of crude oil. Energy costs have increased at their fastest rate since the 1973 oil crisis, according to the World Bank (2022), and they are predicted to soar by more than 50% in 2022 before declining in 2023 and 2024. The price of Brent crude oil is anticipated to average $100 per barrel in 2022, its highest level since 2013 and an increase of more than 40% over 2021 due to trade and production interruptions brought on by war. Both coal and natural gas prices are anticipated to reach all-time highs in 2022, with European natural gas prices likely to increase by twice the amount they reached in 2021. This has an impact on the industrial sector since oil and gas are viewed as inputs to the manufacturing sector. In fact, the rise in crude oil prices leads to an inflationary situation, lowers industrial production, and other issues including a wealth transfer from oil-importing to oil-exporting countries and worsening unemployment. Additionally, Balke et al. (2002), Kilian & Vigfusson (2009), Dirk Jan & Roger (2014), and Abbas et al. (2000) who verified these findings by demonstrating that an increase in energy prices can have significant effects on industrial productivity. Therefore, a short-term negative impact of rising energy prices on industrial production. The traditional theory applies to natural gas over the long term, but not to crude oil.

6.Conclusion

In this paper, we modeling the investigates the symmetric or asymmetric impact of the Natural Gas and Oil Prices on Industrial Production in G7 countrise in Times of Russia-Ukraine war, by utilizing non linear panel ARDL and asymmetrical Granger Causality test.

- ✓ The literature evaluated the the Energy Price Shocks (Natural Gas and Oil Prices) on industrial production, where this literature shows that Energy Price Shocks had a impact on industrial production to some extent.
- ✓ The results of this study reveal that there is a non-linear connection among the variables in the long run.
- ✓ There existe a long run equilibrium relationship between the industrial production and this determinats according to Kao and Pedroni Residual co-integration Test (1999)
- ✓ The Panel-NARDL model estimation shows that the response of Industrial Production to positive oil shocks is greater than the negative shocks. Other result the response of Industrial Production to negative Natural Gas shocks is greater than the positive shocks. According to Hatemi-J (2012), there is a bi-directional causality running from

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positive shocks and negative shocks to the oil price and natural Gas price to Industrial Production.

- ✓ Increased economic uncertainty, geopolitical dangers, and rising energy prices as a result of the Russian-Ukrainian conflict have had a severe effect on the manufacturing sector.

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