Study the Possibility of Address Complex Models in Linear and Non-Linear Causal Relationships between Oil Price and GDP in KSA: Using the Combination of Toda-Yamamoto, Diks-Panchenko and VAR Approach

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ABSTRACT

This paper is about the causal relationship between Oil price, GDP in KSA and to that end, we apply a linear Granger causality test introduced by Toda and Yamamoto 1995 and the nonlinear Granger causality test of Diks-Panchenko (2006). By combining linear causality effects with the nonlinear ones, and VAR approach to possibility of treating complex models in relationships causal. The study applied a battery of unit root tests to ascertain the time series properties of Oil price and GDP in KSA. The results from both the unit root tests indicate that Oil price and GDP are stationary in the 1st difference. The ARDL Bounds-Cointegration test results show that, dynamically, both (Oil price and GDP) are significantly related to each other. The cointegrating equation outcomes demonstrate elasticities whereby both coefficients have positive signs this helps in treating the complexity problem in the models used. The empirical analysis presents three key findings: the linear TY causality analysis supports the neutrality hypothesis, which means that the oil price do cause to GDP in KSA. The nonlinear DP causality test shows that there are nonlinear causal linkages between the oil price and GDP. The nonlinear causality from the Oil price to GDP seems to be strict and accurate, In all models used TY, DP and VAR approach We build upon our empirical findings and draw some policy recommendations for Vision 2030 of KSA, As well as the repercussions of the Covid-19 on KSA economy. The study will help and give guiding principle to policymaker make scheme to prop up economic growth in KSA through windows other than oil.

Keywords: Linear and Non-Linear Causal, Toda and Yamamoto, Diks-Panchenko, VAR Approach, Oil Price, Gross Domestic Product
JEL Classifications: O1, Q3

1. INTRODUCTION

Oil is one of the major energy sources for both the developed and the developing economies of the world. And a large body of research suggests that oil price fluctuations have considerable consequences on economic activity. These consequences are expected to be different in oil importing and in oil exporting countries. Whereas an oil price increase should be considered good news in oil exporting countries and bad news in oil importing countries, may reduce aggregate output temporarily because they delay business investment by raising uncertainty or induce costly sectorial resource reallocation.

One of the major objectives of macroeconomic policies in many countries is sustained economic growth, the gross domestic product (GDP) measures of national income and output for a given country's economy. The GDP is equal to the total expenditures for all final goods and services produced within the country in a stipulated period of time, The Gross Domestic Product (GDP) in Saudi Arabia was worth 785 billion US dollars in 2019, according to official data from the World Bank and projections from Trading Economics. The GDP value of Saudi Arabia represents 0.65 percent of the world economy.

The revenue from oil constitutes a large proportion of GDP. Oil revenue has also been used in financing government spending that

stimulated the investment and growth in the economy. Resultantly, GDP has been growing at 15.2% during 1970-74 and at 8.7% during 1974-1980. During 1980-1984, GDP growth rate became negative (−4.1% per annum) and recorded at modest growth of around 3% during 1985-1994. During the last decade of the 20th century, the GDP almost remained stagnant. In this scenario, the recent shocks in oil price are also expected to adversely affect the oil based economy like Saudi Arabia by affecting government revenue, foreign exchange reserves, and its financial viability to meet growing needs of the economy.

Causality was introduced by (Wiener 1956) and mathematically formulated by Granger to study cause and effect between variables for econometric applications (Granger, 1969). Formally, causality quantifies interactions between variables and identifies cause-effect relationships through modeling, prediction and assessment of the goodness-of-fit when past information from one variable (cause) are incorporated into the prediction of another variable (effect). Granger causality is quantified from the goodness-of-fit of Autoregressive models fitted onto the effect on its own (univariate model), and fitted onto the effect and the cause together (bivariate model).

The traditional Granger causality test does not take into account the nonlinearity observed in time series dynamics. However, macroeconomic and financial variables exhibit nonlinear behaviors across the time. Neglecting these nonlinear dynamics may cause to misidentification the relationship between two variables or may reduce the estimation power of the test, enhances the complexity of the models used for the estimation. Therefore, the aim of this study is to explore the effects of oil price changes on the growth of GDP in KSA. It will help the policy makers in redirecting their attention to the vulnerable sectors and facilitate them according to their unique requirements. Similarly, the investment in such sectors is encouraged and they can withstand the detrimental impacts of oil price shocks.

The oil price crisis observed at the beginning of 1970 due to the OPEC oil embargo was followed by the global recession. Consequently, many studies (Jawadi et al., 2019, Musa Foudeh, 2017, Khalid A. Alkhathlan 2013) examined if the recessions were attributable to the oil price shocks. However, these studies indicated a casualty correlation between oil prices and GDP, Most studies examining the relationship between oil price movements and economic growth are concerned with the KSA economy, although numerous, the previous literature focuses on the specific impact of oil price movements on GDP on the KSA economy.

Indeed the lack of approach to quantitatively analyse the linearity and nonlinearity between economic variables. By combining methods (linear and Non-linear causality) and extending the causality approach (Granger, 1969) to address complexity in these models and approaches, here In this study we extend the scope of the analysis to the various links between oil prices and GDP using linear and non-linear model to measure the causal relationship between Oil price and GDP in KSA using the combination of Toda and Yamamoto (1995), Diks-Panchenko (2006) and VAR approach to treating complexity in this models.

1.1. Hypothesis

H_1: There is long run relationship exist between Oil Price and GDP in KSA during the study period 1970-2019.

H_0: There is no long run relationship exist between Oil Price and GDP in KSA during the study period 1970-2019.

2. DATA, MODEL AND METHODS

2.1. Data and Empirical Modeling

Data were collected the annual data for Oil Price and GDP from the International Monetary Fund. This study covers the annual sample period from 1970 to 2019. The descriptive statistics show that the standard deviations differ among variables. In addition, at the 5% significance level, we find that all variables are normally distributed (Jarque-Bera, Skewness and Kurtosis statistics) See Table 1.

In the analysis of this study, data employed may be affected seasonally due to seasonal factors such as economic crisis and changes in the economic environment. Table 1 represents the important descriptive statistics for the variables used in this study. The mean or average Oil price stood at USD (35.32560) billion and depicted standard deviation of (24.73000), whereas, maximum GDP are of UDS (39455863929.3) billion and a minimum of USD (−3732394367.2) billion. The mean of GDP stood at USD (6248396260.9) billion along with a standard deviation of (874450102.5), showing maximum Oil price of USD (109.45) billion and minimum of USD (1.210) billion.

2.2. Methodology

The linear and nonlinear Granger causality test methods, which were developed by economist (Granger1969) to test whether a historical or current information of a time series has a predictive effect on current or future values of another time series. Based on the classical Granger causality, many variants have been invented. In this paper, we focus on the classical Granger causality model, and called Granger causality for short. The Granger causality can be tested by both linear and nonlinear approaches. And some advanced tests like Toda and Yamamoto (1995), Diks-Panchenko (2006) and VAR approach.

2.2.1. Linear granger causality test method
Causal influence measurement notation for time series was firstly proposed by Wiener-Granger. We can determine a causal influence of one time series on another, if the predication of one time series can be improved by incorporating the knowledge of the second one. Granger applied this notation by using the context of linear vector auto-regression VAR model of stochastic processes (Akaike, 1969), (Morf 1978). In the AR model, the variance of

Table 1: Descriptive statistics

Statistics	Oil Price	GDP
Mean	35.32560	6248396260.924869
Median	24.73000	874450102.521353
Maximum	109.4500	39455863929.3334
Minimum	1.210000	−3732394367.24856
Std. Deviation	29.49430	11082189552.44239
Skewness	1.197126	1.754655550165247
Kurtosis	3.436323	5.039691293436434
Jarque Bera	12.33922	34.32417702379836

the prediction error is used to test the perdition improvement. For instance, assume two time series; if the variance of the autoregressive prediction error of the first time series at the present time is reduced by inclusion of past measurements from the second time series, then one can conclude that the second time series have a causal influence on the first one. Geweke (Geweke, 1982) decomposed the VAR process into the frequency domain, it converted the causality measurement into a spectral representation and made the interpretation more appealing.

2.2.2. Toda and Yamamoto (1995) causality

Overcoming the shortcomings in Granger (1969), an efficient methodology Toda and Yamamoto (1995) has been introduced. It is relatively more efficient in dealing small sample size and disregarding order of integration for the relative variables (not known, not same or more than 2). Besides this, it does not believe in pre-testing the time series for the cointegration properties so long as integration order of the series does not cross the model's true lag length. Toda and Yamamoto (1995) is directly performed for Granger causality test, testing the coefficient of VAR at level. This methodology minimizes associated risk that was wrongly identified in the time series for order of integration and the existence of cointegration relationship (Mavrotas and Kelly, 2001). The Toda and Yamamoto causality technique involves the estimation of the following models:

$$Oil - price = \alpha_\circ + \sum_{i=1}^{k+d\max} \alpha_2 Oil - price_{t-1} + \sum_{i=1}^{k+d\max} \alpha_3 GDP_{t-i} + \eta_1$$

$$GDP = \beta_\circ + \sum_{i=1}^{k+d\max} \beta_2 GDP_{t-i} + \sum_{i=1}^{k+d\max} \beta_3 Oil - price_{t-i} + \eta_2$$

Where, Oil-price and GDP indicate to study variables. In the models, each variable is regressed on each other with lag order starting from 1 towards $k + d\max$, η_1 and η_2 are the error terms, k indicates the maximum number of lags to be taken while d shows order of integration of running variables. Since the procedure requires a VAR only in levels, it does not lead to a loss of information as it would happen in the case of differencing. For this reason, the procedure can be used only as a long-run test. Basically, Toda and Yamamoto (1995) augments the correct VAR (k) with d extra lags, where d is the maximum order of integration in the sampled system. As the optimal lag length in the VAR model is determined by Akaike Information Criteria (AIC) or Schwartz Information Criterion (SIC), say, k. In the third step, VAR (p) where (p=k+dmax) is estimated using Seemingly Unrelated Regression (SUR). At last, the no causality null hypothesis is tested by the Wald statistic (W). Now, here are the basic steps for the Toda and Yamamoto procedure (Lütkepohl2006):

1. Test each of the time-series to determine their order of integration. Ideally, this should involve using a test (such as the ADF test) for which the null hypothesis is non-stationarity; as well as a test (such as the KPSS test) for which the null is stationarity. It's good to have a cross-check.
2. Let the maximum order of integration for the group of time-series be m. So, if there are two time-series and one is found

to be I(1) and the other is I(2), then m = 2. If one is I(0) and the other is I(1), then m = 1, etc.
3. Set up a VAR model in the levels of the data, regardless of the orders of integration of the various time-series. Most importantly, you must not difference the data, no matter what you found at Step 1.
4. Determine the appropriate maximum lag length for the variables in the VAR, say p, using the usual methods. Specifically, base the choice of p on the usual information criteria, such as AIC, SIC.
5. Make sure that the VAR is well-specified. For example, ensure that there is no serial correlation in the residuals. If need be, increase p until any autocorrelation issues are resolved.
6. If two or more of the time-series have the same order of integration, at Step 1, then test to see if they are cointegrated, preferably using Johansen's methodology (based on your VAR) for a reliable result.
7. No matter what you conclude about cointegration at Step 6, this is not going to affect what follows. It just provides a possible cross-check on the validity of your results at the very end of the analysis.
8. Now take the preferred VAR model and add in m additional lags of each of the variables into each of the equations.
9. Test for Granger non-causality as follows. For expository purposes, suppose that the VAR has two equations, one for X and one for Y. Test the hypothesis that the coefficients of (only) the first p lagged values of X are zero in the Y equation, using a standard Wald test. Then do the same thing for the coefficients of the lagged values of Y in the X equation.
10. It's essential that you don't include the coefficients for the "extra" m lags when you perform the Wald tests. They are there just to fix up the asymptotics.
11. The Wald test statistics will be asymptotically chi-square distributed with p d.o.f., under the null.
12. Rejection of the null implies a rejection of Granger non-causality. That is, a rejection supports the presence of Granger causality.
13. Finally, look back at what you concluded in Step 6 about cointegration

However, Toda and Yamamoto approach has some weaknesses as well. The approach is inefficient and suffers some loss of power since the VAR model is intentionally over-fitted (Toda and Yamamoto, 1995: 247). Kuzozumi and Yamamoto (2000) also warn that for small sample size, the asymptotic distribution may be a poor approximation to the distribution of the test statistic.

2.2.3. Nonlinear granger causality test method
2.2.3.1. Diks and Panchenko (2006):
The linear Granger causality test does not account for nonlinear causal relationships among the variables. In order to test for nonlinear Granger causality, various non-parametric methods are developed. In an early study, (Baek and Brock 1992) propose a nonparametric statistical method for detecting non-linear Granger causality by using correlation integral between time series. In the Baek and Brock's test, the time series are assumed to be mutually and individually independent and identically distributed. By relaxing this strict assumption, (Hiemstra and Jones 1994) develop a modified test statistic for the non-linear causality which allows

each series to display short-term temporal dependence. However, (Diks and Panchenko 2005) show that the test advocated by Hiemstra and Jones (1994) may over reject the null hypothesis of non-causality in the case of increasing sample size since it ignores the possible variations in conditional distributions. In a recent study, (Diks and Panchenko 2006), hereafter DP) develop a new nonparametric test for Granger causality that overcomes the over-rejection problem in the Hiemstra and Jones's test.

Diks and Panchenko (2006) argue that under certain variance conditions, the (HJ) Hiemstra and Jones (1994) statistic could over-reject the null hypothesis of no Granger causality. As a robustness check, we also employ the Diks-Panchenko (DP) statistics. Diks - Panchenko (2005) identify a drawback resulting from ignoring the possible variations in conditional distributions in the test proposed by Hiemstra and Jones (1994), which may cause over reject the null hypothesis of noncausality in the case of increasing sample size. In order to overcome the over rejection problem in the Hiemstra and Jones's test. Diks-Panchenko (DP) developed a new nonparametric technique to apply for the residuals of the VAR model. This nonparametric and nonlinear Granger causality approach provides more robust informations about the causality relationships between variables (Rahimi et al., 2016).

Let us consider the simplest setting, where $£X = £Y = 1$ so that $W = (X, Y, Z)$ denotes a three-variate random variable, distributed as $W_t = (X_t, Y_t, Y_{t+1})$. (We investigate the problems associated with increased dimensionality in the next section. Throughout we will assume that W is a continuous random variable.) The DP test restates the null hypothesis in terms of the joint probability distribution $f_{X,Y,Z}(X, Y, Z)$ and its marginals, i.e.

$$Q \equiv E\left\{\int X, Y, Z(X, Y, Z) fY(Y) - fX, Y(X, Y) fY, Z(y, Z)\right\} = 0$$

Given the standard correlation integral density estimator

$$fw(Wi) = +\frac{e|-dw|}{n-1}\sum_{n=1}^{j}[I](Wi - Wj)/€\varepsilon$$

In fact, it might be verified that α is of the same magnitude as the local kernel estimator bias and Diks and Panchenko (2006) show that two remaining parameters depend on the dimensionality of the system as $\gamma = d_x + d_y + d_z$ and $\delta = d_x + 2d_y + d_z$

2.2.4. VAR approach
A linear Granger causality test can be performed under the VAR model framework as we introduced previously. Due to the nonlinear characteristics of financial time series, nonlinear Granger causality test is also required in this paper. As the classical VAR model cannot be directly used in nonlinear causality test, (Baek and Brock1992) proposed a nonlinear statistical Granger causality test based on nonparametric statistics. However, Baek and Brock's method is still not suitable for the problem studied in this paper, because their model is based on such a hypothesis that the tested time series are independent of each other and obey independent identity distribution, which is too strict in practical cases. Hiemstra

and Jones (1994) modified this hypothesis, and derive a weak correlation testing method.

Figure 1 shows that Saudi GDP is increasing during the study period because the increase in the rates of Oil Price increased during the study period. It was found that during the period 1990 and 2019 the increase and change was a quick and simple. The researcher finds that the change is consistent for all variables during this period.

It is evident from Figure 1 that (the price of oil) in the first period of the study increased and decreased to the year 2010 AD, where the rates (oil price) increased at an unstable pace until 2015, and after that it continued to stabilize and fluctuate slightly.

It is noticed from Figure 2 that the rates of economic growth in the KSA in general are high, as they rose in the period (1970-1980), then decreased slightly and continued to rise until the year 2000, and after that they continued to rise at high rates.

3. EMPIRICAL RESULTS AND DISCUSSION

The starting point is to study the time series properties of the variables under consideration to avoid any spurious relationships between them. If the time series properties of the variables are satisfied, then possible long-term relationships or co-integration are likely to exist, the analytical procedure adopted in this study include: the specification of the empirical models, the concept of Toda and Yamamoto causality (1995), Diks and Panchenko (2006). The baseline empirical model is specified to capture the hypothesized relationship among the core variables namely Oil Price, GDP in
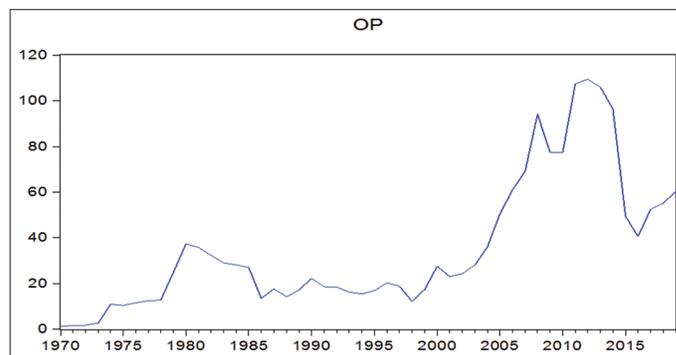
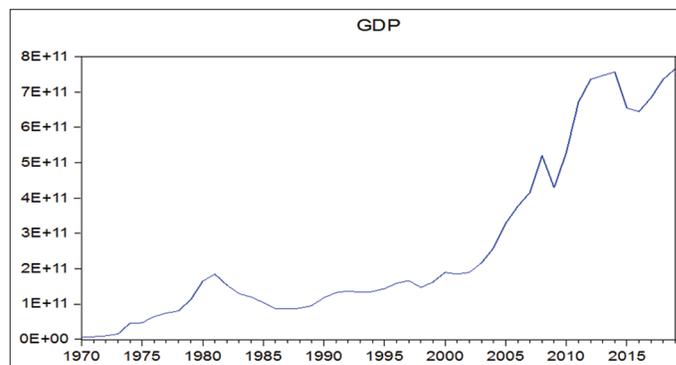**Figure 1:** Oil Prices (1970-2019)

Figure 2: GDP in KSA (1970-2019)

Table 2: Unit root tests

Variables	Augmented Dickey- Fuller			Philip-Perron test (PP)		
	Level	1st difference	Remarks	Level	1st difference	Remarks
Oil Price	−1.40765	−5.59643*	I (1)	−1.5239	−5.61534*	I (1)
GDP	−0.84985	−5.53136*	I (1)	−0.8498	−5.53136*	I (1)

* represent stationary at 1and 5 percent level

Table 3: Confirmatory analysis

Variables	ADF	PP	Decision
Oil price	I (1)	I (1)	Conclusive decision (Non-Stationary) in the level
GDP	I (1)	I (1)	Conclusive decision (Non-Stationary) in the level

Table 4: ARDL bounds test for cointegration

Estimated model	$F_{LnOil Price}$ (LnOP/LnGDP)		F_{LnGDP} (LnGDP/LnOP)	
F-Statistics (Bounds Test)	13.63**		10.53*	
Critical Values	1%	2.%	5%	10%
Lower Bounds I (0)	8.74	7.46	6.56	5.59
Upper Bounds I (1)	9.63	8.27	7.3	6.26
Ect−₁	−0.2168*	−0.01635*		
R^2	0.987	0.981		
Adj. R^2	0.991	0.989		
DW	1.89	1.93		
F-Statistics	2374.07*	2056.28*		

*and **represents the significance level at 1% and 5%, respectively. The optimal lag length for the ARDL model was chosen on the basis of AIC. The critical values mentioned in the above table were obtained from Pesaran et al. (Pesaran et al., 2001).

Table 5: Granger causality test results

Null Hy	F- statistics	p value
D (OP) does not Cause D (GDP) Or (Oil price⇏GDP)	1.85987	0.1680
D (GDP) does not Cause D (OP) Or (GDP⇏Oil price)	0.10111	0.9040

Table 6: Toda and Yamamoto (1995) causality test

Null Hypothesis:	Wald test statistic	p-value	Granger Causality
D (OP) does not Cause D (GDP)	12. 72820	0.0354	causality
D (GDP) does not Cause D (OP)	2.083446	0.3528	No causality

KSA. The test for the stationarity status of all variables to determine their order of integration is necessary before proceeding with the casualty tests, the ADF and PP methods are used to determine the stationarity of the variables and the results are presented in Table 2.

The Unit root test on all variables was carried out using the Augmented Dickey-Fuller (ADF) and Philip-Perron (PP) tests with intercept only and the result was presented in Table 2. The result showed that all the variables (Oil Price, GDP) were non-stationary at level. That is, they were not integrated at order zero but they became stationary on first different.

Confirmatory analysis presented in Table 3 is drawn from the two unit root tests shown in Table 2 and it shows that (Oil Price, GDP) is stationary at 1st different. However, the unit root decision is conclusive. Hence, VAR models and Diks-Panchenko (2006) causality will add a way to tackle the complexity problem.

These coefficients represent the speed of adjustment of the short-term disequilibrium to the long-term equilibrium. In Model 1, the speed of adjustment is close to 14%, whereas for the second, it is approximately 11%. Both coefficients are significant at 1% and negative, which provides data for the short-run dynamics. With these coefficients, it is evident that both variables (Oil Price, GDP) affect each other. This implies that each variable converges to its long-run equilibrium, with its speed of adjustment in one period, by channeling with the other variable. It can therefore be concluded from the ARDL bounds test that there is a long-run relationship among the Oil Price, GDP in KSA (Table 4).

3.1. (CUSUM) and (CUSUMSQ) - (ARDL 1.4)
The stability of the long run parameters were tested using the cumulative sum of recursive residuals (CUSUM) and CUSUM of recursive squares (CUSUMSQ). The results are illustrated in Figures 3 and 4. The results fail to reject the null hypothesis at 5 percent level of significance because the plot of the tests fall within the critical limits. Therefore, it can be realised that our selected ARDL (1.4) model is stable.

3.2. Granger Causality Test Results
The test of long-run Granger causality has been performed. For this purpose, two Granger null hypotheses have been tested. First is that Oil price do not Granger because of GDP (Oil price ⇏ GDP) and second is that GDP does not Granger because of Oil price (GDP ⇏ Oil price). After this, a short-run Granger causality test has also been performed. The results of the Granger causality test are provided in Table 5. They reveal that calculated F-values for null hypotheses Oil price ⇏ GDP and GDP ⇏ Oil price are (1.859) and (0.101), respectively. Both the hypotheses can be rejected at 1 per cent and

Table 7: VAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1458.391	NA	1.29e+25	63.49526	63.57477	63.52505
1	-1328.415	242.9981	5.40e+22	58.01806	58.25658*	58.10741
2	-1322.757	10.08631*	5.03e+22*	57.94596*	58.34349	58.09488*
3	-1322.448	0.524686	5.92e+22	58.10642	58.66297	58.31491
4	-1318.973	5.589435	6.09e+22	58.12927	58.84483	58.39732

5 per cent level of significance. Based on these results, it can be concluded that there is a bidirectional causal relationship between Oil price and GDP for KSA. Furthermore, if the relationship between these variables is nonlinear, then employing a linear model would lead to estimation bias. Therefore, the study deals with the issue of nonlinearity in Diks and Panchenko (2006) test.

3.3. Linear Causality Test for (Toda and Yamamoto 1995)

We employed the modified Wald test (MWALD) proposed by (Toda and Yamamoto 1995) (hereafter T-Y) procedure in conjunction with bootstrapped critical values following the work of (Hacker and Hatemi-J 2006) to run the causality test between study variables. This test is able to overcome the finite sample problems in the conventional Granger causality test (Granger 1969), which is usually employed to detect a linear correlation between the current values of one time series with the past values of another time series. In addition to that, the T-Y approach allows fitting of a standard augmented vector autoregressive (VAR) model in the level of the series even when the data is nonstationary and perhaps cointegrated. So this penultimate stage of our empirical analysis, we test for the causal relationship among our variables of interest according to Toda and Yamamoto (1995) causality test.

The empirical results of Granger Causality test based on Toda and Yamamoto (1995) methodology is estimated through MWALD test and reported in Table 6. The estimates of MWALD test show that the test result follows the F - test distribution with degrees of freedom in accordance with the appropriate lag length along with their associated probability. From table 6, we conclude that for Oil Price and GDP. Generally, there is an the existence of the unidirectional causality between Oil Price, GDP. The empirical results support the existence of a unidirectional causality that runs from Oil Price to GDP, when a sufficiently high lag order is selected.

Table 7 shows that the maximum lag length to be used in a standard VAR model for (Oil Price, GDP) may vary depending on the criteria used. However in general the three criteria, i.e. Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC), indicate the maximum lag length varies from one to two.

3.4. Nonlinear Causality Test for (Diks and Panchenko 2006)

Toda and Yamamoto (1995) for linear tests suggest evidence of bidirectional causality at higher but uncommon lags, the Diks and Panchenko (2006) nonlinear test suggest evidence of bidirectional causality at all common lags.

The results from the Diks-Panchenko (2006) nonlinear Granger causality test. The p-values of the test statistics are reported in

Table 8: Nonlinear causality method for (Diks and Panchenko 2006)

$L_{Oil\ price} = L_{GDP}$	H0: Oil Pric$\nRightarrow$GDP	H0: GDP$\nRightarrow$Oil Pric
1	0.042b	0.000a
2	0.000a	0.007a
3	0.004a	0.002a
4	0.000a	0.000a
5	0.001a	0.000a
6	0.000a	0.107c
7	0.004a	0.000a
8	0.000a	0.057b
9	0.002a	0.000a
10	0.141c	0.043b

This Table reports the *P* values of the Diks-Panchenko (2006) causality tests. (a), (b) and (c) indicate the rejection of the null hypothesis of absence of causality at the 1%, 5% and 10% levels.
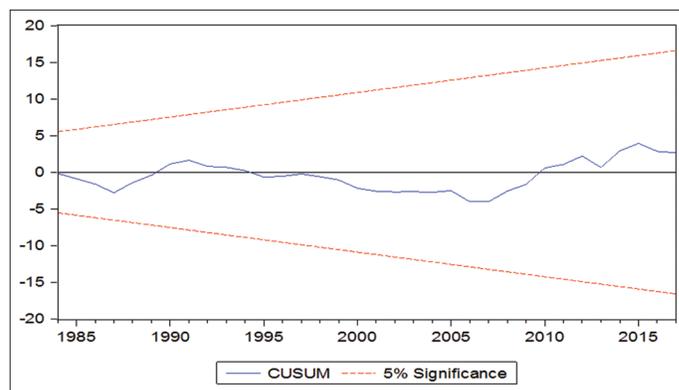
Figure 3: CUSUM
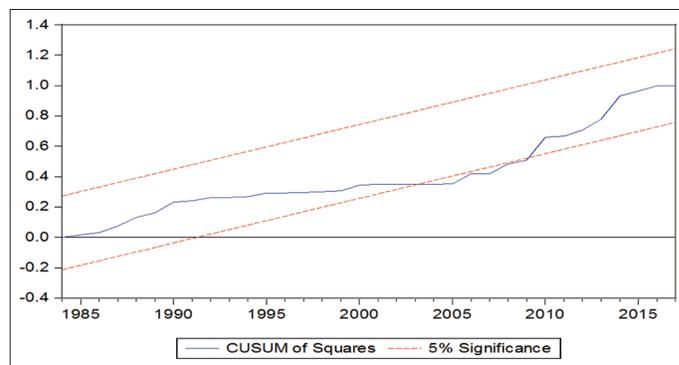

Figure 4: CUSUMSQ

Table 8. The results suggest evidence of bidirectional nonlinear causality between Oil price and GDP. However, looking at the levels of significance, it is observed that Oil price has stronger predictive power for GDP than does GDP for Oil price. The evidence suggests that the Oil price can be more helpful in predicting movements in the GDP index. Also the results show that the nonlinear causality

for Diks-Panchenko (2006) running from Oil Price towards GDP exists only at lag order of 1, while the same running from GDP to Oil Price occurs at lag orders 8. Therefore, an existence of nonlinear causal relationship running from both directions can be observed. Thus, it can be concluded that there is a bidirectional nonlinear causal relationship between Oil Price and GDP in the case of KSA and the study period extends from 1970-2019.

4. CONCLUSION

Due to shortcomings of the linear Granger causality test like Toda and Yamamoto 1995, especially in the presence of nonlinearity and structural breaks, our study also relies on the nonlinear variants of the Granger causality test as developed by Diks and Panchenko (2005). We find extensive and significant evidence of Uncertainty in the behavior of economic variables associated with time. No previous studies have analyzed linear and nonlinear causality between Oil Price, GDP using merging Form Toda and Yamamoto with Diks-Panchenko. It has been widely noted in the literature that a linear approach to causality testing can have low power in the case of nonlinear relationships. Since many economic time series exhibit significant nonlinear features, nonlinear causality tests should be included in the analysis. In order to determine the causal linkages among the variables in question, we employ both the linear and nonlinear causality methods. The empirical analysis presents three key findings: (i) the linear Toda and Yamamoto 1995 causality analysis supports the neutrality hypothesis, which means that the oil price do cause to GDP in KSA, (ii) the nonlinear Diks-Panchenko 2006 causality test shows that there are nonlinear causal linkages between the oil price and GDP. And finally (iii) the nonlinear causality from the oil price to GDP seems to be strict and accurate,

In all models used (Toda and Yamamoto 1995), (Diks-Panchenko 2006) and (VAR) approach. The augmented tests confirmed that data is not stationary at level but it is stationary at first difference. The Result of co integration test indicates that there exist co-integration equations at the 0.05 level. We have used Toda and Yamamoto (1995) linear causality test in order to test the causal relationship between Oil Price, GDP in KSA. The evidence, based on MWald-tests, generally supports the existence of the unidirectional causality between Oil Price, GDP. The empirical results support the existence of a unidirectional causality that runs from Oil Price to GDP, when a sufficiently high lag order is selected. And it can be concluded from the ARDL(1.4) bounds test that there is a long-run relationship among the Oil Price, GDP in KSA. It is evident that both variables (Oil Price, GDP) affect each other. This implies that each variable converges to its long-run equilibrium, with its speed of adjustment in one period, by channeling with the other variable.

The results of Diks-Panchenko (2006) test suggest evidence of bidirectional nonlinear causality between Oil price and GDP. However, looking at the levels of significance, it is observed that Oil price has stronger predictive power for GDP than does GDP for Oil price. The evidence suggests that the Oil price can be more helpful in predicting movements in the GDP index. Also the results show that the nonlinear causality for Diks-Panchenko (2006) running from

Oil Price towards GDP exists only at lag order of 1, while the same running from GDP to Oil Price occurs at lag orders 8. Therefore, an existence of nonlinear causal relationship running from both directions can be observed. Thus, it can be concluded that there is a bidirectional nonlinear causal relationship between Oil Price and GDP in the case of KSA and the study period extends from 1970-2019. The study will help and give guiding principle to policymaker and investor make scheme to prop up economic growth in KSA.

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