INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN ECONOMICS & MANAGEMENT SCIENCES

OPEN ACCESS JOURNAL

Vol 14, Issue 3, (2025) E-ISSN: 2226-3624

Yemen's Inflation Asymmetric Response to Oil Price Shocks

Dhaif Allah Musaeed Al-hamdhi , Venus Khim-Sen Liew

Faculty of economic and business(FEB), UNIMAS, Sarawak, Malaysia, Jln Datuk Mohammad Musa, 94300 Kota Samarahan, Sarawak

Corresponding Author Email: 17010146@siswa.unimas.my

To Link this Article: http://dx.doi.org/10.6007/IJAREMS/v14-i3/25998 DOI:10.6007/IJAREMS/v14-i3/25998

Published Online: 30 July 2025

Abstract

Like other oil-reliant economies, Yemen's economy is vulnerable to oil price shocks. This study examines the asymmetric responses of Yemen's inflation rate to oil price shocks starting right after unification in 1991 to 2022. To this end, the Nonlinear autoregressive distributed lag (NARDL) and Augmented ARDL applied to NARDL rather than ARDL (bootstrap NARDL) are used for the analysis. Overall findings found that negative oil price shocks following oil price decline have a bigger impact on inflation compared to positive ones resulting from rising oil prices. Moreover, the Augmented NARDL results found that inflation and oil price shocks have an asymmetric cointegration. The results of NARDL indicate that the inflation rate (INFY) exhibits short-term asymmetric impact in response to negative shocks only but is insignificant yet positive to both shocks in the long term. The study suggests that Existing strategies, such as expanding the money supply, have proven unsuccessful, exacerbating inflation and encouraging illicit economic activities. The government is advised to implement strict monetary regulations through the Central Bank of Yemen, including tightening monetary policy to bring stability to currency markets and reduce inflation. Proper implementation and supervision of these measures are crucial for achieving economic stability.

Keywords: Asymmetry, Inflation Rate, NARDL, Augmented ARDL, Oil Price Shocks

Introduction

Economies of all oil- exporting and importing nations with no exception are exposed to shocks of oil prices (henceforth, SOP) and their consequences (Ahmad,2016). The impact of these oil shocks on the globe can be explained by the percentage of oil price changes over time. Such big changes in oil prices are what can be termed oil shocks which the world has witnessed over the years as depicted in Figure 1 below.

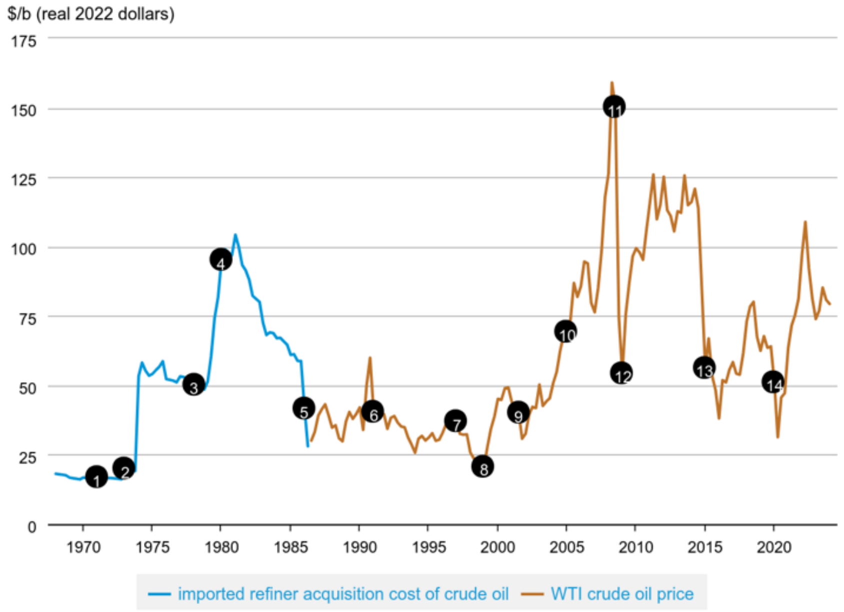


Figure 1: Oil price shocks since the 1970s
Source: U.S Energy information Administration, EIA (2024)

As shown in the figure above, the history of oil price shocks dates back to the early 1970s, precisely with the Arab embargo shock resulting from the 1973 Arab-Israel war where it witnessed an increase of about 18 % hitting an approximately ($20/bbl) and continuing through different shocks such as Iran -Iraq war in the 1980s to the recent late shocks following the Arab uprising in 2010 and covid-19 pandemic in 2020. The history of shocks of oil prices clearly indicates that the shocks can be either positive or negative and with a substantial change and can be caused by different factors. Researchers have been investigating the origins of oil price shocks since the 1980s, following the second major price shock of the late 1970s. While Baumeister and Peersman (2013) attributed these shocks to both supply and demand factors, Hamilton (1983) blamed the supply disruptions caused by external events like wars. Furthermore, ample attention has been put into exploring the inflationary impact of these changes and shocks in oil prices. For instance, LeBlanc and Chin (2004) mentioned that while inflation rises in the 1970s have been attributed, in part, to accelerated oil prices, the slow downward trend in inflation in the 1980s and 1990s has then been linked to shocks resulting from the drops in oil prices. On the contrary in the 2000s, despite the high price of oil, lower inflation in many countries was observed differently from the similar case for oil price shocks following a hike in oil prices in the 1970s and 1980s as stated (De Gregorio et al). Although opinion is still divided as to whether to blame oil shocks alone for an economic recession, most researchers agree that oil prices play a role in domestic inflation (Chou and Lin, 2013).

Concerning what has been stated, Yemen's economy was classified as a least developed economy (henceforth, LDC) by the United Nations (UN) in 2020, which is far behind the other 3 classifications: developed, in transition, and developing countries. Nevertheless, it is vulnerable to this influencing factor (i.e., SOP) as it is among the many economies that have relied primarily on the revenues from oil and gas sectors since the reunion of its south and north parts in 1990 and the discovery of oil started to attract the attention of the united government. According to the world bank (henceforth, WB), The industry sector, the largest revenue generator sector with a 41 % share, has been dominated by oil with 70 % of this sector's revenues as depicted in the figure below.

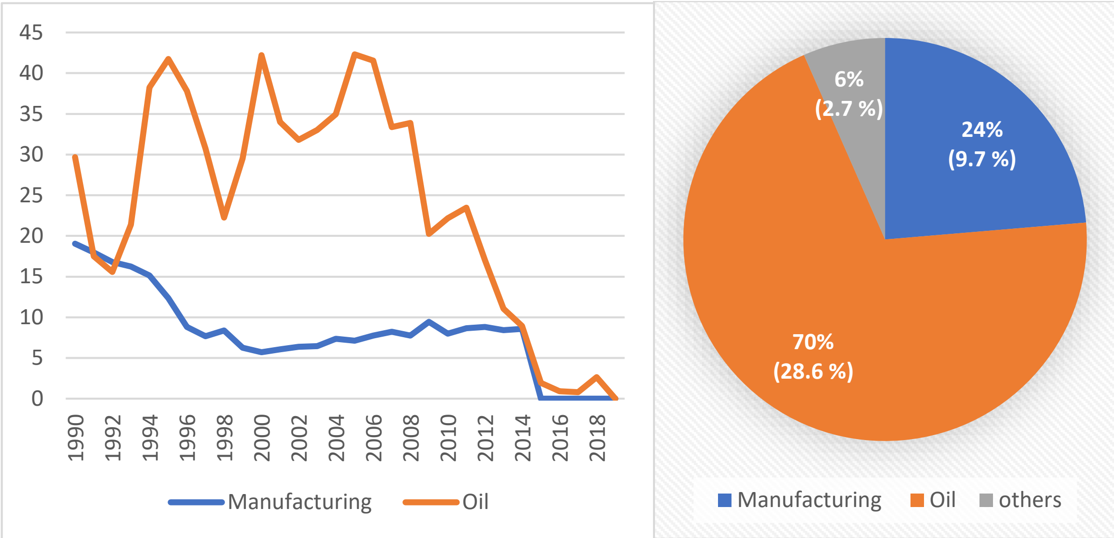


Figure 2: Oil contribution to Yemen’s economy
Source: Adopted from WB (2020)

As seen from the figure above, the contribution of oil has been on continuous fluctuations up and down across the observed period which raises the question about the relationship between SOP and oil contribution to the economy which inflation is considered a key indicator within it. Concerning this, Yemen’s inflation rate (henceforth, INFY) itself is of importance as it influences the level of income per capita and capita’s ability to obtain their necessities from basic goods to housing to health to education, etc. According to MPIC (2017), waves of inflation in the country between 2014 and 2017 have been swarming all basic commodities such as F&B with a cumulative high of 38.7 %, clothes with an accumulative high of 42.8%, education with 14.9 %, fuel & gas with 88 % and so on. However, the overall annual Inflation as seen in Figure 3 below is highly oscillating marking an all-time high in 1994 with 71 % followed by 2017 and 2018 and an all-time low in 2009 with 3.6 % and averaging at about 23 % across the observed period. Additionally, regardless of the economic growth's slight recovery in 2022, INFY continues to increase to about 27 % in 2021 and 30 % in 2022.

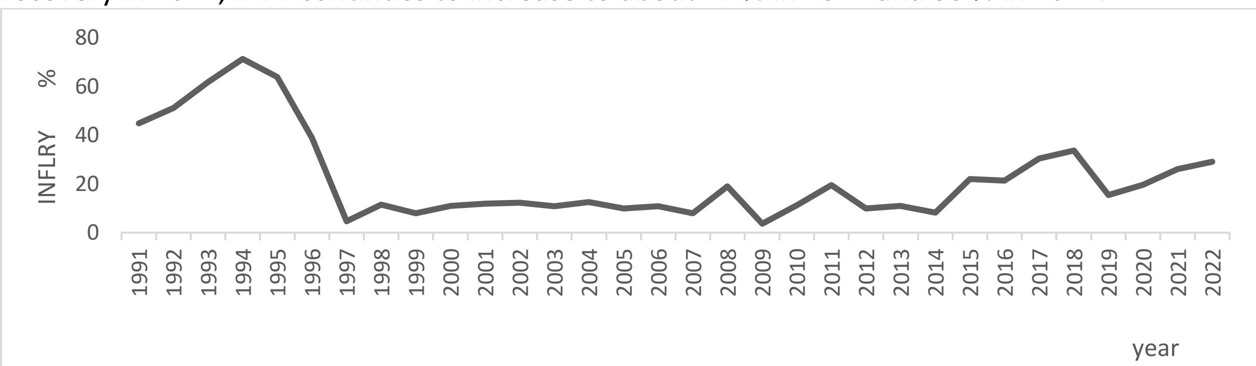


Figure 3: Yemen’s Annual inflation growth
Source: Adopted from IMF (2023)

Hence, taking into account the high dependency of the country's economy on oil, the question is 'Does such oscillation have to do with SOP? Given the foregoing, this study aims to ascertain the impact of oil price shocks that may imposed on the country's inflation by taking into account the asymmetric-like impact. Moreover, both short- and long-term relationships of INFY to SOP are to be examined as well. To make this possible, nonlinear autoregressive distributed lag model (henceforth, NARDL) by Shin et al. (2014) and the novel Augmented ARDL developed by McNown et al. (2027). However, since the study focus on asymmetry, the bootstrap ARDL will be considered under the asymmetric or non-linear form "NARDL" (henceforth, A-NARDL).

Given the scarcity of related studies on Yemen's economy, in particular, and LDC countries in general, alongside Yemen's prolonged economic instability that has been shaped by the oil price movements, the motivation for this study stems. Additionally, the study's main contribution, but not limited to, falls in the comprehensive analysis for the past 32 years on the interplay between SOP and inflation. Hence, by incorporating recent data and considering a longer period span, a significant gap in the literature is filled. As a result, this research holds significant value for both policymakers and future researchers. For future researchers, the study underscores the ongoing relevance of oil's impact on Yemen's economy, which remains susceptible to oil price fluctuations. This research provides a foundation for further in-depth studies on Yemen's macroeconomy. Policymakers, in turn, will gain a deeper understanding of the impacts of oil price shocks on Yemen's macroeconomy, which can help them design effective policies in the face of ongoing and future shocks.

The rest of the research comprises chapters on the literature review, methodology, empirical results and lastly, conclusion.

Literature Review

From a theoretical perspective, Brown and Yucel (2002) and Tang et al. (2010) identified several channels through which SOP affects macroeconomic indicators, including the monetary policy or inflation channel. On the one hand, this channel suggests that inflation may be directly affected in response to SOP following a rise in oil price or a rise in money supply (henceforth, MS). On the other hand, the effect of SOP can be spotted on inflation if the money supply or so-called rate of money aggregate is held constant by the monetary authorities. The explanation of asymmetry in the effect is possible through this mechanism as argued by Rahman and Serletis (2010), among others and opposed by Federer (1996), among others.

Empirically, the relationship and the impact between SOP and inflation also received ample attention from empirical studies. Among these is the study by Sa'ad et al. (2023) which adopted NARDL to find the asymmetric impact of SOP on Nigerian inflation. Asymmetry was found with rising SOP (positive shocks) showed a bigger impact as compared to the declining or negative ones.

Taufani et al. (2022) used VECM and to study the economies of Malaysia, Brunei, Thailand, and Indonesia's responses to negative and positive SOP. The overall results suggested asymmetry due to the difference in response rate to the declining (negative) SOP from the response rate to the rising (positive) SOP. More specifically, Malaysia and Brunei inflation declined in response to positive SOP and increased in reaction to positive ones, while the exact opposite occurred in the case of Thailand and Indonesia.

Lacheheb and Sirag (2019) used NARDL to find that Algeria's inflation was affected asymmetrically in response to positive SOP in both long and short terms, while there was no effect in response to declining oil prices. Similarly, Long and Liang (2018) employed ARDL and NARDL models to study the asymmetric response of China's inflation to SOP. While the impact was not clear through the results of symmetric ARDL, the NARDL model results indicated the existence of asymmetry in the effect of SOP on the inflation of China in the long run but with oil price increase having a bigger effect in comparison to the decrease of it. Opposite to this study, the negative SOP was found to impose a bigger asymmetric effect compared to positive ones on the inflation of African OPEC members targeted by the study of Chin and Bala (2018) which used NARDL for the analysis. this difference reflects the fact that China is a large oil importer while OPEC members are among the largest exporters.

Unlike previous studies, the asymmetrical impact of SOP on Thailand's inflation was not found in the study of Jiranyakul (2018), which analysed data from 1993 to 2016 through the application of unrestricted VAR. Similarly, there was no inflationary impact for SOP whether positive or negative shocks in Kazakhstan, but negative SOP significantly impacts the exchange rate in particular, and the overall economy of the country in general as compared to positive SOP (Kose and Baimaganbetov, 2017).

Differently from some previous studies which suggested a bigger asymmetric impact of negative SOP in comparison to positive ones, Choi et al. (2018) in broader research studied 72 countries of both developing and developed ones through the use of impulse response function (IRF) to analyse their inflation data between 1970 to 2015. they found that inflation increased by 0.4 % on average in response to a 10 % spike in the prices of Oil regardless of whether the country is developed or developing making positive shocks impose greater impact in comparison to negative ones. Similarly, Al Rasasi and Yilmaz (2016) found with the use of the VEC-VAR model that Turkey's inflation rises as the oil price hikes which indicates a bigger and asymmetric effect for Positive SOP compared to negative shocks. The researchers suggested the use of tightening or expansive monetary policy to mitigate such a rise in inflation.

Focusing on how countries of different dependency on oil are affected by SOP, Sek et al. (2015) used ARDL to find how SOP affects the inflation of some high-oil-reliant countries versus low-oil-reliant ones. findings showed that in the low-reliant ones, the impact was direct and indirect in the high-reliant ones, with the exchange rate and production cost playing the key role in high-oil -reliant ones. Accommodating some monetary policies may help in mitigating such impact in both sets of countries

Earlier studies, such as the study of Cologni and Manera (2008) , targeted the G-7 members by analysing data from 1980-2003 through the use of SVAR. The results indicated inflation increased while output declined following SOP. However, since the 1990s some tightening monetary policies adopted by some countries were the direct cause of the inflationary impact while the SOP impact was indirect. Additionally, Hooker (2002) found a direct stronger impact for the SOP on the US inflation particularly in the period before 1981 in comparison to a smaller or no impact in the period after it. These results as well as most of the mentioned studies oppose the perception before 1886 which assumes the SOP has a symmetric impact rather than an asymmetric on counties' economies.

In light of the aforementioned, this study addressed the gap spotted in the reviewed literature including the scarcity of studies on LDC countries such as Yemen which will enrich the literature with facts regarding such country economies. Moreover, the timeframe of the study ascertained the inclusion of the latest SOP such as the Arab uprising which Yemen itself is one of the Arab uprisings' countries. such events' periods were not widely considered by studies of countries that have been directly witnessing these events. Methodologically, the use of novel Augmented ARDL under the nonlinear version of ARDL (I.e., NARDL) is another contribution to the fewer studies in the literature that used it with NARDL. To the best knowledge of the author, the use of augmented ARDL was widely used as it is (i.e., with linear "ARDL).

Methodology

Data Collection and Variable Discerptions

Considering a period from 1991 to 2022, this paper aims to examine how the inflation rate in Yemen (INFY) responds asymmetrically to both positive and negative shocks of oil prices (SOP^+ & SOP^-). The data collected from the international monetary fund (IMF) and world bank data bases (WB). INFY represents the yearly percentage change in the average consumer's expense for obtaining a set of goods and services. This collection may remain constant or be modified at predetermined intervals, such as annually. In the global market, SOP is measured in US dollars per barrel. This price is typically represented by the average of three major oil benchmarks: Dubai crude, West Texas Intermediate (WTI), and Brent crude. Hence, considering the part related to the monetary policy/inflation channel in the framework developed by Tang et al. (2010), The following framework in Figure 4 illustrates the link between the study's explanatory variables of positive SOP following rising oil price and negative SOP following declining oil price (SOP^+ & SOP^-) and the explained variable (INFY).

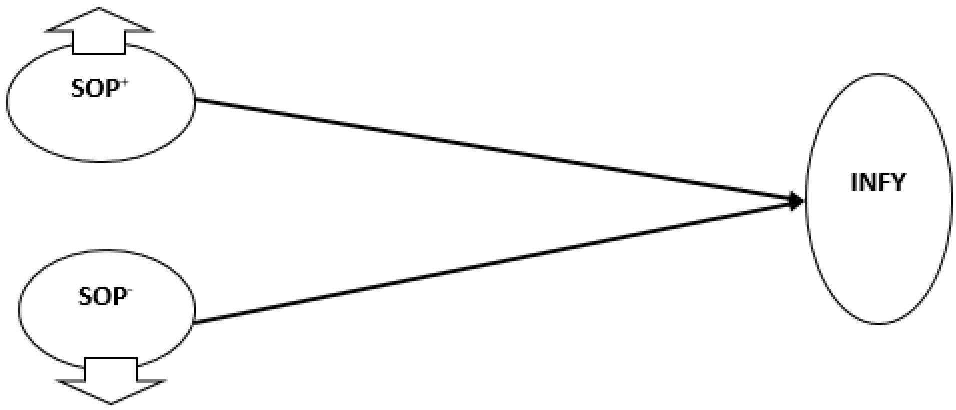


Figure 4. Study's conceptual framework
source: Author's construct

Notes: SOP^+ denotes positive Shocks of oil prices, SOP^- denotes negative Shocks of oil prices, INFY is Yemen's inflation rate

According to the figure above, it is presumed that explanatory/independent variables (SOP^+ & SOP^-) impose an asymmetric effect on the dependent variable (INFY). The control variable (henceforth, CV) of monetary supply (MS) is to be included given the suggestion of the monetary policy transmission channel where it is to be constant (Brown and Yucel,2002). The MS is measured by the total amount of money outside banks, demand deposits, savings, foreign currency deposits, banks' checks, travellers' checks, and some other securities and commercial paper certificates.

Model Specification and Analysis Tehniques
To empirically examine the objective of this study, the Nonlinear autoregressive distributed lag- model (henceforth, NARDL) developed by Shin et al. (2014) was adopted. NARDL is straightforward and adaptable for modelling complex phenomena such as the one widely discussed in the literature, which asserts that positive shocks have a greater short-term impact, while negative shocks have a more substantial long-term effect, or vice versa, suggesting possible directional asymmetry between short and long terms (Shin et al., 2014). In addition to this, NARDL is flexible to be used with variables of different integration orders (i.e., I(0), I(1), or a mix of both) and can account for asymmetries in the SOP-INFY nexus in both runs (Lacheheb and Sirang,2019).

NARDL was an extension of the linear autoregressive distributed lag (ARDL) by Pesaran et al. (2001). As in Long and Liang (2018), among others, ARDL estimation considering this study variables is as follows:

$$\Delta LINFY_t = a_0 + a_1 LINFY_{t-1} + a_2 LSOP_{t-1} + a_3 LMS_{t-1} + \sum_{i=1}^{p} \delta_i \Delta LINFY_{t-i} + \sum_{i=0}^{q} \vartheta_i \Delta LSOP_{t-i} + \sum_{i=0}^{q} b_i \Delta LMS + \varepsilon_t \quad (1)$$

here , Δ is variable differnce , $\mathrm{LINFY_t}$ is the IV in its logarithm form , $\mathrm{L}SOP_\mathrm{t}$ is the DV in logarithm, p &q are optimal lag lengths, $\mathrm{a_1, a_{2,} a_3}$ are long-term coefficients while $\delta, \delta, \mathrm{b}$ are the short-term ones and lastly the ε_t denots the error term . Hence and as Inspired by ARDL in (1), Shin et al. (2014) started NARDL by the estimation of simple regression equation as follows:

$$INFY_t = \beta^+ SOP_t^+ + \beta^- SOP_t^- + \varepsilon_t \quad (2)$$

where $\mathrm{INFY_t}$ is the explained variable, β^+, β^- are associated long-term parameters while SOP_t is the explanatory variable which is being split into its positive partial sum SOP_t^+ and negative-partial sum $\mathrm{SOP_t^-}$. This is the process of "partial sum decomposition" which was suggested by Schorderet (2003) and extended by Shin et al. (2014). Hence, equation (2) can be further rewritten as follows:

$$SOP_t^+ = \sum_{i=1}^{t} \Delta SOP_i^+ = \sum_{i=1}^{t} max(\Delta X_i, 0) \quad (3)$$

$$SOP_t^- = \sum_{i=1}^{t} \Delta SOP_i^- = \sum_{i=1}^{t} min(\Delta X_i, 0) \quad (4)$$

According to Shin et al. (2014), equation (2) taken into account steps in (2-4) can be rewritten to form NARDL as follows:

$$\Delta LINFY_t = a_0 + a_1 LINFY_{t-1} + a_2^+ LSOP_{t-1}^+ + a_2^- LSOP_{t-1}^- + a_3 LMS_{t-1} + \sum_{i=1}^{p} \delta_i \Delta LINFY_{t-1} + \sum_{i=0}^{q} b_i \Delta LMS_{t-i} + \sum_{i=0}^{q} (\vartheta_i^+ \Delta LSOP_{t-i}^+ + \vartheta_i^- \Delta LSOP_{t-i}^-) + \varepsilon_t \quad (5)$$

Where, most variables are similar to what has been defined in equation (1), the associated long-term parameters in equation (2),that is $\beta^{+}=\frac{-a_2^{+}}{a_1}$ *and* $\beta^{-}=\frac{-a_2^{-}}{a_1}$, measure the impact of SOP_t^{+}& SOP_t^{-} on the $\mathrm{INFY_t}$,respectively. While $\sum_{i=0}^{q}\vartheta_i^{+}$, $\sum_{i=0}^{q}\vartheta_i^{-}$ measures the short-run impact of both SOP_t^{+}& SOP_t^{-} on the $\mathrm{INFY_t}$,respectively.

Hence, to execute equation (5), several steps are required: the first step is unit root testing which will be done through the augmented dicky fuller test (henceforth, ADF) by Dicky and Fuller (1981) and Phillips and Perron test (henceforth, PP) (1988). These tests are important to ensure the assumption of no I(2) in the time series is present which makes the application of NARDL possible. As mentioned by Afriyie et al. (2020) the underlying hypotheses of the tests are the null hypothesis (H_0) of there is unit root test (H_0: β=0) versus the alternative (H_a) of there is no unit root (H_a: β<0). Hence, the rejection of the null suggests the absence of unit root in the time series. The hypotheses tested in ADF and PP are similar because both utilize the same regression specifications, differing only in the dependent variable's form: level in PP and first difference in ADF (Wang and Tomek, 2007). For this reason, The PP test was used as it is more robust to serial correlation which may arise from the lag difference in ADF specifications. Nevertheless, such traditional unit root tests lack the power to detect the structural changes in the time series. Hence, the multiple breakpoint unit root test by Bai and Perron (2003a) (henceforth, BP) is used to ensure unbiased results and account for any potential structural changes in the model. The Sequential test under BP is used to determine any break dates in the series. This test hypothesizes the null (H_0) of there is "L" break dates versus the alternative (H_a) of there is "L+1" break dates. In case of any break dates found, dummy variable for each break point (henceforth, D) will be added to equation (5). D is assumed (1) right after the identified break dates up to the end of the series & (0) otherwise (see among others, Cunado & Gracia,2005; and Basher et al.,2012).

Second step includes cointegration testing through F-bound test by Pesaran et al. (2001) and the novel augmented bootstrap ARDL (henceforth, A-NARDL) by McNown et al. (2017). Generally, the F-bound test suggests the cointegration when the long-run coefficients of all lagged explained and explanatory variables in equation (5) that is, a_1=$a_2^{+}=a_2^{-}=a_3=0$ which rejects the null (H_0) of no cointegration in favour of the alternative (H_a) there is cointegration, that is, a_1=$a_2^{+}=a_2^{-}=a_3\neq 0$. Nevertheless, for this test to better decide on the cointegration, the explained variable (INFY) needs to be of I(1) order only as it is a key assumption under NARDL, and having the test applicable on all lagged explained and explanatory variables causes confusion on which variable is significant (Pesaran et al., 2001).Worth mention, the condition of DV to be in first-order integration (I(1)) under NARDL has been greatly ignored by vast majority of studies in the literature leaving the decision on cointegration solely reliant on the F-bound test. Concerning this, the A-NARDL test is used whereas it offsets the assumption of DV to be in I(1) making it possible for the source of significance to be on the lagged level of the IV variables. Hence, with this test, the false conclusion on the DV's order of integration due to the low power of traditional unit root test is taken care of and an augmented decision on the cointegration can be made (McNown et al. 2017). A-NARDL on the IV's coefficients only in equation (5) test the null ($\mathrm{H_0}$) of no cointegration, that is, $H_0=a_2^{+}=a_2^{-}=0$, versus the alternative (H_a) there is cointegration, $\mathrm{H_1}=a_2^{+}\neq a_2^{-}\neq 0$. However, to robustly decide on the cointegration, two different sets of critical values will be used for each test, the F-bound test results to be compared with upper (henceforth, UCV) and lower (henceforth, LCV) Critical values of Narayan(2005) while A-NARDL test to be compared with Sam et al. (2018) critical values. Therefore, only the value greater than the UCV in both tests confirms the cointegration, the value that's in between UCV & LCV Is indecisive and the one under LCV implies of no cointegration. It is worth mentioning, before cointegration testing, Akaike information criterion (henceforth, AIC) will be used for lag selection.

Step three involve finding the long and short run asymmetries. For this , the NARDL associated Wald test (henceforth, W-test) are used . W-test in the short-run asymmetry (henceforth, SRA) tests the null,$H_0 = a_2^+ = a_2^-$(i.e. no SRA response) versus the alternative $H_1 = a_2^+ \neq a_2^-$ (i.e. there is SRA response). Similarly under the long-run asymmetry (henceforth, LRA), the null, $H_0 = \vartheta_i^+ = \vartheta_i^- = 0$ (i.e. no LRA response) versus the alternative, $H_1 = \vartheta_i^+ \neq \vartheta_i^- \neq 0$ (i.e. there is LRA response). The rejection of the null in both runs confirms that INFRY responds asymmetrically to both negative and positive SOP.

In addition, the dynamic multiplier effect (henceforth, DME) for the model will be performed. DME assets to determine the period it takes for the INFY to be transmitted into a new stable or equilibrium state in response to changes in SOP^+ & SOP^-.

Last but not least, to ensure the model is valid and stable, some misspecification tests including R^2 for model fit . R^2 was developed in 1921 by Wright to determine the percentage of DV's variance that can be predicted by the IV (Chicco et al. 2021). In addition, Lagrange multiplier (henceforth, LM test) autoregressive conditional heteroskedasticity (henceforth, ARCH test) to ascertain that the model is autocorrelation and heteroscedasticity-free. Each test hypothesizes the null (H_0) of there is no autocorrelation correlation/heteroskedasticity up to lag order p. Additionally, to ascertain the model stability , the cumulative sum (henceforth, CUSUM) of recursive residuals and the CUSUM of square (henceforth, CUSUMSQ) are used . The said model is stable as long as the CUSUM & CUSUMQ plots fall within the critical bounds of the 5 % significance. This test surpasses some other instability tests including the test of Chow (1960) as it can be used in the case where the breakpoint in the time series is not unknown as in our model series case.

Results and Discussion

To ensure the assumptions of NARDL are met and to execute the first step of it , Table 1 & 2 shows the results of used unit root tests.

Table 1

Traditional Unit roots tests' results

A: Traditional unit root tests determine variables' order of integration					
Variable	**ADF-test**				
	I(0)		**I(1)**		
	T&C	**C**	**None**	**T&C**	**C**
INFY	(0.758)	(0.303)	(0.084)	(0.017)**	n/a
Trend[a]	0.102			1.474	
Constant[b]		1.893			
SOP	(0.576)	(0.624)	(0.728)	(0.003)*	n/a
Trend[a]	1.527			0.133	
Constant[b]		1.5334			

MS *Trend*[a] *Constant*[b]	(0.002)* -2.632	n/a	n/a	n/a	n/a
Variable	**PP-test**				
INFY *Trend*[a] *Constant*[b]	(0.787) 0.102	(0.351) 1.286	(0.169)	(0.000)* 1.015	n/a
SOP *Trend*[a] *Constant*[b]	(0.518) 1.527	(0.675) 1.533	(0.778)	(0.004)* 0.133	n/a
MS *Trend*[a] *Constant*[b]	(0.002)* -2.632	n/a	n/a	n/a	n/a

B: Critical values of Mackinnon (1996) (Makinnon's CVs)

Sig.level	I(0)		I(1)	
	T&C	C	T&C	C
1 %	-4.2845	-3.6616	-4.2967	-3.6701
5 %	-3.5628	-2.9604	-3.5683	-2.9639
10 %	-3.2152	-2.6191	-3.2183	-2.6210

Notes for output (A) & (B): INFY, SOP & MS denote model variables, that is inflation rate, shocks of oil price & money supply; I(0) &I(1)= level & first difference integration order; T&C denotes the trend & constant, C is the constant; *, ** = H_0 is rejected at 1 %,5 significance level; values in () denote p-values and others denote the t-statistics; Probability based on CVs of MacKinnon (1996); [a] =Trend is significant if t-stats > CVs of Mackinnon (1996); [b] = Constant is significant if t-stats > CVs of Mackinnon (1996); n/a = "stationarity " has been confirmed so no further test is needed under that certain assumption

Table 2
Breakpoint Unit roots tests' results

Sequential BP breakpoint test determines the model's structural changes (break dates).

Potential Break tests	Scaled F-statistics	Critical values [c]	Detected Break dates
*0 vs. 1 **	59.6334	11.47	1997
*1 vs. 2 **	26.5047	12.95	2015
2 vs. 3	13.3540	14.03	-

Notes : *= potential break test is Significant at 5 % where (0 vs1*) means the H_0 of "0" is rejected vs H of "1" and the H_0 of "1" is rejected vs H_a of "2" at 5 % concluding the existence of "2" break dates. [c]= Bai-Perron (2003) critical values of sequential test.

In general, ADF and PP produced similar results as seen in output (A) in Table 1 above where all variables were found to meet the NARDL assumption of having a mixture of I(1) & I(0) order of integration and the DV (i.e. INFY) of I(1). Specifically, INFY and SOP for instance rejected the H_0 of "there is unit root" in the first difference, categorizing both under the I(1) integration orders. The MS, however, rejected the H_0 in the level indicating I(0) integration of order. The similarity in the outcomes of ADF and the more powerful test of PP implies better and more augmented findings regarding the variables' order of integration.

The testing procedures followed Doldado et al. (1990) and Enders (2010). First, estimate the model with trend and constant (T&C). If the null is rejected, the series is stationary. If not, compare t-statistics with Mackinnon's (1996) critical values to test the trend's significance. A significant trend indicates stationarity with T&C; if insignificant, exclude it, suggesting unit roots and further tests under the constant (C) assumption. Next, test under the (C) assumption focusing on the constant's significance. If still non-stationary, proceed to test under the "none" assumption. If non-stationary after all level assumptions, repeat steps under first difference assumptions. For instance, under the ADF, the trend of INFY under T&C is found to have a t-stats value of 0.102, that is > all CVs of Mackinnon (1996) under T&C implying its significance which calls for estimating the model under the T&C assumption. However, INFY's p-value (0.758) under the T&C assumption failed to reject the H_0: β=0 at all sig-levels implying the need for further testing under the following assumption that is, constant (C). Under the C and after that under the "none", the model still non-stationary which calls for estimating it under the 1st difference starting with T&C assumption as well. Hence, under the first difference, the INFY value of (0.017) rejected the H_0: β=0 at the 5 % level concluding the model is stationary in the first difference or I(1) and no further test is required (n/a).

The second part of unit root testing as in Table 2 includes the detection of possible structural changes in the model by making use of the BP multiple breakpoint test. The presence of an unknown number of break dates was confirmed first through the double max test under BP.

However, it was not possible to find the exact dates and number of breaks without applying the sequential test of BP as shown above. Considering the scaled F-stats values of (59.6334 & 26.5047) which are greater than the CV of Bai & Perron (2003) that is, 11.47 & 12.95, the alternative potential breaks 1& 2 for the null breaks of 0 & 1 is said to be significant at 5 % level. This means rejecting the null of breaks 0&1 versus the alternative of breaks 1& 2 implying the existence of two break dates. Hence, two break dates were found, that is, 2015 & 1997 indicating the need for two dummy variables inserted into equation (5) to account for these break dates.

The second step in the ARDL execution is the cointegration test. The results are summarized in Table 3 below.

Table 3
Cointegration test results

A:Optimal lag selection			
Model	**Lags included**	**AIC**	**Lags length selected** [a]
INFY-SOP model	0	4.033245	
	1	-0.196623*	1
	2	0.112051	
B: Cointegration tests			
	F-bound test	**A-NARDL test**	**Cointegration's decision** [d]
INFY-SOP model	28.857	26.431	A Robust cointegration is confirmed.
C: Critical values of Narayan (2005) & Sam et al.(2018) [b]			

Sig-level	*I (0)[c]*	*I (1)[c]*	*I (0)*	*I (1)*
1 %	4.76	6.67	4.15	6.83
5 %	3.35	4.77	2.80	4.70
10 %	2.75	3.99	2.22	3.84

Notes: [a] = Lags length selected based on The Akaike's information criterion (AIC); [b] = Critical values for F-bound test taken from Narayan (2005) >> [case 3, N=30, K=4]; Critical values for A-NARDL from Sam et al. (2018)>> [case 3, N=30, K=4. [c] = 1(0) is the lower bound critical value (LCV) and I(1) is the upper bound ones (UCV); [d] = the decision of robustness is made based on the two test values together as both > UCV critical values at all sig-levels.

Table 3 (A) shows the results of optimal lag length selection. The results through the VAR estimation and selection criteria of AIC indicated that one lag length order is appropriate for the model. A proper lag length determination is vital to avoid any autocorrelation issues in the model (Lütkepohl,1993). As appropriate lag order was determined, the decision on cointegration can be made based on the results of the tests in Table 3 (B).

To this end, it is found that the F-bound test value of (28.857) and the A-NARDL value of (26.431) are greater than the UCV associated with each test at all sig-levels in table 3 (C) . These results imply the rejection of the null (H_0) stating there is no cointegration (i.e. a_1=$a_2^+ = a_2^- = a_3 = 0$). Hence, robust long-run association (I.e. cointegration) among variables of interest is confirmed.

Testing for the short-long run asymmetric response of INFY to positive-negative SOP is the third step in the execution of NARDL. Table 4 below shows NARDL results for the study's model.

Table 4
INFY-SOP NARDL model results

	A: INFY-SOP model :INFY is the DV.										
	Variabl		**Coeffic**		**Prob**		**Variable**		**Coeffic**		**Pro**
es		**ients**		**.**		**s**		**ients**		**b.**	
	LR						**SR**				
	LSOP_P		0.0514		0.64		LINFY(-1)		-1.4859		0.00
OS			0.1362	17			LSOP_PO		0.0765	00*	
	LSOP_		-1.7462		0.65	S			0.2024		0.64
NEG			0.9723	25			LSOP_NE		1.6135	11	
	D1				0.00	G(-1)			-0.0107		0.65
	D2			00*			D(LSOP_			29	
					0.00	NEG)					0.00
				13*			LMS			72*	
											0.83
										21	

	B: Asymmetric response test (Wald-test)				
	W	**Coefficients(ch$^{2)}$**		**Prob.**	**Decision [a]**
-test					
	LRA	0.1177		0.731	No asymmetry
			5		
	SRA	9.2916		0.002	Asymmetric
			3*		

Notes: *, **, *** = 1 %,5 % & 10 % significance level, respectively; LR= long-run coefficients; SR= short-run coefficients; LSOP_POS & LSOP_NEG denotes the positive SOP & negative SOP; D1,D2= dummies to account for structural breaks, LRA=long-run asymmetry SRA= short-run asymmetry. [a] = the decision is based on w-test (Wald test) results through the significance of prob.value.

As Table 4 (A) shows, there is an insignificant p-value for both shocks (0.6417 & 0.6525) compared to significant values at 1 % for the structural changes (0,0000 & 0.0013) that occurred in some years following some events as has been determined earlier. This means that a unit rise in SOP causes a 0.05% rise in inflation and a 1-unit decline in SOP causes a 0.13 % decline in INFY but both effects are not significant implying an indirect impact through some events. On the contrary, in the short run, the INFY declined by almost 2 % and this negative impact is significant at 1 % (0.0007). These results indicate negative SOPs impose bigger effect on INFY compared to positive ones. Hence, it is no surprise that the asymmetric response of INFY to SOP is only spotted in the short-run as W-test results in Table 4 (B) show. This means that the null (H_0) of no SRA asymmetric response (0.0023) is rejected at 5 % suggesting an asymmetric impact in the short run only. The results also show no effect for the monetary policy proxied by MS in such an asymmetric response. The results regarding the positive impact in the LR in line with studies such as but not limited to Chin and Bala (2018) and in line with Cunado and Gracia (2005) regarding the asymmetry in SR and positive significant impact in the SR. As for the indirect impact due to the determined structural breaks in 2015 and 1997, one breakpoint occurred following the Asian financial crisis in 1997 and had no noticeable impact on the country's inflation This decline may be due to the fact Yemen as a Western Asian country was not among those countries who was hit directly and hard by the crisis such as Southeast Asian countries. However, the break detected in 2015 might have to do with the political unrest in the country, has contributed to the inflation rise as well.

The asymmetry in the response of INFY to SOP can also be seen through the dynamic multiplier effect (DME) as shown in Figure 5 which illustrates the adjustment path taken by INFY into new equilibrium even in the case where no asymmetries were confirmed through modelling ECM (Shin et al. (2014). Concerning this, the "0" line deviates away from inside the upper and lower boundaries of the critical intervals (C.I). deviation of this line from C.I boundaries indicate asymmetries as suggested by (Almalki et al., 2022). This deviation ended at the 2nd period when the "0" line got back to within the boundaries of CI implying a short-run asymmetric effect as same as suggested by previous results. Moreover, the figure also shows that in response to a unit change in negative SOP, INFY needed up to 8-9 years in the process of switching into an equilibrium state. Hence ,this means responding more quickly to negative SOP compared to positive ones.

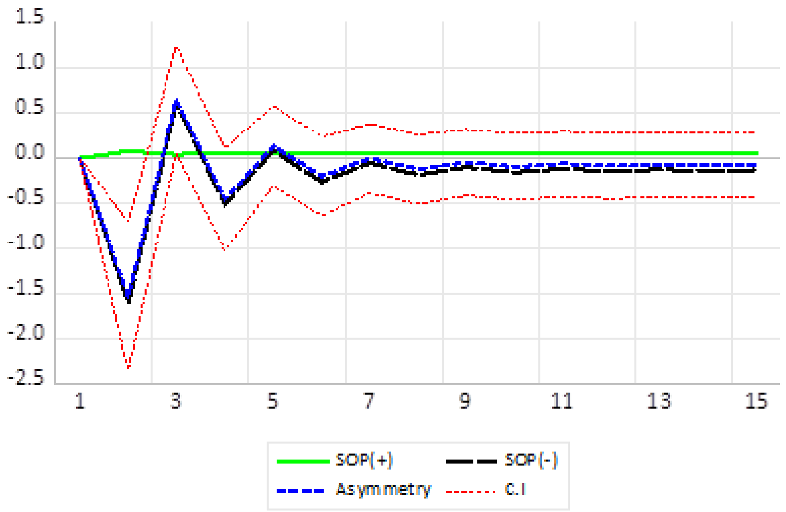


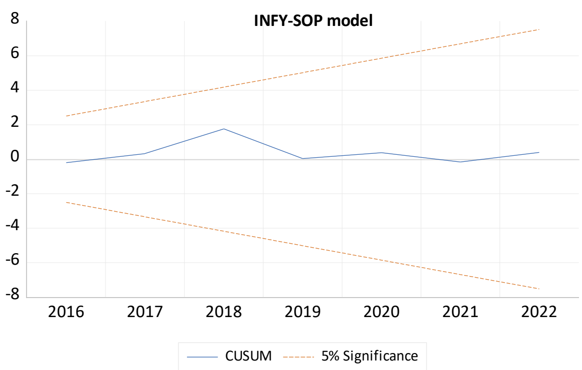
Figure 5: DME for INFY-SOP model
Source: Authors construct based on EViews output

In the last step, several diagnostic tests were conducted to check how valid, adequate, and stable the used model to ensure unbiased findings. The results are shown in Table 5 below.

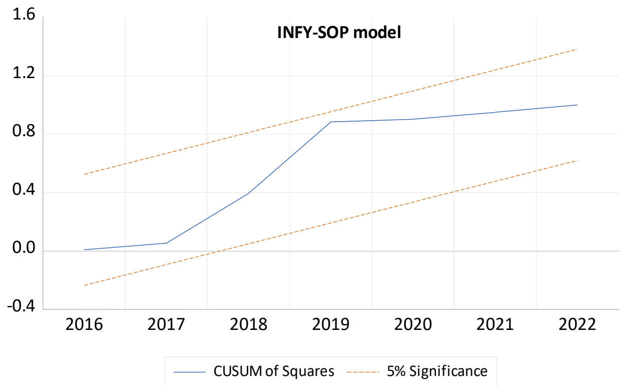
Table 5
Diagnostic Checks tests

Diagnostics & Misspecifications' tests			
Test type	**Coefficients**	**Prob.**	**Decision**
R^2	0.8692	-	Good fitted
LM test [a]	1.2150	0.2703	No autocorrelation issue
ARCH test [a]	2.6438	0.1039	No heteroskedasticity issue

CUSUM



CUSUMQ



Notes: [a] = H_0 under LM & ARCH tests" there is no serial correlation/heteroskedasticity up to lag order p"

Table 5 shows that 87 % of INFY can be explained by SOP as suggested by R^2 . this indicates the good fit of the model . According to Stare (1995), R^2 remains an acceptable measure for the model's goodness of fit regardless of the criticisms received by some researchers but there is no clear justification for such criticism. LM test value of (0.27) and ARCH value of (0.11) are not significant indicating to the failure to reject the null (H_0) of no serial correlation/heteroskedasticity up to lag order p. this means the model is serial correlation-free and autocorrelation-free. Finally, model is found to be stable as CUSUM & CUSUMQ plots indicate that the coefficients of the model fall within the critical bounds of the 5 % significance. The model's stability has been greatly assisted by accounting for detected structural breaks in the series and the incorporation of dummies to account for such breaks. overall, the model successfully passed the diagnostics checks based on the obtained results.

Conclusion and Implication

oil price shocks whether negative or positive can be very effective e to the economy of any country as oil plays a major role in the economy of most of the world nations. Regarding this, the paper in hand targeted the LDC of YEMEN to find the asymmetric association and impact between the country's inflation and the shocks of this important commodity, given oil is the major source of revenue in the country. To this end, the study made use of the nonlinear autoregressive distributed lag (NARDL) model alongside the novel test of augmented NARDL for a robust finding of the long-run association "cointegration" in particular. Several associated techniques and tests related directly and indirectly to the main methodology were also used for the complete analysis of the results. To this, the assumptions of the model used were found to be perfectly met based on unit root tests, and the unwanted breaks in the series were detected and dealt with throughout the analysis to avoid any biased outcomes or effects on the efficacy of the model. a robust long-run association (cointegration) between shocks of oil prices (SOP) and the country's inflation rate (INFY) were confirmed. As for the main outcomes, the inflation of the country (INFY) was found to respond asymmetrically to SOP only in the short run with negative SOPs imposing a bigger impact compared to positive ones. Moreover, it was ascertained that inflation needs around 8 years to switch to an equilibrium level in response to one-unit changes in these negative shocks. Last but not least, the model is found to pass all diagnostic checks implying its validity and stability. Hence, in light of these findings, an important implication related to the inflation rate is drawn. Current policies, like increased monetary supply, have been ineffective, worsening inflation and fostering black-market activities. Through the Central Bank of Yemen, the government is encouraged to implement stringent monetary controls such as tightening monetary policy to stabilize currency markets and mitigate inflation. Effective execution and monitoring of these policies are essential for stable prices. Moreover, diversifying revenues instead of depending heavily on oil revenues is another way of avoiding inflation as it was proved through findings there is a strong association between oil price shocks and inflation.

References

Ahmed, S. (2016). The Impact of Oil Prices on the Economic Growth and Development in the MENA countries. Munich Personal RePEc Archive, (89073), 1–23. https://mpra.ub.uni-muenchen.de/89073/

Almalki, A. M., Hassan, M., & Amin, M. F. B. (2022). The asymmetric relationship between structural oil shocks and food prices: evidence from Saudi Arabia. Applied Economics,54(54),6216–6233. https://doi.org/10.1080/00036846.2022.2083065

Al Rasasi, M., & Yilmaz, M. (2016). The effects of oil shocks on Turkish macroeconomic aggregates. International Journal of Energy Economics and Policy, 6(3), 471–476

Bai, J., & Perron, P. (2003). Critical values for multiple structural change tests. The Econometrics Journal, 6(1), 72–78. https://doi.org/10.1111/1368-423x.00102

Bai, J., & Perron, P. (2003a). Computation and Analysis of Multiple Structural Change Models. Journal of Applied Econometrics, 18(1), 1-22.https://doi.org/10.1002/jae.659

Bala, U., & Chin, L. (2018). Asymmetric Impacts of Oil Price on Inflation: An Empirical Study of African OPEC Member Countries. Energies, 11(11), 3017. DOI.10.3390/en11113017

Basher, S. A., Haug, A. A., & Sadorsky, P. (2012). Oil prices, exchange rates and emerging stock markets. Energy Economics, 34(1), 227–240. https://doi.org/10.1016/j.eneco.2011.10.005

Baumeister, C. and Kilian, L. (2016). Forty Years of Oil Price Fluctuations: why the price of oil May Still Surprise Us. Journal of Economic Perspectives, 30(1),139-160.

Brown, S. P. A., & Yücel, M. K. (2002). Energy prices and aggregate economic activity: an interpretative survey. The Quarterly Review of Economics and Finance, 42(2), 193–208.https://doi.org/10.1016/s1062-9769(02)00138-2

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The Coefficient of Determination R-squared Is More Informative than SMAPE, MAE, MAPE, MSE and RMSE in Regression Analysis Evaluation. PeerJ Computer Science, 7(5), e623.

Choi, S., Furceri, D., Loungani, P., Mishra, S., & Poplawski-Ribeiro, M. (2018). Oil prices and inflation dynamics: Evidence from advanced and developing economies. Journal of International Money and Finance, 82, 71–96. doi.org/10.1016/j.jimonfin.2017.12.004

Chou, K.-W., & Lin, P.-C. (2013). Oil price shocks and producer prices in Taiwan: an application of non-linear error-correction models. Journal of Chinese Economic and Business Studies, 11(1), 59–72. https://doi.org/10.1080/14765284.2012.755302

Cologni, A., & Manera, M. (2008). Oil prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries. Energy Economics, 30(3), 856–888. https://doi.org/10.1016/j.eneco.2006.11.001

Cunado, J., & Perez de Gracia, F. (2005b). Oil prices, economic activity and inflation: evidence for some Asian countries. The Quarterly Review of Economics and Finance, 45(1), 65–83. https://doi.org/10.1016/j.qref.2004.02.003

De Gregorio, J., Landerretche, O., & Neilson, C. (2007). Another Pass-Through Bites the Dust? Oil Prices and Inflation. Economía, 7(2), 155–196.https://doi.org/10.1353/eco.2007.0014

Dickey, D. A., & Fuller, W. A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. Econometrica, 49(4), 1057–1072. https://doi.org/10.2307/1912517

Dolado, J. J., Jenkinson, T., & Sosvilla-Rivero, S. (1990). cointegration and unit roots. Journal of Economic Surveys, 4(3), 249–273.https://doi.org/10.1111/j.1467-6419.1990.tb00088.x

EIA. (2024). Energy & Financial Markets: What Drives Crude Oil Prices? Energy Information Administration. https://www.eia.gov/finance/markets/crudeoil/spot_prices.php

Enders, W. (2010). Applied Econometric Time Series (3rd ed.).New York: John Wiley & Sons.

Ferderer, J. (1996). Oil price volatility and the macroeconomy. Journal of Macroeconomics, 18(1), 1-26. https://doi.org/10.1016/s0164-0704(96)80001-2

Hamilton, J. D. (1983). Oil and the Macroeconomy since World War II. Journal of Political Economy, 91(2), 228–248. https://doi.org/10.1086/261140

Hooker, M. A. (2002). Are Oil Shocks Inflationary?: Asymmetric and Nonlinear Specification versus Changes in Regime. Journal of Money, Credit, and Banking, 34(2), 540–561. https://doi.org/10.1353/mcb.2002.0041

IMF. (2023). World Economic Outlook database: April 2023. International monetary fund.

Jiranyakul, K. (2015). Oil Price Shocks and Domestic Inflation in Thailand. SSRN ElectronicJournal. https://doi.org/10.2139/ssrn.2578836

LeBlanc, M., & Chinn, M. D. (2004). Do High Oil Prices Presage Inflation? The Evidence from G-5 Countries. SSRN Electronic Journal.doi.org/10.2139/ssrn.509262

Lacheheb, M., & Sirag, A. (2019). Oil price and inflation in Algeria: A nonlinear ARDL approach.The Quarterly Review of Economics and Finance, 73, 217-222

Long, S., & Liang, J. (2018). Asymmetric and nonlinear pass-through of global crude oil price to China's PPI and CPI inflation. Economic Research-Ekonomska Istraživanja, 31(1), 240–251. https://doi.org/10.1080/1331677x.2018.1429292

Lütkepohl, H. (1993). Introduction to Multiple Time Series Analysis (2nd ed.). Berlin: Springer

MacKinnon, J. G. (1996b). Numerical distribution functions for unit root and cointegration tests. Journal of Applied Econometrics, 11(6), 601–618. https://doi.org/10.1002/(sici)1099-1255(199611)11:6%3C601::aid-jae417%3E3.0.co;2-t

McNown, R., Sam, C.Y. and Goh, S.K. (2017). Bootstrapping the Autoregressive Distributed L ag Test for cointegration', Applied Economics, 50(13), 1509–1521. https://doi.org/10.1080/00036846.2017.1366643

MoPIC. (2016). Yemen socio-economic update 2016. Ministry of Planning & International Cooperation.

Narayan, P. K. (2005b). The saving and investment nexus for China: evidence from cointegration tests. Applied Economics, 37(17), 1979–1990.Doi.org/10.1080/00036840500278103

Phillips, P. C. B., & Perron, P. (1988). Testing for a Unit Root in Time Series Regression. Biometrika, 75(2), 335–346.https://doi.org/10.1093/biomet/75.2.335

Rahman, S., & Serletis, A. (2010). The asymmetric effects of oil price and monetary policy sh ocks: A nonlinear VAR approach. Energy Economics, 32(6), 14601466. https://doi.org/1 0.1016/j.eneco.2010.06.003

Sa'ad, S., Usman, A. B., Omaye, S. O., & Yau, H. (2023). Asymmetric Passthrough Effects of Ol Price Shocks and Exchange Rates on Inflation in Nigeria: Evidence from a Nonlinear AR DL Model. European Scientific Journal, ESJ, 19(4), 1–1. doi.org/10.19044/esj.2023.v1 n4p1

Sam, C. Y., McNown, R., & Goh, S. K. (2018). An augmented autoregressive distributed lag b nds test for cointegration. Economic Modelling, 80, 130141. doi.org/10.1016/j.econmo d .2018.11.001

Sek, S. K., Teo, X. Q., & Wong, Y. N. (2015). A Comparative Study on the Effects of Oil Price C hanges on Inflation. Procedia Economics and Finance, 26, 630636. doi.org/10.1016/s2 212-5671(15)00800-x

Shin, Y.,Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In R Sickles &W. Horrace,Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications(eds). New York. Springer. 281-314

Schorderet, Y. (2003). Asymmetric Cointegration Working paper no.2003.01. Geneva: University of Geneva.

Stare, J. (1995). Some Properties of R2 in Ordinary Least Squares Regression. In A. Ferligoj & A.Kramberger (Eds.), Contributions to Methodology and Statistics,Metodološki zvezki, 10. (pp. 134–145). Ljubljana, Slovenia.

Tang, W., Wu, L., & Zhang, Z. (2010). Oil price shocks and their short- and longterm effects o n the Chinese economy. Energy Economics, 32(1), S3S14. doi.org/10.1016/j.eneco.201 0.01.002

Taufani, A., Hakim, D. B., & Widyastutik, W. (2022). The impact of oil price shocks on macroeconomic indicators: Evidence from four ASEAN countries. Economic Journal of Emerging Markets, 14(2), 257–272. https://doi.org/10.20885/ejem.vol14.iss2.art10

Wang, D., & Tomek, W. G. (2007). Commodity Prices and Unit Root Tests. American Journal of Agricultural Economics, 89(4), 873–889. doi.org/10.1111/j.1467-8276.2007.01031.x

WB. (2020). World Development Indicators | DataBank. Retrieved from databank.worldbank .org website: https://databank.worldbank.org/reports.aspx?source=2&series=NY.GDP. PETR.RT.ZS&country=YEM#.