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Key Macroeconomic Indicators' Response to Oil Price Shocks in Yemen: Asymmetry in Focus

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

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Abstract
The oil-based economy of Yemen is like other oil-based economies susceptible to global oil price shocks. Hence, this study examines the asymmetric responses of some Yemen's key macroeconomic indicators to oil price shocks from 1991 to 2022. To achieve this, the Nonlinear autoregressive distributed lag (NARDL) and its associated bootstrap NARDL are adopted for an augmented analysis of such response and association. Overall findings indicate that all variables are cointegrated and respond asymmetrically to shocks in oil prices with a greater magnitude for the negative shocks. Specifically, gross domestic product (GDPY) responds positively and significantly to negative shocks only in the short-term, and to both positive and negative shocks in the long-term. The exchange rate (EXCHRY) responds asymmetrically to shocks in both the short and long run, with significant long-term appreciation in response to positive shocks and significant short-term response to negative shocks. The study recommends that Yemen's policymakers develop a long-term strategy to diversify revenue sources beyond oil dependency.
Keywords: Asymmetric Response, GDP, Exchange Rate, Bootstrapping Nardl, Yemen

Introduction

Oil's significance as a high-demand commodity impacts global economies reliant on it. Park (2007) asserted that oil price has been the primary economic influence since 1973, referencing the global recession caused by the 1973-1974 OPEC oil embargo during the Arab-Israel war. Ahmed (2016) and Paparoditis & Politis (2016) noted that oil prices affect both exporting and importing nations, regardless of their development status. WEcouncil (2016) reported Oxford economists' calculation predicting 0.4% global economic growth over 2018-2019 for a $20 oil price drop, aligning with IMF estimates. This illustrates the strong link between oil prices and global economic growth.

The historical context of oil price shocks (OPS, hereafter) reveals a pattern of significant volatility, with various geopolitical events contributing to these fluctuations. For instance, the Arab embargo in 1973 led to an 18% increase in oil prices, while subsequent events, such as the Gulf War with 53 % increase, Asian financial crises in mid-1997 marking a huge decrease and the latest COVID-19 pandemic with huge drop in the price of oil, have further illustrated the susceptibility of oil prices to external shocks. The concept of "oil price shock, "defined as substantial volatility in oil prices has been a focal point of research since the 1980s (Baumeister and Kilian, 2016). Hence, the literature in general identifies three primary determinants of such OPS: supply shocks due to political instability in oil-producing regions, demand shocks linked to global economic cycles and shifts in expectations regarding future supply and demand (Baumeister & Kilian, 2016; Hamilton, 1983).

For specific instances, Baumeister and Peersman (2012, 2013) and Fueki et al. (2018) argued that both supply and demand shocks explain historical oil price fluctuations, while Hamilton (1983) and Loungani (1986) attributed these to supply disturbances due to external factors like wars. Additionally, the relationship between these shocks and macroeconomic activities has been explored. According to Kose and Baimaganbetov (2015), earlier studies until the mid-1980s used linear models to examine the relationship between economic activities and OPS, suggesting symmetric behavior. However, these models overestimated the positive impact of the oil price drop in the late 1980s, revealing an asymmetric impact on economic activities. Farhani (2012) noted that empirical studies post-1986 indicated that the relationship between oil prices and economic growth had changed. In other words, the substantial changes in oil price can be negative as well as positive leading to an adverse impact on countries' economic activities Such an adverse impact in terms of the type of shock whether negative or positive is what calls for asymmetric-alike behavior investigation. It is worth mentioning that most of these studies, which focused on the asymmetry in impact, have focused on developed and major oil-exporting and importing economies rather than developing and least developing ones such as the case of this study (Al-Mawali et al. 2016)

Yemen's economy which was classified by the united nation (UN) as a least developed country (LDC, hereafter) (UN,2020) , like many others, heavily relies on oil and gas revenues since its reunification in 1990 when oil discovery gained government attention. OPEC (2019) states that 64.5% of global oil reserves are in the Middle East. Yemen, a Middle Eastern country with 3 billion barrels of proven oil reserves, may see this figure rise. Despite not being a major oil exporter, oil revenue remains crucial for Yemen's budget, making it susceptible to oil price volatility.

For instance , in 2011, over $5 billion in oil revenues were reported, with oil and gas exports accounting for approximately 63% of total government revenues and 89% of total export revenues between 2010 and 2012 (EIA, 2017). However, these figures declined in 2013 and 2014, with contributions dropping to 83.3% of total export earnings and 45% of the government budget (MoPIC, 2016). In 2015, oil revenues fell by $3.7 billion, resulting in a 36% decrease in GDP per capita and a 34.5% drop in GDP. Similarly, TWB (2019a) reported a 39% cumulative GDP contraction between 2015 and 2019, with projections for recovery in the future . This raises the question: do changes in crude oil prices affect country's economic growth?

Additionally, key macroeconomic indicators, as depicted in Figure 1 below, exhibit significant fluctuation across the observed period. More specifically, the country' gross domestic product (GDPY, hereafter) displayed a significant drop in some years, such as 2011 and 2015, and a notable rise in 2000 and 2010. The figure shows a general slowdown in economic growth, especially in recent years. Additionally, the same fluctuating case could be seen in the exchange rate (EXCHRY, hereafter) trend with a continuing fall in the last decade.

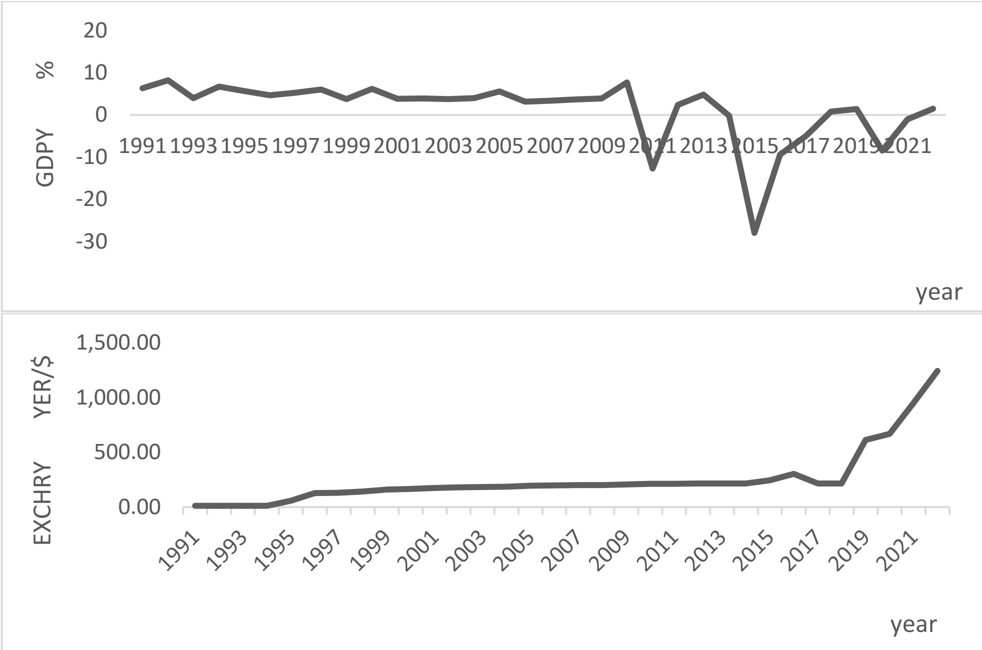


Figure 1: key economic indicators of Yemen
Source: adopted from IMF (2023).

MoPIC attributes the sharp decline in economic growth drivers and oil revenues to the significant drop in global crude oil prices before 2015 and the combined effects of oil prices and political unrest in 2015. The IMF estimates that an oil price of $215 per barrel is needed for the country to balance its budget, heavily reliant on oil export revenues (EIA, 2017). Hence, the question is “does the fluctuation in the country’s macroeconomic indicators is due to the substantial fluctuation in oil prices or so-called oil price shocks?

To this end and to answer those questions , The main goal is to study how OPS affect macroeconomic indicators in Yemen, focusing on asymmetry. Specific objectives include analyzing the long and short-term relationships between oil price shocks and key indicators, as well as exploring any varying or asymmetric impacts of these shocks. The study to achieve these objectives will utilize the nonlinear ARDL (NARDL, hereafter) developed by Shin et al. (2014) alongside its associated bootstrap ARDL (BNARDL, hereafter) suggested by McNown et al. (2017) but with NARDL rather than ARDL.

This study Considering its objectives and outcomes emphasizes the importance of understanding how macroeconomic activities in Yemen respond to OPS. In the case of Yemen, a country heavily reliant on oil revenues for fiscal and external stability, OPS present serious challenges to country's economy. Hence, Studying the asymmetric effects of OPS on GDP and exchange rates is therefore essential, as these shocks may not affect the economy in the same way when prices spike as compared to when they fall. Understanding these dynamics is necessary to design effective policies that can mitigate vulnerability, enhance stability, and promote sustainable development. Furthermore, This study is significant as it provides empirical evidence on how asymmetric OPS impact key macroeconomic indicators of the country. Results from the present study are useful for government authorities in the development of fiscal and monetary policies, for international donor institutions in their support for Yemen's economic stabilization policies, and for researchers exploring the impact of oil price shocks on oil-dependent economies.

The remaining outlines of the study including chapters on literature review, methodology, empirical results, and lastly findings, discussion, and conclusions.

Literature Review

Earlier theoretical views on the nexus between oil prices and macroeconomic activities focused on supply and demand effects (Bruno & Sachs, 1982). Additionally, several transmission mechanisms through which OPS impact the macroeconomy have been considered (Brown and Yucel, 2002). For instance , the supply-side mechanism(also known as the classic Keynesian theory) suggests a direct effect on the economy in response to the oil price rise, given the oil being an important production's input(Tang et al., 2010). Consequently, Brown and Yucel (2002) and Brown et al. (2003) argued that supply shocks from sharp oil price hikes can hinder real GDP and boost inflation. Consumers anticipating temporary oil price increases may borrow more or save less, loosening consumption and causing inflation.

Income shift from oil-importing to exporting nations is another mechanism by which macroeconomy is affected by OPS (Mork,1994). According to this mechanism, Increased oil prices lead to higher market prices in importing countries, weakening consumer purchasing power, curtailing spending, and lowering GDP (Brown et al., 2003). The income transfer effect also impacts the exchange rate as OPS cause wealth reallocation between oil importers and exporters, depreciating importers' currencies and appreciating exporters' currencies (Golub, 1983).

Empirically, great numbers of research have been devoted to studying the asymmetric response of economic activities to OPS and have been applied to different cases at different periods with the use of various methodologies. Osman et al. (2023) analyzed quarterly data from 2009 to 2020 using structural vector autoregressive (SVAR) to examine the impact of OPS on Ghana's macroeconomic indicators. The study found that GDP and exchange rate reacted positively to positive OPS following an oil prices' rise , while inflation responded negatively. However, the positive GDP response is constrained by Ghana's low oil production and export as an emerging oil producer.

In India and oppositely to Ghana case, Bhadury et al.(2023) through the use of a quantile regression model, found that Indian GDP responded negatively to positive OPS but also asymmetrically reflecting the fact that India is an importer rather than an oil exporter. Similarly , Kriskkumar et al. (2022) analyzed data from 1981 to 2017 through the use of both ARDL and NARDL to determine whether Malaysian GDP responds symmetrically or asymmetrical to OPS. The results found both positive and negative OPS significantly boost economic growth and strengthen the Malaysian GDP, indicating an asymmetric response rather than a symmetric one.

Focusing on the big oils' exporters , Bass (2019) found through the VEC framework that the Russian GDP and OPS have a significant long-term relationship but insignificant short-term effects. Alsamara et al. (2017) employed NARDL to examine the effects of OPS on the GDPs of Saudi Arabia and Turkey. Results indicated asymmetry in both countries, with Saudi Arabia's GDP more responsive to positive shocks and Turkey's GDP more reactive to negative shocks. This different response is due to the fact that Saudi Arabia is a huge exporter of oil while Turkey is a huge importer.

Similarly, in a broader sample, Nusair (2016) employed panel-NARDL to analyze the impact of oil price shocks on GCC countries' GDP. The results indicated a more substantial effect from positive shocks on GCC's GDP than from negative ones. Specifically, positive shocks led to GDP increases, while negative shocks caused GDP declines only in Qatar and Kuwait, with no significant impact on the other three countries. These findings suggest asymmetries in the effect on GCC's GDP.

Moshiri (2015) studied the asymmetric impact of OPS on OPEC oil exporters, including six developing and three developed countries. Initially, using VAR without assuming asymmetry, no significant impact was detected. However, after decomposing shocks into positive and negative and applying the Granger causality test and long-run VAR multiplier, asymmetry was confirmed. Negative shocks significantly affected the economic growth of developing countries, while positive shocks did not. Conversely, neither shock type significantly impacted the economic growth of developed exporters (Canada, Norway, UK), highlighting a clear asymmetry for developing countries and a neutral one for developed countries due to their diversified economies. This study of Moshiri (2015) was an extended work for the work by Moshiri and Banihasehm's (2012), which focused on six developing exporters, using similar methods and achieving consistent results. The researchers concluded that OPS do affect the economies of exporters, just like many previous studies proved the same fact in the case of oil importers.

Earlier studies, including Iwayemi and Fowowe (2011) found an asymmetric impact for negative OPS on the GDP and exchange rate of Nigeria with no effect for positive OPS. Furthermore, the study by Lardic and Mignon (2008) found an asymmetric long-run relationship between OPS and the GDP of G7 countries and euro-area countries, with the asymmetric impact even greater in the case of an oil price rise than in the case of an oil price drop. The exchange rate response to OPS was also a topic of several studies on different cases. For instance, the study by Bamaiyi (2024) used the VAR model and found a negative trend in the Nigerian exchange rate following OPS. Similarly, Mohammed et al. (2019) applied the GARCH method and found that Nigerian currency goes up in response to oil price hikes(i.e. positive OPS) and vice versa. The searchers think that's not surprising given that Nigeria is oil-reliant and such a serious effect needs more diversifying revenue sources.

The exchange rate in India was found to react asymmetrically and positively (i.e., appreciates) to OPS and positive ones in particular (Deheri and Ramachandran, 2023). However, and opposite to these results, negative OPS not positive ones were found to be more effective in explaining exchange rates in some emerging oil-exporting countries in both long and short terms according to results analyzed by NARDL (Sanusi, 2020). Similarly, the Romanian exchange rate was found to be negatively affected in response to negative OPS only (Taşar, 2017).

In an extensive study, Gao et al. (2022) used non-causality tests and the Wavelet coherence method on data collected between 1983 and 2018 to investigate the nexus and effect of OPS and the exchange rate of India, Bangladesh, Pakistan, and Sri Lanka. OPS's positive impact was spotted in all countries. However, the nexus is bidirectional for India and Bangladesh and unidirectional for Pakistan and Sri Lanka.

NARDL was used by Baek (2021) to investigate the association of asymmetry between OPS and some OPEC member countries' exchange rates. The results were found to vary according to the exchange rate regime adopted by each country. long-short-run asymmetric relation was spotted only in the countries adopting floating regimes and no asymmetry in those using fixed exchange rate regimes. In the same vein but Considering whether the country is an exporter or importer of oil, Abed et al. (2016) studied selected MENA countries and found that appreciation in exchange rate occurs in response to positive OPS for exporters (i.e., UAE, Qatar & Saudi Arabia) while occurs in response to negative ones for importers (Tunisia, Morocco, Egypt, Jordan).

Hence ,by targeting the Yemen economy, This study addresses the gap in the literature that often overlooks Least Developed Countries (LDCs) or minimally focuses on their economies compared to the extensive research on developed and major oil-exporting and importing nations. It significantly contributes to the literature by analyzing the period from 1990 to 2022, which experienced notable oil price shocks due to events like the Iraq war, the Asian financial crisis, the global financial crisis, the Arab uprisings, and the COVID-19 pandemic. Yemen, as a Middle Eastern country, was directly affected by some of these events, such as the Arab uprising. Few studies cover this timeframe, and those that do often target countries indirectly impacted. Another key contribution is the use of two cointegration tests, including the novel bootstrap NARDL-cointegration test, while considering data breakpoints. This approach ensures that NARDL model assumptions are fully met, addressing a common limitation in some previous studies that ignored the effect of breakpoints in time series data. To my knowledge, few studies have employed both tests to determine non-linear cointegration. Some studies have used the bootstrap method to detect linear cointegration related to ARDL, but not NARDL, as this study attempts.

Methodology

Data and Variables Description

As stated earlier, the study main focus is finding the asymmetric response of key macroeconomic indicators of YEMEN including gross domestic products (GDPY), and exchange rate (EXCHRY) to shocks of oil prices (OPS). The study uses secondary data spanning from 1991 to 2022, and which were mainly collected from the international monetary fund (IMF) database and the World Bank database (TWB).

The choice of this period as the study’s sample can be justified because the unity of south and north Yemen took place in 1990 whereas official records of macroeconomic indicators popped up. Moreover, this period has witnessed most of the oil price shocks identified by economists and researchers among which are the ones related to geopolitical events that took place in the region. A brief description of these variables is summarized in Table 1.

Table 1
Study's variables definitions

Variable of interest	Description
GDPY	The sum of value added by all producers in the economy within the country. Depreciated assets, natural resources depletion and degradation are not neglected when GDP is calculated. Measured in constant LCU by dividing nominal GDP by GDP deflator.
EXCHRY	The rate of exchange as determined by the domestic authorities based on an annual average measure (i.e., Yemeni riyal unit relative to the US$).
OPS	The oil price in the global market measured in US$ /Barrel & proxied by the average of Dubai, west Texas" WTI" & Brent crudes.

Empirical Model Specification

Based on the mentioned transmission mechanisms, it is presumed that negative OPS (OPS^-) and positive OPS (OPS^+) (i.e., explanatory variables/independent variable "IV") have an asymmetric effect on Yemen's macroeconomic indicators of GDPY and EXCHRY (i.e., explained variables/dependent variable "DV"). The effect might be direct as suggested by the supply mechanism or direct and partially indirect as suggested by the monetary supply mechanism. However, to empirically test such theoretical assumption in the case of YEMEN , an empirical analysis is vital.

At first, it is important to measure both positive and negative OPS to capture the asymmetric impact. Thus, to account for such asymmetry, Schorderet (2003) suggested the time series is to be split into its initial value as well as into its partial sum of both positive and negative shocks as follows:

$$X_t = X_0 + X_t^+ + X_t^- \tag{1}$$

Where X_0 is the initial value while $X_t^+ \ and \ X_t^-$ are the partial sum of positive and negative shocks. The flexibility of this measure to capture the difference in the magnitude of both increase /decrease in the price of oil on macroeconomic indicators as compared to other measures has favorited it over other measures.

Following Schorderet's specification, Shin et al. (2014) developed an innovative model called nonlinear autoregressive distributed lag (NARDL) which in turn was inspired by the autoregressive distributed lag (ARDL) developed by Pesaran et al. (2001) attempting to extend previous approaches which were focusing on variables of first order I(1) only. Hence, as in Long and Liang (2018), Menegaki (2019) among others, the general form of ARDL-ECM (p, q) is represented as follows:

$$\Delta \mathrm{In}Y_t = a_0 + a_1 \mathrm{In}Y_{t-1} + a_2 \mathrm{In}X_{t-1} + \sum_{i=1}^{p} \delta_i \Delta \mathrm{In}Y_{t-i} + \sum_{i=0}^{q} \vartheta_i \Delta \mathrm{In}X_{t-i} + \varepsilon_t \tag{2}$$

Here, Y_t and X_t is the logarithm of the DV, and the IV, respectively. Δ is variable difference, i=1, …, k is the number of variables in the model while t and $t-1$ represent the value of the variable at current time and the lagged values of it ,respectively. p and q are the lag length, E_t is the error term, a_0 is the constant (i.e., intercept), a_1, a_2 Indicate the long run coefficients and δ_i, ϑ_i represent the short-run ones. However, ARDL-ECM as mentioned by Khan et al. (2019) lacks distinguishing between the negative and positive impact of IV on the DV. Additionally, Granger and Yoon (2002) introduced what is known as the hidden cointegration framework to explore the probability of unobserved relationships. The unobserved cointegrations were identified as an example of the asymmetric relationship. Thus, to analyze such asymmetric-like behavior, the asymmetric version of (2) known as the Nonlinear autoregressive distributed lag(NARDL) developed by Shin et al. (2014) was adapted.

In addition to the advantages of hidden cointegration detection, NARDL is the best fit for data of small sample size plus its neglection to the assumption stating that the variables should be of the same order of integration ((i.e., NARDL is applicable with variables of I(1) or I(0) or mixture of both). Moreover, NARDL is simple and flexible in modeling complex phenomena such as the one found and argued widely in the literature which claims that in the short-term, the impact of positive OPS is larger while the impact of negative OPS is larger in the long-term or the other way around indicating the possibility of asymmetries' direction to be switched between short-long-terms (Shin et al., 2014).

Within the development process of NARDL, the Author starts with the introduction of a simple regression as in (3) that account for the asymmetric long-run cointegration through decomposing the explanatory variable into negative and positive sub-variables following the specification of Schorderet (2003) shown previously in (1) in what's so-called "partial sum decomposition" as follows:

$$\mathrm{Y_t} = \beta^{+}\mathrm{X_t^{+}} + \beta^{-}\mathrm{X_t^{-}} + \mathrm{u_t} \quad (3)$$

where Y_t is DV, while X_t is IV which is decomposed into its positive partial sum X_t^{+} and negative-partial sum X_t^{-}. This process of partial sum can be further defined as below.

$$\mathrm{X_t^{+}} = \sum_{i=1}^{t} \Delta\, \mathrm{X_i^{+}} = \sum_{i=1}^{t} \max(\Delta \mathrm{X_i}\,, 0) \quad (4)$$

$$X_t^{-} = \sum_{i=1}^{t} \Delta\, X_i^{-} = \sum_{i=1}^{t} min(\Delta X_i\,, 0) \quad (5)$$

where X_t^{+}= the greater of the changes in X_i, or 0, otherwise, and X_t^{-}= the lower of the changes in X_i, or 0, otherwise. Hence and considering study's explanatory variable/DV (i.e., OPS) where $X_t^{+} = OPS_t^{+}$ and $X_t^{-} = OPS_t^{-}$, (3 to 5) can be rewritten as:

$$\mathrm{Y_t} = \beta^{+}\mathrm{OPS_t^{+}} + \beta^{-}\mathrm{OPS_t^{-}} + \mathrm{u_t} \quad (6)$$

$$\mathrm{OPS}_t^+ = \sum_{i=1}^{t} \Delta\mathrm{OPS}_t^+$$

$$= \sum_{i=1}^{t} \max(\Delta\mathrm{OPS}_i , 0) \quad (7)$$

$$\mathrm{OPS}_t^- = \sum_{i=1}^{t} \Delta\, \mathrm{OPS}_t^-$$

$$= \sum_{i=1}^{t} \min(\Delta\mathrm{OPS}_i , 0) \quad (8)$$

where $\beta^{+/-}$are the associated parameters in the long run with positive and negative changes in OPS ,respectively. Hence, applying (6 to 8) can modify (2) to account for the asymmetric impact an IV may have on a DV, yielding NARDL-ECM as follows:

$$\Delta\mathrm{InY}_t = a_0 + a_1\mathrm{InY}_{t-1} + a_2^+\mathrm{InOPS}_{t-1}^+ + a_2^-\mathrm{InOPS}_{t-1}^- + \sum_{i=1}^{p} \delta_i\Delta\mathrm{InY}_{t-i} + \sum_{i=0}^{q}(\vartheta_i^+\Delta\mathrm{InOPS}_{t-i}^+ + \vartheta_i^-\Delta\mathrm{InOPS}_{t-i}^-) + \varepsilon_t \quad (9)$$

Replacing the Y_t *in* (9) with study's dependents variables of GDPY& EXCHRY, the following NARDL models namely GDPY-model, and EXCHRY-model are developed as follows:

$$\Delta\mathrm{InGDPY}_t = a_0 + a_1\mathrm{InGDPY}_{t-1} + a_2^+\mathrm{InOPS}_{t-1}^+ + a_2^-\mathrm{InOPS}_{t-1}^- + \sum_{i=1}^{p} \delta_i\Delta\mathrm{InGDPY}_{t-i} + \sum_{i=0}^{q}(\vartheta_i^+\Delta\mathrm{InOPS}_{t-i}^+ + \vartheta_i^-\Delta\mathrm{InOPS}_{t-i}^-) + \varepsilon_t \quad (10)$$

$$\mathrm{InEXCHRY}_t = a_0 + a_1\mathrm{InEXCHRY}_{t-1} + a_2^+\mathrm{InOPS}_{t-1}^+ + a_2^-\mathrm{InOPS}_{t-1}^- + \sum_{i=1}^{p} \delta_i\Delta\mathrm{InEXCHRY}_{t-i} + \sum_{i=0}^{q}(\vartheta_i^+\Delta\mathrm{InOPS}_{t-i}^+ + \vartheta_i^-\Delta\mathrm{InOPS}_{t-i}^-) + \varepsilon_t \quad (11)$$

where in (10 and 11),the variables are expressed in logarithms for the purpose of minimizing the issue of heteroscedasticity & ensuring normality. $a_1, a_{2,}^+ a_2^-$ *and* $\vartheta_i^+, \vartheta_i^-$ Represent the long run and short run asymmetric coefficients, respectively. Hence, the associated parameters in the long run β^+& β^- presented in (6) is found considering (10 and 11) by $\frac{-a_2^+}{a_1}$ and $\frac{-a_2^-}{a_1}$,respectively. A dummy variable (D) may be added to the models (10 and 11) to account for potential structural breaks which will be ascertained through a breakpoint unit root test.

Data Analysis Techniques

To empirically implement NARDL models (10 and 11) and as stated by Ibrahim. (2015),and Niran et al. (2018) the following steps are performed:

STEP1: Establishing the orders' integration for variables through unit root tests to ensure there is no variable of I (2). To this end, Phillips and Perron (hereafter, PP) unit root test (1988) is used. PP is robust to issues of autocorrelation, and heteroscedasticity as it ignores the lag difference in ADF regression test which may cause a serial correlation in the model. The PP regression test is as follows:

$$X_t = \alpha_{Dt} + \beta X_{t-1} + \omega_t \quad (12)$$

where, X_t is the time series of interest, ω_t is the error term with "zero" mean & D_t deterministic term (constant or trend). Hence, (12) can be rewritten to accommodate for the constant (c) and trend (δ) as follows:

$$X_t = c + \delta t + \beta X_{t-1} + \omega_t \quad (13)$$

The PP tests the null hypothesis of unit root test (H_0: $\beta = 0$) versus the alternative (H_1) of there is no unit root (H_1: $\beta < 0$) (Lee & Shie,2004). However, in order to decide which form of estimation (none, constant or constant & trend) to be considered firs in testing the H_0 of $\beta = 0$, the suggestion by Dolado et al. (1990) , Pfaff (2008), and Enders (2010) were taken into account. They stated that it is more appropriate to start considering the estimation form that includes both constant and trend at the level as in (13) followed by testing the significance of trend and then the significance of constant to lastly the random walk (None) form of regression and once the H_0 of $\beta = 0$ under any estimation is rejected, the is no further test is required. For instance, if the H_0 was rejected at level with constant and trend, it can be concluded that time series has no unit root test, and no further estimation is needed under constant or none anymore. Moreover, Pfaff (2008) stated, the non-rejection of H_0 at level under all estimation forms implies that the series is of higher order than zero(i.e., I(0)) which require testing the series for Stationarity in higher orders in a process called “bottom-up” starting from first difference all the way up into higher orders as needed and as the series still contains unit root.

Worth mentioning that, any time series is vulnerable to structural changes (breakpoints) across the period of testing that cannot be detected by traditional tests such as PP leading to biased and incorrect conclusions (Perron,1989). To this end, Bai and Perron (hereafter, BP) (2003a) developed his breakpoints unit root test to allow for the detection of multiple breaks in the series. Three tests under BP including SUP F test which is firstly used when breakpoints are known only, double max test which is used to detect the presence of unknown breakpoints in the series and lastly the sequential test to determine the number of breakpoints in the time series and the dates of these breaks. Sequential is used when the H_0 of double max is rejected indicating the presence of breakpoints (Wu et al.,2019). The following Table summarize the hypotheses under used PP & BP tests

Table 2
Summary of the underlying hypotheses of proposed unit roots tests.

	PP test	**BP test**		
Hypotheses		**Sup F test**	**double max test**	**Sequential test**
$\mathbf{H_0}$	There is unit root	There is no breakpoint	There is no breakpoint	There is “L” breakpoint
$\mathbf{H_1}$	There is no unit root	There is a k number of known breakpoints	There is an unknown number of “m” breaks	There is “L+1” breakpoints

STEP2: Estimating of (10 and 11) through the standard ordinary least square (OLS) to check the availability of cointegration (i.e., long run nexus) between models’ variables. The selection of optimal lag structure is carried out in advance to testing for cointegration. The cointegration between variables is null hypothesized of no cointegration ($i.e. a_1$=$a_2^+ = a_2^- = a_3 = 0$). This step can be called “cointegration analysis” stage. To this end, Two cointegration tests were conducted. The first is the F-bound test by Pesaran et al. (2001), commonly referred to as the F-test, widely used since the ARDL model and its extension (NARDL) for

testing cointegration among variables. The second is the bootstrap ARDL test by McNown et al. (2017), with consideration of NARDL rather than ARDL (Hereafter, BNARDL). The F-test jointly tests the significance of all coefficients of all lagged variables in the models of (10 and 11) drawing a null hypothesis of there is no cointegration ($\mathrm{H_0}: \mathrm{a}_1 = \mathrm{a}_2^+ = \mathrm{a}_2^- = 0$) against the alternative of there is no cointegration (($\mathrm{H_1}: \mathrm{a}_1 \neq \mathrm{a}_2^+ \neq \mathrm{a}_2^- \neq 0$). To decide for cointegration ,the value of F-test (i.e., F-statistic) is compared with upper bound and lower bound critical values (hereafter, UBCV & LBCV) suggested by Narayan (2005) as it is best fit for observations of less than 80 as compared to Pesaran et al. (2001) critical values (Nkoro and Uko,2016). The model variables are said to be cointegrated when F-statistic is greater than upper bound critical value only. However, The F-test as stated by Pesaran et al.(2001) is best when the DVs are I(1) only and the IVs of I (0) or I (1), or both causing an unclarity about the source of significance whether from the lagged level of DV or IV. Thus, the decision of cointegration made on the F-test is not robust. The reason as mentioned by McNown et al. (2017) is that the shortcoming of the unit-roots test of having low power may falsely lead the researcher to assume the DV is of order I (1). Therefore, to overcome such an issue, the second test of BNARDL came in handy. BNARDL ignores the F-test assumption of having the DV of the first order only allowing the significance level test applicable on the lagged level of the IV. Based on this test , The coefficients of lagged levels of the IV (ie., OPS_t^+ & OPS_t^-) in models (10 and 11) is tested for the null hypothesis of no cointegration ($\mathrm{H_0} = \mathrm{a}_2^+ = \mathrm{a}_2^- = 0$) against the alternative of there is no cointegration ($\mathrm{H_1} = \mathrm{a}_2^+ \neq \mathrm{a}_2^- \neq 0$). Similarly to first test, the results of this test are compared with UBCV & LBCV developed by Sam et al. (2018) and only a value that's greater than UBCV confirms the presence of cointegration. Although, a researcher may obtain through BNARDL a better and genuine insight to decide on the model cointegration compared to F-test, having both tests' nulls rejected introduces an augmented and robust decision on the cointegration (McNown et al., 2017). Table 3 summarizes the possible decision cases and outcomes of both tests.

Table 3
Possible decisions cases and outcomes based on both cointegrations' tests

Possible outcomes	**F-test**	**BNARDL-test**	**Decision**
1	**H_0** is Not rejected	**H_0** is Not Rejected	No cointegration [a]
2	**H_0** is Rejected	**H_0** is Not Rejected	Non-robust cointegration[b]
3	**H_0** is Not rejected	**H_0** is Rejected	Non-robust cointegration
4	**H_0** is Rejected	**H_0** is Rejected	Robust cointegration [c]
Possible cases			
1	BNARD/F-test value **>** UBCV		cointegration exist
2	BNARDL/F-test **<** LBCV		no cointegration exist
3	UBCV > BNARDL/F-test > LBCV		indecisive

Notes :
[a] : both tests failed to confirmed the cointegration;
[b] : one test only confirmed the cointegration ;
[c] :both tests confirmed the cointegration.

STEP 3: Once cointegration is proven, the model is valid, and the test of both asymmetric long-short-run relationships for models (10 and 11) is carried out by making use of Wald test. The null of a symmetric long-run (hereafter, SLR) is no asymmetric response ($\mathrm{H_0} = \mathrm{a}_2^+ = \mathrm{a}_2^-$) versus the alternative there is an asymmetric response ($\mathrm{H_1} = \mathrm{a}_2^+ \neq \mathrm{a}_2^-$) and for a symmetric short-term (hereafter, SSR, hereafter) of no asymmetric response($\mathrm{H_0} = \vartheta_i^+ =$

$\vartheta_i^- = 0$ (i=1, 2,.,q)) against the alternative of there is asymmetric response($H_1 = \vartheta_i^+ \neq \vartheta_i^- \neq 0$). The possible decisions of asymmetries based on the Wald -test are tabulated in Table 4.

Table 4
Possible decisions of asymmetries based on the Wald -test

Null hypotheses	**Decision**	**Conclusion**
H_0 of SLR	- Rejected - Not-rejected	- The asymmetric response in the long term is confirmed - No asymmetric response is detected
H_0 of SSR	- Rejected - Not-rejected	- The asymmetric response in the short term is confirmed - No asymmetric response is detected

STEP4: Evaluating the asymmetric impact of the dynamic multipliers ($dm_h^+ \& dm_h^-$) of changes in (OPS_t^+) &(OPS_t^-) as follow:

$$\mathrm{dm}_h^+ = \sum_{i=0}^{h} \frac{\vartheta y_{t+i}}{\vartheta OPS_t^+} \ \& \ \mathrm{dm}_h^- = \sum_{i=0}^{h} \frac{\vartheta y_{t+i}}{\vartheta OPS_t^-} \qquad , h = 0.1.2 \ldots \rightarrow \infty$$

Here, $dm_h^+ and\ dm_h^-$ are the positive-negative cumulative dynamic multipliers (hereafter, DM) of changes in OPS_t^+ and OPS_t^-,respectively.
Lastly, a diagnostic checks to ensure the efficacy of study's models are carried out as summarized in the table below:

Table 5
Proposed Model's diagnostics tests.

Digsonstics tests	**Functionality**
R^2	Checking the "goodness of NARDL's fit"
LM test [*a]	Ensuring NARDL is autocorrelation-free
ARCH-LM test [*a]	Ensuring the "homoscedasticity" of NARDL
CUSUM & CUSUMQ	Checking NARDL's short-long term coefficients stability

Notes:
[*a:] H_0 of there is no serial correlation/heteroskedasticity up to lag order p

Results and Discussion

Stationarity Results

The PP unit root test is conducted to establish the order of integration and ensuring all models are of I(0) or I(1) or mixture of both. The H_0 of PP suggests that "a variable has a unit root". To this end, Table 6 represents the results of PP unit root test.

Table 6
PP test results

Variables	**PP test**					**Decision**
	Level			**1st difference**		
	Trend & intercept	**Intercept**	**None**	**Trend & intercept**	**Intercept**	
Gdpy	(0.9601)	(0.4636)	(0.6648)	(0.0029)*	-	I (1)
(T)*a	-1.7991			-1.8617		
(C)*b		1.5985				
Exchry	(1.0000)	(1.0000)	(0.9999)	(0.1415)		I(1)
(T)*a	0.7198			0.0136**		
(C)*b		-0.4258				
OPS	(0.5180)	(0.6752)	(0.7789)	(0.0044)*	-	I(1)
(T)*a	1.5272			0.1332		
(C)*b		1.5334				

Mackinnon (1996) critical values

Sig.level	**Level**		**1st difference**	
	Trend and intercept	Intercept	Trend and intercept	Intercept
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:
*, **, *** : H_0 is rejected at 1 %,5 % & 10 % significance level, respectively; values in () are the p-values while others are the t-statistics; Probability based on MacKinnon (1996);
*a : Trend (T) significance ,trend is significant when t-stats > critical values of Mackinnon (1996);
*b : constant (C) significance ,constant is significant when t-stats > critical values of Mackinnon (1996);
(-) : proceed no further with other deterministic as "stationarity " is already achieved.

Source: Author's construct based on EViews results

The PP test results are presented in Table 6. The trend term was significant for all variables since the t-statistics in levels and first differences exceeded Mackinnon's (1996) critical values, prioritizing test for stationarity under trend and intercept assumption as Enders (2010) suggested. Hence, results with trend and intercept showed all variables (Gdpy, Exchry, and OPS) were non-stationary in level under all assumptions which required further tests. Hence, The variables were tested in the first difference and found to be stationary with trend and intercept after being found to be nonstationary under the level's remaining assumption (i.e., intercept and none). Specifically, Gdpy, and OPS rejected the null at 1% with a p-value of 0.0029, 0.0000, and 0.0044, respectively, indicating stationarity in the first difference with trend and intercept. Exchry did also reject the null with trend and intercept in the first difference but at 5% level instead, with a p-value of 0136. Since all variables are stationary, no further tests under "intercept" & "none" assumption are required. The null hypotheses of unit roots in the first difference are rejected, indicating no I(2) variables in the model. Hence, it can be concluded that the conditions for applying NARDL such as the variables to be of any order of integration whether I (0) or/and I (1), and the explanatory to be of I (1) are met.

BP test is another unit root tests used mainly to detect the potential breakpoints in study models, and the results are as tabulated in Table 7.

Table 7
BP Tests Results

Variables	**BP double max test**				**BP Sequential test**
	UDMax[a]	**WDMax**[b]	**Break test**[c]	**Scaled-F test**	**Break dates**
Gdpy	(94.4152*)	(180.3957*)	0 vs. 1 *	(46.6342) 11.47**[d]	1996 2016
			1 vs. 2 *	(54.5964) 12.95**[d]	-
			2 vs. 3	(6.51365) 14.03**[d]	
	11.70**[c]	12.81**[c]			
Exchry	(229.3291*)	(297.3375*)	0 vs. 1 *	(56.2551) 11.47**[d]	1995 2019
			1 vs. 2 *	(135.063) 12.95**[d]	-
			2 vs. 3	(11.5332) 14.03**[d]	
	11.70**[c]	12.81**[c]			

Notes:
* : Significant at the 0.05 (5%) level;
**[c] : Bai-Perron (2003b) critical values of unweighted & weighted double max test;
**[d] : Bai-Perron (2003b) critical values of sequential test.
[a]: The unweighted double max where values in () indicate the maximized values of scaled F-statistics for UDMax (H_0 of no break is rejected as the maximized F-statics > CVs of UDMax);
[b]: The weighted double max where values in () indicate the maximized values of weighted F-statistics for WDMax (H_0 of no break is rejected as the maximized weighted F-statics > CVs of WDMax);
[c] : The break test of H_0 of L vs H_1 of L+1 where for all models "0 vs. 1" means the null of "0" break is rejected in favor of "1" break and for "1 vs. 2" the null of 1 break is rejected in favor of '2" breaks both at 5 % level implies "2" breaks in the regressor of "OPS".

The first BP of SUP F test requires the breakpoints to be known and for this reason it was unfit to be used (Bellamy & Blackstone,2015). Hence , the BP of double max and sequential tests were considered as shown in the results in Table 7 above. Both unweighted and weighted double max (UDMax and WDMax) values are significant at the 5% level, indicating breakpoints in the time series. The maximized UDMax and WDMax values exceed critical values from Bai & Perron (2003b), rejecting the null hypothesis of no breakpoints. Hence, the double max test ascertained the presence of unknown breakpoints in the time series. However, only through the results of the sequential test results ,the exact break dates were determined . Table 7 shows that the alternative breakpoints (1 & 2) for the null breakpoints (0 & 1) for GDPY, INLFRY, and EXCHRY are significant at the 5% level, with scaled F-test values exceeding the critical values from Pai and Perron (2003b). This leads to the rejection of the null hypotheses for breakpoints (0) and (1) in favor of alternative breakpoints

(1) and (2), while the null hypothesis for breakpoint (2) is not rejected in favor of alternative test (3). Consequently, two significant break dates were identified for each model of GDPY, and EXCHRY. Hence , based on sequential test results , a dummy variable (D) will be considered in the models of (10 and 11) to account for these determined breakpoints in the series.

Cointegration Results

The test for cointegration among variables in all models started with the selection of the optimal lag through Akaike's information criterion (AIC) which was favored against other criterions due to its better performance in the case of small sample studies (<60 observations) and is recommended for the lang length selection of autoregressive models (liew,2004 and Asghar & Abid, 2007). The results of selecting model lags are shown in Table 8.

Table 8
Optimal lag section results

Models	# of Lags	AIC	Selected lags
Gdpy	0	0.746998	2
	1	-3.663919	
	2	-4.304653*	
Exchry	0	2.215135	2
	1	-2.313997	
	2	-2.580739*	

Source: Authors construct based on EViews output.

As the optimal lags of all variables have been determined, the test of cointegration is inevitably important. The results of both cointegration tests as well as the summary of corresponding critical values to be compared with are illustrated in the Table 9 .

Table 9
Cointegration Tests Results

Cointegration tests		
Variables	**Joint F-test**[b]	**BNARDL-test**[c]
Gdpy	5.8473	6.1045
Exchry	6.6317	7.8188

Significance level	10 %		5%		1%	
LBCV and UBCV[d]	***I (0)***	***I (1)***	***I (0)***	***I (1)***	***I (0)***	***I (1)***
Joint F-test *	2.75	3.99	3.35	4.77	4.76	6.67
BNARDL test **	2.22	3.84	2.80	4.70	4.15	6.83

Notes:
[b]: cointegration is confirmed through F-test as the null is rejected given upper bound(UBCV) and lower bound (LBCV) critical values of Narayan (2005) in either 1 %,5 % or 10 % significance level;
[c]: robust cointegration is confirmed through Bootstrap NARDL (BNARDL) as the null is rejected given upper bound(UBCV) and lower bound (LBCV) critical values of Sam et al. (2018) in either 1 %,5 % or 10 % significance level;
[d]: Lower bound critical values , I (0) and Upper bound critical values, I (1);
*: Critical values taken from Narayan (2005) >> [case 3, N=30, K=4];
**: Critical values taken from Sam et al. (2018)>> [case 3, N=30, K=4.

Source: Authors construct based on EViews output.

In general, the results shown in Table 8 of both, the F-test and BNARDL tests suggested the rejection of the null hypothesis of no cointegration for both tests confirming the existence of cointegration between the IVs and the DV of all models. For instance, , the F-test/BNARDL test values for the Gdpy (5.8473/6.1045 > 4.77/4.70) at 5 % , and Exchry (6.6317/7.8188 > 4.77/6.83) at 5% and 1 %. To conclude, referring to the possible outcomes summarized in Table 3 of conducting both tests together to genuinely detect the cointegration among variables, the fourth outcome (i.e., robust cointegration exists) was dominant for all models.

The Asymmetric Response Results

In the third step of performing NARDL , the asymmetric response in both SLR & SSR of GDPY & EXCHRY in all models (10 and 11) to positive-negative OPS through Wald test is performed and the results as shown in the Tables 10 & 11.

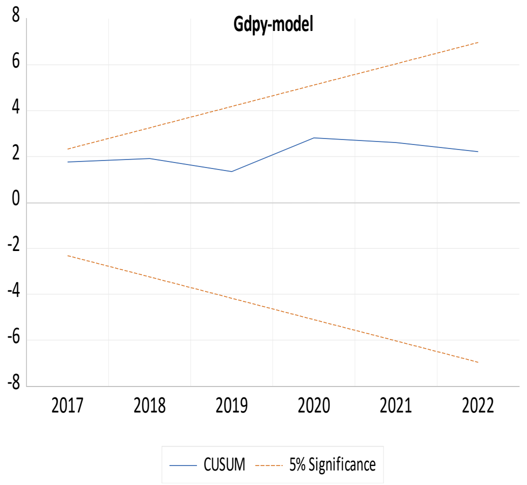
Table 10

Asymmetric response results for GDPY-OPS model

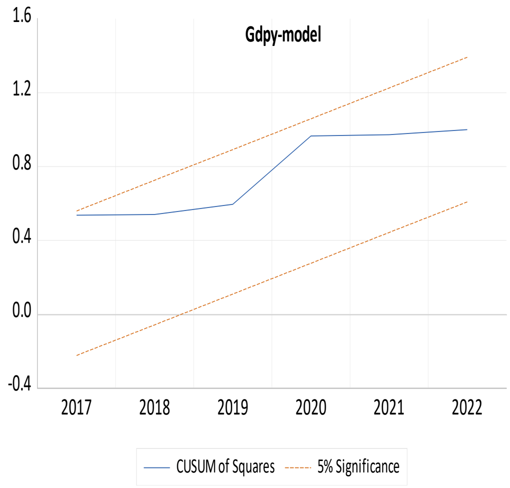
NARDL-ECM					
Variables	**Coefficients**	**Prob.**	**Variables**	**Coefficients**	**Prob.**
Long run (LR)			**Short run (SR)**		
INOPS_POS	0.3520	0.0000*	INGDPY (-1)	-0.7578	0.0008*
INOPS_NEG	0.6298	0.0004*	INOPS_POS (-1)	0.2668	0.0013*
			INOPS_NEG(-1)	0.4773	0.0008*
			D(INGDPY (-1)	0.2777	0.1409
			D(INOPS_POS)	0.0299	0.7639
			D(INOPS_NEG)	0.4024	0.0001*
			D(INOPS_NEG(-1)	-0.2690	0.0199*
			D(D1_GDPY)	0.0709	0.2879
			D(D1_GDPY(-1)	-0.1599	0.0185*

Wald test (Asymmetry test)			
Wald-test	**Coefficients($ch^{2)}$**	**Prob.**	**Decision**
SLR	5.15654	0.0232**	Asymmetric
SSR	27.4850	0.0000*	Asymmetric
Diagnostic tests			
Test type	**Coefficients**	**Prob.**	**Decision**
R^2	0.7933	-	model demonstrates a good fit
LM test	4.4302	0.1091	Serial correlation-free
ARCH test	2.9904	0.2242	heteroskedasticity-free

CUSUM



CUSUMQ



Notes:
*, **, *** : 1 %,5 % & 10 % significance level, respectively.

Source: Author's construct based on results of EViews.

Table 10 generally provides the results related to the response and the relationship of GDPY to /with OPS$^+$ & OPS$^-$. In the long run, GDPY increases by 0.35 % in response to a unit rise in OPS$^+$ and falls by 0.63% in response to a unit fall in OPS$^-$. Thus, both shocks have a significant effect at the 1 % level, given the p-value of (0.0000 & 0.0004) but with a bigger impact for (OPS$^-$). In the short run, positive (0.02 %) but insignificant (0.76) effect for POS$^+$ while the positive (0.26 %) and significant (0.019) effect for POS$^-$ in the past period has turned to negative (-0.40%) and significant at 1 % level (0.0001) in the current period. Thus, a unit decrease in OPS$^-$ reduces the GDPY by 0.40 % making the negative shocks again impose a bigger effect in the short run as well. As for the asymmetry test through the Wald test, the response or the impact is said to be asymmetric if the difference between the coefficients of OPS$^+$ & OPS$^-$ is statistically significant. Hence, the Wald test values in both long-run "SLR" (0.0232) and short-run "SSR" (0.0000) suggested asymmetries given both are statistically significant at 5 % & 1 % level. This implies the rejection of the H_0 that "no asymmetric response in the long-short run). Consequently, GDPY responds asymmetrically to OPS. Lastly, the model was tested for its stability and efficacy through diagnostics tests as the results in Table 10 show. R^2 value indicated that the % of changes in GDPY that can be caused by OPS is 79 % implying the model goodness of fit. LM test and ARCH test results confirm the model is serial correlation and heteroskedasticity-free since the p-value (0.11 %) & (0.22 %) of both is greater than the 5 % level suggesting the failure to reject the H_0 of there is no serial correlation/heteroskedasticity up to lag order p. Finally, CUSUM & CUSUMQ plots indicate that the coefficients of the model are stable as it falls within the critical bounds of the 5 % significance. These results agreed with several studies about the presence of asymmetric short-term and short-term response to positive & negative SoOP and slight disagreement with some regarding which shock is more effective including but not limited to Lardic and Mignon (2008), Aziz and Dahalan (2015), Alsamara et al. (2017) & Niran et al. (2018). For instance, of some disagreement, Alsamara et al. (2017) argued that positive shocks magnitude is bigger than negative ones on Saudi's GDP which is different from our finding that negative ones have a stronger effect on our case. This difference might be due to Saudi being a large exporter while Yemen is a small oil exporter.

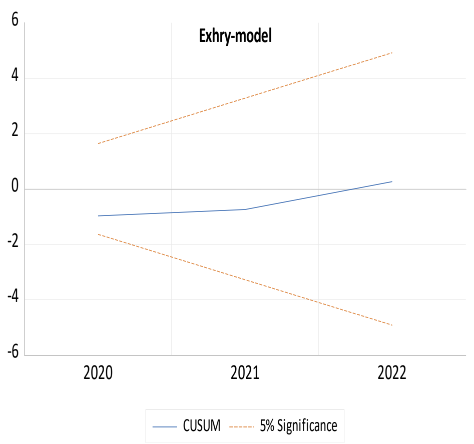
Table 11
Asymmetric response results for EXCHRY-OPS model

NARDL-ECM					
Variables	**Coefficients**	**Prob.**	**Variables**	**Coefficients**	**Prob.**
Long run (LR)			**Short run (SR)**		
INOPS_POS	0.2032	0.0507**	INEXCHRY(-1)	-0.4196	0.0557**
INOPS_NEG	0.2096	0.4167	INOPS_POS(-1)	0.0852	0.1315
			INOPS_NEG(-1)	0.0879	0.2992
			D(INEXCHRY(-1)	-0.1145	0.2772
			D(INOPS_POS)	-0.0515	0.7420
			D(INOPS_POS(-1)	0.1903	0.1592
			D(INOPS_NEG)	-0.1340	0.2808
			D(INOPS_NEG(-1)	-0.4029	0.0079*
			D(D1_EXCHRY)	1.6229	0.0000*
			D(D1_EXCHRY(-1)	0.5758	0.0470**
			D(D2_EXCHRY)	1.0451	0.0000*
			D(D2_EXCHRY(-1)	-0.2417	0.093***

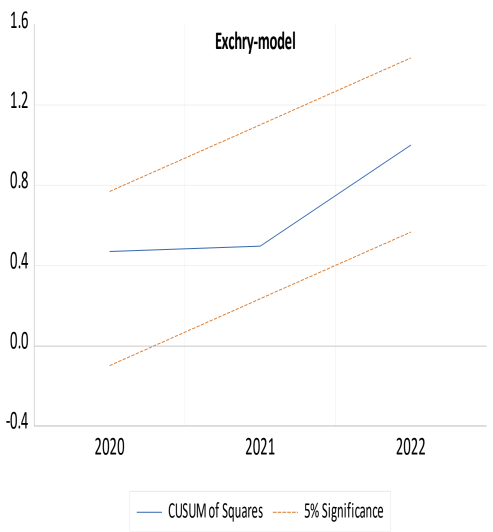
Wald test (asymmetry test)			
Wald-test	**Coefficients($ch^{2)}$**	**Prob.**	**Decision**
SLR	3.6123	0.0574**	Asymmetric
SSR	5.1395	0.0234*	Asymmetric

Diagnostic tests			
Test type	**Coefficients**	**Prob.**	**Decision**
R^2	0.9817	-	model demonstrates a good fit
LM test	1.2794	0.5274	Serial correlation-free
ARCH test	7.4323	0.0243	Non-heteroskedasticity-free

CUSUM



CUSUMQ



Source: Author's construct based on results of EViews.

Table 11 reveals the EXCHRY-OPS model-related outputs, in the long run, Exchry may appreciate by about 0.20 % in response to a 1 % increase in OPS^+ at a significance level of 5 %

(0.0507) while it responds insignificantly to negative OPS. In the short run, however, the Exchry appreciates by about 0.40 % in response to one unit fall in the negative OPS. Results also implied to the significant role played by the external events represented by structural changes along the period in determining the effect of OPS on the Exchry in both runs. Thus, negative OPS plays a bigger role in the short run while positive ones are in the long run. As for whether this impact is symmetric or asymmetric, the Wald test results in both SLR (0.057) & SSR (0.023) rejected the H_0 of no asymmetric response in long-short runs. These results revealed that the impact of OPS on the EXCHRY is asymmetric. Diagnostic tests indicated that the model is of better fit and stable . More specifically value of (0.9817) indicate that 98 % of EXCHRY can be explained by OPS while the LM test value of (0.5274) that is greater than 5 % level revealed the model is free of the issue of autocorrelation . The ARCH p-value of (0.0242) is significant at 5 % which means the model has a heteroskedasticity issue. However, according to Bessler et al. (2014) and Hayes & Cai (2007), the OLS model parameters are still valid and non-biased when the homoscedasticity condition is violated. Finally, CUSUM & CUSUMQ test plots reveal the stability of the model as the coefficient of EXCHRY falls within the critical bounds of the 5 % significance. the stability revealed in all models is not of surprise as the inclusion of dummy variables to models (10 and 11) that account for any breakpoint in the series has played a role in stabilizing them. Results are more or less in line with studies including but not limited to Kose and Baimaganbetov (2015), Abed et al. (2016), Taşar (2017) among others. Furthermore, two break dates were found to have some effect on the EXCHRY alongside OPS, the civil war related event in 1995 and the emergence of a parallel exchange market (i.e., black market) in 2019.

The Asymmetric Dynamic Multiplier Response

In the fourth step of performing NARDL, Shin et al. (2014) suggested deriving the asymmetric response of the dynamic multiplier(DM) to keep track of how DVs in all models including GDPY, and EXCHRY are being adjusted from their initial equilibrium to a new one over time following a unit change in (OPS_t^+) &(OPS_t^-). Furthermore, asymmetry in the effect can be also spotted through DM when the "upper" and "lower" boundaries of the critical intervals "C.I" do not contain any of the "zero" line within (Almalki et al., 2022). To this end, figure 2 shows the DM effect of all models.

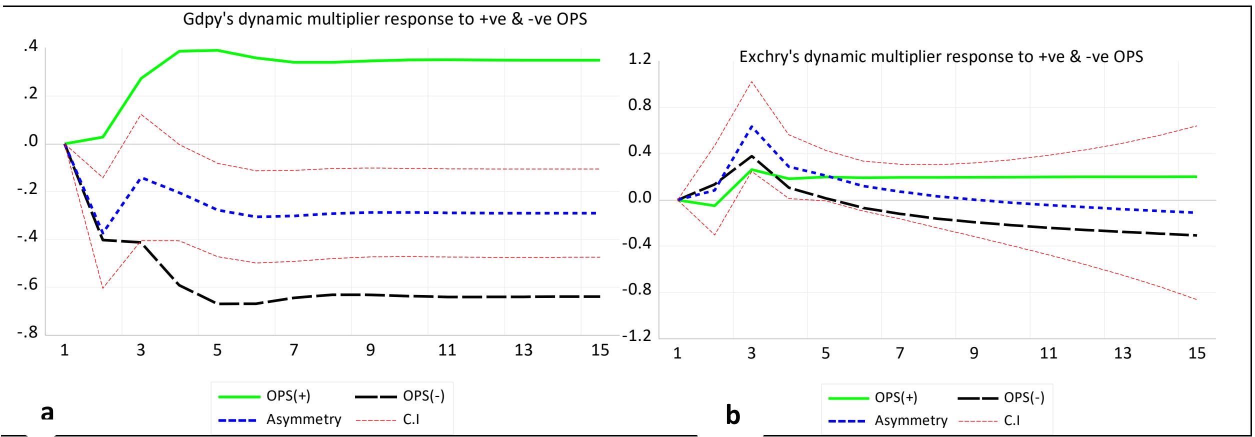


Figure 2: dynamic multiplier (DM) for all models.
Source: Author's construct based on (EViews output)

Similar to the previous results, all DM graphs of all models indicated the presence of asymmetric response to OPS due to the deviation of the zero line within the boundaries of the upper-down bands of the critical intervals (C.I) at some point. More specifically, the DM for the GDPY shown in Figure 2(a) indicated that GDPY responds quicker to negative OPS compared to positive ones and takes approximately 6-7 years to reach an equilibrium state on both sides (I.e., following both OPS). As for the EXHRY, DM plot in Figure 2 (b) showed that, after a unit change in positive OPS, EXCHRY could achieve equilibrium after 4-5 years and around 14 years to be in an equilibrium state in response to negative shocks.

Conclusion and Implication

The research reveals the role of oil price shocks and their asymmetric effects on certain economic parameters including GDP, and exchange rates in the case of Yemen economy. Hence to achieve the objective of this study, the study adopted the methodology of NARDL along with the new test of cointegration (i.e., augmented bootstrap ARDL) but in the nonlinear form. The results from the proposed methods ascertained the presence of the cointegration among variables included in the models. Moreover, asymmetry in the response to price oil shocks was confirmed in GDP and exchange rate which at both ends faced asymmetries in long and short in response to OPS. Furthermore, Negative shocks were found to significantly impact the economy, highlighting its vulnerability due to heavy reliance on oil revenue. This underscores the urgent need for economic diversification to reduce oil dependency. Revitalizing agriculture, manufacturing, and other non-oil sectors can create alternative revenue streams and enhance stability.

Additionally, boosting foreign exchange earnings through non-oil tradable sectors is crucial. With the Yemeni rial significantly affected by oil price shocks, strengthening agriculture and manufacturing can generate much-needed foreign currency, stabilizing the exchange rate and reducing vulnerability to external shocks. Addressing these challenges requires a comprehensive approach combining economic diversification, improved monetary policy, and support for non-oil sectors. Following these recommendations, Yemen can mitigate the negative effects of oil price shocks, promote sustainable growth, and build a resilient economy. Decision-makers are urged to take decisive action, using these insights to craft policies that secure the country’s economic future.

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