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# Modeling the nexus between oil shocks, inflation and commodity prices: Do Asymmetries really matter?

Naveed Raza
*Energy and Sustainable Development (ESD), Montpellier Business School, France*

Syed Jawad Hussain Shahzad
*Energy and Sustainable Development (ESD), Montpellier Business School, France*

Muhammad Shahbaz
*Energy and Sustainable Development (ESD), Montpellier Business School, France*

Aviral kumar Tiwari
*Energy and Sustainable Development (ESD), Montpellier Business School, France*

## Abstract

This study examines the asymmetric relation between oil shocks, U.S inflation and major commodity price indices of energy and non-energy commodities, vegetable oil and meals, raw material, industrial metal and precious metals. We utilize a novel technique namely nonlinear autoregressive distributed lags (hereafter NARDL) on a large monthly data set, ranging from January 1970 till December 2016, to study the short- and long-run asymmetric dynamics between major commodity price indices and oil and inflation shocks. Our findings reveal that both the oil and inflation shocks have differential impact across commodity prices over the both short- and long-run. Findings also support the proposition that moderate inflation and stable oil prices are conducive to the both short- and long-run stability in the prices of commodities. However, commodities may be regarded as better hedging tool and may retain their purchasing power during high inflationary periods.

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**Contact:** Naveed Raza - naveedrazza@gmail.com, Syed Jawad Hussain Shahzad - jawad.kazmi5@gmail.com, Muhammad Shahbaz - muhdshahbaz77@gmail.com, Aviral kumar Tiwari - aviral.eco@gmail.com.
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## 1. Introduction

There has been a great interest of researcher, policy makers and investors in understanding the asymmetric determinants of commodity price movements, since the sharp rise in commodity prices in the beginning of the 21st century and the subsequent dramatic collapse (Rafiq and Bloch, 2016). Commodities dynamics reveal the most relevant qualities for investors such as the correlation with other financial assets, store of wealth and source of liquidity in the times of heightened uncertainty (Raza et al., 2016). The macroeconomic factors that drive the commodity prices are interconnected and have immense importance for commodity pricing and valuation of their underlying assets (Tiwari and Sahadudheen, 2015).

Inflation has a profound impact on investor's perception to invest in commodities because domestic level inflation and inflation expectation directly impact the purchasing power of the consumers (Delatte and Lopez, 2013). Besides, inflation also impacts the stock return which in turn affects the major macroeconomic variables. Therefore, owing to its adverse implications for economic expansion and income redistribution, inflation is considered a worldwide macroeconomic problem as achieving a moderate level of inflation is one of the main objectives of all the economies (Zhao et al, 2016) which is considered good for progressive economies as it creates positive environment among investors. Numerous studies (noteworthy to mention, Aktürk, 2016; Bampinas and Panagiotidis, 2016; Brown et al., 2016; Tiwari et al., 2015; Alagidede and Panagiotidis, 2010; Li et al., 2010 and Lee, 2010) document that stocks move directly with inflation. These findings support the Fisher's hypothesis, which is based on argument that stocks are claims on real assets and should offer full hedge against inflation. Thus, if Fisher's hypothesis holds, stocks should move directly with the inflation rate because of their positive relation (Beckmann et al., 2014). Only in the long-run, stocks are considered an effective hedge against inflation because the historical trends show that the stock returns and inflation move together in the long-run while in the short-run, they do not seem to be significantly correlated (Tripathi and Kumar, 2014).

Surprisingly, among other commodities, only gold performs better hedge against inflation, except for large inflation shocks, and source of liquidity during the deflationary periods (Iqbal, 2017). In the global markets, the investors require liquid assets like gold to cater down the systemic shocks and downsize risk, due to their irregular nature these risks are difficult to predict but have profound devastating effect on investment (Namvar et al., 2016). The systemic risks change the behavior and portfolio management practices of the investor. Therefore, gold helps to mitigate these losses and is considered as the strategic component in their asset allocation (Lawrence, 2011).

The notion of commodity as an inflation hedge mainly depends upon the economic scenarios and it varies according to the economic conditions. However, in case of high inflation or deflation, gold proved as a strong hedge because of its positive correlation with inflation (Ciner et al., 2013). Inflation is also said to be the basic reason for gold price movements in the long-run. However, in the short-run few other forces such as financial stress, political risk, real interest rate, central bank activity and exchange rate are held responsible for the gold price movement. Contrary to this, few researchers document a negative correlation between the prices of gold and inflation. For instance, Wang et al. (2011) documented that gold cannot offer a full or an absolute hedge against inflation as it behaves differently in different markets and momentum.

Whereas, oil supply/demand shocks have devastating impact on the commodities prices. Hence, it is of immense importance to re-examine the reactions of commodity prices to inflation and oil shocks. Some recent studies (e.g., Raza et al., 2016; Rafiq and Bloch, 2016) explored the asymmetric impacts of oil and/or inflation on stocks and commodities. Raza et al. (2016) study the asymmetric impact of gold and oil prices and their associated volatilities on the stock prices of emerging markets. Rafiq and Bloch (2016) explores the asymmetric relationship between oil shocks and commodity prices. However, majority of the prior works (for example, Lee and Lin, 2012; Ghazali et al., 2013; Beckmann et al., 2014) on the relationship of gold and inflation with commodities use linear models and provide mixed findings. Studies modeling the impact of inflation and oil shocks, in a nonlinear setting, are scarce.

This study, for the first time as per authors knowledge, models the combined impact of inflation and oil shocks on commodity prices in a nonlinear setting. We argue that analyses of the relationship between variables in a nonlinear setting have at least two important reasons: (1) a time series can have hidden cointegration if positive and negative components of a series are cointegrated (Granger and Yoon, 2002), and (b) asymmetry and structural breaks (e.g. major credit events, and bankruptcy etc.) are types of nonlinearities that affect the commodity prices, especially when the sample period is marked with the high inflationary and oil shocks regimes. To achieve these purposes, we employ the nonlinear ARDL (NARDL) approach which allows testing the long-run and short-run asymmetries. In the presence of asymmetries, the dynamic multipliers[1] quantify the respective responses of the commodity prices to positive and negative changes in each of the explanatory variables by taking positive and negative partial sum decompositions of these variables. Moreover, unlike the standard cointegration techniques, this method permits time series to have different orders of integration (Shin et al., 2014). It is worth mentioning that the other nonlinear modeling techniques such as smooth transition regression (See e.g., Beckmann (2013)) require pre-testing the cointegration through multivariate cointegration test of Johansen (1988)[2], for example. Whereas, the NARDL model allows simultaneous confirmation of cointegration and estimation of asymmetric short- and long-run elasticities.

It is worth arguing that assuming an identical impact of both positive and negative inflation and oil shocks on commodities prices is too restrictive. We evident, in this study, that the magnitude and direction of impact in many cases is indeed asymmetric. We find that the negative and positive oil and inflation shocks have differential impact on commodity prices. Commodity prices respond positively to increase in oil prices and inflation expectation. Thus, commodities may be regarded as better hedging tool because of their positive integration with inflation and may retain their purchasing power during high inflationary periods. Detection and understanding of asymmetries can help institutional arrangements such as; market structure, price cap regulation and in marketing cartels e.g., adjusting the output according to current scenario in the market. It will help policy makers and exporters to understand the true dynamics of commodity prices in the presence of oil and inflation shocks while designing their development and macroeconomic policies. Understanding the impact of oil and inflation shocks on commodity prices is worthwhile for the countries with heavy exposure to commodities such as Australia in

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[1] To manage the length of the paper, dynamic multiplier figures are not included and can be provided on request.

2 One common problem with these cointegration techniques is that they require that all variables should be integrated of same order.

terms of exports, Japan in terms of imports and some of emerging economies those are particularly exposed to fluctuation in commodity prices. Finally, these asymmetries are of immense importance for resource companies, investors and fund managers to hedge against oil and inflation shocks.

Rest of the paper is structured as follows. Section 2 outlines the empirical model. Section 3 describes the data and interprets the empirical results. Section 4 provides some concluding remarks.

## 2. Methodology

In this study, we use the nonlinear autoregressive distributed lag (hereafter, NARDL) model of Shin et al. (2014) to examine the short- and long-run asymmetric reactions of commodities price indices to inflation and oil shocks. This approach can be employed irrespective of the order of integration with the exception that the series is integrated with the maximum order of one (Ghatak and Siddiki, 2001). The asymmetric cointegration is implied if the time series are noted to have cointegration using their positive and negative components (Granger and Yoon 2002). The asymmetries in the relation can arise due to extreme volatility, asymmetric adjustment process, nonlinear transaction costs and inter alia due to the noise traders. The asymmetries in time series become highly plausible if the sample includes high volatile regimes such as financial crisis. The nonlinear cointegration approach of (Shin et al. 2014) is specified as:

$$CM = f(Oil^{+}, Oil^{-}, CPI^{+}, CPI^{-}) \tag{1}$$

The above specification allows detecting the asymmetric relationship in both short- and long-run using positive and negative partial sum decompositions (Narayan, 2005) and thus the estimated results are robust (See e.g., Pesaran et al. (2001), Lahiani et al. (2016) and Raza et al. (2016), among others). It also allows the joint analysis of the issues of non-stationarity and nonlinearity in the context of an unrestricted error-correction model. A simple form of nonlinear cointegration regression (Shin et al. 2014) may be specified as:[3]

$$y_t = \beta^{+} x_t^{+} + \beta^{-} x_t^{-} + \mu_t, \tag{2}$$

where $\beta^{+}$and $\beta^{-}$ show the long-term parameters of $k$ x *1* vector of regressors $x_t$, decomposed as:

$$x_t = x_0 + x_t^{+} + x_t^{-} \tag{3}$$

where $x_t^{+}$ ($x_t^{-}$) are the partial sums of positive (negative) change in $x_t$ as follows:

$$x_t^{+} = \sum_{j=1}^{t} \Delta x_j^{+} = \sum_{j=1}^{t} \max(\Delta x_j, 0) \tag{4}$$
$$x_t^{-} = \sum_{j=1}^{t} \Delta x_j^{-} = \sum_{j=1}^{t} \min(\Delta x_j, 0) \tag{5}$$

The NARDL(p, q) form of the Eq. (2), in the form of asymmetric error correction model (AECM) can be specified as:

[3] For a more extensive derivation of the model see Shin et al. (2014).

$$\Delta y_t = \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \varphi_j \Delta y_{t-j} + \sum_{j=0}^{q} \left(\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{j-t}^-\right) + \varepsilon_t \tag{6}$$

where, $\theta^+ = -\rho\beta^+$ and $\theta^- = -\rho\beta^-$. However, to asertian the cointegration relation between the variables in above asymmetric framework, the first two steps remains the same as in linear (ARDL) framework i.e., estimating equation (6) using OLS and conducting the joint null ($\rho = \theta^+ = \theta^- = 0$) hypothesis test. However, the Wald test is used to examine the long-run ($\theta^+ = \theta^-$) and short-run ($\pi^+ = \pi^-$) asymmetries in the relationship in NARDL model. Finally, the asymmetric cumulative dynamic multiplier effect of a unit change in $x_t^+$ and $x_t^-$ on $y_t$ is examined respectively as follows:

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^+}, m_h^- = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^-}, h = 0,1,2, \dots \dots \tag{7}$$

where as $h \to \infty$, the $m_h^+ \to \beta^+$and $m_h^- \to \beta^-$. Recall that $\beta^+$ and $\beta^-$ are the asymmetric long-run coefficients and here can be calculates as $\beta^+ = -\theta^+/\rho$and $\beta^- = -\theta^-$, respectively.

## 3. Data and Findings

### 3.1. Data

This study utilized the monthly data of major commodity indices namely Energy, Beverages, Veg Oil and Meals, Grains, Food Items, Raw Material, Fertilizer, Industrial Metals and Precious Metals. Monthly oil prices are used to cater the impact of oil shocks and US inflation rate is used to measure the impact of inflation on commodity prices. All the data is sourced from DataStream International (Thomson Financials). The study period is from January 1970 till December 2016, a total of 552 monthly observations. Moreover, different cycles in commodity prices can affect the results of linear models. It is worth mentioning that the asymmetries (both short- and long-run) in the relationships arise when the time series exhibit structural breaks, the results of LM tests, not reported in the manuscript for brevity, for structural break (Lee and Strazicich, 2003, 2004) confirm such breaks. These structural breaks occur mainly due to different cycles as is the case with commodities prices. The NARDL accounts for the asymmetries arising due to different cycles by decomposing the time series into its positive and negative cumulative sums and hence cater for different cycles in time series.

**Table 1:** Descriptive Statistics

| | Mean | Std. Dev | Skewness | Kurtosis | J-B |
|---|---|---|---|---|---|
| Energy | 3.6045 | 0.7351 | -0.1383 | 3.41 | 5.40*** |
| Beverages | 4.1926 | 0.3405 | -0.1014 | 2.02 | 21.9*** |
| Veg Oil and Meals | 4.1265 | 0.3212 | 0.7589 | 2.82 | 51.0*** |
| Grains | 4.2145 | 0.3142 | 0.8481 | 3.15 | 63.5*** |
| Food Items | 4.1396 | 0.3016 | 0.2962 | 2.35 | 16.6*** |
| Raw Material | 3.9575 | 0.2990 | 0.8241 | 4.33 | 98.4*** |
| Fertilizer | 3.8643 | 0.5385 | 0.9054 | 3.08 | 71.9*** |
| Industrial Metals | 3.7903 | 0.4619 | 0.6714 | 2.45 | 45.9*** |
| Precious Metals | 3.5643 | 0.6447 | 0.4048 | 2.81 | 15.1*** |

| | | | | | |
|---|---|---|---|---|---|
| Crude oil | 3.3050 | 0.7728 | -0.1111 | 3.46 | 5.92*** |
| Inflation | 4.8949 | 0.4707 | -0.7397 | 2.54 | 52.4*** |

**Note:** J-B stands for Jarque-Bera test of normality. *** indicates that the null hypothesis of normality is rejected at 1% level.

Table 1 reports the descriptive statistics for monthly commodity returns which show that commodity indices of Beverages, Vegetable oil and meals, Grains, Food items have highest returns as compared to other commodity indices. The standard deviation of the energy commodities index and precious metals index is higher than other commodities indices. The Jarque-Bera test of normality rejects the null hypothesis for all return series at the 1% level of significance and states that the returns are not normally distributed.

### 3.2 NARDL Estimation

The existence of a long-run asymmetric relationship between commodity price indices and inflation and oil shocks is ascertained using the bound testing procedure. The empirical estimates of nonlinear specifications are summarized in lower panel of Table 2 and shown by the BDM and PSS, where the BDM is the t-statistic proposed by Banerjee et al. (1998) for testing the null of no long-run relationship and PSS is the F-statistic proposed by Pesaran et al. (2001) for testing the null hypothesis of no cointegration. Both test statistics confirm the presence of nonlinear long-run relationship between commodity price indices and the explanatory variables (i.e., oil and inflation shocks). After confirmation the evidence of cointegration among the variables, we proceed with the analysis of short and long-run asymmetric impact of inflation and oil price shocks on major commodity price indices. The estimated coefficients of the short-run asymmetries are reported in upper panel of the Table 2 which show that previous month's shock in the commodity prices has significant positive impact on their future prices. It seems that positive oil price shocks have positive impact on all commodity price indices, but it is more pronounced on energy commodity price index where the coefficient value is highest i.e., 0.87 and highly significant. Our findings demonstrated that commodity prices respond positively to increasing oil prices and adjust their prices accordingly.

However, asymmetric features reveal that the positive and negative shocks are not of equal magnitude, where a positive oil price shock has more pronounced effect on commodity price as compared to a negative oil price shock. On the other hand, all the commodities react weakly to a negative oil price shock. In the long-run, a positive oil price shock ($L^{+}_{Oil}$) has positive impact on energy, beverages, vegetable oil and meals, fertilizer and precious metals indices, significant at conventional levels. This implies that these commodities can provide significant protection against losses occurring due to oil price changes. This positive oil price shocks ($L^{+}_{Oil}$) have a weak and statistically insignificant impact in case of grains, food items and industrial metals, which implies that these commodities will react weakly to a positive oil price shock. A positive oil price shock has a negative impact on the raw material only.

Moreover, the commodity prices also react weakly to a negative ($L^{-}_{Oil}$) oil price shock except energy, fertilizer and precious metal indices, they respond positively to a negative oil price shock as well. Our findings regarding the long-run asymmetric positive impact of oil on commodity prices are in line with Rafiq and Bloch (2016). They also find that commodity prices response asymmetrically and positively to the oil price movements.

**Table 2:** NARDL estimation results.

| | Energy | | Beverages | | Veg Oil and Meals | | Grains | | Food Items | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | Standard errors | Coefficient | Standard errors | Coefficient | Standard errors | Coefficient | Standard errors | Coefficient | Standard errors |
| C | 0.201*** | (0.023) | 0.169*** | (0.035) | 0.194*** | (0.049) | 0.204*** | (0.040) | 0.403*** | (0.056) |
| $CM_{t-1}$ | -0.174*** | (0.020) | -0.034*** | (0.008) | -0.046*** | (0.013) | -0.052*** | (0.010) | -0.120*** | (0.016) |
| $\mathrm{Oil}^{+}_{t-1}$ | 0.166*** | (0.019) | 0.020*** | (0.007) | 0.013** | (0.007) | -0.002 | (0.005) | -0.007 | (0.006) |
| $\mathrm{Oil}^{-}_{t-1}$ | 0.164*** | (0.018) | 0.011 | (0.011) | -0.001 | (0.011) | 0.006 | (0.009) | 0.005 | (0.009) |
| $\mathrm{CPI}^{+}_{t-1}$ | 0.010 | (0.017) | 0.003 | (0.052) | 0.076 | (0.054) | -0.054 | (0.044) | 0.015 | (0.044) |
| $\mathrm{CPI}^{-}_{t-1}$ | 0.465*** | (0.101) | -0.598** | (0.322) | 0.374 | (0.309) | 0.708*** | (0.251) | 0.109 | (0.253) |
| $\Delta\mathrm{CM}_{t-1}$ | | | 0.270*** | (0.041) | 0.395*** | (0.042) | 0.364*** | (0.041) | 0.171*** | (0.041) |
| $\Delta\mathrm{CM}_{t-2}$ | | | | | 0.162*** | (0.042) | | | | |
| $\Delta\mathrm{Oil}^{+}_{t}$ | 0.878*** | (0.009) | 0.140*** | (0.027) | 0.088*** | (0.028) | | | | |
| $\Delta\mathrm{Oil}^{+}_{t-1}$ | -0.023*** | (0.008) | | | | | | | 0.137*** | (0.024) |
| $\Delta\mathrm{Oil}^{+}_{t-7}$ | | | | | | | | | 0.089*** | (0.024) |
| $\Delta\mathrm{Oil}^{-}_{t}$ | 0.773*** | (0.013) | | | | | | | 0.112*** | (0.040) |
| $\Delta\mathrm{Oil}^{-}_{t-2}$ | | | 0.123*** | (0.042) | | | | | | |
| $\Delta\mathrm{CPI}^{+}_{t}$ | | | | | | | | | 2.626*** | (0.831) |
| $\Delta\mathrm{CPI}^{+}_{t-1}$ | 0.816** | (0.319) | -2.961*** | (0.948) | -2.606*** | (0.977) | | | | |
| $\Delta\mathrm{CPI}^{+}_{t-5}$ | -0.984*** | (0.304) | -2.472*** | (0.942) | -3.579*** | (0.991) | | | 2.132** | (0.839) |
| $\Delta\mathrm{CPI}^{-}_{t}$ | | | | | | | -5.845*** | (1.837) | | |
| $\Delta\mathrm{CPI}^{-}_{t-1}$ | | | | | | | -5.660*** | (1.841) | 4.249** | (1.759) |
| **Long-run asymmetric dynamics and diagnostics** | | | | | | | | | | |
| $\mathrm{L}^{+}_{\mathrm{Oil}}$ | 0.955*** | (0.013) | 0.594*** | (0.227) | 0.293* | (0.160) | -0.048 | (0.109) | -0.055 | (0.049) |
| $\mathrm{L}^{-}_{\mathrm{Oil}}$ | 0.941*** | (0.020) | 0.335 | (0.320) | -0.03 | (0.251) | 0.115 | (0.173) | 0.045 | (0.075) |
| $\mathrm{L}^{+}_{\mathrm{CPI}}$ | 2.677*** | (0.598) | 0.098 | (1.534) | 1.656*** | (1.378) | -1.04 | (0.825) | 0.127 | (0.727) |
| $\mathrm{L}^{-}_{\mathrm{CPI}}$ | 0.055 | (0.097) | -17.676** | (9.190) | 8.202 | (7.112) | 13.726*** | (5.267) | 0.913 | (2.101) |
| ***BDM*** | -8.715*** | | -5.060*** | | -5.565*** | | -4.960*** | | -7.659*** | |
| ***PSS*** | 15.093*** | | 6.363*** | | 7.192*** | | 6.506*** | | 8.958*** | |
| $\mathrm{W}_{Oil}$ | 6.866*** | | 5.022*** | | 1.966*** | | 1.579 | | 2.963* | |
| $\mathrm{W}_{CPI}$ | 17.78*** | | 3.495** | | 6.852*** | | 7.386*** | | 0.131 | |
| Adj- $R^2$ | 0.972 | | 0.292 | | 0.351 | | 0.306 | | 0.427 | |
| $\chi^2_{NORM}$ | [0.449] | | [0.910] | | [0.219] | | [0.191] | | [0.630] | |
| $\chi^2_{SC}$ | [0.886] | | [0.828] | | [0.855] | | [0.684] | | [0.472] | |
| $\chi^2_{HET}$ | [0.060] | | [0.271] | | [0.643] | | [0.982] | | [0.200] | |
| $\chi^2_{FF}$ | [0.406] | | [0.397] | | [0.803] | | [0.126] | | [0.509] | |

**Note:** The superscript "+" and "-" denote positive and negative cumulative sums, respectively. $L^{+}$ and $L^{-}$ are the estimated long-run coefficients associated with positive and negative changes, respectively, defined by $\hat{\beta} = -\hat{\theta}/\hat{\rho}$. $\chi^2_{SC}$, $\chi^2_{FF}$, $\chi^2_{HET}$, and $\chi^2_{NORM}$ denote LM tests for serial correlation, normality, functional form and Heteroscedasticity, respectively. $\mathrm{W}_{\mathrm{LR}}$ represents the Wald test for the null of long-run symmetry for respective variable. Value in [ ] are p-values. S.E stands for standard errors. ***, ** & * indicate significance at 1%, 5% and 10% level, respectively.

**Table 2:** Continued…

| | Raw Material | | Fertilizer | | Industrial Metals | | Precious Metals | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | Standard errors | Coefficient | Standard errors | Coefficient | Standard errors | Coefficient | Standard errors |
| C | 0.159*** | (0.033) | 0.113*** | (0.036) | 0.143*** | (0.034) | 0.151*** | (0.030) |
| $CM_{t-1}$ | -0.042*** | (0.010) | -0.062*** | (0.011) | -0.041*** | (0.012) | -0.083*** | (0.015) |
| $\mathrm{Oil}^{+}_{t-1}$ | -0.010** | (0.004) | 0.022** | (0.009) | -0.004 | (0.006) | 0.025*** | (0.008) |
| $\mathrm{Oil}^{-}_{t-1}$ | -0.014** | (0.007) | 0.050*** | (0.013) | -0.011 | (0.010) | 0.029** | (0.012) |
| $\mathrm{CPI}^{+}_{t-1}$ | 0.091*** | (0.032) | -0.215*** | (0.061) | 0.101** | (0.049) | 0.172*** | (0.061) |
| $\mathrm{CPI}^{-}_{t-1}$ | -0.149 | (0.181) | 0.809** | (0.380) | 0.444 | (0.326) | -0.926*** | (0.332) |
| $\Delta\mathrm{CM}_{t-1}$ | 0.426*** | (0.038) | 0.231*** | (0.042) | 0.181*** | (0.040) | 0.236*** | (0.040) |
| $\Delta\mathrm{CM}_{t-2}$ | | | | | 0.131*** | (0.040) | | |
| $\Delta\mathrm{Oil}^{+}_{t}$ | 0.044*** | (0.017) | 0.416*** | (0.032) | 0.110*** | (0.025) | 0.128*** | (0.028) |
| $\Delta\mathrm{Oil}^{+}_{t-1}$ | | | 0.127*** | (0.037) | | | | |
| $\Delta\mathrm{Oil}^{+}_{t-7}$ | | | | | | | 0.102*** | (0.027) |
| $\Delta\mathrm{Oil}^{-}_{t}$ | 0.103*** | (0.026) | | | 0.117*** | (0.044) | | |
| $\Delta\mathrm{Oil}^{-}_{t-2}$ | 0.093*** | (0.030) | | | 0.111** | (0.043) | | |
| $\Delta\mathrm{CPI}^{+}_{t}$ | | | | | | | | |
| $\Delta\mathrm{CPI}^{+}_{t-1}$ | | | 3.596*** | (1.162) | | | 0.162*** | (0.042) |
| $\Delta\mathrm{CPI}^{+}_{t-5}$ | | | 7.897*** | (2.244) | -2.361*** | (0.893) | 0.395*** | (0.042) |
| $\Delta\mathrm{CPI}^{-}_{t}$ | | | 3.677*** | (1.162) | 7.045*** | (1.720) | | |
| $\Delta\mathrm{CPI}^{-}_{t-1}$ | -3.605*** | (1.303) | | | 6.620*** | (1.961) | | |
| **Long-run asymmetric dynamics and diagnostics** | | | | | | | | |
| $L^{+}_{\mathrm{Oil}}$ | -0.233** | (0.119) | 0.353*** | (0.132) | -0.11 | (0.163) | 0.299*** | (0.086) |
| $L^{-}_{\mathrm{Oil}}$ | -0.326 | (0.207) | 0.801*** | (0.219) | -0.26 | (0.289) | 0.349*** | (0.132) |
| $L^{+}_{\mathrm{CPI}}$ | 2.156** | (0.930) | 13.002** | (6.283) | 2.477** | (1.457) | 2.068*** | (0.633) |
| $L^{-}_{\mathrm{CPI}}$ | -3.555 | (4.390) | 3.461*** | (1.053) | 10.867*** | (6.922) | -11.145*** | (3.672) |
| ***BDM*** | -6.270*** | | -5.613*** | | -5.336*** | | -6.457*** | |
| ***PSS*** | 7.902*** | | 7.329*** | | 6.435*** | | 7.801*** | |
| $\mathrm{W}_{Oil}$ | 3.484** | | 7.157*** | | 0.494 | | 6.263*** | |
| $\mathrm{W}_{CPI}$ | 1.477** | | 6.247** | | 11.290*** | | 12.041*** | |
| Adj- $R^2$ | 0.338 | | 0.405 | | 0.323 | | 0.386 | |
| $\chi^2_{NORM}$ | [0.995] | | [0.137] | | [0.380] | | [0.380] | |
| $\chi^2_{SC}$ | [0.373] | | [0.906] | | [0.960] | | [0.016] | |
| $\chi^2_{HET}$ | [0.816] | | [0.004] | | [0.068] | | [0.126] | |
| $\chi^2_{FF}$ | [0.798] | | [0.323] | | [0.156] | | [0.124] | |

**Note:** The superscript "+" and "-" denote positive and negative cumulative sums, respectively. $L^{+}$ and $L^{-}$ are the estimated long-run coefficients associated with positive and negative changes, respectively, defined by $\hat{\beta} = -\hat{\theta}/\hat{\rho}$. $\chi^2_{SC}$, $\chi^2_{FF}$, $\chi^2_{HET}$, and $\chi^2_{NORM}$ denote LM tests for serial correlation, normality, functional form and Heteroscedasticity, respectively. $\mathrm{W}_{\mathrm{LR}}$ represents the Wald test for the null of long-run symmetry for respective variable. Value in [ ] are p-values. S.E stands for standard errors. ***, ** & * indicate significance at 1%, 5% and 10% level, respectively.

Further, we find that commodity prices increase with an increase in inflation in the short-run except for vegetable oil and industrial metal indices. The values of estimated coefficient of short-run asymmetries are highly significant and positive in case of energy, beverages, grains, food items, raw material, fertilizer and precious metals. This implies that these commodities may be regarded as an effective hedging instrument against inflation in the short-run. However, a negative shock in the inflation (i.e. deflation) decreases the prices of grains and raw material in the short-run. In long-run, a negative inflation shock leads to a strong positive impact on all commodity prices except for the beverages and precious metals.

## 4. Concluding Remarks

This study examines the short- and long-run asymmetric reaction of commodity prices to negative and positive oil and inflation shocks. In doing so, we employ the NARDL model proposed by Shin et al. (2014). Considering the asymmetric effects of explanatory variables, Wald test results support the presence of nonlinearity in the linkages. Our findings reveal that both the oil and inflation shocks have differential impact across commodity prices over both short- and long-run. Negative oil price and inflation shocks do not seem to have much impact on major commodity prices. They have substantial impact on agricultural commodities (i.e., grains) and raw material. This asymmetric impact of inflation and oil shocks in short- and long-run indicates possibilities to diversify the commodity investments for possible inflation and oil shocks.

However, despite the variations on the impact, there is still a preponderance of positive co-movement between oil prices and other commodities. Thus, from the smoothing future global economic development, our findings clearly support to the proposition that the moderate inflation and the stable oil prices are conducive to the both short and long-run stability in the prices of other commodities. Further, commodities may be regarded as better hedging tool because of their positive integration with inflation and may retain their purchasing power during high inflationary periods.

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