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Asymmetric Impact of Food Inflation Determinants in India: An NARDL Framework

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ABSTRACT

Food inflation is a major concern worldwide. This study applied ARDL and NARDL econometric models to identify and estimate the determinants of food inflation and their symmetric or asymmetric impacts. The results reveal that food price inflation is not merely a monetary phenomenon but is influenced by several other factors. The NARDL estimates show that net agricultural trade, wages, exchange rates, and weighted average call money rates exert significant asymmetric effects on food price inflation, implying that positive and negative shocks to these factors influence food prices differently. Interestingly, a significant unidirectional passthrough price effect was observed from non-food to food commodities.

Keywords: Food inflation, determinants, symmetric and asymmetric effects, ARDL, NARDL

JEL Codes: C22, E31, E52

I

INTRODUCTION

Food inflation has become, and will remain, a significant concern for countries worldwide, particularly for households in the low- and middle-income categories in emerging economies (FAO, 2011). Food is a basic necessity for survival, alongside clothing, water, and shelter; therefore, rising food prices directly impact consumers. Higher food prices diminish consumers' purchasing power and increase the risk of food insecurity for households that allocate a substantial share of their income to food (Nsabimana and Habimana, 2017). Furthermore, inflation in food prices can have political implications, potentially leading to changes in government policies to ensure food security in the country. This subsequently affects resource allocation and the functioning of the pricing system (Anusha et al., 2022). The bottom three income deciles of households in rural India spend nearly 60% of their expenditure on food, whereas for urban families, food expenditure accounts for about 57% of their total expenditure (Bhattacharya and Gupta, 2018). Additionally, food inflation shocks may be strongly transmitted to non-food inflation, and vice versa (Ismaya and Anugrah, 2018). Thus, any major surge in food prices affects food price stability and national-level inflation, particularly in countries where the share of food in total expenditure is higher (Hoang et al., 2020).

Food inflation is driven by multiple factors, including supply, demand, and cost-related factors, as well as domestic and global factors. Moreover, the impact of shocks to the determinant variable of food inflation on food prices is not necessarily symmetrical, meaning that positive shocks to the determinant variable may not have

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the same impact on food inflation as negative shocks. A significant positive or negative shock in a variable can lead to noticeable changes in the symmetric effect, whereas a minor change may remain unnoticed. Thus, shocks to the determinants can have either symmetric or asymmetric effects on the food prices. Hence, it is vital to understand the dynamics of the effects of significant food inflation causal factors. Understanding the determinants of food inflation and their symmetric or asymmetric impacts is crucial for policymakers to maintain medium-term retail inflation within the target range through appropriate measures.

Most studies in India have identified the determinants of food price inflation by considering either demand- or supply-side factors, using commonly employed cointegration and error-correction approaches. However, these studies assume linear (symmetric) relationships between determinants and food inflation, and thus do not capture non-linear (asymmetric) effects. In reality, macroeconomic and agricultural variables often respond nonlinearly, where increases and decreases in determinants may produce different magnitudes and directions of effect on food inflation. Despite the growing importance of asymmetric price dynamics in macroeconomic analysis, empirical evidence on the asymmetric impact on food inflation determinants in India remains limited. Furthermore, existing studies rarely examine the interaction between food and non-food inflation through the pass-through effect.

The present study adds to the existing literature on numerous critical fronts. First, it comprehensively explains how domestic and global supply, demand, and cost-related factors affect domestic food price inflation in the ARDL framework. Second, it investigates whether shocks in these determinants exert symmetric or asymmetric effects on food inflation using the nonlinear autoregressive distributed lag (NARDL) approach. The ARDL and NARDL frameworks offer significant advantages, as they can be applied irrespective of whether the time series variables are stationary at different or the same level, and to small sample sizes. The NARDL model decomposes the determinants of food inflation into positive and negative shocks, providing insights into their complex nonlinear dynamics. Third, this study explores the second-round pass-through effects between food and non-food prices to determine the influence of non-food prices on food prices and vice versa (Rangasamy, 2011).

A detailed review of the pertinent literature is presented in the next section. Section 3 discusses the trends in food inflation in India. Section 4 provides particulars of the data and methodology used in this study. The results are presented and discussed in Section 5 of this paper. Finally, Section 6 presents the conclusions and policy recommendations.

II

REVIEW OF LITERATURE

Several empirical studies have investigated the supply- and demand-side factors, domestic or international, that affect food price inflation in India and other emerging economies. Early studies primarily emphasized structural demand factors and supply constraints as key drivers of rising food prices. For instance, Kumar et al. (2010) revealed that increasing per capita income is one of the main determinants of rising food prices, alongside stagnant per capita food availability. Chand (2010) reported that the rise in export of food commodities increases domestic food prices and the transmission of international prices to domestic prices. Mishra and Roy (2012) identified the widening gap between commodity demand and supply as a long-term driver of food inflation, whereas short-term adverse supply shocks arise from changes in weather, stockholding, and MSP. Gulati and Saini (2013) used linear regression to show that fiscal deficits, rising farm wages, and the transmission of global food inflation are the major causes.

Subsequent studies have employed more advanced econometric approaches to analyse the determinants of food inflation. Bhattacharya et al. (2015) analyze the role of demand and supply side factors in determining food inflation using a Structural VAR, and reported that food inflation in India is mainly driven by rising demand relative to supply, fuel prices, and farm wages. Similarly, Sonna et al. (2014) employed a VECM and found that higher support prices for rice and wheat, rural wages, and input cost inflation are key determinants of higher food inflation in India. In a recent study, Samal et al. (2022) investigated the effects of macroeconomic factors on food inflation by employing the ARDL and VECM approaches. They revealed a significant positive impact of per capita income, money supply, global food prices, and agricultural wages on food price inflation in both the short and long run, whereas foodgrain availability had a significant negative effect. The real exchange rate positively affects food price inflation in the short term.

Evidence from other emerging economies also highlights the importance of macroeconomics and structural factors in determining food price inflation. Using the GMM estimator, Ismaya and Anugrah (2018) reported that food production, agricultural sector output, infrastructure, food imports, agriculture sector credit, money supply, and seasonal events significantly affect food price inflation in Indonesia. Similarly, Malaviarachchi and Korale-Gedara (2024) applied cointegration analysis and a vector error correction model to investigate the role of supply- and demand-side factors in determining food inflation in Sri Lanka. The study identified changes in farm wages, fuel prices, fertilizer prices, exchange rates, and money supply as the major determinants of food inflation. The study also found that an increase in money supply has a significant effect on food inflation in the long run, while world food prices exert a stronger effect in the short run.

Several studies have also emphasized the importance of structural demand shift in food consumption patterns. Rising income levels and urbanization have led to changes in consumption patterns from staple foods to high-value food commodities, such as fruits and vegetables, milk and dairy products, and animal-sourced food products that drive food inflation (Bandara, 2013; Bhattacharya and Sen, 2018; Mishra and Roy, 2016). In addition, many scholars have revealed that money supply is a driver of food inflation (Dua and Goel, 2021; Qayyum and Sultana, 2018; Mishra et al., 2023). On the supply side, domestic supply side shocks (Anand et al., 2015) due to weather variations, input costs (Kose and Unal, 2024; Loening et al., 2009), crude oil prices, and exchange rates (Baek and Koo, 2010; Sarwar et al., 2020) significantly influence food price inflation. Wages and input costs affect production costs and contribute to cost-push inflation (Bhattacharya and Sen, 2018).

Most existing studies on food inflation in India have relied on linear econometric frameworks, including VAR, VECM, and ARDL models (e.g., Kumar et al., 2010; Gulati and Saini, 2013; Bhattacharya et al., 2015; Samal et al., 2022). While these studies provide important insights into the demand- and supply-side drivers of food price dynamics, they implicitly assume symmetric responses of food prices to macroeconomic and agricultural shocks. However, in reality, economic variables often respond asymmetrically due to market rigidities, adjustment costs, policy interventions, and structural constraints in agricultural markets. For instance, increases in wages, exchange-rate depreciation, or trade shocks may affect food prices differently than declines in these factors. Furthermore, the interaction between food and non-food inflation through pass-through mechanisms has received relatively limited empirical attention in the Indian context. Against this backdrop, the present study contributes to the literature in two important ways. First, it employs the Nonlinear Autoregressive Distributed Lag (NARDL) framework to capture asymmetric responses of food inflation to both positive and negative shocks in its determinants. Second, it examines the second-round pass-through effects between food and non-food prices using a Dynamic OLS approach, thereby providing a more comprehensive understanding of inflation transmission dynamics in India.

III

FOOD INFLATION IN INDIA

In India, the Reserve Bank of India is a regulatory body responsible for maintaining a medium-term retail inflation (CPI-based) target of 4 per cent, with a band of +/- 2 per cent. Retail inflation (CPI) peaked at 11.5% in November 2013, declined gradually but mostly remained above 4% until October 2016, dropped below 2% in January 2019, and started rising again, mostly hovering around the upper bound of 6% continuously and intermittently above 7% (Figure 1). It remained above 6% in most months in 2020 and 2022, peaking at 7.8% in April, 2022. Retail price inflation has been driven mainly by the rising prices of food and beverages, and fuel and light (with weights of 45.86% and 6.84%, respectively). Together, these contributed more than 60% of the total retail inflation in 2013, from October 2019 to November 2020, and since July 2023.

Retail food inflation (CFPI) remained elevated at approximately 10-12% from April 2012 onwards, peaking at 17.9% in November 2013, and declining thereafter. After remaining below 4% from September 2016 to August 2019, it reached a high of 14.2% in December 2019, declined gradually, and hovered at 4% until December 2021. After hovering around 4 per cent for a few months, it started increasing and crossed 6% in March 2022, remaining above it until October 2022. It remained mostly above 8% from July 2023 onwards (Figure 1).

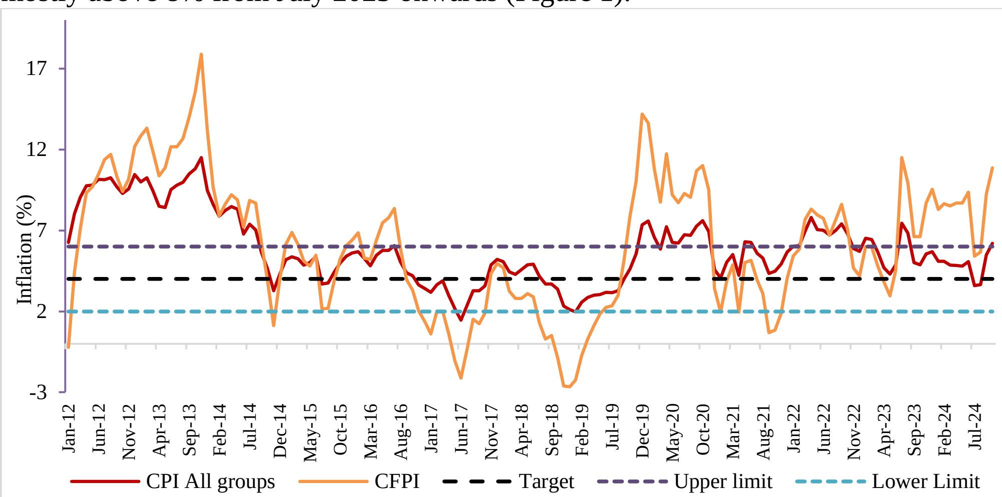

FIGURE 1. FOOD AND GENERAL INFLATION TREND IN INDIA

Vegetables, pulses, edible oils and fats, and cereals drive food price inflation (Figure 2). Cereal inflation remained above 8% from August 2012 to April 2014 and again from August 2022 onwards, reaching above 16% during January-February 2023. Vegetable inflation fluctuates more than that of other food items, remaining elevated most of the time, with intermittent slowdowns. Recently, inflation in spices also increased significantly from less than 5% in January 2022 to above 15% from September 2022 to January 2024, and even above 23% during August-September 2023; however, it has been negative in recent months. The inflation in edible oils and fats was 11-35% from April 2020 to May 2022, but started declining afterwards. Food inflation remained mostly above the target limit after September 2019, except in 2021.

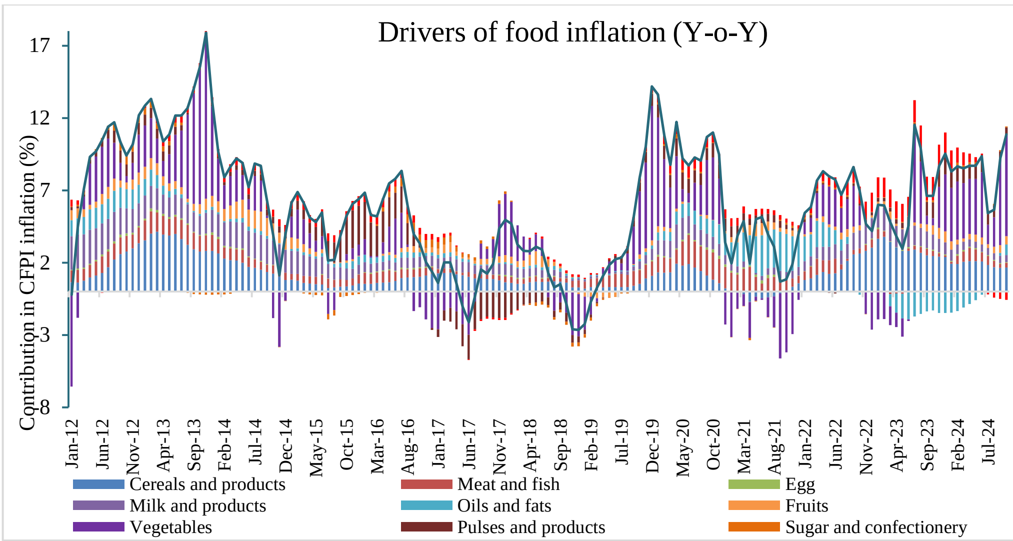

FIGURE 2. DRIVERS OF FOOD INFLATION

Furthermore, a sharp increase in global prices due to the Russia-Ukraine war has fuelled record increases in edible oil prices through import linkages and in cereal prices through export linkages. Terminal heat stress has adversely affected wheat production in recent years. Seasonality plays a crucial role in the supply of agricultural commodities, particularly perishables such as fruits and vegetables, and random shocks, such as untimely heavy rainfall, affect their supply. The supply of agricultural products is seasonal, particularly for perishables, and inelastic in the short run. Varying production patterns of perishables create seasonality in prices, and shocks mainly stem from uncertain weather conditions and other unpredictable events, leading to high price volatility. The high wholesale-retail markup for perishables may also lead to high food inflation.

IV

METHODOLOGY

4.1 Data and Data Source

This study is based on a monthly time series of data, from January 2011 to March 2024, collected from different sources published by the Government of India (GoI). Food inflation is measured using the Consumer Food Price Index (CFPIcfpi) with base year 2011-12, collected from the National Statistical Office (NSO), Ministry of Statistics and Programme Implementation (MoSPI). Other macroeconomic and agricultural variables were collected from official sources to ensure data reliability. Quarterly Agricultural GDP (aggdp) data were sourced from the Ministry of Finance, Government of India. These data were converted to monthly data using the spline method. Monthly data related to the weighted average call money rate (wacr), real effective exchange rates (reer), and money supply (M3) were collected from the Reserve Bank of India (RBI) database. Monthly agricultural export and import data were sourced from the Ministry of Commerce, GoI, to workout net agricultural trade (nagrtrd). The world food CPI (wfcpi) was obtained from the Food and Agriculture Organization (FAO) of the United Nations. Farm wage rates (wager) were collected from the Directorate of Economics and Statistics (DES). All variables used in the study, except for diesel prices and the bank rate, were transformed into logarithmic form to control for potential data skewness. Table 1 presents the summary statistics for the variables used in this study.

TABLE 1. SUMMARY STATISTICS OF THE VARIABLES (JANUARY 2011 TO MARCH 2024) USED IN THE STUDY

Variable	Description	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
l_cfpi (Y)	Log of CPI food (2011-12=100)	4.91	0.20	4.48	5.28	-0.29	2.38
l_m$_3$ (X_1)	Log of money supply (Rs. crore)	16.20	0.27	15.70	16.61	-0.36	1.78
l_nagrtrd (X_2)	Log of net agri. trade (Rs. lakhs)	8.96	0.41	7.71	9.82	-0.36	2.78
l_wager (X_3)	Log of wage rate (Rs.)	5.37	0.21	4.87	5.62	-1.18	2.97
l_aggdp (X_4)	Log of real agri. GDP (Rs. crore)	11.73	0.21	11.27	12.13	-0.16	2.22
l_crude(X_5)	Crude oil rate (US$/brl)	4.08	0.40	2.80	4.80	-0.02	2.61
l_wfcpi (X_6)	Log of World food CPI (2015=100)	4.73	0.24	4.45	5.57	1.59	5.00
l_input (X_7)	Log of input price index (2011-12=100)	4.76	0.16	4.52	5.17	1.20	3.37
l_reer (X_8)	Log of Real effective exchange rate (Index)	4.61	0.04	4.48	4.68	-0.86	3.01
wacr (X_9)	Weighted average call money rate (%)	6.32	1.66	3.14	9.97	-0.43	2.55
l_cpi	Log of CPI (2011-12=100)	4.89	0.20	4.48	5.23	-0.21	2.19
l_cnfpi	Log of non-food CPI (2011-12=100)	4.88	0.21	4.47	5.21	-0.15	2.06

4.2 Methodological Framework

This study used nine variables in the analysis as determinants of food inflation, identified through a comprehensive literature review. The linear regression equation for food price inflation can be expressed as follows (Eq 1):

$$Y_t = \alpha_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \beta_3 X_{3,t} + \beta_4 X_{4,t} + \beta_5 X_{5,t} + \beta_6 X_{6,t} + \beta_7 X_{7,t} + \beta_8 X_{8,t} + \beta_9 X_{9,t} + \varepsilon_t \quad \ldots(1)$$

Where Y_t denotes the log of the consumer food price index (cpfi), and X_1 to X_9 are the independent variables included in the model (Table 1). The β_1 to β_9 coefficients denote long-run elasticity, and ε_t is the error term. However, eq. (1) provides only the long-run effect of the explanatory variables on CFPI.

The autoregressive distributed lag (ARDL) model is a widely used econometric method, particularly for analyzing the relationship between variables in both the short and long run (Pesaran and Shin, 1999; Pesaran *et al.*, 2001). The ARDL model is employed due to their advantages in analysing time-series relationships. It can be applied even if the time-series variables are not integrated to the same order. This allows for the inclusion of both I(0) and I(1) processes; however, the time series should not be I(2), meaning that some variables are stationary and some are non-stationary at levels but become stationary upon differencing (Sharma *et al.*, 2023). This model also adopts the correct lag order and reduces the possibility of multicollinearity. The model given by Pesaran and Shin (1999) and extended by Pesaran *et al*. (2001) and Narayan (2004) was applied in this study. The eq. (1) in the ARDL framework is used in the following form (Eq.2):

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{n} \gamma_i \Delta Y_{t-i} + \sum_{i=0}^{n} \varphi_1 \Delta X_{1,t-i} + \sum_{i=0}^{n} \varphi_2 \Delta X_{2,t-i} + \sum_{i=0}^{n} \varphi_3 \Delta X_{3,t-i} + \sum_{i=0}^{n} \varphi_4 \Delta X_{4,t-i} + \sum_{i=0}^{n} \varphi_5 \Delta X_{5,t-i} + \sum_{i=0}^{n} \varphi_6 \Delta X_{6,t-i} + \sum_{i=0}^{n} \varphi_7 \Delta X_{7,t-i} + \sum_{i=0}^{n} \varphi_8 \Delta X_{8,t-i} + \sum_{i=0}^{n} \varphi_9 \Delta X_{9,t-i} + \rho ecm_{t-1} + \theta_1 X_{1,t-1} + \theta_2 X_{2,t-1} + \theta_3 X_{3,t-1} + \theta_4 X_{4,t-1} + \theta_5 X_{5,t-1} + \theta_6 X_{6,t-1} + \theta_7 X_{7,t-1} + \theta_8 X_{8,t-1} + \theta_9 X_{9,t-1} + \omega_t \quad \ldots (2)$$

Where Δ is the first difference operator, n is the optimal lag length, which is selected based on the Akaike Information Criterion (AIC), and α_0 is the intercept. The φ_1 to φ_{10} and θ_1 to θ_{10} coefficients represent the short and long-run elasticities, respectively, while ω_t is the white noise term. The null hypothesis of no cointegration was tested using the F-statistic in the ARDL bound test. The test uses two critical bound values- the upper and lower bounds. The null hypothesis is rejected if the F-statistic is higher than the upper bound. If the test statistic falls below the lower bound, we conclude that the variables are not cointegrated. The test is inconclusive if the test statistic lies between the lower and upper critical bounds. This model also provides an error correction term (ECT), which indicates the speed of adjustment to equilibrium after a short-run shock. A significant negative ECT coefficient implies a stable long-run relationship. To assess the robustness of the model, diagnostic tests, including the Breusch-Pagan heteroscedasticity test, the Breusch-Godfrey LM test, and the Durbin-Watson (DW) test for autocorrelation, were conducted.

However, the ARDL model assumes a linear symmetric relationship between two variables. In reality, the relationship between macroeconomic variables may be nonlinear, leading to asymmetric effects that this analysis does not capture. Therefore, this study applied a non-linear ARDL (NARDL) approach (Shin *et al.*, 2014) to examine the long- and short-run asymmetric effects. This approach enables disentangling the favorable and unfavorable impacts of independent variables. To introduce nonlinearity, the NARDL model uses partial sum decomposition to separate positive and negative deviations in the regressors. The process of defining the partial sum for variable X_t is as eq. (3) below:

$$X_t^+ = \sum_{i=1}^{t} \Delta X_i^+ = \sum_{i=1}^{t} \max(\Delta X_{i,}^+ 0);\ \ X_i^- = \sum_{i=1}^{t} \Delta X_i^- = \sum_{i=1}^{t} \min(\Delta X_{i,}^- 0) \quad \ldots(3)$$

where, X_i^+ and X_i^- denote the positive and negative changes around zero, respectively, representing the positive and negative shocks in the variables. The series in first differences (ΔX_t) is expected to follow a normal distribution with a mean of zero (Demeke & Tenaw, 2021). To estimate both the long and short run asymmetries, the NARDL (p, q) model in error-correction form is given in equation 4:

$$\Delta Y_t = \alpha_0 + \beta_1 Y_{t-1} + \beta_2 X_{1,t-1}^+ + \beta_3 X_{1,t-1}^- + \beta_4 X_{2,t-1}^+ + \cdots + \beta_{21} X_{8,t-1}^+ + \beta_{22} X_{8,t-1}^- + \sum_{i=1}^{p} \varphi ecm_{t-i} + \theta_1^+ \Delta X_{1,t-i}^+ + \theta_1^- \Delta X_{1,t-i}^- + \cdots + \theta_9^+ \Delta X_{9,t-i}^+ + \theta_9^- \Delta X_{9,t-i}^- + \varepsilon_t \quad \ldots(4)$$

The set of explanatory variables (X_t) is decomposed as $X_t = X_0 + X_t^+ + X_t^-$; $\emptyset_i^+$ and $\emptyset_i^-$ are the coefficients associated with long-run asymmetry, and φ denotes the non-linear error correction term coefficient.

Like ARDL, the F-statistic using the bound test was used to check the presence of non-linear cointegration among variables, for testing the null of no cointegration ($\varphi' = \beta_i^+ = \beta_i^- = 0$) against the alternative hypothesis of asymmetric cointegration. Further, the Wald test was used to confirm the existence of short and asymmetries in the long run by testing the null of long run asymmetry as $\beta_i^+ = \beta_i^-$, and the null of asymmetry in the short run as $\sum_{i=0}^{q-1} \emptyset_i^+ = \sum_{i=0}^{q-1} \emptyset_i^-$. We also calculated the long-run dynamic multiplier for all variables to estimate the cumulative effect of a one unit change in the determinant variable (positive or negative) on food inflation. Post-diagnostic tests were also carried out to check robustness using the Portmanteau test for autocorrelation, the Breusch-Pagan test for heteroscedasticity, the Ramsey RESET test to detect specification errors in a regression model, and the Jarque-Bera test for normality distribution.

The overall effect of the food and non-food price indices on the aggregate price index is not merely determined by their share; the pass-through second round effects were examined.

4.3 Pass-Through Second Round Effects

The overall effect of food and non-food commodity prices on aggregate inflation extends beyond their respective weights in the indices (Rangasamy, 2011; Zaman et al., 2018). Hence, we examined how changes in non-food prices affect food prices (or vice versa) by investigating the second-round pass-through effects. The impact of one inflation group on the collective inflationary pressure may be transmitted through another group; therefore, this provides valuable insights into the mechanism of inflation transmission and helps achieve price stability (Demeke &

Tenaw, 2021). This study uses Dynamic Ordinary Least Squares (DOLS) to analyze the pass-through effects, following Rangasamy (2011). Using a fully efficient OLS-based approach for estimating and assessing long-run cointegrating relationships, this method provides an asymptotically unbiased estimator (Stock & Watson, 1993) by handling the issues of endogeneity and autocorrelation. The pass-through effect between food and non-food price indices was examined using equations 5 and 6:

$$cnfpi_t - cnfpi_{t-k} = \alpha_1 + \beta_1(cpi_{t-k} - cnfpi_{t-k}) + \varepsilon_{it} \quad \ldots(5)$$

$$cfpi_t - cfpi_{t-k} = \alpha_2 + \beta_2(cpi_{t-k} - cfpi_{t-k}) + \varepsilon_{2t} \quad \ldots(6)$$

where, $cnfpi_t$ denotes non-food inflation in period t, $cfpi_t$ represents food price inflation in period t, and *cpi* denotes overall inflation in period t, and *k* is the number of lags. $cpi_{t-k} - cnfpi_{t-k}$ represents the gap between general and non-food prices in period t, and $cpi_{t-k} - cfpi_{t-k}$ denotes the gap between overall and non-food prices, signifying the impact of non-food on food prices. The positive and significant values of β_1 and β_2 coefficients in equations (5) and (6) signify that changes in nonfood (food) prices are transmitted to the prices of food (nonfood). This confirms the evidence of pass-through effects between the food to nonfood prices and vice-versa. The magnitudes of β_1 and β_2 indicate the extent of pass-through.

V

RESULTS AND DISCUSSIONS

Before applying the ARDL model, unit root tests, i.e., the Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) tests, were employed to check the stationarity of all variables at the level and first difference, including the constant and time trend (Table 2). The results show that all variables are integrated at either I(0) or I(1), but not at I(2), which indicates the suitability of the ARDL model to analyze the relationship between variables in both the short and long run and the NARDL approach to examine the asymmetric effects of the determinant variables on food prices.

We employed the ARDL bounds test developed by Pesaran and Shin (2001) to test for cointegration between the variables included in the study. The results are shown in Table 3. The computed F-statistics and t-statistics are significant at the 1% level, which confirms that the null hypothesis of no cointegration can be rejected. A long-run relationship exists between the dependent food prices (food inflation) and their determinants. The magnitude and direction of the long-run coefficients, short-run dynamics, and other post-diagnostic estimates of the ARDL model are reported in Table 4.

TABLE 2. UNIT ROOT TESTS FOR STATIONARITY

Variables	At Level I(0)			At First Difference I(1)		
	No c/t	C	C/T	No c/t	C	C/T
			ADF Test			
l_cfpi	2.783***	-1.302	-3.324*	-6.265***	-7.099***	-7.115***
l_m_3	4.255***	-0.995	-1.662	-6.640***	-8.011***	-8.006***
l_nagrtrd	0.136	-2.277	-2.371	-6.462***	-6.439***	-6.405***
l_wager	2.645***	-2.930**	-1.580	-6.009***	-6.626***	-7.155***
l_aggdp	0.248	-0.781	-0.800	-8.911***	-8.880***	-8.842***
l_crude	-0.639	-2.366	-2.565	-9.528***	-9.517***	-9.514***
l_input	1.629	-0.378	-1.207	-6.033***	-6.265***	-6.272***
l_wfcpi	-0.199	2.502	2.021	4.139***	3.453**	1.346
l_reer	0.118	-1.966	-3.214*	-8.382***	-8.358***	-8.346***
wacr	-0.527	-1.296	-1.410	-7.071***	-7.048***	-7.017***
l_cpi	5.728***	-3.137**	-4.008***	-2.257**	-5.221***	-5.810***
l_cnfpi	4.814***	-1.786	-3.229*	-4.374***	-6.627***	-6.779***
			PP Test			
l_cfpi	3.295***	-1.303	-2.995	-10.173***	-10.765***	-10.727***
l_m_3	5.274***	-1.212	-1.624	-8.980***	-10.435***	-10.436***
l_nagrtrd	0.063	-4.616***	-4.590***	-16.488***	-16.423***	-16.340***
l_wager	2.911***	-3.002**	-1.607	-9.555***	-10.050***	-10.393***
l_aggdp	-0.137	-3.172**	-3.230*	-9.213***	-9.133***	-9.048***
l_crude	-0.621	-2.219	-2.410	-11.384***	-11.362***	-11.346***
l_input	1.712*	-0.161	-1.113	-9.673***	-9.887***	-9.865***
l_wfcpi	3.416***	11.292***	12.525***	-6.367***	-7.766***	-8.990***
l_reer	0.027	-2.180	-3.492**	-11.471***	-11.436***	-11.404***
wacr	-0.320	-1.225	-1.614	-9.834***	-9.802***	-9.773***
l_cpi	13.427***	-2.839*	-2.531	-4.414***	-10.145***	-10.844***
l_cnfpi	7.096***	-1.713	-2.677	-7.189***	-9.446***	-9.492***

Note: ***, ** *and* * *represent significance at the 1%, 5% and 10% levels, respectively. C denotes constant and D denotes trend.*

TABLE 3. ARDL BOUND TEST FOR COINTEGRATION

F-statistics	10.675***
t-statistics	-6.256***

Note: *** *represents significance at the 1% level; critical values for ARDL Bounds Test are F: I(0): 2.65, I(1): 3.97 at the 1% significance level for k-10, t: I(0): -3.43, I(1): -5.54 at the 1% significance level for k-9.*

The ARDL results showed that world food prices have a positive and significant association with domestic food prices (0.21%), indicating that changes in world food prices lead to increases in domestic food prices in the long run. However, in the short run, current world food prices do not significantly influence domestic food prices. Previous studies have also revealed that domestic prices follow trends in the international prices of food commodities (Geda and Tafere, 2011; Gulati and

Saini, 2013; Loening et al., 2009). Similarly, the coefficient on wage rates is positive and significant, indicating that a 1% rise in wage rates increases food prices, on average, by 0.35%. Furthermore, input costs had a positive and significant influence on food prices (0.28%). The results imply that as farm wages and other input costs rise, the cost of producing commodities increases, which in turn leads to higher food prices for consumers. This aligns with the cost-push inflation theory.

TABLE 4. ARDL (3,0,1,0,2,3,1,2,2,0) MODEL RESULTS

Variables (Dependent: l_cfpi)	Short-Run		Variables (Dependent: l_cfpi)	Long-Run	
	Coefficient	Std. Err.		Coefficient	Std. Err.
Δl_cfpi	0.141*	0.073	l_m_3	0.037	0.078
Δl_cfpi-1	0 .110	0.073	l_nagrtrd	0.023*	0.012
Δ l_nagrtrd	-0.011***	0.003	l_wager	0.345***	0.065
Δ l_aggdp	0.016*	0.008	l_aggdp	-0.145***	0.039
Δ l_$aggdp_{-1}$	0.062***	0.010	l_wfcpi	0.212***	0.067
Δ l_wfcpi	0.042	0.244	l_crude	-0.084***	0.020
Δ l_$wfcpi_{-1}$	0.152	0.251	l_input	0.277***	0.070
Δ l_$wfcpi_{-2}$	-0.600**	0.240	l_reer	0.138	0.138
Δ l_crude	0.032***	0.010	wacr	-0.011**	0.023
Δ l_input	0.014	0.065			
Δ l_$input_{-1}$	0.166**	0.062			
Δ l_reer	0.005*	0.067			
Δ l_$reer_{-1}$	0.174**	0.066			
Constant	0 .506	0.331			
ECT	-0.351***	0.056			
R-Square	0.569				
Log-likelihood	495.77				
Model diagnostic test					
				chi^2	Prob > chi^2
Breusch-Godfrey LM test for autocorrelation				0.76	0.857
Breusch-Pagan / Cook-Weisberg test for heteroscedasticity				0.06	0.966
Ramsey RESET test (F(3, 129))				1.95	0.125

*Note: ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.*

The long-run relationship between food prices and net agricultural trade (exports minus imports) is positive and significant (0.02), although the coefficient is small. These results imply that higher exports may reduce the domestic food supply, increasing food prices. By contrast, an increase in agricultural GDP resulting from higher farm productivity leads to a higher domestic food supply. The significant negative coefficient (-0.15) for agri GDP indicates that higher supplies exert downward pressure on food commodity prices in the long run. Aurangzeb and Haq (2012) and Tien (2022) reported that increases in agricultural GDP reduce food price inflation in Pakistan and Vietnam, respectively.

The call money rate, short-term interest rate, significantly negatively influences food inflation, as indicated by the negative and significant coefficient for wacr (-0.01). An increase in interest rates is often part of monetary policy to reduce food demand, which can ultimately lower prices and help combat inflation (Aurangzeb & Haq, 2012). However, it is surprising that crude oil prices have a negative effect on food inflation in the long run, as higher energy prices generally increase production and transportation costs (Ibrahim, 2015). Furthermore, the findings show that an increase in food prices in the previous month has a significant positive impact on current food inflation (0.14%) in the short term. The results highlight the significance of inflation inertia and the ongoing food price movements.

The coefficient of the error correction term (ECT) in the ARDL model is negative and statistically significant (-35.10%), which confirms that food prices converge to a long-run equilibrium. Though food price inflation may deviate from equilibrium in the short run because of shocks to the determinants. Post-diagnostic estimates of the Breusch-Godfrey, Breusch-Pagan, and Ramsey RESET tests indicate that there is no serial correlation in the ARDL model and that the residuals are homoscedastic and normally distributed.

5.1 Asymmetric Response of Food Price to its Determinants

The ARDL model assumes that the parameters are linear (symmetric) and inelastic in response to changes in their determinants. It does not consider the nonlinear (asymmetric) adjustment process (Chen *et al.*, 2020; Demeke and Tenaw, 2021). Therefore, we investigated whether food prices respond asymmetrically to their determinants using the NARDL approach developed by Shin et al. (2014) to provide consistent and robust estimates. Moreover, before estimating the NARDL model, we examined cointegration between food prices and their determinants using the NARDL bound F- and t-statistics. The results show significant cointegration among the variables at the 1% significance level (Table 5), a necessary condition for employing the NARDL approach.

Table 5 presents the results of the asymmetric adjustment responses of food prices to their determinants. The results of the asymmetric test (Wald statistics) reveal the significant asymmetric effects of net agri trade, wage rates, and exchange rates on food inflation in the long run and of agricultural GDP in the short run. However, call money rates have asymmetric effects in both the long and short run. The results suggest that the coefficient of the positive partial sum of net agricultural trade is significant, implying that an increase in net agricultural trade asymmetrically affects food prices. The long-run coefficient for the positive change in net agricultural trade is 0.042, indicating that a 1% increase in net agricultural trade, either an increase in exports or a decrease in imports, raises food prices by 0.04%. An increase in exports or a decrease in imports of agricultural commodities reduces the domestic food supply, leading to higher food prices.

TABLE 5. NARDL RESULTS SHOWING ASYMMETRIC DYNAMICS IN FOOD PRICES AND DETERMINANTS

Exog. var.	Long-run effect [+]			Long-run effect [-]		
	coef.	F-stat	P>F |	coef.	F-stat	P>F
l_m3	0.212	0.172	0.679	0.784	2.524	0.115
l_nagrtrd	0.042	5.794	0.018	-0.014	0.777	0.380
l_wager	-0.154	0.381	0.538	-1.197	5.729	0.019
l_aggdp	-0.158	9.799	0.002	0.041	0.299	0.585
l_wfcpi	0.102	1.039	0.311	2.745	0.898	0.346
l_crude	-0.078	2.701	0.103	-0.028	0.492	0.485
l_input	0.271	2.317	0.13	-0.150	0.325	0.569
l_reer	0.989	7.000	0.009	-0.243	1.212	0.274
wacr	0.008	0.398	0.529	0.061	11.790	0.001
Test for long run and short run asymmetry						
	Long-run asymmetry			Short-run asymmetry		
	F-stat		P>F	F-stat		P>F
l_m3	1.093		0.298	0.903		0.344
l_nagrtrd	3.784		0.055	0.261		0.610
l_wager	6.348		0.013	0.006		0.935
l_aggdp	1.332		0.251	10.54		0.002
l_wfcpi	0.938		0.335	0.388		0.534
l_crude	3.367		0.070	0.049		0.825
l_input	0.104		0.748	0.173		0.678
l_reer	3.344		0.070	2.336		0.130
wacr	8.737		0.004	5.399		0.022
Cointegration Test Statistics						
t-BDM			-5.847^{***}			
F_PSS			6.080^{***}			
Model diagnostic test			Stat	p-value		
Portmanteau test up to lag 40 (Chi^2)			50.69	0.1198		
Breusch/Pagan heteroscedasticity test (chi^2)			0.225	0.6353		
Ramsey RESET Test (F)			1.902	0.1203		

Note: ***, **, *and* * *represent significance at the 1%, 5%, and 10% levels, respectively.*

Similarly, for agricultural GDP, the coefficient on the positive partial sum is negative and significant; thus, food prices are adjusted asymmetrically in response to increases in agricultural GDP. The positive long-run effect coefficient is -0.158, implying that a 1% increase in agricultural GDP decreases food prices by 0.15%. This is because higher agricultural GDP indicates greater production of food commodities, increasing domestic supply and thereby moderating food prices. Earlier studies have also reported that a higher food supply reduces food inflation (Bandara, 2011; Bashir *et al.*, 2012; Bhat and Laskar, 2016).

The coefficient of the negative partial sum of the wage rate is negative (-1.197) and significant, implying that a reduction in farm wages has a stronger impact on food prices than wage increases. This asymmetry may reflect structural rigidities in agricultural labour markets and the cost structure of food production. When wages decline, production costs fall immediately, potentially increasing supply and exerting downward pressure on food prices (Lamm, 1979; Sonna et al., 2014). At the same time, a lower wage rate negatively impacts the purchasing power of labour class, which leads to a deceleration in food demand and a decline in food inflation (Samal et al., 2022). In contrast, wage increases may not fully translate into higher food prices because farmers often absorb part of the increased labour costs due to market competition or limited pricing power. Therefore, the asymmetric wage response highlights the role of labour market dynamics and imperfect price transmission in the agricultural sector.

The significant coefficient of the negative partial sum of the call money rate confers the asymmetric effect of interest rate on food price inflation, which suggests that if the call money rate decreases by 1%, food prices increase by 0.06%. This result implies that a decrease in the interest rate discourages bank savings, that may lead to an increase in consumer demand (Hordijk *et al*., 2020), resulting in pressure on food prices. Thus, demand-pull inflation contributes to rising price pressure on food commodities (Friedman and Schwartz, 2008). Qayyum and Sultana (2018) and Bhattacharya and Jain (2020) also reported that unexpected monetary tightening is positively related to food price inflation in emerging economies. Furthermore, Orphanides and Solow (1990) find that differences in the long-run growth of the money supply are reflected in different inflation rates.

The results also confirm the asymmetric effect of a change in the foreign exchange rate on food prices, as the positive effect coefficient is significant. The results further suggest that a weaker domestic currency makes food commodity exports more profitable and raises the cost of imported agricultural inputs, which may lead to a supply shortage in the domestic market, exerting upward pressure on food prices (Hoang *et al*., 2020; Iddrisu and Alagidede, 2020). Given India's growing role in global agricultural trade, exchange rate fluctuations can significantly influence domestic food markets.

The lower part of Table 5 presents the results of the model diagnostic tests, including the Durbin-Watson, Breusch-Pagan, Jarque-Bera, and Ramsey RESET tests. The Breusch-Pagan test indicates no heteroscedasticity in the data. Furthermore, the results suggest that autocorrelation is not a significant issue and that the F-value from the Ramsey Reset test indicates a reliable relationship between the dependent and independent variables. Additionally, the plots of recursive cumulative sum (CUSUM) and CUSUM SQURE statistics are within critical bounds, confirming the stability of the model parameters (Figure 3). If the CUSUM plot is within the critical boundaries, it indicates that the model is stable. However, if it surpasses the critical bounds, it shows potential instability and must be addressed (van Krimpen-Stoop *et al*., 2000).

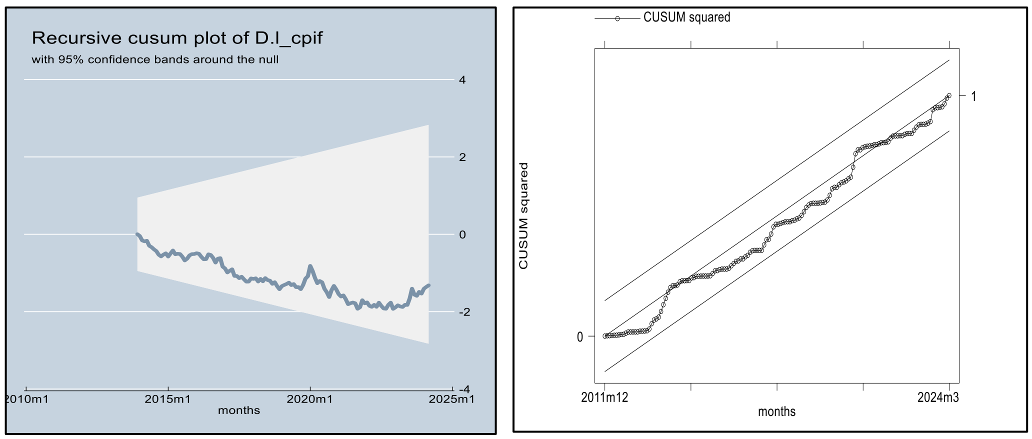

FIGURE 3. MODEL STABILITY TEST USING CUSUM AND CUSUM SQUARE TESTS

Finally, the plot of the dynamic multiplier effects further provides evidence of the asymmetric dynamic relationship between shocks and food price determinants (Figure 4). The results provide insight into the dynamic relationship and help quantify the duration and magnitude of the effects. The dynamic multiplier graph within the 95% confidence interval, with positive and negative effects, reveals an asymmetric relationship between food prices and the determining factors (Shin *et al*., 2014). The graphs strengthen the reliability of the NARDL model, confirm its stability, and effectively capture the dynamic responses over time. This association confirms the model's robustness in producing accurate results, thereby augmenting confidence in using NARDL for the analysis.

5.2 Pass-Through Effect Between Food and Non-Food Prices

Table 6 presents the results of the pass-through effect from nonfood prices to food prices (and vice versa). The results show that the pass-through coefficients of non-food prices to food prices are positive and significant, increasing in magnitude over the lag periods. For example, a 1% change in non-food prices in the first-quarter lag leads to a 0.36% increase in food prices, which further increases to 0.71% and 0.80% in the second- and third-quarter lags, respectively.

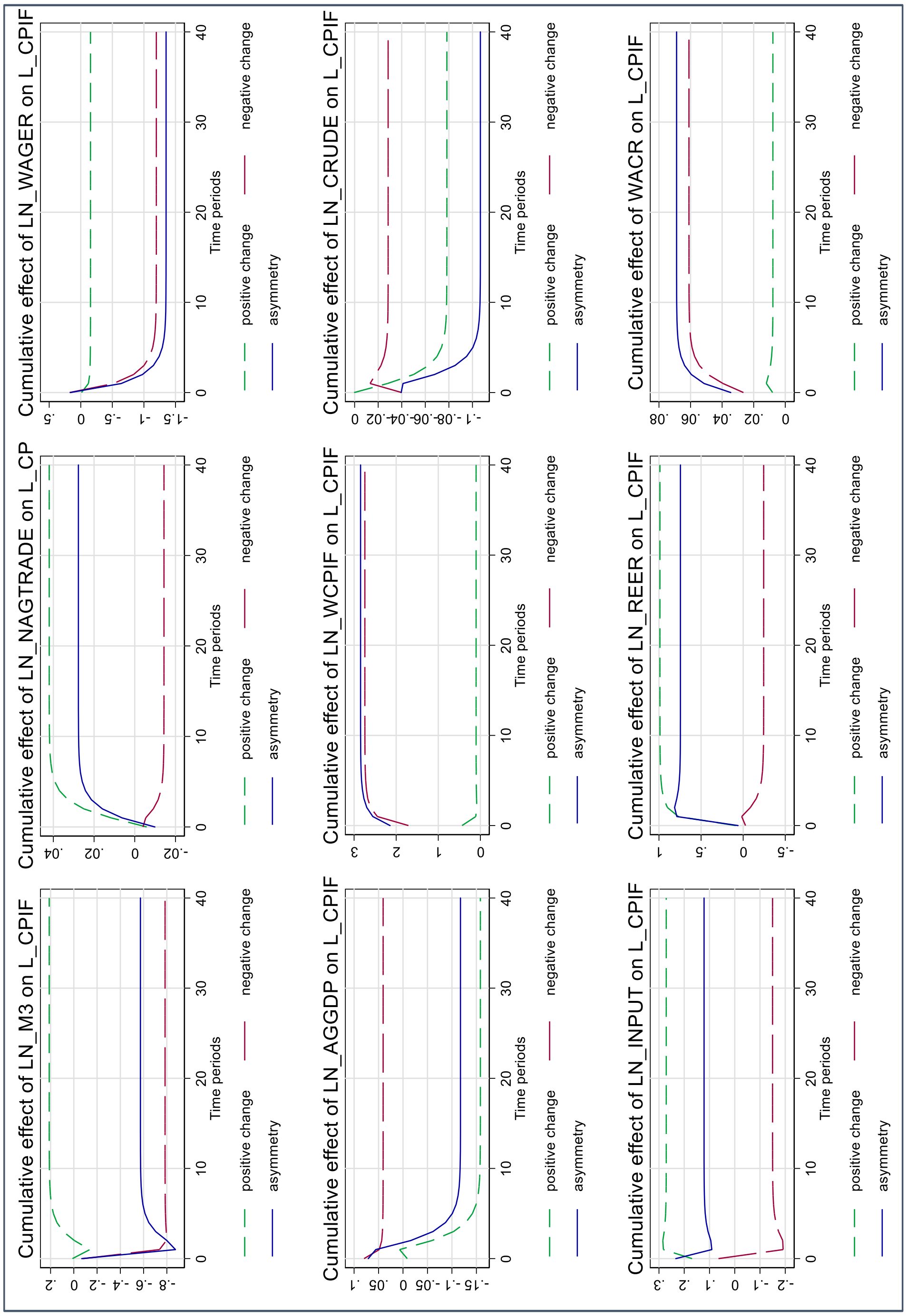

FIGURE 4. DYNAMIC MULTIPLIER EFFECTS OF DETERMINANTS ON FOOD PRICES

These results reveal that non-food price shocks have a strong pass-through effect on food prices. The rising cost in non-food sectors, such as energy, transportation, and manufacturing, can directly influence food prices through production, processing, and distribution costs. However, there was no significant pass-through price effect from food to non-food commodities. Furthermore, to test a stable long-run relationship between nonfood and food inflation, we applied Hansen's Parameter Instability (HPI) test (Hansen, 1992). The results indicate the existence of stable cointegration. Hence, considering price movements in both the food and nonfood sectors is required to control inflationary pressures (Demeke and Tenaw, 2021; Misati and Munene, 2015). Furthermore, it is crucial to understand the two-way connections between food and nonfood price shocks to achieve price stability by reducing pass-through effects (Rangasamy, 2011).

TABLE 6. PASS-THROUGH EFFECT BETWEEN FOOD AND NON-FOOD PRICES

Pass-through effects	Lags	Slope Coefficient	Constant	Adjusted-R^2	HPI
From non-food to food inflation	Lag3	0.363***	0.020	0.523	0.008 (>0.2)
	Lag6	0.717***	0.039	0.421	0.004 (>0.2)
	Lag9	0.808**	0.055	0.361	0.004 (>0.2)
	Lag12	1.146***	0.075	0.331	0.003 (>0.2)
From food to non-food inflation	Lag (-3)	-0.045	0.015	-0.011	0.0042 (>0.2)
	Lag (-6)	-0.100	0.030	0.011	0.0037 (>0.2)
	Lag (-9)	-0.218	0.044	0.004	0.0041 (>0.2)
	Lag (-12)	-0.257	0.058	0.008	0.0038 (>0.2)

*Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Automatic lags were selected based on the AIC. The null hypothesis of HPI is that series are cointegrated against the null of no cointegration, and the results support the existence of cointegration (stable long-run relationship); HPI refers to Hansen's Parameter Instability, and the values reported in parentheses represent the statistical significance level.*

VI

CONCLUSIONS AND POLICY IMPLICATIONS

Food prices are a major concern in low- and middle-income countries, where households allocate most of their income to food. Food inflation poses significant challenges for the country, not only in maintaining a medium-term retail inflation target but also in improving the well-being of many households living below the poverty line. Multifaceted factors, such as supply, demand, costs, and international prices, may drive food inflation. Furthermore, these factors may have symmetrical and asymmetrical effects on food prices. Therefore, understanding the factors driving food inflation and their impact is vital for policymakers to keep it within target limits. This study examines the potential determinants of food inflation and their symmetric or asymmetric effects on food prices using the ARDL and NARDL econometric frameworks. We also examined the passthrough effects between non-food to food price indices, and vice versa.

The results show that net agri trade, wage rates, world prices, and input costs have positive and statistically significant long-run effects on food prices. In contrast, GDP and interest rates negatively and statistically significantly affect food prices. Furthermore, the NARDL estimates show asymmetric impacts of net agri trade, wage rates, exchange rates, and weighted average call money rates on food inflation, implying that positive and negative shocks to these factors affect food prices differently. Furthermore, the dynamic ordinary least squares (DOLS) results show a significant unidirectional price pass-through effect from nonfood to food commodities. Overall, the results indicated that food inflation is driven by a combination of global market forces, domestic supply, and macroeconomic factors.

The findings of this study have several policy implications for managing food inflation in India. The asymmetric responses of food prices to macroeconomic shocks suggest the need for flexible and forward-looking policy interventions. Since wage shocks and exchange rate movements exert strong asymmetric effects, labour market dynamics and exchange rate stability should be closely monitored. Further, increasing domestic food supply through improved access to institutional credit, investment in agricultural research, and strengthening value chain infrastructure can also help moderate food price pressures. The evidence of pass-through from non-food to food prices indicates that rising input costs, such as fuel, transportation, and fertilizers, can indirectly contribute to food inflation, highlighting the importance of coordination between fiscal authorities and the Reserve Bank of India in maintaining price stability. Improving buffer stock management and timely market interventions through the Food Corporation of India can help stabilize prices of key staples. Additionally, calibrating Minimum Support Prices in line with productivity improvements and market conditions may help moderate cost-push pressures on food prices. Strengthening agricultural supply chains and market integration can further reduce price volatility and improve the transmission of productivity gains to consumers.

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