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INDIRA GANDHI INSTITUTE OF DEVELOPMENT RESEARCH

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ABSTRACT

Food price shocks are often treated as transitory and largely irrelevant for underlying inflation. In emerging economies, where food has a large weight, such shocks may be more persistent and broader in their effects. Using monthly CPI data for India from 2012 to 2025, this paper examines how inflation transmits across horizons from food to headline and core inflation, and whether food shocks affect core inflation directly or through headline inflation. Three findings emerge. First, food inflation leads headline inflation at medium- to long-run horizons, indicating that food price shocks are not purely short-lived. Second, headline inflation leads core inflation at longer horizons, consistent with second-round effects. Third, food and core inflation co-move at longer horizons. However, the predictive role of food inflation weakens for the exclusion-based core measure once controls are included, but persists for some statistical core measures. These results point to a sequential, horizon-dependent transmission mechanism and highlight the policy relevance of persistent food shocks.

Keywords: Inflation Dynamics; Food Inflation; Headline Inflation; Core Inflation; Emerging Economies

JEL Code: E31, E52, C32

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Food price shocks are often treated as transitory and largely irrelevant for underlying inflation. In emerging economies, where food has a large weight, such shocks may be more persistent and broader in their effects. Using monthly CPI data for India from 2012 to 2025, this paper examines how inflation transmits across horizons from food to headline and core inflation, and whether food shocks affect core inflation directly or through headline inflation. Three findings emerge. First, food inflation leads headline inflation at medium- to long-run horizons, indicating that food price shocks are not purely short-lived. Second, headline inflation leads core inflation at longer horizons, consistent with second-round effects. Third, food and core inflation co-move at longer horizons. However, the predictive role of food inflation weakens for the exclusion-based core measure once controls are included, but persists for some statistical core measures. These results point to a sequential, horizon-dependent transmission mechanism and highlight the policy relevance of persistent food shocks.

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[*] The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the Indira Gandhi Institute of Development Research.

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1 Introduction

Inflation dynamics in emerging market economies such as India pose important challenges for monetary policy. This can be attributed to the prominence of supply-side food price shocks and the large share of food in the consumption basket[1] (Ha et al., 2019). While such shocks lie largely outside the direct control of central banks, they can complicate inflation stabilization under flexible inflation targeting[2] by spilling over into broader inflation. This raises a central policy question: should monetary policy respond to headline inflation, which is significantly influenced by food price shocks, or should core inflation (excluding food and fuel) serve as a better indicator of underlying inflationary pressures (Government of India, 2024)?

The case for targeting core inflation rests on the assumption that food price shocks are transitory. However, when such shocks are persistent, they can generate second-round effects[3] (Anand et al., 2014). In such a setting, a narrow focus on core inflation may understate inflation persistence. This makes it important to understand how inflationary pressures transmit across different components of the price index.

Against this backdrop, the paper asks four questions. Does food inflation lead headline and core inflation, and at which horizons? Does headline inflation transmit to core inflation over medium- to long-run horizons? Does food inflation affect core inflation directly, or through headline inflation? Finally, are these relationships stable over time and robust across alternative measures of core inflation?

The existing literature shows that food inflation influences headline inflation (Cecchetti and Moessner, 2008; Walsh, 2011; Anand et al., 2014; Eichengreen and Gupta, 2024), while the

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[1] Food and Beverages accounted for 45.86% of the Consumer Price Index (CPI) basket under the 2012 base year, declining to 36.75% under the revised 2024 base year in India.

[2] India adopted a flexible inflation targeting framework in 2016, following the recommendations of the Urijit Patel Committee (2013). Under this framework, headline inflation, measured as the year-on-year percentage change in the All-India Consumer Price Index (Combined), serves as the formal policy anchor, with a target of 4% and a tolerance band of ±2 percentage points.

[3] Second-round effects refer to the indirect and persistent propagation of an initial price shock to other prices and wages in the economy. For example, an increase in food prices may raise production costs, inflation expectations, and wage demands, which in turn lead firms to increase prices of non-food goods and services. This embeds the original shock into broader and more persistent inflation.

relationship between headline and core inflation remains mixed and context-dependent (Thornton, 2007; Cecchetti and Moessner, 2008; Liu and Weidner, 2011; Eichengreen and Gupta, 2024).

While these studies establish important linkages, several gaps remain. First, they do not examine how these relationships vary across different horizons or how they evolve over time. From a policy perspective, this distinction is crucial. What matters is not only whether inflation transmits across components, but also the horizons over which such transmission occurs. Transmission at short horizons is of limited concern, whereas transmission at medium- to long-run horizons can embed food price shocks into broader inflation dynamics.

Second, the existing literature does not clearly distinguish whether food inflation affects core inflation directly or operates primarily through headline inflation. Third, approaches that examine average relationships across frequencies, such as Patnaik (2019), do not capture how these linkages change over time. More recent work, such as Giri (2022), uses wavelet methods to study headline–core dynamics but focuses on comovement and not the direction of transmission. Fourth, most studies rely on a single measure of core inflation, raising concerns about the robustness of their findings.

This paper addresses these gaps by combining wavelet-based[4] time–frequency analysis with Toda–Yamamoto causality tests to examine how inflation transmission evolves across horizons and to distinguish between direct and mediated channels. It also assesses robustness across exclusion-based, trimmed-mean, and weighted-median measures of core inflation.

Using monthly CPI data for India (base year 2012) from January 2012 to December 2025, the analysis yields three main findings. First, food inflation leads headline inflation at medium- to long-run horizons, indicating that food price shocks are not purely transitory. Second, headline inflation leads core inflation at longer horizons, consistent with second-round effects. Third, food and core inflation co-move at longer horizons. However, the predictive role of food inflation for core inflation weakens under the exclusion-based core measure once headline inflation and common supply-side

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[4] This study makes use of wavelet coherence and phase differences. Wavelet coherence measures localized correlation between two series simultaneously in the time and frequency domains. Phase differences indicate whether one series systematically leads or follows another, and by how much, at a given frequency band.

shocks are accounted for. In contrast, it remains present for some statistical core measures. This suggests that transmission operates largely through headline inflation.

Taken together, these findings point to a sequential, horizon-dependent pattern. Food inflation feeds into headline inflation. Headline inflation, in turn, feeds into core inflation. These findings make two contributions. First, food price shocks are not purely transitory, as they lead headline inflation at horizons relevant for monetary policy. Second, the effect of food inflation on core inflation operates largely through headline inflation, although some direct effects may also be present.

From a policy perspective, this implies that food shocks cannot be treated as purely transitory. Even when driven by supply factors, they can become embedded in underlying inflation through headline inflation. Ignoring such dynamics risks understating inflationary pressures.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and the construction of the inflation measures. Section 4 presents the empirical framework, combining time–frequency analysis with time-domain causality methods. Section 5 reports the main empirical results. Section 6 discusses the findings and their implications for inflation dynamics and monetary policy. Section 7 concludes.

2 Literature Review

A large literature emphasizes the role of food prices in shaping inflation dynamics, particularly in emerging market economies where they constitute a substantial share of consumption (Soto, 2003; Walsh, 2011; Anand et al., 2014; Mohanty and John, 2015). Country-level evidence from Tanzania, Kenya, and Chile shows that food prices are major drivers of headline inflation (Adam et al., 2012; Durevall and Ndung'u, 2001; Ginn and Pourroy, 2020). Cross-country studies further find that economies with higher food and fuel shares are more vulnerable to persistent inflation following commodity price shocks (Cecchetti and Moessner, 2008; Gelos and Ustyugova, 2017). Similar patterns have also been observed in advanced economies, where food inflation contributed significantly to headline inflation during recent inflation episodes (Zhu and Yu, 2025).

In India, this role is particularly pronounced. Anand et al. (2014) and Anand et al. (2016) show that food inflation is a major source of headline inflation volatility and can sustain inflation in the absence of adequate supply responses. Beyond its direct contribution, food inflation has also been linked to underlying inflation dynamics. Using time-domain models, Eichengreen and Gupta (2024) find that food inflation Granger-causes core inflation and that headline inflation contains predictive information for core inflation. Goyal and Kumar (2025) also document significant pass-through from food to non-food inflation.

Overall, this evidence suggests that food price shocks can propagate beyond their immediate impact and influence broader inflation dynamics. However, the nature of this transmission remains unclear. Existing studies do not show whether these effects persist over horizons relevant for inflation dynamics. They also do not clarify whether food inflation affects core inflation independently or mainly through headline inflation.

A related strand of the literature examines the relationship between headline and core inflation. The central question is whether movements in headline inflation spill over into core inflation or whether core inflation instead drives headline inflation. The evidence is mixed. Some studies find limited pass-through from headline to core inflation (Cecchetti and Moessner, 2008), while others report significant spillovers and argue that headline inflation contains useful information about underlying inflationary pressures (Thornton, 2007). There is also evidence that this relationship is time-varying and state-dependent. For example, Gamber et al. (2015) show that headline inflation shocks affect core inflation primarily during periods of accommodative monetary policy, while Liu and Weidner (2011) and Mehra and Reilly (2009) find that the strength and direction of transmission vary across macroeconomic conditions.

Evidence from India points to similar linkages. Anand et al. (2014) find that core inflation tends to revert to headline inflation. These findings suggest that headline inflation plays an important role in shaping core inflation dynamics.

However, it remains unclear over which horizons these relationships operate. In particular, existing studies do not establish whether headline inflation influences core inflation only in the short run or over longer horizons. This distinction is crucial for monetary policy, since second-round effects require transmission that is both strong and sustained over time.

Approaches that examine relationships across frequencies in the Indian context, such as Patnaik (2019), capture average effects within frequency bands but do not account for how these relationships evolve over time. As a result, existing studies do not jointly capture both the time and frequency dimensions of inflation transmission.

More recent work, such as Giri (2022), applies time–frequency methods to study headline–core dynamics in the US economy. While wavelet coherence captures localized comovement, it does not identify lead–lag relationships. As a result, it cannot establish whether transmission runs from headline to core or vice versa. The underlying mechanism therefore remains unclear.

A common feature of the existing literature is that it relies on a single measure of core inflation to analyse inflation dynamics. However, evidence suggests that the effects of inflation shocks can differ across alternative core measures. For instance, Gamber et al. (2015) show that headline inflation shocks affect exclusion-based core measures more strongly than trimmed-mean measures. This indicates that different core indicators capture distinct aspects of underlying inflation. Findings based on a single core measure may therefore lack robustness.

Taken together, the literature leaves several important gaps. First, existing studies do not account for both time and frequency variation. They therefore do not show how inflation transmission evolves across horizons and over time. Second, it remains unclear which relationships matter for monetary policy. In particular, there is limited evidence on whether transmission is strong enough to generate second-round effects. Third, the channels of transmission are not clearly identified. It is not clear whether food inflation affects core inflation directly or through headline inflation. Fourth, most studies rely on a single measure of core inflation, raising concerns about the robustness of their findings.

This paper addresses these gaps in four ways. First, it combines time–frequency analysis with time-domain causality tests. This allows us to examine how inflation transmission evolves across horizons and over time. Second, the analysis focuses on horizon-specific lead–lag relationships. This helps identify which transmission patterns are relevant for second-round effects. Third, the paper examines the transmission mechanism by distinguishing between direct and indirect channels between food and core inflation. Fourth, the analysis uses alternative measures of core inflation. This allows us to assess whether the results are robust to different definitions of underlying inflation.

Overall, this paper provides a unified framework to analyze inflation transmission in emerging economies like India.

3 Data

3.1 Inflation Measures

This study uses monthly group-level All-India Consumer Price Index (CPI) Combined indices and group-level weights published by the Ministry of Statistics and Programme Implementation (MOSPI) from January 2011[5] to December 2025 for the base year 2012 to construct headline, food, fuel, and core inflation series.

Monthly headline inflation (year-on-year) is computed as:

$$\pi_t^{\text{YoY}} = \left(\frac{\text{CPI}_t - \text{CPI}_{t-12}}{\text{CPI}_{t-12}} \right) \times 100, \tag{1}$$

where CPI_t denotes the All-India CPI (Combined) in month t, and CPI_{t-12} denotes the corresponding value in the previous year.

Food and fuel inflation are computed analogously as year-on-year percentage changes in the All-India ‘Food and beverages’ and ‘Fuel and Light’ CPI Combined indices.

Following Raj et al. (2020) and Reserve Bank of India (2026), exclusion-based core inflation is constructed by removing the ‘Food and beverages’ and ‘Fuel and Light’ groups from the CPI basket. A core CPI index is obtained by netting out the weighted contributions of these groups

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[5] The time series on group-level monthly CPI data for the base year 2012 is available from January 2011 onwards.

from the ‘General Index (All Groups)’ and re-normalising by the combined weight of the remaining components. Specifically, let CPI_t^{H} denote the headline index, CPI_t^{F} the food index, and CPI_t^{Fu} the fuel index. Let w_{F} and w_{Fu} denote the corresponding weights[6]. The core CPI is constructed as:

$$\text{CoreCPI}_t = \frac{\text{CPI}_t^{\text{H}} - w_{\text{F}}\,\text{CPI}_t^{\text{F}} - w_{\text{Fu}}\,\text{CPI}_t^{\text{Fu}}}{1 - w_{\text{F}} - w_{\text{Fu}}}. \tag{2}$$

This construction follows the standard approach of approximating exclusion-based core inflation using available group-level indices and weights.

Year-on-year core inflation is then computed as:

$$\pi_t^{\text{core}} = \left(\frac{\text{CoreCPI}_t - \text{CoreCPI}_{t-12}}{\text{CoreCPI}_{t-12}}\right) \times 100, \tag{3}$$

where CoreCPI_t denotes the core CPI in month t.

We also construct a measure of global food inflation using the year-on-year percentage change in the monthly nominal Food Price Index published by the Food and Agriculture Organization (FAO). This variable is included as a proxy for common external supply shocks in the Toda–Yamamoto specifications.

3.2 Statistical Measures of Core Inflation

In addition to the exclusion-based measure, statistical measures of core inflation are constructed using trimmed-mean and weighted-median estimators. These are based on monthly All-India item-level inflation rates published by MOSPI for the base year 2012 from January 2015 to December 2025.[7]

Inflation-rate data for March–May 2020 and March–June 2021 are missing for all items due to pandemic-related disruptions in price collection. To ensure continuity of the monthly time series,

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[6] Official weights are scaled such that total CPI weights sum to unity.

[7] Items with missing inflation rates in a given month are excluded, resulting in the deletion of 586 observations. The final dataset contains 36,748 observations and retains, on average, 99.85 percent of the total CPI basket weight in each month.

the resulting trimmed-mean and weighted-median inflation series for these periods are completed using linear interpolation.

Let $\pi_{i,t}$ denote the year-on-year inflation rate of item i in month t, and let $w_{i,t}$ denote its normalised expenditure weight, such that:

$$\sum_{i=1}^{N_t} w_{i,t} = 1, \tag{4}$$

where N_t is the number of items available in month t.

Trimmed-mean inflation. Following Bryan and Cecchetti (1994), items are sorted in ascending order of inflation within each month. Using the associated weights, cumulative weights are computed as:

$$C_{(j),t} = \sum_{k=1}^{j} w_{(k),t}, \tag{5}$$

where $\pi_{(j),t}$ denotes the j-th ordered inflation rate.

The 15% trimmed-mean inflation excludes items accounting for the lowest and highest 7.5 percent of cumulative weight, while the 20% trimmed-mean excludes the lowest and highest 10 percent. The trimmed-mean inflation rate is then computed as the weighted average of the remaining observations.

Weighted-median inflation. The weighted-median inflation rate is defined as the inflation rate of the item at which the cumulative weight first reaches 50 percent (Bryan and Pike, 1991; Apel et al., 1999).

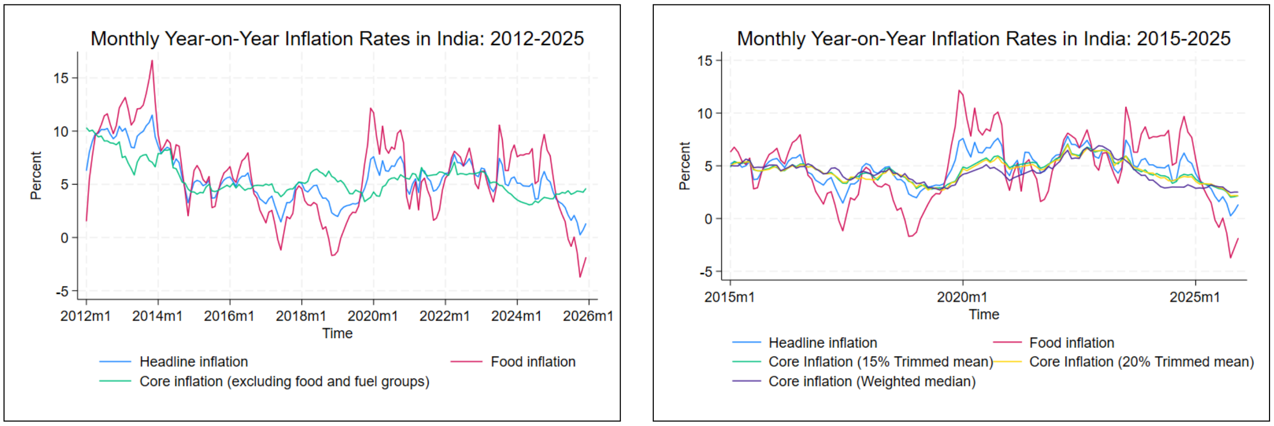
3.3 Descriptive Statistics

Table 1 and Figure 1 summarise the main features of inflation dynamics in India. To account for data availability, results are presented separately for the full sample (2012–2025) and for the period including statistical core measures (2015–2025).

Across both periods, food inflation is substantially more volatile than headline and core inflation. In the full sample, the standard deviation of food inflation is 3.88, compared to 2.31 for headline inflation and 1.58 for exclusion-based core inflation. Statistical core measures exhibit even lower dispersion, with standard deviations close to one, indicating that these measures effectively filter out extreme price movements. Despite these differences in volatility, mean inflation rates are broadly similar across all measures, suggesting that differences arise primarily from fluctuations rather than long-run average levels.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Panel A: Full Sample (2012–2025)				
Headline inflation	5.58	2.31	0.25	11.51
Food inflation	5.78	3.88	-3.72	16.65
Core (excl. F&F)	5.49	1.58	3.07	10.32
Panel B: Statistical Core (2015–2025)				
Headline inflation	4.74	1.60	0.71	7.79
Food inflation	4.70	3.27	-3.72	12.16
TM15	4.56	1.07	2.03	7.07
TM20	4.47	1.04	2.16	6.99
Weighted Median	4.35	1.06	2.46	6.91



(a) Headline, Food, and Core Inflation (2012–2025)

(b) Headline, Food, and Statistical Core Inflation (2015–2025)

Figure 1: Monthly Year-on-Year Inflation Rates in India

Correlation patterns[8] further highlight the role of food inflation in shaping overall price dynam-

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[8] See Appendix Table A1 for details.

ics. Headline inflation is strongly correlated with food inflation in both samples, with correlations above 0.90. It is also strongly correlated with core inflation measures, particularly the trimmed-mean indices. In contrast, correlations between food inflation and core inflation are more moderate, suggesting that the transmission from food to underlying inflation may be indirect or occur with a lag.

Inflation series also exhibit a high degree of persistence[9]. Autoregressive coefficients are generally above 0.90 for headline, food, and core inflation, while statistical core measures display even higher persistence, with coefficients close to 0.98. Unit root tests[10] provide consistent evidence of non-stationarity: Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests fail to reject the null of a unit root, while KPSS tests strongly reject the null of stationarity.

Three key features emerge. First, food inflation is significantly more volatile than headline and core inflation, while statistical core measures display comparatively smooth behaviour. Second, headline inflation is strongly correlated with both food and core inflation, whereas correlations between food and core inflation are weaker, suggesting potentially delayed or indirect transmission. Third, all inflation measures exhibit a high degree of persistence and display non-stationary behaviour.

These stylised facts motivate the use of time–frequency methods to examine horizon-dependent lead–lag relationships between food, headline, and core inflation, complemented by time-domain causality analysis.

4 Methodology

4.1 Wavelet Analysis

To analyze the dynamic linkages between different inflation measures in India, this study employs wavelet analysis. Unlike conventional time-series methods that assume stable relationships over

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[9] See Appendix Table A2 for details.

[10] See Appendix Table A3 for details.

time, wavelets allow the study of comovement across both time and frequency domains (Crowley, 2007; Aguiar-Conraria and Soares, 2014; Rua, 2010).

4.1.1 Wavelet Transform

Wavelet transform decomposes a time series into localized fluctuations at different frequencies and time points. This study applies the Continuous Wavelet Transform (CWT)[11] with a Morlet wavelet, which balances time and frequency resolution and captures both short-lived and persistent dynamics (Rua and Nunes, 2009; Grinsted et al., 2004).

For interpretation, horizons are grouped into short (2–8 months), medium (8–16 months), and long (16–32 months). This classification reflects the Indian context, where food and fuel shocks dominate high-frequency volatility, policy cycles operate over one to two years, and structural factors persist over longer horizons.

4.1.2 Wavelet Coherence and Phase Analysis

To examine comovement across time and frequency, the analysis employs wavelet coherence, which measures localized correlation between two series (see Appendix C). Statistical significance is assessed using Monte Carlo simulations following Grinsted et al. (2004).

While coherence captures the strength of comovement, phase differences provide information on direction (lead–lag relationships). A positive phase indicates that one series leads the other, while a negative phase implies the reverse (see Appendix C). Taken together, this framework allows us to distinguish between contemporaneous comovement and systematic lead–lag relationships across horizons, which is central to identifying transmission mechanisms

The analysis focuses on time–frequency regions with strong and statistically significant coherence ($R^2 \geq 0.70$ at the 5% level). Within these regions, phase differences are used to identify whether one inflation series systematically leads or lags another.

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[11] See Appendix B for mathematical details.

Interpretation of Coherence Plots: Wavelet coherence is visualized using time–frequency plots, where warmer colors indicate stronger comovement. Statistically significant regions are identified using Monte Carlo-based thresholds, and phase differences are represented by arrows indicating the direction of lead–lag relationships. Detailed interpretation is provided in Appendix C.

4.2 Time-Domain Causality Analysis: Toda–Yamamoto Approach

Standard Granger causality tests require stationary variables. By contrast, cointegration-based approaches depend on pretesting, which can be sensitive to specification choices and sample size. Given the strong persistence and non-stationary behaviour of inflation series, this study adopts the Toda–Yamamoto (TY) approach (Toda and Yamamoto, 1995), which permits valid inference irrespective of integration and cointegration properties (Dolado and Lütkepohl, 1996).

Let $\mathbf{y}_t$ denote an $n \times 1$ vector of inflation variables. The augmented VAR is specified as:

$$\mathbf{y}_t = \alpha + \sum_{i=1}^{p} A_i \mathbf{y}_{t-i} + \sum_{j=p+1}^{p+d_{\max}} A_j \mathbf{y}_{t-j} + \varepsilon_t, \tag{6}$$

where p is the optimal lag length and $d_{\max}$ is the maximum order of integration. Unit root tests suggest $d_{\max} = 1$. Granger causality is tested using Wald tests on the first p lags, while the additional lag ensures correct asymptotic inference. Lag length is selected using the Akaike Information Criterion (AIC), with a maximum lag of 12.

Two complementary specifications are considered. First, bivariate VAR models examine pairwise relationships between headline, food, and core inflation. Second, a multivariate VAR includes all three main inflation series along with global food inflation and domestic fuel inflation as controls for common supply-side shocks.

To assess the stability of causal relationships over time, models are estimated for both the full sample and a pre-COVID subsample. Robustness is further examined using alternative statistical measures of core inflation (15% trimmed mean, 20% trimmed mean, and weighted median).

5 Results

5.1 Wavelet Analysis

5.1.1 Food and Headline Inflation

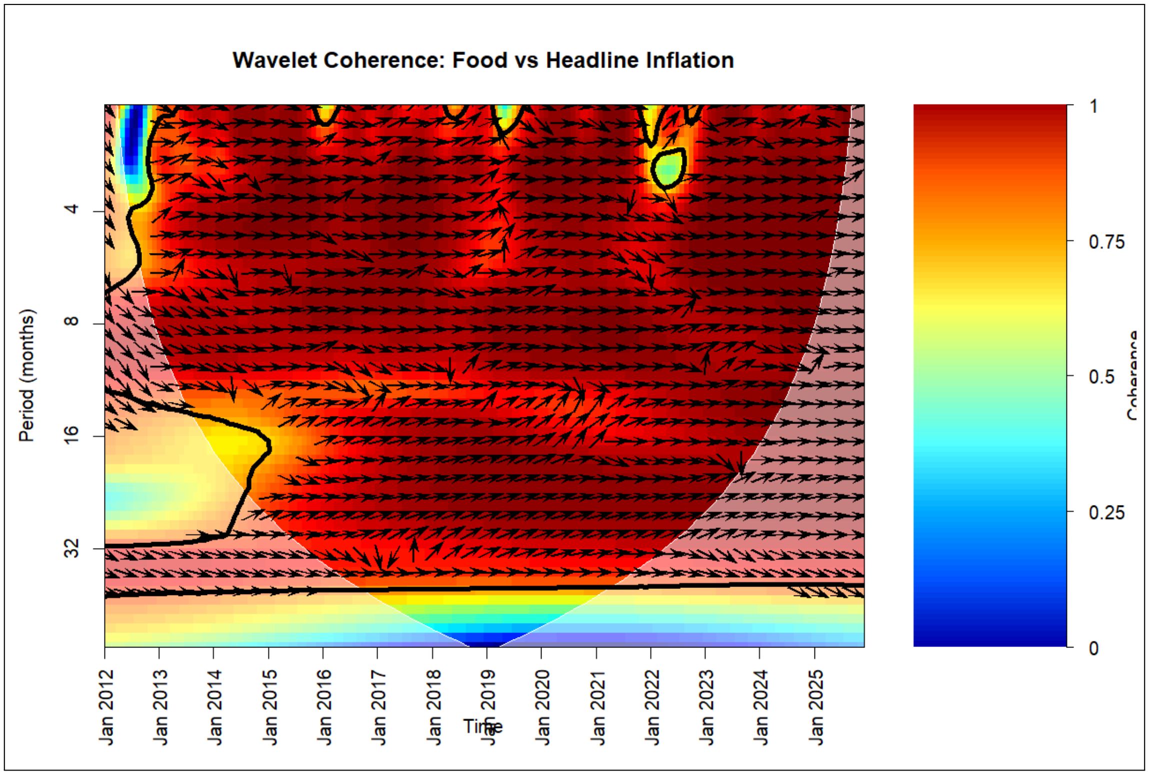

Figure 2: Wavelet Coherence between Food and Headline Inflation

Table 2: Phase-Difference Statistics: Food and Headline Inflation

Sample Period	Horizon (Months)	Mean Phase	Median Phase	Interpretation
Jan 2015–Jan 2023	4–12	0.99	1.03	In-phase; No clear lead–lag
Jan 2016–Jan 2022	12–24	14.23	12.69	In-phase; Food → Headline
Jan 2016–Jan 2019	12–24	12.92	13.17	In-phase; Food → Headline

Notes: Phase difference values are in degrees. Here, Series 1 is Food Inflation and Series 2 is Headline Inflation. Positive phase difference value indicates that food leads headline; negative indicates headline leads food. In-phase relationships typically lie within the interval (–90°, 90°).
*The *Visually Significant Region* is defined by the time and period coordinates shown in the column headers, with a minimum squared coherence (R^2) of 0.70.

Figure 2 presents the wavelet coherence between food and headline inflation, along with phase arrows. Large and statistically significant regions of high coherence appear across both short- and long-run horizons. This points to strong comovement between the two series. Within these regions, arrows are predominantly oriented to the right, confirming positive correlation. They are also slightly tilted upward, suggesting that food inflation tends to lead headline inflation.

This visual evidence is consistent with the phase-difference statistics reported in Table 2. At short- to medium-run horizons (4–12 months), the mean and median phase differences are close to zero. This reveals near-synchronous movements and no systematic lead–lag relationship.

At longer horizons (12–24 months), the mean and median phase differences are positive and lie in the range of 12–14 degrees. This implies that food inflation leads headline inflation by approximately 0.5–1 month.[12] These values correspond to clusters of arrows pointing slightly upward and to the right within high-coherence regions, particularly during 2016–2022.

Importantly, this long-run food-leading pattern appears in both the pre-COVID subsample (2016–2019) and the broader sample (2016–2022). This suggests that the direction of transmission is stable over time.

Overall, the results indicate a clear horizon-dependent pattern. At short horizons, movements in food and headline inflation are largely contemporaneous. At longer horizons, food inflation systematically precedes headline inflation. This suggests that food price movements that persist over time are associated with subsequent increases in headline inflation.

5.1.2 Headline and Core Inflation

Figure 3 displays the wavelet coherence between headline and core inflation (excluding food and fuel groups), along with phase arrows. Coherence appears in distinct episodes across both short and long horizons. This indicates time-varying comovement between the two series.

At short horizons (approximately 2–6 months), significant coherence is observed during Jan 2014–Jan 2016, Mar 2017–Jan 2019, and Jan 2020–Jan 2022. In these regions, arrows point predominantly to the right and slightly downward. This highlights a positive comovement, with a

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[12] A phase difference of ϕ degrees at period P corresponds approximately to $(\phi/360) \times P$ months.

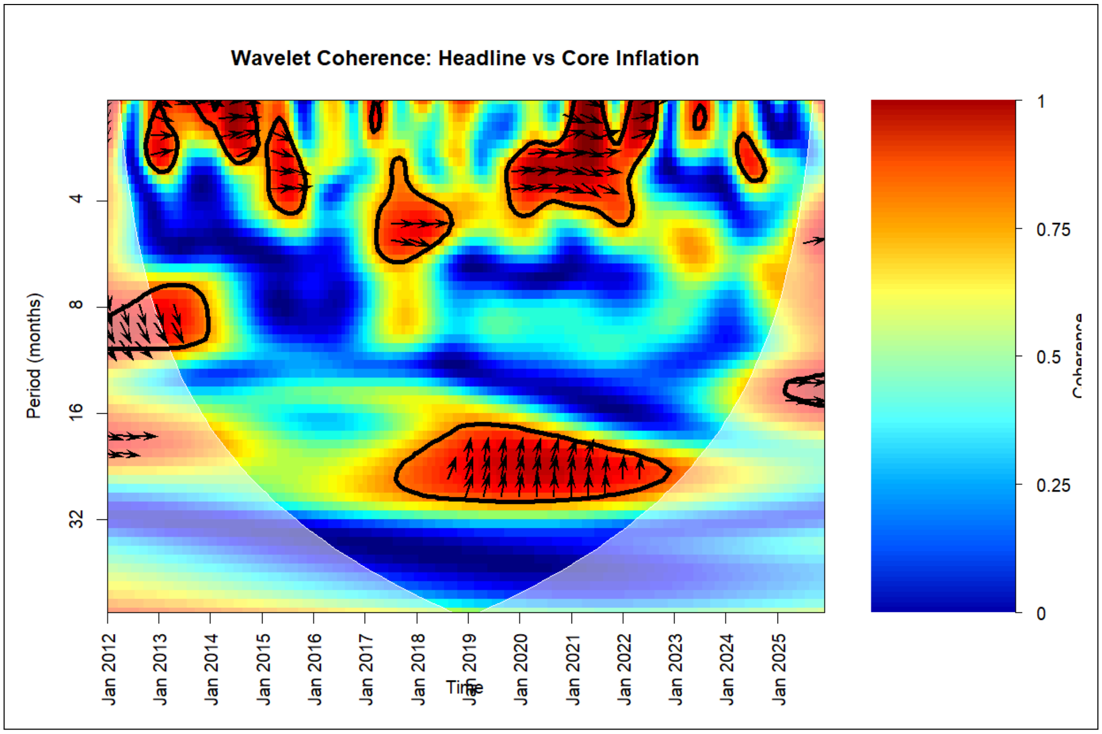

Figure 3: Wavelet Coherence between Headline and Core Inflation

Table 3: Phase-Difference Statistics: Headline and Core Inflation

Sample Period	Horizon (Months)	Mean Phase (deg.)	Median Phase (deg.)	Interpretation
Jan 2014 – Jan 2016	2–6	-1.43	2.24	In-phase; Core → Headline
Mar 2017 – Jan 2019	4–6	-2.95	2.20	In-phase; Core → Headline
Jan 2020 – Jan 2022	2–4	-7.24	-6.25	In-phase; Core → Headline
Jan 2018 – Jan 2020	20–28	74.70	75.99	In-phase; Headline → Core
Jan 2018 – Sep 2022	20–28	80.34	79.91	In-phase; Headline → Core

Notes: Phase difference values are in degrees. Here, Series 1 is Headline Inflation and Series 2 is Core Inflation. Positive phase difference value indicates that headline leads core; negative indicates core leads headline. In-phase relationships typically lie within the interval (–90°, 90°).

*The *Visually Significant Region* is defined by the time and period coordinates shown in the column headers, with a minimum squared coherence (R^2) of 0.70.

mild tendency for core inflation to lead headline inflation. This pattern is confirmed by the phase statistics in Table 3, where mean phase differences are small and slightly negative (between –1 and –7 degrees).

In contrast, a broad region of high coherence appears at longer horizons (20–28 months) during Jan 2018–Sep 2022. Within this band, arrows tilt upward and to the right, indicating that headline inflation leads core inflation. The corresponding phase statistics show large positive mean and median phase differences (approximately 75–80 degrees). This implies that headline inflation leads core inflation by roughly 4–6 months. This long-run leadership is present both in the pre-COVID subsample (2018–2020) and in the extended period (2018–2022), suggesting stability in the direction of transmission.

Overall, the evidence points to a clear horizon-dependent pattern. At short horizons, movements are largely contemporaneous, with a weak tendency for core inflation to lead. At longer horizons, headline inflation systematically precedes core inflation. This pattern is consistent with second-round effects, whereby sustained movements in headline inflation are followed by adjustments in core inflation.

To assess robustness, the wavelet coherence and phase-difference analysis is replicated using alternative statistical measures of core inflation (15% trimmed mean, 20% trimmed mean, and weighted median). The resulting coherence patterns and phase relationships are qualitatively similar. Detailed figures and phase statistics are reported in Appendix C.

5.1.3 Food and Core Inflation

Figure 4 displays the wavelet coherence between food and core inflation (excluding food and fuel groups), along with phase-difference arrows. A dominant and persistent region of high coherence appears at long-run horizons (approximately 20–28 months) during 2018–2022. Within this region, phase arrows are oriented predominantly upward. This points to positive comovement, with food inflation leading core inflation.

This visual evidence is consistent with the phase-difference statistics reported in Table 4. Mean

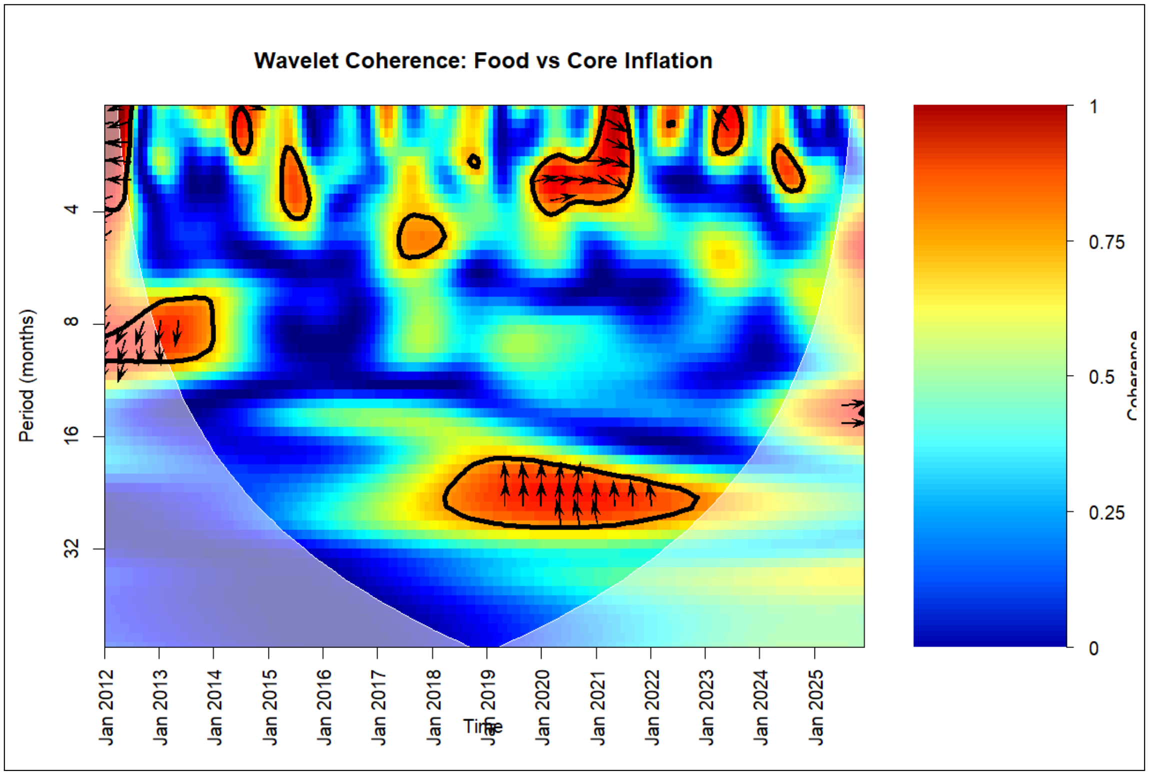

Figure 4: Wavelet Coherence between Food and Core Inflation

Table 4: Phase-Difference Statistics: Food and Core Inflation

Sample Period	Horizon (Months)	Mean Phase (deg.)	Median Phase (deg.)	Interpretation
Jan 2017 – Sep 2018	4–6	-1.41	-1.83	No clear lead–lag
Jan 2020 – Jan 2022	2–4	-12.34	-14.03	Core → Food
Mar 2018 – Jan 2020	20–28	90.43	90.53	Food → Core
Mar 2018 – Sep 2022	20–28	93.92	93.44	Food → Core

Notes: Phase difference values are in degrees. Here, Series 1 is Food Inflation and Series 2 is Core Inflation. Positive phase difference value indicates that food leads core; negative indicates core leads food. In-phase relationships typically lie within the interval (−90°, 90°).

*The *Visually Significant Region* is defined by the time and period coordinates shown in the column headers, with a minimum squared coherence (R^2) of 0.70.

and median phase angles are close to 90° for the periods March 2018–January 2020 and March 2018–September 2022. This implies that movements in food inflation precede those in core inflation by approximately 5–7 months at these horizons.

At shorter horizons, smaller and intermittent pockets of significant coherence appear around 2–4 months during 2020–2022. In these regions, phase arrows tend to point slightly downward. This indicates a weak tendency for core inflation to lead food inflation. This pattern is consistent with the negative mean phase angle of about $-12°$.

Overall, the evidence reveals a clear horizon-dependent pattern. In the short run, core inflation weakly tends to lead food inflation. At longer horizons, food inflation persistently precedes core inflation. This pattern is consistent with gradual transmission from food price movements to underlying inflation.

To assess robustness, the wavelet coherence and phase-difference analysis is replicated using alternative statistical measures of core inflation (15% trimmed mean, 20% trimmed mean, and weighted median). The resulting coherence patterns and phase relationships are qualitatively similar. Detailed figures and phase statistics are reported in Appendix C.

5.2 Time-Domain Causality Analysis: Toda–Yamamoto Approach

Table 5: Bivariate Toda–Yamamoto Granger Causality Tests (Selected Directions)

		Full Sample (2012–2025)			Pre-COVID (2012–2020)		
Dependent	Independent	χ^2	Lag	p-value	χ^2	Lag	p-value
Headline	Food	9.50	3	0.023	27.48	10	0.002
Core	Headline	29.60	11	0.002	43.15	10	0.000
Core	Food	24.31	11	0.012	39.60	10	0.000

Notes: Entries report modified Wald (χ^2) statistics from Toda–Yamamoto augmented VAR models estimated in levels. Lag denotes the number of restrictions tested (p), selected using the Akaike Information Criterion (AIC). The VAR is estimated with $p + d_{max}$ lags. The null hypothesis is that the independent variable does not Granger-cause the dependent variable.

Table 5 reports bivariate Toda–Yamamoto Granger causality tests for headline, food, and core inflation for both the full sample and the pre-COVID period.

In the full sample, food inflation Granger-causes headline inflation, indicating that food price movements contain predictive information for headline inflation. Headline inflation, in turn, Granger-causes core inflation, consistent with the transmission of price pressures into underlying inflation. In addition, food inflation also appears to Granger-cause core inflation in the bivariate setting.

For the pre-COVID subsample, these relationships become stronger. Food inflation continues to predict headline inflation, and headline inflation transmits to core inflation. The predictive relationship from food to core inflation is also reinforced in this period.

Taken together, the bivariate results highlight the important role of food inflation in shaping inflation dynamics in India. Food inflation not only predicts headline inflation but also predicts core inflation in the bivariate setting. These findings complement the wavelet evidence by confirming that the observed comovement is associated with predictive relationships in the time domain.

Robustness checks using alternative statistical measures of core inflation (trimmed mean and weighted median), reported in Appendix D, yield broadly similar patterns. In particular, food inflation continues to predict statistical core measures. However, the strength of the relationship varies across specifications and is stronger in the pre-COVID sample.

5.2.1 Trivariate Causality Tests

Table 6: Toda–Yamamoto Granger Causality: Trivariate VAR with Controls (Selected Directions)

		Full Sample (2012–2025)			Pre-COVID (2012–2020)		
Dependent	Independent	χ^2	Lag	p-value	χ^2	Lag	p-value
Core	Headline	16.07	11	0.139	35.30	10	0.000
Core	Food	11.74	11	0.384	32.54	10	0.000
Headline	Food	42.20	11	0.000	36.40	10	0.000

Notes: Results are based on Toda–Yamamoto augmented VAR models estimated in levels with headline, food, and core inflation as endogenous variables. Global food inflation and domestic fuel inflation are included as exogenous controls. Lag length (p) is selected using AIC (maximum lag = 12), and the VAR is estimated with $p + d_{max}$ lags. Modified Wald (χ^2) tests are applied to the first p lags. The null hypothesis is that the independent variable does not Granger-cause the dependent variable.

Table 6 reports Toda–Yamamoto Granger causality results from trivariate VAR models that include headline, food, and core inflation as endogenous variables, with global food inflation and domestic fuel inflation as exogenous controls.

In the full sample, food inflation continues to Granger-cause headline inflation, indicating a persistent relationship between these two series even after controlling for common supply-side shocks. In contrast, headline inflation does not Granger-cause core inflation. This suggests that headline inflation does not independently transmit to core inflation once broader cost conditions are accounted for.

A similar pattern emerges in food–core interactions. Food inflation does not Granger-cause core inflation. This contrasts with the bivariate results and suggests that the predictive content of food inflation for core inflation weakens once headline inflation and common supply shocks are explicitly controlled for.

These findings suggest that the influence of food inflation on core inflation operates largely through headline inflation rather than through a direct channel. However, the strength of the direct relationship depends on the measure of core inflation.

For the pre-COVID period, the results differ. Both headline and food inflation Granger-cause core inflation, with stronger statistical significance than in the full sample. This suggests that inflation transmission was more broadly distributed across inflation components prior to the pandemic.

These findings complement the wavelet results. Wavelet analysis shows that food inflation leads headline inflation at medium- to long-run horizons, and that headline inflation leads core inflation. The multivariate causality results indicate that this transmission is largely indirect. Overall, the results support a mediated transmission mechanism from food to headline to core inflation.

Robustness checks using alternative statistical measures of core inflation (trimmed mean and weighted median), reported in Appendix D, broadly support the baseline findings. Food inflation retains predictive power for statistical core measures even after controlling for headline inflation. However, the relative importance of direct and indirect transmission channels varies across specifications.

6 Discussion

This paper combines time–frequency and time-domain approaches to examine the dynamic linkages among food, headline, and core inflation in India. Taken together, the results point to a horizon-dependent transmission mechanism in which food price movements systematically lead headline and core inflation. Pass-through from food inflation to the exclusion-based measure of core inflation is more gradual and operates largely through headline inflation.

A central finding from the wavelet analysis is the presence of persistent long-run comovement between food and headline inflation, with food inflation modestly but systematically leading headline inflation at horizons of roughly 12–24 months. At shorter horizons, fluctuations are largely contemporaneous. This suggests that while transitory food price shocks dissipate quickly, persistent food price movements spill over into headline inflation over time. This pattern is consistent with the large weight of food in the consumption basket and the persistence of food price shocks.

The wavelet evidence also reveals a clear horizon asymmetry in headline–core dynamics. At short horizons, core inflation weakly leads headline inflation. This indicates that underlying inflationary pressures influence near-term movements in headline inflation. At longer horizons (20–28 months), however, headline inflation significantly leads core inflation by several months. This pattern is consistent with second-round effects, whereby sustained increases in overall inflation translate into broader price pressures.

Overall, these results suggest a sequential transmission mechanism at longer horizons: food inflation feeds into headline inflation, which in turn feeds into core inflation.

The relationship between food and core inflation further supports this interpretation. While short-run interactions are weak and sometimes reversed, food inflation significantly leads core inflation over longer periods. This indicates that persistent food price shocks can eventually affect underlying inflation, even if the adjustment is slow.

The time-domain causality results help clarify the mechanism underlying these patterns. In the bivariate Toda–Yamamoto framework, food inflation predicts both headline and core inflation. This suggests that, in reduced-form terms, food inflation appears closely linked to both headline and core inflation.

However, the trivariate results present a more nuanced picture. Once headline inflation and common supply-side shocks are explicitly controlled for, the strength of direct causality from food to core inflation weakens for the exclusion-based core measure. But it remains statistically significant for several statistical core measures. At the same time, headline inflation does not consistently Granger-cause core inflation in the full sample once controls are included.

The contrast between bivariate and trivariate results is informative. While the bivariate relationships capture reduced-form associations, the trivariate framework helps disentangle transmission channels. Overall, the results suggest that the influence of food inflation on the exclusion-based measure of core inflation operates largely through headline inflation. However, a direct channel remains present in some specifications.

The comparison between the pre-COVID and full samples also points to a shift in the structure of inflation transmission. Prior to the pandemic, inflation dynamics were more tightly connected: food inflation Granger-causes both headline and core inflation, and headline inflation Granger-causes core inflation even after controlling for common supply shocks. In the full sample, transmission becomes more asymmetric. Food inflation remains closely linked to headline inflation, but its predictive power for core inflation weakens, particularly for the exclusion-based core measure.

The combined evidence supports the following interpretation. Persistent food price shocks transmit into headline inflation over medium- to long-run horizons. Sustained increases in headline inflation then generate second-round effects that raise core inflation. The pass-through from food to core inflation is primarily indirect and gradual, operating through headline inflation for exclusion-based core measures. However, a direct channel remains present for statistical core measures. This interpretation reconciles the long-run food leadership observed in the wavelet analysis with the weaker direct food-to-core causality in multivariate time-domain tests.

From a policy perspective, these findings underscore the importance of monitoring persistent food price pressures, even when food inflation is excluded from core measures. Central banks may appropriately look through temporary food price spikes. However, sustained food inflation can become embedded in broader inflation dynamics through headline inflation and expectations. Managing persistent food inflation pressures therefore remains relevant for maintaining medium-term price stability under an inflation-targeting framework.

7 Conclusion

This paper provides new evidence on how inflation transmits across food, headline, and core components in India. The analysis highlights how these relationships evolve across horizons and transmission channels.

The results from the time–frequency analysis show clear horizon-dependent patterns. Food inflation systematically leads headline inflation at medium- to long-run horizons. In turn, headline inflation leads core inflation at longer horizons, consistent with second-round effects. The wavelet evidence also reveals strong long-run comovement between food and core inflation.

The time-domain causality results provide further insight into the underlying mechanism. In bivariate settings, food inflation appears to predict both headline and core inflation. However, once headline inflation and common supply-side factors are accounted for, the direct predictive role of food inflation for exclusion-based core inflation weakens. This suggests that transmission from food to core inflation operates largely through headline inflation. At the same time, the persistence of some direct effects for statistical core measures indicates that the strength of this channel depends on how underlying inflation is measured.

Taken together, the evidence suggests a sequential and horizon-dependent transmission process. Food price shocks first influence headline inflation and then feed into core inflation over time. The wavelet results capture these long-run linkages, while the multivariate causality analysis highlights the mediating role of headline inflation.

These findings have important implications for monetary policy. While food price shocks are often viewed as transitory, persistent increases in food prices can generate second-round effects through headline inflation. Ignoring such dynamics may lead to an underestimation of medium-term inflationary pressures. Although monetary policy cannot directly offset supply-driven shocks, it must account for their propagation into broader inflation.

Overall, the results suggest that inflation dynamics in India are structured and interconnected across components and horizons. Core inflation cannot be assessed in isolation from persistent movements in food and headline inflation. Monitoring the persistence of food-driven inflation therefore remains important for maintaining medium-term price stability under an inflation-targeting framework.

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Appendix

A Additional Data and Descriptive Evidence

Table A1: Correlation Matrix

	Headline	Food	Core
Panel A: Full Sample (2012–2025)			
Headline	1.000		
Food	0.920^{**}	1.000	
Core	0.705^{**}	0.383^{**}	1.000
Panel B: Statistical Core (2015–2025)			
Headline	1.000		
Food	0.908^{**}	1.000	
TM15	0.840^{**}	0.613^{**}	
TM20	0.801^{**}	0.576^{**}	
W. Median	0.619^{**}	0.353^{**}	

Table A2: Inflation Persistence: AR(1) Estimates

Variable	AR(1)	Std. Error
Panel A: Full Sample (2012–2025)		
Headline	0.955^{***}	0.026
Food	0.933^{***}	0.030
Core (excl. F&F)	0.941^{***}	0.019
Panel B: Statistical Core Sample (2015–2025)		
Headline	0.907^{***}	0.041
Food	0.915^{***}	0.039
TM15	0.976^{***}	0.026
TM20	0.977^{***}	0.025
Weighted Median	0.975^{***}	0.023

Notes: Each row reports the coefficient from an AR(1) regression of the form $\pi_t = \alpha + \rho\pi_{t-1} + \varepsilon_t$. *** denotes significance at the 1% level.

Table A3: Unit Root Tests

Variable	ADF	PP	KPSS
Panel A: Full Sample (2012–2025)			
Headline	-1.57	-1.87	1.74***
Food	-1.91	-2.79	1.20***
Core (excl. F&F)	-2.47	-3.11**	1.57***
Panel B: Statistical Core Sample (2015–2025)			
Headline	-1.38	-2.44	1.05***
Food	-2.09	-2.56	0.62***
TM15	-1.05	-1.39	1.34***
TM20	-1.10	-1.39	1.32***
Weighted Median	-1.79	-1.68	1.10***

Notes: ADF and PP test the null of a unit root. KPSS tests the null of trend stationarity. Lag length = 12. ** and *** denote significance at the 5% and 1% levels, respectively.

B Wavelet Methodology

This appendix presents the wavelet-based framework used in the paper, including the continuous wavelet transform, wavelet coherence, and phase-difference measures.

B.1 Continuous Wavelet Transform

Wavelet analysis decomposes a time series into time–frequency space using localized basis functions. A wavelet is generated from a mother wavelet $\psi(t)$ through scaling and translation:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right), \tag{7}$$

where τ denotes the time location and s the scale parameter, which is inversely related to frequency (Rua and Nunes, 2009).

The continuous wavelet transform (CWT) of a time series $x(t)$ is defined as:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t)\,\frac{1}{\sqrt{|s|}}\,\psi^*\left(\frac{t-\tau}{s}\right)\,dt, \tag{8}$$

where * denotes the complex conjugate. The CWT captures both the magnitude and phase of fluctuations at different time–frequency combinations.

B.2 Morlet Wavelet

This study employs the Morlet wavelet, defined as:

$$\psi(t) = \pi^{-1/4} \, e^{i\omega_0 t} \, e^{-t^2/2}, \tag{9}$$

where ω_0 governs the trade-off between time and frequency resolution. Following Grinsted et al. (2004), $\omega_0 = 6$, which provides a balanced representation of time and frequency dynamics.

The Morlet wavelet is widely used in applied macroeconomic analysis because it allows a direct mapping between scale and frequency and facilitates phase-difference analysis.

B.3 Wavelet Coherence

Following Torrence and Webster (1999) and Rua and Nunes (2009), the squared wavelet coherence between two series $x(t)$ and $y(t)$ is defined as:

$$R^2(\tau, s) = \frac{\left|S\big(W_{xy}(\tau, s)\big)\right|^2}{S\big(|W_x(\tau, s)|^2\big) \cdot S\big(|W_y(\tau, s)|^2\big)}, \tag{10}$$

where $W_{xy}(\tau, s) = W_x(\tau, s) W_y^*(\tau, s)$ is the cross-wavelet transform and $S(\cdot)$ denotes a smoothing operator in both time and scale.

The coherence measure ranges between 0 and 1, with higher values indicating stronger localized co-movement. Statistical significance is assessed using Monte Carlo simulations following Grinsted et al. (2004).

B.4 Phase Difference

Phase differences capture the lead–lag relationship between two series across time and frequency:

$$\phi_{xy}(\tau, s) = \arg\big(W_x(\tau, s)\big) - \arg\big(W_y(\tau, s)\big), \tag{11}$$

where $\arg(\cdot)$ denotes the phase angle of the complex wavelet transform. Equivalently, this can be expressed in terms of real and imaginary components of the cross-wavelet transform.

Phase angles are interpreted as follows:

- $\phi = 0$: series move together (in phase)
- $0 < \phi < 90°$: x leads y
- $-90° < \phi < 0$: y leads x
- $\phi = \pm 180°$: series move in opposite directions (anti-phase)
- $90° < |\phi| < 180°$: lead–lag with partial opposition in movement

B.5 Interpretation of Coherence Plots

Wavelet coherence is typically presented using time–frequency plots. The horizontal axis denotes time, while the vertical axis represents the period (inverse of frequency). Warmer colors indicate stronger coherence, whereas cooler colors indicate weaker or no co-movement.

Regions of statistically significant coherence, based on Monte Carlo simulations, are outlined by contour lines. Areas outside the cone of influence are affected by edge effects and are not considered reliable.

Phase differences are represented by arrows within significant regions. Arrows pointing to the right indicate in-phase movement, while arrows pointing to the left indicate anti-phase movement. Arrows tilted upward (downward) indicate that the first (second) series leads the other.

B.6 Application in This Study

In the empirical analysis, attention is restricted to regions where wavelet coherence exceeds 0.70 and is statistically significant at the 5% level. Within these regions, phase differences are used to infer lead–lag relationships across horizons.

Since scale is approximately proportional to periodicity for the Morlet wavelet, short-, medium-, and long-run dynamics can be interpreted directly in terms of time horizons. This enables distinguishing between short-lived shocks and persistent transmission mechanisms in inflation dynamics.

The joint use of coherence and phase analysis provides a unified framework to examine how the strength, direction, and persistence of relationships between food, headline, and core inflation evolve over time and across frequencies.

C Wavelet Results with Statistical Core Measures

This appendix reports wavelet coherence and phase-difference results using alternative statistical measures of core inflation—namely the 15% trimmed mean, 20% trimmed mean, and weighted median—to assess the robustness of the main findings. The objective is to examine whether the horizon-dependent transmission patterns documented using the exclusion-based core measure persist across alternative definitions of underlying inflation.

Across all three measures, the qualitative results remain unchanged. Food inflation exhibits systematic leadership over statistical core inflation at medium- to long-run horizons, while headline inflation also leads statistical core inflation over similar horizons. In contrast, short-run interactions are weaker and often characterized by near-synchronous movements.

C.1 Food Inflation and Statistical Core Inflation

Figure A1 shows large and statistically significant coherence regions at medium- to long-run horizons for all three statistical core measures. Within these regions, phase arrows predominantly indicate positive comovement with food inflation leading statistical core inflation.

Table A4 confirms this pattern. Mean phase differences at long horizons range from approximately 40 to 75 degrees, implying that food inflation leads statistical core inflation by roughly

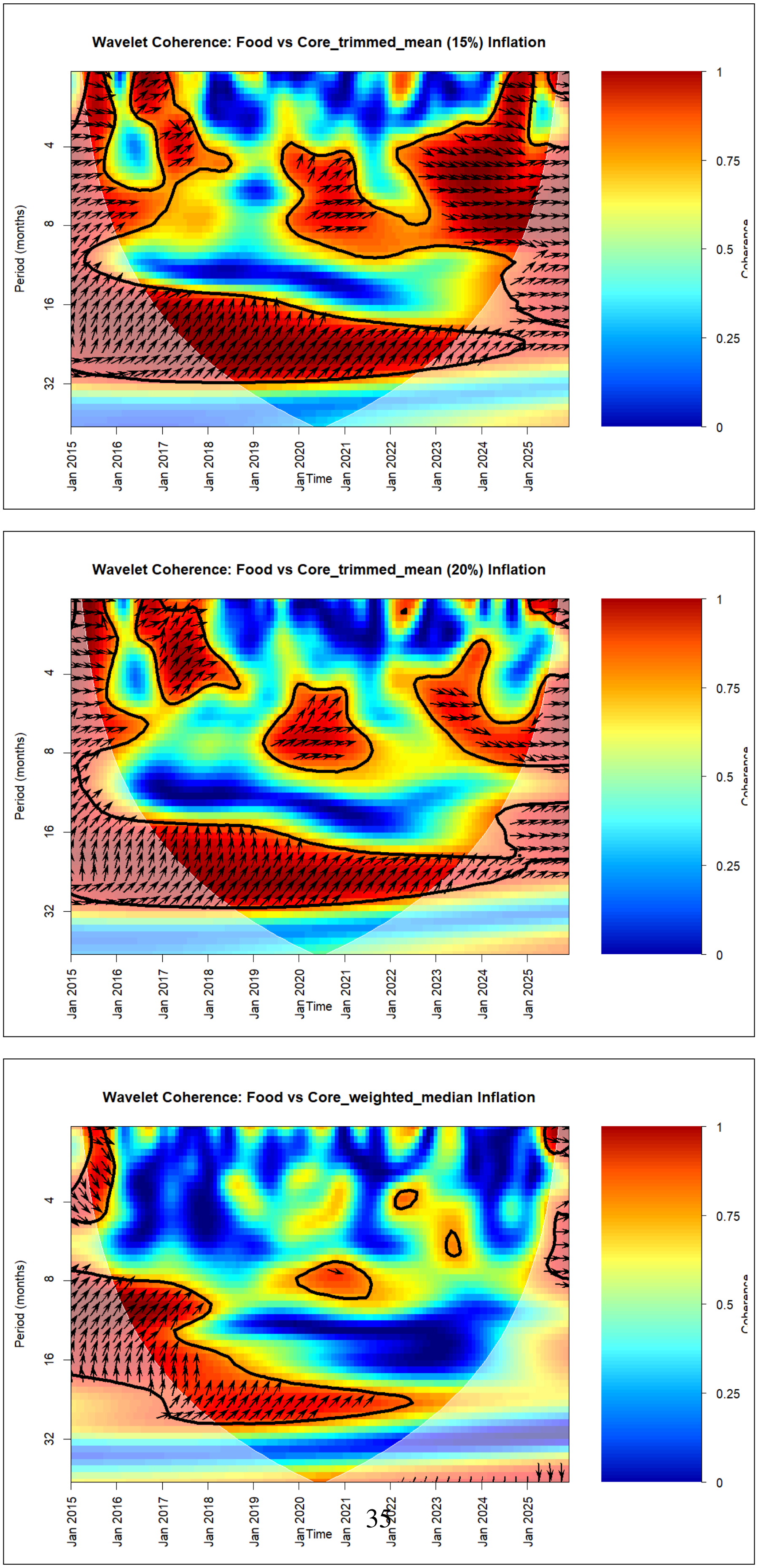

Figure A1: Wavelet Coherence between Food Inflation and Statistical Core Inflation Measures

Table A4: Dominant Long-Run Phase-Difference Results: Food and Statistical Core Inflation

Core Measure	Horizon (Months)	Mean Phase (deg.)	Direction
Trimmed Mean (15%)	20–28	≈ 47–49	Food → Core
Trimmed Mean (20%)	16–28	≈ 50–75	Food → Core
Weighted Median	24–28	≈ 40–42	Food → Core

Notes: Positive phase values indicate that food inflation leads statistical core inflation. Results summarize regions with squared coherence $R^2 \geq 0.70$.

2–5 months, depending on the periodicity. Short-horizon interactions are limited and occasionally display weak contemporaneous or reverse relationships.

Overall, these results reinforce the main-text finding that food price movements precede changes in underlying inflation at medium- to long-run horizons.

C.2 Headline Inflation and Statistical Core Inflation

Table A5: Dominant Long-Run Phase-Difference Results: Headline and Statistical Core Inflation

Core Measure	Horizon (Months)	Mean Phase (deg.)	Direction
Trimmed Mean (15%)	20–28	≈ 34–36	Headline → Core
Trimmed Mean (20%)	20–28	≈ 36–39	Headline → Core
Weighted Median	26–28	≈ 25–31	Headline → Core

Notes: Positive phase values indicate that headline inflation leads statistical core inflation.

Significant coherence between headline inflation and statistical core measures is concentrated at medium- to long-run horizons. Phase patterns in these regions indicate that headline inflation tends to lead statistical core inflation.

The phase statistics in Table A5 show mean phase differences between approximately 25 and 40 degrees, implying a lead of around 2–4 months. This is consistent with the headline-to-core transmission documented in the main text and aligns with the presence of second-round effects.

Taken together, the evidence based on statistical core measures confirms that the transmission mechanism identified in the main analysis is robust to alternative definitions of core inflation. Food inflation leads underlying inflation at medium- to long-run horizons.

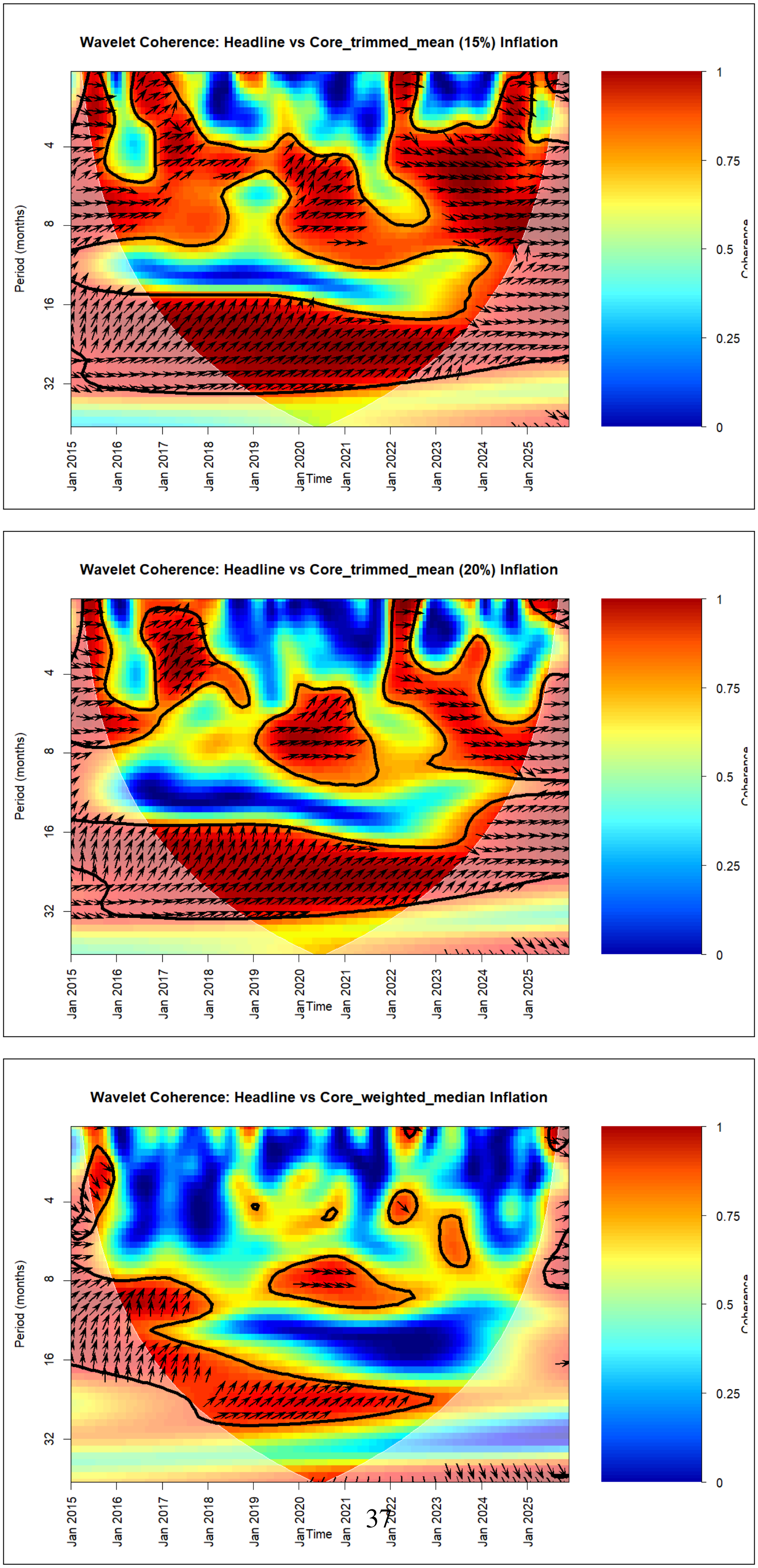

Figure A2: Wavelet Coherence between Headline Inflation and Statistical Core Inflation Measures

D Toda–Yamamoto Causality with Statistical Core Measures

This appendix reports Toda–Yamamoto Granger causality tests using alternative statistical measures of core inflation (15% trimmed mean, 20% trimmed mean, and weighted median) in place of the exclusion-based core measure. The objective is to assess whether the transmission from food to underlying inflation, and the role of headline inflation as an intermediary, are robust to the definition of core inflation.

Both bivariate and multivariate specifications are considered.

Table A6: Bivariate Toda–Yamamoto Causality with Statistical Core Measures

Core Measure	Direction	Lag	χ^2	p-value
Panel A: Full Sample				
Trimmed Mean 15%	Food → Core	6	13.56	0.035
Trimmed Mean 20%	Food → Core	3	7.55	0.056
Weighted Median	Food → Core	11	11.29	0.420
Trimmed Mean 15%	Headline → Core	3	6.02	0.111
Trimmed Mean 20%	Headline → Core	3	6.41	0.093
Weighted Median	Headline → Core	3	1.40	0.707
Panel B: Pre-COVID Sample				
Trimmed Mean 15%	Food → Core	3	10.61	0.014
Trimmed Mean 20%	Food → Core	3	17.69	0.001
Weighted Median	Food → Core	4	20.47	0.000
Trimmed Mean 15%	Headline → Core	3	14.81	0.002
Trimmed Mean 20%	Headline → Core	3	19.09	0.000
Weighted Median	Headline → Core	12	64.51	0.000

The bivariate results for the full sample suggest that food inflation Granger-causes trimmed mean based statistical core inflation, while the relationship is weaker for the weighted median measure. Headline inflation does not systematically predict statistical core inflation in the bivariate setting.

In contrast, for the pre-COVID period, both food and headline inflation Granger-cause statistical core inflation across most measures, indicating stronger transmission into underlying inflation prior to the pandemic.

The trivariate results provide additional insight into the transmission mechanism. In the full sample, both food and headline inflation Granger-cause statistical core inflation, indicating that

Table A7: Trivariate Toda–Yamamoto Causality with Statistical Core Measures

Sample	Core Measure	Direction	Lag	p-value
Full	Trimmed Mean 20%	Food → Core	5	0.001
Full	Trimmed Mean 20%	Headline → Core	5	0.029
Full	Weighted Median	Food → Core	12	0.019
Full	Weighted Median	Headline → Core	12	0.006
Pre-COVID	Trimmed Mean 15%	Food → Core	12	0.000
Pre-COVID	Trimmed Mean 20%	Food → Core	12	0.000
Pre-COVID	Weighted Median	Food → Core	12	0.000

predictive relationships persist even after controlling for common supply-side factors.

In the pre-COVID period, food inflation continues to strongly predict core inflation across all measures.

Overall, the evidence suggests that food inflation retains predictive power for statistical core measures even after controlling for headline inflation and common supply-side factors. At the same time, headline inflation also contributes to explaining movements in core inflation in some specifications, indicating that both direct and indirect channels may be relevant.