Are Food Prices the 'True' Core of India's Inflation?

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The recent experience with the prolonged elevation in food prices in India has motivated our investigation into core-like properties of food inflation, namely volatility, persistence, spillovers and cyclical sensitivity. We find that there are times when some of these properties are satisfied. Hence, wielders of monetary policy need to ascertain the sources and nature of food price shocks, while being mindful of the risks of overreaction to transitory shocks as well as of the dangers of ignoring persistent food price shocks.

Introduction

In the wake of the pandemic – and exacerbated by the war in Ukraine – the intersecting incidence of food price spikes has had an overbearing influence on headline inflation in India. Widely regarded as transient, these shocks appear to have imparted volatility and persistence to food inflation which averaged 6.7 per cent during April 2022 to November 2023. Moreover, food has a weight of 45.9 per cent in the consumer price index (CPI) but its contribution to overall inflation has increased from 48 per cent in April 2022 to 67 per cent in November 2023. Two features stand out in this experience. First, the rising vulnerability of food prices to climate change – the heat wave during March-May 2022; crop production shortfalls due to uneven south-west monsoons; *La Nina* conditions for the third year in a row impacting rainfall patterns in the post-monsoon season; unseasonal rainfall and hailstorms in March 2023; temporal monsoon variability in 2023 (which included

its delayed onset; torrential rainfall in July; and historic dry conditions in August); and strengthening *El Nino* conditions – suggests that food inflation in India may be acquiring a structural character. Second, the weaponisation of food as a consequence of geo-political conflict and restrictive trade practices embedded in geo-economic fragmentation is resulting in large spillovers propagating into non-food inflation and across geographies. These forces are causing headline inflation in India to diverge, often persistently, from its target of 4 per cent. On the other hand, non-food non-fuel inflation has been responding *albeit* unevenly and laggedly to monetary policy and to easing input costs, gravitating towards 4 per cent. This is noteworthy, since it constitutes the significant other half of headline inflation that is widely believed to lie within the realm of influence of monetary policy; food inflation is generally considered to be outside its ambit.

An influential strand in the literature has argued that in emerging and developing economies in which food price inflation is more volatile and on an average higher than non-food inflation, a policy focus on measures of inflation that exclude or minimise the influence of food prices can result in a misspecification bias in forecasts, unhinged inflation expectations and lags in policy responses (Walsh, 2016). This is not just an issue relating to the greater weight of food in the consumption basket but also of the relationship between food and non-food prices (Cecchetti, 2007). If food inflation rises faster and remains more persistent than a measure of inflation that excludes food, the measurement of underlying inflation will be biased significantly downwards – means do matter, not just volatility and persistence, in maximising the signal to noise ratio that is the *raison d'etre* of any measure of core inflation. Measures that exclude food are also found to not perform well in terms of predictive power in country specific cases (Rich and Steindad, 2007; Alvarez *et al.* 2006). Furthermore, in

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^ The authors are from the Reserve Bank of India. The views expressed in this article are those of the authors and do not represent the views of the Reserve Bank of India.

the context of international commodity price cycles, it has been observed that mechanisms transmitting food price shocks may be changing – in many countries, headline inflation is not reverting to core in the same degree it did earlier, implying that secular forces may be at work (Anand and Prasad, 2010; Catao and Chang, 2015; Walsh, 2016).

Against this backdrop and the recent experience of persistence of elevated food prices in India, the appropriate monetary policy response would be conditioned by the question: will relative prices adjust without any spillovers so that the monetary policy reaction can be to look through food price movements on the grounds that they are supply-driven and transitory in nature? or do food prices exhibit some core-like properties, which are relevant for monetary policy and cannot be ignored? Large relative price changes triggered by adverse supply side factors have been identified as cost-push shocks that shift the Phillips curve upwards and to the right (Ball and Mankiw, 1995). In the Indian context, relative food price shocks triggered by monsoon failures have been found to be significant in explaining Phillips curve dynamics (Patra *et al.*, 2014). Households' inflation expectations formation in India are considerably influenced by food prices (Goyal and Parab, 2021). Moreover, food prices do tend to co-move, but they also exhibit considerable heterogeneity in their underlying dynamics, with the nature of inflation persistence differing across categories and type of shocks – global or domestic. There is also evidence of spillovers of persistently high food inflation to underlying inflation (RBI, 2014; Anand *et al.* 2016; Nadhanael, 2020; Patra *et al.*, 2021b).

In this context, this article attempts to explore answers to the questions posed to the conduct of monetary policy by the food inflation behaviour in India. Section II examines the stylised facts regarding food inflation. Section III attempts a formal analysis of the behaviour of food inflation persistence. Section IV delves into spillovers of food prices to non-food

components. Section V probes whether demand or cyclical factors impact food inflation and also brings it all together to draw out monetary policy implications of high and persistent food price inflation. Section VI concludes.
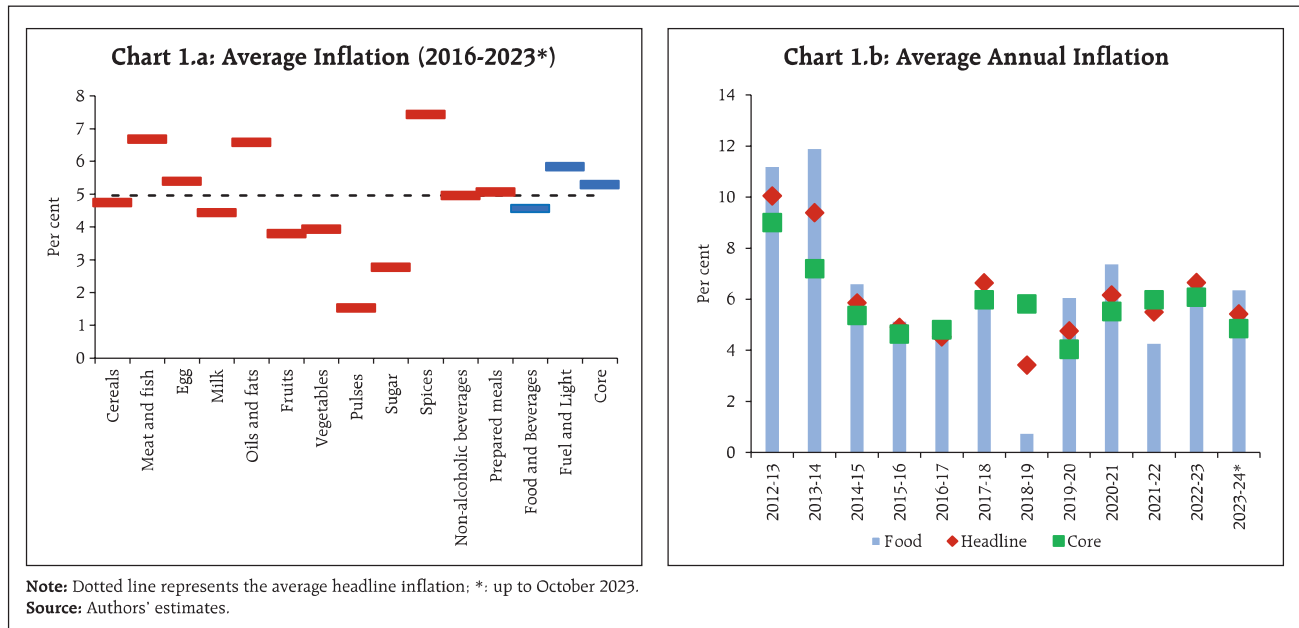
II. Food and Non-food Inflation: Some Stylized Facts

By convention, a core measure of inflation is constructed by minimising or excluding volatile components of the CPI – typically food and energy – to inform the setting of forward-looking monetary policy with medium-term objectives, since the data can measure developments only up to the recent past. The goal is to eliminate transitory developments and skews, and focus on the underlying longer-term trends. The possibility that such a core measure will be representative of overall inflation is based on two premises. First, it is assumed that means of food and non-food inflation are equal. If this is the case, then bringing down non-food inflation will eventually result in lower food inflation. Hence, monetary policy makers can focus on the so-called core[1] inflation while responding to headline inflation in terms of which the price stability target of monetary policy is defined. Second, it is assumed that the volatility in food inflation is higher than non-food inflation, bringing in noise and weakening the signal on underlying inflationary pressures. If, however, food inflation shocks are large and persistent, they can affect non-food inflation through second-round effects (Walsh, 2016).

Beginning with the equality of means assumption, average food inflation in India for the period 2016-2023[2] has remained close to the average of headline and core inflation. Average inflation in each of the food sub-groups has, however, been different and not equal to the averages of headline and core inflation (Chart 1.a). Certain sub-groups like oils and fats, spices and meat and fish have, in fact, exhibited higher
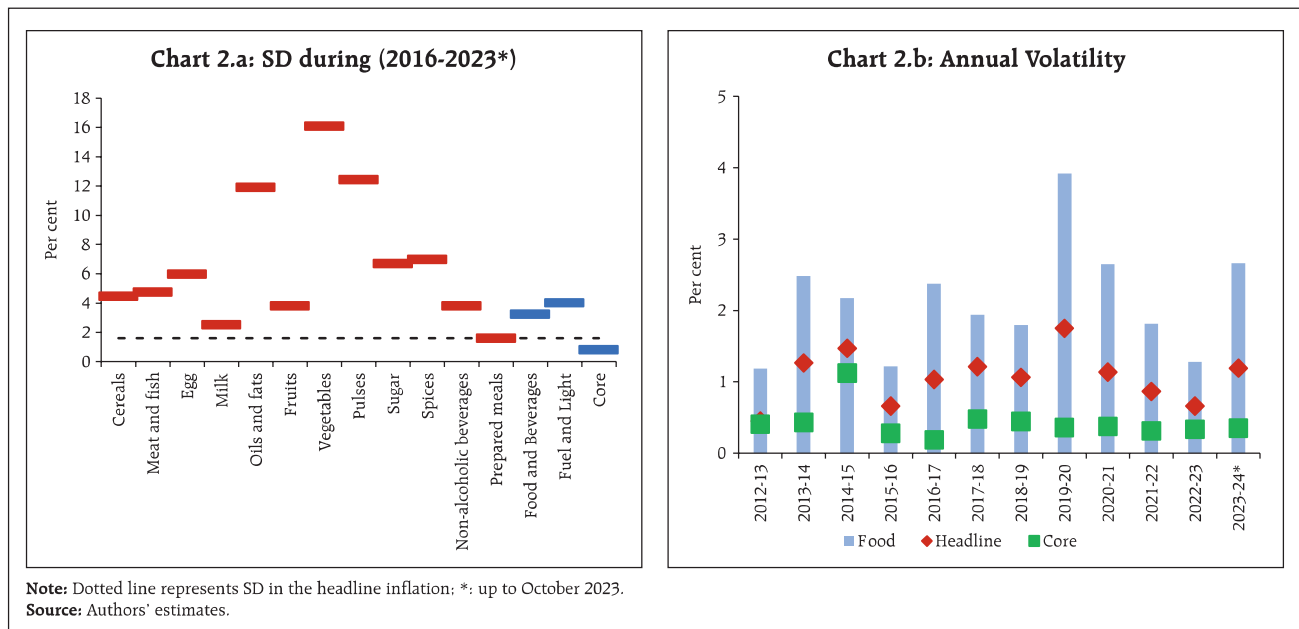
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[1]   *i.e.* CPI inflation excluding food and fuel.

[2]   Period under the flexible inflation targeting (FIT) regime.

Chart 1.a: Average Inflation (2016-2023*)

Chart 1.b: Average Annual Inflation

Note: Dotted line represents the average headline inflation; *: up to October 2023.
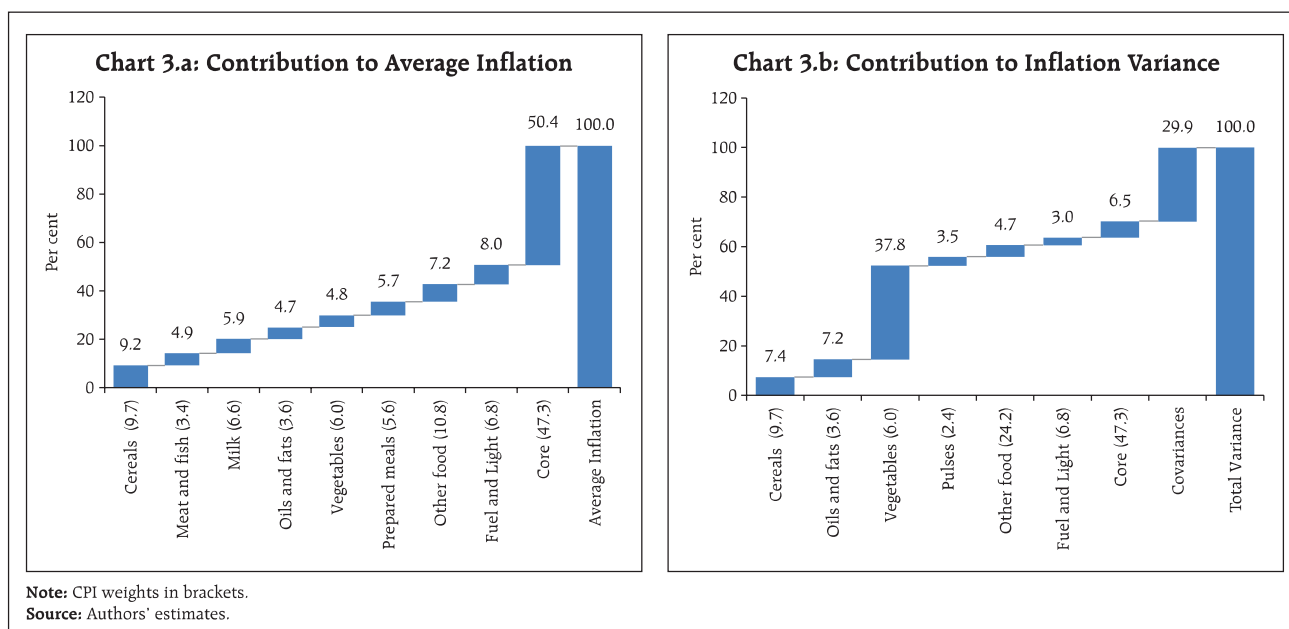**Source:** Authors' estimates.

average inflation during this period. In some years, food inflation has remained lastingly higher than the headline and core (Chart 1.b).

Food inflation volatility, measured by the intertemporal standard deviation (SD), has been markedly higher than the volatility of headline and core inflation. Certain food sub-groups like

vegetables, oils and fats and pulses have recorded high SDs, while certain sub-groups like prepared meals and milk have shown lower variability relative to other sub-groups in food (Chart 2.a). As in most countries[3], food inflation in India has been more volatile than core inflation during all the years in the past decade (Chart 2.b).

Chart 2.a: SD during (2016-2023*)

Chart 2.b: Annual Volatility

Note: Dotted line represents SD in the headline inflation; *: up to October 2023.
Source: Authors' estimates.

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[3] Walsh (2016).

Chart 3.a: Contribution to Average Inflation

Chart 3.b: Contribution to Inflation Variance

Note: CPI weights in brackets.
Source: Authors' estimates.

Food inflation contributed 43 per cent of average headline inflation between 2016 to 2023 (Chart 3.a). In the total variance of headline inflation, vegetables dominated all other sub-groups, contributing 38 per cent (Chart 3.b). The covariances among the sub-groups also contributed significantly to the total variance in headline inflation at around 30 per cent. This signifies the role of spillovers and second-round effects.

The implications of large changes in relative prices of food on headline inflation are evaluated by the correlation and cross-correlation among the moments[4] of headline, food and core inflation (Annex).

Average food inflation is positively correlated with its skewness, while it is uncorrelated with its SD. This indicates that large changes in relative prices of food have a considerable bearing on the food inflation trajectory, impacting the distribution of headline inflation. On the other hand, skewness and SD of core inflation exhibit no correlation with its mean (Table 1).

Table 1: Correlation Coefficient of CPI Inflation Moments (Within Groups)

	Mean	Standard Deviation	Skewness	Kurtosis
a. Headline				
Mean	1.00			
SD	0.11	1.00		
Skewness	0.40*	0.27*	1.00	
Kurtosis	-0.22*	0.26*	0.23*	1.00
b. Food				
Mean	1.00			
SD	0.15	1.00		
Skewness	0.34*	0.31*	1.00	
Kurtosis	-0.14	0.14	0.30*	1.00
c. Core				
Mean	1.00			
SD	0.11	1.00		
Skewness	0.08	0.09	1.00	
Kurtosis	-0.08	-0.26*	0.04	1.00

Note: *: Denotes significance at 5 per cent level.
Source: Authors' estimates.

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[4] The four statistical moments are quantitative measures related to the shape of a probability distribution. The first moment is the measure of central tendency (average); the second moment represents variability (measured using SD); the third moment is a measure of asymmetry (skewness); and the fourth provides the information on peakedness (kurtosis).

The calculations are carried out by using monthly CPI data from January 2012 to October 2023 at sub-group/group level due to issues in higher level aggregation when using item level CPI data (Das, P. and George, A.T., 2023).

High correlations among the averages of food, core and headline inflation is indicative of the composition of the CPI basket. The SD and skewness in headline inflation is having high positive correlation with those of food inflation, signifying the role of food inflation in determining the variability and asymmetry of headline inflation (Table 2).

Moreover, the cross-correlation between the moments of food and headline inflation suggests that the skewness in food inflation is positively correlated with the mean and SD of headline inflation, implying that large relative price changes in food inflation impacts the headline inflation path.

Thus, food inflation has exhibited intertemporal and cross-sectional variation. Inflation in certain food sub-groups has contributed excessively to the volatility in headline inflation. Furthermore, the analysis of moments points to spillovers, *i.e.*, shocks transmitted

from food to non-food inflation could be large if food price shocks are persistent. To sum up large changes in food prices have the potential to affect headline inflation lastingly.

III. Persistence in Food inflation

Persistence tends to vary over time and across components. Hence, we estimate the time varying persistence[5] in inflation[6], its major groups and the sub-groups of food inflation.

First, we estimate persistence from monthly data from October 2016 to October 2023 in

$$\pi_t = c_t + \rho_t * \pi_{t-1} + \varepsilon_t^\pi$$

and $\varepsilon_t^\pi \sim N(0, \sigma_t^\pi)$.   ...(1)

where π_t is alternatively inflation in headline, core, food and different food sub-groups. Errors (ε_t^π) follow normal distributions with stochastic volatility. ρ_t is the time varying inflation persistence.

A comparison of persistence in headline, core and food inflation suggests that core inflation has been on average more persistent than food inflation during October 2016 through October 2023 (Chart 4). The persistence in food inflation has shown considerable variation across time.

Certain sub-groups like prepared meals, non-alcoholic beverages, milk, cereals, oils and fats, pulses and spices display higher degrees of persistence than other sub-groups like vegetables, reflecting the influence of international developments and structural domestic supply bottlenecks (Chart 5).

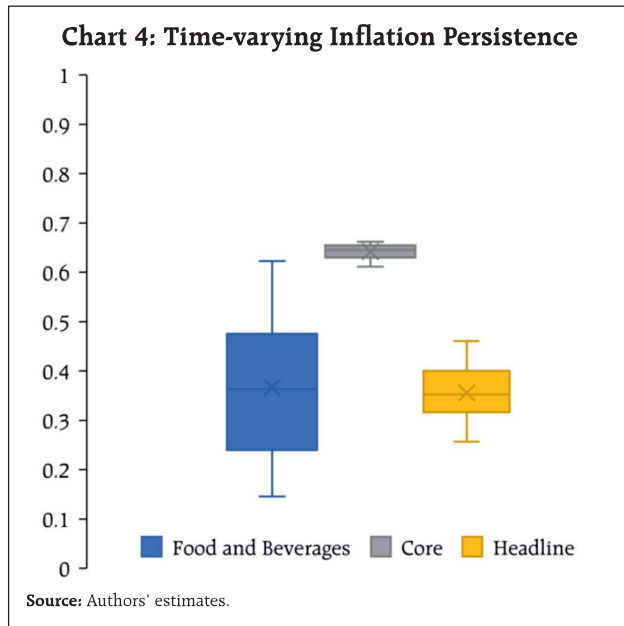### Table 2: Correlation Coefficient of CPI Inflation Moments (Between Groups)

	Headline	Food	Core
a. Mean			
Headline	1.00		
Food	0.93*	1.00	
Core	0.74*	0.47*	1.00
b. SD			
Headline	1.00		
Food	0.99*	1.00	
Core	0.06	0.01	1.00
c. Skewness			
Headline	1.00		
Food	0.95*	1.00	
Core	-0.27*	-0.26*	1.00
d. Kurtosis			
Headline	1.00		
Food	0.93*	1.00	
Core	0.25*	0.17*	1.00

Note: *: Denotes significance at 5 per cent level.
Source: Authors' estimates.

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[5] We have used the time varying parameter model with stochastic volatility for our estimation (Stock and Watson, 2007). For estimating the time varying parameter regression, we used the TVP package (Nakajima, 2011). The time varying parameters and stochastic volatility are estimated by using the Bayesian Markov Chain Monte Carlo (MCMC) method.

[6] We use year-on-year inflation for estimating the persistence. A note of caution is that persistence tends to be higher for this measure of inflation than annualised month-on-month rates as it represents average annualised month-on-month changes over a 12-month period.
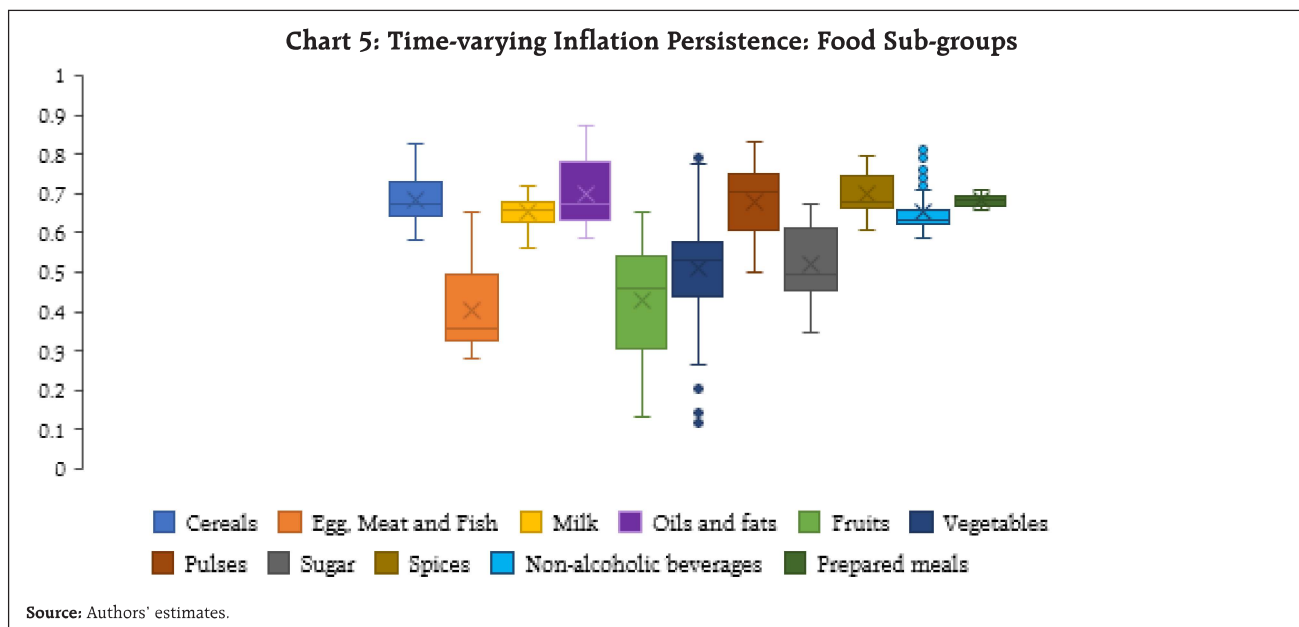
Chart 4: Time-varying Inflation Persistence

Source: Authors' estimates.

The non-trivial degree of inflation persistence in certain food sub-groups increases the risk of spillovers to non-food inflation through inflation expectations and cost-push pressures. Hence, monetary policy will have to be on guard to avoid the unanchoring of inflation expectation and generalisation of inflation.

IV. Food Inflation Spillovers

The significance of food inflation spillovers to non-food inflation is tested in an auto regressive distributed lag (ARDL) cointegration framework (Pesaran *et al.*, 2001) using seasonally adjusted monthly data from January 2011 to October 2023.

The bounds test suggests a long run cointegration between prices of food and non-food items (Table 3). The error correction term is negative and statistically significant for food inflation, while it is not significant for non-food inflation. This indicates that food prices undergo deviations from equilibrium after a shock but they converge to non-food prices within a year. The large residual volatility of food price changes (relative to non-food) indicates that, in general, food price shocks are transitory in nature. On the other hand, a positive and statistically significant coefficient on food price changes in the short-run equation for non-food inflation indicates that spillovers happen from food prices to non-food prices. The low magnitude of this coefficient indicates that only large and persistent food price shocks affect non-food prices. Nevertheless,

Chart 5: Time-varying Inflation Persistence: Food Sub-groups

Source: Authors' estimates.

Table 3: Food and Non-food Inflation Dynamics

	ΔNon-food	ΔFood
Cointegration Test (F-Statistic)	7.424**	5.050*
Error Correction Term	0.009	-0.080***
ΣΔNon-Food	0.137*	-0.136
ΣΔFood	0.048**	0.231***
Residual SD$	0.239	0.839
Residual White Noise Test (p-value)	0.469	0.381

***, ** and * represent significance at 1 per cent, 5 per cent and 10 per cent, respectively.
$ The SD corresponds to non-annualized m-o-m changes.
Note: Estimated using Sebastian Kripfganz and Daniel C. Schneider ARDL Module in STATA.
Source: Authors' estimates.

the significance of food price spillovers underscores the importance of anchoring inflation expectations in the wake of persistent and large food price shocks.

V. Cyclical Sensitivity of Food Inflation

Food prices are regarded as predominately driven by supply factors – demand is assumed not to play any meaningful role in the determination of these prices. The cyclical sensitivities of sub-group level food inflation and their contribution to overall food inflation are estimated in a time varying regression framework using quarterly data from Q1:2011 to Q3:2023 (Stock and Watson, 2007, 2020; Patra *et al.*, 2022, 2023).

First, we determine the time varying regression[7] coefficients of each of the food sub-groups with a measure of the economic cycle proxied by the output gap[8].

$$\pi_t^i = c + \rho_t^i * \pi_{t-1}^i + \alpha_t^i * OG_t + \varepsilon_t^{\pi^i}$$

and $\varepsilon_t^{\pi^i} \sim N(0, \sigma_t^{\pi^i})$.   ...(3)

where π_t^i is the seasonally adjusted quarter-on-quarter annualised inflation rate of ith food sub-

group. Errors $(\varepsilon_t^{\pi^i})$ follow a normal distribution with stochastic volatility. The stochastic volatility in errors is introduced to control for time-varying supply-side effects. α_t^i represents the short-term elasticity of ith food sub-group inflation with respect to the output gap, while $\frac{\alpha_t^i}{(1-\rho_t^i)}$ is the long-run elasticity.

We use $\frac{\alpha_t^i}{(1-\rho_t^i)}$ to readjust the CPI weight of the subgroup (w^i). If $\frac{\alpha_t^i}{(1-\rho_t^i)}$ is negative, a zero weight is assigned. Thus, the readjusted weight (W_t^i) of each subgroup is

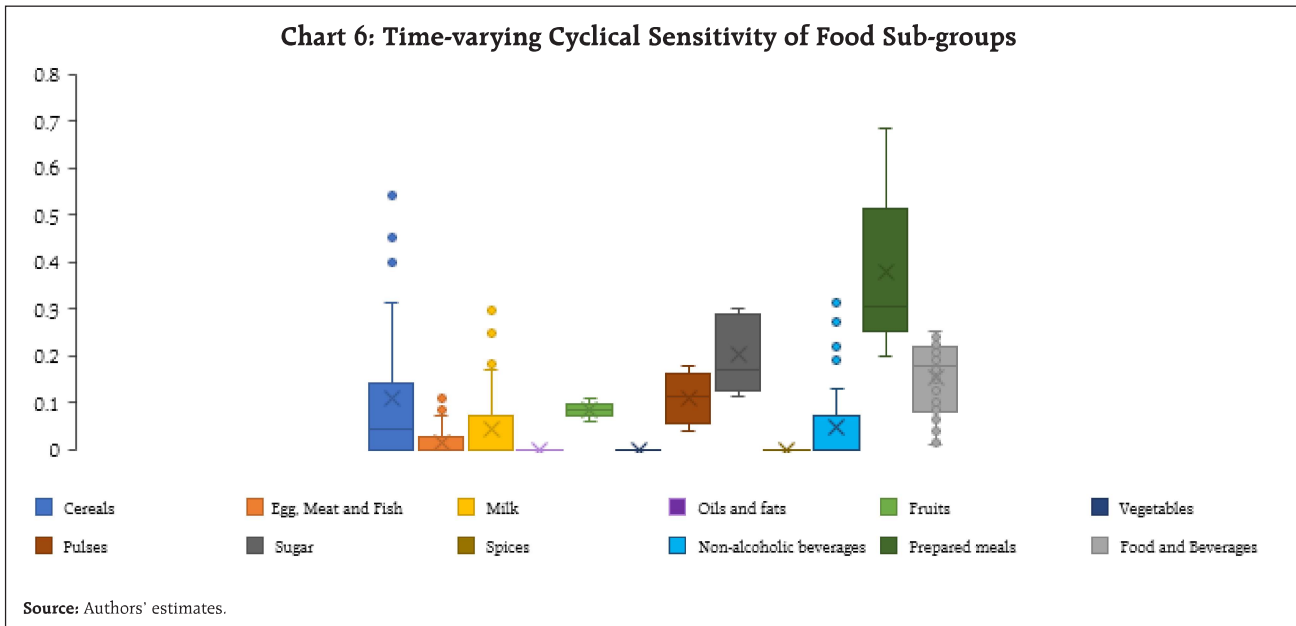$$W_t^i \quad = \frac{\alpha_t^i}{(1 - \rho_t^i)} * w^i, \quad if \ \alpha_t^i > 0$$

$$= 0, Otherwise \qquad\qquad ...(4)$$

W_t^i is normalized to 100 to get the weights of the sub-groups.

The long-run elasticities of the output gap on different food inflation sub-groups indicate wide intertemporal and cross-sectional variations (Chart 6). While certain sub-groups like vegetables, oils and fats, and spices do not show any cyclically sensitivity and are fully driven by supply conditions and international prices, other sub-groups reveal sensitivity to demand conditions of varying intensity. We use this to capture the contribution of demand conditions to the evolution of food inflation over the last decade (Chart 7).

About 90 per cent of food inflation is determined by non-cyclical factors like the weather, supply conditions, international prices and availability. On an average, however, 10 per cent of food inflation is driven by demand factors with significant time variation. This warrants vigil – counterfactual experiments using the RBI's workhorse quarterly projection model (QPM)[9] indicate the need to closely evaluate the sources and nature of shocks to food prices in order to determine

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[7] We have used the time varying parameter model with stochastic volatility for our estimation, based on the methodology by Stock and Watson (2007). For estimating the time varying parameter regression, we used TVP package by Nakajima (2011). The time varying parameters and stochastic volatility are estimated by using the Bayesian Markov Chain Monte Carlo (MCMC) method.

[8] We use the output gap measure as in Patra *et al.* (2021a).

[9] For details see John *et al.* (2023).

Chart 6: Time-varying Cyclical Sensitivity of Food Sub-groups

Source: Authors' estimates.
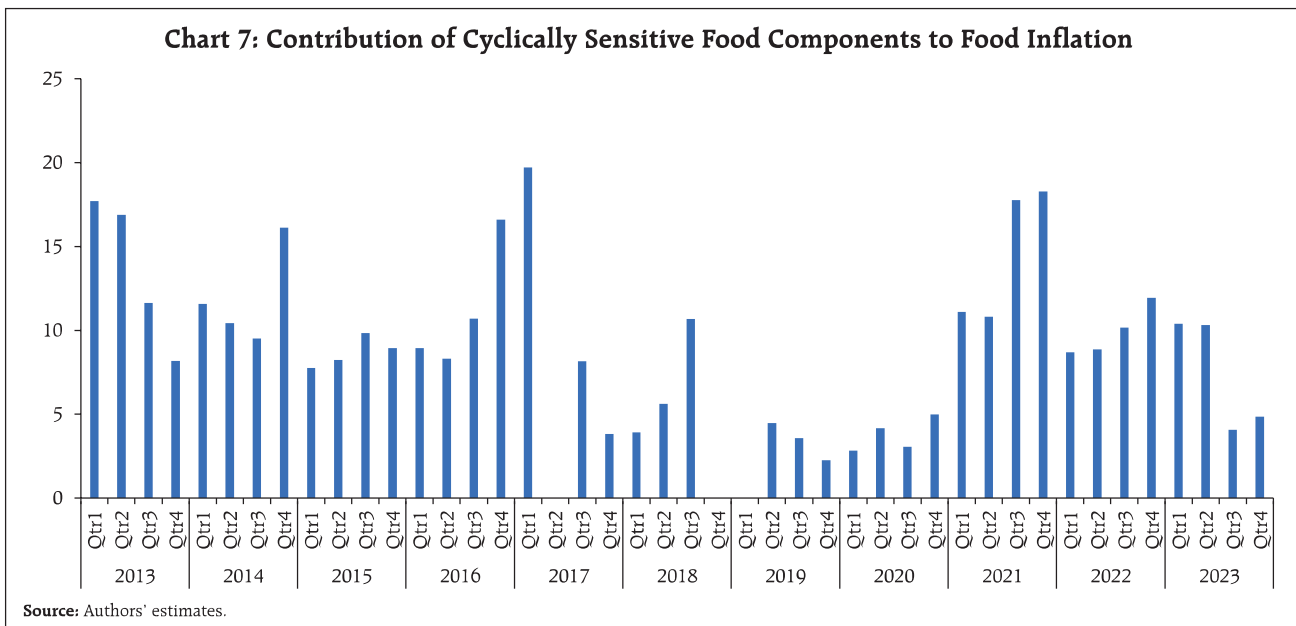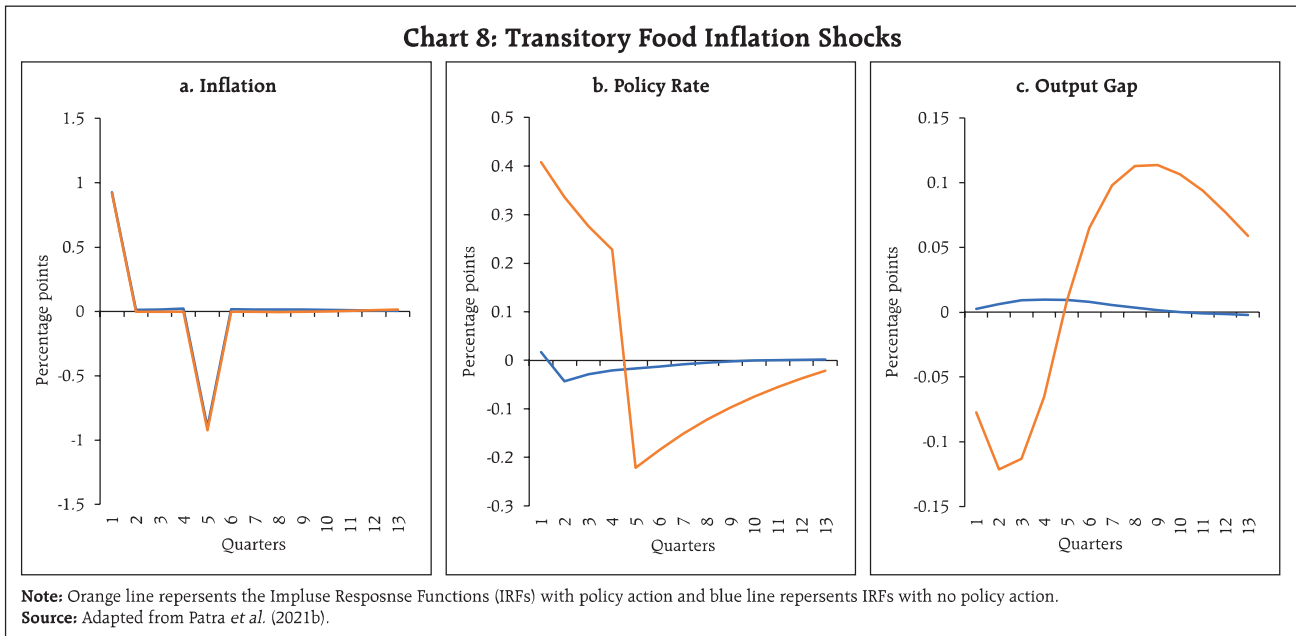
the appropriate monetary policy response so as to avoid generalisation.

Two types of shocks are experimented with: (i) transitory shocks from vegetables prices; and (ii) persistent shocks due to monsoon failures. Under (i), inflation falls, allowing monetary policy to see through

the shock by not changing the policy rate (Chart 8). On the other hand, if monetary policy misjudges the shock and chooses to react to this transitory shock by increasing the policy rate, it will induce volatility in the output gap without having any noticeable impact on the inflation path.

Chart 7: Contribution of Cyclically Sensitive Food Components to Food Inflation

Source: Authors' estimates.

Chart 8: Transitory Food Inflation Shocks

a. Inflation — **b. Policy Rate** — **c. Output Gap**

Note: Orange line repersents the Impluse Resposnse Functions (IRFs) with policy action and blue line repersents IRFs with no policy action.
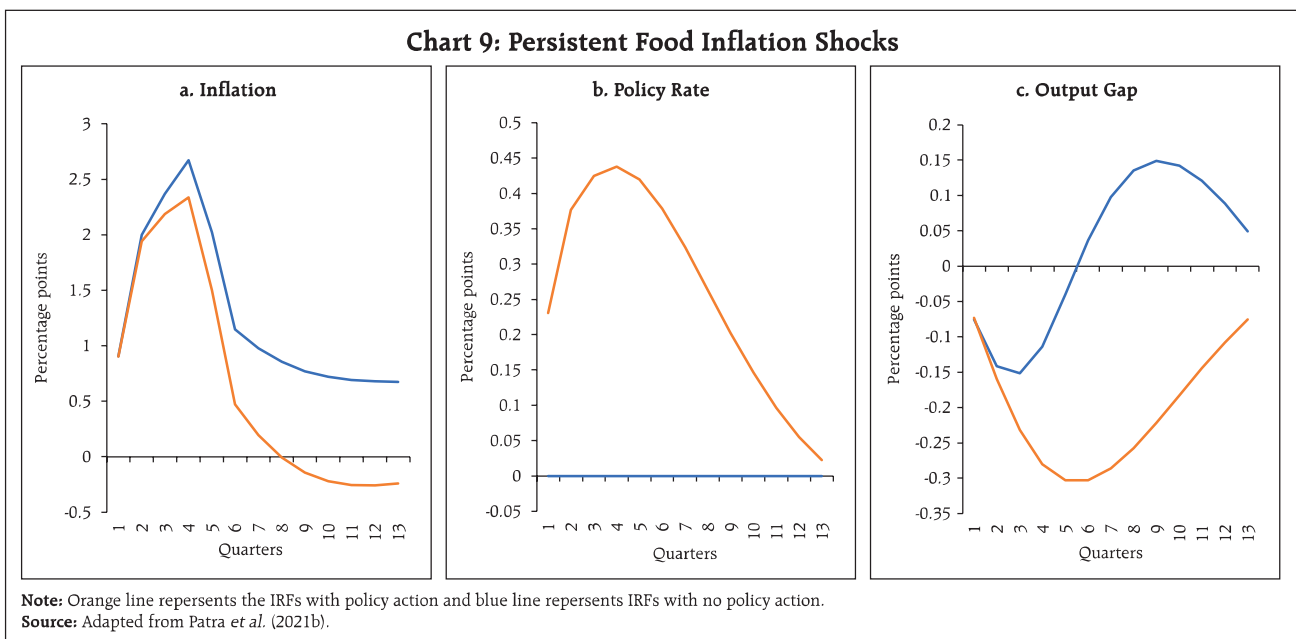**Source:** Adapted from Patra *et al.* (2021b).

A persistent food price shock warrants monetary policy action to avoid unanchoring of inflation expectations and second-round effects (Chart 9). *Per contra*, if monetary policy chooses to neglect a persistent food price shock, inflation expectations become unanchored, leading to generalised inflation.

VI. Conclusion

Armed with these empirical findings, we circle back to the question we posed to ourselves at the beginning of the paper: are food prices the 'true' core of India's inflation? First of all, we scoured the literature[10] to determine the properties of core

Chart 9: Persistent Food Inflation Shocks

a. Inflation — **b. Policy Rate** — **c. Output Gap**

Note: Orange line repersents the IRFs with policy action and blue line repersents IRFs with no policy action.
Source: Adapted from Patra *et al.* (2021b).

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[10] Marques *et al.* (2003); Das *et al.* (2009); Raj and Misra (2011); Schembri (2017); Dholakia and Kadiyala (2018); Raj *et al.* (2020); Bańbura *et al.* (2023).

inflation, at least from a practitioner's perspective. A core measure should reflect the underlying trend of overall inflation. The data-driven approach is to damp or remove volatile and transitory elements in the inflation formation process so as to maximise the signal to noise ratio in visualising future headline inflation – a defining requirement for policy formulation. Second, core inflation displays persistence; hence shocks to the core have long-lived effects on overall inflation, warranting monetary policy responses. Third, non-core inflation should converge to the core and there are no spillovers from non-core inflation to core. Fourth, the core measure is cyclically sensitive and hence amenable to monetary policy actions and stance.

How do our findings on food inflation dynamics in India stack up against these core properties? First, on an average, food inflation has ruled close to headline inflation, satisfying the condition of equality of means. On the other hand, food inflation has been markedly more volatile than the headline, imparting more noise than signal. It is important to note, however, that not all food sub-groups contribute to this amplification of the noise to signal ratio – the main culprit is vegetable prices. Second, food inflation has exhibited persistence in some years, but this is concentrated in some sub-groups. Third, when food inflation shocks have been large and persistent, they have spilled over to prices in the non-food categories, although in the long-run, food inflation tends to converge to non-food inflation. Fourth, even though food inflation is primarily driven by supply-side factors, the influence of demand on several of its components is non-trivial and time varying.

Reading all this together, there are times when food inflation mimics core inflation. With its large share in the consumption basket, food inflation has the potential to affect headline inflation and it can also affect non-food inflation in the event of large and repeated food price shocks. Ascertaining the sources

and nature of these shocks is clearly the remit of risk-minimising monetary policy as its goal of price stability can easily be undermined by the de-anchoring of inflation expectations and the broadening of inflation pressures due to food price shocks. At the same time, wielders of monetary policy need to be conscious of the dangers of overkill in reactions to a transitory food price shock and also of the pitfalls of benign neglect of looking through persistent food price shocks.

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Annex

Table A1. Correlation among the various moments of Headline, Food and Core Inflation

		Headline				Food				Core			
		Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis
Headline	Mean	1.00											
	SD	0.11 *0.20*	1.00										
	Skewness	0.40* *0.00*	0.27* *0.00*	1.00									
	Kurtosis	-0.22* *0.01*	0.26* *0.00*	0.23* *0.01*	1.00								
Food	Mean	0.93* *0.00*	0.16 *0.06*	0.55* *0.00*	-0.14 *0.10*	1.00							
	SD	0.10 *0.25*	0.99* *0.00*	0.27* *0.00*	0.32* *0.00*	0.15 *0.08*	1.00						
	Skewness	0.21* *0.01*	0.30* *0.00*	0.95* *0.00*	0.27* *0.00*	0.34* *0.00*	0.31* *0.00*	1.00					
	Kurtosis	-0.20* *0.01*	0.08 *0.35*	0.26* *0.00*	0.93* *0.00*	-0.14 *0.09*	0.14 *0.09*	0.30* *0.00*	1.00				
Core	Mean	0.74* *0.00*	-0.06 *0.50*	-0.04 *0.61*	-0.32* *0.00*	0.47* *0.00*	-0.07 *0.39*	-0.15 *0.08*	-0.28* *0.00*	1.00			
	SD	0.11 *0.19*	0.06 *0.46*	0.18* *0.03*	-0.34* *0.00*	0.08 *0.32*	0.01 *0.91*	0.24* *0.00*	-0.24 *0.00*	0.11 *0.18*	1.00		
	Skewness	-0.06 *0.48*	-0.10 *0.25*	-0.27* *0.00*	-0.28* *0.00*	-0.11 *0.19*	-0.11 *0.18*	-0.26* *0.00*	-0.28* *0.00*	0.08 *0.38*	0.09 *0.27*	1.00	
	Kurtosis	0.16 *0.06*	0.09 *0.28*	0.30* *0.00*	0.25* *0.00*	0.25* *0.00*	0.12 *0.17*	0.22* *0.01*	0.17* *0.05*	-0.08 *0.32*	-0.26* *0.00*	0.04 *0.65*	1.00

Note: * Denotes significance at 5 per cent level; p-values in italics.
Source: Authors' estimates.