Journal of Asian Economics 95 (2024) 101817

Contents lists available at ScienceDirect

Journal of Asian Economics

journal homepage: www.elsevier.com/locate/asieco

Food inflation and monetary policy in emerging economies

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ARTICLE INFO

JEL Classification:
E31
E52

Keywords:
Emerging Economies
Food Inflation
Monetary Policy
Causality
Price Stability

ABSTRACT

The rising inflationary pressure has been linked with supply-side disruptions and rising energy and food prices against the background of the COVID-19 pandemic and the Russia-Ukraine crisis. This paper investigates the role of monetary policy in stabilizing food inflation in emerging economies (India, China, Brazil, Russia, and South Africa). We also investigate the causal linkage between monetary policy and food inflation using frequency domain-based Granger causality and find strong feedback causal effects between food inflation and monetary policy changes. Our results are robust to different estimation methodologies, possible asymmetry, and alternative model specifications, which include climate change. While oil prices, world food prices, and exchange rates have heterogeneous effects on domestic food inflation, a contractionary monetary policy stance leads to a decline in domestic food inflation in all countries. Thus, we provide strong evidence that well-coordinated macroeconomic policies in emerging economies are essential for stabilizing food inflation.

1. Introduction

Twenty years have passed since Kenneth Rogoff, described a "near-universal fall in inflation," and offered the first comprehensive analysis of inflation on a global scale (Rogoff, 2003). Global inflation has fluctuated dramatically after remaining largely stagnant in the last decade. More recently, a growing number of economies have seen a significant increase in inflation driven by high commodity prices, supply-side disruptions, and rising energy and food prices. Economic stimulus packages, commonly known as quantitative easing policy, that were adopted over the years also contributed to rising consumer inflation. The world food inflation rate reached its peak in 2021 – the highest since 2005, contributed by various factors of changing importance through regions (World Bank, 2022). Consequently, over the past three years, numerous central banks worldwide have been fighting resurgent inflation to maintain their hard-earned credibility.

Emerging and developing economies have also experienced high food inflation (see Figs. 1 and 2 in the appendix). Fig. 2 presents the headline and food inflation for the advanced and emerging countries. It shows that, on average, food inflation continued to be higher than overall inflation. This indicates that a significant contributor to inflation in these economies is food inflation. Further, in 78 out of 109 economies categorized as emerging markets and developing economies (EMDEs) by the International Monetary Fund, the inflation rate was above 5 % in 2021 (World Bank, 2022). The currency depreciation due to lower capital inflows as a result of COVID-19 also impacts inflation through the import channel. Given that the inflation expectations in emerging and developing economies are influenced by currency movements, the pass-through from foreign exchange rates to domestic prices tends to be quicker

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https://doi.org/10.1016/j.asieco.2024.101817
Received 17 February 2023; Received in revised form 20 August 2024; Accepted 1 October 2024
Available online 5 October 2024

and more prevalent. An important component of overall inflation is food price inflation. It is seen that food price inflation has also been increasing in emerging and developing economies. For instance, in 2021, 86 out of 109 (79 %) of the economies experienced a food price hike of over 5 % (World Bank, 2022)[1]. Rising food prices have a serious negative impact, particularly the low-income households. In EMDEs, the share of food expenditure takes on a much larger share of an average consumer budget, which implies that inflation in these economies would be more persistent.

Against this background and building upon the sparse empirical literature, this paper attempts to undertake a comprehensive study of monetary policy and food inflation nexus in five emerging economies (Brazil, China, India, Russia, and South Africa) also known as BRICS. These economies together contribute about 32 % to global GDP, compared to 31 % from G7 economies (IMF-International Monetary Fund, 2023). These economies also dominate global food production and supply. With only 40 % of the global population, these countries accounted for more than 50 % of global agriculture production in 2018 (Ren et al., 2020). In 2020, Brazil ranked as the fourth-largest agricultural producer, worth $135.8 billion. In 2021, it was the third largest exporter of agriculture products, behind the European Union and the USA (Valdes, 2022). While India produces enough grain to feed itself, it also exports a lot of cotton, meat, and soybeans, ranking ninth in the world in 2019 for agricultural exports. In 2019, China's agricultural output made up more than 25 % of the total worldwide output (Liu and Zhou 2021). As a result, these diverse emerging economies are becoming a true 'food power' for the rest of the world and can significantly influence the food industry. Despite this, food inflation has increasingly become a growing concern for policymakers in these emerging economies.

Rising food inflation is an important element not only in the current inflationary environment but also reinforces future inflation expectations and contract negotiations (Anand et al., 2015) and is unfavourable to household well-being (Hanif, 2012). In the absence of any concrete global policy response to mitigate food prices and supply-line disruptions, the work of addressing high inflation is left to monetary authorities. The supply-chain crisis due to the COVID-19 pandemic has re-emphasized as well as renewed interest in the significance of understanding the relationship between monetary policy and food inflation. Therefore, a better and more robust understanding of the relationship between monetary (central bank) policy rates and food inflation is essential for monetary authorities to appropriately use monetary policy to maintain lower food inflation.

The recent assertion has been that food inflation is mainly driven by supply-side factors and its effects are short-lived (Anand and Prasad, 2010; Anand et al., 2015; Moorthy and Kolhar, 2011), therefore it is beyond the influence of monetary policy. The significant food price volatility over recent years has led policymakers and scholars globally to rethink the effectiveness of monetary policy in managing food inflation and achieving price stability. However, the intriguing issue is that the relationship between monetary policy and food prices is complicated. For instance, commodity prices matter for aggregate inflation and influence monetary policy stance (Bernanke and Gertler, 2000; Hammoudeh et al. 2015). On the other hand, studies (Aoki, 2001; Mishkin, 2001; Soto, 2003; Anand et al., 2015) emphasize the role of optimal monetary policy in stabilizing commodity prices, particularly food prices. In developing economies, where households are credit-constrained and the share of food expenditure is high, monetary policy can influence welfare by targeting aggregate inflation (Anand et al., 2015; Catão, Chang, 2015; Pourroy et al., 2016).

Furthermore, the recent ongoing concerns regarding the impact of climate change have renewed academic and policy interest in understanding its implications for monetary policy and food price stability. It is believed that climate change and global warming play a significant role in determining food prices. Temperature variations can have a substantial effect on the environment and food costs (Mukherjee and Ouattara, 2021). The economies of emerging countries are still developing. As mentioned above, agricultural products make up a sizable amount of their exports. It is well known that poor populations, who spend a significant portion of their income on food, are particularly vulnerable to global food price increases. Food security is a critical issue in developing countries including emerging economies (Mekonnen et al., 2021). Hence, a better understanding of the role of monetary policy on food price stability, amid climate change concerns remains limited and suggests further analysis is necessary.

This paper contributes to the literature in four ways. First, while many studies have studied the relationship between monetary policy and general inflation (Assenmacher-Wesche, Gerlach, & Sekine, 2008; Crowder, 1998; Jiang, Chang, & Li, 2015), this paper specifically focuses on the relationship between monetary policy and food inflation. High food prices affect overall inflation and its forecasting ability, particularly in inflation-targeting countries (Šoškić, 2015). De Gregorio (2012) argues that only considering the contemporaneous impact of food inflation could underrate the indirect and second-round effect on other components of the consumer price index and consequently overall inflation. Furthermore, ignoring food inflation tends to make assessing the cost of living and its impact on households erroneous (Alper et al., 2017). Second, to the best of our knowledge, unlike existing literature on advanced economies, this study is the first to undertake a robust country-specific comparative analysis of monetary policy and food inflation in five emerging economies and builds on extant literature. Few studies (Akram, 2009; Hammoudeh et al., 2015) have attempted to look at the monetary policy and disaggregated constituents such as oil and food, however, the focus has been on the United States and other selected advanced countries. Unfortunately, empirical examination of the role of monetary policy in stabilizing food inflation in emerging economies has been inadequate. Consequently, this creates a major policy challenge for central bankers to prudently use monetary policy and stabilize food inflation.

Third, this paper contributes to the literature by assessing the effects of monetary policy on food inflation within a multivariate framework by including world food prices, oil prices, exchange rates, as well as climate change. Consequently, by adopting this modelling approach, this paper avoids not only omitted variable bias but also provides new insights into the role of climate change in monetary policy - food inflation nexus for policymakers in emerging economies. Furthermore, this paper may serve as a plausible framework to stimulate further discussion and analysis for scholars to investigate the role of climate change in monetary policy and the food inflation nexus in developing economies that are prone to climate change. Fourth, the study examines the causal relationship between monetary policy and food inflation by using a number of empirical methodologies. A variety of time series and causality analyses are complemented by sensitivity checks, including panel and asymmetric analysis that provide additional insight into the topic under consideration. We employ, for the first time, the frequency domain Granger causality test developed by Breitung and Candelon (2006). This method examines the causality linkage between two variables over various frequencies and assists in better understanding the predictability of monetary policy for food inflation (or vice versa).

We document five important findings. First, we find robust evidence that monetary policy has a significant influence over food inflation in all five emerging economies. The results reveal that consistent with our theoretical expectations, a contractionary monetary policy stance (increase in monetary policy rate) helps stabilize food inflation in all economies. Second, compared to other factors (for example, world food prices, climate change, oil prices, and exchange rate) affecting food inflation, monetary policy has a consistent negative (or stabilizing) effect on food inflation, implying that it is a reliable policy tool for managing food inflation in emerging economies. Third, climate change significantly exacerbates food inflation challenges in Brazil and South Africa. Fourth, we document evidence of bi-directional or feedback causality between monetary policy and food inflation, implying both variables are significant for the predictability of each other. Fifth, the effect of monetary policy on food inflation remains negative but weak after the Global Financial Crisis.

The rest of the paper is structured as follows : Section 2 reviews the related literature on monetary policy and food inflation. Section 3 outlines the data sources and econometric methodology. Section 4 presents results and discussion, while Section 5 presents results from sensitivity analysis. Finally, Section 6 provides the conclusion with policy implications.

2. Literature review

2.1. Theoretical underpinnings of monetary policy and food inflation

The theoretical literature has mostly focused on whether monetary authorities should concentrate on core inflation such as food and other commodities or overall inflation for monetary policy stance and welfare reasons. In an open economy condition, Catão, Chang, (2015) used a dynamic stochastic general equilibrium approach and showed that following a global food price shock, headline consumer price index targeting enhances welfare outcomes. This is in a situation where food takes a larger proportion of the consumer basket irrespective of imported or non-traded goods. Further, they show that when financial markets are incomplete, targeting the producer price index enhances welfare outcomes. Furthermore, Anand et al. (2015) show in the presence of financial frictions and credit-constrained households, monetary authorities can enhance welfare benefits by stabilizing overall inflation compared to core inflation.

Pourroy et al. (2016) examined the monetary policy response to shocks emanating from world food prices for low and high-income economies and showed that the monetary policy stance depends on the income level of different countries. Essentially, they show that for low-income countries with food dominance in their consumer basket, monetary policy is effective and efficient when the central bank's target is the overall consumer price index. In high-income countries, they find that targeting commodity prices other than food exacts monetary policy optimality. Ginn and Pourroy (2019) examined some middle-income countries where high food prices are subsidized by the government as a fiscal policy measure to insulate the world food price shock transmitting to domestic food prices. The authors find that in the absence of a complete financial market and lack of access to consumer credit, fiscal food subsidies smooth consumption patterns and food prices. Smoothing consumption and food prices then imply that monetary policy need not be excessively tightened.

Theoretically, there are three channels through which monetary policy affects food inflation as argued by Akram (2009), Scrimgeour (2015), and Frankel (2008). The *first channel* is where contractionary monetary policy (higher interest rates) leads to an increase in the cost of inventory, resulting in stock reduction, a surge in the supply of the commodities, and a fall in the food commodity prices. The *second channel* is when higher interest rates due to contractionary monetary policy, make interest-bearing assets attractive causing investors to adjust their portfolio by selling commodities and purchasing other assets, leading to a decline in food commodity prices. The *third channel* is where restrictive monetary policy works through aggregate demand by negatively impacting consumption (Scrimgeour, 2015). However, the impact of contractionary monetary policy on food inflation could be less relative to its effect on non-food inflation. This is particularly relevant for countries where food occupies a large share of the consumption bundle, and a large proportion of people practice subsistence consumption. In this situation, such an effect of monetary policy stance is likely to fall on non-food prices. Therefore, the monetary policy stance to some extent is informed by the development stage and consumption pattern of the economy (Iddrisu and Alagidede, 2020). As a result, when the central banks respond to a rise in food inflation by monetary tightening, it would affect both non-food and food prices, which would affect headline inflation.

2.2. Review of empirical studies

Many studies have examined the effects of monetary policy on food inflation for large, advanced economies. For instance, Frankel (2008) using the US data from 1950 to 2005 found that restrictive monetary policy instance (or increase in real interest rate) reduces the cumulative real commodity price indices, including the food commodities. He also compared the results with other advanced and emerging economies using the aggregate price index indices. He found similar results for Australia, Canada, Switzerland, and New Zealand. With respect to emerging economies, while the author found a similar result for Brazil and Chile, the restrictive monetary policy shows a positive impact on commodity prices for Mexico.

Akram (2009) investigated the response of commodity prices to a decline in real interest and a weaker dollar in the US using a structural VAR framework for the period 1990:1-2007:4. The author finds that a decrease in the real interest rate and depreciation of the dollar is associated with an increase in commodity prices. Anzuini, Lombardi, and Pagano (2013) examined the effect of monetary policy on commodity prices by using a VAR model. They found that the expansionary monetary stance significantly drives up the commodity price index, although the increase is not tremendously large. Scrimgeour (2015) examined the effect of a monetary policy surprise on commodity price response in the United States using quarterly data for the sample period 1957:1–2008:3 and found that a positive interest rate shock of 10 basis-point leads to an immediate decline in commodity prices of 0.6 %. Lambert and Miljkovic (2010) show that farm prices and wage costs in the manufacturing sector instead of income or cost of production input such as energy are the key determinants of food prices in the US. However, Šoškić, (2015) observed that increasing demand due to income surges can drive food prices. Irz, Niemi, and Liu (2013) examine the relationship between food prices and prices of agricultural commodities, labour, and energy in Finland using monthly data from January 1995 to February 2010. They find farm prices and wages to be the main determinants of food prices. In contrast, energy plays a significant but limited role in food prices.

Hammoudeh, Nguyen, and Sousa (2015) investigated the effect of contractionary monetary policy on sectoral commodity prices in the United States and found that a positive interest rate shock (contractionary policy) also results in a rise in volatile food prices. Bhattacharya and Jain (2020) estimated a Panel VAR model using quarterly data over the period 2006Q1 to 2016Q2 to examine the effects of the monetary policy on food inflation in a panel of advanced and emerging countries (US, UK, Japan, Canada, France, Italy, Germany, Brazil, Russia, India, China, South Korea, Chile, Mexico, Turkey, and Hungary). They found that an unexpected monetary tightening positively affects food inflation and can further destabilize food inflation.

Bhattacharya and Gupta (2018) estimated a SVAR model to examine food inflation in India over the sample period from April 1998 to September 2014 and found that agricultural wages are an important driver of food inflation while fuel inflation has a moderate effect on food prices. Other studies (Anand, Ding, & Tulin, 2014; Holtemöller & Mallick, 2016) on India also found that monetary tightening leads to a decline in food inflation. In contrast, Sasmal (2015) studied food price inflation in India and found that income per capita and supply shortage are responsible for the food price hike. The author found no relationship between agricultural prices and money supply.

Iddrisu and Alagidede (2020) employed quantile regression analysis and found that monetary policy has positive effects on food prices in South Africa, suggesting contractionary monetary policy further destabilizes domestic food prices. Exchange rates, world food prices, and transport costs are also important determinants of food prices. Using the methodology, Iddrisu and Alagidede (2021) investigated the impact of monetary policy on food prices in Ghana over the sample period from January 2002 to November 2018. They again found that monetary policy destabilizes food prices from the 20th to the 45th quantiles. However, world food prices and exchange rates were not found to be important drivers of food prices. Norazman, Khalid, and Ghani (2018) investigated determinants of domestic food inflation in Malaysia using monthly data over the sample period 1991:1–2013:12 and found that real exchange rates and world food prices are the major determinants. Sahoo and Sethi (2018) examined the relationship between inflation, export, import, and foreign direct investment for India over the sample period 1975–2019 and found that domestic inflation is positively affected by exports[2]. More recently, Samal and Goyari (2022) examined the effect of monetary policy on food inflation in India spanning 2009–2019. In quantile analysis, they find tightening monetary policy stabilizes food inflation, while transport cost and exchange rate are significant in rising food inflation. Similarly, in the case of Iran, Mahmoudinia (2023) using a similar methodology, examined the monetary policy and food inflation dynamics and found a significant positive effect of monetary policy, sanctions, and currency crisis on food inflation.

Furthermore, few recent studies have examined the effects of climate-related factors on inflation. For instance, Abril-Salcedo et al., (2020) examined the relationship between intense weather events like El Nino and food inflation in Colombia and found that the effects of weather shocks on food inflation are asymmetric and temporary. Food inflation was significantly impacted by an El Nino shock. Using a factor-augmented VAR with volatility in a mean model, Nam (2021) examined the effects of climate uncertainty on the world's commodity markets. He shows that uncertainty about the climate generally drives up the price of food globally. Kunawotor et al. (2022) examined the impact of extreme weather events on food prices in Africa and found that weather conditions had no statistically significant effect on food inflation, while drought could have a positive and statistically significant effect on food inflation. Köse and Ünal (2022) examined the effect of temperature on food prices in Latin America and found the impact of temperature was limited in the earlier periods, they generated larger changes in food prices over time based on impulse response analysis.

To sum up, literature overlaps on three strands. First, the empirical evidence has been inconclusive implying that whether targeting core or headline inflation is welfare-enhancing or not is still ambiguous for central bankers across countries and might be conditional upon various factors such as access to credit, share of food expenditure, import, and export capacities, incomplete markets, and other country-specific features (Anand et al., 2015, Pourroy et al., 2016; Catão, Chang, 2015; Ginn and Pourroy, 2020). Second, how food inflation is differently impacted by global food prices, oil prices, and exchange rate, relative to monetary policy is still unclear in developing and emerging economies. Third, there is a paucity of research studies that examine the role of climate-related factors in monetary policy-food inflation nexus. Few recent studies have found inconclusive evidence and imply that the existing belief regarding the effects of climate-related factors on food inflation is preliminary. The growing concerns about climate change underscore the importance of further analysis.

3. Data and econometric methodology

3.1. Data and variable description

This paper examines the relationship between monetary policy and food inflation in five emerging economies: India, Brazil, China, Russia, and South Africa. We use monthly data for all the countries. The sample period is different for each country due to data availability and is as follows: Brazil (1986:6–2019:7); China (1996:1–2019:12); India (2013:1–2019:5); Russia (2004:1–2019:12);

South Africa (1981:1–2019:12). We collected monetary (central bank) policy rates (measured in nominal terms) for these countries from the Bank of International Settlements. Food inflation is computed using food CPI data from the OECD website. The original data series were transformed into natural logarithms to de-emphasise the outliers and obtain a normal distribution (Metcalf & Casey, 2016).

3.2. Empirical model

Following the empirical literature, we employ the following econometric model to examine the effect of monetary policy rates on food inflation:

$$f_t = \alpha + \beta m_t + u_t \tag{1}$$

An increase in the monetary policy rate (m_t) is expected to reduce food inflation (f_t) and thus we expect coefficient β to be negative. The last term in equation (1) is the error term. Fears of inflation and political and public pressure to safeguard price stability will cause central banks to raise the monetary policy rate to reduce aggregate demand and reduce inflationary pressure. Given time series data on monetary policy rate and food inflation, ADF (Dickey & Fuller, 1979, 1981) and PP (Phillips & Perron, 1988) unit root tests are used to verify the order of integration of variables. To conserve space, we do not include their details as they are widely used in the applied economics literature.

3.3. Frequency domain granger causality test

We briefly describe the frequency domain causality (FDC, hereafter) test developed by Breitung and Candelon (2006) that enables us to investigate the causal relationship between food inflation and monetary policy rates. Let's define $z_t = [x_t, y_t]'$ represent a two-dimensional vector of monthly time series of food inflation and monetary policy rates observed at $t = 1, \ldots., T$ and has a finite-order vector autoregressive (VAR) representation as follows:

$$\Theta(L) z_t = \varepsilon_t \tag{2}$$

where $\Theta(L) = I - \Theta_1 L - \ldots - \Theta_p L^p$ is a 2 ×2 lag polynomial with $L^k z_t = z_{t-k}$. We assume that the error vector ε_t is white noise with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t') = \Sigma$, where Σ is positive definite. Consistent with past studies, we neglect any deterministic terms from Eq. (2) above. We now let G be the lower triangular matrix of the Cholesky decomposition $G'G = \Sigma^{-1}$ such that $E(\varepsilon_t \varepsilon_t') = I$ and $\eta_t = G\varepsilon_t$.

Assuming the system is stationary, the MA representation of the system can be described by:

$$z_t = \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \tag{3}$$

where $\Phi(L) = \Theta(L)^{-1}$ and $\Psi(L) = \Phi(L)G^{-1}$. Using this representation, the spectral density of x_t can be expressed as:

$$f_x(\omega) = \frac{1}{2\pi}\left\{ \left|\Psi_{11}(e^{-i\omega})\right|^2 + \left|\Psi_{12}(e^{-i\omega})\right|^2 \right\}.$$

The measure of causality proposed by Geweke (1982) and Hosoya (1991) is defined as:

$$M_{y\to x}(\omega) = \log\left[\frac{2\pi f_x(\omega)}{|\Psi_{11}(e^{-i\omega})|^2}\right] \tag{4}$$

$$= \log\left[1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right] \tag{5}$$

If $|\Psi_{12}(e^{-i\omega})| = 0$, the measure is zero and then y does not cause x at frequency ω. In the stationary case, the causality measure is given as follows:

$$M_{y\to x}(\omega) = \log\left[1 + \frac{|\widetilde{\Psi}_{12}(e^{-i\omega})|^2}{|\widetilde{\Psi}_{11}(e^{-i\omega})|^2}\right] \tag{6}$$

Breitung and Candelon (2006) point out that the causality measure can be extended to higher-dimensional systems. Within a bivariate setting, we test the hypothesis that y does not cause x at frequency ω by considering the null hypothesis of $M_{y\to x}(\omega) = 0$. The VAR equation representing the link between x and y is reformulated as:

$$x_t = \alpha_1 x_{t-1} + \ldots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_{1t.} \tag{7}$$

The hypothesis of $M_{y\to x}(\omega) = 0$ is equal to the linear restriction:

$$H_0 \quad : R(\omega)\beta = 0 \tag{8}$$

where $\beta = [\beta_1, \quad \ldots, \quad \beta_p]^{'}$ and

$$R(\omega) = \begin{bmatrix} \cos(\omega)\cos(2\omega)\ldots\cos(p\omega) \\ \sin(\omega)\sin(2\omega)\ldots\sin(p\omega) \end{bmatrix}$$

The ordinary F statistic for Eq. (8) is approximately distributed as F (2, T - $2p$) for

$\omega\epsilon(0, \pi)$.

Time-domain causality tests have some limitations. First, the test computes a single test statistic that summarizes the causal relationship between variables over the time horizon and lacks the flexibility to detect causality at varying frequencies (Bozatli, Bal, & Albayrak, 2023) and implicitly assumes the statistic to be valid across all points of frequency distribution (Ciner, 2011b). In addition, if the relationship between variables is conditional upon more than a single frequency, the time-domain causality test tends to be insufficient to utilize the information from the data set effectively. The FDC test overcomes these limitations (Bozatli et al., 2023), and allows policymakers and scholars to obtain more comprehensive insights into food inflation and monetary policy relationships, which in turn, inform the development of appropriate monetary policy intervention strategies. Thus, this technique is a useful tool for understanding the complex interplay between food inflation and monetary policy in emerging economies.

The FDC test employed in this study generates test statistics at various frequencies across the spectra and enables a decomposition of the linkage between food inflation and monetary policy into short-term and long-term components (Ciner, 2011a, 2011b). The FDC test is also flexible and allows the causal relationship between food inflation and monetary policy to vary across different frequencies thereby permitting us to detect high-frequency (short-term) and low-frequency (long-term) dynamics individually[3] (Batten, Ciner, & Lucey, 2017; Ciner, 2011a). By allowing causality analysis at different frequencies, the frequency-domain approach allows policymakers to unravel short-run and long-run predictability, acquire a better understanding of the causal dependency between monetary policy and food inflation and introduce required policies in five emerging economies.

The FDC test accurately detects causality between variables relative to other causality tests (Zhang, Zhao, & Wang, 2024), capture both linear and nonlinear causal relationships, and is useful even if variables are not cointegrated (Ghaemi Asl, Rashidi, Tiwari, Lee, & Roubaud, 2023). The test is still applicable even in cases of non-stationary variables, and cointegrated systems and can be easily extended to examine causal relationships within a multivariate framework (Breitung & Candelon, 2006). Furthermore, the FDC test has reasonable size properties, and the power of the test increases considerably with the sample size (Breitung & Candelon, 2006). The results from Monte Carlo simulation experiments suggest that the FDC test does not inevitably suffer from low power even if the causality is examined at the extreme ends of the frequency spectrum (Yamada & Yanfeng, 2014). Wei, Zhang, Guo, and Yang (2021) based on theoretical and simulation analysis, conclude that when the root of the VAR model is close to 1 or −1, the FDC test is likely to have maximal power even at the extreme ends of the frequency spectrum. The frequency domain causality test is also appropriate for nonlinear series and generates better outcomes for small samples with seasonal and other possible economic episodes (Olasehinde-Williams, 2021). Therefore the causal relationship between food inflation and monetary policy is analysed for five emerging economies within the FDC framework.

Given that all variables are stationary and not cointegrated, panel VECM is not estimated to examine the causal relationship between variables. Furthermore, since the purpose of the paper is not to examine the transmission of shocks across countries and the relative importance of variables in explaining the variability in the system, a panel VAR approach is not employed[4]. Furthermore, a Panel VAR approach is relatively less insightful for individual central banks as the casual linkage between food inflation and monetary policy is likely to be heterogeneous. In this regard, individual country-by-country analysis of the causal relationship between food

Table 1
Descriptive statistics and correlation matrix.

	Brazil		China		India		Russia		South Africa	
	f_t	m_t	f_t	m_t	f_t	m_t	f_t	m_t	f_t	m_t
Mean	0.422	1.636	1.835	0.768	2.004	0.836	1.827	0.978	1.477	1.016
Median	1.629	1.267	1.834	0.767	2.015	0.829	1.843	0.989	1.552	1.061
Maximum	2.083	5.55	2.086	1.081	2.045	0.903	2.073	1.230	2.116	1.340
Minimum	−7.227	0.813	1.648	0.638	1.918	0.778	1.483	0.740	0.549	0.699
Std. Dev.	2.624	0.906	0.139	0.099	0.033	0.045	0.180	0.103	0.455	0.180
Skewness	−1.816	1.606	0.179	1.049	−0.931	0.247	−0.289	−0.018	−0.485	−0.159
Kurtosis	4.875	4.768	1.409	4.272	2.992	1.538	1.848	2.418	2.101	1.792
Obs	398	398	288	288	77	77	193	193	470	470
	1		1		1		1		1	
	−0.678	1	−0.489	1	−0.798	1	−0.549	1	−0.682	1

inflation and monetary policy is relatively more insightful for central banks.

4. Results and discussion

4.1. Descriptive analysis

Table 1 provides the descriptive statistics and correlation matrix of the variables. The mean food inflation ranges from 0.4 to 2.0 for emerging countries. Among the five emerging economies, India has the highest average food inflation at about 2 % with the lowest variation of 0.033 % while Brazil has the lowest food inflation of 0.422 % but with a high variation of 2.624 %. The average food inflation in Russia and South Africa is 1.827 and 1.477 %, respectively. The correlation matrix in Table 1 reports the correlation coefficient between monetary policy rates and food inflation. This indicates a negative relationship between the two series over time. The size of the coefficient is quantitatively similar among the countries and indicates a high negative correlation between food inflation and monetary policy[5].

4.2. Unit root test results

Table 2 presents the ADF and PP unit root test results. For Russia, the unit root hypothesis is not rejected in levels for monetary policy rates and food inflation but rejected in the first difference form – implying both series are non-stationary, I(1). Monetary policy rates in India and South Africa are also I (1) series. In contrast, for food inflation, the unit root hypothesis in South Africa and Brazil is rejected at the 1 % significance level. For India, the unit root hypothesis is rejected for food inflation at the 5 % significance level in the case of ADF but not in the case of the PP unit root test. Finally, the monetary policy rate is found to be stationary series, however, the

Table 2
ADF and PP unit root results.

Country	Variable	ADF	PP
Brazil	m_t	−1.443 (0.561)	−2.146 (0.227)
	Δm_t	−8.068*** (0.000)	−21.800*** (0.000)
	f_t	−4.579** (0.000)	−5.516*** (0.000)
	Δf_t	−1.770 (0.400)	−3.861*** (0.003)
India	m_t	−0.756 (0.825)	−0.806 (0.812)
	Δm_t	−4.804*** (0.000)	−8.592*** (0.000)
	f_t	−3.320** (0.018)	−2.486 (0.123)
	Δf_t	−6.267*** (0.000)	−4.904*** (0.000)
Russia	m_t	−2.226 (0.198)	−2.074 (0.255)
	Δm_t	−5.351*** (0.000)	−10.979*** (0.000)
	f_t	−1.711 (0.424)	−1.901 (0.332)
	Δf_t	−3.170** (0.023)	−6.138*** (0.000)
South Africa	m_t	−1.698 (0.432)	−1.725 (0.418)
	Δm_t	−6.175*** (0.000)	−19.589*** (0.000)
	f_t	−3.217** (0.020)	−4.043*** (0.001)
	Δf_t	−4.328*** (0.000)	−14.232*** (0.000)
China	m_t	−3.128** (0.026)	−2.915** (0.045)
	Δm_t	−14.267*** (0.000)	−15.192*** (0.000)
	f_t	0.389 (0.982)	0.850 (0.995)
	Δf_t	−2.222 (0.199)	−11.841*** (0.000)

Notes: *** and ** denotes statistical significance at 1 % and 5 % level, respectively. Only constant is included in the test regression. Figures in brackets denote the p-values.

results for food prices are inconclusive evidence in China – as these tests do not account for possible structural breaks.

4.3. Unit root test results with breaks

Table 3 reports the unit root test results allowing for a single break and multiple structural breaks. The Zivot and Andrews (1992) unit root test considers a single break, and we employ the model C version of the test, which considers a structural break in both the intercept and trend. Furthermore, Sen (2003) shows that model C is better compared to model A which only allows a break in the intercept. The test statistics for food inflation and the monetary policy rate for Brazil are statistically significant at the 1 % level and imply that both series are stationary. We can reject the unit root hypothesis for food inflation for India and South Africa, but not for Russia. However, the monetary policy rate is I(0) for Russia. To ensure the robustness of our inferences regarding the unit root properties of the variables, we also use the model CC version of Lee and Strazicich's (2003) unit root test, which considers two breaks in the intercept and the slope.

The results are summarized in Table 3, and we only report the main test statistics and the estimated break dates. The test statistics for Brazil confirm that both the monetary policy rate and food inflation rate are stationary at the 1 % significance level. The unit root hypothesis allowing two breaks is easily rejected at the 1 % significance level. The second break dates for 1994:6 and 1995: 1 coincide with the adoption of the floating exchange rate regime in July 1994 (Minella & Souza-Sobrinho, 2013). The unit root hypothesis is rejected for food inflation but not for the monetary policy rate in India. The break dates 2015:9; 2016:11; and 2015:7 coincide with the adoption of flexible inflation targeting by the Reserve Bank of India (Mohan & Ray, 2019).

For Russia, both the unit root test results indicate that monetary policy rates are stationary at the 1 % significance level. The estimated break dates of 2014:11, 2014:9, and 2016:3 coincide with the decision by the Bank of Russia to give up on the exchange rate target in November 2014 and the formal adoption of inflation targeting in February 2015 (Korhonen and Nuutilainen, 2017). For South Africa and China, the unit root hypothesis is not rejected for monetary policy rate in level, indicating the presence of a unit root. The second estimated break date of 1999:1 for monetary policy in South Africa is close to the adoption of inflation targeting in February 2000 (Iddrisu & Alagidede, 2020).

For China, the first break date in the monetary policy rate is 2009:12, which is found to be close to monetary policy easing (reduction of reserve requirements, loan rates, and benchmark deposit) by the People's Bank of China in the second half of 2008 (Yu, 2013). Food inflation is found to be stationary in South Africa and China as we can reject the unit root hypothesis at the 5 % and 1 % levels, respectively. We also applied Elliot, Rothenberg, and Stock (ERS) unit root and confirmed that the monetary policy rate in India, China, and South Africa and food inflation in Russia is stationary (results available upon request).

4.4. Baseline estimates of monetary policy rates on food inflation

Table 4 presents the baseline estimates of the impact of monetary policy rate changes on food inflation for five countries. Since food inflation and monetary policy are stationary I(0), spurious regression is not a concern, and we do not test for cointegration before the estimation of the relationship. Table 4 presents our baseline estimates using three different estimators. First, we use ordinary least squares (OLS) to estimate the effect of monetary policy on food inflation. For all countries, we find a negative and statistically significant impact of monetary policy rates on food inflation. Next, we re-estimate Eq. (1) by applying two-stage least squares (2SLS), and robust least squares to ensure our results are not sensitive to possible endogeneity and measurement errors.

The results confirm that our estimates are close except for Brazil. For Brazil, applying robust least-squares changes the magnitude of the coefficient, however, the sign and significance remain unchanged. The estimated effect is statistically significant at the 1 % level and the coefficient ranges from −0.7 to about −2, suggesting a relatively differential effect in terms of size. This is possibly due to country-specific factors such as the size of the agriculture sector, the extent of financial sector development, the nature of the exchange rate regime, and the level of economic development.

Table 3
Unit root test allowing for structural breaks.

Country	Variable	Zivot and Andrews test			Lee and Strazicich test		
		t-statistic	k	break date	t-statistic	k	break dates
Brazil	m_t	−10.160***	0	1994:7	−6.926***	14	1990:5, 1994:6
	f_t	−8.394***	4	1993:8	−6.796***	13	1989:9, 1995:1
India	m_t	−2.929	2	2015:9	−5.722	7	2015:7, 2018:4
	f_t	−5.342**	1	2016:11	−6.729***	4	2017:1, 2017:7
Russia	m_t	−6.584***	1	2014:11	−6.353**	9	2014:9, 2016:3
	f_t	−3.517	2	2014:11	−5.379	12	2011:5, 2014:12
South Africa	m_t	−4.578	3	2009:2	−4.482	8	1985:1, 1999:1
	f_t	−5.406**	1	1991:7	−5.587**	15	1986:10, 1993:3
China	m_t	−3.481	10	2009:12	−4.602	14	2002:2, 2014:9
	f_t	−4.352	12	2006: 11	−6.170***	13	2003:5, 2013:9

Notes: *** and ** denote statistical significance at 1 % and 5 % level, respectively. For Zivot-Andrews (1992) test, the critical values at 1 % and 5 % are −5.57 and −5.08, respectively.

Table 4
Baseline estimates.

	OLS	OLS with breaks	2SLS	Robust Least Squares (MM-Estimation)
Brazil	−1.962***	−2.006**	−1.962***	−0.773***
	(−18.343)	(−18.802)	(−18.343)	(−17.030)
China	−0.685***	−0.688***	−0.695***	−0.698***
	(−9.482)	(−9.558)	(−9.398)	(−8.335)
India	−0.581***	−0.588***	−0.573***	−0.483***
	(−11.485)	(−11.343)	(−11.577)	(−14.886)
Russia	−0.953***	−0.961***	−0.953***	−1.360***
	(−8.927)	(−8.995)	(−8.928)	(−12.638)
South Africa	−1.737***	−1.742***	−1.737***	−1.676***
	(−20.491)	(−20.439)	(−20.649)	(−22.708)

Notes: ***denotes statistical significance at the 1 % level. The figures in brackets are *t*-statistics. One period lag of regressors were used as instruments for 2SLS.

To control for structural breaks, we used the estimated break dates in monetary policy rates as found in Lee and Strazicich test and created dummy variables. We re-estimated the relationship including the dummy variables. The estimated coefficients are reported in column 2 of Table 4. The estimated effect of the monetary policy rate on food inflation is still negative and statistically significant at the 1 % significance level. Thus, we find no major change in the sign, size, and significance even after controlling for structural breaks[6].

Overall results reported in Table 4 reveal that an increase in the monetary policy rate (contractionary monetary policy) leads to a decline in food inflation. This finding is consistent with the theoretical argument that restrictive monetary policy negatively affects food prices through aggregate demand channels in five emerging economies (Scrimgeour, 2015). Hence, our finding of the negative effect is consistent with Scrimgeour (2015), Akram (2009), and Anzuini et al. (2013). However, our finding differs from the positive effect found for South Africa and Ghana (see for example, Iddrisu & Alagidede, 2020, 2021). While their study finds that restrictive monetary policy is associated with a rise in food prices, our results indicate that restrictive monetary policy leads to a fall in food inflation. Sasmal (2015) also found no relationship between agricultural prices and money supply in India. We, on the other hand, find evidence of a negative association between the monetary policy and food inflation in India. Therefore, monetary policy appears to be a useful tool for stabilizing domestic food inflation in all five emerging economies. Thus, prudent management of monetary policy is essential to manage domestic food inflation in emerging economies.

4.5. Frequency domain granger causality tests

We next examine the causal relationship between monetary policy and food inflation in five emerging countries. Table 5 presents a summary of the FDC test results. We report the frequencies at which the null hypothesis of no Granger causality from monetary policy rate to food inflation or vice versa is rejected. The results indicate that the null hypothesis of no Granger causality between the variables is rejected for Brazil, India, Russia, and South Africa. This indicates evidence of a bi-directional causal relationship between monetary policy and food inflation in four countries. However, frequencies differ across emerging economies. For example, there is a very strong feedback causal relationship between food inflation and monetary policy in Brazil and South Africa.

In India, food inflation is useful for predicting the monetary policy rate changes at both lower and upper frequencies, while the monetary policy rate contains useful information for predicting food inflation only at the lower frequencies between 0.01 and 0.22. In South Africa, we also find evidence of bi-directional causality from the monetary policy rate to food inflation. Finally, there is evidence of uni-directional causality from food inflation to the monetary policy rate in China at a lower frequency. This implies food inflation is

Table 5
Summary of frequency domain granger causality tests.

Country	$f_t \rightarrow m_t$	$m_t \rightarrow f_t$	Decision
Brazil	0.01–0.06; 0.6–2.34; 2.49–3.05	0.01–0.89; 1.0–2.03; 2.17–3.14	↔
China	0.01–0.15	-	→
India	0.01–0.35; 2.48–3.14	0.01–0.22	↔
Russia	0.01–3.14	0.01–3.14	↔
South Africa	0.01–0.07; 0.7–1.02; 1.43–1.87	1.06–1.43; 1.84–2.09	↔

Notes: The reported values are frequencies at which the null hypothesis of no Granger causality is rejected. ↔ denotes bi-directional causality; → denotes one-way causality. The direction of causality between variables remains the same if we include additional control variables. The results are available from authors upon request.

useful for predicting monetary policy changes at frequencies 0.01–0.15 in China. The null hypothesis of no Granger causality from monetary policy to food inflation is not rejected, implying the information on monetary policy rate is unlikely to be useful for predicting changes in food inflation in China.

Figs. 3a and 3b show the Wald statistics for causality analysis for the monetary policy and food inflation nexus for Brazil (see Appendix). Fig. 3a suggests that there is evidence of causality from the food inflation to the monetary policy at lower, medium and upper frequencies (about 0.6–2.34). Fig. 3b suggests that the monetary policy changes Granger causes food inflation throughout various frequencies. Comparing Figs. 3a and 3b reveals evidence of permanent as well as temporary causality between the monetary policy changes and food inflation in Brazil. These findings enhance our current understanding of the causal dynamics of monetary policy and inflation in Brazil.

Figs. 4a and 4b reveal that the null hypothesis of no Granger causality from the monetary policy rate to food inflation (and vice versa) can be rejected only at a lower frequency for India (see Appendix). Thus, both plots confirm the presence of bi-directional causality between the monetary policy rate and food inflation rate at a lower frequency. However, at higher frequencies, monetary policy and food inflation are not useful predictors of one another at the 5 % significance level.

In contrast to Brazil, India, South Africa and China, there is clear evidence of causality between monetary policy and food inflation in Russia. For instance, Figs. 5a and 5b show evidence of bi-directional causality between the monetary policy rate and food inflation (and vice versa) across the entire frequency from 0.01 to 3.14 for Russia (see Appendix). This reveals strong feedback causal relations between the monetary policy rate and food inflation in Russia. Food inflation and monetary policy are useful for predicting changes in Russia, regardless of the frequency.

Figs. 6a and 6b reveal significant causality between the monetary policy rate and food inflation in South Africa (see Appendix). The null hypothesis of no Granger causality from the monetary policy to the food inflation is rejected at the 5 % at various frequencies. Similarly, we find evidence of Granger causality from the food inflation to the monetary policy at various frequencies. This indicates food inflation is useful for predicting monetary policy (or vice versa) at lower frequencies. Figs. 7a and 7b indicate evidence of no causality from the monetary policy rate to food inflation in China but causality from food inflation to the monetary policy at a lower frequency (see Appendix).

Therefore, we document significant evidence of a bi-directional or feedback relationship between monetary policy and food inflation in all economies except for China, based on the individual country analysis. Our findings uncover a great deal of

Table 6
Estimation results based on extended model specification.

Country	Variable	OLS		2SLS		RLS(MM)	
		Coef	*t-stats*	*Coef*	*t-stats*	*Coef*	*z-stats*
Brazil	m_t	−0.040***	−3.375	−0.040***	−2.673	−0.040**	−2.961
	wf_t	1.333***	25.818	1.281***	20.381	1.313***	24.110
	op_t	−0.127***	−5.119	−0.129***	−4.508	−0.117***	−4.474
	ex_t	−0.983***	−56.597	−0.959***	−40.494	−0.984***	−53.674
	ci_t	0.161***	6.100	0.397***	5.187	0.162***	5.786
China	m_t	−0.335***	−7.974	−0.362***	−7.154	−0.484***	−13.786
	wf_t	0.907***	22.704	0.941***	20.007	0.792***	23.749
	op_t	−0.138***	−8.267	−0.145***	−7.329	−0.073***	−5.232
	ex_t	0.936***	11.384	0.859***	6.273	1.021***	14.883
	ci_t	0.012	0.906	0.065	0.341	0.020*	1.834
India	m_t	−0.356***	−7.411	−0.299**	−2.001	−0.364***	−6.834
	wf_t	−0.384***	−3.958	−0.312	−1.526	−0.344***	−3.195
	op_t	0.014	0.437	0.038	0.471	−0.001	−0.023
	ex_t	−0.498***	−4.061	−0.338	−0.758	−0.510***	−3.749
	ci_t	0.006	1.244	0.062	0.689	0.006	1.077
Russia	m_t	−0.220***	−5.942	−0.159***	−3.377	−0.251***	−7.090
	wf_t	0.551***	10.326	0.565***	4.902	0.458***	8.976
	op_t	0.064	1.542	0.102	1.640	0.132***	3.310
	ex_t	−1.250***	−38.241	−1.297***	−26.373	−1.285***	−41.128
	ci_t	−0.003	−0.290	−0.038	−0.286	−0.005	−0.653
South Africa	m_t	−0.282***	−9.861	−0.222***	−4.882	−0.298***	−10.787
	wf_t	0.354***	10.139	0.361***	7.824	0.303***	8.983
	op_t	0.015	0.741	0.049	1.463	−0.003	−0.161
	ex_t	−1.127***	−42.711	−1.035***	−16.859	−1.164***	−46.269
	ci_t	0.034**	2.483	0.237***	2.190	0.024*	1.780

Notes: *** and ** denote statistical significance at the 1% and 5% levels, respectively. The sample period for Brazil is 1993:1–2019:7; India is 2013:1–2019:5; Russia is 2004:1–2019:7; South Africa is 1993:1–2020:1; China 1996:1–2020:1. The sample period is dictated by data availability. For 2SLS, we use lagged variables of regressors as instruments. We obtain similar results if we use real exchange rates rather than nominal exchange rates. The results are not reported here to conserve space.

interdependency between monetary policy and food inflation in the majority of emerging economies. It is also important to note that there is relatively more evidence of causality from food inflation to monetary policy. These findings reflect that food inflation contains predictive power for future changes in monetary policy. These insights are useful for financial market participants and as well as further analysis of monetary policy in emerging economies. However, it is also important to note that causality between food inflation and monetary policy (interest rates) could also be dependent upon the choice of monetary policy (targeting headline inflation vs targeting core inflation).

5. Sensitivity analysis

5.1. Re-estimating the effects of monetary policy using alternative model specification

We re-estimate the effect of monetary policy on food inflation, including oil prices (op_t), world food prices (wf_t), climate change (ci_t) and nominal exchange rate (ex_t), to verify if there is any major change in the sign and significance of the coefficient of the monetary policy rate variable. We include monthly data on world food prices and temperature change (proxied as mean temperature change on land, relative to a baseline climatology) from FAO, oil prices (measured by Spot Crude Oil Price (West Texas Intermediate (WTI), in dollars per Barrel) from the Federal Reserve Bank at St. Louis, and nominal exchange rates from Darvas's (2012) exchange rate database. The rationale behind including these additional variables is that food inflation is also affected by world food prices, oil prices, and exchange rates. The theoretical justification for including world food prices is as follows. World food prices are more volatile than domestic food prices and can have little impact on domestic food prices due to weak transmission because of trade and price support policies (Norazman et al., 2018; Vavra & Goodwin, 2005).

Oil price shocks also influence domestic food prices. Norazman et al. (2018) point out that the agriculture sector is quite energy-intensive by nature and thus vulnerable to shocks to oil prices. A rise in fuel (oil) prices will influence food prices by increasing the cost of transportation and fertilizer and raising input costs to power relevant machines (Bhattacharya & Gupta, 2018). Oil prices affect the costs of energy for food processing firms and the cost of delivery for food retailing firms. Hence, shocks to oil prices will increase the cost of importing as well as production, processing, and distribution of food prices. Higher oil prices tend to raise domestic food prices. Thus, we expect an increase in oil prices to have a positive effect on domestic food inflation. Norazman et al. (2018) note that higher exchange rates (depreciation) make imports expensive and raise the prices of domestic food.

Climate change also influences food inflation in several ways. Given that the agriculture sector is quite sensitive to weather conditions, climate change tends to adversely affect food production systems, natural resource bases, and agriculture productivity and contribute to food shortages and therefore lead to higher food prices (Mukherjee & Ouattara, 2021). Higher temperatures also adversely affect productivity, reduce the quantity of exports and affect food prices (Deryugina & Hsiang, 2014; Gassebner, Keck, & Teh, 2010; Jones & Olken, 2010). Extreme temperature (higher or lower) also increases energy demand but also reduces energy supply by reducing the productive efficiency of energy infrastructure (Mukherjee & Ouattara, 2021). This will push up prices and lead to inflation.

Table 6 presents the estimated effect of monetary policy rates on food inflation rates including world food prices, oil prices, and exchange rates. To account for possible endogeneity and the presence of outliers in the dependent and independent variables, we use two-stage least squares and MM-based robust least squares, respectively. For all countries, we report the estimated coefficient and *t*-statistics.

We find consistent evidence that higher monetary policy rates are associated with a decline in food inflation across all five countries. The estimated effect of monetary policy rate on food inflation is quite close across three estimators suggesting our results are robust to not only alternative model specification but also concerns regarding endogeneity and outliers. The results in Table 6 indicate that including additional determinants of food inflation does not alter the results – reflecting the robustness of our results. We still find that monetary policy has an influential role in food inflation in these five emerging economies.

An increase in the monetary policy rate (contractionary monetary policy stance) is also associated with a decline in the food inflation rate in India and China. The estimated relationship is found to be statistically significant at the 1 % level. It is worth noting that estimated the coefficient across three estimators is about −0.4 for India and China. Changes in monetary policy rates also have a statistically significant negative impact on food inflation in Russia and Brazil at the 1 % level. The estimated effect of the monetary policy rate on food inflation is about −0.04 in Brazil and −0.20 in Russia and is statistically significant at the 1 % level even after accounting for other factors. Changes in the monetary policy rates also matter significantly for food inflation in South Africa. The estimated effect of the monetary policy rate on food inflation is about −0.3 and statistically significant at the 1 % level across all three estimators even after accounting for other factors. Thus, monetary policy changes still have a significant influence over food inflation even after we control the effects of world food prices, oil prices, and exchange rates.

In all five countries, three estimators provide robust and consistent econometric evidence that the monetary policy rate is an important determinant of domestic food inflation. While the size of the estimated coefficient of monetary policy does vary across countries as one would expect, the sign of the coefficient is still negative regardless of the estimator employed. This finding here confirms our earlier result that a contractionary monetary policy (increase in monetary policy rate) will negatively impact food inflation. This implies contractionary monetary policy is useful for stabilizing food inflation in all five countries, controlling for oil prices, world food prices, climate change[7] and exchange rates.

The exchange rate is negatively related to domestic inflation in all countries, except for China. Rangasamy (2011) finds the exchange rate to have positive effects on domestic prices in South Africa. We find world food prices are positively related to domestic inflation in all countries except for India. Therefore, increasing world food prices is an important driver of domestic food inflation in most emerging economies, except India. This finding is consistent with past studies for South Africa (Iddrisu & Alagidede, 2020; Rangasamy, 2011) and Malaysia (Norazman et al., 2018). However, Iddrisu and Alagidede (2021) found world food prices are not a significant factor in domestic inflation in Ghana.

Our results reveal that oil prices exert a positive but statistically insignificant on food inflation in India, South Africa and Russia. In contrast, oil prices are negatively associated with food inflation in Brazil and China. Norazman et al. (2018) also found a negative impact of oil prices on food prices in Malaysia. However, the effect might be cushioned by price control or energy subsidy programs. Therefore, oil prices are not a significant robust determinant of food inflation across all five emerging countries. The results reported in Table 6 also suggest that world food prices are a significant and robust influence on food inflation in all economies, except for India. Therefore, higher world food prices tend to exacerbate domestic food inflation in all emerging economies except for India. This to some extent suggests that India is quite immune to adverse shocks to world food prices because it is one of the highest agricultural producers.

Table 6 also reports the estimated effects of climate change (measured by temperature) on food inflation. The results indicate that climate change adversely affects food inflation in Brazil and South Africa. In both economies, a higher temperature tends to exacerbate food inflation. This suggests that climate change tends to adversely affect agricultural production and push up food prices. In China and India, climate change also adversely affects food inflation. However, the effect is insignificant.

Overall, the results in Table 6 do confirm, that an increase in the monetary policy rate is associated with a decline in food inflation in all five countries. Compared to our baseline estimates, we do note a decline in the magnitude of the estimated coefficient of monetary policy as more variables are considered. However, the sign and significance of the coefficient remain consistent and robust. We find that there are important differences across the countries, particularly looking at the effect of world food prices, oil prices, climate change and exchange rates. Therefore, the results in Table 6, however, reaffirm our earlier finding that the monetary policy helps stabilize food inflation. Table 6 also confirms that out of all factors considered, the monetary policy rate is the only variable whose effect has a "consistent" negative effect on food inflation.

5.2. Sub-sample analysis of monetary policy on food inflation

We re-examine the relationship between the monetary policy rate and food inflation before and after the global financial crisis (GFC). This will help us understand if there was any change in the nature of the relationship in the post-GFC era for emerging economies. Since the onset of the GFC, many central banks around the world began to ease monetary policy (Banerjee & Vashisht, 2010). The post-GFC period was also characterized by fluctuations in food prices. Thus, we examine if the link between monetary policy and food inflation changed after the GFC. The results are summarized in Panels A and B of Table 7. We first examine the coefficients of monetary policy and find two important results. First, in the pre-GFC period, the estimated effects of the monetary policy rate on food inflation were relatively higher (in absolute terms) compared to the post-GFC period. This is particularly true for Brazil, Russia, and South Africa. This implies the monetary policy had a strong influence on food inflation, however, the effect appears to have weakened after the GFC. This perhaps also indicates the increasing effects of other factors such as oil prices, world food prices, and exchange rates, amongst others, on food inflation.

The second important observation is for China, where contractionary monetary policy appears to have been positively associated with food inflation before the GFC. In the post-GFC period, the contractionary monetary policy led to stabilizing food inflation. We also find that in the post-GFC period, there is no causality from monetary policy to food inflation in China. Thus, during the post-GFC

Table 7
Monetary policy and food inflation.

Panel A: Monetary Policy and Food Inflation (Pre-GFC Period)		
Country	Coefficient	Direction of Causality
Brazil (1986:6–2007:6)	−1.815*** (−11.536)	$f_t \leftrightarrow m_t$
China (1996:1–2007:6)	0.066** (2.457)	$f_t \rightarrow m_t$
Russia (2004:1–2007:6)	−0.932*** (−11.915)	No causality
South Africa (1981:1–2007:6)	−0.964*** (−6.254)	$f_t \rightarrow m_t$
Panel B: Monetary Policy and Food Inflation (Post-GFC Period)		
Country	Coefficient	Direction of Causality
Brazil (2007: 7 - 2019:7)	−0.233*** (−2.728)	$f_t \leftrightarrow m_t$
China (2007: 7 -2019:12)	−0.621*** (−11.489)	No causality
Russia (2007: 7 - 2019:12)	−0.230** (−2.101)	$f_t \leftrightarrow m_t$
South Africa (2007: 7 - 2019:12)	−0.361*** (−4.843)	No causality

Notes: Figures in brackets in the second column are *t*-statistics. *** and ** denotes statistical significance at 1 % and 5 % level, respectively.

period, changes in monetary policy rates still had a negative impact on food inflation, suggesting monetary policy did play an important role in stabilizing food inflation in Brazil, Russia, and South Africa[8].

In this second part, we compare the direction of causality between the monetary policy rate and food inflation covering the pre-GFC period and post-GFC period. To conserve space, we do not report all the graphs for all countries, rather report the main result in Table 7 (all graphs are available from the authors upon request). There is evidence of bi-directional causality between the monetary policy rate and food inflation in Brazil in both the pre-GFC period and post-GFC period. In the post-GFC period, food inflation is useful for predicting monetary policy rates at a lower frequency.

There is evidence of uni-directional causality from food inflation to monetary policy rate at a lower frequency in China in the pre-GFC period. However, there is no causality between the monetary policy rate and food inflation in the post-GFC period. In Russia, there is evidence of bi-directional causality in the post-GFC period, but no causality in the pre-GFC period. This finding suggests that in the post-GFC period, monetary policy rate and food inflation become increasingly important for predicting each other. For South Africa, we find evidence of uni-directional causality from food inflation to monetary policy rate in the pre-GFC period. However, there is no evidence of causality in the post-GFC period. This leads us to conclude that food inflation and monetary policy rate lost their predictive power for each other in China and South Africa in the post-GFC period. In contrast, monetary policy rates and food inflation were still useful for predicting each other in Brazil and Russia.

Table 8
Quantile Estimates.

Country	Quantile	Coefficient	t-statistic
Brazil	0.1	−3.991***	−7.641
	0.2	−3.202***	−8.494
	0.3	−2.561***	−9.011
	0.4	−1.812***	−9.064
	0.5	−1.675***	−11.533
	0.6	−1.464***	−12.342
	0.7	−1.129***	−8.707
	0.8	−0.839***	−9.058
	0.9	−0.640***	−5.549
India	0.1	−0.993***	−8.919
	0.2	−0.593***	−4.667
	0.3	−0.592***	−5.103
	0.4	−0.527***	−9.684
	0.5	−0.493***	−9.001
	0.6	−0.497***	−10.572
	0.7	−0.470***	−9.837
	0.8	−0.404***	−7.942
	0.9	−0.420***	−12.1
Russia	0.1	−1.006***	−15.917
	0.2	−1.211***	−12.55
	0.3	−1.401***	−17.476
	0.4	−1.416***	−20.519
	0.5	−1.486***	−10.026
	0.6	−1.389***	−4.188
	0.7	−1.099***	−3.285
	0.8	−0.222	−0.965
	0.9	−0.226***	−13.027
South Africa	0.1	−2.976***	−14.664
	0.2	−2.240***	−11.365
	0.3	−1.735***	−14.724
	0.4	−1.594***	−18.863
	0.5	−1.600***	−20.816
	0.6	−1.447***	−20.561
	0.7	−1.415***	−14.376
	0.8	−1.548***	−16.900
	0.9	−1.382***	−22.794
China	0.1	0.099***	9.753
	0.2	0.020	0.537
	0.3	−0.117	−0.528
	0.4	−0.644***	−6.526
	0.5	−0.749***	−9.912
	0.6	−0.807***	−9.775
	0.7	−0.748***	−12.505
	0.8	−0.713***	−10.079
	0.9	−0.740***	−30.731

Notes: *** denotes statistical significance at the 1 % level. The figures in brackets are t-statistics.

5.3. Asymmetric effects of monetary policy on food inflation

Because food inflation has been extremely volatile at times especially when it is driven by changes in weather conditions and supply-side factors, implies that food prices exhibit tail dynamics. Therefore, a mean-based approach might not be fully informative and capture the entire effect. Furthermore, given that food inflation and monetary policy rates are I(0), we also resort to the quantile regression developed by Koenker and Bassett (1978). The use of the quantile regression analysis allows us to capture the asymmetric effects of monetary policy on food inflation (Iddrisu & Alagidede, 2021). Moreover, quantile regression does not require specification assumptions about the type of error distribution (Iddrisu & Alagidede, 2020; Yu & Moyeed, 2001). The quantile regression is also robust to potential outliers (as expected in food inflation due to volatility) and heteroscedasticity and thus appears to be more useful compared to OLS and VAR approach (Benoit & Van den Poel, 2017; Iddrisu & Alagidede, 2020; Yang, Wang, & He, 2016).

Table 8 presents the estimates at various quantiles (0.1–0.90). First, the effect of monetary policy rates on food inflation is statistically significant and negative at almost all quantiles for all economies at the 1 % significance level. Second, the size of coefficients changes (in absolute terms) as we move from lower to higher quantiles. For example, the effect of the monetary policy rate in Brazil is 3.99 at 0.1 quantile but changes to 0.640 at 0.9 quantile. For India, the coefficient changes from 0.99 to 0.42. For Russia, the coefficient changes from 1.006 to 0.226, for South Africa the coefficient changes from 2.976 to 1.382. For China, the coefficient changes from 0.64 to 0.74. Third, the change in the coefficient of monetary policy rates is quite significant in Brazil, China, India, Russia, and South Africa. Therefore, the relationship between monetary policy rates and food inflation is asymmetric. However, these results confirm that the monetary policy rate has a negative effect on food inflation – a rise in the monetary policy rate (contractionary monetary policy) is associated with a decline in food inflation.

5.4. Panel data analysis

We also undertake a panel analysis of the impact of monetary policy on food inflation. In recent years, panel data analysis has become popular amongst researchers for several reasons. Firstly, the rationale for resorting to panel data analysis is because time series analysis (unit-root and cointegration tests) suffers from distortion especially given the small sample size. Panel analysis overcomes sample-related issues and has been argued to have enhanced testing power over univariate tests (Levin, Lin, & James Chu, 2002). Secondly, panel data analysis helps us overcome the limitation of standard time-series analysis and controls for possible sources of omitted variable bias (see, for instance, Lin, 2009).

Thirdly, panel data analysis allows us to deal with endogeneity and non-stationarity in regression analysis. Fourthly, panel data analysis enables efficient estimation, and therefore helps capture dynamic relationships (Ho, 2004). Following previous panel studies (Gupta et al., 2021; Haddou, 2022; Lee et al., 2023), the analysis is based on unbalanced panel data which is due to the unavailability of consistent high-frequency (monthly data) for different countries. We consider the following specification:

$$f_{it} = \alpha + \beta m_{it} + u_{it} \tag{9}$$

All variables are defined as earlier. We pool the data for five countries and found evidence of stationarity of both series using first-

Table 9
Panel results.

Panel A: Panel Estimates					
Variable	Panel OLS	Panel FE	Panel 2SLS	Panel OLS[†]	Panel FE[†]
m_{it}	−1.874***	−1.935***	−1.957***	−1.876***	−1.935***
	(−40.088)	(−34.522)	(−34.885)	(−8.870)	(−8.220)
No of obs.	1427	1427	1422	1427	1427
R-squared	0.530	0.536	0.548	0.530	0.456
F-stats	1607.052***	329.264***	313.851***	33.540***	30.140***

Panel B: Panel Granger Causality Test Results				
Lag Length	Unbalanced Panel Stack test (common coefficient)		Unbalanced Panel Dumitrescu Hurlin (individual coefficients)	
	$m_{it} \rightarrow f_{it}$	$f_{it} \rightarrow m_{it}$	$m_{it} \rightarrow f_{it}$	$f_{it} \rightarrow m_{it}$
1	2511.960***	69.324***	469.630***	10.389***
	(0.000)	(0.000)	(0.000)	(0.000)
2	298.134***	44.142***	60.568***	8.663***
	(0.000)	(0.000)	(0.000)	(0.000)
3	216.287***	33.917***	51.793***	8.855***
	(0.000)	(0.000)	(0.000)	(0.000)
4	171.006***	24.937***	45.714***	7.589***
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: For panel A, *t*-statistics are reported in brackets. *** statistical significance at 1 % level. For Dumitrescu Hurlin-based test results in Panel A, the reported values are Z bar-statistics. [†] denotes regression with Driscoll-Kraay standard errors to account for cross-sectional dependency. We used the residuals from the fixed effect regression and test for serial correlation using Born and Breitung (2016) heteroscedasticity-robust (HR) test. The HR-stat was 1.31 with a *p*-value of 0.191. We find similar results with balanced panel data analysis.

general panel unit root tests regardless of the presence of cross-sectional dependency. We use Panel OLS, Panel Fixed Effects, and Panel 2SLS to examine the effects of monetary policy on food inflation. The results are summarized in Panel A of Table 9. The result reported is consistent with earlier individual country analysis. To ensure our estimates are robust to the presence of cross-sectional dependency, we re-estimate the regression with Driscoll-Kraay standard errors (Driscoll & Kraay, 1998). The regression with Driscoll-Kraay standard errors allows us to obtain results that are robust to cross-sectional dependency and can be used with both balanced and unbalanced panels. The estimated effect of the contractionary monetary policy is still negative and statistically significant at the 1 percent level.

The five-panel estimators provide consistent results of the negative impact of monetary policy rates on food inflation. This confirms our baseline estimates from the time-series analysis that an increase in monetary policy rate is associated with a decline in food inflation in emerging economies. We also examined the panel causality relationship between the monetary policy rate and food inflation using Dumitrescu and Hurlin's (2012) panel causality test. The results reported in Panel B of Table 9 confirm evidence of bi-directional causality between the monetary policy rate and food inflation in five economies. The results are robust to alternative lag lengths.

6. Conclusion and policy implications

Food inflation is an important component of overall inflation dynamics in many countries. For policymakers, food price inflation poses serious challenges both from the welfare perspective of vulnerable households as well as maintaining inflation targets. The formulation and implementation of monetary policy depend heavily on an understanding of the causes of changes in food inflation. As noted by Rogoff (2003) twenty years ago, as a result of the introduction of numerous factors that impact inflation, globalization has over time made it more difficult to pinpoint the causes of inflation. Since the start of the COVID-19 pandemic, there have been a number of significant shocks such as interest rate changes, geopolitical tensions, supply-side disruptions and swings in commodity prices making it apparent for a more thorough examination of the relationship between monetary policy and food inflation necessary.

We extend the literature and offer a more a nuanced perspective by investigating the impact of monetary (central bank) policy rates on food inflation in emerging economies (Brazil, China, India, Russia, and South Africa). Given the evidence of stationarity, we use a number of estimators, and a novel frequency domain-based Granger causality test to investigate the relationship between the monetary policy rate and food inflation. We provide robust evidence that: a) an increase in the monetary policy rates will reduce food inflation; b) there is a strong feedback effect between monetary policy and food inflation in almost all economies. We find that our results are robust to alternative model specifications, possible asymmetry, sub-sample analysis, and the use of panel methodology.

From a policy perspective, compared to oil prices, world food prices, climate change and exchange rates, we find the monetary policy to have a relatively robust negative impact on food inflation. The central banks in emerging economies can use carefully calibrated and coordinated macroeconomic policies to stabilize food inflation and safeguard the welfare of vulnerable households who are susceptible to adverse food price shocks. The findings also provide useful lessons for future work on the predictability of monetary policy rates and food inflation in emerging economies. The evidence of bi-directional causality signifies the importance of both variables as food inflation and monetary policy rates are useful for predicting each other. There are several avenues to extend this study. Future research can consider additional factors (for example, gross value-added in agriculture, fiscal policy (food subsidies), and supply-side disruptions from economic and geopolitical contestations) as well as monetary policy shocks or dimensions of monetary policy in better understanding the relationship between food inflation and monetary policy. Moreover, future research on other developing economies differentiating between headline inflation and core inflation and using panel VAR to understand the transmission channels through which diverse factors influence food inflation can provide useful insights for policymakers.

Funding

None

Notes

1. In comparison to EMDEs, 27 % of the advanced countries have experienced food price inflation of more than 5 %.
2. Mallick and Sethi (2014) estimate core inflation using trimmed mean and SVAR method for India.
3. Low frequency (w = 0.5) corresponds to permanent (long-term) causality, while high frequency (w = 2.5) corresponds to temporary (short-term) causality (Bozatli et al., 2023; Mbratana, Fotié, & Amba, 2021).
4. We thank an anonymous reviewer for bringing this to our attention. This, however, remains a useful area for future research.
5. This is only an initial analysis. We also examine correlation with additional variables but find quantitatively similar estimates.
6. The estimated coefficients of dummy variables are found to be generally statistically insignificant and not reported. Results are available upon request.
7. We thank an anonymous reviewer for this suggestion.
8. Note, India is excluded as sample period for India started from 2013:1. The analysis for India is therefore focused on post-GFC period.

CRediT authorship contribution statement

Janesh Sami: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Keshmeer Makun:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

No potential conflict of interest was reported by the authors.

Data availability

Data will be made available on request.

Acknowledgements

We are grateful to the editor and anonymous reviewers for their valuable comments and suggestions.

Appendix

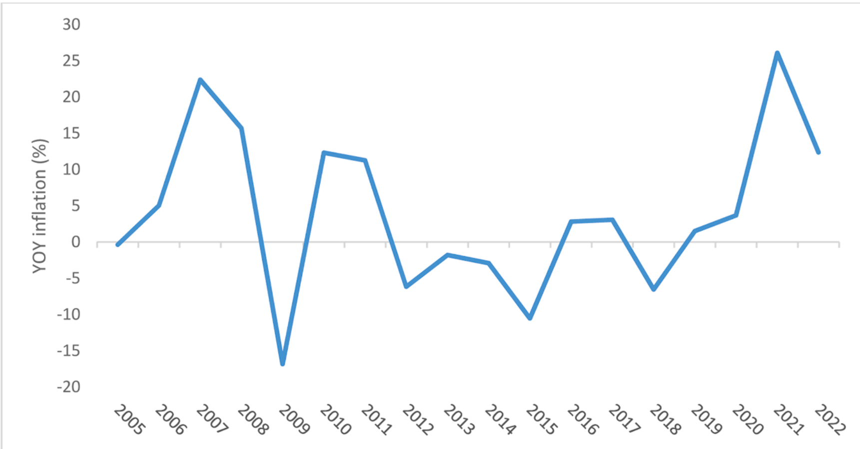

Fig. 1. World food inflation Alt Text: Graph showing year-on-year world food inflation rate from 2006 to 2021.*Source*: FAO and authors' calculation.

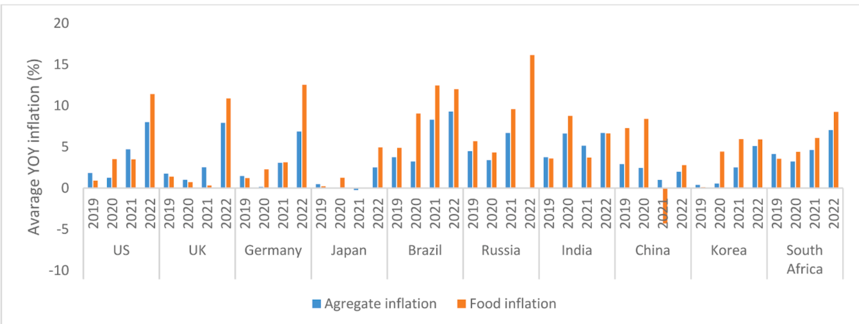

Fig. 2. The Average Headline and Food Inflation Alt Text: Graph comparing the average headline and food inflation rate in emerging and advanced economies from 2019 and 2020. *Source*: World Bank and Food and Agriculture Organisation.

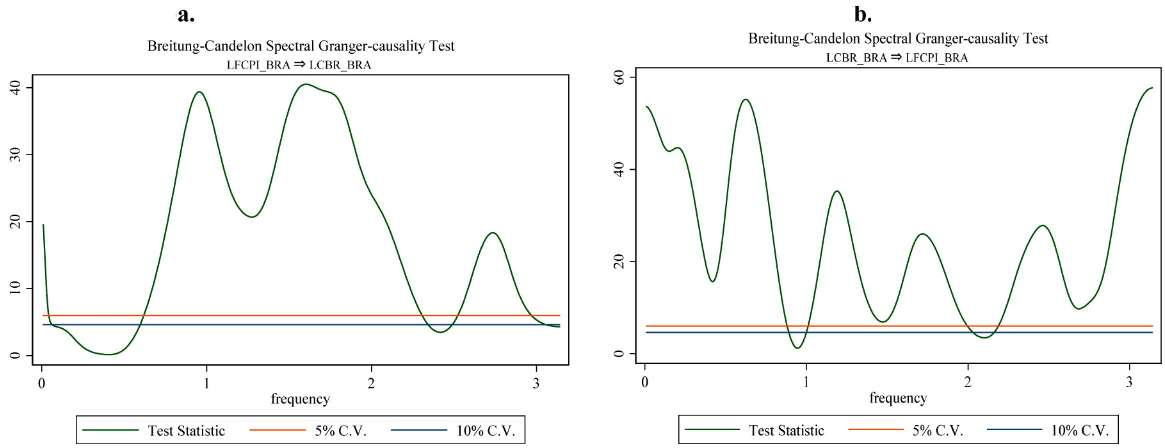

Fig. 3. a. Granger causality test results Alt Text: Graph showing causality from food inflation to monetary policy rate in Brazil. **3b.** Granger causality test results **3b.** Alt Text: Graph showing causality from monetary policy rate to food inflation in Brazil.

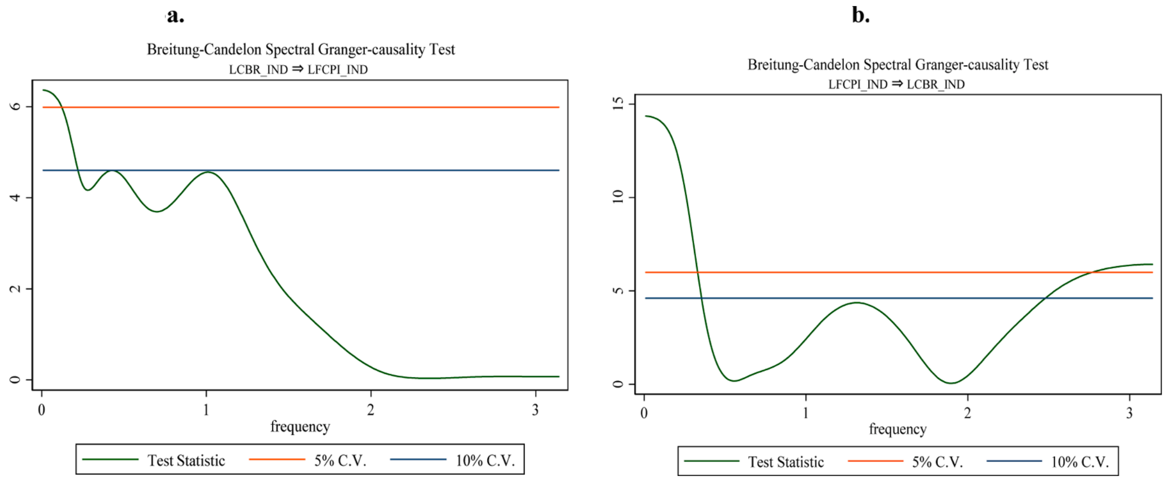

Fig. 4. a. Granger causality test results Alt Text: Graph showing no causality from monetary policy rate to food inflation at higher frequencies in India. **4b.** Granger causality test results Alt Text: Graph showing causality from food inflation to monetary policy rate at lower frequencies in India.

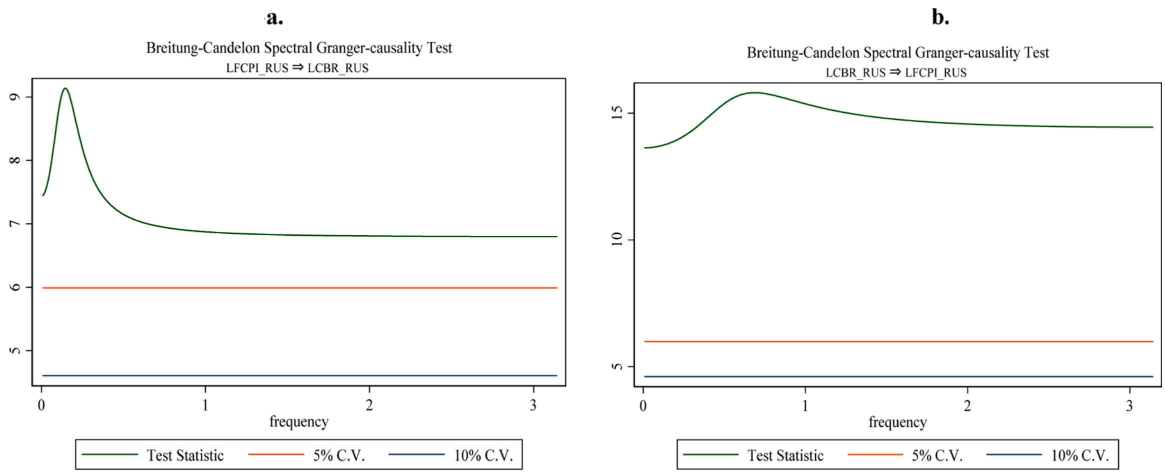

Fig. 5. a. Granger causality test results Alt Text: Graph showing causality from food inflation to monetary policy rate in Russia. **5b.** Granger causality test results Alt Text: Graph showing causality from monetary policy rate to food inflation in Russia.

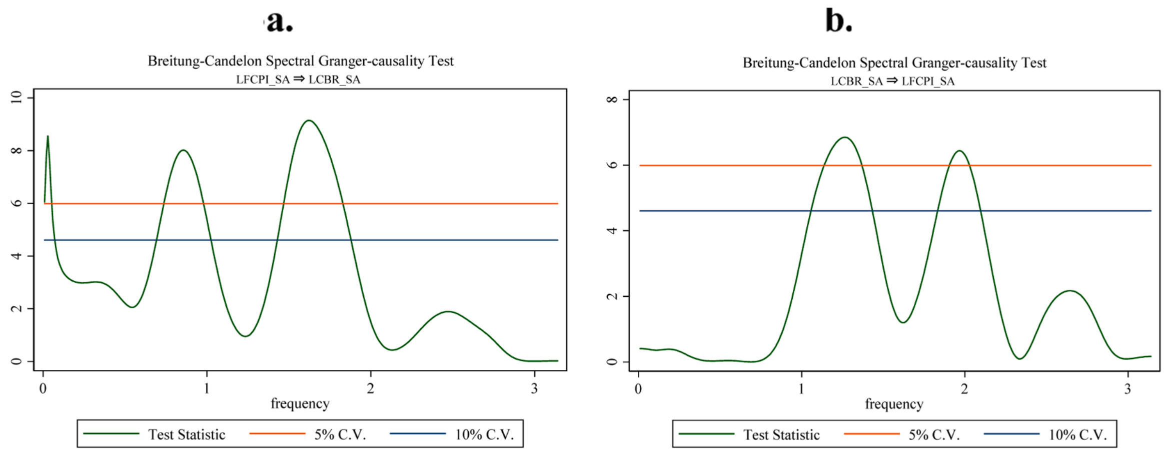

Fig. 6. **a.** Granger causality test results Alt Text: Graph showing weak causality from food inflation to monetary policy rate in South Africa. **6b.** Granger causality test results Alt Text: Graph showing weak causality from monetary policy rate to food inflation in South Africa.

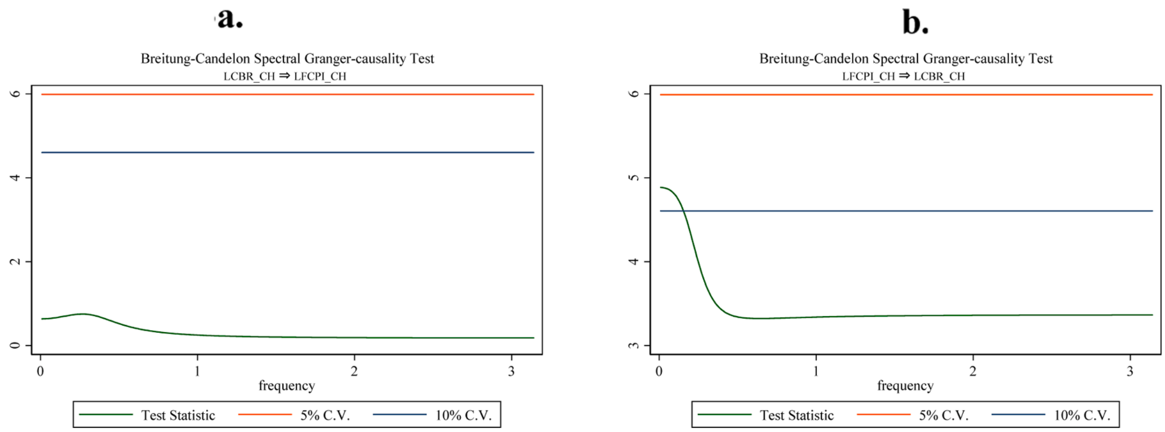

Fig. 7. **a.** Granger causality test results Alt Text: Graph showing no causality from monetary policy rate to food inflation in China. **7b.** Granger causality test results Alt Text: Graph showing no causality from food inflation to monetary policy rate in China.

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