Impact of food inflation on core inflation in Brazil: a time-varying parameter approach

Abstract

This paper examines the influence of food inflation on core inflation in Brazil by employing a VAR model with time-varying parameters and stochastic volatility. The estimation is conducted through Bayesian simulation spanning the period from January 1999 to February 2023. In light of the recent upswing in commodity prices and the inflationary repercussions of the pandemic, a thorough evaluation of the impact of food prices on core inflation becomes imperative. The results uncover a notable degree of uncertainty during the pandemic era. Furthermore, the study identifies a significant and statistically meaningful impact of food inflation on core inflation, especially in the recent period. Given that food inflation poses a big challenge, especially for Central Banks in emerging economies, these findings carry important implications for policymakers.

Keywords: food inflation, core inflation, time-varying models, bayesian econometrics, stochastic volatility

JEL Classification: E58 , E31 , C32 , C11

1 Introduction

Food inflation in Brazil is one of the main components of the Extended National Consumer Price Index (IPCA) calculated by the Brazilian Institute of Geography and Statistics (IBGE). In 2022, the IPCA closed with a 5.8% increase, and the food and beverages group accounted for nearly half of this result. The significant contribution of this group to inflation reflects the importance of this variable in the country's consumption basket, particularly affecting low-income groups. As highlighted by Walsh (2011), economies with a significant portion of expenditure allocated to food in the consumption basket may experience larger and more prolonged effects of food inflation on non-food inflation. Therefore, food inflation is a big challenge for central banks, particularly in low- and middle-income economies. According to Cecchetti and Moessner (2008), policymakers encounter various challenges when addressing elevated inflation resulting from surges in commodity prices. One of these challenges is to identify whether increases in commodity prices are likely to generate second-round effects on headline inflation.

Food inflation can have both direct and indirect effects on overall inflation (Cecchetti and Moessner (2008)). The direct effect occurs because food is part of the consumption basket used in price indices calculation. The indirect effect can occur through its impact on inflation expectations and also through inertial effects. Therefore, even though core inflation excludes food items, they can still have a relevant impact through indirect effects [1]. These impacts may vary over time, depending, for example, on the state of the economy (recession, expansion) or the level of inflation (high, low). As pointed out by Ha, Ivanova, Montiel, and Pedroni (2019), core inflation in low-income countries responds more strongly to global food inflation than does core inflation in the other country groups [2]. Given the recent increase in commodity prices and the pandemic effects on inflation, it is crucial to assess the impact of food prices on core inflation in Brazil, an emerging economy. In this context, the objective of this study is to evaluate the impact of a food inflation shock on core inflation in Brazil.

The methodology employed in this study is a three-variable time-varying parameter vector autoregression model with stochastic volatility (TVP-VAR-SV). The model includes output gap, core inflation and food inflation over the period 1999:M1-2023:M2. Considering the econometric challenges inherent in traditional time-varying parameter regressions, a Bayesian estimation procedure is employed to yield parameter estimates that are more robust. Moreover, a stochastic volatility specification is incorporated to account for the potential existence of conditional heteroskedasticity, which may result from stochastic shocks affecting the volatility of the analyzed macroeconomic aggregates.(Hamilton (2008)).

[1]The September 2018 Inflation Report from the Central Bank of Brazil presents compelling evidence regarding the indirect influence of food prices on inflation cores in Brazil. Furthermore, the findings underscore the heightened importance of food prices for the inflation core in Brazil compared to other countries under analysis. Further details available inBanco Central do Brasil (2018).

[2]The low-income countries used in this study include Afghanistan, Burundi, Benin, Burkina Faso, the Comoros, Ethiopia, Guinea, Liberia, Mali, Mozambique, Malawi, Niger, Rwanda, Senegal, Sierra Leone, Togo, Tanzania, and Uganda.

Given the challenges of identifying structural changes before estimation and the potential gradual nature of such changes, the TVP-VAR method emerges as a robust and flexible approach to capture these time-varying effects (Nakajima (2011)). By accommodating time variations in autoregressive parameters and stochastic volatility, this method can effectively address potential non-linearity during estimation. With parameters following a first-order random walk process, the approach can effectively capture both temporary and permanent shifts. In our particular context, the adopted methodology will aid in addressing the following question: has the transmission of food price inflation to core inflation undergone changes over time? This is of particular significance, considering the impacts of the Covid pandemic on inflation, especially on food inflation.

As to the contribution to the debate, to the best of our knowledge, this paper is the first application of a Bayesian approach to deal with potential parametric instability while estimating the impact of food inflation on core inflation in Brazil. Therefore, the novelty presented in our research lies in examining the impact of food inflation on core inflation using a time-varying parameter model and Bayesian inference.

Besides this introduction and the concluding remarks, the paper is organized in two sections. Section 2 briefly describes the model structure and the estimation procedure of the TVP-VAR framework, based on Primiceri (2005) and Krueger (2015). Section 3 presents the data and the results, focusing on stochastic volatility and impulse response function.

2 The TVP-VAR model in a nutshell

Primiceri (2005) proposes a Bayesian approach to estimate time-varying parameters (TVP) in vector autoregressive (VAR) models. This methodology is called the TVP-VAR model. The model can be written as (Krueger (2015)):

$$\begin{aligned} y_t &= \mathbf{X}_t' B_t + A_t^{-1} \Sigma_t \varepsilon_t \\ B_t &= B_{t-1} + \nu_t \\ \alpha_t &= \alpha_{t-1} + \zeta_t \\ \log \sigma_t &= \log \sigma_{t-1} + \eta_t, \end{aligned}$$

where y_t is a $n \times 1$ vector stacking the variables at a given date, $\mathbf{X}_t' = I_n \otimes [1, y_{t-1}, \ldots, y_{t-p}]$, B_t are the parameters - intercept and coefficients, A_t is a lower triangular matrix (with ones on the main diagonal) whose free elements are stacked in the vector α_t, and Σ_t is a diagonal matrix with positive elements $\sigma_t = \operatorname{diag}(\Sigma_t) . \varepsilon_t$ follows an n-variate standard normal distribution, and $\{\nu_t, \zeta_t, \eta_t\}$ are mean zero, homoscedastic and mutually independent normal random vectors.

As can be noted, the TVP-VAR model allows for the parameters B_t to vary over time. To capture this variation, Primiceri (2005) assumes that the parameters follow random walks. The TVP-VAR model is estimated using Bayesian methods, which requires the specification of prior distributions for the model parameters. Primiceri (2005) uses a diffuse prior for the initial values of the parameters, and conjugate priors for the covariance matrices Q_α and Q_Φ. The posterior distributions of the TVP-VAR parameters are estimated using Markov chain Monte Carlo (MCMC) methods. The posterior distributions can be used to obtain point estimates and credible intervals for the time-varying intercepts and coefficients.

The MCMC algorithm used is the one proposed by Primiceri (2005) with the correction suggested by del Negro and Primiceri (2015). The MCMC sampler can be concisely described as (Krueger (2015) and Primiceri (2005)):

1. Initialize A^T, Σ^T, s^T and V;
2. Sample B^T from $p\left(B^T \mid \theta^{-B^T}, \Sigma^T\right)$, using the algorithm proposed by Carter and Kohn (1994) ;
3. Sample Q from $p\left(Q \mid B^T\right)$, which is an inverse Wishart (IW) distribution;
4. Sample A^T from $p\left(A^T \mid \theta^{-A^T}, \Sigma^T\right)$, again using Carter and Kohn (1994);
5. Sample S from $p\left(S \mid \theta^{-S}, \Sigma^T\right)$, which consists of several blocks that are IW;
6. Sample the auxiliary discrete variables s^T from $p\left(s^T \mid \Sigma^T, \theta\right)$ for the algorithm proposed byKim, Shephard, and Chib (1998);
7. Draw Σ^T from $p\left(\Sigma^T \mid \theta, s^T\right)$, using Carter and Kohn (1994);
8. Sample W from $p\left(W \mid \Sigma^T\right)$, which is IW;
9. Go to Step 2.

where B^T is the entire path of the parameters $\{B_t\}_{t=1}^T$ (and similarly for Σ^T and A^T), $\theta = \left[B^T, A^T, V\right]$ and $V = [Q, S, W]$ collect the VCV matrices of the iid shock components $\{\nu_t, \zeta_t, \eta_t\}$.

3 Data and Results

The data utilized consists of monthly seasonally adjusted observations from August 1999 to February 2023 for the following variables:

1. Household inflation (measured by IPCA), in percentage. Source: IBGE
2. Core IPCA (%) (i.e., IPCA excluding food and energy), in percentage. Source: BCB
3. Output gap (calculated using the Hodrick-Prescott filter and the monthly GDP series in R$), in percentage. Source: Own elaboration based on BCB data

The estimations were conducted based on Krueger (2015). The number of lags was selected based on Bayesian Information Criteria, with 2 lags used for estimating the proposed model. Identification is achieved through Cholesky decomposition, with the following ordering of variables: output gap – food inflation – core inflation. Thus, the output gap is considered the most exogenous variable, contemporaneously influencing both of the other two variables, while they do not have a contemporaneous effect on the output gap. Food inflation is influenced contemporaneously only by the output gap and affects contemporaneously only core inflation. Finally, core inflation is affected by both preceding variables.

The estimated stochastic volatility of the variables included in the model is illustrated in Graph 1 - 3. It reveals a significant increase in uncertainty during the pandemic period for all three considered variables, with the output gap standing out prominently. Despite a recent decline, the levels of uncertainty remain higher than at the beginning of the sample. The blue line in the presented graphs represents the volatility of a time-invariant model. These findings underscore the crucial role of incorporating stochastic volatility for analyzing issues pertaining to these variables, as well as the significance of investigating the effects of uncertainty on the trajectory of macroeconomic variables.

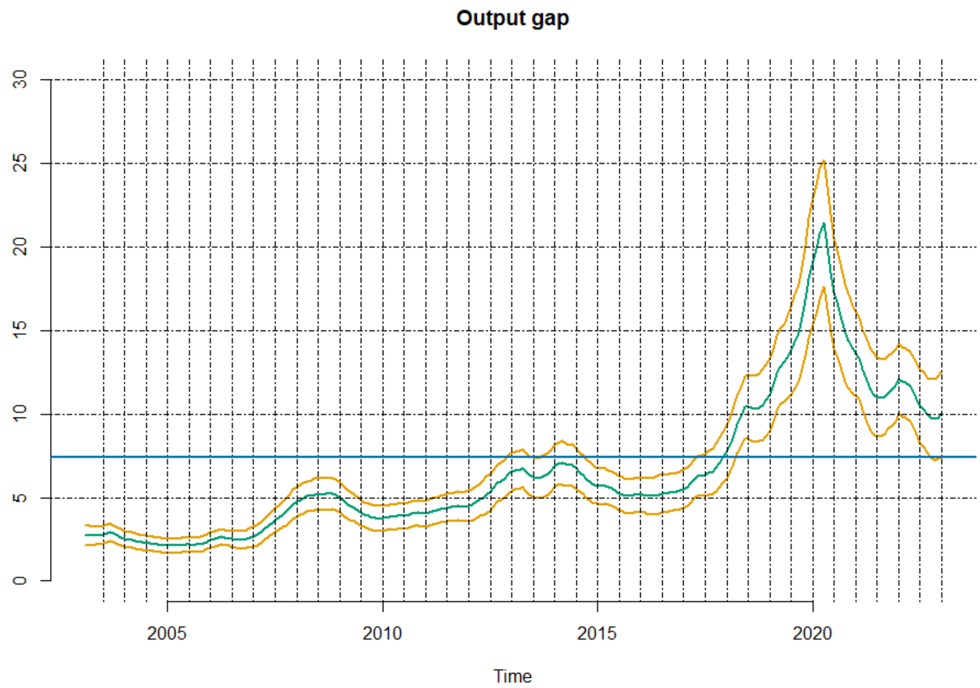

Fig. 1 Stochastic volatility from the TVP-VAR-SV model: output gap

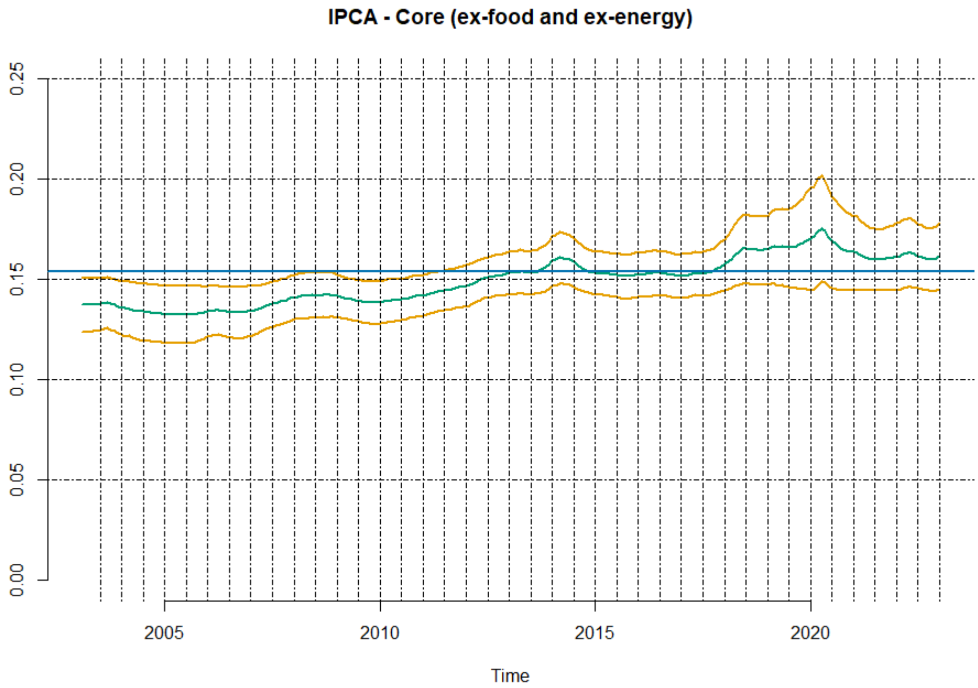

Fig. 2 Stochastic volatility from the TVP-VAR-SV mode: core

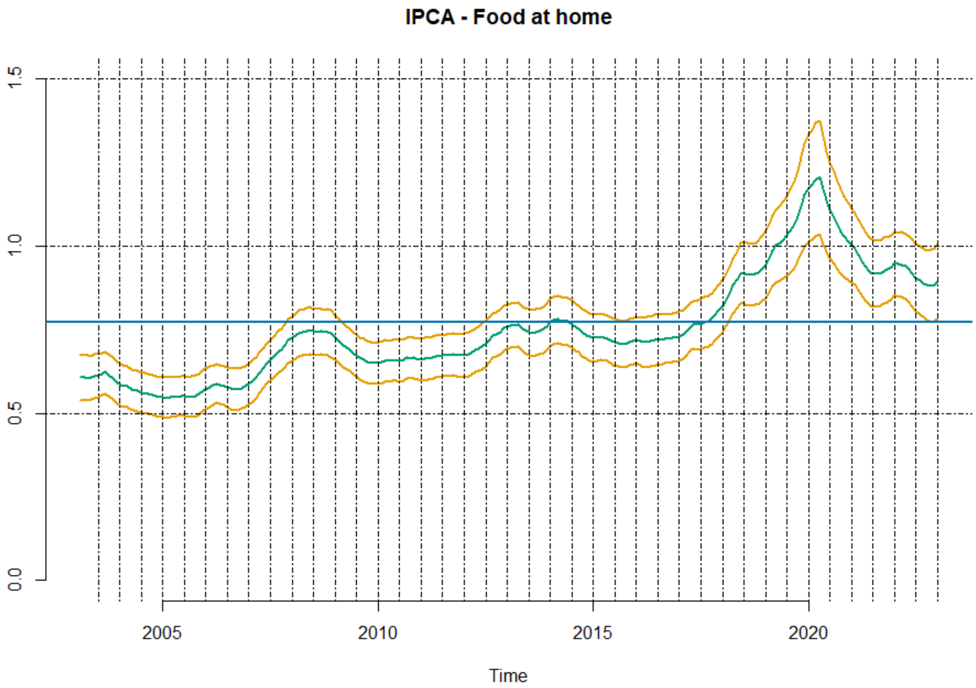

Fig. 3 Stochastic volatility from the TVP-VAR-SV model: food at home

The Impulse Response Function (IRF) to a one-percentage-point shock in food inflation on core inflation is depicted in Figure 2. In the case of TVP-VAR models, the impulse response functions can vary at each chosen time point. To facilitate exposition and considering the intended objective here, we selected the period before the pandemic (January 2019) and the last available point in the sample (January 2023). As observed, the peak effect for the pre-pandemic period is slightly smaller than in the current period. Nevertheless, the behavior between the two selected periods is the same. Following a shock in food inflation, the core rises significantly, reaching its peak in three months and dissipating the shock after approximately 15 months.

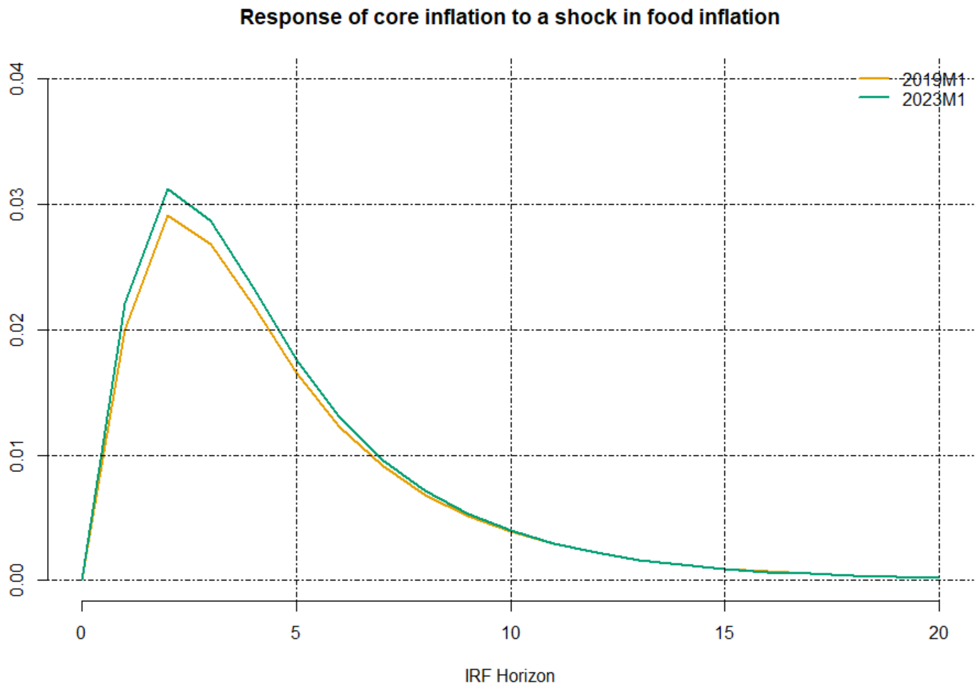

Fig. 4 Impulse response function: shock in food inflation on core inflation

The analysis of the cumulative response, presented in Figure 3, corroborates that the impact of a shock in food inflation in the recent period is slightly greater than in the pre-pandemic period.

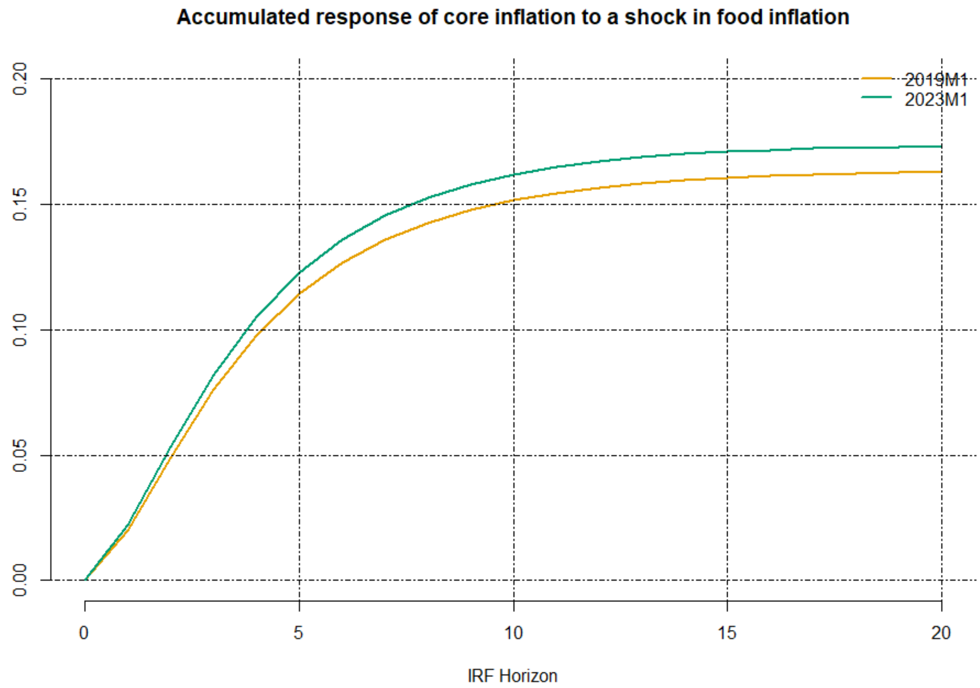

Fig. 5 Cumulative IRF of a shock in food inflation on core inflation for different time horizons

Graph 4 displays the Impulse Response Function (IRF) of a one-percentage-point shock to the core inflation for the period of January 2023, along with credibility intervals (5, 25, 50, 75, and 95). As observed, the impact of the food inflation shock on the core inflation is statistically significant.

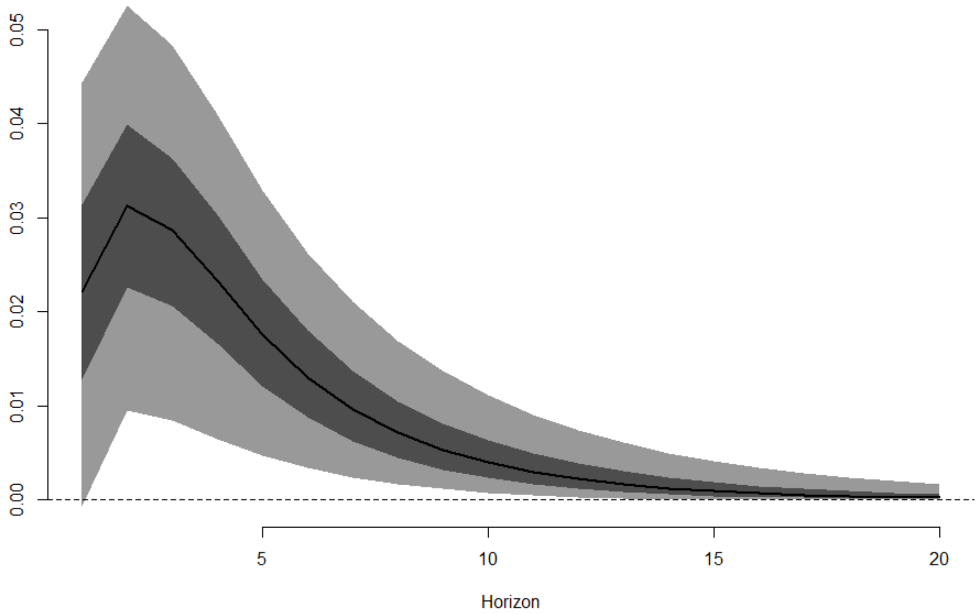

Fig. 6 Cumulative IRF and credibility interval: food inflation on core inflation for January 2023

4 Conclusion

In this study, we investigate the effects of a shock in food inflation on core inflation using a time-varying parameter approach, incorporating stochastic volatility to adequately capture the various shocks that impacted the economy during the analyzed period. Our findings suggest a substantial element of uncertainty during the pandemic. Furthermore, the impact of food inflation on core inflation is significant and statistically meaningful, particularly in the recent period. This impact is slightly more pronounced in the current period compared to the pre-pandemic phase. These results bear strong relevance for policymakers, given the elevated levels of food inflation in the recent economic scenario and the recent trajectory of Brazilian inflation. Moreover, this result can be explored for the definition of new measures of core inflation or in the discussion of whether the central bank should react to food prices or not.

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