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

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Abstract

TThis paper investigates the impact of food inflation on core inflation in Brazil using a time-varying parameter vector autoregression model with stochastic volatility (TVP-VAR-SV). Employing Bayesian methods, we estimate the model using monthly data from August 1999 to January 2023. Our findings reveal a substantial increase in the volatility of the relationship between food and core inflation during the COVID-19 pandemic. We find a statistically significant pass-through from food inflation to core inflation. Food inflation represents a substantial challenge, especially for Central Banks in emerging economies, and these findings carry important implications for monetary policy formulation and implementation.

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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, for example, the IPCA closed with a 5.8% increase, and the food and beverages group accounted for nearly half of this result. In 2024, food inflation also became a source of concern. According to data from the IPCA, the cumulative inflation in the "food and beverages" category up to November 2024 reached 6.44% — well above the overall index, which stood at 4.29%. 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 represents a substantial challenge for central banks, particularly in low-and middle-income economies. According to Cecchetti and Moessner (2008), policymakers face various challenges in addressing the elevated inflation resulting from the 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 (second-round effects) on overall inflation (Cecchetti and Moessner (2008)). The direct effect occurs because food is part of the consumption basket used in the calculation of the price indices. The indirect effect can occur through its impact on inflation expectations and through inertial mechanisms. Therefore, even though core inflation excludes food items, these 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. This study therefore aims to evaluate the dynamic relationship between food inflation shocks and core inflation in Brazil, with particular attention to potential time-varying patterns in this relationship.

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:M8-2023:M1. Considering the econometric challenges inherent in traditional time-varying parameter regressions, a Bayesian estimation procedure is employed to yield more robust parameter estimates. 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)).

Given the challenges of identifying structural changes before estimation and the potential gradual nature of such changes, the TVP-VAR-SV 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-linearities during estimation. With parameters following a first-order random walk process, it is well-suited to capture both temporary and permanent shifts. In our specific context, the adopted methodology assists in addressing the following question: Has the transmission of food price inflation to core inflation changed over time? This question holds particular relevance, considering the impacts of the Covid-19 pandemic on inflation— especially food inflation — and the current concerns surrounding food price dynamics in Brazil.

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

[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 core inflation in Brazil compared to other countries under analysis. Further details available inBanco Central do Brasil (2018).

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

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-SV 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 TVP-VAR-SV Model and Estimation Procedures[3]

We rely on a standard VAR model which provides us with a flexible tool to deal with the interlinkages between variables without imposing too much structure on the data.

Primiceri (2005) proposes a Bayesian approach to estimate time-varying parameters (TVP) in vector autoregressive models (VAR). This methodology is called the TVP-VAR-SV 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-SV 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-SV 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-SV 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.

[3]For a comprehensive explanation of the methodology employed in this study, readers are encouraged to consult Krueger (2015) and Primiceri (2005).

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

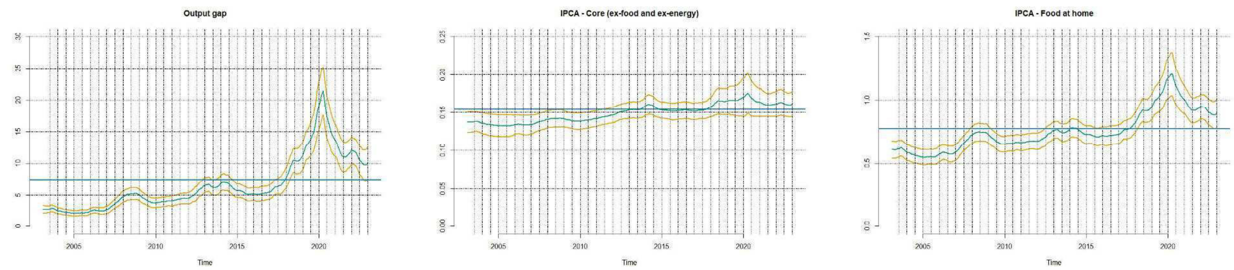
3 Data and Results

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

- Household inflation (measured by IPCA), in percentage. Source: The Brazilian Institute of Geography and Statistics - IBGE;
- Core IPCA (i.e., IPCA excluding food and energy), in percentage. Source: Central Bank of Brazil (BCB);
- Output gap (calculated using the Hodrick-Prescott filter and the monthly GDP series in Brazilian Reais)[4], in percentage. Source: Own elaboration based on data from the Central Bank of Brazil (BCB);

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 it does 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 Figure 1. The results reveal a significant increase in uncertainty during the pandemic period for all three variables, with the output gap exhibiting the most pronounced volatility. The higher level of uncertainty associated with the output gap stems from its unobserved nature, in contrast to the observed variables. Despite a recent decline, the levels of uncertainty remain elevated compared to those observed at the beginning of the sample period. The blue line in each figure represents the volatility estimated from a time-invariant model specification. These findings underscore the crucial role of incorporating stochastic volatility in analyzing issues related to these variables, as well as the importance of investigating the effects of uncertainty on the trajectory of macroeconomic variables.



(a) Output gap (b) Core inflation (c) Food at home

Fig. 1: Stochastic volatility from the TVP-VAR-SV model for different variables

The Impulse Response Function (IRF) to a one-percentage-point shock in food inflation on core inflation is depicted in Figure 2. In TVP-VAR-SV models, impulse responses can vary at each point in time. To facilitate exposition and align with our research objectives, we selected two representative periods for comparison: the pre-pandemic period (January 2019) and the most recent observation in our sample (January 2023). As observed, the peak effect for the

[4]We rely on the Central Bank's Economic Activity Index (IBC-Br), a monthly indicator that serves as a good proxy for the Gross Domestic Product (GDP).

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, core increases significantly, reaching its maximum impact after three months and dissipating the shock after approximately 15 months. The analysis of the cumulative response, presented in Figure 3, corroborates that the impact of a food inflation shock in the recent period is slightly greater than in the pre-pandemic period. Figure 4 illustrates the IRF of a one-percentage-point shock to core inflation for January 2023, accompanied by credibility intervals (5, 25, 50, 75, and 95 percentiles). As observed, the impact of food inflation shocks on core inflation is statistically significant.

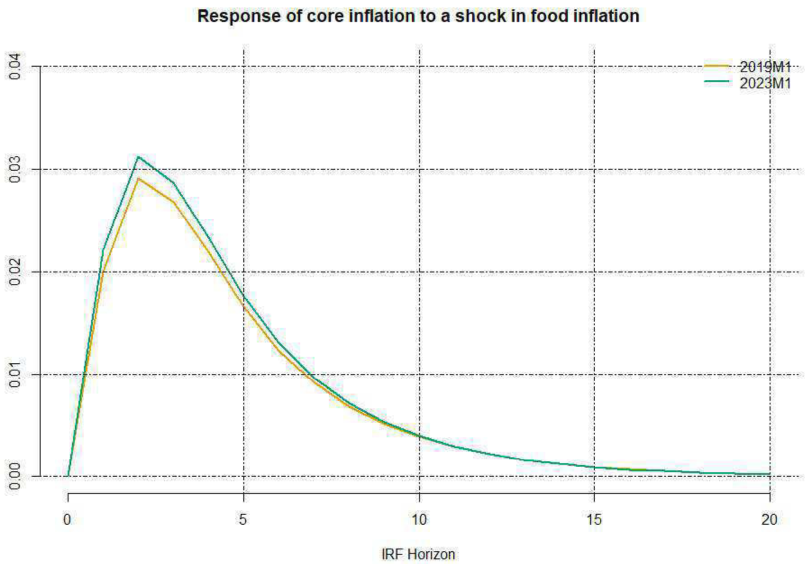


Fig. 2: Impulse response function: shock in food inflation on core inflation

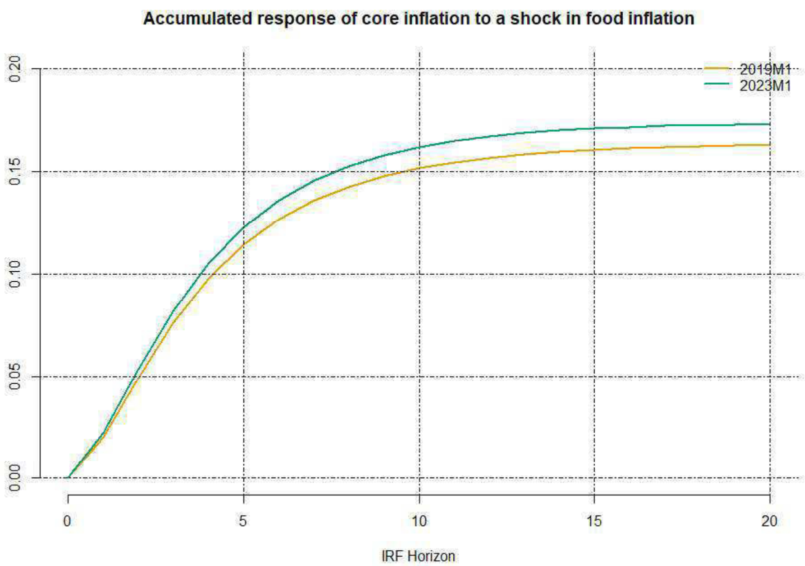


Fig. 3: Cumulative IRF of a shock in food inflation on core inflation

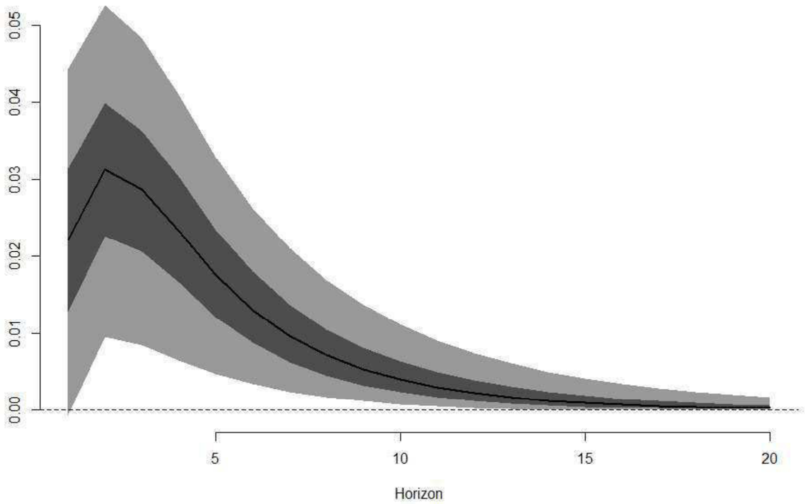


Fig. 4: Cumulative IRF and credibility interval: food inflation on core inflation for January 2023

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 considerable and statistically significant, particularly in the more recent period. This pass-through effect is slightly more pronounced in the current period compared to the pre-pandemic phase. These results have considerable relevance for policymakers, given the elevated levels of food inflation in the recent economic scenario and the trajectory of Brazilian inflation. Moreover, these findings can be explored for the definition of new measures of core inflation and contribute to the debate regarding whether central banks should respond to food price fluctuations in their policy decisions.

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