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Measuring inflation persistence under time-varying inflation target and stochastic volatility with jumps

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Abstract

We analyze whether the presence of a time-varying inflation target and stochastic volatility affect inflation persistence. We estimated different autoregressive specifications for inflation with and without time-varying parameters. The results show that the inflation persistence diminishes when we consider time-varying inflation target and stochastic volatility with jumps. We conclude that neglecting the time variation in inflation target and inflation volatility results in an upward biased estimation of persistence.

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1 Introduction

How long inflation shocks last, and the magnitude of these shocks are measures that interest monetary policymakers. These quantities are related to inflation persistence and volatility, which can be obtained by estimating reduced-form models for inflation. Inflationary processes may present changes in the mean (or inflation target) and the variance (volatility) over time, and these changes may affect inflation persistence. Thus, the implications of the time-varying inflation target and time-varying volatility on the estimation of inflation persistence, if any, should be considered to give more accurate information to policymakers. This paper addresses these implications.

The unconditional expectation of inflation may change over time due to shifts in the inflation target, for instance. To capture these changes, researchers proposed the use of time-varying mean parameters to model inflation and measure its persistence (Cogley and Sargent, 2001; Dossche and Everaert, 2005; Bilici and Çekin, 2020). Their results showed evidence against constant mean for inflation. Furthermore, the variance of inflation may be higher or lower over time. According to the literature on modeling inflation, the volatility of shocks affecting inflation is also governed by a time-varying parameter (Cogley and Sargent, 2005; Laurini and Vieira, 2013). Consequently, measures of inflation persistence based on constant mean and homoskedastic models for inflation may be unreliable.

The literature on transitory and permanent decomposition in macroeconomic time series usually applies it for the first moment. Examples of this approach are the work by Stock and Watson (2007), which separates transitory and permanent components for inflation, and Krane (2011), which uses the decomposition for the transitory and permanent shocks to the output. The transitory and permanent decomposition of time series second moment is less common and has been little explored in the literature for inflation. The volatility may vary due to institutional or structural changes, representing permanent shifts, while other sporadic variations represent transitory movements. The model of stochastic volatility with jumps introduced by Qu and Perron (2013) allows us to separate these two kinds of changes in the inflation volatility, just as the finance literature has done (see, e.g., Chaim and Laurini (2018)). Extracting these two components of inflation volatility gives us information about the magnitude of shocks affecting inflation.

Besides the inclusion of jumps in the inflation volatility, there is no evidence of the effects of stochastic volatility with jumps (SVWJ) and time-varying inflation target (TVIT) on inflation persistence. Thus, this paper aims to verify if the presence of a TVIT and SVWJ affect inflation persistence. To this end, we examine Brazilian inflation data from 1995 to 2020, which is an interesting case since it includes different levels in the mean and a relevant institutional change with the inflation target adoption in 1999.

The contribution of this paper is two-folded. First, we analyze how the inclusion of TVIT and SVWJ affects inflation persistence. Accordingly, we compare specifications with and without these characteristics. To model the TVIT, we use the approach of Dossche and Everaert (2005). Second, we verify if there exist permanent changes in inflation volatility by implementing the Qu and Perron (2013) approach to model volatility.

Our approach to decompose the inflation time series is related to the literature initiated by Nelson and Plosser (1982), which argues that, in general, macroeconomic time series are better described by a non-stationary process. Later, this literature was extended by Perron (1989), which showed that if one considers a breaking point in the time series, the measure of persistence is affected. Our approach allows multiple breaks in the inflation time series by introducing a TVIT, and additionally, we introduce time-varying variance by introducing SVWJ. In this way, we show that, at least for inflation, these two features affect the persistence of the inflation time series.

The results showed that both TVIT and SVWJ affect inflation persistence. The specification that includes these two characteristics exhibits an intrinsic inflation persistence of 0.56 compared to 0.76 in the specification without them. Moreover, the SVWJ presents evidence of permanent shifts in the volatility. These results point to the importance of considering a TVIT and heteroskedastic model to find an accurate measure for inflation persistence.

2 Modeling Inflation

The literature on inflation persistence usually models inflation using the k-order autoregressive process, AR(k). This approach allows us to extract a measure of intrinsic inflation persistence by summing the autoregressive coefficients (Fuhrer, 2010). We adopt this approach and incorporate TVIT and SVWJ.

To introduce TVIT, we follow Dossche and Everaert (2005) and Kozicki and Tinsley (2005). The inflation is allowed to follow an AR(k) process around the inflation target perceived by the private agents, π_t^P:

$$\pi_t = \left(1 - \sum_{i=1}^{k} \varphi_i\right) \pi_t^P + \sum_{i=1}^{k} \varphi_i \pi_{t-i} + \sigma_t \nu_t, \quad \nu_t \sim \mathcal{N}(0,1), \tag{1}$$

where σ_t represents the standard deviation of shocks affecting inflation.

The perceived inflation target π_t^P evolves as a convex combination of the perceived inflation target in the previous period and the inflation target pursued by the Central Bank, π_t^T. That is:

$$\pi_{t+1}^P = (1-\delta)\pi_t^P + \delta \pi_{t+1}^T. \tag{2}$$

Private agents may obtain information about π_{t+1}^T by comparing the interest rate set by the Central Bank and their expectation about the interest rate (see Kozicki and Tinsley (2005), for details). The Central Bank inflation target follows a driftless random walk with innovation $\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$, which reflects, for instance, changes in Central Bank preferences. Using this assumption in equation (2), we obtain:

$$\pi_{t+1}^P = (2-\delta)\pi_t^P + (\delta - 1)\pi_{t-1}^P + \delta \eta_{t+1}. \tag{3}$$

Equations (1) and (3) model the inflation around a TVIT. Moreover, the way we model inflation target allows us to extract an expectation-based inflation persistence component, measured by $(1-\delta)$. Note that if δ is close to one, then the private agents perfectly predict the Central Bank's inflation target, and there is no persistence effect due to expectations errors (Dossche and Everaert, 2005).

Following Qu and Perron (2013), we decompose the log-variance as the sum of a transitory component, h_t, and a permanent component, μ_t, that is, $\log(\sigma_t^2) = h_t + \mu_t$, so that $\sigma_t = \exp(h_t/2 + \mu_t/2)$. The transitory component follows a stationary AR(1), while the permanent component is a compound binomial process:

$$h_t = \rho h_{t-1} + \sigma_h \varepsilon_{h,t}, \quad -1 < \rho < 1 \quad \varepsilon_{h,t} \sim \mathcal{N}(0,1), \tag{4}$$

$$\mu_t = \mu_{t-1} + d_t \sigma_w w_t, \quad w_t \sim \mathcal{N}(0,1), \text{ and } d_t \sim \text{Bernoulli}(p) \tag{5}$$

Equations (4)-(5) allow us to separate transitory changes from permanent shifts in level of stochastic volatility. These equations together with equations (1) and (3) form the complete model. Note that, this general model nested several specifications: *Model 1)* π_t^P and σ_t are constant; *Model 2)* only π_t^P is constant; *Model 3)* π_t^P varies over time, but σ_t is constant; and *Model 4)* both π_t^P and σ_t varies over time.

All models are estimated using Bayesian methods. Prior distributions are not presented here to save space but are available upon request. We use Markov Chain Monte Carlo procedures by combining Metropolis-Hastings and a threshold sampling scheme with an auxiliary variable to draw the posterior distribution of a permanent component of volatility, as described in Laurini et al. (2016).

3 Data

We used the Brazilian monthly inflation measured by the IPCA (*Índice Nacional de Preços ao Consumidor Amplo* - broad national consumer price index) as the observable variable for inflation in the model presented in section 2. The period ranges from January 1995 to March 2021, including different levels for the inflation target and variance. The unconditional mean for this sample is 0.55% per month with a variance of 0.18. For the first half of observations, these sample moments are 0.63% and 0.27, while for the second half, they are 0.46% and 0.07

The autocorrelation function and partial autocorrelation function are interesting to determine the number of lags to use in the AR. Figure 1 displays these statistics, which motivate us to use an AR in the estimation.

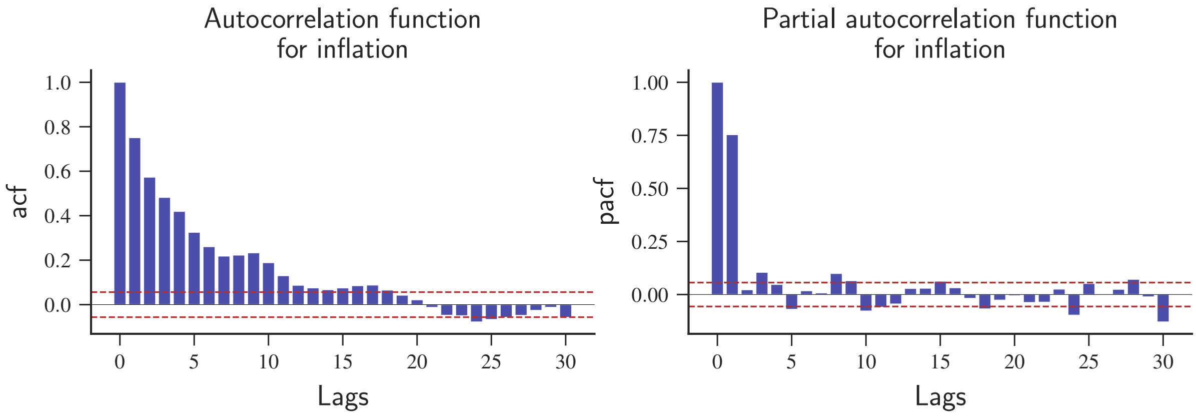

Figure 1: Autocorrelation function (acf) and partial autocorrelation function (pacf).

4 Results and Discussion

Table I summarizes the posterior distribution of the models. Since we choose $k = 1$ lag for the AR for inflation, the parameter φ measures the intrinsic inflation persistence.

For the models with a TVIT, we can obtain the expectation-based inflation persistence using the parameter δ.

Table I: Posterior distribution for all models: 25% quantile, mean and 75% quantile

	Model 1			Model 2			Model 3			Model 4		
	q25%	mean	q75%	q25%	mean	q75%	q25%	mean	q75%	q25%	mean	q75%
φ	0.732	0.759	0.785	0.637	0.669	0.702	0.612	0.65	0.689	0.515	0.556	0.597
π^P	0.484	0.531	0.576	0.43	0.454	0.48	-	-	-	-	-	-
σ_ν	0.28	0.288	0.295	-	-	-	0.271	0.279	0.287	-	-	-
ρ	-	-	-	0.715	0.775	0.846	-	-	-	0.673	0.738	0.81
p	-	-	-	0.016	0.031	0.041	-	-	-	0.013	0.028	0.038
σ_w	-	-	-	0.606	0.967	1.213	-	-	-	0.548	0.969	1.227
σ_ϵ	-	-	-	0.255	0.343	0.428	-	-	-	0.329	0.418	0.507
σ_η	-	-	-	-	-	-	0.048	0.069	0.085	0.045	0.061	0.075
δ	-	-	-	-	-	-	0.116	0.141	0.163	0.112	0.135	0.153

The main result is that the intrinsic inflation persistence reduces when we include the TVIT (Model 2) and SVWJ (Model 3). Considering both TVIT and SVWJ (Model 4), the intrinsic inflation persistence falls drastically from a mean of 0.76 to 0.56. Indeed, the entire posterior distribution of φ shifts to the left when we consider these two characteristics, as illustrated by figure 1. This result indicates that both the TVIT and SVWJ affect intrinsic inflation persistence. Thus, neglecting both the time-varying mean and variance can bias the intrinsic inflation persistence. Note that the forward-looking inflation persistence $(1 - \delta)$ is almost unaffected by including stochastic variance (see table I).

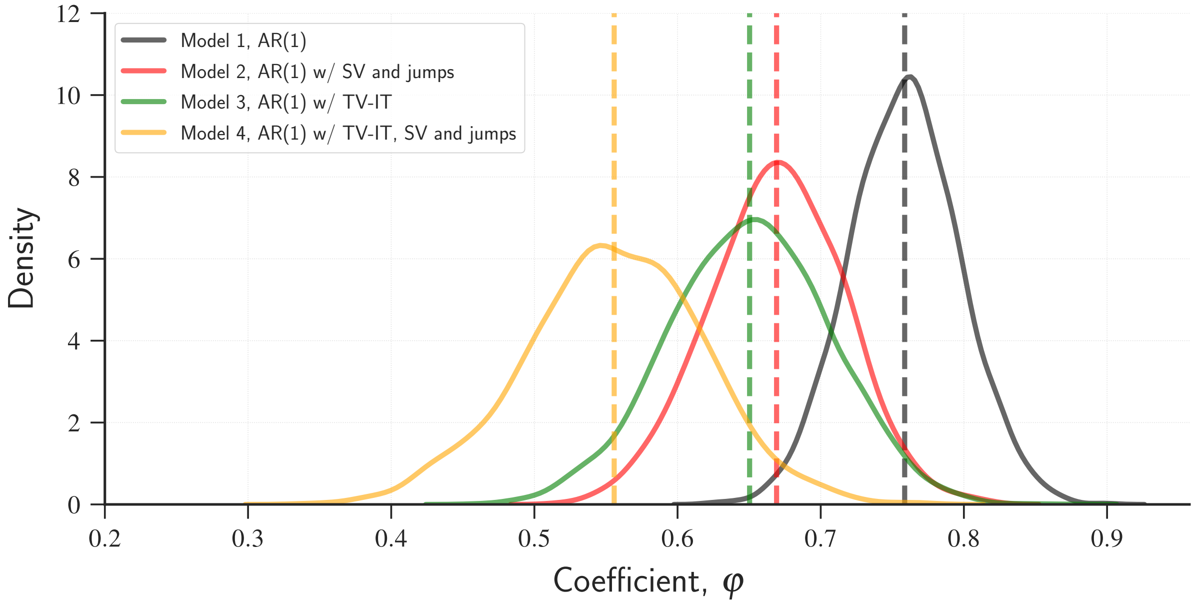

Figure 2: Posterior distribution of autoregressive coefficient for all models.

There are results about inflation persistence in the literature that disregards the time-varying effects of inflation target and volatility. Dossche and Everaert (2005) consider the effect of a TVIT, but their models are homoskedastic. Antonakakis et al. (2016) shows that there is a difference between inflation persistence when measured by online and official price index but also ignores the effects of heteroskedasticity. Luengo-Prado et al. (2018), which considers sectoral inflation data to estimate inflation persistence, considers only structural breaks in the mean process, and also considers homoskedastic errors for inflation. As shown by our results, this homoskedastic assumption for the inflation process may bias the estimation of inflation persistence.

For the Brazilian case, the inflation target perceived by the private agents moves smoothly, as the unobservable component extracted from Model 4 indicates (see figure 3). At the beginning of the sample, the perceived inflation target is higher, which is an expected result since the economy was in a hyperinflation process before 1995. After 1999, with the implementation of the inflation target system, the perceived inflation target shows some picks like in mid-2003 and mid-2015, both periods, marked by conturbation in political issues.

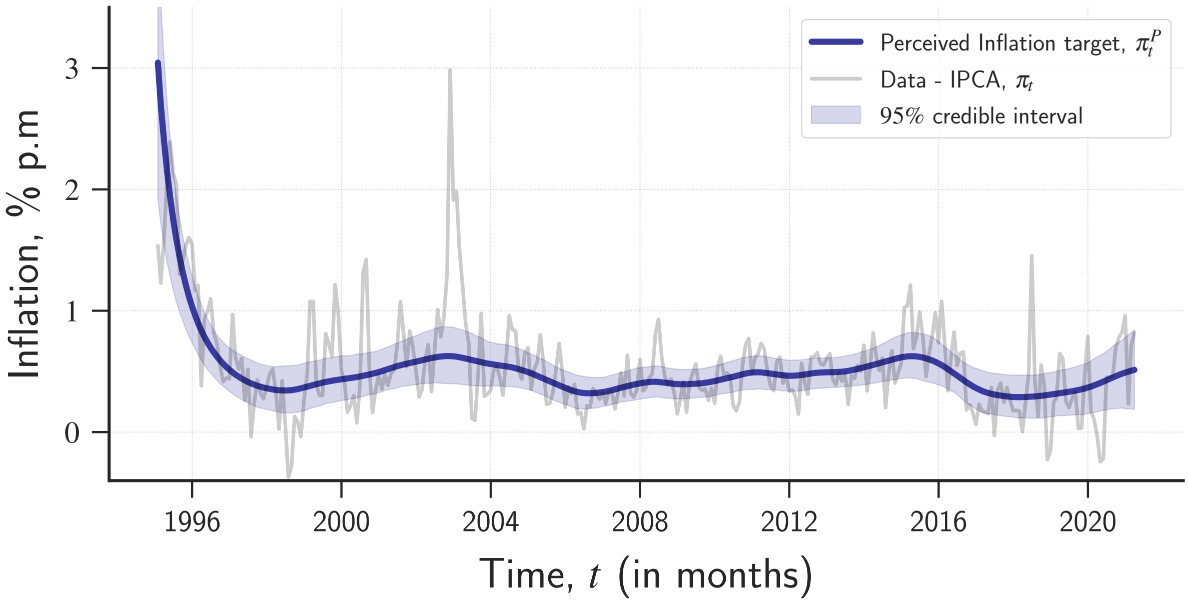

Figure 3: Observed inflation and unobserved perceived inflation target.

The agents' perception of macroeconomic variables has been a relevant topic in the literature. This is the case, for instance, of the work of Krane (2011), Jain (2019) and, more recently, Clements (2021). This line of inquiry uses professional forecasters' data and the revision of their forecasts to identify the agents' perception of the shocks affecting the economy. While Krane (2011) and Clements (2021) concentrate on the agents' view of GDP shocks, Jain (2019) specifically considers the perception of forecasters to build a measure of perceived inflation persistence. Her results indicate that the proposed perceived inflation persistence is well below the inflation persistence of the actual data. The author attributes this difference to the informational rigidity faced by the forecasters.

Our measure of expectation-based inflation persistence is related to the literature on agents' perception of macroeconomic variables since it is related to the perceived inflation target. The expectation-based inflation persistence considers the presence of information rigidity, as the agents do not have full information about the actual inflation target that the central bank is pursuing. As argued by Dossche and Everaert (2005), this rigidity is similar to those by Mankiw and Reis (2002). The expectation-based inflation persistence, however, cannot be directly compared to the perceived inflation persistence proposed by Jain (2019) because it depends on the perceived inflation target, which is a lower frequency time series than inflation forecasts. Finally, while our approach considers the general perceptions of agents in the economy, Jain (2019) considers only the perception of professional forecasts. Thus, a natural extension for future research is to apply our decomposition to professional forecasters' data.

The stochastic volatility extracted from Model 4 confirms the effects of time-varying variance for both transitory (left panel) and permanent components (right panel), see figure 4. The right axis of the left panel of 4 measures the probability of the jumps that occur at each period.

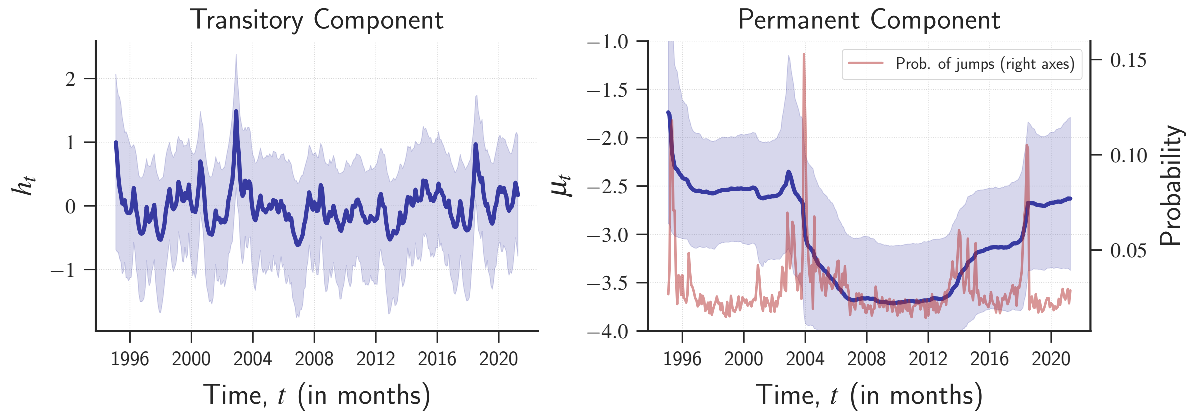

Figure 4: Transitory and permanent component of stochastic volatility.

There are three probability peaks. The first occurs in April 1995, which bring the volatility to a lower level, is possibly associated with the stabilization plan adopted in the previous year. The second jump was in November 2003, and the permanent component of volatility also decreases. In mid-2002 and mid-2003, Brazil experienced a confidence crisis triggered by the presidential election. Since the victorious candidate continued to follow the policies initiated in the previous government, the permanent component volatility has decreased and remained at a low level until the next jump in May 2018.

5 Conclusion

We have assessed if TVIT and SVWJ affect inflation persistence. We find that including these characteristics reduces intrinsic inflation persistence. Moreover, results indicate the importance of include jumps in the stochastic volatility.

Neglecting the time variation in inflation target and inflation volatility with jumps results in an upward biased estimation of persistence. Thus, including these characteristics to model inflation persistence results in a better measure for inflation persistence. These results are potentially relevant to the inflation literature since measuring inflation persistence and measuring the magnitude of shocks are fundamental to guide policymakers' decisions.

Future research could apply the decomposition proposed in this paper to other economies. Since our model does not make any specific assumption about the Brazilian economy, it can be used without modifications for other countries, especially for those whose current inflation is accelerating and with higher volatility.

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