Evidences on inflation persistence and inflation volatility in Brazil

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Abstract

This paper aims to investigate the inflation persistence in Brazil from 1995 to 2019. The inflation persistence was estimated using the Bayesian approach in a model with two main characteristics. The first is to introduce the expectation-based persistence, which is related to the Central Bank's inflation targeting strategies, in addition to intrinsic persistence. The second characteristic is the control for stochastic volatility, with a transitory and a permanent component. Comparing the model with and without stochastic volatility, it was found that the intrinsic persistence decreases when the effects of volatility are considered, while the expectation-based persistence remained unchanged. Also, the permanent component of stochastic volatility shows a jump at the end of 2003, and from this date onward remains at a lower level for a long period. Thus, the introduction of stochastic volatility with jumps and persistence based on expectations allow finding better estimates for inflationary persistence.
Keywords: Inflation persistence, Monetary policy, Stochastic volatility.
Jel Codes: E31, C32, C11.

Resumo

O objetivo deste artigo é investigar a persistência inflacionária no Brasil no período de 1995 a 2019. Estimou-se a persistência da inflação por meio da abordagem Bayesiana em um modelo com duas características principais. A primeira é introduzir a persistência baseada nas expectativas, que está relacionada com as estratégias de metas de inflação do banco central, além da persistência intrínseca. A segunda caracterísitca é o controle para volatilidade estocástica, com um componente transitório e um componente permanente. Comparando o modelo com e sem volatilidade estocásitica, identificou-se que a persistência intrínseca diminui quando se considera os efeitos de volatilidade, enquanto a persistência baseada nas expectativas se mantém inalterada. Além disso, o componente permanente da volatilidade estocástica apresentou um salto no final de 2003 e, a partir de então, permaneceu em um patamar mais baixo por um longo período. Assim, a introdução de volatilidade estocástica com saltos e da persistência baseada na expectativas permite encontrar melhores estimativas para a persistência inflacionária.
Palavras-Chaves: Persistência inflacionária, Política monetária, Volatilidade estocástica.
Jel Codes: E31, C32, C11.

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1 Introduction

After more than two decades of the so-called Real Plan, which stabilized the price level in Brazil after a long hyperinflation period (Garcia (1996)), the inflationary process still remains a relevant theme in Brazilian economy. This relevancy could be noted from the results of monetary policy, especially after the implementation of inflation target regime in 1999 (Minella et al. (2003)). The interest rate, the instrument of monetary policy, has been high if compared to international levels (e. g., Segura-Ubiergo (2012)), even with the recent trend of decreasing interest rates. On the other hand, it is not rare the case in which inflation is greater than upper limits imposed by the inflation target regime. In the light of hyperinflation experienced in Brazil, these facts suggest that the characteristics underlying the inflationary process must be better understood.

In particular, two characteristics of inflation are important: inflation persistence and inflation volatility. The latter is related to the variance of shocks affecting inflation, while the former is associated to remnants of inflationary memory still present in Brazilian economy. Measuring the degree of inflation persistence is a way to verify the magnitude that inflationary memory affects the inflation dynamic. The inflation persistence is related to how quickly the inflation returns to its initial value after a shock. The consequences of a higher persistent inflation is that the costs of monetary policy, in terms of products, will be higher.

The traditional way to measure the inflation persistence is to assess the intrinsic inflation persistence, as discussed by Fuhrer (2010). In this approach, the inflation persistence is usually measured by the sum of autoregressive parameters based on an appropriate specification of AR process for inflation. Empirical examples of this approach are the studies of Cecchetti and Debelle (2006) and Pivetta and Reis (2007), which analyzed the inflation persistence in United States, and De Oliveira et al. (2010) and da Silva et al. (2011) for the Brazilian case.

Once the inflation target may change over time, standard autoregressive models which assume constant mean are not appropriated for modelling inflation. If this change in inflation target is ignored, then the intrinsic inflation persistence estimation, measured by the sum of autoregressive parameters, may be biased. To deal with this challenge, the literature has proposed three principal approaches: i) consider rolling samples regression, adopted by Pivetta and Reis (2007), for example; ii) allow discrete breaks in the mean of inflation process, employed by Levin and Piger (2002); and iii) estimate time-varying parameters, with mean parameters governed by a random walk process, as proposed by Cogley and Sargent (2005).

However, these approaches have some disadvantages, as argued by Dossche and Everaert (2005). The rolling sample approach is limited by the degree of freedom problem and do not rule out the possibility of the change occur in a specific subsample. Also, although the discrete breaks and time-varying parameters specified as random walk can overcome some problems of rolling sample approach, they are not appropriate "if the perceived inflation target differs from the central bank's inflation target" (Dossche and Everaert, 2005, p. 9). To overcome these problems, Dossche and Everaert (2005) proposed a structural approach to take into account the perceived inflation target and the actual inflation target pursued by central bank. This approach introduces a new measure of inflation persistence, which can be called expectation-based persistence, which is related to the expectation about the inflation target.

In the case of Brazilian inflation target system, it can be noted that from 2005 to 2011 the inflation seems to remain between upper and lower limits, converging to the center of the target, as shown in Figure 1. From 2011 onward, however, the inflation presents several periods above the upper limit, and the inflation seems to converge to the upper limit, instead of the target. It is also in 2011 that the Chairman of central bank was substituted by a new one, and

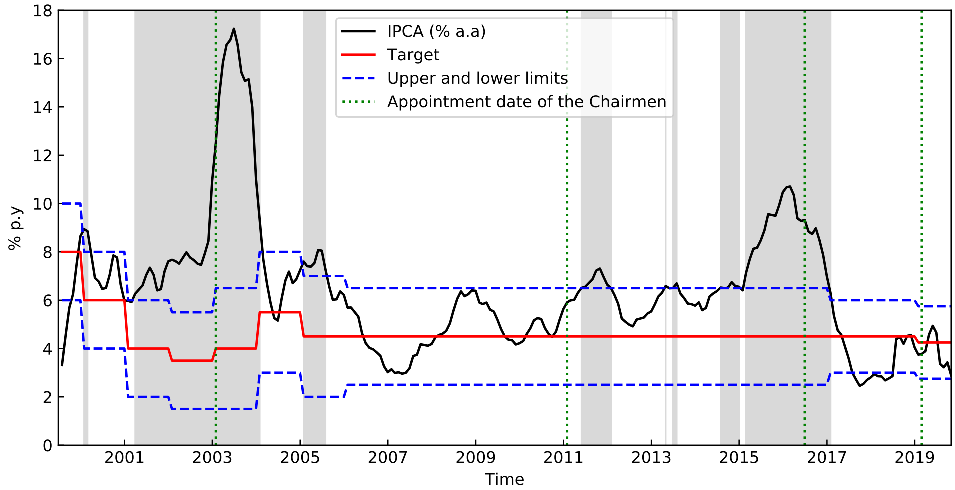


Figure 1: Inflation Target. The black line shows the behavior of inflation measured by IPCA (accumulated in 12 months). The red line shows the inflation target publicized by the Central Bank and blue-traced lines show the upper and lower limits. Green-dotted line shows the appointment of Chairman. The grey shaded area represents the periods that inflation is above the upper limit.

the new Chairman seems to consider a target closer to the upper limit. In this sense, the degree of inflation persistence in Brazil seems to be subject to the effects of expectation-based inflation persistence, besides the intrinsic measure.

Besides the inflation persistence, another important characteristic of inflation dynamic is its volatility. Since the volatility of shocks affecting inflation may vary over time, there has been much attention in modelling the variance of inflation. Cogley and Sargent (2005), Stock and Watson (2007) and Eisenstat and Strachan (2016) are examples of researches that consider heteroscedasticity to model inflationary process, as well as Laurini and Vieira (2013) and Fasolo (2019) in Brazilian case. Changes in volatility of shocks affecting inflation may affect the inflationary dynamics or even change the persistence of inflation. In the Bayesian literature, it is well know that a model with random coefficients and constant variance can be transformed in a heteroscedastic model with constant coefficients, as discussed in Tsay (1987). Therefore, control for heteroscedasticity is an important point to correctly model inflation dynamics.

A common specification for heteroscedasticity in macroeconomics is the stochastic volatility using a random walk or an autoregressive process for the logarithm of volatility. The most recent literature on stochastic volatility allows volatility to jump, that can be considered as a regime switching model in which the number of regimes is not specified previously (Qu and Perron, 2013; Laurini et al., 2020). This new way of modelling volatility has been little explored to analyze inflation dynamic and to measure inflationary persistence. Although the literature on inflation persistence has already account for stochastic volatility (Cogley and Sargent, 2005; Stock and Watson, 2007), the stochastic volatility with random level shifts is still an unexplored field in this literature.

Considering stochastic volatility with jumps has some advantages over traditional ways to model inflation volatility, since the changes in inflation volatility may be transitory or permanent. The structure of stochastic volatility with random level shifts allows capturing both sort of changes. The shifts in level of volatility could be thought of as a regime change model. However, the number of times that this change can occur is unknown and the stochastic volatility model with jumps allows determining this number endogenously. Moreover, the stochastic volatility with jumps collapses in the standard stochastic volatility model when do not exist jumps in volatility.

In the Brazilian context, the literature on inflationary persistence have already produced some results. Several researches have focused on the hyperinflation period[1]. Some studies consider both the hyperinflation period and stabilization period. Figueiredo and Marques (2011), for example, considered the period between 1944 and 2009 and used an ARFIMA model allowing regime changes. The authors found that at least two regimes of inflation are present in Brazilian economy: the first one is the hyperinflation period and the second one is the period of low inflation. They concluded that the low inflation regime is the most persistent one. Another example is De Oliveira et al. (2010) who used quarterly data to assess the inflation persistence considering the presence of unknown structural break. In a rolling sample estimation of a reduced-form model, they found that inflation persistence is around 0.5 and remained relatively stable for the Brazilian case.

Regarding the studies that emphasize the period after stabilization of price level, a branch of researches has relied on ARFIMA (Autoregressive Fractionally Integrated Moving Average) models to capture inflation persistence by analyzing the long memory of the process. The results of these studies, however, are not convergent. Figueiredo and Marques (2009), for example, estimated an ARFIMA-FIGARCH and concluded that for the period after implementation of Real Plan, the persistence was very high, both in mean and in variance. On the other hand, Silva and Leme (2011), estimated an ARFIMA model for similar period [2] and concluded that only a small degree of inflation persistence was present in Brazilian economy.

In addition to the long memory literature, some researches measure the degree of inflation persistence considering the magnitude of autoregressive parameters. Example of these papers are the following. Laurini and Vieira (2013) used monthly data from 1994 to 2003 in a model that allows parameters to vary over time and control heteroscedasticity effect with a GARCH structure. The result of this paper shows that the persistence is greater in crises moments. Machado and Portugal (2014) studied the inflation persistence considering both intrinsic and expectation-based inflation, as proposed by Dossche and Everaert (2005), for Brazilian economy. This study considered to estimate a model using quarterly data and the results indicate that both intrinsic and expectation-based inflation persistence are present in Brazilian economy. Furthermore, their result pointed out a decrease in intrinsic inflation persistence. On the other hand, Roache (2014), comparing Brazilian inflation persistence with a group of country that also adopt inflation target system, concluded that the persistence increased through early 2013.

In particular, it can be noted that the literature on inflation persistence in Brazil has some drawbacks. First, the results do not allow to reach a convergent conclusion. Second, the studies either do not consider the effects of volatility affecting inflation or do not consider the effects of another source of inflation persistence, as the expectation-based persistence. Third, the studies do not consider recent data. In general, it seems that the literature on inflation persistence do not explore the stochastic volatility with random level shifts model. In this sense, the objective of the present paper is to investigate the presence of both intrinsic and expectation-based inflation persistence in a context of stochastic volatility with jumps for Brazilian economy from 1995m8 to 2019m12. To achieve this goal, a macroeconomic model was estimated using Bayesian

[1] For instance Cati et al. (1999); Durevall (1999); Campêlo and Cribari-Neto (2003)

[2] Figueiredo and Marques (2009) consider a subsample from 1994:08 to 2008:01 while Silva and Leme (2011) consider data from 1999:07 to 2010:12

methods.

This paper contributes to existing literature in two ways. First, the inflation persistence is considered in a context of a structural macroeconomic model, considering both sticky price and sticky information, and controlling for heteroscedastic effects. Stickiness in price is considered by measuring the intrinsic inflation persistence and stickiness in information is contemplated by measuring the expectation-based inflation persistence. Moreover, it is argued that, in additional to the structural model, controlling for heteroscedasticity allows to achieve a better measure for inflation persistence. The second contribution is related to the structure adopted to model inflation volatility. It is argued that the stochastic volatility model with jumps, which allows capturing transitory and permanents changes in the volatility of shocks affecting inflation, is an appropriate form to control for heteroscedasticity, given its advantages over the standard stochastic volatility model.

Another important advantage of the stochastic volatility with jumps methodology is that it is able to explain possible long memory phenomena observed in time series. Chaim and Laurini (2019) show that a model of jumps in the mean and volatility similar to the one used in the present work generates observations with long memory properties, even though in fact the real process is short memory with regime changes. In this way, the proposed model can be thought of as an alternative explanation for the patterns of long dependence observed in inflationary processes.

The main results are the following. Together with the intrinsic inflation persistence, the expectation-based inflation persistence play a role in Brazilian inflationary process. Moreover, considering the transitory and permanent changes in inflation volatility diminishes the intrinsic inflation persistence, but do not affect the expectation-based inflation persistence. Regarding the results about volatility, the stochastic volatility structure revealed a jump in the end of 2003 and from this date onward, the volatility remained lower than before for a long period. However, in recent years this volatility has increased again. The results of disaggregated inflation in free and supervised prices show that the intrinsic persistence is originated mainly by the behavior of agents in formation of free prices, while the supervised prices has only a small effect in intrinsic inflation persistence. Also, the volatility of supervised prices has an additional jump in the beginning of 2015, which is possibly related to the maintenance of supervised prices in a lower level to meet the political calendar

This paper is organized as follow. In the next section, we describe the main aspects of the methodology. The Section 3 presents and discuss the results obtained. Section 4 presents the final remarks.

2 Method

2.1 The model

The model used to measuring inflation persistence is based on Dossche and Everaert (2005) and Machado and Portugal (2014), which is able to deal with two types of inflation persistence: i) the intrinsic inflation persistence; and ii) the expectation-based inflation persistence. Additionally, stochastic volatility in shocks affecting inflation is introduced. We denote the basic model as model 1, and the model with stochastic volatility as model 2. The model 1 is presented first. In this model, inflation is allowed to follow a stationary autoregressive process around the perceived inflation target, π_t^P:

$$\pi_t = \left(1 - \sum_{j=1}^{k} \varphi_j\right) \pi_t^P + \sum_{j=1}^{k} \varphi_j \pi_{t-j} + \nu_{1t}, \qquad \nu_{1t} \sim N(0, \sigma_{\nu_1}^2). \tag{1}$$

The variable π_t^P represents agents expectations about the inflation target and is treated as an unobserved variable. This unobserved variable is linked to the actual inflation target pursued by the monetary authority, denoted by π_t^T. This link is described by the following equation:

$$\pi_{t+1}^P = (1 - \delta)\pi_t^P + \delta \pi_{t+1}^T + \eta_{1t}, \qquad \eta_{1t} \sim N(0, \sigma_{\eta_1}^2), \tag{2}$$

where $\delta \in [0, 1]$. Equation (1) says that the perceived inflation target guiding agents decisions is a convex combination of the perceived inflation target in the previous period, π_t^P, and the actual inflation target, π_{t+1}^T. If δ is equal to one, then the perceived inflation target exact matches the actual inflation target. On the other hand, if δ is equal to zero, the perceived inflation will be based only on the value that agents expected to inflation target in previous period. In this sense, the quantity $1 - \delta$ is a measure of expectation-based inflation persistence.

Although in an inflation target system the target to inflation is usually a variable that is publicized, the effective target pursued by the central bank is obviously an unobserved variable. For this reason, the actual inflation target is also treated as an unobserved variable, and it is assumed to follow a random walk:

$$\pi_{t+1}^T = \pi_t^T + \eta_{2t}, \qquad \eta_{2t} \sim N(0, \sigma_{\eta_2}^2). \tag{3}$$

Changes in monetary authority preferences can be a factor that make the inflation target to vary over time. As an example, the changes in Central Bank Chairman or the board could alter the preferences of monetary authority. By simplification, suppose that η_{1t} is equal to zero for all period t. Using equation (3) to substitute in equation (2), the perceived inflation target can be rewritten as:

$$\pi_{t+1}^P = (2 - \delta)\pi_t^P + (\delta - 1)\pi_{t-1}^P + \delta \eta_{2t}, \tag{4}$$

thus, the macroeconomic model is described by equations (1) and (4). The intrinsic component is captured by $\sum_{i=1}^{k} \varphi_i$, while the expectation-based component of inflation persistence is captured by $(1 - \delta)$.

The model 2 extend the model 1 to allow stochastic volatility in shocks affecting inflation. In order to model this stochastic volatility, the following structure based on Qu and Perron (2013) and Laurini et al. (2020) is assumed:

$$\pi_t = \left(1 - \sum_{j=1}^{k} \varphi_j\right) \pi_t^P + \sum_{j=1}^{k} \varphi_j \pi_{t-j} + \left(e^{\frac{h_t}{2} + \frac{\mu_t}{2}}\right) \nu_{1t}, \qquad \nu_{1t} \sim N(0, 1), \tag{5}$$

$$\pi_{t+1}^P = (2 - \delta)\pi_t^P + (\delta - 1)\pi_{t-1}^P + \delta \eta_{2t}, \tag{6}$$

$$h_t = \phi h_{t-1} + \sigma_\epsilon \epsilon_t, \qquad \epsilon_t \sim N(0,1), \tag{7}$$
$$\mu_t = \mu_{t-1} + d_t \sigma_w w_t, \qquad w_t \sim N(0,1), \tag{8}$$
$$d_t \sim \text{Bernoulli}(p). \tag{9}$$

In this set up, the volatility of shocks affecting inflation in equation (5) is driven by the two unobserved component h_t and μ_t. The component h_t is allowed to follow a stationary first order autoregressive process and it represents a mean reverting component of stochastic volatility of inflation. On the other hand, the component μ_t is allowed to follow a random walk and it represents permanent changes in volatility.

All the innovations $(\nu_{1t}, \eta_{2t}, \epsilon_t, w_t)$ are assumed to be independent. Note that, in particular, the innovation w_t in equation (8) is multiplied by d_t, which assumes the values zero or one depending on the hyperparameter p. If $d_t = 0$, then μ_t is exactly the same of previous period; else, the permanent component is affected by the innovation w_t. In this sense, this model can be seen as a regime switching model in which the number of regimes is not specified a priori and instead it is data-driven.

The way of modelling inflation volatility as specified in Equations (7) to (9) has advantages over the standard stochastic volatility model, since the model allows a greater flexibility through the μ_t component and, at the same time, it contains the traditional stochastic volatility model as a particular case, according to the information contained in the probability p. Note that the effects of innovation over the inflationary process in Equation (5) have different behavior depending on what is the origin of the innovation: if the innovation occur through the transitory component h_t, it will quickly die out; on the other hand, if the innovation occur through the permanent component μ_t, the effect will remain until the next jump. Moreover, the number of times that these changes can occur is determined endogenously. Finally, if the standard stochastic volatility model is the correct one, the model approximately nests the traditional stochastic volatility model. If this is the case, the posterior distribution of p will have a large mass around zero. Else, if the correct model is the model with jumps, the posterior probability of p will be informative about the frequency of changes (Qu and Perron, 2013).

2.2 Estimation of model 1

Since the macroeconomic model is based on latent factors, it is useful to write the model in a state-space representation. Besides, the unobserved components implies a large number of parameter to be estimated, which represents a problem in a context of short time series. The Bayesian approach is used to overcome this problem, adding prior information to the model. Equations (1) and (4) can be represented by the following general state-space representation:

$$y_t = Zs_t + Ax_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, H) \tag{10}$$
$$s_t = Fs_{t-1} + R\eta_t, \qquad \eta_t \sim N(0, Q) \tag{11}$$

where y_t represents the observed time series (inflation), s_t is a vector of unobserved components, x_t is a vector of lagged observed variable or exogenous variable and Z, A, H, F, R and Q are matrices used to link the state variables to observed variables. This matrices are formed by the following set of parameters to be estimated: $\theta = (\varphi_i, \delta, \sigma_{\nu_1}, \sigma_{\eta_2})$. Besides this set of parameters, the states s_t also represents parameters to be estimated. To complete the state-space formulation, the initial state is assumed to follow a normal distribution, $s_0 \sim N(s_{0|0}, P_{0|0})$.

In the Bayesian approach, the quantity of interest is the posterior distribution of parameters. The posterior distribution is proportional to the product of the likelihood function and the prior distribution. A first challenge in the model (10)-(11) is to evaluate the likelihood function, since the state s_t are unobserved. To deal with this challenge, the Kalman filter can be used to jointly integrate the latent states and evaluate the likelihood function, given the linear and Gaussian structure of the model. Moreover, the Kalman Smoother can be used to obtain a posterior distribution for each state s_t.

Therefore, using the Kalman filter together with the Kalman smoother make it possible to jointly evaluate the likelihood and to obtain the density of latent state. Once the likelihood function is evaluated for a given set of parameters, it can be combined with the prior density evaluated at this set of parameter to obtain the posterior density. Given the structure of the model and the set of prior density chosen, it is not possible to characterize the posterior density of parameters in closed form. Instead, a Markov Chain Monte Carlo method is needed to simulate the posterior distribution.

A possibility to obtain a sample from posterior such as one describe above is to use the Random Walk Metropolis-Hastings. This algorithm generates a Markov Chain that converges to a stationary distribution corresponding to posterior distribution.

After a burn-in period, B, the realizations of Random-Walk Metropolis-Hastings can be used to approximate moments of posterior distribution using empirical moments of the sample $\{\theta^i\}_{i=B}^{N_{\text{sim}}}$.

2.3 Estimation of model 2

In order to conduct inference on parameters of model 2, Bayesian estimation can be performed by using Markov Chain Monte Carlo (MCMC). In this model, the aim of inference procedure is to obtain the posterior distributions of the parameters $(\varphi_j, \delta, \phi, \sigma_\eta, \sigma_\epsilon, \sigma_w, p)$ and estimate for the latent states $(\pi_t^P, h_t, \mu_t, d_t)$. The method used to estimate these quantities is based on a Metropolis-within-Gibbs, and it is similar to those proposed by Laurini et al. (2020).

The stochastic volatility introduce non-linearities to the model, implying that the state space representation is no longer linear and Gaussian as in model 1, making the filtering process difficult. An approach to deal with this difficult is to use a linearization by using logarithm. This approach would transform the innovation ν_{1t} in a new one that follow a logarithm Chi-squared distribution that can be approximated by a mixture of Gaussian distributions Qu and Perron (2013). To avoid this approximation, the problem of filtering can be address by directly sampling the latent states using Metropolis-Hastings, as proposed by Laurini and Mauad (2015).

Another difficult to estimate this model is to sample the jump process in the volatility. In order to sample d_t, an auxiliary latent variable with uniform distribution was introduced. If this auxiliary variable exceed a given threshold, then d_t is equal to one and else d_t is equal to zero. This threshold is determined by the value of $p \sim$ Beta(a,b) of the previous iteration of the Gibbs sampler. After initialize the latent states $s_t \equiv (\pi_t^P, h_t, \mu_t, d_t)$ and parameters $\Theta \equiv (\varphi, \delta, \sigma_{\eta_2}^2, \phi, \sigma_\epsilon^2, \sigma_w^2, p)$, the complete Gibbs sampler scheme have the following blocks:

In the above algorithm, the steps 1 to 8 are done using Gibbs-sampler for the conjugated distribution and Metropolis-Hastings for those steps that have non-conjugated distribution.

Algorithm 1 Gibbs Sampler

- Initialize the latent states $s_t \equiv (\pi_t^P, h_t, \mu_t, d_t)$ and parameters $\Theta \equiv (\varphi, \delta, \sigma^2_{\eta 2}, \phi, \sigma^2_{\epsilon}, \sigma^2_w, p)$

    1. Sampling $\sigma^2_{\eta_2}$ and δ, conditional on s_t and $\Theta_{(-\sigma^2_{\eta_2}, -\delta)}$;
    2. Sampling d_t, conditional on $s_{t(-d_t)}$ and Θ;
    3. Sampling σ^2_{ϵ}, conditional on s_t and $\Theta_{(-\sigma^2_{\epsilon})}$
    4. Sampling φ, ϕ, p, conditional on s_t and $\Theta_{(-\varphi, -\phi, -p)}$
    5. Sampling σ^2_w, conditional on s_t and $\Theta_{(-\sigma^2_w)}$
    6. Sampling μ_1, conditional on $s_{t(-\mu_t')}$ and Θ;
    7. Sampling h_t, conditional on $s_{t(-h_t)}$ and Θ;
    8. Sampling the states π_t^P, , conditional on $s_{t(-\pi_t^P)}$ and Θ;

2.4 Data and prior information

To estimate the model, the observable variable used was the monthly inflation measured by the IPCA (*Indice Nacional de Preços ao Consumidor Amplo* - broad national consumer price index), seasonally adjusted and constructed by IBGE. Additionally, the inflation was disaggregated in free and supervised prices, which also was adjusted for seasonal effects[3]. The data ranges from the August 1996 to December 2019, totaling 305 observations. The reason for the period of analysis is because it includes all the period after stabilization of price level. The information of data was complemented by prior information about the parameters. This complementary information helps to overcome the problem of a large number of unknown components in the model, which is introduced by the latent factors of the macroeconomic model and by the stochastic volatility structure. The prior elicitation was based on previous research made for Brazilian economy as well for foreign economies.

Table 1 presents some descriptive statistics of data used in estimation, and Figure 2 presents the autocorrelation and partial autocorrelation function for the headline IPCA. The behavior of the autocorrelation and partial autocorrelation function indicates that the inflation dynamics it is compatible with an autoregressive process of order one, AR(1).

	count	mean	std	min	25%	50%	75%	max
IPCA headline	305.0	0.582	0.474	-0.330	0.310	0.466	0.702	2.913
IPCA free prices	305.0	0.533	0.480	-0.329	0.243	0.447	0.693	3.273
IPCA supervised prices	305.0	0.738	1.028	-1.110	0.200	0.440	0.970	5.860

Table 1: Descriptive statistics of inflation measured by the monthly IPCA - headline, free prices and supervised prices

For the equations (1) and (5) of inflation dynamics, only one lag was used, consistent with the autocorrelation function observed. The parameter φ was assumed to follow a (prior)

[3]The seasonal adjustment was done using X13-ARIMA-TRAMO

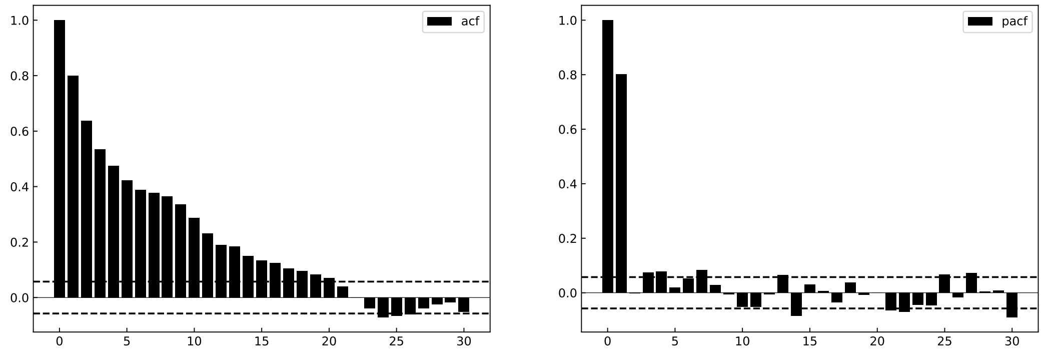


Figure 2: Autocorrelation function and partial autocorrelation function

Beta distribution, in order to assure that the process is stationary. The hyperparameters of each of this Beta distribution was chosen based on De Oliveira et al. (2010). These author estimated intrinsic inflation persistence using data from 1995 to 2009 and their results shows that inflation persistence ranges from 0.41 to 0.50. Therefore, the Beta distribution are centered at 0.5. The variance hyperparameter was chosen to be 0.02, reflecting little probability of being close to zero or close to one.

For the parameter δ, the prior distribution was also a Beta distribution. The hyperparameters of this distribution was based on Machado and Portugal (2014), which estimated δ using quarterly data and find that this parameter is around 0.16. The variance of this prior distribution was 0.02. For the parameters of variance, σ_ν and σ_η, the Gamma distributions were used, since its support guarantees the positiveness of these parameters. The mean of each Gamma distribution was 1.3 and 0.4, for σ_ν and σ_η, respectively. The variance of Gamma distribution was inflated to reflect the uncertainty about the information contained in these prior, making them non-informative priors.

The parameters above are also estimated in model 2, and the same set of priors are used. Additionally, for model 2 the following parameters need a prior distribution: $\sigma_w, \sigma_\epsilon, \phi, p$. For the variance parameters σ_w and σ_ϵ a Gamma distribution was selected, in order to guarantee the positivity of theses parameters. This distribution was centered in 1 with variance equal to 4. The parameter ϕ follow a truncated Normal distribution with mean 0.95 and variance equal to 5, which is relatively non-informative. Finally, the parameter p follows a Beta prior distribution with hyperparameter $a = 1$ and $b = 40$. This parameter reflect the frequency of regime change in the latent variable d_t. The chosen prior hyperparameters reflect the fact that the regime changes are not frequent, with changes occurring on average at each 40 periods.

3 Results and Discussion

Based on the data set and prior distributions presented previously, this section presents the results of the estimated macroeconomics model 1 and model 2, using Bayesian techniques explained in section 2.2 and 2.3. First, the results for headline inflation are explained and then the results for inflation of free and supervised prices are described and discussed.

3.1 Headline inflation

For the model 1, to simulate from posterior, the first step was to build the candidate distribution. The BFGS numerical optimization routine was used to find the posterior mode and the hessian evaluated at mode. Then the scale factor of variance matrix was set to obtain an acceptance rate around 25%, as suggested by Roberts et al. (1997). Using this candidate distribution, $100,000$ replications were performed (1 every 10 draws is saved), in order to achieve convergence of the Markov Chains.

For the model 2, with stochastic volatility, the Gibbs sampler to simulate from posterior and $400,000$ replications were performed (1 every 10 draws is saved), aiming at achieving convergence and reducing Markov Chain autocorrelation. For both model 1 and model 2, the first 50% of replications were excluded as burn-in, and only the second half of draws was used in inference. The recursive means of the samples, univariate and multivariate diagnostics indicated that the Markov Chain has converged to the invariant distribution The Table 2 presents the mean and 90% credible interval for the estimation [4].

	Model 1			Model 2		
Parameter	Posterior Mean	5%	95%	Posterior Mean	5%	95%
φ	0.655	0.567	0.739	0.553	0.462	0.640
δ	0.137	0.086	0.202	0.125	0.075	0.185
σ^2_η	0.265	0.248	0.284	0.010	0.003	0.021
σ^2_ν	0.049	0.011	0.105			
σ^2_ϵ				3.354	1.354	7.182
σ^2_w				1.473	0.306	3.470
ϕ				0.455	0.089	0.793
p				0.016	0.003	0.042

Table 2: Posterior distribution and credible interval for model 1 and model 2.

As long as the models have only one lag for inflation (as indicated by the autocorrelation and partial autocorrelation function), the inflation persistence is capture only by the parameter φ. The posterior mean of this parameter indicated that the intrinsic inflation persistence is around 0.66 for model 1 and around 0.55 for model 2, as shown by the Table 2. Compared to previous studies that used quarterly data (e.g. Machado and Portugal (2014) and De Oliveira et al. (2010)), both model 1 and model 2 indicate a higher intrinsic inflation persistence.

It is noteworthy that there is a difference in inflation persistence from model 1 to model 2. The model 2, which include stochastic volatility, presented a lower intrinsic inflation persistence compared to model 1. This means that including stochastic volatility reduces the inflation persistence reflected by the autoregressive coefficients. In this sense, the consequences of time-varying volatility on inflationary dynamic can improve the measure of intrinsic persistence, since the specification of variance has an effect in parameters related to the specification of the mean. This issue is especially important when trying to capture changes in inflation persistence.

For Brazilian case, some papers argued that inflation persistence has changed over time, by conducting recursive estimation (Gaglianone et al., 2015; Roache, 2014) or by considering subsamples (Machado and Portugal, 2014). These studies have the limitation of losing degrees of freedom in estimation and, in addition, they do not consider an adequate specification for volatility. The changes found by these researches may be affected if they are corrected by a

[4] The convergence diagnostic details are not present to save space, but they can be obtained from the authors

stochastic volatility specification. In fact, the statement that changes in inflation persistence can be confused with changes in volatility have already been alerted by Stock (2001) and Sims (2001).

Regarding the expectation-based inflation persistence, measured by $1 - \delta$, it was around 0.86 for model 1 and around 0.88 for model 2, considering the mean of parameter δ. This result means that around 86% and 88% of inflation target perceived by agents rely on their expectation of inflation target in previous period, while around 14% and 12% are resulted from the actual inflation target pursued by Central Bank. In this sense, as expected, Brazilian inflationary process is subject to another sort of inflation persistence besides the intrinsic one, which is the expectation based-inflation persistence.

The results above about expectation-based inflation persistence are in line with those found by Machado and Portugal (2014) in their univariate model, which analyzed quarterly data from 1996 to 2011. However, using a multivariate model, these authors found evidences that expectation-based inflation persistence was lower. Although the present research does not use a multivariate model, the use of monthly data allows a greater information from sample, and this information corroborates the results found by Machado and Portugal (2014) in their univariate model. It is also worth to note that the difference of expectation-based inflation persistence from model 1 to model 2 is not expressive.

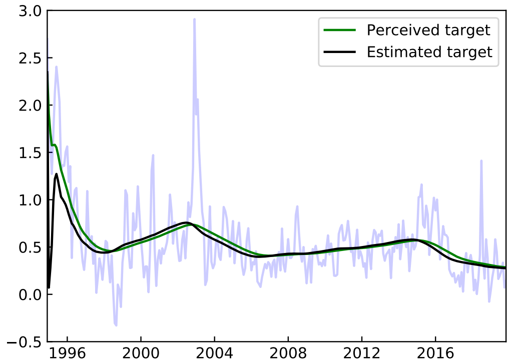
With the introduction of this new measure of inflation persistence, it is possible to separate what in fact is the intrinsic inflation persistence and what is the expectation-based component. Additionally, as noted above, the insertion of stochastic volatility also have effects on the intrinsic inflation persistence. Although the methodology adopted in this paper allows to obtain a better measure of inflation persistence, it should be mentioned that a limitation of this approach is that neither the intrinsic nor the expectation-based inflation persistence is allowed to change over time.

In contrast, the evolution over time of the unobserved components – that is, the perceived inflation target and the inflation target pursued by the monetary authority –, can be evaluated. The Figure 3 shows the unobserved component estimated for model 1 and model 2 in panel (a) and panel (b), respectively. Regarding model 1, it is possible to observe that the target perceived by agents presents a mean-reverse behavior and especially in the period between 2008 and 2013 the target perceived by agents is very close to the estimated target pursued by Central Bank. The model 2 presents a similar behavior, but it describes more dynamic behavior and the difference between the estimated and, in general, the perceived target was more expressive.

Machado and Portugal (2014) found a similar result considering data up to 2011. However, from around 2015 onwards the difference between the expected inflation target and the target estimated increases, meaning that expectations distortions to inflation persistence increased in recent periods. Considering the difference between the target perceived by agents and the estimated target of Central Bank, it is possible to conclude that these differences confirm that expectation-based inflation persistence play a role in the inflationary process. Therefore, in general, the results pointed out that expectation-based inflation persistence is present in the inflationary process and should be considered together with the intrinsic inflation persistence.

Finally, the stochastic volatility introduced in model 2 allows assessing the evolution of volatility of shocks affecting inflation. Figure 4 presents some results about the volatility model, dividing the volatility in two components: i) transitory component, which is mean-reversible; and ii) permanent component. The permanent component is related to the jumps in volatility. The Figure 4 also presents the probability of jumps (panel (b) right-axes).

Considering only the transitory component of inflation volatility, it is possible to notice that the volatility varies over time, as shown by Figure 4 in panel (a). The permanent component



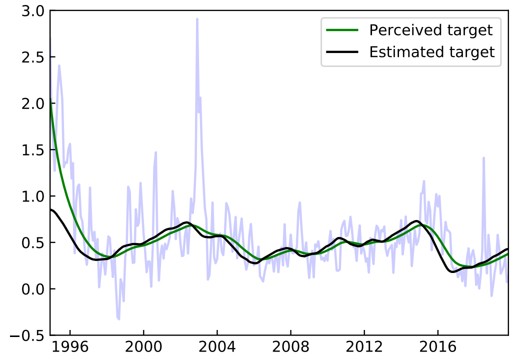


Figure 3: Smoothed states. The solid blue line shows the inflation measured by monthly IPCA. The green line shows the inflation target perceived by agents, π_t^P using model 1. The black line shows the estimated target pursued by monetary authority (central bank), π_t^T, for model 1 (left) and model 2 (right).

also varies over time with expressive jump in December 2003, when the posterior probability of jump achieve its maximum (see panel (b) of Figure 4). The total volatility, that is, the sum of the two components achieved its maximum around 2003 and then decreased to a lower level from 2004 onwards. However, around 2018 the volatility has increased again. In general, the total volatility extracted by the model is in line with previous research such as Fasolo (2019), which found a higher level of inflation volatility in the early 2000s, stabilizing over the decade at a lower level and a further increase in more recent years.

The higher total volatility at the beginning of sample observed in Figure 4, panel (c), is associated to the period before the implementation of inflation target system and the transition of this regime. This volatility achieves a peak in 2003, which is characterized by the confidence crises in 2002-2003 triggered by the presidential election. Since the victorious candidate in the elections continued to follow the policies initiated in the previous government (maintaining the inflation target and choosing a conservative Chairman for Central Bank, for example) the inflation volatility has decreased (permanent component) and remained at a low level. At the end of the sample, the volatility has another peak and even the permanent component has an increase, although the probability of jump is lower. This last peak may also be associated with a very polarized presidential election and possibly, with the effects of truckers strike that occurred in May 2018.

3.2 Free and supervised prices

In this section, the model 2 is used to evaluate the inflation persistence and inflation volatility for free and supervised prices. Using free prices, Gibbs sampler required 600,000 replications to achieve convergence, excluding the first 500,000 as burn-in. For supervised prices, the convergence was achieved after 400,000 replications and excluding the first 50% of sampled values as burn-in. For both free and supervised estimation, one every 10 draws is saved in order to reduce Markov Chain autocorrelation. The Table 3 summarizes some moments of posterior distributions.

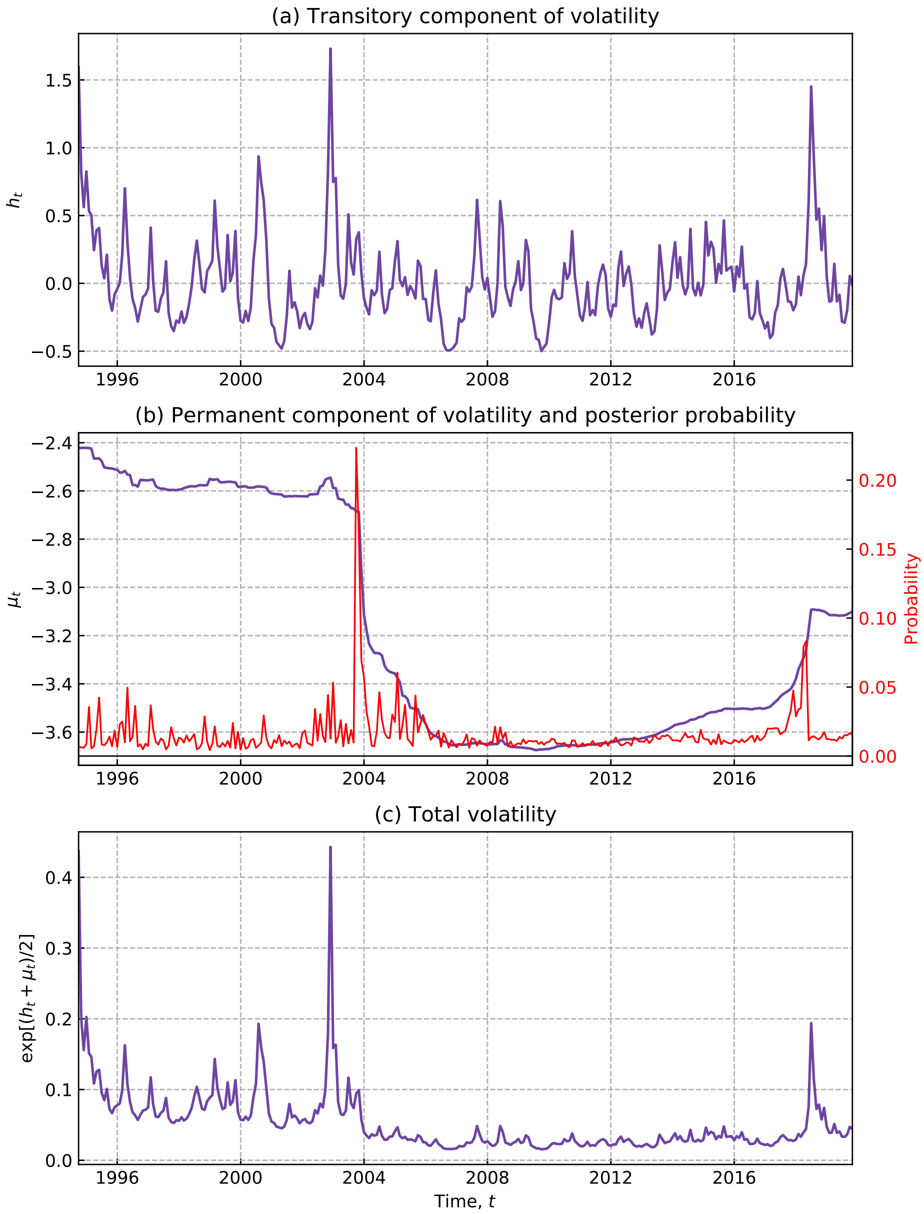


Figure 4: Volatility of inflation. Panel (a) presents the transitory component of volatility, h_t. Panel (b) presents the permanent component of volatility μ_t (left) and the posterior probability of jump (right). Panel (c) presents the total component of volatility inflation.

Comparing the intrinsic inflation persistence, measured by φ, for free and supervised prices, it is possible to notice a great difference: The intrinsic inflation persistence was much higher in free prices than in supervised prices. This result means that a large fraction of the origin of intrinsic inflation persistence is due to the agents' behavior in form free prices and

	Free prices			Supervised prices		
Parameter	Posterior Mean	5%	95%	Posterior Mean	5%	95%
φ	0.577	0.494	0.659	0.271	0.195	0.352
δ	0.115	0.089	0.149	0.162	0.102	0.231
σ_η^2	0.005	0.001	0.011	0.005	0.001	0.012
σ_ϵ^2	12.14	3.613	31.443	0.875	0.480	1.549
σ_w^2	1.421	0.240	3.644	0.931	0.245	2.118
ϕ	0.807	0.631	0.915	0.351	0.057	0.652
p	0.012	0.001	0.032	0.041	0.012	0.085

Table 3: Posterior distribution and credible interval for model 2 with free and supervised prices.

only a small proportion is a result of policies that control prices in key sectors. This result is in line with previous conclusions reached in Laurini and Vieira (2013). Regarding the expectation-based persistence, measured by $1-\delta$, the free prices also have more persistence than supervised prices, but the difference is not too large.

Other important characteristic that the model allows to analyze is the volatility. First, it is worth to note that persistence ϕ of transitory component of volatility h_t is greater for free prices than for supervised prices. On the other hand, the estimation identified more jumps in volatility for supervised prices. Figure 5 presents the two components of volatility as well as the total volatility for both free and supervised prices. In general, for free prices the behavior of volatility is similar to that of headline inflation: there is a period of more volatility in the beginning of sample and then the volatility decrease to a lower level. A difference from headline prices is that there is a higher probability to jump in the last period of the sample.

The behavior of supervised prices, however, is very different from the headline inflation. The volatility of supervised prices presents two important jumps of the permanent component. Regarding the first jump, it can be observed that, although in the beginning of sample the volatility is also greater, the shift to a lower level of volatility happens later, compared with the headline inflation and with the free prices. Moreover, in January 2015 there is another jump, but in this case to a higher level of volatility. It is important to note that the dynamic of supervised prices is closely related to the policies adopted by the policymakers.

In particular, in 2013 the prices of electricity have an expressive decrease and remain stable until the end of 2014. Since 2014 was an election year, the price of electricity and, in general, all supervised prices were kept artificially low, possibly to avoid bad results close to the election and, thus, disrupt the electoral dispute. However, after the results of election, the price of electricity and the other supervised prices quickly increased and caused a greater volatility, that is, put the volatility in a higher level. These changes represented a permanent change in volatility, and it still do not return to a lower level.

4 Conclusion

This paper investigated the inflation persistence in Brazilian economy in a context of stochastic volatility with jumps. Two types of inflation persistence were considered: the traditional intrinsic inflation persistence and the expectation-based inflation persistence. The volatility was also divided in two sorts. The first is a mean-reversible transitory component and the second is a permanent component that is allowed to jump.

Using the Bayesian approach, a macroeconomic model was estimated to capture the two

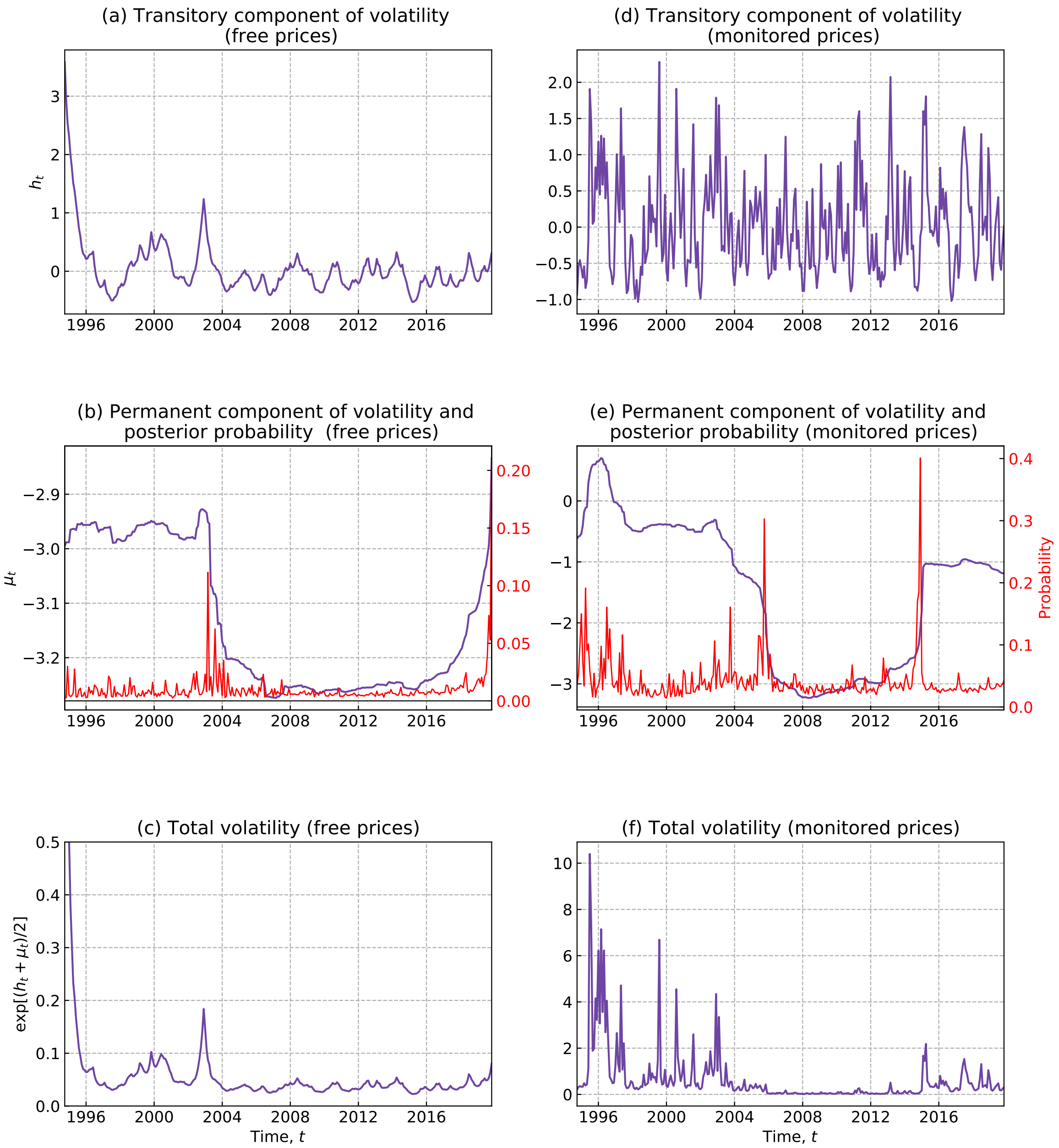


Figure 5: Volatility of inflation for free and supervised prices. Panel (a) to panel (c) presents the transitory, permanent and total volatility for free prices. Panel (d) o (f) presents the transitory, permanent and total volatility for supervised prices.

measures of inflation persistence and to extract the stochastic volatility. In general, the results show that both types of inflation persistence are important to understand the inflationary process. Moreover, the results show that the inclusion of stochastic volatility with jumps diminishes the intrinsic inflation persistence, while the expectation-based persistence remain unchanged. The extract volatility varies over time and presents a jump at the end of 2003, shifting to a lower level. In recent years, especially in 2018, the volatility increased again.

The analysis of free and supervised prices indicates that the intrinsic persistence is originated mainly from the behavior of agents in formation of free prices, while the supervised prices have only a small effect in intrinsic inflation persistence. For both free and supervised prices, the results point to the presence of expectation-based inflation persistence. Regarding the volatility of free and supervised prices, it can be concluded that both has a higher volatility in the beginning of sample, but the change to a lower level in the volatility of supervised prices happened later, compared to the change in the volatility of free prices. Additionally, for supervised prices another jump occurred at the beginning of 2015, bringing the volatility to a higher level from this date onward.

Summarizing, the main contribution of this paper is to take into account stick price and information, by considering intrinsic and expectation-based persistence, respectively, and account for stochastic volatility with jumps. The stochastic volatility introduced implies a lower intrinsic inflation persistence, while the expectation-based inflation persistence remains unchanged. The shifts in volatility may be associated with policies conducted by the government and periods of political uncertainty. Since the volatility has an effect on inflation persistence, the variance of shocks affecting inflation should be take into account by the policy makers. In this sense, the results found in this paper can elucidate the debate on inflation persistence and volatility and refine the discussion on monetary policy framework.

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