Inflation and Inflation Uncertainty in Latin America: a Time-Varying Stochastic Volatility in Mean Approach

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Abstract

This paper proposes a stochastic volatility in mean (SVM) model with time-varying parameters (TVP) in order to assess whether the effect of inflation uncertainty on inflation has changed over time in Latin America. Considering inflation series for the last two decades, we report evidences of high uncertainty from 1996 to early 2000s. Moreover, despite being positive throughout the sample, the overall relationship between inflation uncertainty and inflation has changed over the years in Latin America, underscoring the importance of our time-varying specification.

Keywords: inflation uncertainty, Latin America, stochastic volatility, time-varying parameter.

JEL Classification: C11, C15, E31, N16.

Área 8 - Microeconomia, Métodos Quantitativos e Finanças

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1 Introduction

Inflation uncertainty, as well as the rate of inflation, has recently drawn significant attention in the macroeconomic literature. Even though understanding the interaction of the price level and its uncertainty plays central role in successfully implementing monetary policy, there remains no theoretical or empirical consensus about the nature of this relationship. Following Friedman (1977), which informally postulated the potential adverse effects of the inflation-inflation uncertainty nexus in real economic activity, Ball (1992) provides a formal justification for the latter hypothesis in the context of a game-theoretic asymmetric information setting between the monetary authority and the public, predicting that higher inflation might potentially lead to higher inflation uncertainty in the future. As explained by Hossain and Arwatchanakarn (2016), increasing inflation puts pressure on the monetary authority to reduce inflation. Nonetheless, policymakers may be loath to implement contractionary policy (that increase unemployment and decrease growth). This fact increase the uncertainty in relation to the monetary policy and consequently in relation to the price level. On the other hand, subsequent theoretical research advocated for causality in the opposite direction, namely from inflation uncertainty to inflation. By employing the Barro-Gordon set-up (Barro and Gordon, 1983), Cukierman and Meltzer (1986) argue that increases in inflation uncertainty induce a higher optimal average inflation rate as the central bank might opportunistically create an inflation surprise in order to stimulate output growth. Alternatively, rejection of the high inflation harmful effects on the predictability of the price level has also been in debate. For instance, Holland (1995) stresses the existence of a *stabilization motive* in high inflation periods, with the policymaker lowering inflation uncertainty as to reduce the welfare costs of disinflationary policies, thus postulating a negative relation between inflation and inflation uncertainty.

Despite some early empirical research relying on cross-sectional dispersion of inflation survey forecasts or moving standard deviations of the inflation series as measures for inflation uncertainty (Jaffee and Kleiman, 1977; Cukierman and Wachtel, 1979; Fischer, 1981; Frohman et al., 1981; Zarnowitz and Lambros, 1987), Evans (1991) emphasizes that uncertainty should not be taken as variability. For instance, observing *ex post* low volatility does not imply low uncertainty as economic agents might still have little information about inflation and, therefore, consider the future as highly uncertain. Moreover, survey based measures are considered inappropriate as they only represent the dispersion of forecasts across professional forecasters, without taking into account the individual's uncertainty about their own forecast (Chan, 2015). From the seminal paper of Engle (1982), Autoregressive Conditional Heteroskedasticity (ARCH) and generalized ARCH (GARCH) techniques have emerged as common approaches to proxy uncertainty. However, papers based on the latter conditional heteroskedasticity models still have produced divergent results (Brunner and Hess, 1993; Baillie et al., 1996; Caporale and McKiernan, 1997; Grier and Perry, 1998, 2000; Nas and Perry, 2000; Fountas, 2001; Kontonikas, 2004; Berument and Dincer, 2005; Conrad and Karanasos, 2005; Thornton, 2006; Chowdhury, 2014; Payne, 2008).

Even though ARCH-type models have been extensively employed in empirical research, their deterministic framework is unable to provide information on the effects of unanticipated uncertainty shocks on the level of inflation. By modeling the conditional variance as an unobserved component that follows a low-order Markov process, the attractiveness of Stochastic Volatility (SV) models has recently increased. As the latent volatility specification embodies two separate disturbance terms, it is therefore considered more flexible than its deterministic counterpart in fitting the data (Danielsson, 1994; Kim et al., 1998; Fleming and Kirby, 2003; Carnero et al., 2004). Nonetheless, results from SV models concerning the interplay of inflation and inflation uncertainty are ambiguous as well as scarce [see, e.g., Berument et al. (2009, 2011) and Chan (2015)].

For the specific case of Latin America, empirical evidence is also rather limited. In general, macroeconomic research has advocated in favor of the Friedman-Ball hypothesis for the Latin American economies, therefore implying that their central banks have incentives to lower inflation in order to further reduce the costs of its volatile behavior (Daal et al., 2005). Moreover, as for the inflation-targeting countries, the implementation of the latter monetary framework seems to have contributed to the decrease in inflation volatility persistence (Broto, 2008). Other Latin American country-specific studies are in line with these findings (Della Mea and Pena, 1995; Baillie et al., 1996; Ma, 1998; Vale, 2005; Grier and Grier, 2006; Castilho et al., 2007; Thornton, 2008).

However, this paper proposes to go beyond the earlier work for Latin America. As empirical research for the Latin America has struggled so far to provide results evaluating whether the relationship between inflation and inflation uncertainty has changed over time, this paper aims to shed some light on this matter. According to Lucas (1976), the structure of an econometric model is based upon the optimal decision rules of economic agents, thus shifts in policy regime might influence the estimated coefficients of behavioral equations. For instance, Evans and Wachtel (1993) stress that disregarding regimes changes in the inflation process might underestimate its level of uncertainty. Our econometric strategy is based on a Time-Varying Parameter Stochastic Volatility in Mean (TVP-SVM) model in which the stochastic volatility effects on the level of inflation are both direct and time-varying, following closely Chan (2015). To the best of our knowledge, this is the first attempt to apply this class of models to assess how uncertainty affects inflation over time in the region. We focus on five Latin American economies – Argentina, Brazil, Colombia, Mexico and Uruguay – for which monthly inflation data span from January 1996 to February 2015.

Overall, the obtained results show that inflation uncertainty is relative higher until early 2000s. Moreover, as for the relationship between inflation and inflation uncertainty, we document a time-varying positive interplay in Latin America. Also, there are evidences of the considered Latin American countries being able to mitigate the adverse shocks from the 2008 Global Financial Crisis.

The remainder of the paper is organized as follows. Section 2 introduces the time-varying parameter stochastic volatility in mean (TVP-SVM) model, highlighting how it can be applied to the unobserved components approach model of Stock and Watson (2007). We also describe the data set used in this paper. Estimation results are summarized in Section 3. Finally, Section 4 concludes.

2 Econometric Methodology

2.1 Stochastic Volatility in Mean (SVM) Model with Time-Varying Parameters (TVP)

In order to evaluate whether the effects of inflation uncertainty on inflation have changed over time, we adopt a stochastic volatility in mean model with time-varying parameters (TVP-SVM) proposed by Chan (2015). The model structure is given by:

$$y_t = \boldsymbol{x}_t^{'}\boldsymbol{\beta}_t + \alpha_t e^{h_t} + \varepsilon_t^y, \qquad \varepsilon_t^y \sim \mathcal{N}(0, e^{h_t}), \tag{2.1}$$
$$h_t = \mu + \phi(h_{t-1} - \mu) + \varepsilon_t^h, \qquad \varepsilon_t^h \sim \mathcal{N}(0, \sigma^2), \tag{2.2}$$
$$\boldsymbol{\gamma}_t = \boldsymbol{\gamma}_{t-1} + \varepsilon_t^\gamma, \qquad \varepsilon_t^\gamma \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega}), \tag{2.3}$$

where y_t is the time series of interest, $\boldsymbol{x}_t$ is a $k\times 1$ vector of covariates, $\boldsymbol{\beta}_t$ is a $k\times 1$ vector of time-varying parameters, $\boldsymbol{\Omega}$ is a $(k+1)\times(k+1)$ covariance matrix and the disturbance terms ε_t^y and ε_t^h are considered mutually and serially uncorrelated. The conditional variance function is specified in logarithmic form in which h_t follows a stationary AR(1) process with $|\phi| < 1$, being initialized with $h_1 \sim \mathcal{N}(\mu, \sigma^2/(1-\phi^2))$. The vector of coefficients $\boldsymbol{\gamma}_t = (\alpha_t, \boldsymbol{\beta}_t^{'})^{'}$ in (2.3) evolves as a first-order random walk process, being initialized with $\boldsymbol{\gamma}_1 \sim \mathcal{N}(\boldsymbol{\gamma}_0, \boldsymbol{\Omega}_0)$ for constant matrices $\boldsymbol{\gamma}_0$ and $\boldsymbol{\Omega}_0$. One should notice that this random walk specification increases model flexibility as it allows us to capture both temporary and permanent shifts, thus considered a more suitable framework for describing changes in private sector behavior or the learning dynamics of both private agents and policymakers (Primiceri, 2005).

Since equations (2.1)–(2.3) define a nonlinear Gaussian state-space model, the traditional Maximum Likelihood (ML) approaches cannot provide reliable estimates for the parameters due to intractability of the likelihood function. Moreover, even though the Bayesian approach of Markov Chain Monte Carlo (MCMC) using Kalman filter-based algorithms is considered standard in dealing with this class of models, Chan (2015) argues that the TVP-SVM approach cannot be easily dealt by the latter methods as the likelihood evaluation would involve "integrating out" both types of states (namely, $\boldsymbol{\gamma}_t$ and h_t), creating an even more complex and high-dimensional nontrivial problem. From the recent advances in band and sparse matrix algorithms, Chan (2015) proposes an efficient MCMC sampling approach that can simulate each type of states individually as it exploits the fact that the Hessian of the log-conditional density of the log-volatilities is a band matrix containing only a few nonzero elements arranged along a diagonal band.

Let $\boldsymbol{x}$ denote the covariates, $\boldsymbol{y} = (y_1, \ldots, y_T)^{'}$, $\boldsymbol{\gamma} = (\boldsymbol{\gamma}_1^{'}, \ldots, \boldsymbol{\gamma}_T^{'})^{'}$ and $\boldsymbol{h} = (h_1, \ldots, h_T)^{'}$. The posterior drawing process can be described by sequentially sampling from[1]:

1. $p(\boldsymbol{h}|\boldsymbol{y}, \boldsymbol{x}, \boldsymbol{\gamma}, \mu, \phi, \sigma^2, \boldsymbol{\Omega}) = p(\boldsymbol{h}|\boldsymbol{y}, \boldsymbol{x}, \boldsymbol{\gamma}, \mu, \phi, \sigma^2)$;
2. $p(\boldsymbol{\gamma}|\boldsymbol{y}, \boldsymbol{x}, \boldsymbol{h}, \mu, \phi, \sigma^2, \boldsymbol{\Omega}) = p(\boldsymbol{\gamma}|\boldsymbol{y}, \boldsymbol{x}, \boldsymbol{h}, \boldsymbol{\Omega})$;
3. $p(\boldsymbol{\Omega}, \sigma^2|\boldsymbol{y}, \boldsymbol{x}, \boldsymbol{\gamma}, \boldsymbol{h}, \mu, \phi) = p(\boldsymbol{\Omega}|\boldsymbol{\gamma})p(\sigma^2|\boldsymbol{h}, \mu, \phi)$;
4. $p(\mu, \phi|\boldsymbol{y}, \boldsymbol{x}, \boldsymbol{\gamma}, \boldsymbol{h}, \sigma^2, \boldsymbol{\Omega}) = p(\mu, \phi|\boldsymbol{h}, \sigma^2)$.

Finally, regarding the choice of priors, this paper assumes independent priors for σ^2, μ, ϕ and $\boldsymbol{\Omega}$, following Chan (2015):

$$\begin{gathered} \mu \sim \mathcal{N}(\mu_0, V_\mu), \quad \phi \sim \mathcal{N}(\phi_0, V_\phi)\mathbb{1}(|\phi| < 1), \\ \sigma^2 \sim \mathcal{IG}(\nu_{\sigma^2}, S_{\sigma^2}), \quad \boldsymbol{\Omega} \sim \mathcal{IW}(\nu_{\boldsymbol{\Omega}}, \boldsymbol{S}_{\boldsymbol{\Omega}}), \end{gathered} \tag{2.4}$$

where $\mathcal{IG}$ and $\mathcal{IW}$ denote the inverse-gamma distribution and the inverse-Wishart distribution, respectively. Additionally, the stationary condition $|\phi| < 1$ is imposed on the prior for ϕ.

[1]For technical details, see Chan (2015).

2.2 Decomposing Inflation: An Unobserved Components (UC) Approach

In order to decompose inflation into a trend and a transitory component, Chan (2015) embodies the TVP-SVM framework to the unobserved components model of Stock and Watson (2007). Despite the variance of the trend being constant, this version assumes that the transitory component has stochastic volatility as well as a volatility feedback mechanism in which the level of inflation might be affected by its own volatility. Furthermore, the specification also encompasses past inflation effects (but not contemporaneous effect) on the current inflation volatility. Thus, future inflation can be affected by volatility - inflation uncertainty. That is, the model structure is given as:

$$\pi_t = \tau_t + \alpha_t e^{h_t} + \varepsilon_t^{\pi}, \qquad \varepsilon_t^{\pi} \sim \mathcal{N}(0, e^{h_t}), \tag{2.5}$$
$$h_t = \mu + \phi(h_{t-1} - \mu) + \beta\pi_{t-1} + \varepsilon_t^{h}, \qquad \varepsilon_t^{h} \sim \mathcal{N}(0, \sigma^2), \tag{2.6}$$
$$\boldsymbol{\gamma}_t = \boldsymbol{\gamma}_{t-1} + \varepsilon_t^{\gamma}, \qquad \varepsilon_t^{\gamma} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega}), \tag{2.7}$$

where π is inflation, $\boldsymbol{\gamma}_t = (\alpha_t, \tau_t)'$ and $\boldsymbol{\Omega}$ is a 2×2 covariance matrix. The coefficient α_t measures the impact of the transitory volatility – $\exp(h_t)$ – on the level of inflation. As past inflation π_{t-1} is a covariate in the conditional variance equation, its associated parameter β enters the MCMC algorithm as an extra block, sampling it from its full conditional distribution: $(\beta|\boldsymbol{y}, \boldsymbol{h}, \mu, \phi, \sigma^2) \sim \mathcal{N}(\hat{\beta}, D_\beta)$, where $D_\beta^{-1} = V_\beta^{-1} + \boldsymbol{X}_\beta'\boldsymbol{X}_\beta/\sigma^2$ and $\hat{\beta} = D_\beta(V_\beta^{-1}\beta_0 + \boldsymbol{X}_\beta'\boldsymbol{z}_\beta/\sigma^2)$ with $\boldsymbol{X}_\beta = (y_1, \ldots, y_{T-1})'$ and $\boldsymbol{z}_\beta = (h_2 - \phi h_1 - \mu(1 - \phi), \ldots, h_T - \phi h_{T-1} - \mu(1-\phi))'$.

Following equation (2.4), independent priors are assumed for equations (2.5)–(2.7). As for the hyper-parameters, μ has a Gaussian distribution with mean $\mu_0 = 0$ and variance $V_\mu = 10$, ϕ follows a truncated Gaussian distribution with $\phi_0 = 0.97$ and variance $V_\phi = 0.1^2$, and β has a normal prior $\mathcal{N}(\beta_0, V_\beta)$ with $\beta_0 = 0$ and $V_\beta = 10$. In regard to the variance parameters, $\nu_{\sigma^2} = \nu_{\boldsymbol{\Omega}} = 10$, $S = 0.36$ and $\boldsymbol{S}_{\boldsymbol{\Omega}} = \text{diag}(0.13, 0.8125)$, so that $\mathbb{E}\sigma^2 = 0.2^2$ and $\mathbb{E}\boldsymbol{\Omega} = \text{diag}(0.1^2, 0.25^2)$. Besides being considered rather noninformative, Chan (2015) underscores that these chosen priors are in accordance with the desired smoothness of the corresponding state transition.

2.3 Data Description

The data set consists of seasonally adjusted[2] monthly Consumer Price Index (CPI) inflation, computed as $\pi_t = 1200 \times \ln(CPI_t/CPI_{t-1})$, for five Latin American economies, namely Argentina, Brazil, Colombia, Mexico and Uruguay. The period spans from 1996:M1 to 2015:M2, which gives $T = 230$ for each country. The time series were downloaded from the National Institute of Statistics and Census of Argentina (INDEC), the Brazilian Institute of Geography and Statistics (IBGE), the National Administrative Department of Statistics of Colombia (DANE), the Bank of Mexico (BANXICO) and the National Institute of Statistics of Uruguay (INE).

Table 2.1 reports the descriptive statistics, unit root tests and ARCH-LM tests for inflation rate in Latin America. From the table, the following observations can be made: (i) due to high excess kurtosis, inflation rate tends to have a leptokurtic distribution with values concentrated around the mean which seems to justify the use of a time changing

[2]In order to perform the seasonal adjustment of the data set, we applied the X-12-ARIMA method developed by U.S. Census Bureau.

volatility model. The ARCH-LM test confirms this result; (ii) the distribution also seems to be biased to the right; (iii) the region displays high inflation variability given that the standard deviation is nearly equal (or superior, in the case of Argentina) to the mean; and (iv) both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests rejected the null hypothesis of a unit root at the 1% significance level[3].

Table 2.1: Decriptive Statistics and Unit Root Tests

	Argentina	Brazil	Colombia	Mexico	Uruguay
Mean	7.6972	6.2511	6.9368	7.0207	8.9242
Median	7.6405	5.3054	5.0803	5.1949	7.8757
Std. Dev.	10.9648	4.1657	5.6162	6.2547	7.6135
Minimum	-8.8137	-3.0577	-1.2055	-6.2205	-8.6286
Maximum	111.4142	34.0769	30.2239	36.3858	61.5282
Skewness	4.4486	2.1826	1.5261	1.7838	2.6858
Kurtosis	38.0638	12.6877	5.2277	6.8761	16.8499
ARCH-LM test(10)	31.7037	85.0167	150.6584	156.5991	129.3013
P-value	(4.4859e-04)	(5.1847e-14)	(0.0000)	(0.0000)	(0.0000)
ADF	-4.3512^{*}	-6.3531^{*}	-2.7557^{***}	-4.1029^{*}	-6.8406^{*}
PP	-5.4528^{*}	-6.3965^{*}	-4.6444^{*}	-4.5908^{*}	-6.8270^{*}

Notes. *, ** and *** indicate that the null hypothesis of the unit root test is rejected at the 1%, 5% and 10% significance level. Both tests were performed in the presence of an intercept as the deterministic term. *Source:* Compiled by the author.

Figure 2.1 presents the Latin America monthly CPI inflation for the 1996:M1–2015:M2 period. In general, these time series show contrasting patterns, which can be seen as a first indication that a time-varying framework might be the suitable choice for modeling inflation. For instance, Brazil has clearly undergone a more volatile behavior from 1996 to 2002 whereas Colombia, Mexico and Uruguay have shown a downward trend during the same period.

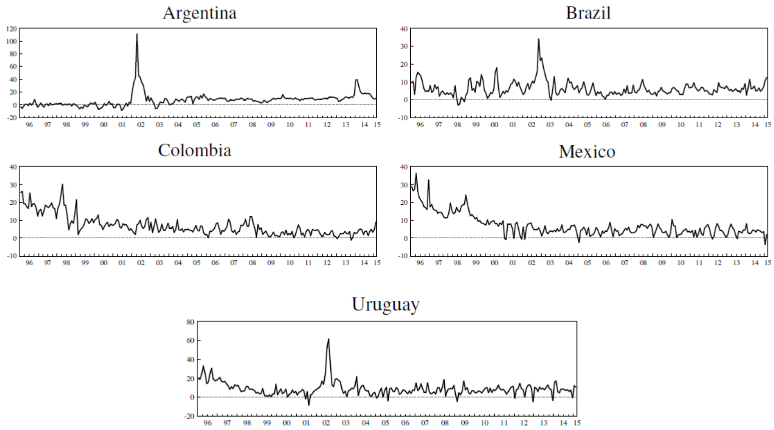
3 Estimation Results

As mentioned before, we estimate a time-varying parameter stochastic volatility in mean (TVP-SVM) model to assess the potential time-variation in the effects of inflation uncertainty on the level of inflation for Latin America. In order to compute the posterior estimates for each country, we draw 50,000 samples after the initial 5,000 samples were discarded in the burn-in period. We use the conditional variance estimates as the measure of inflation uncertainty.

In the particular case of Argentina, Figure 3.1 shows a substantial increase in log-volatility estimates from 1998 to 2002, reflecting the rather unstable Argentine macroeconomic configuration that later led to the default on public debt and a significant business cycle contraction. After abandoning the peso-dollar parity in January 2002, inflation uncertainty in Argentina entered a downward trend period until late-2007. Even though volatility slightly peaks in 2010, our results suggest that the recent U.S. Financial Crisis had a short-lived and mild impact on the country economic performance. As for the sharp

[3]Regarding the unit root tests for Colombia, the ADF test rejected the null hypothesis at the 10% significance level.

Figure 2.1: Monthly CPI inflation for five Latin American countries (1996:M1–2015:M2)



Source: National Institute of Statistics and Census of Argentina (INDEC), Brazilian Institute of Geography and Statistics (IBGE), National Administrative Department of Statistics of Colombia (DANE), Bank of Mexico (BANXICO) and National Institute of Statistics of Uruguay (INE).

increase after 2012, this behavior might be mostly attributed to a demand-led macroeconomic strategy and the lack of an anti-inflationary commitment in face of the increasing fiscal deficits and the rapid-paced exchange rate appreciation.

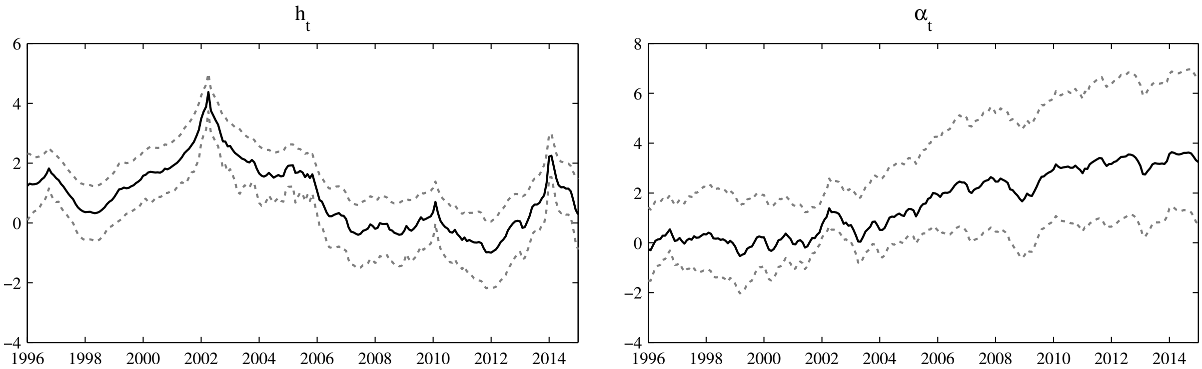
Regarding the inflation uncertainty impacts on the level of inflation, the α_t estimates display an overall steady upward trend which indicates that the responsiveness of Argentine inflation to uncertainty shocks has increased over the last two decades. In addition, these results strongly support the existence of a *positive* relationship between the latter variables, particularly after 2000. However, when considering the 90% credible intervals, the parameter is apparently different from zero only after 2010. This time-variation in α_t thus corroborates the use of our TVP-SVM approach.

The results for Brazil are presented in Figure 3.2. Even though the inflation-targeting (IT) regime was adopted in June 1999, one could say that the regime consolidation was only achieved after 2003 given the previous Brazilian Central Bank inability to maintain the level of inflation near its target. The increased volatility observed in 2002/2003 corresponds to '"Lula effect"' (political uncertainty during the pre-election period in Brazil). From 2003 until 2006, the conditional variance estimates had a substantial decrease, becoming less volatile and reflecting the gains of credibility associated to the IT regime. Furthermore, despite the aftermath of the Global Financial Crisis leading to an slight increase in uncertainty, its effects were not as severe as in other emerging countries.

As for assessing the effects of uncertainty on inflation, the estimates of α_t for Brazil are rather time-invariant. However, the coefficient is statistically different from zero throughout the whole sample. Given its positive sign, one can therefore infer that periods with high inflation uncertainty are accompanied by periods of high inflation in Brazil.

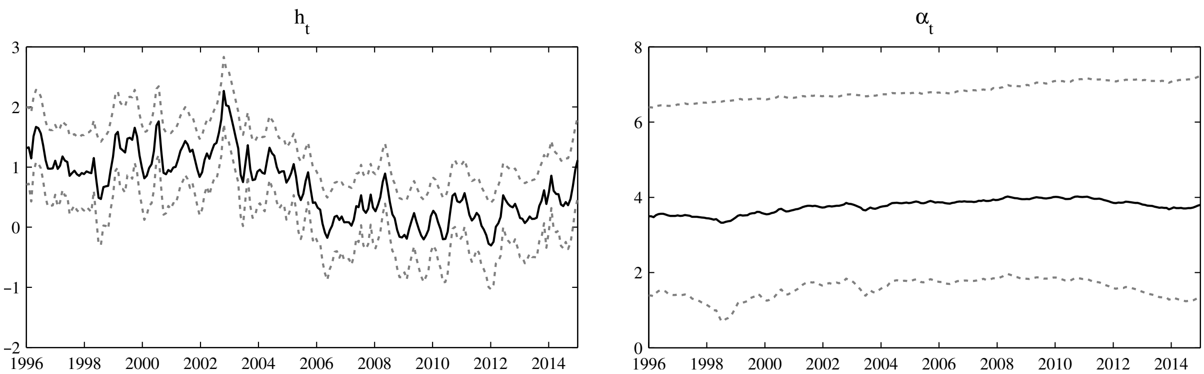
The results for Colombia are qualitatively similar to the ones for Brazil (Figure 3.3).

Figure 3.1: Posterior estimates of h_t (left panel) and α_t (right panel) for Argentina



Notes: Posterior mean (solid line) and 90% credible intervals (dotted line). *Source:* Compiled by the author.

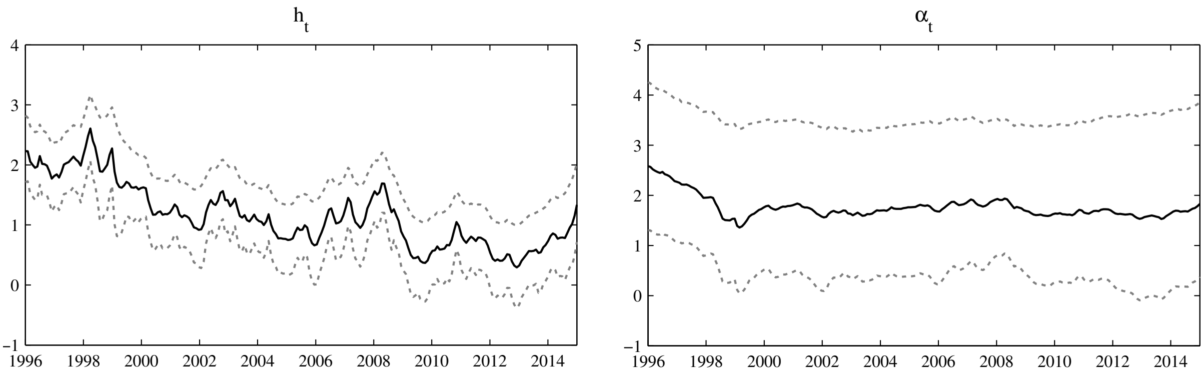
Figure 3.2: Posterior estimates of h_t (left panel) and α_t (right panel) for Brazil



Notes: Posterior mean (solid line) and 90% credible intervals (dotted line). *Source:* Compiled by the author.

For instance, we find evidences that the Colombian economy sustained successive uncertainty decreases from 1998 until 2002. The slight short-run volatility increase in 2002 coincides with the breakout of the Argentine Financial Crisis. Likewise, the conditional variance estimate peaks once again in early-2008 as a potential outcome of the Global Financial Crisis.

Figure 3.3: Posterior estimates of h_t (left panel) and α_t (right panel) for Colombia



Notes: Posterior mean (solid line) and 90% credible intervals (dotted line). *Source:* Compiled by the author.

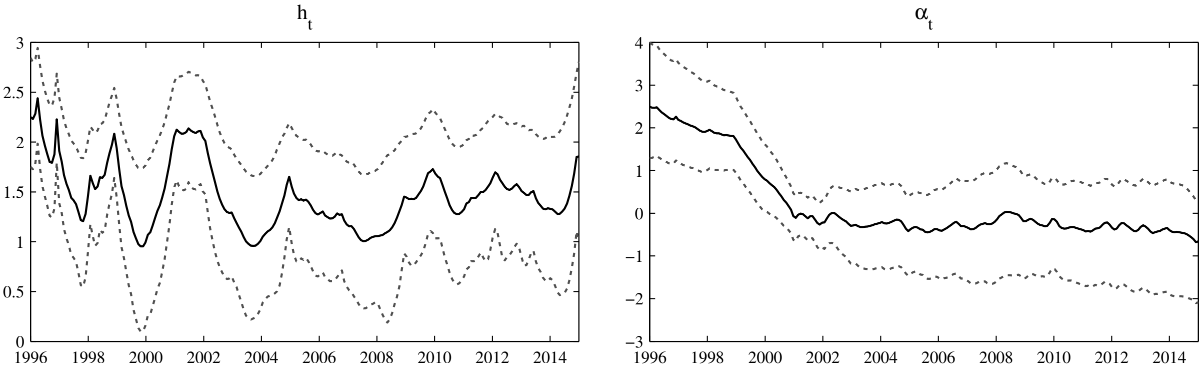
The estimates of α_t for Colombia follow the same overall time-invariant pattern of Brazil. Although, one should note that the impact of uncertainty on inflation in Colombia had an initial decrease from 1996 to 1999. Therefore, this might constitute an evidence that the use of a crawling band for exchange rate and an intermediate monetary target were effective in partly offsetting the transmission mechanism of inflation uncertainty on inflation.

In contrast, the aftermath of the Tequila Crisis in December 1994 led to serious macroeconomic instability in Mexico. For instance, from 1996 to 2002, the posterior estimates of the log-volatility show considerable erratic movements despite h_t being higher in the beginning of the sample (Figure 3.4). After officially adopting the IT regime in 2001, uncertainty entered a more stable period. Moreover, our results indicate that the 2008 Financial Crisis was responsible for increasing inflation uncertainty until late-2009.

Our TVP-SVM specification is also capable of capturing a significant drop in α_t estimates from 1996 to 2001. Hence, there are evidences for the soothing effect of the financial assistance of the U.S. and the International Monetary Fund (e.g., the Mexican Debt Disclosure Act of 1995) on the inflation-inflation uncertainty dynamics. Concerning the rest of the sample period, α_t estimates seem to be time-invariant. However, when considering the 90% credible intervals, the latter estimates are only statistically different from zero from 1996 until late-1999.

Figure 3.5 plot the evolution of the inflation uncertainty (h_t) and its time-varying impact (α_t) for Uruguay. The results for h_t are in line with those ones from Argentina, especially until 2006. The sharp increase in uncertainty, peaking in mid-2002, exposes the fragility of Uruguay's economy to the external adverse shocks from the Argentine Financial Crisis. However, de la Plaza and Sirtaine (2005) argue that, despite the occurrence of 2002 Uruguayan banking crisis being intrinsically correlated to Argentina's financial system collapse, some inherent weaknesses of the Uruguayan economy and banking sector

Figure 3.4: Posterior estimates of h_t (left panel) and α_t (right panel) for Mexico

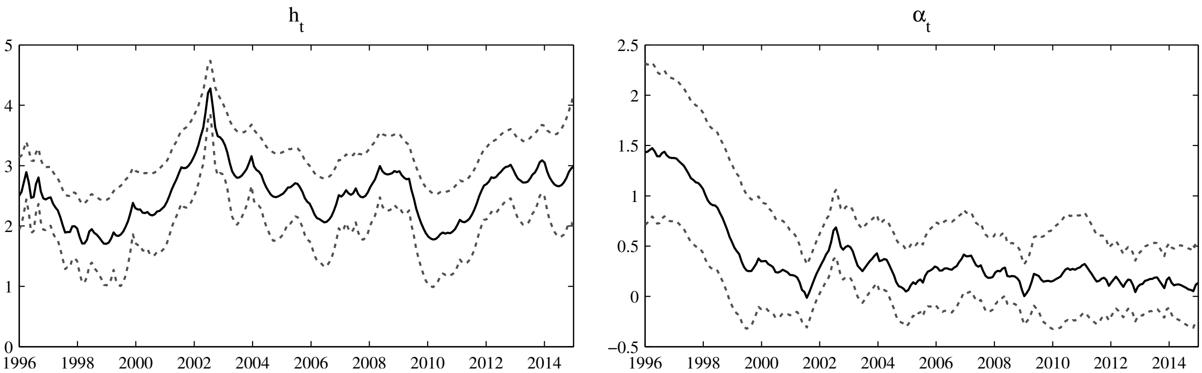


Notes: Posterior mean (solid line) and 90% credible intervals (dotted line). *Source:* Compiled by the author.

were responsible for magnifying the adverse impact on the financial sector. Additionally, the relative small impact of 2008 Global Financial Crisis on uncertainty reveals the ongoing improvement on the resilience of the Uruguayan economy.

It can be seen from the right panel of Figure 3.5 that the impacts of inflation uncertainty on the level of inflation decreased substantially since 1996, stabilizing after 2004. Yet, when considering the 90% credible intervals, the positive relationship between inflation uncertainty and inflation is only statistically different from zero from 1996 to 1999 and from 2002 to 2004.

Figure 3.5: Posterior estimates of h_t (left panel) and α_t (right panel) for Uruguay



Notes: Posterior mean (solid line) and 90% credible intervals (dotted line). *Source:* Compiled by the author.

We estimate two alternative models in order to compare the performance of TVP-SVM model: the unobserved components model (UC) and the SVM model with constant parameter (UC-SVM-constant). The first model was proposed by Stock and Watson (2007) and it is the standard unobserved components model with stochastic volatility. In this model, we set $\alpha_t = 0$ for t = 1, ...,T. In the second model, we set $\alpha_1 = ... = \alpha_T = \alpha$. Thus, the effect of uncertainty on inflation does not change over time. The models were compared using marginal likelihood, calculated by the method of Chib and Jeliazkov

(2001). The results are presented in Table 3.1.

Table 3.1: The estimated log marginal likelihoods

	Argentina	Brazil	Colombia	Mexico	Uruguay
UC-SVM	**-609.17**	577.75	**-558.28**	**-569.56**	**-705.83**
UC	-639.80	-594.38	-580.33	-597.34	-738.13
UC-SVM-Constant	-628.32	**-548.68**	-563.73	-582.68	-709.84

The TVP-SVM model is the most appropriate for all countries but Brazil. This is not surprising, since the α_t is approximately constant over the period, as can be seen in Figure 3.2.

The broad conclusions from the obtained results are that Latin America has presented a high volatile inflation behavior over the sample period, implying the existence of considerable uncertainty in the region. Moreover, when dealing with the inflation-inflation uncertainty dynamics, the countries considered (with exception of Brazil) have shown time-varying estimates. For Colombia, although the impact of inflation uncertainty on inflation is apparently time-invariant, the TVP-SVM model was more appropriate than time invariant models (see Table 3.1). In the Brazil, we analyzed the post-Real Plan period, which achieved the stabilization of the economy and significant decrease in the inflation rate. This fact improved economic predictability, which may help explain the time-invariant result. However, it is important to note that the relationship between inflation and inflation uncertainty in Brazil is significantly different from zero, which highlights the relevance of volatility in determining inflation in the period. This result confirms the analysis contained in Broto (2008), which found no evidence that the introduction of inflation targeting regime in Brazil is associated with lower inflation. For the other countries analyzed in Broto (2008), including Colombia and Mexico, there are evidences that the introduction of inflation targeting regime is associated with a decrease in the inflation level, which may help explain the difference between the results. The results obtained by Chan (2015) for USA, UK and Germany in the period from 1955Q1 to 2013Q4 show significant time variation in the parameter which measures how inflation volatility affects the level of inflation. Moreover, Chan (2015) concludes that inflation uncertainty effect on inflation in Germany is less important compared to the USA and UK.

As for policy recommendation, the overall positive link between inflation and inflation uncertainty in Latin America consequently leads to incentives for the policymaker to decrease uncertainty in order to effectively reduce the welfare costs of inflation. This can be obtained through a predictable and credible monetary policy. High transparency and clear communication may be reduce the uncertainty inflation and consequently the inflation.

4 Conclusions

In this paper, we have proposed a time-varying parameter stochastic volatility in mean (TVP-SVM) model in order to evaluate the the effects of inflation uncertainty on inflation in Latin America over the 1996:M1-2015:M2 period. By allowing for time-varying parameters, our specification is thus less susceptible to the Lucas (1976) critique.

The obtained results indicate that the TVP-SVM is indeed capable of capturing the structural instability of the inflation series. However, in the case of Brazil, the inflation-inflation uncertainty interplay is rather time-invariant. Moreover, there are evidences of a greater volatile inflation behavior in the beginning of the sample period in comparison to the last few years. Overall, the considered Latin American economies seem to have endured relatively well the external adverse shocks from the 2008 Global Financial Crisis. Moreover, these results have important implications for monetary policy since both inflation and inflation uncertainty may adversely affect the real economic variables and make the price mechanism less efficient. Even, these results confirm the conclusion in Broto (2008), which shows that the inflation targeting regime has been useful to reduce the inflation.

As for further research, we intend to apply our TVP-SVM specification to a multivariate framework to also evaluate, for instance, the time-varying effects of inflation uncertainty on economic activity in Latin America. Rahman and Serletis (2008) uses the multivariate GARCH-M model to analyze this issue to USA, UK, Japan and Canada . Another interesting point is to analyse the transmission mechanism of external shocks (US inflation, for example) to inflation uncertainty in Latin America. Some studies have addressed this issue, as Hossain and Arwatchanakarn (2016) for Thailand and Buth et al. (2015) for the case of Cambodia,Lao PDR, and Vietnam. Furthermore, it would be interesting to evaluate the degree of inflation uncertainty co-movements in Latin America in order to assess the fragility of these economies to the behavior of their respective neighboring countries.

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