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DOCUMENTO DE TRABAJO

N° 544

THE INFLATION UNCERTAINTY-INFLATION RELATIONSHIP: TIME VARIATION ACROSS LATIN AMERICA AND THE G7

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Marzo, 2025

DOCUMENTO DE TRABAJO 544
http://doi.org/10.18800/2079-8474.0544

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Documento de Trabajo 544

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https://departamento-economia.pucp.edu.pe/publicaciones/documentos

Encargado de la Serie: Gabriel Rodríguez
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Primera edición – Marzo, 2025

ISSN 2079-8474 (En línea)

The Inflation Uncertainty-Inflation Relationship: Time Variation Across Latin America and the G7*

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This Version: March 20, 2025

Abstract

This paper examines the evolution of the inflation uncertainty-inflation relationship in seven Latin American countries and the G7 from Q1 1948 to Q4 2023, using the time-varying parameter stochastic volatility in mean (TVP-SVM) model of Chan (2017) and its extension incorporating time-varying mixture innovations (TVP-SVM-TVMI) from Hou (2020). The key findings are as follows: (i) the TVP-SVM model is preferred in 8 out of 14 countries; (ii) inflation uncertainty has been higher in Latin America than in the G7, particularly during the 1980s "lost decade"; (iii) log-inflation uncertainty is more persistent in Latin America; (iv) there is no evidence supporting the hypothesis of Friedman (1977) in any of the countries analyzed; (v) the Cukierman-Meltzer hypothesis (1986) holds, as the uncertainty-inflation relationship is positive and time-varying in all countries; (vi) this relationship is stronger and statistically significant during periods of high inflation uncertainty; and (vii) there is evidence of more structural breaks in this relationship in Latin America than in the G7.

JEL Classification: C11, C15, C58, E31, N16.

Keywords: Inflation Uncertainty, Inflation, Latin America, G7, Bayesian Estimation and Comparison, Stochastic Volatility in Mean, Time-Varying Parameters, Structural Breaks.

*We acknowledge Akemi Andrade's participation in an early version of this document. We appreciate the comments of Paul Castillo B. (BCRP). Any remaining errors are the sole responsibility of the authors.

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Variación Temporal de la Relación entre la Incertidumbre Inflacionaria y la Inflación en América Latina y el G7*

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Versión: 20 de Marzo 2025

Resumen

Este trabajo examina la evolución de la relación entre la incertidumbre inflacionaria y la inflación en siete países latinoamericanos y el G7 desde el primer trimestre de 1948 hasta el cuarto trimestre de 2023, utilizando el modelo de volatilidad estocástica de parámetros variables en el tiempo en la media (TVP-SVM) de Chan (2017) y su extensión que incorpora innovaciones de mezcla variables en el tiempo (TVP-SVM-TVMI) de Hou (2020). Los hallazgos clave son los siguientes: (i) el modelo TVP-SVM es preferido en 8 de los 14 países; (ii) la incertidumbre inflacionaria ha sido mayor en América Latina que en el G7, particularmente durante la "década perdida" de los años ochenta; (iii) la incertidumbre logarítmica de la inflación es más persistente en América Latina; (iv) no hay evidencia que respalde la hipótesis de Friedman (1977) en ninguno de los países analizados; (v) la hipótesis de Cukierman-Meltzer (1986) es válida, ya que la relación incertidumbre-inflación es positiva y varía en el tiempo en todos los países; (vi) esta relación es más fuerte y estadísticamente significativa durante períodos de alta incertidumbre inflacionaria; y (vii) hay evidencia de más rupturas estructurales en esta relación en América Latina que en el G7.

Clasificación JEL: C11, C15, C58, E31, N16.

Palabras Claves: Incertidumbre Inflacionaria, Inflación, América Latina, G7, Estimación y Comparación Bayesiana, Volatilidad Estocástica en Media, Parámetros Variantes en el Tiempo, Quiebres Estructurales.

*Agradecemos la participación de Akemi Andrade en una versión preliminar de este documento. Agradecemos los comentarios de Paul Castillo B. (BCRP). Cualquier error restante es responsabilidad exclusiva de los autores.

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1 Introduction

There is broad consensus that high uncertainty about inflation expectations complicates monetary policy and raises costs for market participants (Friedman, 1977; Ball, 1992; Golob, 1994). Understanding the relationship between inflation and inflation uncertainty is essential, as both factors play a central role in policy design.

The literature identifies two main views: (i) Friedman (1977) argues that higher inflation leads to greater inflation uncertainty, while (ii) Cukierman and Meltzer (1986) claim that rising inflation uncertainty drives inflation upward. Studies in advanced economies offer mixed evidence for both views (Brunner and Hess, 1993; Evans and Wachtel, 1993; Golob, 1994; Holland, 1995; Crawford and Kasumovich, 1996; Grier and Perry, 1998; Kontonikas, 2004; Berument and Dincer, 2005; Daal et al., 2005; Berument et al., 2009; Balcilar and Ozdemir, 2013; Chan, 2017; Hou, 2020; Le, 2023). In contrast, evidence from Latin America, although less extensive, supports Friedman's view, while offering only limited backing for Cukierman and Meltzer (e.g., Ferreira and Palma, 2017; Le, 2023).

This paper examines the evolving relationship between inflation and inflation uncertainty for seven Latin American countries (Brazil, Chile, Colombia, Ecuador, Mexico, Peru, and Uruguay) and the G7. The analysis centers on the Cukierman-Meltzer hypothesis, adopting a time-varying perspective drawn from recent contributions (Chan, 2017; Ferreira and Palma, 2017; Varlik et al., 2017; Hou, 2020). This approach is particularly relevant for monetary policy: if the Cukierman-Meltzer hypothesis holds, policymakers could leverage this positive relationship by introducing surprise measures to temper inflation expectations during periods of heightened uncertainty.

The analysis employs a time-varying parameter stochastic volatility in mean (TVP-SVM) model based on Chan (2017). This model captures how inflation uncertainty influences inflation over time. The results are compared with those from an extended version that accounts for structural breaks—the time-varying parameter stochastic volatility model with time-varying mixture innovations (TVP-SVM-TVMI) from Hou (2020). These models address the Lucas critique (1976) by incorporating the regime changes in monetary policy, such as the adoption of inflation targeting (IT), in the uncertainty-inflation relationship dynamic.

The key findings are as follows: (i) the TVP-SVM model outperforms its extended version in 8 of the 14 countries analyzed; (ii) inflation uncertainty has been significantly higher in Latin America than in the G7, particularly during the 1980s "lost decade"; (iii) log-inflation uncertainty is more persistent in Latin America than in the G7; (iv) Friedman's view does not hold for any country in the sample; (v) conversely, the Cukierman-Meltzer hypothesis is supported across all countries, as the uncertainty-inflation relationship is positive and time-varying; (vi) the uncertainty-inflation relationship is stronger and statistically significant during periods of high inflation uncertainty; and (vii) structural breaks in the uncertainty-inflation relationship are more frequent in Latin America, likely reflecting the region's experience with hyperinflation.

The paper is structured as follows. Section 2 reviews the literature on inflation and uncertainty, highlighting evidence from various economies. Section 3 introduces the models developed by Chan (2017) and Hou (2020), explains the estimation methodology, and outlines the evaluation criteria. Section 4 compares the models, presenting statistics for the estimated parameters, the evolution of log-inflation uncertainty, and the uncertainty-inflation relationship. Section 5 discusses alternative results using the model of Chan (2017). Section 6 concludes with a summary of findings and policy implications.

2 Literature Review

Empirical studies have yet to reach consensus on the causal relationship between inflation uncertainty and inflation, with the literature divided into two main views: (i) Friedman (1977) suggests that higher inflation leads to greater future inflation uncertainty; and (ii) Cukierman and Meltzer (1986) argue that inflation uncertainty drives inflation.

The first view posits that inflation affects inflation uncertainty. According to Friedman (1977), when overall price levels rises, agents find it increasingly difficult to anticipate future inflationary trends and macroeconomic conditions. This uncertainty undermines the ability of plan and make informed decisions about consumption, investment, and wage setting.

This position was initially tested empirically using the ARCH and GARCH models introduced by Engle (1982) and Bollerslev (1986), respectively, but found limited empirical support. Studies by Ball et al. (1990) and Evans (1991) suggest that the uncertainty-inflation relationship is weak in the short run but becomes more pronounced over the long run, as uncertainty driven by permanent shocks can be further amplified by high inflation.

Brunner and Hess (1993) attribute the failure to detect a short-run relationship in earlier research to two factors: (i) Friedman's hypothesis was not directly tested, as ARCH models define conditional variance in terms of inflation innovations rather than inflation levels; and (ii) the models imposed symmetry constraints inconsistent with the hypothesis. Using a state-dependent model, Brunner and Hess (1993) confirmed that inflation significantly impacts inflation uncertainty in the US. Subsequently, Grier and Perry (1998), applying Granger causality tests, validated Friedman's hypothesis for both the US and other G7 countries.

Further support for this view has been found in advanced economies (AEs) (Kontonikas, 2004; Berument and Dincer, 2005; Daal et al., 2005) and emerging market economies (EMEs) such as Argentina, Bolivia, Brazil, Chile, Costa Rica, Mexico, Paraguay, and Venezuela (Grier and Grier, 1998; Magendzo, 1998; Carvalheiro, 1999; Fernández Valdovinos, 2000; Daal et al., 2005; Bojanic, 2013; Solera, 2003). Solera (2003) highlights asymmetric effects in a study of Costa Rica, where unexpected inflation increases have a greater impact on inflation uncertainty than unexpected decreases.

The second view posits an inverse causal relationship, where inflation uncertainty affects inflation. According to Cukierman and Meltzer (1986), there is ambiguity about the exact timing for a central bank to adopt policies aimed at reducing inflation. A credible central bank can implement unanticipated policies during periods of high inflation uncertainty to alter expectations and leverage the trade-off between inflation and unemployment, resulting in a positive uncertainty-inflation relationship. On the contrary, Holland (1995) argues a negative uncertainty-inflation relationship, suggesting that if policymakers view inflation uncertainty as costly, they have strong incentives to implement policies to control inflation.

Empirical evidence for this view is mixed regarding the sign of the relationship. Studies supporting a positive relationship in AEs include research on Canada, Germany, Japan, Italy, the UK, and the US (Crawford and Kasumovich, 1996; Grier and Perry, 1998; Daal et al., 2005; Berument et al., 2009); OECD countries (Le, 2023); and EMEs such as Korea, Egypt, Hungary, Indonesia, and Turkey (Daal et al., 2005; Thornton, 2007; Varlik et al., 2017). Conversely, research reporting a negative relationship include works on AEs such as Canada, France, Germany, the UK, and the US (Grier and Perry, 1998; Berument and Dincer, 2005; Balcilar and Ozdemir, 2013) and EMEs such as Argentina, Colombia, Israel, Mexico, Turkey, and Venezuela (Daal et al., 2005; Thornton, 2007).

Integrating volatility into the conditional mean equation has facilitated the study of the uncertainty-inflation relationship. The first univariate ARCH-in-mean model was proposed by Engle et al. (1987), with Bollerslev et al. (1988) later developing a multivariate extension. Koopman and Uspensky (2002) introduced the stochastic volatility-in-mean (SVM) model, which Chan (2017) extended to include time-varying parameters (TVP-SVM), reflecting the potential for the uncertainty-inflation-relationship to shift with economic conditions. Hou (2020) further extended Chan's model by incorporating structural breaks through time-varying mixture innovations, resulting in the TVP-SVM-TVMI model. For additional extensions of the univariate SVM model, see Abanto-Valle et al. (2011, 2012, 2021, 2023), Leão et al. (2017), Dimitrakopoulos and Kolossiatis (2020), and Huber and Pfarrhofer (2021).

Chan (2017) find a positive and statistically significant uncertainty-inflation relationship during periods of high inflation in Germany, the UK, and the US. Ferreira and Palma (2017) also observe a positive relationship in Latin America, with its magnitude declining in the early 2000s in Colombia, Mexico, and Uruguay, likely due to IT adoption. However, the short time horizon in their study limits the analysis of hyperinflation episodes in the 1980s. Hou (2020) identified a negative and statistically significant uncertainty-inflation relationship in the US following the Global Financial Crisis (GFC), attributed to structural breaks. In Canada and New Zealand, the positive relationship weakened starting in the 1990s, coinciding with IT adoption.

This article examines the time-varying relationship between inflation uncertainty and inflation in seven Latin American countries, comparing them with the G7 and analyzing the dynamics of this relationship during recessions, hyperinflation episodes, and pre- and post-IT adoption periods.

3 Methodology

Section 3.1 introduces the time-varying parameter stochastic volatility-in-mean (TVP-SVM) model by Chan (2017). Section 3.2 presents Hou's (2020) TVP-SVM model with time-varying mixture innovations (TVP-SVM-TVMI). Section 3.3 describes the Bayesian estimation algorithm for both models. Finally, Section 3.4 outlines the marginal log-likelihood (LogML) criterion developed by Hou (2020).

3.1 TVP-SVM Model

The TVP-SVM model by Chan (2017) is expressed as follows:

$$\begin{aligned} y_t &= \tau_t + \alpha_t e^{h_t} + \epsilon_t^y, & \epsilon_t^y &\sim \mathcal{N}(0, e^{h_t}), \\ h_t &= \mu + \phi(h_{t-1} - \mu) + \beta y_{t-1} + \epsilon_t^h, & \epsilon_t^h &\sim \mathcal{N}(0, \sigma_h^2), \\ \boldsymbol{\gamma}_t &= \boldsymbol{\gamma}_{t-1} + \epsilon_t^\gamma, & \epsilon_t^\gamma &\sim \mathcal{N}(0, \boldsymbol{\Sigma}), \end{aligned} \tag{1}$$

where τ_t is the time-varying trend in inflation (y_t), based on the unobserved components (UC) model by Stock and Watson (2007). The innovations ϵ_t^y and ϵ_t^h are mutually and serially uncorrelated. Inflation depends on log-inflation uncertainty (e^{h_t}) through the time-varying coefficient α_t. The vector $\boldsymbol{\gamma}_t = (\alpha_t, \tau_t)'$ follows a random walk process, allowing the model to capture both transitory and permanent changes. The variance-covariance matrix of $\boldsymbol{\gamma}_t$, denoted by $\boldsymbol{\Sigma}$, is a 2×2 matrix where σ_α^2 and σ_τ^2 are the variances of α_t and τ_t, respectively, and $\sigma_{\alpha,\tau}$ is their covariance.[1]

The log-volatility of the inflation innovation, h_t, follows a stationary AR(1) process with $|\phi| < 1$ and initial condition $h_1 \sim \mathcal{N}(\mu, \sigma_h^2/(1-\phi^2))$. This process includes the parameter β, which captures the impact of past inflation (y_{t-1}) on current log-volatility. Notably, h_t also represents log-inflation uncertainty. Consequently, the Friedman (1977) and Cukierman-Meltzer (1986) hypotheses can be analyzed through β and α_t, respectively.

Additionally, the following independent prior distributions are assumed for μ, ϕ, β, σ_h^2, and $\mathbf{\Sigma}$: $\mu \sim \mathcal{N}(\mu_0, V_\mu)$, $\phi \sim \mathcal{N}(\phi_0, V_\phi)\mathbb{1}(|\phi| < 1)$, $\beta \sim \mathcal{N}(\beta_0, V_\beta)$, $\sigma_h^2 \sim \mathcal{IG}(\nu_{\sigma^2}, S_{\sigma^2})$, and $\mathbf{\Sigma} \sim \mathcal{IW}(\nu_{\mathbf{\Sigma}}, S_{\mathbf{\Sigma}})$, where $\mathcal{N}$, $\mathcal{IG}$, and $\mathcal{IW}$ represent the normal, inverse-gamma, and inverse-Wishart distributions, respectively; and $\mathbb{1}(A)$ is an indicator function equal to 1 if condition A is true and 0 otherwise. This enforces the stationarity restriction $|\phi| < 1$ on h_t. For more details, see Sections 2.1 and 3.1 of Chan (2017).

3.2 TVP-SVM-TVMI Model

The TVP-SVM-TVMI model by Hou (2020) is expressed as follows:

$$\begin{aligned} y_t &= \tau_t + \alpha_t e^{h_t} + \epsilon_t^y, & \epsilon_t^y &\sim \mathcal{N}(0, e^{h_t}), \\ h_t &= h_{t-1} + \epsilon_t^h, & \epsilon_t^h &\sim \mathcal{N}(0, \sigma_h^2), \\ \boldsymbol{\gamma}_t &= \boldsymbol{\gamma}_{t-1} + \epsilon_t^\gamma, & \epsilon_t^\gamma &\sim \mathcal{N}(0, \mathbf{\Sigma}). \end{aligned} \tag{2}$$

The innovations ϵ_t^y and ϵ_t^h are assumed to be mutually and serially uncorrelated. The vector $\boldsymbol{\gamma}_t = (\alpha_t, \tau_t)'$ follows a random walk process, with a 2×2 diagonal variance-covariance matrix ($\mathbf{\Sigma}$) that implies independence between α_t and τ_t ($\sigma_{\alpha,\tau} = 0$). Thus, the transition equations for the components of $\boldsymbol{\gamma}_t$ are defined as follows:

$$\begin{aligned} \alpha_t &= \alpha_{t-1} + \epsilon_t^\alpha, & \epsilon_t^\alpha &\sim \mathcal{N}(0, \sigma_{K_t}^2), \\ \tau_t &= \tau_{t-1} + \epsilon_t^\tau, & \epsilon_t^\tau &\sim \mathcal{N}(0, \sigma_\tau^2), \end{aligned}$$

where $K_t \in \{0, 1\}$ denotes the states of the variance for α_t's innovation. The distribution of $\sigma_{K_t}^2$ is defined as $(\sigma_0^2, \sigma_1^2) \sim (\mathcal{IG}(\nu_0, S_0) \times \mathcal{IG}(\nu_1, S_1))\mathbb{1}(\sigma_0^2 < \sigma_1^2)$, forming the joint distribution of (σ_0^2, σ_1^2) as the product of two $\mathcal{IG}$ distributions but truncated as to satisfy the restriction $\sigma_0^2 < \sigma_1^2$. When $K_t = 1$, the variance of the innovation ϵ_t^α experience a level shift and changes to σ_1^2 with a time-varying mixture probability of $\Pr(K_t = 1|\pi_t) = \pi_t$, where π_t is Beta distributed as $\mathcal{B}(p_{1,t}, p_{2,t})$.[2]

The innovation mixture approach is used to address both gradual and abrupt changes in the dynamics of α_t through a variance level shift in its innovation (McCulloach and Tsay, 1993; Gerlach et al., 2000). Consequently, it is crucial that $\sigma_0^2 < \sigma_1^2$, so the variance of the innovation ϵ_t^α is higher when a structural break occurs in order to capture the abrupt change in α_t. For simplicity, we hereafter adopt the qualitative convention that a structural break occurs whenever π_t exceeds 50%. Further information on the model can be found in Section 2 of Hou (2020).

[1] The original symbols for the variances of the innovations ϵ_t^h and ϵ_t^γ in the TVP-SVM model of Chan (2017) have been replaced to ensure consistency with the notation used in Hou (2020).

[2] Hou (2020) compares the TVP-SVM-TVMI model with a TVP-SVM model featuring time-invariant mixture innovations ($\pi_t = \pi$), known as the TVP-SVM-MI model. However, the latter is discarded, as the TVP-SVM-TVMI model more effectively identifies breaks in the sample. A detailed comparison of both models is available in Section 3 of Hou (2020). For earlier research on models with a constant probability $\pi_t = \pi$; see Koop et al. (2009), and Liu and Morley (2014).

Note that the h_t process in the TVP-SVM model does not behave as a random walk as in the TVP-SVM-TVMI model. To ensure comparability between the models, we impose the constraints $\mu = 0$, $\phi = 1$, and $\beta = 0$ in the TVP-SVM model, similar to $\sigma_{\alpha,\tau} = 0$. These constraints apply to the remainder of Section 3 as well as to Section 4. Section 5 presents alternative results in which these constraints are lifted.

3.3 Bayesian Estimation

To simulate the posterior distributions of the parameters, Hou (2020) utilizes the Markov Chain Monte Carlo (MCMC) method proposed by Chan (2017), which offers two significant advantages.

First, it reduces the high dimensionality of the model by estimating each state individually, thereby simplifying the estimation process. It is important to note that high dimensionality often renders the evaluation of likelihood impracticable. Second, it enhances efficiency in simulating h_t using an algorithm based on band and sparse matrices, as the Hessian matrix of the conditional log-density of h_t is a band matrix (Chan and Jeliazkov, 2009; Chan and Strachan, 2014).

Let $\boldsymbol{y} = (y_1, \ldots, y_T)'$, $\mathbf{h} = (h_1, \ldots, h_T)'$, $\boldsymbol{\tau} = (\tau_1, \ldots, \tau_T)'$, $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_T)'$, $\boldsymbol{\pi} = (\pi_1, \ldots, \pi_T)'$, and $\mathbf{K} = (K_1, \ldots, K_T)'$. The posterior parameters of the TVP-SVM-TVMI model are then obtained through the following sequential sampling: (i) $p(\mathbf{h}|\boldsymbol{\tau}, \boldsymbol{\alpha}, \sigma_h^2, \boldsymbol{y})$; (ii) $p(\boldsymbol{\tau}, \boldsymbol{\alpha}|\mathbf{h}, \sigma_\tau^2, \mathbf{K}, \sigma_0^2, \sigma_1^2, \boldsymbol{y})$; (iii) $p(\sigma_\tau^2|\boldsymbol{\tau})$; (iv) $p(\sigma_h^2|\mathbf{h})$; (v) $p(\mathbf{K}|\boldsymbol{\alpha}, \boldsymbol{\pi}) = \prod_{t=1}^T p(K_t|\boldsymbol{\alpha}, \pi_t)$; (vi) $p(\boldsymbol{\pi}|\mathbf{K}) = \prod_{t=1}^T p(\pi_t|K_t)$; (vii) $p(\sigma_0^2, \sigma_1^2|\boldsymbol{\alpha}, \mathbf{K})$; and (viii) steps (i)-(vii) are iterate N times. Detailed information on the estimation process can be found in Section 4 and Appendix A of Hou (2020). To obtain the posterior parameters of the TVP-SVM model, steps (v) and (vi) are omitted, and in step (vii), the parameter σ_α^2 is sampled instead of (σ_0^2, σ_1^2).

3.4 Model Comparison

To compare models, we use the marginal log-likelihood (LogML) criterion from Hou (2020), which is based on a predictive likelihood approach. For further information about the discussion on marginal and predictive likelihood, see Kass and Raftery (1995), and Geweke and Amisano (2011).

For a given model M_i, the marginal likelihood is defined as:

$$p(\boldsymbol{y}|M_i) = \int p(\boldsymbol{y}|\boldsymbol{\theta}_i, M_i)p(\boldsymbol{\theta}_i|M_i)d\boldsymbol{\theta}_i,$$

where $\boldsymbol{\theta}_i$ is the parameter vector of model M_i. Thus, the marginal likelihood is represented as the product of one-step-ahead predictive likelihoods evaluated at each data point:

$$p(\boldsymbol{y}|M_i) = p(y_1|M_i)\prod_{t=2}^{T} p(y_t|y_1, ..., y_{t-1}, M_i).$$

Additionally, this criterion allows for the comparison of different models using the Bayes Factor (BF) to determine which model is more likely to have generated the data. The BF is defined as $\text{BF}_{i,j} = \frac{p(\boldsymbol{y}|M_i)}{p(\boldsymbol{y}|M_j)}$, then model M_i is favored $\text{BF}_{i,j}$ times over model M_j.

4 Empirical Results

4.1 Data

The dataset comprises annualized quarterly inflation rates for seven Latin American countries (Brazil, Chile, Colombia, Ecuador, Mexico, Peru, and Uruguay)[3] and the G7 (Canada, France, Germany, Italy, Japan, the UK, and the US). Inflation rates are calculated using the Consumer Price Index (CPI), expressed as $y_t = 400 \times (\log CPI_t - \log CPI_{t-1})$. CPI data for the G7 and Latin American countries were sourced from the International Financial Statistics (IFS), except for the US, which was obtained from the Federal Reserve Economic Data (FRED).

Figure 1 shows inflation rates for each country, highlighting that Latin American economies experienced significantly higher inflation compared to the G7, particularly during the 1980s and early 1990s. Sample sizes vary among countries due to the availability of data at the beginning of the period. For Canada and the US, the data span from Q1 1948 to Q4 2023 ($T = 304$); for Colombia, France, Germany, Italy, Japan, and the UK, from Q2 1955 to Q4 2023 ($T = 275$); for Ecuador, Mexico, Peru, and Uruguay, from Q2 1957 to Q4 2023 ($T = 267$); for Chile from Q2 1970 to Q4 2023 ($T = 215$); and for Brazil from Q1 1980 to Q4 2023 ($T = 176$).

The broad timeline is intended to encompass various significant events that have likely impacted inflation: (i) the post-World War II economic adjustments during the late 1940s to the 1950s; (ii) the industrialization of Latin America during the 1950s and 1960s; (iii) the oil crisis of the 1970s, also referred to as the Great Inflation; (iv) periods of high inflation or hyperinflation in Latin American countries during the 1980s and 1990s; (v) IT adoption from 1991 to 2013; (vi) trade liberalization and the commodity price boom in the 2000s; (vii) the GFC from 2008 to 2010; and (viii) the surge in freight, hydrocarbon, and fertilizer prices from 2020 to 2022 due to pandemic-related restrictions and the Russia-Ukraine conflict, with price adjustments toward the end of 2023.

4.2 Priors

The priors employed in estimating the TVP-SVM and TVP-SVM-TVMI models are in line with those used by Chan (2017) and Hou (2020), respectively. For the TVP-SVM model, $\sigma_h^2 \sim \mathcal{IG}(\nu_{\sigma^2}, S_{\sigma^2})$ and $\mathbf{\Sigma} \sim \mathcal{IW}(\nu_{\mathbf{\Sigma}}, S_{\mathbf{\Sigma}})$, with relatively small and non-informative degrees of freedom set at $\nu_{\sigma^2} = \nu_{\mathbf{\Sigma}} = 10$, and scale parameters $S_{\sigma^2} = 0.36$ and $S_{\mathbf{\Sigma}} = diag(0.5625, 0.09)$. These parameters imply $\mathbb{E}(\sigma_h^2) = 0.2^2$, $\mathbb{E}(\sigma_\alpha^2) = 0.1^2$, $\mathbb{E}(\sigma_\tau^2) = 0.25^2$, and $\mathbb{E}(\sigma_{\alpha,\tau}) = 0$. Consistent with Hou (2020), we adapted the scale parameter $S_{\mathbf{\Sigma}}$ from Chan (2017) to ensure that the priors for σ_τ^2 and σ_α^2 in the TVP-SVM model match the priors for σ_τ^2 and σ_0^2 in the TVP-SVM-TVMI model. Additionally, the TVP-SVM-TVMI model includes further priors: $\nu_0 = \nu_1 = 10$, $S_0 = 0.09$, $S_1 = 90$, and $p_{1,t} = 1$ and $p_{2,t} = 99$ that imply that $\mathbb{E}(\pi_t) = 0.01$. The results are derived from 50,000 posterior draws after a burn-in period of 5,000.

4.3 Model Selection

Table 1 presents the LogML criterion for the TVP-SVM and TVP-SVM-TVMI models, which are compared with an unobserved components (UC) model—a special case of the TVP-SVM model where $\alpha_t = 0$; i.e., there is no uncertainty-inflation relationship.

[3] Argentina was excluded due to missing values in the inflation series over the sample period.

The results indicate that the uncertainty-inflation relationship has evolved over time, where (i) the TVP-SVM model is preferred for Chile, Colombia, Ecuador, Peru, Germany, Italy, Japan, and the UK; i.e., 8 out of 14 countries; and (ii) the TVP-SVM-TVMI model is favored for Brazil, Mexico, Uruguay, Canada, France, and the US; i.e., 6 out of 14 countries. For the latter group, the LogML criterion provides evidence supporting the presence of structural breaks in the uncertainty-inflation dynamics (detailed in Section 4.5).

Using the BF, we find that the TVP-SVM and TVP-SVM-TVMI models are practically equivalent given the low magnitudes of the BF. For instance, where the TVP-SVM model is preferred, the BF values are as follows: Chile 1.3×10^0, Colombia 1.1×10^1, Ecuador 7.2×10^0, Peru 1.5×10^0, Germany 9.2×10^0, Italy 1.8×10^0, Japan 1.4×10^1, and the UK 9.3×10^0. Where the TVP-SVM-TVMI model is preferred, the BF values are: Brazil 3.2×10^3, Mexico 2.2×10^0, Uruguay 6.7×10^0, Canada 1.2×10^0, France 2.0×10^0, and the US 3.4×10^0. Therefore, the comparison is limited to the TVP-SVM and TVP-SVM-TVMI models, as they are practically equivalent, allowing for an examination of changes in the dynamics of α_t without and with structural breaks, respectively.

Finally, when comparing both models against the UC model, the BF values are much larger; e.g., the BF for the TVP-SVM model relative to the UC model for Peru is 3.4×10^{37}, and for the TVP-SVM-TVMI model relative to the UC model for the US is 2.2×10^9. The UC model is the least preferred among the three models, except for Germany, where it ranks second. This aligns with the findings in Section 4.5.2, where α_t is not statistically significant in Germany for most of the time horizon.

4.4 Estimated Parameters

Tables 2 and 3 present the statistics of the posterior parameter distributions for the TVP-SVM and TVP-SVM-TVMI models, respectively. The mean of σ_h^2 is higher in Latin American countries compared to the G7, reflecting the higher volatility associated with hyperinflation episodes and the increased magnitude of h shocks in the former group. Moreover, the mean of σ_1^2 substantially exceeds that of σ_0^2 across all countries in the TVP-SVM-TVMI model, consistent with its role in modeling drastic changes in the dynamics of α_t.

4.5 Dynamics of h_t and α_t

Figure 2 shows the log-inflation uncertainties (h_t) estimated for the TVP-SVM model (first column) and the TVP-SVM-TVMI model (fourth column). The dynamics of h_t are similar across both models, with slight differences due to the structural breaks in α_t within the TVP-SVM-TVMI model. We discuss the potential underlying factors of inflation uncertainty increases for each country, regardless of the model used.

Latin American economies have generally faced higher inflation uncertainty compared to the G7, particularly during the 1980s "lost decade," characterized by fiscal imbalances, excessive money creation, rising external debt, shortages of essential goods, and currency depreciation. Although inflation remained high in Brazil, Colombia, Ecuador, Peru, and Uruguay during the early 1990s, inflation uncertainty significantly declined at the onset of the new millennium, coinciding with IT adoption in many Latin American countries (Broto, 2011).

Three common scenarios of high inflation uncertainty emerge among Latin American and G7 countries. The first scenario, known as the Great Inflation of the 1970s, was marked by worldwide high inflation driven by two crude oil price shocks: (i) the first in 1973, linked to the OPEC's decision to cease oil exports to Canada, Japan, the UK, the US, and other nations supporting Israel during the Yom Kippur War; and (ii) the second in 1979, caused by disruptions in oil production and exports due to the Iranian Revolution and heightened geopolitical tensions in the Middle East. The second scenario was the global recession during the GFC in 2008-2009. The third scenario, unfolding in 2022, was driven by adverse impacts on hydrocarbon and fertilizer prices due to the Russia-Ukraine conflict, alongside the lingering effects of pandemic-related restrictions on freight costs.

Figure 2 illustrates the time-varying inflation-uncertainty relationship α_t in the TVP-SVM models (second column) and the dynamic probability test of $\alpha_t \neq 0$ for the same model (third column), following Koop et al. (2010). This test is defined by $\Pr(\alpha_t \neq 0|\boldsymbol{y}) = 1/(1 + \mathrm{PO}_t)$, where PO_t is the posterior odds ratio favoring the hypothesis $\alpha_t = 0$, calculated using the Savage-Dickey density ratio: $\mathrm{PO}_t = \frac{p(\alpha_t=0|\boldsymbol{y})}{p(\alpha_t=0)}$. A probability exceeding 50% indicates statistical significance for the α_t component in the TVP-SVM model. The dynamics of α_t in the TVP-SVM-TVMI model, alongside its associated probabilities of structural breaks (fifth column), is also detailed. Table 4 complements this analysis by listing quarters with the highest likelihood of identifying structural breaks in α_t.

Across both models, α_t remains positive and statistically significant during periods of elevated inflation uncertainty. This supports the Cukierman-Meltzer hypothesis (1986), which posits that monetary authorities can deploy surprise policies under high uncertainty to dampen inflation expectations, thereby capitalizing on this positive correlation. The TVP-SVM-TVMI model reveals ten structural breaks in α_t among Latin American countries and two in G7 economies, highlighting the sharper volatility experienced by the former group during hyperinflation episodes. In contrast, significant changes in the G7 do not generally meet the threshold for structural breaks, as their probabilities fall below 50%.

4.5.1 Latin American Countries

Panel (A) of Figure 2 presents the dynamics of h_t, α_t, and the $\Pr(\alpha_t \neq 0|\boldsymbol{y})$ test for the TVP-SVM model and h_t, α_t, and $\Pr(K_t = 1|\pi_t) = \pi_t$ for the TVP-SVM-TVMI model across Latin American countries.

In Brazil, inflation uncertainty climbed steadily throughout the 1980s, reaching a peak in Q2 1990 and surging again by mid-1994 due to rampant monetary issuance. The first of three failed attempts at price freezes occurred in 1986 under the "Plan Cruzado," which introduced the "cruzado" to replace the "cruzeiro" (Cardoso, 1991; Carvalheiro, 1999). In response to persistent inflation, Brazil reverted to the "cruzeiro" and later adopted the "cruzeiro real" in 1993. The continued economic challenges prompted the introduction of the "real" in 1994 as the new official currency. After the switch, uncertainty significantly declined from late 1994 through mid-2003. However, Lula da Silva's election that year raised concerns about his economic policy stance amid an adverse external environment, leading to the sharpest currency depreciation in three decades (Ferreira et al., 2018).

The median α_t consistently exhibits positive values across the timeline for the TVP-SVM model. The $\Pr(\alpha_t \neq 0|\boldsymbol{y})$ test indicates that α_t is statistically significant, except during specific periods: (i) 1996-1999, following the transition to the "real"; (ii) 2005-2007, a period characterized by relative economic stability; (iii) 2017-2020, marked by political turmoil and corruption scandals, shortly before the COVID-19 pandemic; and (iv) from Q3 2022 to the end of the sample, during a phase of moderated inflation and economic uncertainty. The TVP-SVM-TVMI model documents a significant decline in α_t dynamics in Q2 1986, driven by a structural break associated with the "Plan Cruzado," where median α_t decreased from 3.57 to 1.47. As the plan failed to control inflation, in Q1 1987 the median α_t adjusted upwards (from 1.53 to 3.47), indicating another structural break. Following the currency transition, inflation uncertainty significantly decreased, highlighted by a structural break in Q4 1994, where the median α_t sharply decreased from 3.53 to 0.67.

Chile's inflation uncertainty peaked in the 1970s, a decade before other Latin American countries. In early 1974, h_t reached its highest estimated level, driven by political instability following the 1973 coup d'état and the impact of escalating crude oil prices due to Chile's heavy dependence on imports of this commodity (Martner, 1975). Subsequently, inflation uncertainty began to decline. The TVP-SVM model underscores a positive, statistically significant inflation-uncertainty relationship, lasting until late 1996, which supports the Cukierman-Meltzer hypothesis from the beginning of the sample until the mid-1990s. In Q1 2020, this relationship became significant again, likely influenced by currency depreciation amid political and economic uncertainties, the entrance of President Gabriel Boric, and increased international prices for food and hydrocarbons due to pandemic-related restrictions. However, the TVP-SVM-TVMI model detected no structural breaks in α_t.

From the 1950s to the 1980s, Colombia experienced significantly higher levels of h_t than in the early 2000s. In mid-1962, the central bank's extensive dollar purchases due to low terms of trade and scant international reserves drove inflation higher, peaking in Q3 1977. After IT adoption in 1999, inflation uncertainty significantly decreased. Yet, in early 2016, uncertainty spiked again due to rising food prices from a lengthy truckers' strike. The inflation-uncertainty link remained positively and consistently significant from 1972 until the turn of the century, corroborated by IT adoption in 1999, marking the end of the relevance of the Cukierman-Meltzer hypothesis. The TVP-SVM-TVMI model confirms these findings, with no structural breaks identified in α_t, despite marked reductions in inflation uncertainty.

In 1983, various factors contributed to Ecuador's inflationary pressures, including agricultural losses from the Coastal El Niño, market speculation, and shortages of basic goods, compounded by currency depreciation (BCE, 1984). By early 1989, disorderly monetary policies and price deregulation pushed uncertainty higher (BCE, 1990). In Q2 2000, the highest h_t levels were recorded following the adoption of the dollar as the official currency in the early 2000s amid a severe crisis marked by recession, high inflation, and unemployment, with government interventions in bank deposits and defaults on foreign debt (Jácome, 2004; Marí del Cristo and Gómez-Puig, 2016). Despite lacking an IT regime, inflation uncertainty eventually moderated. The TVP-SVM model shows that α_t was positive and statistically significant from 1973 to 2002, by which point several countries had already implemented IT frameworks. Additionally, α_t briefly regained significance during the GFC, with the TVP-SVM-TVMI model identifying no structural breaks.

Mexico's h_t rose in 1982, likely linked to the finance minister's request for IMF economic aid and extended debt negotiations, highlighting the country's financial challenges. By early 1988, inflation uncertainty peaked, tied to adjustments in wages and basic goods prices and the residual impact of the December 1987 price increases (Banxico, 1989). The Tequila Crisis in Q3 1995, triggered by currency depreciation, balance sheet mismatches, and capital flight, further escalated uncertainty, challenging the sustainability of the fixed exchange rate regime (Mishkin, 1999b). However, uncertainty diminished by the early 2000s, partly due to IT adoption in 2001 (Carrasco and Ferreiro, 2013). The TVP-SVM model confirms a positive, significant inflation-uncertainty relationship from 1970 to 2001, enhanced by the Bank of Mexico's greater autonomy and the IT framework (Carrasco and Ferreiro, 2013; Ferreira and Palma, 2017). The TVP-SVM-TVMI model identifies two structural breaks. The first, in Q4 1976, is associated with an increase in h_t due to currency depreciation, which tripled the magnitude of α_t from 1.02 to 2.81. The second, in Q2 1988, led to a downward correction in α_t from 2.87 to 0.94. This quarter follows the peak in inflation uncertainty, suggesting that it captures its sharp moderation. While no structural break is explicitly identified in connection with the Tequila Crisis, Q1 1995 has a 49.6% probability, indicating the potential presence of a third break, given the substantial increase in the median, from 0.60 to 1.58.

In Peru, h_t levels prior to the 2000s were significantly higher than those observed after IT adoption in 2002 (Armas and Grippa, 2006). The peak occurred in Q3 1990, during the 1988–1990 hyperinflation episode. One key factor behind the extreme inflation levels was the lack of BCRP autonomy, as the government resorted to money creation to finance fiscal deficits amid external financing constraints (Castillo et al., 2012). The 1993 Constitution formally established BCRP autonomy, marking the beginning of a sustained decline in inflation uncertainty throughout the 1990s.

Using the TVP-SVM model, α_t remains positive and statistically significant from 1973 to mid-1998, a period of high international and domestic inflation. From 1998 onward α_t is no longer statistically significant, coinciding with moderated inflation, implying that the Cukierman-Meltzer hypothesis no longer holds. However, the uncertainty-inflation relationship becomes relevant again in Q2 2020, reflecting the surge in international prices due to COVID-19-related supply-chain constraints. The TVP-SVM-TVMI model identifies a structural break in α_t in Q4 1990, when its median falls from 2.95 to 1.31. This break captures the sharp disinflation following Q3 1990, the quarter with the highest inflation uncertainty. Notably, in Q3 1990, the probability of a structural break in α_t is 49.5%, given its substantial increase in median, from 1.68 to 2.95.

In Uruguay, h_t follows an upward trend in the 1950s and 1960s. In 1968, President Jorge Pacheco Areco imposed wage and price controls to curb inflation, but these led to market distortions and a rebound effect by mid-1971. In early 1983, volatility spiked due to rapid currency depreciation following the abandonment of the fixed exchange rate policy (the "tablita"), triggered by financial imbalances (Hanson and De Melo, 1985). Finally, in 2002, a sharp increase in h_t coincides with Uruguay's banking crisis, which stemmed from its financial interconnectedness with Argentina. The Argentine crisis, marked by sovereign default and the collapse of the peso-dollar peg, amplified Uruguay's financial distress (Ferreira and Palma, 2017). These effects were exacerbated by structural weaknesses in Uruguay's economy and banking sector (De la Plaza and Sirtaine, 2005).

Using the TVP-SVM model, α_t remains positive and statistically significant until late 1998, with exceptions during lower-inflation periods such as 1960–1963, 1968–1971, and 1981–1982. The uncertainty-inflation relationship becomes relevant again during the 2002–2003 banking crisis. The TVP-SVM-TVMI model identifies four structural breaks in α_t, grouped into two pairs, each marking a sharp rise in inflation, suggesting that these breaks may also capture outlier effects. The first pair, in Q2 and Q3 1983, coincides with the currency depreciation following the collapse of the "tablita." The first break captures the inflation surge through a sharp increase in α_t, from 0.70 to 4.30, while the second reflects the subsequent correction in α_t, from 4.30 to 1.74. The second pair, in Q3 and Q4 2002, aligns with the banking crisis, showing a similar pattern: a sharp increase in α_t, from 0.97 to 3.05, followed by a correction to 1.47.

4.5.2 The G7

Panel (B) of Figure 2 presents the dynamics of h_t, α_t, and the $\Pr(\alpha_t \neq 0|\boldsymbol{y})$ test from the TVP-SVM model, as well as h_t, α_t, and $\Pr(K_t = 1|\pi_t) = \pi_t$ from the TVP-SVM-TVMI model for the G7.

In Canada, inflation uncertainty was elevated in the early 1950s due to the lingering effects of WWII. Following a moderation in h_t, it rose again in 1981, reflecting weaker growth expectations, and in 1990–1991, amid recession. In both cases, Gordon Thiessen—who later served as Governor of the Bank of Canada—stated that Canadians had developed an "inflationary psychology," meaning they increased spending on certain goods based on expectations of imminent price hikes. From 1991 onward h_t declined with IT adoption, except for a temporary rise in mid-2002, linked to the global economic slowdown.

The TVP-SVM model shows that α_t is positive and statistically significant from 1971 to mid-1991, according to the $\Pr(\alpha_t \neq 0|\boldsymbol{y})$ test. The TVP-SVM-TVMI model identifies a structural break in Q2 1991, consistent with Hou (2020), as the median of α_t drops sharply from 2.00 to 0.30. Thus, the Cukierman-Meltzer hypothesis ceases to be relevant following IT adoption. Similarly, Caporale et al. (2022) detect a structural break in inflation in January 1992, also linked to this shift.

In France, several factors drove h_t higher in 1957–1958: (i) currency depreciation aimed at boosting exports and attracting capital inflows; (ii) higher turnover taxes; and (iii) rising prices for state-provided services. By the early 2000s, higher oil prices and consumer spending constraints further increased inflation uncertainty.

The TVP-SVM model shows a positive and statistically significant uncertainty-inflation relationship from late 1966 to mid-1988. In 2022–2023, α_t becomes statistically significant again briefly due to rising global prices. The TVP-SVM-TVMI model detects a structural break in Q3 1985, coinciding with the first Intergovernmental Conference on the Single European Act (IGC on the SEA), which led to SEA adoption in 1986, with the median falling from 2.45 to 0.43. This result aligns with the break in α_t found by Hou (2020) and the inflation break reported by Caporale et al. (2022).

In Germany, h_t peaked in 1957–1959, reflecting rapid postwar economic expansion. According to Stolper and Roskamp (1979), excess demand, rising wages, and balance of payments surpluses drove domestic price increases. While higher interest rates were used to contain demand, they had limited impact, as higher relative rates attracted capital inflows, particularly from the US. In the 1970s, Germany avoided double-digit inflation despite unfavorable global conditions. The 1990 reunification posed a major economic challenge, triggering higher inflation and uncertainty. The adoption of West Germany's currency, the Deutsche Mark, as the national unit led to monetary expansion, fiscal deficits, and a surge in aggregate spending (Beyer et al., 2008).

The TVP-SVM model finds that α_t is positive and statistically significant only in brief periods, consistent with Chan (2017). The TVP-SVM-TVMI model does not detect structural breaks in the uncertainty-inflation relationship. However, Hou (2020) identifies a break in Q4 2008, linked to the GFC.

Italy saw a rise in inflation uncertainty in 1976 due to currency depreciation and rising nominal wages, alongside an unfavorable global environment. Following a significant moderation, h_t increased again in 1995, reflecting concerns over currency depreciation and fiscal adjustments (Gaiotti et al., 1998).

The TVP-SVM model finds that α_t is positive and statistically significant for most of the sample period, indicating that the Cukierman-Meltzer hypothesis largely holds, as monetary authorities were able to implement surprise policies to influence inflation expectations. The TVP-SVM-TVMI model does not detect structural breaks. In comparison, Appendix C of Hou (2020) reports breaks in Q4 2008 and Q3 1996, periods in which our model results report probabilities of 15.8% and 26.3%, respectively.

In Japan, h_t rose slightly in late 1961, likely reflecting the rapid postwar expansion, known as the Japanese Miracle. In late 1990, Japan experienced one of its most severe financial bubbles, marked by the abrupt collapse of the Nikkei index following an era of booming asset prices, particularly in real estate—during this boom, Japanese firms benefited from a stronger yen, which bolstered profitability against the dollar. Inflation uncertainty increased again in mid-1997, following the Asian Financial Crisis, which raised concerns of global spillovers (Mishkin, 1999a). In early 2014, another increase in inflation uncertainty coincided with government efforts to combat deflation through monetary expansion, a sales tax hike, and other policies, though these measures also weakened growth.

The TVP-SVM model shows a positive and statistically significant uncertainty-inflation relationship from the early 1960s to the early 1980s. From then on, α_t is no longer statistically significant, meaning that the Cukierman-Meltzer hypothesis is not relevant beyond the 1980s. The TVP-SVM-TVMI model does not detect structural breaks in α_t.

In the UK, inflation uncertainty rose sharply in late 1979, coinciding with the second oil shock during the Great Inflation. This period saw widespread protests and strikes over real wage losses caused by inflation control policies, including public sector wage caps (Hay, 2010). Additionally, the UK experienced its coldest winter in 16 years—known as the Winter of Discontent—which depressed retail spending. Another surge in uncertainty occurred in the mid-1980s and early 1990s, driven by several domestic factors, including: (i) the Lawson Boom, an economic expansion fueled by financial deregulation, tax cuts, and looser monetary policy; and (ii) the 1991 VAT hike. However, h_t declined sharply following IT adoption in 1992.

The TVP-SVM model estimates a positive and statistically significant uncertainty-inflation relationship throughout the 1970s, linked to the Great Inflation and the Winter of Discontent, and again in the late 1980s and early 1990s, due to the domestic factors mentioned above. Outside these periods, the Cukierman-Meltzer hypothesis does not hold. The TVP-SVM-TVMI model does not detect structural breaks in α_t, consistent with Hou (2020).

In the US, h_t was high in the early 1950s, reflecting the impact of WWII. From the mid-to-late 1960s, uncertainty trended upward due to a rapid economic expansion, with aggregate demand significantly exceeding potential GDP. The Great Moderation began in the mid-1980s and was well underway by 1990, characterized by a forward-looking monetary policy, with interest rates as the primary tool of the Federal Reserve under Paul Volcker and Alan Greenspan (Clarida et al., 2000; Galí and Gambetti, 2009). Inflation uncertainty surged during the GFC but moderated a few quarters later.

According to the TVP-SVM model, the uncertainty-inflation relationship is positive and statistically significant from 1950 to early 1982. From that point until the end of the sample, α_t is no longer statistically significant, indicating that the Cukierman-Meltzer hypothesis no longer holds with the onset of the Great Moderation. These findings are consistent with those of Chan (2017). Unlike Hou (2020), this study does not identify any structural breaks in α_t using the TVP-SVM-TVMI model. While Hou (2020) detects breaks in Q3 1948 and Q3 2008, this study assigns probabilities of 40.1% and 44.4% to Q4 1948 and Q4 2008, respectively. Additionally, the model estimates probabilities of 42.2% in Q4 1981 and 38.3% in Q3 2020, associated with a recession and the post-COVID-19 rebound, respectively.

5 Alternative Results

This section revisits the estimation of the TVP-SVM model from Chan (2017) without the constraints $\mu = 0$, $\phi = 1$, $\beta = 0$, and $\sigma_{\alpha,\tau} = 0$ imposed in Section 3.2. Relaxing these restrictions provides additional insights into the posterior parameter statistics. The priors used in this estimation follow Chan (2017): $\mu_0 = 0$, $\mathbb{V}(\mu_0) = 10$, $\phi_0 = 0.97$, $\mathbb{V}(\phi_0) = 0.1^2$, $\beta_0 = 0$, and $\mathbb{V}(\beta_0) = 10$. Additionally, for $\sigma^2 \sim \mathcal{IG}(\nu_{\sigma^2}, S_{\sigma^2})$ and $\mathbf{\Omega} \sim \mathcal{IW}(\nu_{\mathbf{\Omega}}, S_{\mathbf{\Omega}})$, uninformative priors with low degrees of freedom are assumed: $\nu_{\sigma^2} = \nu_{\mathbf{\Omega}} = 10$, with scale parameters $S_{\sigma^2} = 0.36$ and $S_{\mathbf{\Omega}} = diag(0.13, 0.8125)$. Further details on the estimation process can be found in Section 2.2 and Appendix A of Chan (2017).

Table 5 reports the posterior parameter statistics estimated in this alternative specification. Results indicate that β is not statistically significant for any country, as its credible intervals include zero. This suggests no evidence that lagged inflation affects current inflation uncertainty, implying that Friedman's hypothesis does not hold in any of the cases analyzed. Accordingly, imposing the $\beta = 0$ restriction may improve computational efficiency, since this parameter does not seem to be relevant.

To assess the persistence of log-inflation uncertainty h_t, the analysis examines ϕ using the half-life shock (HLS) metric, which measures the time required for the impulse response of a unit shock to decline to half its initial magnitude: HLS $= |log(0.5)/log(\phi)|$. Although ϕ estimates in the TVP-SVM model generally exceed 0.95, small variations can translate into meaningful differences in shock persistence. The findings indicate that inflation uncertainty shocks are more persistent in Latin America than in the G7, meaning that AEs recover more quickly from uncertainty shocks than EMEs. In Latin America, a shock in Brazil takes 57 quarters to dissipate to half its initial magnitude, compared to 40 quarters in Chile, 31 in Colombia, 34 in Ecuador, 14 in Mexico, 43 in Peru, and 57 in Uruguay. In contrast, among the G7, the dissipation time is 15 quarters for Canada, 26 for France, 27 for Germany, 30 for Italy, 25 for Japan, 29 for the UK, and 17 for the US.

The results also indicate that $\sigma_{\alpha,\tau}$ is not statistically significant for any country, suggesting no evidence that long-run inflation (τ_t) is correlated with the transitory effects of inflation uncertainty on inflation (α_t). As a result, imposing the $\sigma_{\alpha,\tau} = 0$ restriction may further improve computational efficiency, as this parameter does not appear to be relevant.

6 Conclusions

This paper estimates the TVP-SVM model of Chan (2017) and its extension incorporating Gaussian mixtures in the innovations, following Hou (2020). The objective is to examine the time-varying relationship between inflation uncertainty and inflation across seven Latin American countries and the G7 over the period from Q1 1948 to Q4 2023.

The main findings are as follows. First, the TVP-SVM model is preferred over the TVP-SVM-TVMI model in 8 out of 14 countries, based on the LogML criterion, although the magnitude of preference is small. Second, Latin America has experienced greater inflation uncertainty than the G7, particularly during the 1980s—the so-called "lost decade." Third, inflation uncertainty is significantly more persistent in Latin America than in the G7, according to the alternative estimates of ϕ. Fourth, there is no evidence that the hypothesis of Friedman (1977) holds for any of the countries, based on the alternative estimates of β. Fifth, in contrast, the hypothesis of Cukierman and Meltzer (1986) holds, as the uncertainty-inflation relationship is positive and time-varying in all countries. Sixth, this relationship is stronger and statistically significant during periods of high inflation uncertainty, suggesting that monetary authorities can leverage it to implement surprise policies aimed at lowering inflation expectations. Finally, there is greater evidence of structural breaks in the uncertainty-inflation relationship in Latin America—likely due to its history of hyperinflation episodes—than in the G7.

The main policy implication of these findings is that during periods of high inflation uncertainty, monetary authorities may leverage the positive inflation-uncertainty relationship to implement surprise policies geared toward lowering inflation expectations. A sharp decline in inflation expectations due to an unexpected policy intervention could lead to a significant drop in current inflation, consistent with Cukierman and Meltzer (1986). In contrast, there is no evidence supporting the hypothesis of Friedman (1977), which posits that inflation is purely a monetary phenomenon with no direct link to inflation uncertainty.

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Table 1. Log-Marginal Likelihood (LogML)

	UC	TVP-SVM	TVP-SVM-TVMI
	(A) Latin America		
Brazil	-741.034	-646.590	**-638.513**
Chile	-751.809	**-678.405**	-678.667
Colombia	-938.790	**-923.970**	-926.362
Ecuador	-923.208	**-869.012**	-870.981
Mexico	-917.133	-836.434	**-835.630**
Peru	-974.009	**-887.579**	-888.003
Uruguay	-1039.058	-967.495	**-965.591**
	(B) G7		
Canada	-729.298	-715.767	**-715.574**
France	-608.404	-589.790	**-589.106**
Germany	-616.772	**-614.920**	-617.144
Italy	-640.138	**-609.505**	-610.074
Japan	-701.406	**-693.126**	-695.743
UK	-725.241	**-705.649**	-707.884
US	-639.013	-618.746	**-617.509**

For each model we obtain a total of 50,000 posterior draws after a burn-in period of 5,000. The LogML is obtained from the one step ahead predictive likelihoods evaluated at the observed data, following Hou (2020). Bold values are the highest LogML between the models.

Table 2. Estimated Posterior Parameters of the TVP-SVM Model

	σ_h^2	σ_α^2	σ_τ^2	σ_h^2	σ_α^2	σ_τ^2
	Brazil			Canada		
Mean	0.082	0.012	0.060	0.038	0.010	0.061
S.D.	(0.022)	(0.005)	(0.020)	(0.011)	(0.003)	(0.020)
Bands	[0.052, 0.123]	[0.007, 0.021]	[0.035, 0.098]	[0.024, 0.058]	[0.006, 0.016]	[0.036, 0.098]
	Chile			France		
Mean	0.076	0.012	0.060	0.039	0.012	0.060
S.D.	(0.018)	(0.004)	(0.019)	(0.010)	(0.004)	(0.019)
Bands	[0.051, 0.109]	[0.007, 0.019]	[0.035, 0.096]	[0.025, 0.057]	[0.007, 0.019]	[0.036, 0.095]
	Colombia			Germany		
Mean	0.040	0.006	0.059	0.030	0.009	0.057
S.D.	(0.011)	(0.002)	(0.020)	(0.008)	(0.003)	(0.018)
Bands	[0.025, 0.060]	[0.004, 0.009]	[0.035, 0.096]	[0.019, 0.045]	[0.005, 0.013]	[0.034, 0.091]
	Ecuador			Italy		
Mean	0.056	0.008	0.061	0.048	0.011	0.072
S.D.	(0.014)	(0.002)	(0.022)	(0.012)	(0.004)	(0.025)
Bands	[0.037, 0.081]	[0.005, 0.012]	[0.035, 0.103]	[0.032, 0.071]	[0.006, 0.018]	[0.041, 0.118]
	Mexico			Japan		
Mean	0.098	0.009	0.062	0.037	0.007	0.054
S.D.	(0.025)	(0.003)	(0.022)	(0.010)	(0.002)	(0.017)
Bands	[0.062, 0.142]	[0.005, 0.014]	[0.036, 0.102]	[0.023, 0.056]	[0.005, 0.011]	[0.033, 0.085]
	Peru			UK		
Mean	0.085	0.009	0.064	0.038	0.007	0.053
S.D.	(0.015)	(0.003)	(0.021)	(0.010)	(0.002)	(0.016)
Bands	[0.063, 0.111]	[0.005, 0.014]	[0.037, 0.104]	[0.024, 0.057]	[0.005, 0.010]	[0.032, 0.082]
	Uruguay			US		
Mean	0.041	0.010	0.066	0.072	0.018	0.065
S.D.	(0.010)	(0.003)	(0.024)	(0.022)	(0.008)	(0.022)
Bands	[0.027, 0.060]	[0.006, 0.017]	[0.037, 0.112]	[0.043, 0.115]	[0.009, 0.033]	[0.038, 0.106]

For each model we obtain a total of 50,000 posterior draws after a burn-in period of 5,000. Mean, standard deviations (in parentheses) and 90% credibility intervals (in brackets) are reported.

Table 3. Estimated Posterior Parameters of the TVP-SVM-TVMI Model

	σ_h^2	σ_0^2	σ_1^2	σ_τ^2	σ_h^2	σ_0^2	σ_1^2	σ_τ^2
	Brazil				Canada			
Mean	0.086	0.009	9.530	0.061	0.036	0.010	9.344	0.055
S.D.	(0.020)	(0.003)	(3.172)	(0.021)	(0.010)	(0.003)	(3.173)	(0.017)
Bands	[0.060, 0.126]	[0.006, 0.015]	[5.578, 15.398]	[0.035, 0.099]	[0.023, 0.055]	[0.006, 0.015]	[5.460, 15.261]	[0.033, 0.087]
	Chile				France			
Mean	0.075	0.011	9.570	0.061	0.039	0.010	9.346	0.056
S.D.	(0.018)	(0.004)	(3.317)	(0.020)	(0.010)	(0.004)	(3.165)	(0.017)
Bands	[0.050, 0.107]	[0.006, 0.019]	[5.525, 15.804]	[0.035, 0.099]	[0.026, 0.057]	[0.006, 0.017]	[5.480, 15.213]	[0.034, 0.087]
	Colombia				Germany			
Mean	0.040	0.006	9.791	0.059	0.030	0.009	9.651	0.058
S.D.	(0.011)	(0.002)	(3.404)	(0.019)	(0.008)	(0.003)	(3.353)	(0.018)
Bands	[0.025, 0.061]	[0.004, 0.010]	[5.630, 16.181]	[0.035, 0.094]	[0.019, 0.044]	[0.005, 0.014]	[5.571, 15.890]	[0.035, 0.091]
	Ecuador				Italy			
Mean	0.057	0.008	9.695	0.062	0.047	0.011	9.380	0.068
S.D.	(0.014)	(0.002)	(3.407)	(0.021)	(0.012)	(0.004)	(3.191)	(0.023)
Bands	[0.037, 0.083]	[0.005, 0.012]	[5.586, 16.073]	[0.036, 0.102]	[0.030, 0.069]	[0.006, 0.018]	[5.489, 15.289]	[0.039, 0.110]
	Mexico				Japan			
Mean	0.076	0.009	9.244	0.061	0.037	0.007	9.663	0.053
S.D.	(0.022)	(0.003)	(3.107)	(0.020)	(0.010)	(0.002)	(3.363)	(0.016)
Bands	[0.047, 0.117]	[0.005, 0.014]	[5.470, 15.011]	[0.036, 0.097]	[0.023, 0.056]	[0.005, 0.011]	[5.595, 15.846]	[0.032, 0.082]
	Peru				UK			
Mean	0.069	0.009	9.380	0.064	0.038	0.007	9.758	0.053
S.D.	(0.018)	(0.003)	(3.169)	(0.024)	(0.010)	(0.002)	(3.443)	(0.016)
Bands	[0.044, 0.101]	[0.005, 0.014]	[5.464, 15.315]	[0.036, 0.107]	[0.024, 0.057]	[0.005, 0.011]	[5.644, 16.114]	[0.032, 0.082]
	Uruguay				US			
Mean	0.034	0.009	9.576	0.064	0.071	0.013	9.230	0.069
S.D.	(0.010)	(0.003)	(3.117)	(0.023)	(0.023)	(0.006)	(3.085)	(0.026)
Bands	[0.022, 0.052]	[0.006, 0.015]	[5.678, 15.344]	[0.036, 0.109]	[0.041, 0.113]	[0.007, 0.025]	[5.457, 14.961]	[0.038, 0.117]

For each model we obtain a total of 50,000 posterior draws after a burn-in period of 5,000. Mean, standard deviations (in parentheses) and 90% credibility intervals (in brackets) are reported.

Table 4. Five Quarters with Highest Probabilities of Break Occurrence in α_t

	1°	2°	3°	4°	5°
	(A) Latin America				
Brazil	**1994Q4 (1.000)**	**1987Q1 (0.782)**	**1986Q2 (0.767)**	1994Q3 (0.068)	2022Q3 (0.043)
Chile	2009Q1 (0.180)	2021Q4 (0.089)	2013Q3 (0.060)	2021Q3 (0.047)	1984Q4 (0.046)
Colombia	2022Q1 (0.100)	1963Q1 (0.030)	1963Q3 (0.016)	2021Q1 (0.012)	1998Q3 (0.010)
Ecuador	2015Q3 (0.072)	2021Q1 (0.036)	1958Q2 (0.024)	2020Q3 (0.023)	2015Q4 (0.022)
Mexico	**1988Q2 (0.813)**	**1976Q4 (0.692)**	1995Q1 (0.496)	1995Q3 (0.183)	1958Q2 (0.118)
Peru	**1990Q4 (0.686)**	1990Q3 (0.495)	1978Q1 (0.157)	1985Q4 (0.045)	1976Q3 (0.040)
Uruguay	**1983Q1 (0.993)**	**1983Q2 (0.958)**	**2002Q3 (0.712)**	**2002Q4 (0.618)**	1998Q4 (0.195)
	(B) G7				
Canada	**1991Q2 (0.673)**	1952Q1 (0.105)	1973Q2 (0.097)	1973Q1 (0.089)	1991Q1 (0.079)
France	**1985Q3 (0.708)**	1967Q4 (0.159)	1957Q3 (0.099)	1985Q4 (0.092)	1961Q4 (0.091)
Germany	2021Q1 (0.092)	2008Q4 (0.086)	1985Q3 (0.021)	2008Q3 (0.014)	1985Q2 (0.011)
Italy	1996Q3 (0.263)	2023Q1 (0.234)	2008Q4 (0.158)	1959Q4 (0.068)	2021Q1 (0.058)
Japan	2022Q1 (0.125)	2021Q3 (0.094)	2022Q2 (0.055)	2008Q4 (0.030)	2021Q4 (0.023)
UK	2021Q2 (0.022)	2023Q3 (0.008)	2021Q4 (0.008)	1956Q3 (0.008)	1982Q3 (0.007)
US	2008Q4 (0.444)	1981Q4 (0.422)	1948Q4 (0.401)	2020Q3 (0.383)	2021Q2 (0.308)

The quarters are ranked from 1st to 5th based on their posterior probability of a break occurrence in the uncertainty-inflation relationship α_t (in parentheses), also denoted as $\Pr(K_t = 1|\pi_t) = \pi_t$. The probability π_t is estimated using the TVP-SVM-TVMI model. Dates in bold are those that have a probability greater than 50%.

Table 5. Alternative Results. Estimated Posterior Parameters of the TVP-SVM Model

(A) Latin America

	μ	β	ϕ	σ_h^2	σ_α^2	$\sigma_{\alpha,\tau}$	σ_τ^2
	Brazil						
Mean	1.173	0.000	0.988	0.090	0.025	-0.007	0.109
S.D.	(2.222)	(0.000)	(0.010)	(0.025)	(0.014)	(0.025)	(0.067)
Bands	[-2.959, 4.142]	[0.000, 0.000]	[0.967, 0.999]	[0.056, 0.137]	[0.010, 0.053]	[-0.046, 0.026]	[0.046, 0.225]
	Chile						
Mean	1.180	0.000	0.983	0.081	0.022	-0.007	0.101
S.D.	(1.743)	(0.001)	(0.013)	(0.019)	(0.013)	(0.020)	(0.052)
Bands	[-2.212, 3.450]	[-0.001, 0.001]	[0.957, 0.998]	[0.054, 0.116]	[0.010, 0.045]	[-0.040, 0.019]	[0.046, 0.199]
	Colombia						
Mean	2.546	-0.001	0.978	0.048	0.008	-0.003	0.095
S.D.	(1.406)	(0.001)	(0.017)	(0.014)	(0.003)	(0.007)	(0.050)
Bands	[-0.205, 4.136]	[-0.003, 0.001]	[0.946, 0.999]	[0.029, 0.073]	[0.004, 0.013]	[-0.015, 0.007]	[0.044, 0.182]
	Ecuador						
Mean	1.850	0.000	0.980	0.066	0.010	-0.002	0.106
S.D.	(1.751)	(0.001)	(0.016)	(0.017)	(0.004)	(0.009)	(0.054)
Bands	[-1.901, 3.830]	[-0.002, 0.001]	[0.950, 0.998]	[0.042, 0.096]	[0.005, 0.017]	[-0.018, 0.012]	[0.047, 0.209]
	Mexico						
Mean	2.174	0.000	0.951	0.086	0.012	-0.008	0.110
S.D.	(0.707)	(0.001)	(0.027)	(0.021)	(0.005)	(0.013)	(0.058)
Bands	[0.908, 3.053]	[-0.002, 0.002]	[0.903, 0.992]	[0.056, 0.124]	[0.007, 0.022]	[-0.031, 0.008]	[0.049, 0.213]
	Peru						
Mean	1.459	0.000	0.984	0.088	0.014	0.000	0.125
S.D.	(1.875)	(0.000)	(0.012)	(0.016)	(0.007)	(0.016)	(0.084)
Bands	[-1.853, 3.829]	[-0.001, 0.000]	[0.962, 0.999]	[0.065, 0.116]	[0.007, 0.028]	[-0.024, 0.024]	[0.051, 0.257]
	Uruguay						
Mean	1.342	0.000	0.988	0.050	0.021	0.005	0.152
S.D.	(2.388)	(0.000)	(0.011)	(0.012)	(0.010)	(0.024)	(0.135)
Bands	[-2.911, 4.011]	[-0.001, 0.000]	[0.967, 0.999]	[0.033, 0.072]	[0.009, 0.040]	[-0.030, 0.044]	[0.052, 0.375]

For each model we obtain a total of 50,000 posterior draws after a burn-in period of 5,000. Mean, standard deviations (in parentheses) and 90% credibility intervals (in brackets) are reported.

Table 5 (cont.). Alternative Results. Estimated Posterior Parameters of the TVP-SVM Model

(B) G7

	μ	β	ϕ	σ_h^2	σ_α^2	$\sigma_{\alpha,\tau}$	σ_τ^2
	Canada						
Mean	1.369	-0.002	0.955	0.038	0.016	-0.002	0.093
S.D.	(0.415)	(0.004)	(0.025)	(0.010)	(0.007)	(0.012)	(0.042)
Bands	[0.715, 2.066]	[-0.008, 0.004]	[0.911, 0.990]	[0.024, 0.057]	[0.008, 0.029]	[-0.022, 0.016]	[0.045, 0.173]
	France						
Mean	0.879	-0.002	0.974	0.044	0.020	0.002	0.088
S.D.	(0.940)	(0.003)	(0.017)	(0.011)	(0.010)	(0.013)	(0.035)
Bands	[-0.596, 2.542]	[-0.007, 0.003]	[0.943, 0.999]	[0.028, 0.065]	[0.009, 0.038]	[-0.020, 0.021]	[0.045, 0.154]
	Germany						
Mean	1.710	-0.004	0.975	0.032	0.012	-0.006	0.088
S.D.	(1.226)	(0.005)	(0.022)	(0.009)	(0.005)	(0.011)	(0.038)
Bands	[0.172, 4.683]	[-0.013, 0.005]	[0.933, 0.998]	[0.021, 0.048]	[0.006, 0.022]	[-0.026, 0.008]	[0.043, 0.162]
	Italy						
Mean	0.965	-0.002	0.977	0.055	0.019	0.002	0.119
S.D.	(1.443)	(0.003)	(0.018)	(0.014)	(0.011)	(0.017)	(0.057)
Bands	[-1.107, 4.021]	[-0.006, 0.002]	[0.944, 0.998]	[0.036, 0.081]	[0.008, 0.038]	[-0.025, 0.027]	[0.056, 0.230]
	Japan						
Mean	1.000	-0.002	0.973	0.041	0.009	-0.006	0.080
S.D.	(1.944)	(0.004)	(0.022)	(0.012)	(0.003)	(0.009)	(0.037)
Bands	[-4.057, 3.075]	[-0.008, 0.005]	[0.933, 0.998]	[0.025, 0.064]	[0.005, 0.015]	[-0.021, 0.004]	[0.039, 0.149]
	UK						
Mean	1.619	-0.001	0.976	0.042	0.009	-0.007	0.079
S.D.	(1.286)	(0.003)	(0.019)	(0.012)	(0.003)	(0.008)	(0.035)
Bands	[-1.648, 3.727]	[-0.005, 0.004]	[0.940, 0.998]	[0.027, 0.064]	[0.005, 0.015]	[-0.022, 0.003]	[0.040, 0.143]
	US						
Mean	0.283	0.002	0.959	0.073	0.056	0.008	0.105
S.D.	(0.651)	(0.005)	(0.020)	(0.021)	(0.041)	(0.032)	(0.051)
Bands	[-0.678, 1.202]	[-0.006, 0.010]	[0.924, 0.990]	[0.045, 0.111]	[0.017, 0.135]	[-0.042, 0.054]	[0.048, 0.202]

For each model we obtain a total of 50,000 posterior draws after a burn-in period of 5,000. Mean, standard deviations (in parentheses) and 90% credibility intervals (in brackets) are reported.

(A) Latin America

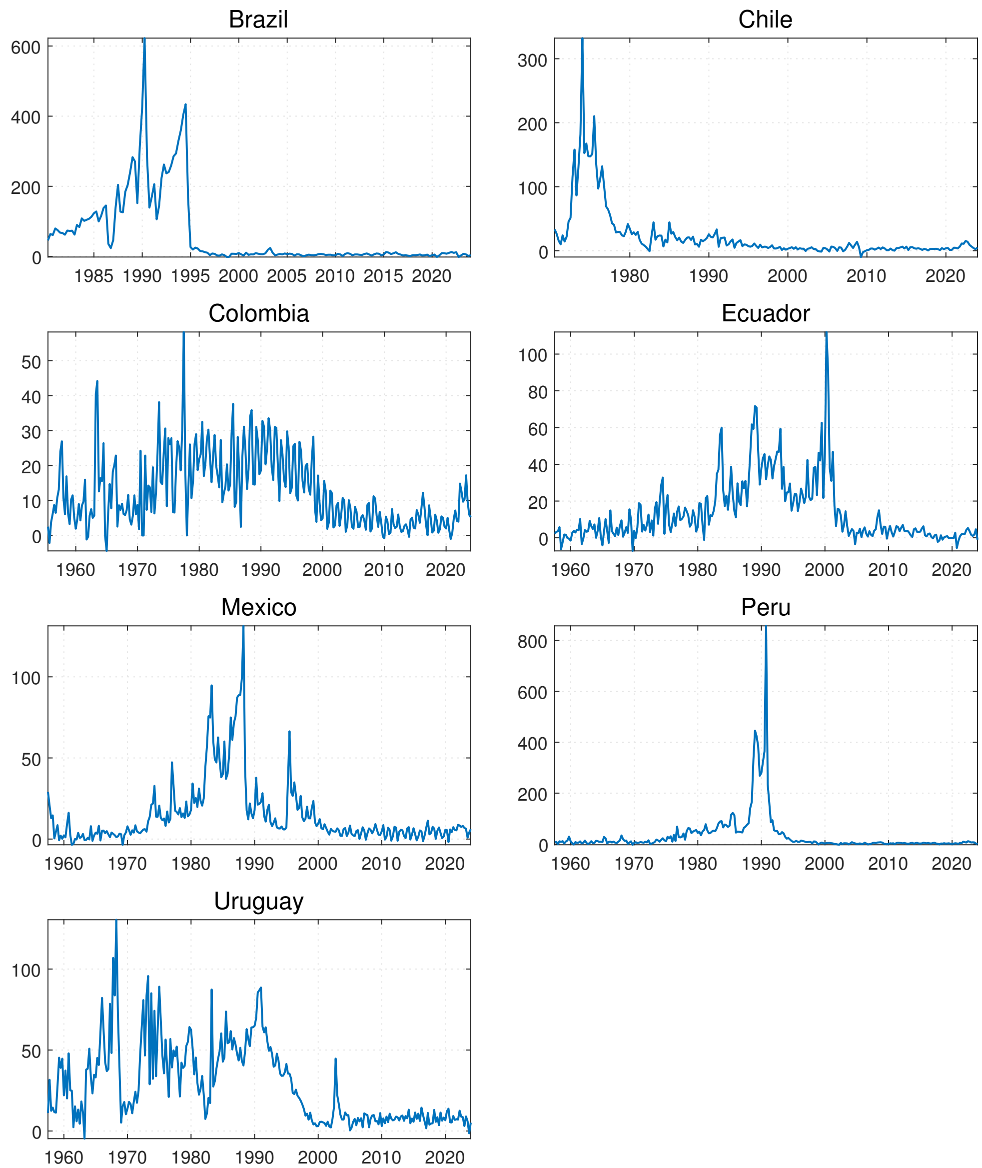

Figure 1. Time Series. Sample: 1948Q1-2023Q4.

(B) G7

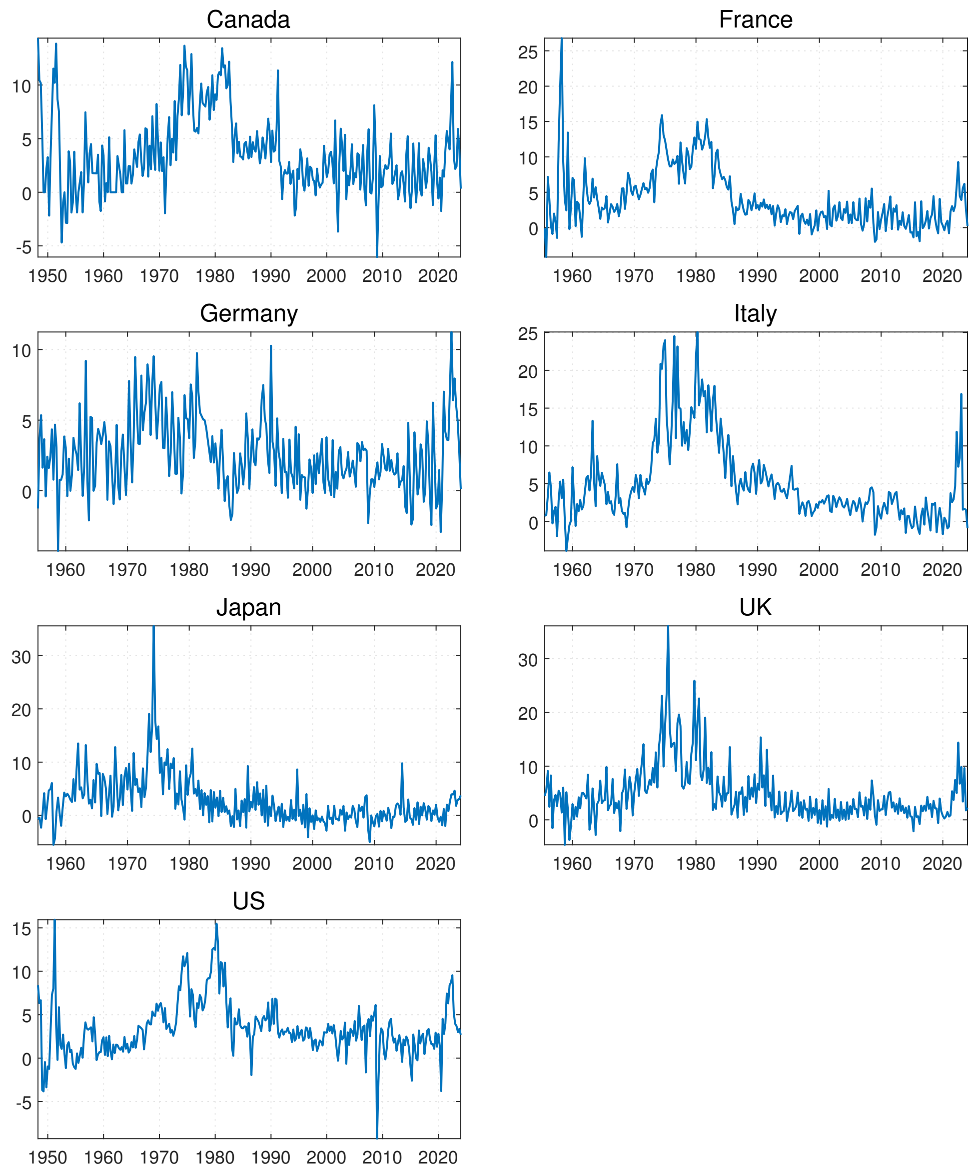

Figure 1 (cont.). Time Series. Sample: 1948Q1-2023Q4.

(A) Latin America

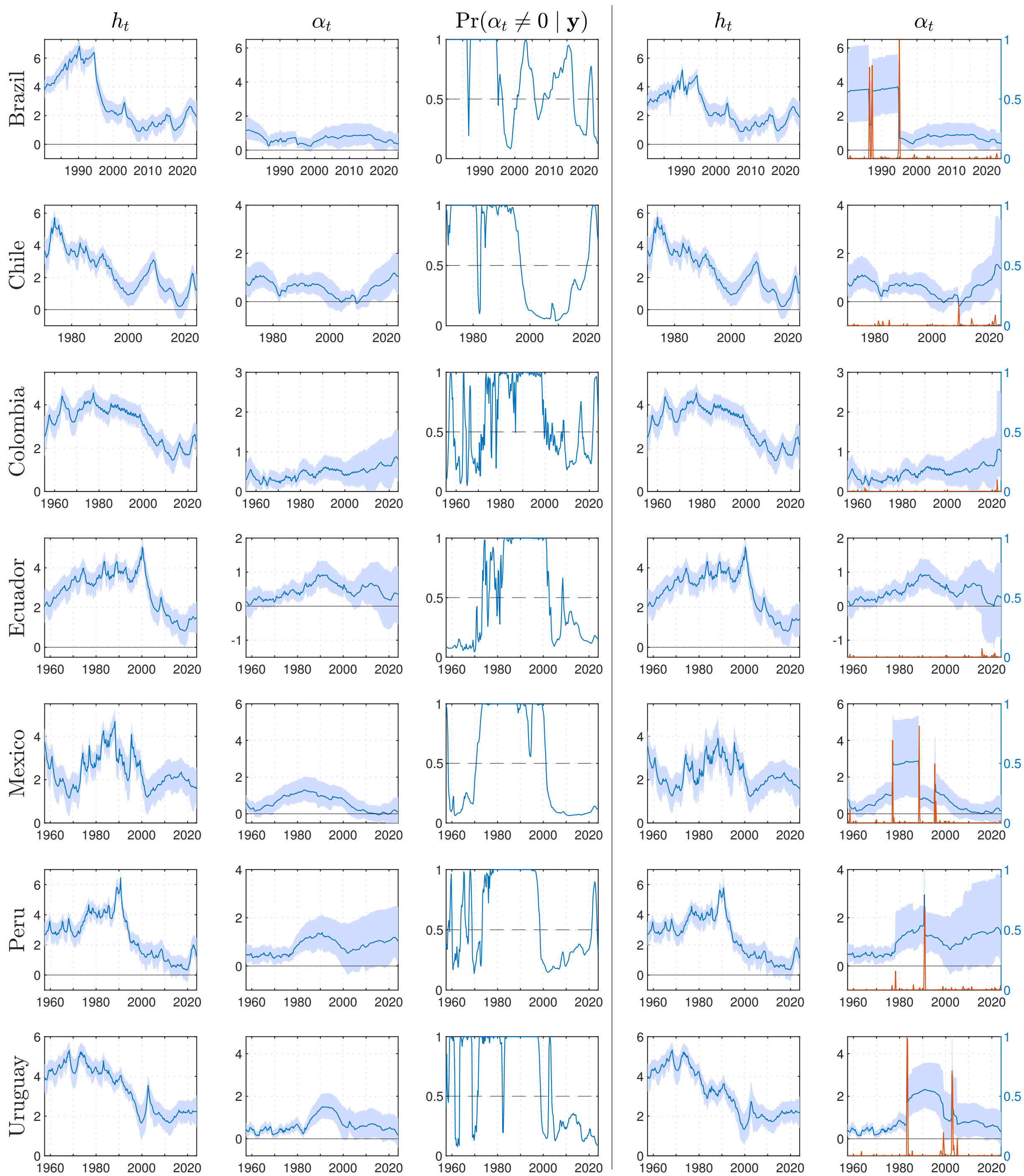

Figure 2. The Evolution of the Logarithmic Inflation Uncertainty h_t (1st column), the Evolution of α_t (2nd column), and the Dynamic Posterior Probabilities of $\alpha_t \neq 0$ (3rd column) for the TVP-SVM Model. The Evolution of the Logarithmic Inflation Uncertainty h_t (4th column), and the Evolution of the α_t and its Probabilities of Break Occurrence $\Pr(K_t = 1|\pi_t) = \pi_t$ (red line) (5th column) for the TVP-SVM-TVMI Model. The blue lines are Median Values. The sky-blue areas are 5- and 95-percentiles Bands.

(B) G7

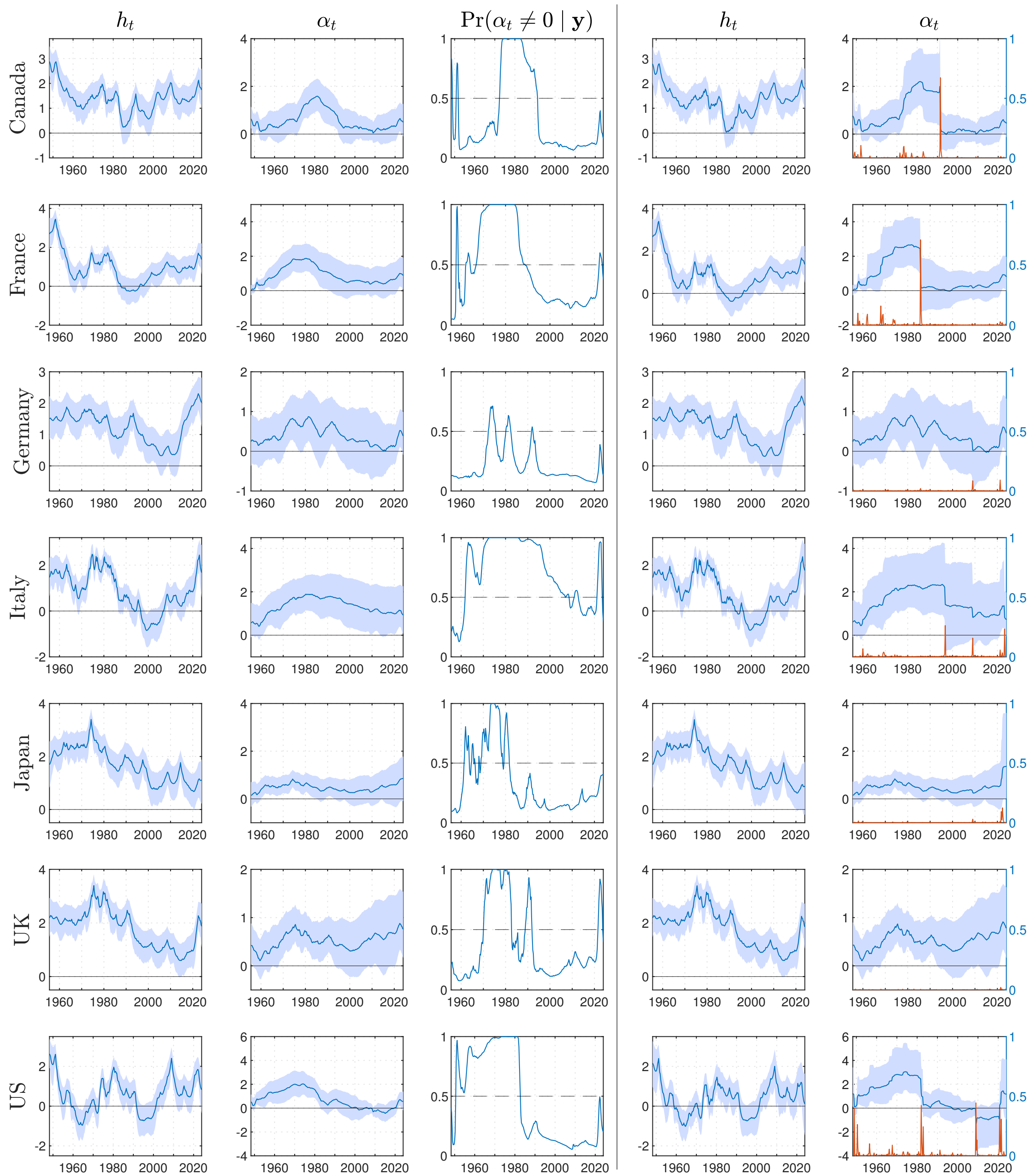

Figure 2 (cont.). The Evolution of the Logarithmic Inflation Uncertainty h_t (1st column), the Evolution of α_t (2nd column), and the Dynamic Posterior Probabilities of $\alpha_t \neq 0$ (3rd column) for the TVP-SVM Model. The Evolution of the Logarithmic Inflation Uncertainty h_t (4th column), and the Evolution of the α_t and its Probabilities of Break Occurrence $\Pr(K_t = 1|\pi_t) = \pi_t$ (red line) (5th column) for the TVP-SVM-TVMI Model. The blue lines are Median Values. The sky-blue areas are 5- and 95-percentiles Bands.

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