Inflation Regimes in Latin America: A Variational Bayesian Approach

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Abstract

This study employs and tests a novel framework to uncover inflation regimes, their dynamics and persistence, and the inflation drivers across nine Latin American countries throughout the 2008-2023 period. A Multivariate Gaussian Hidden Markov Model (MGHMM) with variational Bayesian inference is used to achieve this. The study further employs a Mahalanobis distance-based measure to examine the influence of various drivers on inflation regimes, categorized as monetary policy, international factors, demand-pull factors, expectations, and cost-push factors. The findings reveal that monetary policy instruments significantly impact inflation, especially during economic disruptions. International factors, including international inflation and exchange rates, are also prominent drivers, particularly in Chile, the Dominican Republic, Mexico, and Peru. Private expenditure emerges as the strongest demand-pull factor, with its influence amplified during the pandemic. Finally, inflation expectations and producer prices consistently influence inflation across all the countries examined.

Keywords: Inflation Regimes, Inflation Determinants; Latin America

1 Introduction

High and volatile inflation rates constantly challenge price stability, a fundamental goal of central banks worldwide. These rates reduce purchasing power and create uncertainty about future prices, disrupting business and consumer decision-making and potentially slowing investment and economic growth (Briault, 1995; Lucas, 1972). Inflation also weakens the role of money as a medium of exchange. As the value of money falls, holding cash becomes less attractive, essentially functioning as a tax on those who choose to hold it (Mishkin, 2009).

This paper aims to uncover inflation regimes, their dynamics and persistence, and the inflation drivers across nine Latin American countries: Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Guatemala, Honduras, Mexico, and Peru. The period of interest is from January 2008 to December 2023, characterized by economic downturns and volatile inflation rates. Employing a Multivariate Gaussian Hidden Markov Model (MGHMM) framework with variational Bayesian inference, I uncover inflation regimes and explore their dynamics and persistence. Secondly, I utilize a measure based on the Mahalanobis distance to analyze inflation's short- and medium-term drivers, categorized into five groups: monetary policy, international factors, demand-pull factors, expectations, and cost-push factors. This paper constitutes an enhancement of the methodology proposed and applied by Kinlaw, Kritzman, Metcalfe, and Turkington (2022) for the United States. The model accurately adapts to the economic characteristics of Latin America by including multivariate observations, allowing a rich breakdown of the dynamics of inflation. Moreover, including international factors as inflation drivers is crucial for countries whose economic results highly depend on their activity with the rest of the world. This research is an extension of Sánchez (2023).

As McGrory and Titterington (2009) described, Markov models offer invaluable insights for modeling data that vary over time. At the heart of these models lies the Markov property, which dictates that the probability of transitioning to a particular state at any given time depends only on the state observed in the preceding time step. When examining time series data, it is essential to consider stochastic processes. A stochastic process is a sequence of random variables over time, and we assume that a time series is a collection of observations indexed by time and generated by a stochastic process (Romero-Aguilar, 2020). In this manner, a Hidden Markov Model (HMM) occurs if we assume that the stochastic process that generates a time series follows the Markov property. These are powerful tools for modeling time series because they allow us to obtain the transition probabilities of the underlying data-generating process and the expected value of the inputs conditional on being in a particular state.

By letting the inputs of a HMM be a sequence of time series and assuming that they follow a Gaussian distribution, we obtain a Multivariate Gaussian Hidden Markov Model (MGHMM or Markov Model from now on). In this paper, I use MGHMMs to uncover inflation regimes (traditionally called *states*) by training the model and obtaining the stationary transition probabilities. Moreover, using multiple time series and calculating the expected value of each, conditional on a specific regime, provides a notion of the combined behavior of inflation and its drivers, whose relative importance over time I examine later with the Mahalanobis distance measure.

A variational approach, a second-order technique, is applied to Bayesian inference, introducing a distribution over the hidden variables for the MGHMM. Second-order techniques are employed to determine parameter values of probabilistic models from sample data. This approach does not necessarily require the inclusion of actual prior knowledge, and the primary advantage of depending on training based on variational Bayesian inference is that introducing distributions over the model parameters prevents the model from getting trapped in local minima (Gruhl & Sick, 2016). I also use this approach to define each model's optimal number of regimes and compare it with traditionally-used criteria.

The paper proceeds as follows. Section 2 defines the Multivariate Gaussian Hidden Markov Model (MGHMM) methodology and the Mahalanobis distance approach. In Section 3, I describe the data and the estimation assumptions. Section 4 provides the estimation results and includes the analysis of inflation dynamics. Finally, 5 concludes the paper.

2 Methods

In this section, I present the Multivariate Gaussian Hidden Markov Model (MGHMM) and the Mahalanobis distance approach for analyzing inflation drivers. Vectors and matrices are denoted with bold, lowercase, and uppercase symbols, respectively. For instance, $\boldsymbol{x}$ would represent a vector, and $\boldsymbol{X}$ a matrix. The superscripts $'$ and -1 represent the transpose and inverse of a matrix, respectively.

2.1 Multivariate Gaussian Hidden Markov Model (MGHMM)

Let $\boldsymbol{Y}$ be the sequence of observations $\boldsymbol{y}_t$ taking variables in $\mathbb{R}^p$, with $1 \leq t \leq T$ and $T = |\boldsymbol{Y}|$. Let also $\boldsymbol{Z}$ be the set of latent variables $\boldsymbol{z}_{t,j}$, with $1 \leq t \leq T$, $1 \leq j \leq J$, where J is the number of hidden regimes. $\boldsymbol{Z}$ uses a *1-out-of-K* coding. The state transition matrix is denoted by $\boldsymbol{\Pi}$, with rows $\boldsymbol{\pi}_i$ for $1 \leq i \leq J$, and elements $\pi_{i,j}$ with $i, j \in \{1, \ldots, J\}$. Let also the probability to start in state j defined as π_j. The distributions of $\boldsymbol{Y}$ depend only on contemporary $\boldsymbol{z}_{t,j}$, and are assumed to be multivariate Gaussian of order p. Finally, let $\boldsymbol{\Theta}$ be the parameter matrix containing all model parameters.

2.1.1 Variational Bayesian Inference

When modeling time series, which are by nature stochastic, the inference process of estimating the model parameters relies on the Bayes' rule (Boškoski, Perne, Rameša,

& Mileva-Boshkoska, 2021), which states that

$$\underbrace{p(\boldsymbol{\Theta}|\boldsymbol{Y})}_{\text{Posterior}} = \frac{\overbrace{p(\boldsymbol{Y}|\boldsymbol{\Theta})}^{\text{Likelihood}}\,\overbrace{p(\boldsymbol{\Theta})}^{\text{Prior}}}{\underbrace{p(\boldsymbol{Y})}_{\text{Evidence}}} \tag{1}$$

Bayesian inference aims to estimate the posterior probability distribution $p(\boldsymbol{\Theta}|\boldsymbol{Y})$, which is the appropiate marginal distribution of $p(\boldsymbol{\Theta}, \boldsymbol{Z}|\boldsymbol{Y})$. The variational method aproximates $p(\boldsymbol{\Theta}, \boldsymbol{Z}|\boldsymbol{Y})$ with a simpler $q(\boldsymbol{\Theta}, \boldsymbol{Z})$, known as the *variational distribution*, obtained by maximizing a lower bound on the log-likelihood. Let the observed-data log-likelihood be defined as

$$\ln p(\boldsymbol{Y}|\boldsymbol{\Theta}) = \ln \int p(\boldsymbol{Y}, \boldsymbol{Z}|\boldsymbol{\Theta})\, d\boldsymbol{Z} = \ln \int q(\boldsymbol{Z}) \frac{p(\boldsymbol{Y}, \boldsymbol{Z}|\boldsymbol{\Theta})}{q(\boldsymbol{Z})}\, d\boldsymbol{Z} \tag{2}$$

where, by Jensen's Inequality:

$$\ln \int q(\boldsymbol{Z}) \frac{p(\boldsymbol{Y}, \boldsymbol{Z}|\boldsymbol{\Theta})}{q(\boldsymbol{Z})}\, d\boldsymbol{Z} \geq \int q(\boldsymbol{Z}) \ln \left\{ \frac{p(\boldsymbol{Y}, \boldsymbol{Z}|\boldsymbol{\Theta})}{q(\boldsymbol{Z})} \right\} d\boldsymbol{Z} \tag{3}$$

The latent variables $\boldsymbol{Z}$ absorb the parameters $\boldsymbol{\Theta}$, as both are random variables. Equation (2) can be then rewritten as:

$$\begin{aligned} \ln p(\boldsymbol{Y}|\boldsymbol{\Theta}) &= \int q(\boldsymbol{Z}) \ln \left\{ \frac{p(\boldsymbol{Y}, \boldsymbol{Z}|\boldsymbol{\Theta})}{q(\boldsymbol{Z})} \right\} d\boldsymbol{Z} + \int q(\boldsymbol{Z}) \ln \left\{ \frac{q(\boldsymbol{Z})}{p(\boldsymbol{Z}|\boldsymbol{Y}, \boldsymbol{\Theta})} \right\} d\boldsymbol{Z} \\ &= \mathcal{L}(q, \boldsymbol{\Theta}) + \mathrm{KL}(q||p) \end{aligned} \tag{4}$$

where $\mathcal{L}(q, \boldsymbol{\Theta})$ is the variational lower bound, and $\mathrm{KL}(q||p)$ the Kullback-Leibler divergence between q and p. An optimal model is obtained with a variational distribution $q(\boldsymbol{Z})$ that maximizes the lower bound, which is equivalent to minimizing the $\mathrm{KL}(q||p)$ divergence. Note than an optimum is reached when the variational distribution $q(\boldsymbol{Z})$ is equal to the conditional posterior distribution $p(\boldsymbol{Z}|\boldsymbol{X})$.

The distribution p can be factorized as

$$p(\mathbf{Y}, \mathbf{Z}, \mathbf{\Pi}, \boldsymbol{\mu}, \mathbf{\Lambda}) = p(\mathbf{Y}|\mathbf{Z}, \boldsymbol{\mu}, \mathbf{\Lambda}) p(\mathbf{Z}|\mathbf{\Pi}) p(\mathbf{\Pi}) p(\boldsymbol{\mu}|\mathbf{\Lambda}) p(\mathbf{\Lambda}) \tag{5}$$

Finally, I assume that a factorization of the variational distribution is possible as follows

$$\begin{aligned} q(\mathbf{Z}, \mathbf{\Pi}, \boldsymbol{\mu}, \mathbf{\Lambda}) &= q(\mathbf{Z}) q(\mathbf{\Pi}, \boldsymbol{\mu}, \mathbf{\Lambda}) && (6) \\ &= q(\mathbf{Z}) q(\mathbf{\Pi}) q(\boldsymbol{\mu}, \mathbf{\Lambda}) && (7) \\ &= q(\mathbf{Z}) \prod_{i=1}^{J} q(\boldsymbol{\pi}_i) \prod_{j=1}^{J} q(\boldsymbol{\mu}_j, \mathbf{\Lambda}_j) && (8) \end{aligned}$$

2.1.2 Model Specification

For each state j, I assign an independent Dirichlet prior distribution for the transition probabilities, so that

$$\begin{aligned} p(\mathbf{\Pi}) &= \prod_{j=1}^{J} Dir(\boldsymbol{\pi}_j | \boldsymbol{\alpha}_j^{(0)}) && (9) \\ \boldsymbol{\alpha}_j^{(0)} &= \{\alpha_{j,1}^{(0)}, \ldots, \alpha_{j,J}^{(0)}\} \end{aligned}$$

for given hyperparameters $\boldsymbol{\alpha}_j^{(0)}$. The variational posterior distributions of the transition probabilities have the following form

$$
\begin{aligned}
q(\boldsymbol{\Pi}) &= \prod_{j=1}^{J} Dir(\boldsymbol{\pi}_j|\boldsymbol{\alpha}_j) \qquad (10)\\
\boldsymbol{\alpha}_j^{(0)} &= \{\alpha_{j,1}, \ldots, \alpha_{j,J}\}
\end{aligned}
$$

The means are assigned independent univariate Gaussian conjugate prior distributions, conditional on the precisions. The precisions themselves are assigned independent Wishart prior distributions, so that

$$
\begin{aligned}
p(\boldsymbol{\mu}, \boldsymbol{\Lambda}) &= p(\boldsymbol{\mu}|\boldsymbol{\Lambda})p(\boldsymbol{\Lambda}) \qquad (11)\\
&= \prod_{j=1}^{J} \mathcal{N}(\boldsymbol{\mu}_j|\boldsymbol{m}_0, (\beta_0\boldsymbol{\Lambda}_j)^{-1}) \cdot \mathcal{W}(\boldsymbol{\Lambda}_j|\boldsymbol{W}_0, \nu_0) \qquad (12)
\end{aligned}
$$

for given hyperparameters $\boldsymbol{m}_0, \beta_0, \boldsymbol{W}_0, \nu_0$. For each state j, the variational posterior distributions have the following form:

$$
q(\boldsymbol{\mu}_j, \boldsymbol{\Lambda}_j) = \mathcal{N}(\boldsymbol{\mu}_j|\boldsymbol{m}_j, (\beta_j\boldsymbol{\Lambda}_j)^{-1}) \cdot \mathcal{W}(\boldsymbol{\Lambda}_j|\mathbf{W}_j, \nu_j) \qquad (13)
$$

The variational posterior distribution for the latent variables has the form

$$
q(\mathbf{Z}) \propto \prod_{t=1}^{T}\prod_{j=1}^{J}(b_{t,j})^{z_{t,j}} \prod_{t=1}^{T}\prod_{j=1}^{J}\prod_{s=1}^{J}(a_{j,s})^{z_{t,j}, z_{t+1,s}} \qquad (14)
$$

which is the same as in McGrory and Titterington (2009) for univariate observations. Taking the expected value of the logarithm transforms Equation (14) into

$$
\begin{aligned}
\mathbb{E}[\ln q(\mathbf{Z})] = &\sum_{t=1}^{T}\sum_{j=1}^{J}\gamma(z_{t,j})\mathbb{E}[\ln p(\boldsymbol{y}_n|\boldsymbol{\mu}_j, \boldsymbol{\Lambda}_j^{-1})]\\
&+ \sum_{t=1}^{T-1}\sum_{j=1}^{J}\sum_{s=1}^{J}\xi(z_{t,j}, z_{t+1,s})\mathbb{E}[\ln \tilde{\pi}_{j,s}] \qquad (15)
\end{aligned}
$$

with

$$
\begin{aligned}
\gamma(z_{t,j}) &= \mathbb{E}[z_{t,j}] \qquad (16)\\
\xi(z_{t,j}, z_{t+1,s}) &= \mathbb{E}[z_{t,j}, z_{t+1,s}] \qquad (17)\\
a_{j,s} &= \exp\{\mathbb{E}[\ln \tilde{\pi}_{j,s}]\} \qquad (18)\\
b_{t,j} &= \exp\{\mathbb{E}[\ln p(\boldsymbol{y}_n|\boldsymbol{\mu}_j, \boldsymbol{\Lambda}_j^{-1})]\} \qquad (19)
\end{aligned}
$$

where Equation (16) is the probability that observation at time t was generated by the state j. Equation (17) represents the transition probability of moving from state j at time t, to state s at time $t+1$. Finally, the distribution of the latent variables $\boldsymbol{Z}$ given the transition matrix $\boldsymbol{\Pi}$ is defined as follows

$$
p(\boldsymbol{Z}|\boldsymbol{\Pi}) = p(\boldsymbol{z}_1|\boldsymbol{\pi}) \prod_{t=2}^{T}(p(\boldsymbol{z}_t|\boldsymbol{z}_{t-1}))^{z_{t-1,j}, z_{t,s}} \qquad (20)
$$

2.1.3 Expectation-Maximization

The MGHMM is trained using the Expectation-Maximization (EM) algorithm. In this approach, the E-step estimates the latent variables of the sample, given the chosen hyperparameters. The M-step then uses this information to update the model parameters that maximize the variational lower bound.

The E-Step relies on the Baum-Welch algorithm. Let the forward and backward probabilities, υ and ω, be defined respectively as follows

$$\upsilon(z_{t,j}) = b_{t,j} \sum_{k=1}^{J} \upsilon(z_{t-1,k}) \tag{21}$$

$$\omega(z_{t,j}) = \sum_{s=1}^{J} \omega(z_{t+1,s}) \cdot a_{j,s} \cdot b_{t+1,s} \tag{22}$$

with constraints $\upsilon(z_{1,j}) = \pi_j b_{1,j}$ and $\omega(z_{T,j}) = 1$, $1 \leq j \leq J$. The forward and backward probabilities are used to reformulate Equations (16) and (17) as follows

$$\gamma(z_{t,j}) = \mathbb{E}[z_{t,j}] = \frac{\upsilon(z_{t,j})\omega(z_{t,j})}{\sum_{k=1}^{J} \upsilon(z_{t,k})\omega(z_{t,k})} = \sum_{\boldsymbol{z}} \gamma(\boldsymbol{z}) \cdot z_{t,j} \tag{23}$$

$$\xi(z_{t-1,j}, z_{t,s}) = \frac{\upsilon(z_{t-1,j}) a_{j,s} b_{t,s} \omega(z_{t,s})}{\sum_{k=1}^{J} \sum_{l=1}^{J} \upsilon(z_{t-1,k}) a_{k,l} b_{t,l} \omega(z_{t,l})} \tag{24}$$

The initial probabilities $\boldsymbol{\pi}$ that the model starts in state j are estimated by

$$\pi_j = \frac{\gamma(z_{1,j})}{\sum_{k=1}^{J} \gamma(z_{1,k})} = \gamma(z_{1,j} = 1) \tag{25}$$

which ends the Expectation Step. The Maximization Step is as defined in Appendix A.1. Finally, the variational lower bound[1] introduced in Equation (4) can be derived as

$$\mathcal{L} = \sum_{\boldsymbol{Z}} \int \int \int q(\boldsymbol{Z}, \boldsymbol{\Pi}, \boldsymbol{\mu}, \boldsymbol{\Lambda}) \ln \left\{ \frac{p(\boldsymbol{Y}, \boldsymbol{Z}, \boldsymbol{\Pi}, \boldsymbol{\mu}, \boldsymbol{\Lambda})}{q(\boldsymbol{Z}, \boldsymbol{\Pi}, \boldsymbol{\mu}, \boldsymbol{\Lambda})} \right\} d\boldsymbol{\Pi} d\boldsymbol{\mu} d\boldsymbol{\Lambda} \tag{26}$$

2.2 Inflation Drivers

Let $\boldsymbol{X}$ be a sequence of observations $\boldsymbol{x}_t$ taking variables in $\mathbb{R}^m$, with $1 \leq t \leq \tau$ and $\tau = |\boldsymbol{X}|$. Let also $\bar{\boldsymbol{x}}_r$ be the average of the observations in a certain regime r, $r \in \{1, ..., R\}$. Let $\boldsymbol{\Sigma}_r$ be the nonsingular, symmetric and positive semi-definite covariance matrix of $\boldsymbol{X}$ in regime r. The Mahalanobis squared distance is defined by

$$\delta_{t,r} = (\boldsymbol{x}_t - \bar{\boldsymbol{x}}_r)' \, \boldsymbol{\Sigma}_r^{-1} \, (\boldsymbol{x}_t - \bar{\boldsymbol{x}}_r) \tag{27}$$

Note that Equation (27) considers the difference between the observations in terms of the actual values and their averages in a certain regime, relative to the *within-regime* variation. If the variables were uncorrelated in a certain regime r, the covariance matrix $\boldsymbol{\Sigma}_r$ would be an identity matrix of order m, transforming $\boldsymbol{\delta}_r$ into a vector with the squared Euclidean distances between the contemporary observations and its averages (McLachlan, 1999). Converting (27) into a statistical likelihood with a Gaussian distribution and rescaling it to be interpreted as a probability gets the following

$$L_{t,r} = \frac{1}{\sqrt{\det(2\pi\boldsymbol{\Sigma}_r)}} \exp\left\{ \frac{-\delta_{t,r}}{2} \right\} \tag{28}$$

$$\rho_{t,r} = \frac{L_{t,r}}{\sum_{r=1}^{R} L_{t,r}} \tag{29}$$

Then, I take the derivative of (29) with respect to the observations, so that

$$\boldsymbol{\zeta}_t = \sum_{r=1}^{R} \eta_r \left| \frac{\partial \rho_{t,r}}{\partial \boldsymbol{x}_t} \right| \tag{30}$$

[1] For further details, please consult Gruhl and Sick (2016); McGrory and Titterington (2009).

where η_r represents the weight of regime r in the period of study. For example, if a certain regime r is predicted to happen in 5 out of 10 time steps, $\eta_r = 0.5$. Note that $\sum_{r=1}^{R} \eta_r = 1$. This step is an extension of the method applied in Kinlaw et al. (2022) and Sánchez (2023), where the authors use a sample average.

Finally, rescaling Equation (30) with the standard deviations of the full sample allows to obtain the relative importance vector at each time step t, so that

$$\boldsymbol{\psi}_t = \frac{\boldsymbol{\zeta}_t \boldsymbol{\sigma}}{\sum_{\boldsymbol{z}} |\zeta_{c,t}\sigma_c|} \tag{31}$$

3 Data and Estimation

In this section, I describe the data used in the analysis and the different tested models.

3.1 Data

I use monthly data from the International Monetary Fund (IMF), the Latin American Reserve Fund (FLAR), the Executive Secretariat of the Central American Monetary Council (SECMCA), the Federal Reserve Economic Data (FRED), and the countries' central banks.

Table 1: Data and Measures

Theory	Data	Variable	Measure
-	Headline consumer price index	cpi_t	1M change (%)
-	Core consumer price index	$core_t$	1M change (%)
Monetary policy	Broad money	$broad_t$	36M pct. change (%)
	Policy-related interest rate (%)	mpr_t	12M difference (p.p.)
International	US headline consumer price index	cpi_t^*	1M change (%)
	US core consumer price index	$core_t^*$	1M change (%)
	Nominal exchange rate to $1	er_t	12M change (%)
Demand-pull	Household's final consumption expenditure	$priv_t$	12M change (%)
	Public sector's final consumption expenditure	gov_t	12M change (%)
Expectations	Inflation expectations, 12M ahead (%)	exp_t	12M difference (p.p.)
Cost-push	Producer price index (PPI)	ppi_t	12M change (%)

Data retrieved from: IMF, FLAR, SECMCA, FRED, central banks.

The theories, data, variables, and measures are summarized in Table 1. I run models with two price measures: headline and core inflation rates. An essential factor is that these measures correspond to month-to-month instead of same-month rates. This selection responds to the fact that there could be a bias in the transition probabilities of the Hidden Markov Model if same-month inflation rates were used; that is, considering that a twelve-month change includes eleven months used in the rate of the previous month, at every time step, a factor increasing the transition probability is likely to happen.

The Theory column of Table 1 categorizes the inflation drivers. Monetary policy factors include the three-year change of broad money, $broad_t$, and the twelve-month difference of the policy-related interest rate, mpr_t, as two crucial tools that central banks have to improve the economic environment of the countries. An improvement from Kinlaw et al. (2022) is the inclusion of international factors as potential inflation drivers, taking into account the characteristics of Latin American countries and the importance of the rest of the world in their economic results. This category includes the United States' headline and core inflation rates, cpi_t^* and $core_t^*$, as proxies for international inflation and the nominal exchange rate to $1, er_t. The third category belongs to demand-pull factors, and its breakdown into private and public sector final consumption expenditure, $priv_t$ and gov_t, is a second enhancement from the original methodology. As a fourth category, inflation expectations correspond to a twelve-month difference in the year-ahead expectations of the economic agents, exp_t. Finally, the cost-push factors include the one-year change in the producer price index, ppi_t.

All percentage changes correspond to their log-difference approximation and all time series are available from January 2008 to December 2023, except for exp_t and ppi_t data, available from January 2015 to December 2023. Moreover, ppi_t is unavailable for the Dominican Republic, Guatemala, and Honduras. A summary of the descriptive statistics can be found in Table B1.

3.2 Estimation

To execute the Multivariate Gaussian Hidden Markov Model, I initially set a seed for the pseudo-random number generator to ensure reproducibility and define a range of initial hidden states, ranging from one to five. In this study, the maximum number of states is limited to five due to the potential undefined transition probabilities for a higher number of latent regimes, attributable to the limited number of observations. Each MGHMM undergoes initialization a hundred times, with each initiation comprising a million iterations. Throughout each iteration, the code[2] fits the model to the data, aiming to identify the optimal number of states, J^*, by maximizing the model's variational lower bound, as specified in Equation (4). I compare the resulting criteria with the log-likelihood, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) of a non-variational Markov Model. For the lower bound and log-likehood, I aim to get the maximum possible number, and for the AIC and BIC, the minimum is the better. Once the model best approximating the real distribution is obtained, I extract the stationary transition probabilities and the conditional expected value of the variables for each regime $j \in \{1, ..., J^*\}$, as well as the chain of latent states that best fit the data.

I define six distinct model specifications for analysis, as defined in Table 2. Model 1 focuses exclusively on headline inflation, while Model 2 isolates core inflation, both applied to all countries from January 2008 to December 2023. These two specifications utilize the MGHMM to uncover the transition probabilities of inflation, and I use their predicted sequences of hidden states for the Mahalanobis distance measure of the drivers. Model 3 expands the analysis to include monetary policy and international and demand-pull factors alongside headline inflation for a more comprehensive assessment. Model 4 mirrors Model 3 but with core inflation as the focal variable. Model 5 extends the analysis further by incorporating inflation expectations alongside the variables included in Model 3. Finally, Model 6 encompasses all variables considered in Model 5, along with producer prices, for an exhaustive examination of inflation dynamics across Brazil, Chile, Colombia, Costa Rica, Mexico, and Peru from January 2015 to December 2023, the same period as Model 5. Specifications 3 to 6 not only enclose the variables outlined previously but also utilize the Mahalanobis distance measure to examine the drivers' relative importance throughout the period.

Table 2: Model Specifications

Model	Variables	Countries	Period
Model 1	cpi_t	All	08M1-23M12
Model 2	$core_t$	All	08M1-23M12
Model 3	cpi_t, $broad_t$, mpr_t, cpi_t^*, er_t, $priv_t$, gov_t	All	08M1-23M12
Model 4	$core_t$, $broad_t$, mpr_t, $core_t^*$, er_t, $priv_t$, gov_t	All	08M1-23M12
Model 5	cpi_t, $broad_t$, mpr_t, cpi_t^*, er_t, $priv_t$, gov_t, exp_t	All	15M1-23M12
Model 6	cpi_t, $broad_t$, mpr_t, cpi_t^*, er_t, $priv_t$, gov_t, exp_t, ppi_t	BRA, CHL, COL, CRI, MEX, PER	15M1-23M12

For the MGHMM, I assume that the initial starting probabilities are equal across all regimes and equal to the initial transition probabilities. I also assume that the initial conditional means on the regimes are all equal to the sample average. The scale of the variance over the means is one for all regimes and is equal to the degrees of freedom for each state's Wishart distribution.

[2] I utilize the *hmmlearn* package, available for Python.

4 Results

In this section, I present the results of the models.

4.1 MGHMM

The analysis of regime selection criteria across the models reveals insightful patterns. The log-likelihood consistently suggests a higher number of states, often reaching the maximum available in each model, compared to alternative criteria. Considering the trade-off between model complexity and goodness of fit, the results for models 1 and 2, using the variational lower bound, indicate a prevalence of two or three latent regimes in most countries, suggesting that these models strike a balance, capturing an adequate level of complexity with a small to moderate number of states. Moreover, the AIC tends to suggest a higher number of states than the BIC. In Figure 1, the regime selection criteria for Model 1 in Colombia and Mexico further illustrate these findings. In regards to Model 3, it consistently exhibits two regimes across all countries except Brazil, the Dominican Republic, and Peru. Similarly, Model 4 predominantly shows two regimes for all countries except the Dominican Republic. Model 5 follows a similar pattern, with two regimes observed in all countries except Brazil. Lastly, Model 6 also tends to have two regimes across most countries, except for Brazil and Colombia. Table B2 displays the complete results for all models.

(a) COL (b) MEX

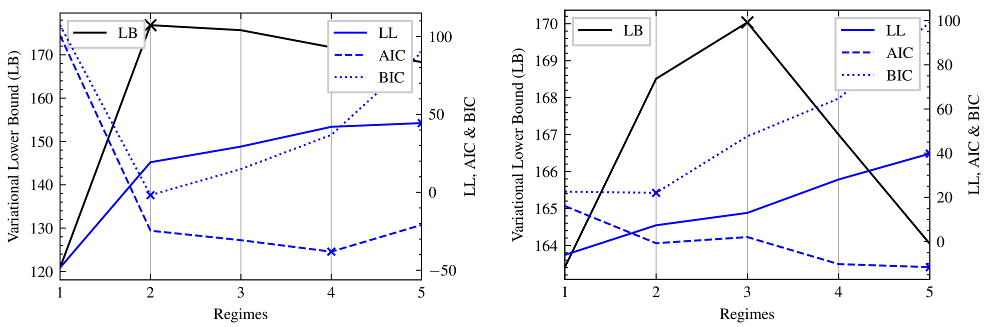


Fig. 1: Regime Selection Criteria, Model 1

The analysis of the relationship between monetary policy drivers and inflation across different countries uncovers essential patterns. Notably, increases in broad money consistently coincide with higher inflation regimes in Brazil, Colombia, Costa Rica, the Dominican Republic, Guatemala, and Honduras. This suggests that expansions in the money supply align with periods of elevated inflation in these countries. However, the situation in Mexico is more nuanced, with the positive relationship with broad money being dependent on the inclusion of core inflation in the model, suggesting that changes in broad money may only influence inflation dynamics in Model 3. The expected values of the variables conditional on the regimes are available in Tables B3 and B4.

Peru presents a unique dynamic where changes in the money supply are negatively associated with inflation rates. In Chile, the relationship between changes in the money supply and inflation is not straightforward, varying across different models. Models 3 and 4 demonstrate an inverse relationship; however, in Models 5 and 6, a positive and expected positive relationship emerges. This complexity underscores the importance of model selection and the intricate nature of monetary policy dynamics in shaping inflation outcomes.

The effectiveness of monetary policy measures is underscored by the inverse relationship between policy-related interest rates and inflation, where higher interest rates coincide with lower inflation rates, reflecting the central bank's efforts to curb inflationary pressures through tightening monetary policy. In Model 3, this inverse relationship is observed in Brazil, the Dominican Republic, and Mexico. Similarly, Model 4 illustrates this pattern solely for Peru, suggesting that changes in interest rates exert a dampening effect on inflation dynamics in this context. In Model 5, Costa Rica and Honduras exhibit the expected inverse relationship between policy-related interest rates and inflation. Moreover, in Model 6, Costa Rica continues to demonstrate this inverse association, further highlighting the efficacy of monetary policy measures in influencing inflation outcomes.

Examining international inflation across different models reveals varied impacts on domestic inflation. In Model 3, excluding the Dominican Republic, higher international inflation coincides with elevated domestic inflation, indicating a positive relationship. Similarly, in Model 4, all countries show a positive relation between international and domestic inflation. However, in Model 5 and Model 6, Brazil exhibits an inverse relationship, with higher international inflation linked to lower domestic inflation.

Across the available models, a positive relationship between the exchange rate and inflation emerges for several countries, including Costa Rica, the Dominican Republic, and Guatemala. Conversely, in Honduras, this relationship consistently shows a negative trend. In Colombia, the relationship is positive in Models 3, 4, and 5 but becomes ambiguous in Model 6. On the other hand, Peru, Mexico, Brazil, and Peru demonstrate an inverse relationship in most models.

Demand-pull factors, containing private and government expenditure, exhibit varying relationships across different countries. In Guatemala and Honduras, private and government expenditures consistently demonstrate a direct relationship in all models. Similarly, Chile consistently displays a direct relationship for both variables, although with a noteworthy inversion for government expenditure in the two most complex models. Conversely, Costa Rica consistently reveals an inverse relationship between private expenditure and a consistent positive association with government expenditure. However, for other countries, such as Colombia, the effects of these factors still need to be clarified across the different models analyzed.

In most cases across the available countries, inflation expectations align positively with the observed inflation rate, except for Costa Rica. This suggests that expectations of future inflation coincide with actual inflation outcomes, contributing to the dynamics of inflationary pressures. Moreover, in Model 6, which includes all countries, there is a clear relationship between producer prices and consumer inflation, highlighting the significance of producer price dynamics in influencing overall inflationary trends.

Transition probabilities for Model 1, as depicted in Figure 2, indicate strong persistence across all countries, with probabilities ranging from 80% to 99%. In this figure, the axes correspond to the month-to-month inflation rate conditional on being in a particular regime. This high level of persistence suggests that once a country enters a particular inflation regime, it is highly likely to remain in that regime in the subsequent period. However, Mexico has a notably lower probability of staying in the same regime, at 9%, when the country experiences a 0.27% inflation rate. This exception underscores the nuanced dynamics of inflation persistence in different contexts. It is worth noting that Mexico also has a regime with a 0.31% month-to-month inflation rate, which could influence these results. The transition probabilities of Model 2 are available in Figure B1.

Table 3 displays transition coefficients for each country across different models, reflecting the weighted average transition probabilities. In most models, countries demonstrate strong persistence across inflation regimes, as evidenced by high coefficients. Notably, Mexico stands out in Model 1, with a coefficient of 92.91%, influenced by a regime characterized by lower month-to-month inflation. Model 2 also shows significant persistence, with consistently high coefficients across countries. However, specific entries, such as Colombia and Peru in Model 2, exhibit relatively lower coefficients, suggesting potentially less stability or greater variability in inflation dynamics. Models 3 to 6 generally maintain high coefficients, ranging from 92.74% to 98.45%, indicating strong regime persistence.

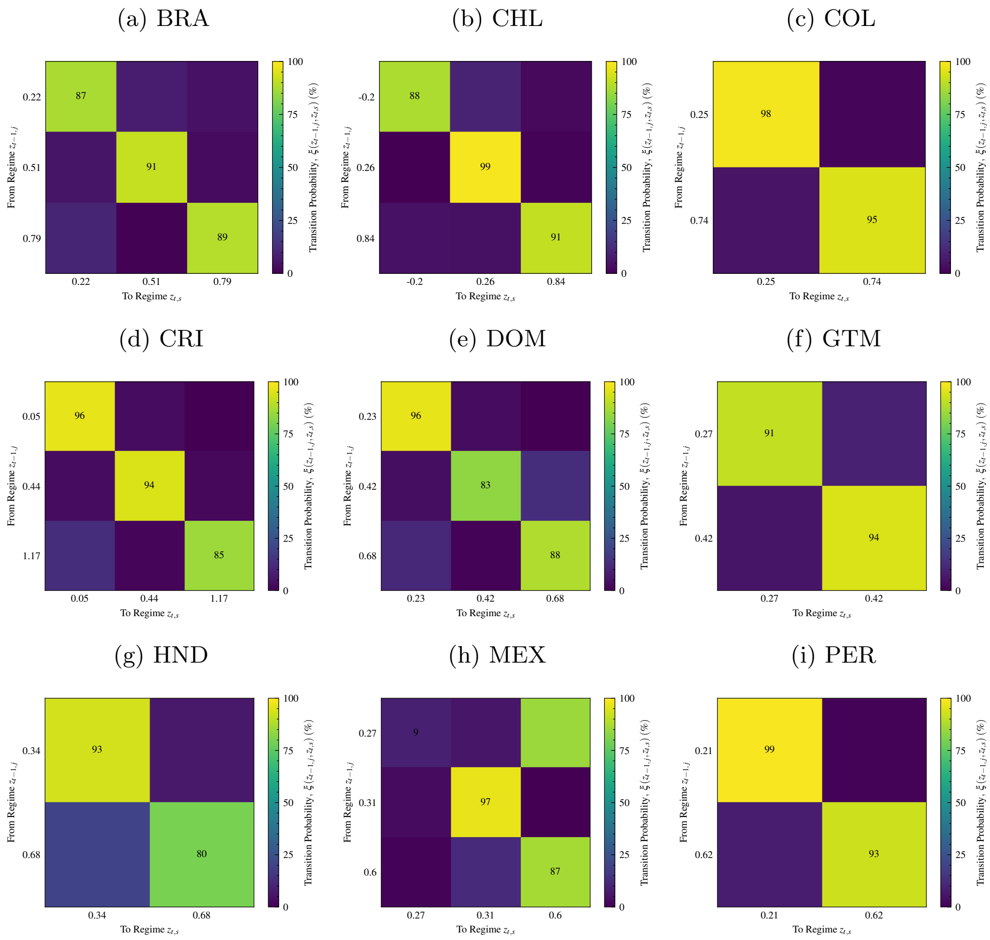


Fig. 2: Transition Probabilities (%), Model 1

Table 3: Transition Coefficient (%)

Cty.	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
BRA	89.43	95.02	93.78	97.92	93.66	92.74
CHL	96.85	94.69	97.93	97.92	98.17	98.17
COL	97.23	79.0	97.42	98.45	95.45	94.62
CRI	90.03	97.38	96.87	97.94	97.24	97.24
DOM	92.57	90.16	96.41	97.17	*nc*	-
GTM	93.1	95.98	95.85	96.9	95.41	-
HND	89.84	90.38	96.89	95.87	97.25	-
MEX	92.91	90.91	94.81	95.84	93.59	94.52
PER	97.78	51.2	95.49	97.92	97.28	*nc*

Note: *nc* represents that the model does not converge.

4.2 Inflation Drivers

The analysis reveals that monetary policy variables exhibit changing relative importance across different periods and countries, as pictured in Figure 3. Broad money emerges as a significant driver of inflation rates, particularly in Brazil, where it accounts for an average influence of approximately 30%. Similarly, its importance is notable in Chile, although to a lesser extent. The significance of broad money peaked following the financial crisis, indicating its heightened role in shaping inflation dynamics during economic turbulence. Furthermore, during the COVID-19 pandemic, broad money's importance surged, particularly in Costa Rica and Guatemala. The policy-related interest rate is also essential in driving inflation. Across all countries, the policy rate tends to represent nearly 40% of the relative importance in explaining inflation dynamics during periods of economic disruption. This highlights its role as a key monetary policy instrument in managing inflationary pressures and stabilizing the economy during turbulent times.

(a) $broad_t$, Model 3 (b) mpr_t, Model 3

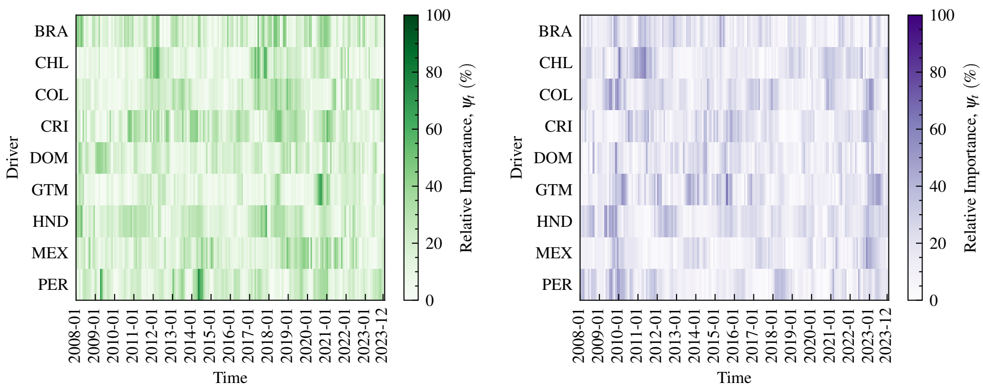
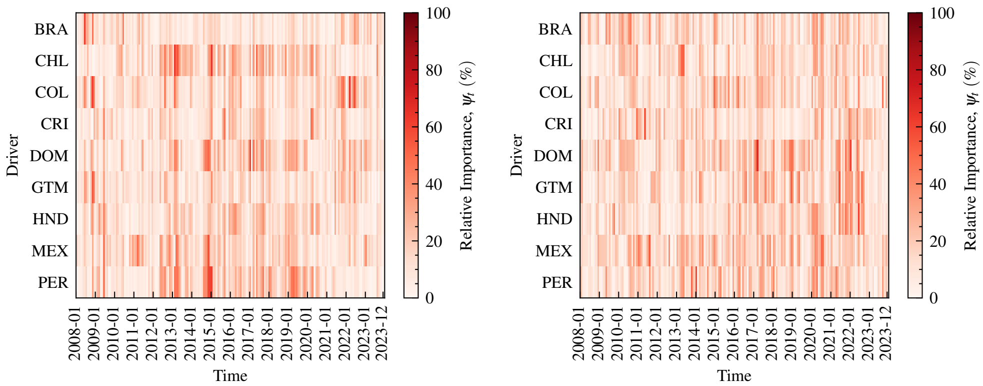


Fig. 3: Monetary Policy Drivers (2008M1-2023M12)

(a) cpi_t^*, Model 3 (b) $core_t^*$, Model 4



(c) er_t, Model 3

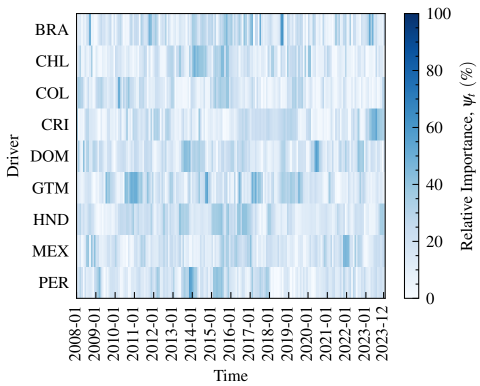


Fig. 4: International Drivers (2008M1-2023M12)

International factors, as displayed in Figure 4, are remarkably persistent and influential in driving inflation in several countries, notably Chile, the Dominican Republic, Mexico, and Peru. In these nations, international factors can represent up to 50%

of the relative importance in explaining inflation dynamics, highlighting the significant impact of global economic conditions on domestic price levels. When considering models with headline and core inflation measures, an interesting distinction emerges. While international headline inflation may exhibit higher relative importance in specific periods, the core measure demonstrates a more enduring and consistent effect as an inflation driver. Additionally, the exchange rate plays a crucial role in driving inflation in countries like Brazil and Costa Rica, with the latter experiencing a particularly pronounced effect in recent years, accounting for nearly half of the inflationary pressures in the last year alone. This underscores the increasing importance of exchange rate movements as a determinant of domestic price levels, especially in economies with significant exposure to international trade. Furthermore, the exchange rate's significance in driving inflationary dynamics is evident in Guatemala, particularly following the financial crisis, highlighting its role as a key transmission channel for external economic shocks to domestic price levels.

When considering demand-pull factors, private expenditure emerges as a dominant force, displaying the highest average relative importance among all models and variables analyzed. Figure 5 displays this, and the relevance is notable across models employing headline and core inflation measures, with the latter exhibiting even greater importance, reaching up to 60% in specific periods. Noteworthy is the pronounced impact of private expenditure during the COVID-19 pandemic, where nearly all countries demonstrate heightened relative importance of this variable. In Model 4, private consumption emerges as a substantial driver, contributing to nearly half of the inflationary pressures in Brazil and Chile before 2015 and Guatemala and Peru after 2015. In contrast, government consumption appears to reach significance primarily in Costa Rica following the financial crisis and in Chile during the COVID-19 pandemic. However, it consistently ranks as the variable with the lowest average relative importance across all models, suggesting a comparatively lesser role in driving inflationary pressures across the analyzed countries and periods.

Finally, in Model 5, inflation expectations emerge as a significant driver, particularly notable in Colombia and Costa Rica from 2017 to 2018. There is a noticeable peek in the expectations' importance across almost all countries in the final year of the analyzed period, suggesting an increasing influence on inflation dynamics as the post-pandemic period progresses. In Model 6, producer prices assume considerable importance, particularly in Peru[3] and Colombia. This driver maintains a consistently high importance level across all countries, contributing to nearly 20% of the overall inflation dynamics throughout the period, emphasing the critical role of producer prices in shaping consumer inflation outcomes across diverse countries. These results are available in Figure 6.

[3] Model 6 does not converge for Peru. For comparing the role of producer prices in this country, I run the model with less iterations than established.

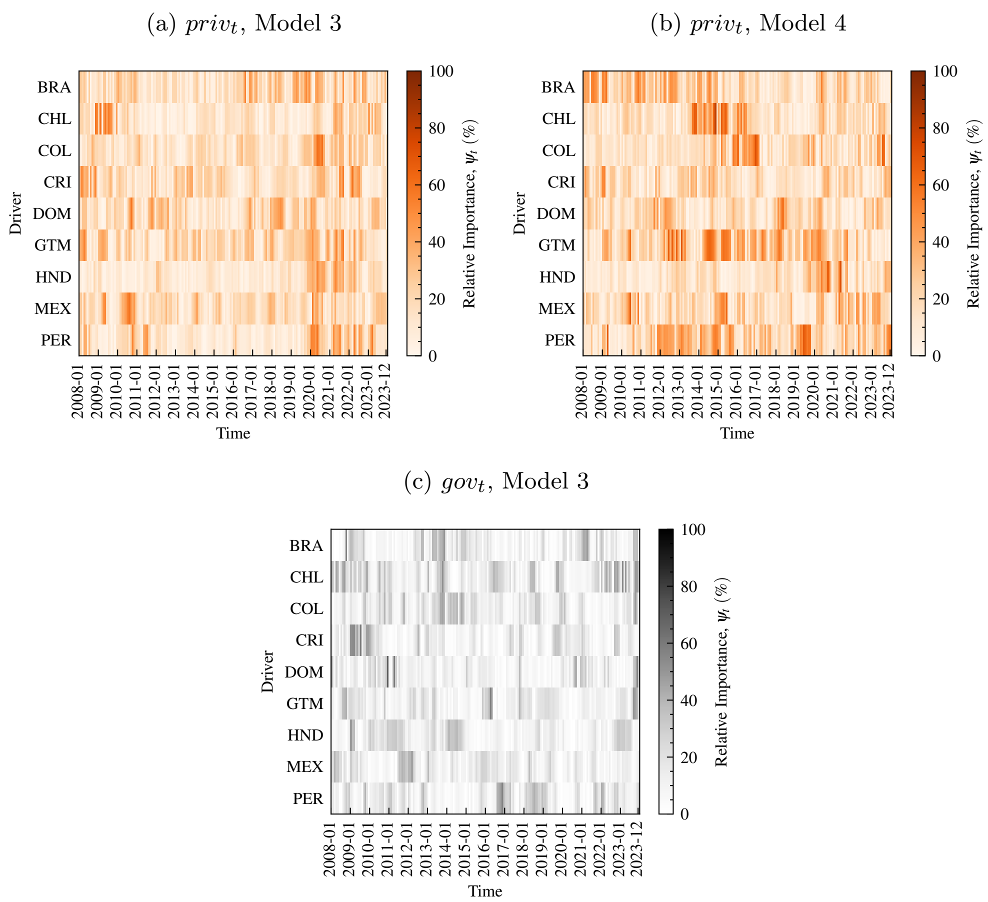


Fig. 5: Demand-Pull Drivers (2008M1-2023M12)

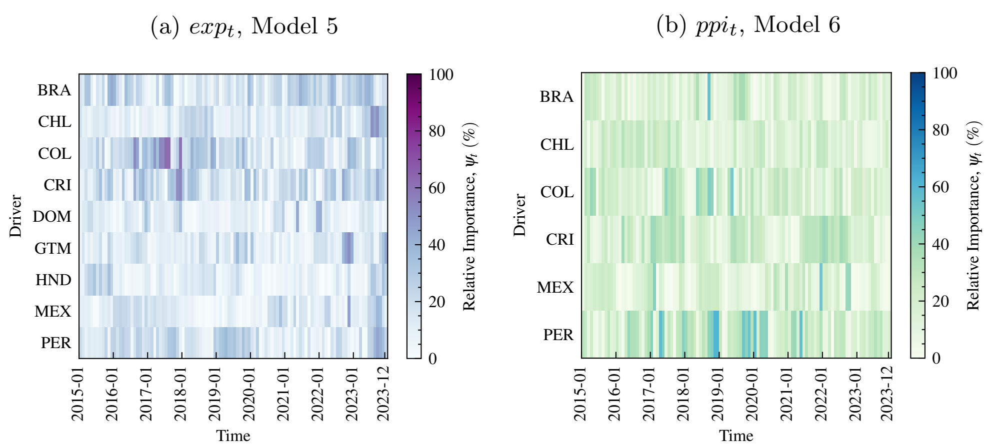


Fig. 6: Expectations and Cost-Push Drivers (2015M1-2023M12)

5 Conclusion

This study proposes and tests a framework for uncovering inflation regimes, their dynamics and persistence, and examine inflation drivers across nine Latin American countries from January 2008 to December 2023. I uncover inflation regimes and their persistence using a Multivariate Gaussian Hidden Markov Model (MGHMM) with variational Bayesian inference. Then, by employing a measure based on the Mahalanobis distance, I analyze the inflation's short- and medium-term drivers divided into five categories: monetary policy, international factors, demand-pull factors, expectations, and cost-push factors.

The variational inference approach offers flexibility in model selection compared to traditional criteria, preventing models from being confined to local minima. Regarding the Markov Model, the inflation regimes generally present high persistence across countries and models. On the effects of variables on inflation regimes, changes in broad money consistently coincide with higher inflation regimes in most countries. The policy-related interest rates demonstrate an inverse relationship with inflation, but only in Brazil, the Dominican Republic, Honduras, Mexico, Peru, and Costa Rica. International factors, such as inflation and exchange rates, also play crucial roles in driving domestic inflation dynamics, with notable impacts in Chile, the Dominican Republic, Mexico, and Peru. Demand-pull factors, including private and government expenditures, exhibit varying relationships across countries, with Guatemala and Honduras showing consistent direct relationships and Costa Rica displaying an inverse relationship between private consumption and inflation. Finally, inflation expectations and producer prices consistently influence positively consumer inflation rates across all countries.

Monetary policy instruments play a significant role with its impact peaking during periods of economic turbulence like the financial crisis and the COVID-19 pandemic. International factors exert a strong influence, particularly in Chile, the Dominican Republic, Mexico, and Peru, with both international inflation and exchange rates impacting domestic price levels. Private expenditure stands out as the dominant force among demand-pull factors, with its importance amplified during the pandemic. Finally, inflation expectations and producer prices consistently influence consumer inflation across all countries.

References

Boškoski, P., Perne, M., Rameša, M., Mileva-Boshkoska, B. (2021). Variational Bayes Survival Analysis for Unemployment Modelling. *Knowledge-Based Systems*, *229*, 107335, https://doi.org/10.1016/j.knosys.2021.107335

Briault, C. (1995). The Costs of Inflation. *Bank of England Quarterly Bulletin*, *35*(1), 33–45,

Gruhl, C., & Sick, B. (2016). *Variational Bayesian Inference for Hidden Markov Models With Multivariate Gaussian Output Distributions.*

Kinlaw, W., Kritzman, M., Metcalfe, M., Turkington, D. (2022). The Determinants of Inflation. *The Journal of Investment Management*, *21*(3), ,

Lucas, R.E. (1972). Expectations and the Neutrality of Money. *Journal of Economic Theory*, *4*(2), 103-124, https://doi.org/https://doi.org/10.1016/0022-0531(72)90142-1 Retrieved from https://www.sciencedirect.com/science/article/pii/0022053172901421

McGrory, C.A., & Titterington, D.M. (2009). Variational Bayesian Analysis for Hidden Markov Models. *Australian & New Zealand Journal of Statistics*, *51*(2), 227-244, https://doi.org/https://doi.org/10.1111/j.1467-842X.2009.00543.x

McLachlan, G. (1999). Mahalanobis Distance. *Resonance*, *4*, 20-26, https://doi.org/10.1007/BF02834632

Mishkin, F.S. (2009). Will Monetary Policy Become More of a Science? *Monetary policy over fifty years* (pp. 93–119). Routledge.

Romero-Aguilar, R. (2020). *Apuntes de Macroeconometría.*

Sánchez, G. (2023). *Inflation Regimes in Latin America, 2020-2022: Persistence, Determinants, and Dynamics.* Latin American Reserve Fund, FLAR.

Appendix A Multivariate Gaussian Hidden Markov Model (MGHMM)

Appendix for Section 2.1. Equations taken from Gruhl and Sick (2016).

A.1 Maximization Step

The Maximization Step is as follows

$$T_j = \sum_{t=1}^{T} \gamma(z_{t,j}) \tag{A1}$$

$$\bar{\boldsymbol{y}}_j = \frac{1}{T_j} \sum_{t=1}^{T} \gamma(z_{t,j}) \boldsymbol{y}_t \tag{A2}$$

$$\boldsymbol{S}_j = \frac{1}{T_j} \sum_{t=1}^{T} \gamma(z_{t,j}) (\boldsymbol{y}_t - \bar{\boldsymbol{y}}_j)' (\boldsymbol{y}_t - \bar{\boldsymbol{y}}_j) \tag{A3}$$

for $j \in \{1, ..., J\}$. The updated parameters are given by

$$\alpha_j = \alpha_j^{(0)} + T_j \tag{A4}$$

$$\alpha_{j,s} = \alpha_{j,s}^{(0)} + \sum_{t=1}^{T-1} \xi(z_{t,j}, z_{t+1,s}) \tag{A5}$$

$$\boldsymbol{m}_j = \frac{1}{\beta_j} (\beta_0 \boldsymbol{m}_0 + \bar{\boldsymbol{y}}_j T_j) \tag{A6}$$

$$\beta_j = \beta_0 + T_j \tag{A7}$$

$$\boldsymbol{W}_j^{-1} = \boldsymbol{W}_0^{-1} + T_j \boldsymbol{S}_j \tag{A8}$$

$$+ \frac{\beta_0 T_j}{\beta_0 + T_j} (\bar{\boldsymbol{y}}_j - \boldsymbol{m}_0)(\bar{\boldsymbol{y}}_j - \boldsymbol{m}_0)' \tag{A9}$$

$$\nu_j = \nu_0 + T_j \tag{A10}$$

$$\tag{A11}$$

for $j, s \in \{1, ..., J\}$.

Appendix B Descriptive

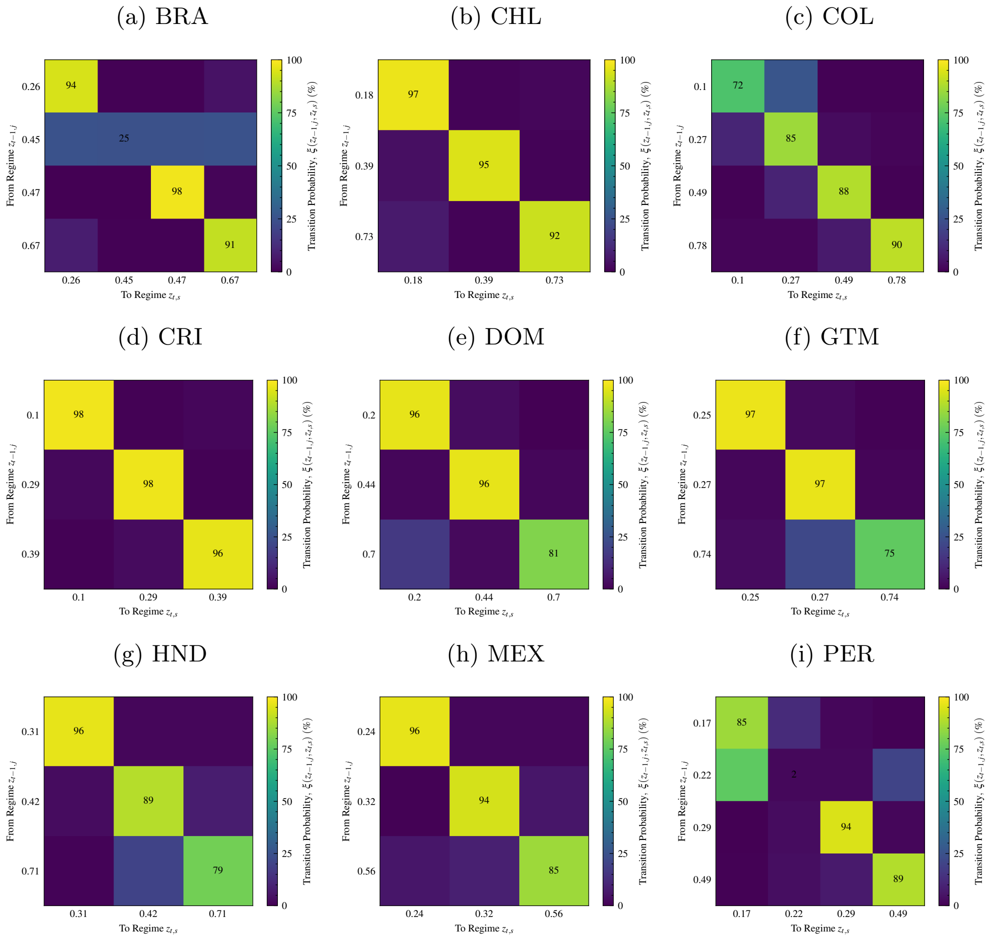


Fig. B1: Transition Probabilities (%), Model 2

Table B1: Descriptive Statistics

Cty.	Stat.	2008M1-2023M12									2015M1-2023M12										
		cpi_t	$core_t$	$broad_t$	mpr	cpi_t^*	$core_t^*$	er	$priv_t$	gov_t	cpi_t	$core_t$	$broad_t$	mpr	cpi_t^*	$core_t^*$	er	$priv_t$	gov_t	exp_t	ppi_t
	Mean	0.47	0.45	11.76	0.08	0.20	0.21	5.94	9.00	8.02	0.47	0.44	10.23	0.25	0.25	0.25	8.34	7.11	5.78	-0.19	10.75
	Std. Dev	0.32	0.24	3.46	3.43	0.33	0.15	16.97	4.36	4.29	0.4	0.29	3.18	3.91	0.3	0.18	17.5	4.88	4.05	3.77	17.43
BRA	Min	-0.53	-0.20	3.68	-6.75	-1.79	-0.20	-29.82	-9.31	-16.27	-0.53	-0.2	3.68	-6.75	-0.79	-0.2	-26.66	-9.31	-16.27	-8.73	-22.35
	50%	0.47	0.46	12.00	0.00	0.21	0.18	5.05	9.86	7.78	0.45	0.41	10.84	-0.25	0.23	0.2	4.58	6.2	5.95	0.16	9.47
	Max	1.50	1.36	19.33	9.25	1.24	0.76	53.12	19.94	17.01	1.5	1.36	17.21	9.25	1.24	0.76	53.12	19.94	12.5	7.24	50.87
	Mean	0.32	0.31	7.96	0.31	0.20	0.21	2.97	7.73	9.05	0.37	0.36	7.85	0.74	0.25	0.25	4.25	6.84	8.09	0.11	7.06
	Std. Dev	0.41	0.28	6.06	2.95	0.33	0.15	11.29	7.07	3.36	0.37	0.29	5.47	2.87	0.3	0.18	9.7	8.43	3.13	1.29	10.67
CHL	Min	-1.07	-0.27	-8.33	-7.75	-1.79	-0.20	-29.37	-20.07	-4.06	-0.4	-0.1	-4.1	-3	-0.79	-0.2	-16.85	-20.07	-4.06	-3.8	-9.48
	50%	0.27	0.26	7.89	0.00	0.21	0.18	3.21	7.68	8.98	0.28	0.26	7.51	0	0.23	0.2	4.76	6.06	8.2	0	4.73
	Max	1.66	1.23	21.22	9.25	1.24	0.76	30.13	35.01	18.18	1.66	1.23	21.22	9.25	1.24	0.76	22.5	35.01	13.98	3.8	34.41
	Mean	0.39	0.32	10.71	0.27	0.20	0.21	4.50	8.77	8.04	0.47	0.38	8.63	1.02	0.25	0.25	8.32	9.37	7.36	0.38	6.73
	Std. Dev	0.31	0.22	3.83	2.91	0.33	0.15	13.34	6.01	4.88	0.34	0.26	2.87	3.13	0.3	0.18	13.12	7.8	5.51	1.25	8.93
COL	Min	-0.29	-0.19	4.13	-6.50	-1.79	-0.20	-28.53	-16.07	-23.26	-0.29	-0.19	4.13	-3	-0.79	-0.2	-23.14	-16.07	-23.26	-2.12	-6.64
	50%	0.35	0.28	10.29	0.00	0.21	0.18	2.99	7.92	8.64	0.39	0.33	8.06	0.25	0.23	0.2	7.61	7.93	8.57	0	4.25
	Max	1.46	1.14	18.81	9.00	1.24	0.76	47.95	28.37	21.07	1.46	1.14	16.37	9	1.24	0.76	47.95	28.37	16.67	4.05	29.79
	Mean	0.29	0.24	6.95	0.09	0.20	0.21	0.31	7.21	8.51	0.15	0.14	4.6	0.25	0.25	0.25	0.04	5.62	4.23	-0.03	2.66
	Std. Dev	0.48	0.25	6.95	2.59	0.33	0.15	7.11	5.63	6.87	0.43	0.22	6	2.95	0.3	0.18	7.41	5.99	2.84	1.05	4.59
CRI	Min	-0.85	-0.45	-10.03	-4.00	-1.79	-0.20	-23.31	-11.92	-2.82	-0.85	-0.45	-10.03	-3.75	-0.79	-0.2	-23.31	-11.92	-2.82	-1.94	-4.4
	50%	0.22	0.21	5.64	-0.25	0.21	0.18	0.61	7.42	6.44	0.09	0.12	3.95	0	0.23	0.2	2.44	5.3	4.4	-0.19	1.71
	Max	1.86	1.22	25.86	8.25	1.24	0.76	14.71	18.73	32.28	1.7	0.94	20.45	8.25	1.24	0.76	10.74	16.57	14.03	2.8	15.42
	Mean	0.35	0.33	10.65	0.04	0.20	0.21	3.28	8.90	9.67	0.35	0.3	10.69	0.19	0.25	0.25	2.83	8.05	8.36	0.03	
	Std. Dev	0.56	0.22	3.59	1.97	0.33	0.15	3.17	4.50	9.67	0.41	0.18	3.95	1.69	0.3	0.18	3.96	4.48	10.2	1.25	
DOM	Min	-3.20	-0.07	2.67	-5.50	-1.79	-0.20	-7.13	-6.25	-52.43	-0.78	0.04	3.75	-2	-0.79	-0.2	-7.13	-6.25	-52.43	-2.92	
	50%	0.35	0.28	10.15	0.00	0.21	0.18	3.29	8.40	10.39	0.33	0.24	9.88	0	0.23	0.2	3.15	7.57	10.13	0.25	
	Max	2.10	1.42	21.01	5.25	1.24	0.76	13.66	19.40	43.92	1.73	0.82	21.01	5.25	1.24	0.76	13.66	17.62	24.21	2.47	
	Mean	0.36	0.29	8.73	-0.04	0.20	0.21	0.12	6.88	8.34	0.36	0.27	8.71	0.03	0.25	0.25	0.17	6.84	6.43	0.06	
	Std. Dev	0.42	0.20	2.44	1.08	0.33	0.15	2.98	4.66	6.24	0.43	0.15	2.95	1.06	0.3	0.18	2.11	4.39	5.96	0.81	
GTM	Min	-0.74	-0.43	4.57	-2.75	-1.79	-0.20	-5.79	-8.55	-16.80	-0.74	-0.43	4.57	-1.5	-0.79	-0.2	-5.11	-8.55	-16.8	-1.77	
	50%	0.31	0.26	8.37	0.00	0.21	0.18	-0.07	6.29	8.47	0.33	0.26	8.08	0	0.23	0.2	0.11	5.97	6.56	0.04	
	Max	1.59	1.17	16.79	3.25	1.24	0.76	10.83	19.09	35.00	1.59	0.65	16.79	3.25	1.24	0.76	5.52	18.24	19.03	2.1	
	Mean	0.43	0.44	9.95	-0.21	0.20	0.21	1.65	8.80	7.26	0.39	0.39	11.68	-0.44	0.25	0.25	1.75	8.96	7.49	0.01	
	Std. Dev	0.34	0.23	4.45	1.36	0.33	0.15	2.03	5.71	4.73	0.31	0.21	3.43	0.68	0.3	0.18	2.17	7.08	3.87	1.66	
HND	Min	-0.55	-0.36	-2.58	-5.00	-1.79	-0.20	-3.77	-16.76	-3.13	-0.55	-0.36	6.26	-2.75	-0.79	-0.2	-3.77	-16.76	1.85	-5.04	
	50%	0.37	0.39	10.00	0.00	0.21	0.18	1.52	8.62	6.26	0.34	0.35	10.98	0	0.23	0.2	2.08	9.11	6.26	0.06	
	Max	1.98	1.47	20.02	3.00	1.24	0.76	5.58	30.03	20.26	1.58	1.35	20.02	0.25	1.24	0.76	5.58	30.03	17.23	5.57	
	Mean	0.37	0.34	9.59	0.24	0.20	0.21	2.97	6.09	6.62	0.39	0.37	9.11	0.88	0.25	0.25	3.08	6.09	5.37	0.1	4.75
	Std. Dev	0.25	0.15	2.66	1.91	0.33	0.15	11.32	5.68	2.41	0.28	0.16	3.02	2.11	0.3	0.18	11.35	6.54	1.9	0.61	2.31
MEX	Min	-0.65	-0.13	2.47	-3.75	-1.79	-0.20	-20.08	-18.73	1.33	-0.65	-0.13	2.47	-3.5	-0.79	-0.2	-20.08	-18.73	1.33	-1.28	0.47
	50%	0.35	0.31	9.89	0.00	0.21	0.18	0.80	6.53	6.61	0.37	0.33	9.56	0.75	0.23	0.2	2.64	5.94	5.37	0	4.67
	Max	1.48	0.84	13.91	5.00	1.24	0.76	33.08	23.94	11.40	1.48	0.84	13.91	5	1.24	0.76	25.43	23.94	9.18	1.84	9.78
	Mean	0.29	0.28	13.30	0.18	0.20	0.21	1.12	7.55	8.68	0.31	0.29	8.95	0.42	0.25	0.25	3.01	6.05	7.25	0.11	3.16
	Std. Dev	0.27	0.15	10.20	2.07	0.33	0.15	6.37	5.97	7.32	0.29	0.16	8.07	2.06	0.3	0.18	5.89	7.22	7.46	0.97	3.96
PER	Min	-0.43	-0.14	-4.55	-5.25	-1.79	-0.20	-14.68	-24.93	-13.48	-0.43	0.04	-4.55	-2.5	-0.79	-0.2	-8.29	-24.93	-13.48	-1.74	-1.76
	50%	0.25	0.26	10.90	0.00	0.21	0.18	0.49	7.79	8.22	0.26	0.25	9.47	0	0.23	0.2	1.97	6.06	6.86	-0.06	1.68
	Max	1.12	0.71	43.00	6.00	1.24	0.76	14.58	30.55	45.57	1.12	0.71	29.41	6	1.24	0.76	14.58	30.55	29.97	2.75	13.05

Data retrieved from: International Monetary Fund (IMF), Latin American Reserve Fund (FLAR), Executive Secretariat of the Central American Monetary Council (SECMCA), Federal Reserve Economic Data (FRED), central banks.

Table B2: Regime Selection Criteria

Cty.	J	Model 1				Model 2				Model 3				Model 4				Model 5				Model 6	
		LB	LL	AIC	BIC	LB	LL	AIC	BIC	LB	LL	AIC	BIC	LB	LL	AIC	BIC	LB	LL	AIC	BIC	LB	LL
	1	114	-55	115	121	174	4	-4	2	-1954	-2888	5846	5960	-1695	-2639	5348	5462	-1444	-1860	3809	3927	-1815	-22
	2	124	-34	81	104	185	19	-25	-2	-1977	-2675	5497	5735	-1688	-2413	4973	5211	-1526	-1603	3388	3632	-1819	-19
BRA	3	130	-15	58	104	184	27	-26	20	-2067	-2539	5304	5672	-1729	-2420	5066	5434	-1556	-1435	3150	3525	-2178	-18
	4	130	-14	75	150	183	49	-51	24	-2005	-2549	5408	5913	-1794	-2093	4497	5002	-1569	-1446	3273	3786	-2492	-16
	5	123	-1	69	180	183	51	-35	76	-2174	-2278	4954	5602	-1874	-1984	4366	5014	-1985	-1236	2960	3614	-2809	-15
	1	69	-100	204	210	145	-25	54	60	-2106	-3035	6141	6255	-1821	-2760	5591	5705	-1313	-1738	3564	3682	-1643	-20
	2	94	-64	141	164	190	-21	57	80	-2067	-2906	5957	6195	-1746	-2493	5131	5369	-1277	-1411	3005	3249	-1624	-17
CHL	3	96	-49	127	172	195	36	-43	2	-2112	-2735	5697	6065	-1833	-2423	5072	5440	-1399	-1357	2994	3370	-1667	-18
	4	93	-64	174	249	189	48	-49	26	-2184	-2730	5769	6274	-1927	-2261	4833	5338	-1345	-1391	3165	3677	-1761	-15
	5	90	-43	154	265	190	42	-16	94	-2259	-2526	5451	6099	-1988	-2104	4607	5255	-1334	-1242	2971	3625	-1650	-14
	1	121	-48	101	107	187	18	-31	-25	-2005	-2938	5946	6060	-1723	-2666	5402	5516	-1245	-1675	3439	3557	-1531	-19
	2	177	19	-25	-2	244	86	-158	-135	-1950	-2770	5687	5925	-1601	-2339	4824	5062	-1245	-1508	3198	3442	-1643	-17
COL	3	176	29	-31	15	252	106	-184	-138	-1972	-2707	5640	6008	-1622	-2243	4711	5079	-1258	-1345	2971	3346	-1793	-14
	4	172	42	-38	37	253	105	-164	-89	-2116	-2397	5104	5608	-1750	-2159	4628	5133	-1259	-1349	3080	3593	-1751	-14
	5	168	44	-21	90	244	107	-146	-35	-2136	-2337	5073	5721	-1849	-2031	4460	5109	-1277	-1009	2505	3160	-1537	-14
	1	36	-133	270	276	166	-3	10	17	-2114	-3043	6156	6270	-1770	-2711	5492	5606	-1201	-1632	3353	3471	-1437	-18
	2	61	-96	206	229	208	50	-86	-64	-2066	-2749	5645	5883	-1705	-2388	4922	5159	-1506	-1405	2991	3235	-1960	-16
CRI	3	61	-95	218	264	229	82	-136	-91	-2067	-2586	5399	5767	-1717	-2315	4857	5225	-1826	-1308	2896	3272	-2300	-15
	4	56	-73	191	266	228	59	-72	3	-2153	-2446	5201	5706	-1761	-2134	4577	5082	-2206	-1213	2809	3321	-3241	-12
	5	53	-73	214	325	226	83	-99	12	-2238	-2219	4835	5483	-1753	-1887	4171	4820	-10326	-1014	2516	3170	-7e8	-12
	1	7	-162	328	335	190	21	-37	-31	-973	-2715	5500	5614	-782	-2396	4861	4975	*nc*	*nc*	*nc*	*nc*	-	-
	2	34	-123	261	283	258	100	-186	-163	-977	-2534	5213	5451	-786	-2220	4585	4823	*nc*	*nc*	*nc*	*nc*	-	-
DOM	3	37	-106	240	285	261	100	-172	-126	-973	-2523	5271	5639	-794	-2015	4256	4624	*nc*	*nc*	*nc*	*nc*	-	-
	4	33	-105	256	331	258	130	-214	-139	-1002	-2190	4690	5195	-1007	-1863	4036	4540	*nc*	*nc*	*nc*	*nc*	-	-
	5	26	-102	272	383	252	141	-213	-103	-980	-2283	4964	5612	-946	-1667	3732	4380	*nc*	*nc*	*nc*	*nc*	-	-
	1	63	-106	216	223	210	41	-77	-71	-1485	-2436	4943	5057	-1143	-2106	4281	4395	-987	-1435	2957	3075	-	-
	2	68	-90	193	216	255	78	-143	-120	-1475	-2217	4580	4818	-1042	-1774	3693	3931	-943	-1261	2704	2949	-	-
GTM	3	64	-80	188	233	261	113	-199	-153	-1640	-2119	4464	4832	-1117	-1741	3707	4075	-1116	-1089	2458	2833	-	-
	4	58	-86	219	294	256	114	-182	-108	-1766	-1951	4211	4716	-1320	-1633	3577	4082	-1307	-1021	2423	2936	-	-
	5	62	-63	193	304	254	118	-168	-58	-1719	-2104	4606	5254	-1472	-1490	3378	4026	-1245	-1115	2717	3372	-	-
	1	103	-67	137	144	181	11	-19	-12	-1517	-2467	5004	5118	-1268	-2226	4523	4637	-963	-1413	2914	3032	-	-
	2	127	-31	76	99	237	78	-143	-120	-1382	-2089	4324	4562	-1079	-2219	4583	4821	-919	-1088	2357	2601	-	-
HND	3	123	-25	78	123	240	84	-139	-94	-1417	-1935	4096	4464	-1107	-2014	4253	4621	-969	-928	2137	2512	-	-
	4	120	-20	86	161	236	88	-130	-55	-1444	-1846	4001	4506	-1109	-1475	3260	3765	-1046	-782	1946	2458	-	-
	5	119	-11	90	201	229	103	-137	-27	-1550	-1651	3698	4346	-1164	-1329	3057	3705	-1107	-798	2084	2738	-	-
	1	163	-6	16	23	258	88	-172	-166	-1643	-2589	5247	5361	-1343	-2299	4668	4782	-1024	-1435	2957	3075	-1200	-16
	2	169	7	-1	22	301	143	-271	-248	-1640	-2387	4920	5158	-1296	-2048	4242	4480	-1030	-1261	2704	2949	-1203	-14
MEX	3	170	13	2	48	301	150	-272	-227	-1689	-2225	4676	5044	-1302	-1833	3892	4260	-1120	-1089	2458	2833	-1534	-12
	4	167	28	-10	65	296	161	-277	-202	-1650	-2135	4581	5086	-1367	-1673	3657	4162	-1093	-1021	2423	2936	-1578	-10
	5	164	40	-12	99	295	156	-245	-134	-1781	-1928	4253	4901	-1389	-1641	3680	4328	-1214	-1115	2717	3372	-1946	-90
	1	147	-23	49	56	269	99	-194	-187	-2075	-3005	6081	6195	-1725	-2667	5405	5519	-1252	-1682	3451	3569	*nc*	*nc*
	2	167	6	3	25	304	99	-184	-161	-1987	-2655	5456	5694	-1580	-2312	4771	5008	-1195	-1354	2890	3134	*nc*	*nc*
PER	3	165	18	-8	37	320	174	-321	-275	-1971	-2566	5357	5725	-1677	-2254	4733	5101	-1461	-1219	2718	3093	*nc*	*nc*
	4	162	24	-2	73	322	176	-306	-231	-2138	-2469	5246	5751	-1699	-2037	4383	4888	-1341	-1043	2467	2980	*nc*	*nc*
	5	160	18	31	142	316	*nc*	*nc*	*nc*	-2090	-2502	5402	6050	-1712	-1863	4123	4772	-1259	-1045	2433	3087	*nc*	*nc*

Note: For the models whose lower bound suggest $J^* = 1$, I choose to take either $J^* = 2$ or $J^* = 3$. This is done to obtain the expected value of the variables conditional on the regimes.

Note: nc represents that the model does not converge.

Table B3: Conditional Expected Value, Models 1-4 (2008M1-2023M12)

Cty.	j	Model 1	Model 2	Model 3							Model 4						
		cpi_t	$core_t$	cpi_t	$broad_t$	mpr_t	cpi^*_t	er_t	$priv_t$	gov_t	$core_t$	$broad_t$	mpr_t	er_t	$core^*_t$	$priv_t$	gov_t
BRA	1	0.22	0.26	0.43	8.72	1.01	0.28	5.23	9.02	7.6	0.44	11.68	-0.65	7.66	0.16	8.45	8.34
	2	0.51	0.45	0.43	13.48	0.01	0.23	-10.73	10.13	8.52	0.55	12.22	3.94	-3.07	0.46	11.85	6.36
	3	0.79	0.47	0.54	13.02	-0.67	0.1	19.98	8.07	7.99							
	4		0.67														
CHL	1	-0.2	0.18	0.26	8.02	-0.25	0.14	4.46	6.4	8.27	0.25	8.13	0.11	3.02	0.17	7.25	8.29
	2	0.26	0.39	0.39	7.89	1	0.27	1.14	9.38	10.02	0.43	7.67	0.67	2.9	0.28	8.58	10.37
	3	0.84	0.73														
COL	1	0.25	0.1	0.34	10.54	-0.04	0.17	3.22	7.8	8.3	0.29	10.69	-0.18	3.17	0.16	7.75	8.26
	2	0.74	0.27	0.58	11.34	1.4	0.29	9.27	12.37	7.08	0.43	10.78	1.93	9.5	0.38	12.59	7.21
	3		0.49														
	4		0.78														
CRI	1	0.05	0.1	0.14	2.04	-0.02	0.19	-2.56	7.14	6.5	0.19	4.13	-0.05	-1.43	0.18	7.27	7.12
	2	0.44	0.29	0.47	12.76	0.22	0.21	3.7	7.31	10.87	0.38	14.43	0.46	4.93	0.27	7.06	12.18
	3	1.17	0.39														
DOM	1	0.23	0.2	0.32	9.31	0.52	0.25	1.62	9.19	10.7	0.2	9.4	-0.74	3.27	0.15	8.2	9.99
	2	0.42	0.44	0.35	10.69	0.19	0.25	2.83	8.05	8.36	0.33	10.65	0.04	3.28	0.21	8.9	9.67
	3	0.68	0.7	0.48	16.51	-1.22	0.22	7.94	3.23	-1.59	0.44	11.69	0.7	3.3	0.26	9.48	9.4
GTM	1	0.27	0.25	0.31	7.9	-0.25	0.14	-0.19	5.79	5.47	0.26	8.01	-0.16	-0.35	0.16	6.16	6.16
	2	0.42	0.27	0.42	9.68	0.19	0.27	0.46	8.11	11.58	0.33	9.85	0.13	0.84	0.28	7.99	11.69
	3		0.74														
HND	1	0.34	0.31	0.36	8.86	-0.41	0.15	2.27	7.98	5.28	0.37	8.87	-0.39	2.25	0.15	8.01	5.43
	2	0.68	0.42	0.55	11.92	0.16	0.28	0.53	10.27	10.84	0.57	11.99	0.13	0.52	0.3	10.27	10.7
	3		0.71														
MEX	1	0.27	0.24	0.33	9.11	0.94	0.17	1.13	6.16	5.82	0.3	10.87	-0.84	5.17	0.15	4.54	8.16
	2	0.31	0.32	0.42	10.18	-0.59	0.23	5.16	6.01	7.58	0.38	8.26	1.37	0.67	0.26	7.71	5.02
	3	0.6	0.56														
PER	1	0.21	0.17	0.23	8.94	-0.25	0.13	3.48	6.23	6.22	0.28	14.95	0.23	1.2	0.16	8.1	7.91
	2	0.62	0.22	0.23	19.07	-0.06	0.21	-3.58	9.41	10.72	0.29	9.95	0.07	0.95	0.29	6.43	10.24
	3		0.29	0.45	11.46	1.06	0.27	4.2	6.84	9.24							
	4		0.49														

Table B4: Conditional Expected Value, Models 5 & 6 (2015M1-2023M12)

Cty.	j	Model 5								Model 6								
		cpi_t	$broad_t$	mpr_t	cpi_t^*	er_t	$priv_t$	gov_t	exp_t	cpi_t	$broad_t$	mpr_t	cpi_t^*	er_t	$priv_t$	gov_t	exp_t	ppi_t
BRA	1	0.33	6.86	-2.57	0.15	6.51	6.05	4.78	-1.28	0.28	9.18	-1.44	0.23	-4.34	6.76	4	-4.03	-5.14
	2	0.5	11.89	3.03	0.41	-5.73	10.75	6.89	-0.27	0.54	10.03	-0.43	0.13	21.77	4.34	5.59	0.97	14.59
	3	0.61	11.95	-0.13	0.15	28.97	3.55	5.47	1.17	0.67	12.81	5.31	0.6	-1.91	15	9.75	4.26	31.7
CHL	1	0.25	5.17	-0.18	0.15	3.75	6.06	8.82	-0.03	0.25	5.17	-0.18	0.15	3.75	6.06	8.82	-0.03	3.05
	2	0.51	10.63	1.69	0.35	4.77	7.65	7.34	0.25	0.51	10.63	1.69	0.35	4.77	7.65	7.34	0.25	11.22
COL	1	0.41	7.36	0.81	0.16	7.71	7.73	7.67	0.05	0.29	7.83	-0.18	0.18	2.51	5.37	6.97	-0.32	1.91
	2	0.57	10.84	1.38	0.4	9.38	12.24	6.81	0.96	0.64	9.77	2.27	0.12	24.92	9.48	7.07	1.01	5.34
	3									0.83	9.74	3.15	0.56	8.13	20.57	8.72	1.73	21.75
CRI	1	-0.13	-1.4	2.5	0.22	-13.02	6.65	2.15	0.44	-0.11	-1.51	1.73	0.2	-14.21	5.94	2.46	0.31	-0.38
	2	0.2	5.7	-0.16	0.25	2.42	5.43	4.61	-0.12	0.19	5.57	0.02	0.26	2.28	5.57	4.51	-0.08	3.15
DOM	1	*nc*								-								
GTM	1	0.32	7.38	-0.04	0.15	0.14	5.71	4.37	-0.02	-								
	2	0.41	10.2	0.11	0.35	0.21	8.12	8.73	0.15									
HND	1	0.32	11.17	-0.25	0.16	2.83	8.48	5.79	-0.63	-								
	2	0.48	12.43	-0.72	0.38	0.2	9.65	9.93	0.91									
MEX	1	0.34	11.72	-0.18	0.15	14.07	2.82	5.6	-0.01	0.29	11.79	-0.3	0.13	14.2	2.43	5.83	-0.06	4.49
	2	0.42	7.38	1.6	0.32	-4.26	8.27	5.21	0.18	0.44	7.46	1.62	0.32	-3.77	8.35	5.09	0.2	4.9
PER	1	0.3	18.82	-1.24	0.27	6.23	2.7	11.95	-0.09	*nc*								
	2	0.31	6.33	0.86	0.24	2.15	6.94	6.01	0.17									

Note: *nc* represents that the model does not converge.