**PONTIFICIA UNIVERSIDAD**
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# Impact of Monetary Policy Shocks in the Peruvian Economy Over Time

Tesis para obtener el título profesional de Licenciado en Economía presentado por:

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Abstract

We investigate the evolution of the impact of monetary policy (MP) shocks in Peru in 1996Q1-2018Q2 using a set of time-varying parameter vector autoregressive models with stochastic volatility (TVP-VAR-SV), as proposed by Chan and Eisenstat (2018). The main results are: (i) the volatilities, intercepts, and contemporaneous coefficients change more gradually than VAR coefficients over time; (ii) the volatility of MP shocks falls from 4% to 0.3% on average during the Inflation Targeting (IT) regime; (iii) in the long run, a contractionary MP shock decreases both gross domestic product (GDP) growth and inflation by 0.28% and 0.1%, respectively; (iv) the interest rate reacts faster to aggregate supply shocks than to both aggregate demand shocks and exchange rate shocks; (v) under the pre-IT regime, MP shocks explain almost 20%, 10%, and 85% of the uncertainty in GDP growth, inflation, and the interest rate, respectively; and under the IT regime, all these percentages shrink to 1-2%. The sensitivity analysis confirms the robustness of the main results across various prior specifications, measures of external and domestic variables, and recursive identifications. In general, the results show that MP has contributed to diminishing macroeconomic volatility in Peru.

Keywords: Time-Varying Parameter VAR, Stochastic Volatility, Marginal Likelihood, Deviance Information Criterion, Monetary Policy, Peru.

Contents Index

## 1 Introduction

Papers like Primiceri (2005), Canova et al. (2007), and Nakajima (2011) analyze the time-varying impact of monetary policy (MP) shocks on inflation, unemployment, and GDP growth in developed economies. However, there is still a gap in the literature for emerging market economies (EMEs). The analysis of these economies is complex, as external shocks are the main source of uncertainty (see, for instance, Drechsel and Tenreyro (2018), Fernández et al. (2018), Ojeda Cunya and Rodríguez (2022), Chávez and Rodríguez (2023), and Rodríguez et al. (2023b)). Research suggests that the potential of MP for stabilizing macroeconomic dynamics increases as it strengthens its impact on domestic variables and its reaction to external shocks. This article discusses the evolving impact of MP shocks on inflation and GDP growth, as well as the MP response to various shocks in Peru.

Peru is a unique case among EMEs, as it has experienced numerous reforms over the past three decades. Until the 1980s, the Peruvian economy experienced high uncertainty due to hyperinflation and a debt crisis. In the early 1990s, the Fujimori administration introduced a stabilization program, deregulated markets, and reduced government involvement in the economy. Price controls were abandoned, capital markets were liberalized, and the FX market was unified. The Central Reserve Bank of Peru (BCRP) was constitutionally granted operational independence, thus putting an end to inflationary fiscal financing. Since then, MP design and implementation have undergone many changes. Initially, to address hyperinflation, price stability was considered the BCRP's sole objective, with the monetary base as the operative instrument, while interest rates and the exchange rate were freely determined by the market.

However, the Asian-Russian crisis led to a dollar outflow, a credit crunch, and deflation, which lasted until 2001. The correlation between the monetary base and inflation also declined, weakening the monetary aggregate regime. As a result, the BCRP adopted an Inflation Targeting (IT) regime in January 2002, with a 1.5%-3.5% target band to anchor inflation expectations and the BCRP's current accounts as the operational instrument. To improve MP signaling, the BCRP introduced a reference interest rate as the primary instrument in September 2003. Since then, various alternative tools, such as FX swaps and reverse repos, have been implemented. In February 2007, the BCRP adjusted the target band to 1%-3%, aiming to increase flexibility in addressing adverse shocks and aligning domestic inflation with that of major developed economies.

These modifications in the instruments lead to potential changes in the transmission of MP shocks, which can be modeled using Time-Varying Parameter Vector Autoregression (TVP-VAR) models, as detailed by Cogley and Sargent (2001) and Boivin and Giannoni (2006). Additionally, some literature suggests that macroeconomic variable volatilities change over time (e.g., Sims and Zha (2006) and Benati (2008)). For instance, during episodes like the Global Financial Crisis (GFC) and the Gulf War, foreign variables such as the S&P GSCI and export price indices typically reach peak local volatility. These changes in the volatility influence MP design, as policymakers assess how to mitigate the impact of diverse shocks on the business cycle. While there are several options for modeling heteroscedasticity in VAR models, the literature mostly agrees that stochastic volatility (SV) outperforms alternative specifications (e.g., Clark (2011) and Clark and Ravazzolo (2015)). Consequently, we employ VAR models that incorporate both TVP and SV, known as TVP-VAR-SV models.

This paper analyzes six recursively identified variables for the period 1996Q1-2018Q2: S&P GSCI growth, exchange rate growth, GDP growth, inflation, money growth, and interest rate. The results indicate that all volatilities and most parameters change over time. Notably, the volatilities of aggregate demand (AD), aggregate supply (AS), money supply (MS), and MP shocks decrease after IT adoption, while the volatilities of external and exchange rate (ER) shocks decline after the GFC. Moreover, we estimate that a 1% increase in MP shocks reduces GDP growth and inflation by a maximum of 0.28% and 0.1%, respectively. The interest rate impulse response functions (IRFs) confirm the BCRP's anti-inflationary bias, as reactions to AS shocks are stronger than to AD shocks. Forecast error variance decompositions (FEVDs) reveal that MP shocks are only relevant during the pre-IT regime, while external shocks are the primary driver for much of the sample. Similarly, historical decompositions (HDs) show that MP shocks are only relevant during the pre-IT regime.

The paper is organized as follows: Section 2 summarizes the empirical literature that uses TVP-VAR-SV models to study the effect of MP shocks on domestic variables. Section 3 presents the TVP-VAR-SV model and its variants, as proposed by Chan and Eisenstat (2018). Section 4 describes the data and hyperparameters and discusses the empirical results. Section 5 examines robustness exercises. Section 6 concludes.

## 2 Literature Review

Since Sims (1980), VAR models have been widely used to analyze the impact of MP shocks. For example, Gordon and Leeper (1994), Bernanke and Mihov (1998), and Christiano et al. (1999) discuss the use of VAR models to analyze MP transmission mechanisms. Although these papers vary in their identification strategies for MP shocks, the results generally indicate that an increase in such shocks diminishes both GDP and prices, with the latter typically reacting with a lag. Moreover, these articles assume that parameters and volatilities are time-invariant; however, given that economic series continuously change and their interrelations evolve, this assumption might be inappropriate. Consequently, macroeconometric literature has addressed this gap by proposing models that assume changes in transmission mechanisms, involving modifications in parameters and volatilities.

One of the first papers to empirically analyze the time-varying dynamics between interest rates, inflation, and the unemployment rate in the US was Cogley and Sargent (2001). They proposed a TVP-VAR model with short-run restrictions and found that the response of interest rates to AS shocks increased during the 1990s, coinciding with greater Fed activism. However, Sims (2001) and Stock (2001) emphasize that homoscedastic variance overestimates time-varying parameters. Using similar data, Cogley and Sargent (2005) employed a TVP-VAR-SV model and demonstrated that the reaction of interest rates to AS shocks increased over time and that the volatilities of interest rates and inflation were time-varying, reaching a peak in the 1980s, coinciding with the beginning of a new MP regime in the US.

Primiceri (2005) extended Cogley and Sargent (2005) by incorporating changes in the matrix of contemporary effects and showed that a contractionary MP shock reduced inflation and increased unemployment in the long run, but these effects were time-invariant. Specifically, a 1% increase in the interest rate reduced inflation by 0.1% in the long run. In contrast, he found that the response of the interest rate to inflation and unemployment shocks increased over time. Finally, he discovered that interest rate volatility explained high-inflation and unemployment episodes during the 1970s.

Using a multivariate regime-switching model, Sims and Zha (2006) analyzed the dynamics between a commodity price index, M2, the Fed funds rate, real GDP, the Consumer Price Index (CPI), and the unemployment rate from 1959M1 to 2003M3. They found that the best fit was achieved assuming constant coefficients but changing variances; however, considering changing coefficients, three MP regimes were identified, one of which showed that MP reduced inflation in the early 1980s. Furthermore, they estimated that a 1% contractionary MP shock reduced GDP by 0.1%, but this shock did not have a statistically significant effect on inflation.

Imposing sign restrictions on the methodology proposed by Primiceri (2005), Canova et al. (2007) study the time-varying dynamics between GDP growth, inflation, the interest rate, and a monetary aggregate for the US, the Eurozone, and the UK from 1959Q1 to 2004Q4. For the US and the Eurozone, they find that the volatility of MP shocks explains 36% and 25% of the volatility of GDP growth and inflation, respectively; for the UK, these percentages are around 11%. Moreover, Canova et al. (2007) estimate that MP shocks have a time-varying impact on inflation for all economies. In a similar vein, Benati (2008) models the macroeconomic dynamics in the UK and argues that the parameters of the interest rate equation change over time, allowing the identification of several MP regimes; and calculates that MP shocks have a time-varying impact on inflation, GDP growth, and money.

Using a mixture innovation approach to estimate whether, where, when, and how parameters change, Koop et al. (2009) study the time-varying dynamics between the interest rate, inflation, and the unemployment rate from 1953Q1 to 2006Q2. The authors show that MP shocks have a time-varying effect on unemployment and inflation. For instance, they estimate a price puzzle in 1975, in a context of high inflation and interest rates; and show that a 1% contractionary MP shock reduced inflation by 0.02% as a minimum in 2006.

For Japan, Nakajima (2011) incorporates the interest rate zero-lower bound and finds that GDP growth and inflation are invariant to MP shocks during periods when the interest rate reaches the zero lower bound. For the Czech Republic, Franta et al. (2013) use sign restrictions and estimate that MP shocks have a time-varying effect on GDP and the CPI. Specifically, at the beginning of the sample, a 1% MP shock diminishes GDP and the CPI by 2.5% and 1%, respectively. In contrast, by the end of the sample these percentages fall to 1.5% and 0.7%, respectively.

For Malaysia from 1981Q1 to 2010Q4, Bittencourt et al. (2016) emphasize that the financial liberalization of 1987 generated a theoretically consistent reaction of inflation to MP shocks. For instance, in 2010, a 1% increase in the interest rate reduces inflation by 0.3%, while in 1986, inflation is invariant. For China from 1996M1 to 2014M12, Wu and Wei (2016) calculate that the response of inflation to MP shocks varies over time and by instrument; i.e., interest rate shocks have a higher impact on inflation than monetary aggregate shocks.

Based on their analysis of the US interest rate, GDP growth, and inflation from 1954Q3 to 2014Q4, Chan and Eisenstat (2018) estimate a set of TVP-VAR-SV models and compare their performance using two Bayesian criteria: the deviance information criterion (DIC) and the log marginal likelihood (Log-ML). Both criteria suggest that incorporating SV improves the fit. As a result, the authors noted a trend of drifting volatilities for all shocks over time, a phenomenon they identified as the Great Moderation, evidenced by a decrease in interest rate and inflation volatilities during the 1980s. Additionally, they find that the impact of MP shocks on GDP growth and inflation varies over time. For example, the benchmark TVP-VAR-SV model indicates that a 1% increase in the interest rate would reduce inflation and GDP growth by 0.03% and 0.35%, respectively, as a minimum.

In Peru, most research has focused on the effect of MP shocks on various macroeconomic variables, primarily utilizing static VAR models. For instance, Quispe (2000) examined the influence of different monetary aggregates (such as the monetary base and banknotes), the interest rate, and the exchange rate on inflation from 1980 to 1998. He concludes that banknotes account for 30% of the inflation variance in the long term, and a 1% MP shock (based on banknotes) would decrease inflation by 0.5% after one year. In a subsequent study, Quispe (2001) expands the range of monetary aggregates and deduces that the monetary base explains 30% of the inflation variance, and a 1% MP shock (based on the monetary base) would reduce inflation by 0.38% after one year. Rossini and Vega (2007), considering various degrees of FX intervention, balance sheet effects, and competitiveness effects, analyzed the impact of MP shocks on GDP growth and inflation. They found that the effect of the interest rate on inflation increased under high FX intervention, while under low FX intervention, the impact of the interest rate on GDP growth was amplified. Furthermore, they showed that the influence of MP shocks on inflation declined when the balance sheet effect outweighed the competitiveness effect.

Bigio and Salas (2006) made the first attempt to model the time-varying dynamics between the interest rate, the real exchange rate, the output gap, and inflation from 1994 to 2004, using a Smooth Transition Vector Autoregressive (STR-VAR) model. They noted that the effects of MP shocks on the output gap and inflation fluctuated over time, with these variables responding more significantly during recessions and booms, respectively. On the other hand, the first study to employ TVP-VAR-SV models, following Primiceri (2005), was conducted by Castillo et al. (2016). The researchers found that MP shocks introduced instability to GDP growth and inflation during the 1980s. Furthermore, under the IT regime, they observed the MP response to AS and AD shocks varied over time. Other studies, such as Portilla et al. (2022), following the methodology of Koop et al. (2009), demonstrated that: (i) an MP shock reduces GDP growth in the short term and inflation in the long term; (ii) the interest rate reacts more swiftly to AS shocks than to AD shocks, and (iii) during the pre-IT regime, MP shocks were a significant driver of GDP growth and inflation.

Our research diverges from the existing Peruvian literature in two respects. Firstly, much of the existing literature focuses on a single monetary variable. For instance, Castillo et al. (2016) utilized M1, while Portilla et al. (2022) focused on the interest rate. Our approach, however, incorporates multiple monetary variables such as the exchange rate, money, and the interest rate, which may enhance the identification of MP shocks. Moreover, many studies neglect the relationship between MP and exchange rate shocks, a crucial aspect in the formulation of the MP, as outlined by Arena and Tuesta (1999), Rossini et al. (2013, 2014), and Rodriguez et al. (2021). For example, Alvarado et al. (2023) consider a monetary aggregate and the interest rate but disregard the exchange rate. Secondly, our analysis of MP marks the first attempt to compare the fit of several TVP-VAR-SV models.

## 3 Methodology

This Section describes the models and some details of the estimation algorithm, and presents the computation of the Log-ML and the DIC.

### 3.1 The TVP-VAR-SV Model

The model in structural form is as follows:

$$\mathbf{B}_{0,t}\mathbf{y}_t = \boldsymbol{\mu}_t + \sum_{j=1}^{p} \mathbf{B}_{j,t}\mathbf{y}_{t-j} + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_t), \tag{1}$$

where $\mathbf{y}_t$ is an $n\times 1$ vector of endogenous variables, $\boldsymbol{\mu}_t$ is an $n\times 1$ vector of time-varying intercepts, $\mathbf{B}_{j,t}$ is an $n\times n$ matrix of time-varying coefficients associated with the $j$-th lag of the vector of endogenous variables, $\mathbf{B}_{0,t}$ is the $n \times n$ lower triangular matrix of contemporary coefficients with diagonal unit values, $\boldsymbol{\Sigma}_t = diag(\exp(\mathbf{h}_{1t}), ..., \exp(\mathbf{h}_{nt}))$, and $\mathbf{h}_t = (\mathbf{h}_{1t}, ..., \mathbf{h}_{nt})'$. The logs of all variables $\mathbf{h}_t = (\mathrm{h}_{1,t}, \ldots, \mathrm{h}_{n,t})$ follow an independent random walk:

$$\mathbf{h}_t = \mathbf{h}_{t-1} + \boldsymbol{\zeta}_t, \quad \boldsymbol{\zeta}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_h), \tag{2}$$

where $\boldsymbol{\Sigma}_h = diag(\sigma^2_{h_1}, ..., \sigma^2_{h_n})$, and the initial conditions $\mathbf{h}_0 \sim \mathcal{N}(\mathbf{a}_h, \mathbf{V}_h)$ must be estimated. Equation (1) can be rewritten as:

$$\mathbf{y}_t = \widetilde{\mathbf{X}}_t\boldsymbol{\beta}_t + \mathbf{W}_t\boldsymbol{\gamma}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_t),$$

where $\widetilde{\mathbf{X}}_t = \mathbf{I}_n \otimes (1, \mathbf{y}'_{t-1}, \ldots, \mathbf{y}'_{t-p})$, $\boldsymbol{\beta}_t = vec((\boldsymbol{\mu}_t, \mathbf{B}_{1,t}, ..., \mathbf{B}_{p,t})')$ is a $k_\beta \times 1$ vector of time-varying intercepts and coefficients associated with the lagged observations, $\mathbf{W}_t$ is an $n\times k_\gamma$ matrix that contains the appropiate elements of $-\mathbf{y}_t$[1] and $\boldsymbol{\gamma}_t = (\gamma_{1,t}, \gamma_{2,t}, \gamma_{3,t}, ..., \gamma_{k_\gamma,t})'$ is a $k_\gamma \times 1$ vector of time-varying coefficients that characterize contemporaneous relationships among variables. It is important to specify that $k_\beta = n(np+1)$ and $k_\gamma = n(n-1)/2$. Considering $\mathbf{X}_t = (\widetilde{\mathbf{X}}_t, \mathbf{W}_t)$, the model can be simplified in the following state-space representation:

$$\mathbf{y}_t = \mathbf{X}_t\boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_t), \tag{3}$$

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_\theta),$$

where $\boldsymbol{\theta}_t = (\boldsymbol{\beta}'_t, \boldsymbol{\gamma}')'$ has a $k_\theta = k_\beta + k_\gamma$ dimension, the initial conditions $\boldsymbol{\theta}_0 \sim \mathcal{N}(\mathbf{a}_\theta, \mathbf{V}_\theta)$

[1] For instance, when $n = 3$, $\mathbf{W}_t = \begin{bmatrix} 0 & 0 & 0 \\ -y_{1,t} & 0 & 0 \\ 0 & -y_{1,t} & -y_{2,t} \end{bmatrix}$ where $y_{i,t}$ is the $i$-th element of $\mathbf{y}_t$ for $i = 1, 2$.

must be estimated, and $\mathbf{\Sigma}_\theta = diag(\sigma^2_{\theta_1}, ..., \sigma^2_{\theta_k})$. Moreover, we consider that the elements $\mathbf{\Sigma}_\theta$ of $\mathbf{\Sigma}_h$ are independently distributed as $\sigma^2_{\theta_i} \sim \mathcal{IG}(\nu_{\theta_i}, S_{\theta_i})$ for $i = 1, ..., k_\theta$ and $\sigma^2_{h_j} \sim \mathcal{IG}(\nu_{h_j}, S_{h_j})$ for $j = 1, ..., k_h$.

### 3.2 Competing Models

We estimate six additional models restricting different sets of parameters from the general TVP-VAR-SV model in (1): (i) a TVP-VAR model that considers homoscedastic variance ($\mathbf{h}_t = \mathbf{h}_0$); (ii) a CVAR-SV model, where only the variances are time-varying; (iii) a TVP-VAR-R1-SV model that assumes constant parameters for the intercepts and the lagged variables ($\boldsymbol{\beta}_t = \boldsymbol{\beta}_0$); (iv) a TVP-VAR-R2-SV model that considers constant coefficients for the contemporaneous relations ($\gamma_t = \gamma_0$); (v) a TVP-VAR-R3-SV model that assumes that only the intercepts and variances are time-varying; and (vi) a CVAR model that keeps everything constant.

### 3.3 Estimation Algorithm: Gibbs-Sampling[2]

We use the Gibbs sampling method in order to estimate the posterior parameters. This algorithm divides the parameters in blocks and estimates each one separately, conditional on updates in the other blocks. The draws are based on the precision sampling proposed by Chan and Jeliazkov (2009) and improved by Chan and Eisenstat (2018). The algorithm for estimating the TVP-VAR-SV model is as follows: (i) we get draws of $\boldsymbol{\theta}$ from $(\boldsymbol{\theta}|\mathbf{y}, \mathbf{h}, \mathbf{\Sigma}_\theta, \mathbf{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{N}\left(\widehat{\boldsymbol{\theta}}, \mathbf{K}_\theta^{-1}\right)$, where $\widehat{\boldsymbol{\theta}} = \mathbf{K}_\theta^{-1}\left(\mathbf{H}_\theta'\mathbf{S}_\theta^{-1}\mathbf{H}_\theta\boldsymbol{\alpha}_\theta + \mathbf{X}'\mathbf{\Sigma}^{-1}\mathbf{y}\right)$ and $\mathbf{K}_\theta = \mathbf{H}_\theta'\mathbf{S}_\theta^{-1}\mathbf{H}_\theta + \mathbf{X}'\mathbf{\Sigma}^{-1}\mathbf{X}$ with $\boldsymbol{\alpha}_\theta = \mathbf{H}_\theta^{-1}\widetilde{\boldsymbol{\alpha}}_\theta$ (the matrices $\mathbf{H}_\theta$, $\mathbf{X}$, $\mathbf{S}_\theta$, $\mathbf{\Sigma}$ and $\widetilde{\boldsymbol{\alpha}}_\theta$ are described in Appendix A of Chan and Eisenstat (2018)); (ii) for the draws of $(\mathbf{h}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{\Sigma}_\theta, \mathbf{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0)$, the auxiliary mixture sampler of Kim et al. (1998) is used; (iii) we obtain draws of $\sigma^2_{\theta_i}$ from $\left(\sigma^2_{\theta_i}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0\right) \sim \mathcal{IG}\left(\nu_{\theta_i} + \frac{T}{2}, S_{\theta_i} + \frac{1}{2}\sum_{t=1}^{T}(\theta_{i,t} - \theta_{i,t-1})^2\right)$ for $i = 1, ..., k_\theta$; (iv) we obtain draws of $\sigma^2_{h_j}$ from $\left(\sigma^2_{h_j}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0\right) \sim \mathcal{IG}\left(\nu_{h_j} + \frac{T}{2}, S_{h_j} + \frac{1}{2}\sum_{t=1}^{T}(h_{j,t} - h_{j,t-1})^2\right)$ for $j = 1, ..., k_h$; (v) we sample draws of $\boldsymbol{\theta}_0$ from $(\boldsymbol{\theta}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \mathbf{\Sigma}_\theta, \mathbf{\Sigma}_h) \sim \mathcal{N}(\widehat{\boldsymbol{\theta}}_0, \mathbf{K}_{\boldsymbol{\theta}_0}^{-1})$, where $\mathbf{K}_{\boldsymbol{\theta}_0} = \mathbf{V}_\theta^{-1} + \mathbf{\Sigma}_\theta^{-1}$ and $\widehat{\boldsymbol{\theta}}_0 = \mathbf{K}_{\boldsymbol{\theta}_0}^{-1}(\mathbf{V}_\theta^{-1}\mathbf{a}_\theta + \mathbf{\Sigma}_\theta^{-1}\boldsymbol{\theta}_1)$; (vi) we obtain draws of $\mathbf{h}_0$ from $(\mathbf{h}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \mathbf{\Sigma}_\theta, \mathbf{\Sigma}_h) \sim \mathcal{N}(\widehat{\mathbf{h}}_0, \mathbf{K}_{\boldsymbol{h}_0}^{-1})$, where $\mathbf{K}_{\mathbf{h}_0} = \mathbf{V}_\mathbf{h}^{-1} + \mathbf{\Sigma}_\mathbf{h}^{-1}$ and $\widehat{\mathbf{h}}_0 = \mathbf{K}_{\mathbf{h}_0}^{-1}(\mathbf{V}_\mathbf{h}^{-1}\mathbf{a}_h + \mathbf{\Sigma}_\mathbf{h}^{-1}\boldsymbol{h}_1)$; and (vii) steps (i)-(vi) are repeated N times. Moreover, $\mathbf{a}_\theta$, $\mathbf{V}_\theta$, $\mathbf{a}_h$, $\mathbf{V}_\mathbf{h}$, $\nu_{\theta_i}$, $\nu_{h_j}$, $S_{\theta_i}$ and $S_{h_j}$ are defined in Section 4.2.

### 3.4 Bayesian Model Comparison

This Section describes the Log-ML and the DIC used to select the best model.

[2]Complete details about the algorithm for estimating the TVP-VAR-SV model and the competing models are detailed in Section 4 and Appendix A of Chan and Eisenstat (2018).

### 3.4.1 Log Marginal Likelihood (Log-ML)[3]

Based on the importance sampling density $g^* = g(\boldsymbol{\theta}_n)$ and the cross-entropy method, Chan and Eisenstat (2015) propose the following estimator for the marginal likelihood:

$$\widehat{p}_{IS}(\mathbf{y}) = \frac{1}{N}\sum_{n=1}^{N}\frac{p(\mathbf{y}|\boldsymbol{\theta}_n)p(\boldsymbol{\theta}_n)}{g^*}, \tag{4}$$

where $\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_N$ are the independent draws of $g^*$. On one hand, regardless the value of $g^*$, the estimator $\widehat{p}_{IS}(\mathbf{y})$ is consistent and unbiased, however, its variance depends on $g^*$. On the other hand, using the posterior density for $g^*$, $\widehat{p}_{IS}(\mathbf{y})$ is equivalent to $p(\mathbf{y})$, but $g^* = p(\boldsymbol{\theta}|\mathbf{y})$ causes endogenity since it depends on $p(\mathbf{y})$. Therefore, using the cross-entropy method, we must select $g$ near to $g^*$ so that the variance of $\widehat{p}_{IS}(\mathbf{y})$ is minimized.

Considering the parametric family $F = \{f(\boldsymbol{\theta}; \mathbf{v})\}$ indexed by $\mathbf{v}$, we calculate the importance sampling $f(\boldsymbol{\theta}; \mathbf{v}) \in F$ near to $g^*$ using the density $f(\boldsymbol{\theta}; \mathbf{v}^*_{ce}) \in F$ that cuts down the cross-entropy distance between $g^*$ and the chosen density $f(\boldsymbol{\theta}; \mathbf{v})$ as follows:

$$\mathbf{v}^*_{ce} = \arg\min\left(\int g^*(\boldsymbol{\theta})\log g^*(\boldsymbol{\theta})\mathbf{d}\boldsymbol{\theta} - p(\mathbf{y})^{-1}\int p(\mathbf{y}|\boldsymbol{\theta})p(\boldsymbol{\theta})\log f(\boldsymbol{\theta}; \mathbf{v})\mathbf{d}\boldsymbol{\theta}\right), \tag{5}$$

that can be simplified to:

$$\hat{\mathbf{v}}^*_{ce} = \arg\max_{\mathbf{v}} \frac{1}{L}\sum_{l=1}^{L}\log f(\boldsymbol{\theta}_l; \mathbf{v}), \tag{6}$$

where $\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_L$ are the posterior draws.

### 3.4.2 Deviance Information Criterion (DIC)

The Deviance Information Criterion (DIC), proposed by Spiegelhalter et al. (2002), ponderates both the fit and the complexity of a model. On one hand, we consider the deviance ($D(\boldsymbol{\theta})$) as a measure of the goodness of fit of the model, which is defined as Chan and Grant (2016) as follows:

$$D(\boldsymbol{\theta}) = -2\log f(\mathbf{y}|\boldsymbol{\theta}) + 2\log h(\mathbf{y}), \tag{7}$$

where $f(\mathbf{y}|\boldsymbol{\theta})$ is the likelihood function of the model and $h(\mathbf{y})$ is a function of the data. Moreover, we consider the effective number of parameters($p_D$) as a measure of the complexity of the model:

[3] Complete details are described in Section 4 and Appendix B of Chan and Eisenstat (2018).

$$p_D = \overline{D(\boldsymbol{\theta})} - D(\widetilde{\boldsymbol{\theta}}),$$

where $\overline{D(\boldsymbol{\theta})} = -2\mathbf{E}_{\boldsymbol{\theta}}[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2\log h(\mathbf{y})$ is the posterior mean deviance and $\widetilde{\boldsymbol{\theta}}$ is an estimate of $\boldsymbol{\theta}$. Therefore, the DIC is the sum of the posterior mean deviance and the effective number of parameters: $DIC = \overline{D(\boldsymbol{\theta})} + p_D$. Considering $h(\mathbf{y}) = 1$, we obtain:

$$DIC = -4E_{\boldsymbol{\theta}}[\log f(\mathbf{y}|\boldsymbol{\theta})] + 2\log f(\mathbf{y}|\widetilde{\boldsymbol{\theta}}), \tag{8}$$

where $-4E_{\boldsymbol{\theta}}[\log f(\mathbf{y}|\boldsymbol{\theta})]$ contains the average of the log of $f(\mathbf{y}|\boldsymbol{\theta})$ over the posterior draws of $\boldsymbol{\theta}$.

## 4 Empirical Evidence

This Section first introduces the data, moves onto the priors, and finally delves into the empirical results. The analysis encompasses the evolution of the estimated parameters, the volatility of exogenous shocks, the IRFs of MP shocks, the FEVDs, and the variables' HD.

### 4.1 Data

We use six variables for the period 1996Q1-2018Q2: S&P GSCI growth (Annex 5a), nominal exchange rate growth (Annex 5b), real GDP growth (Annex 5c), inflation rate (Annex 5d), money growth[4] (Annex 5e), and the interest rate (Annex 5f). The data is sourced from the BCRP website, except for the S&P GSCI, which was obtained from Bloomberg. All variables are expressed as year-on-year percent changes, except for the interest rate. The latter is a combination of the interbank interest rate (until 2003Q3) and the reference interest rate (2003Q4-2018Q2). Until 2009, S&P GSCI growth averages 20%; during the GFC it falls to a low of -43%; and after 2010, it averages almost 1%. The behavior of this variable aligns with EMEs' higher and lower growth before and after the GFC, respectively. Exchange rate growth exhibits a negative trend before the GFC and a positive trend after 2010. This variable increases during both the Asian-Russian crisis and the GFC but reaches a peak during the former. Inflation and GDP growth are less volatile under the IT regime. Specifically, before 2002, inflation is in the double digits; after 2002, it ranges between 1% and 3%. Regarding money growth, it displays a positive trend until 2009, but later a negative trend, stabilizing at the end of the sample. Prior to the IT regime, the interest rate averages double digits; however, under the IT regime, it averages around 3%. The high digits before the IT regime are initially attributable to the financial instability that occurred during the Asian-Russian crisis but persisted for several years.

### 4.2 Priors

In the baseline TVP-VAR-SV model, we set $\mathbf{a}_\theta = 0$, $\mathbf{V}_\theta = 10 \times \mathbf{I}_{k_\theta}$, $\mathbf{a}_h = 0$, $\mathbf{V}_h = 10 \times \mathbf{I}_n$ and $\nu_{\theta_i} = \nu_{h_j} = 5$. Moreover, we fix $S_{\theta_i}$ and $S_{h_j}$ so that the initial means of $\sigma^2_{\theta_i}$ and $\sigma^2_{h_j}$ are $0.01^2$ and $0.1^2$, respectively.

### 4.3 Empirical Results

For the estimations, $p = 2$ is selected based on the BIC for a CVAR model. We perform 11000 draws for all models in 10 parallel chains, discarding the initial 1000.

[4] We use BCRP-issued banknotes held by the private sector as a proxy for the money supply, as proposed by Quispe (1998) and León Fernández (1999).

This leaves 100000 draws, from which we select one out of every 10, resulting in a total of 10000 draws used to estimate the DIC and the Log-ML.

Structural shocks are identified as follows: an external shock for the S&P GSCI growth equation; an ER shock for the nominal exchange rate growth equation; an AD shock for the GDP growth equation; an AS shock for the inflation equation; an MS shock for the money growth equation; and an MP shock for the interest rate equation[5].

### 4.3.1 Evidence on Parameter Evolution

To analyze potential changes in parameters and volatilities over time, we employ the trace test proposed by Cogley and Sargent (2005), the Kolmogorov-Smirnov test (KS-test), and the t-test. The trace test assesses whether the prior trace of $\Sigma_h$ differs statistically from the median posterior trace of $\Sigma_h$. The KS-test analyzes whether, at two different times, each parameter and volatility are drawn from the same continuous distribution, while the t-test evaluates whether, at two different times, the mean of each parameter and volatility originates from the same Normal distribution. We consider two comparison groups for the latter two tests: (i) 1996Q3-2002Q1 vs 2002Q2-2018Q2; and (ii) 1996Q3-2007Q2 vs 2007Q3-2018Q2.

Annex 1 displays the results of these three tests for $\gamma_t$, $\boldsymbol{\beta}_t$, and $\mathbf{h}_t$ in the TVP-VAR-SV model. Firstly, all elements of $\mathbf{h}_t$ change over time. The trace test shows that the trace of the posterior median of $\Sigma_h$ is statistically significant but small. Specifically, at 84% confidence, this trace is between 0.17% and 0.34%. Both the KS-test and the t-test show that all elements of $\mathbf{h}_t$ vary over time for both comparison groups. Secondly, under the KS-test and the t-test, all elements of $\gamma_t$ change over time in both comparison groups. Thirdly, most elements of $\boldsymbol{\beta}_t$ change, although more conclusively for the second comparison group. According to the KS-test, 72% of the components of $\boldsymbol{\beta}_t$ change for the first group, while 81% of the elements of $\boldsymbol{\beta}_t$ vary for the second group. In sum, these results suggest that all volatilities and most of the parameters change over time.

### 4.3.2 Model Comparison

Annex 2 shows both the mean and the standard deviation of the Log-ML and the DIC for all models detailed in Sections 3.1 and 3.2. According to the Log-ML, we select the TVP-VAR-R1-SV and TVP-VAR-R3-SV models as their results are similar, whereas according to the DIC, the CVAR-SV model is selected. Specifically, the Bayes Factor (BF) of the TVP-VAR-R1-SV model against the TVP-VAR-R3-SV model is $2.85$,

[5]Under the pre-IT regime, an MP shock was associated with the monetary base (1995-2001) and the banks' current accounts with the BCRP (2002-2003). However, for the purposes of this study, we assume an MP shock is associated with the interest rate for the entire sample period, as argued by Portilla et al. (2022).

reinforcing the results obtained from the KS-test and t-test that all elements of $\gamma_t$ might vary over time. Both criteria indicate that SV improves fit as all five SV models are in the top five spots. For instance, the BF of the TVP-VAR-SV model, which is the least effective SV model according to both criteria, against the TVP-VAR model is $1.06 \times 10^{32}$, demonstrating that including SV considerably enhances fit. Moreover, fit is reduced by assuming time-varying parameters for the lagged variables; e.g., the BF of the TVP-VAR-R3-SV model against the TVP-VAR-R2-SV model is $5.24 \times 10^{6}$. In addition, with respect to both criteria, the CVAR model is in the last spot, which shows that assuming all parameters and variances are constant sharply reduces the fit; e.g., the BF of the TVP-VAR-SV model against the CVAR model is $1.09 \times 10^{34}$.

#### 4.3.3 Volatility of Exogenous Shocks

Annex 5 illustrates the posterior median of the volatilities of all shocks for all models. Mainly, SV models show that all volatilities change over time following similar patterns. Firstly, the volatilities of AD, AS, MS, and MP shocks decline after IT adoption in 2002. Explicitly, during the pre-IT regime, the average volatility of MP shocks was 4%, while during the IT regime, this average was almost 0.3%. Similarly, the volatility of AD shocks drops from 1.9% on average before IT adoption to 1.2% during the IT regime. Conversely, the volatilities of external and ER shocks increase until the GFC, after which both decrease. Therefore, these results could suggest that even though volatility in the commodity market increased in the 2000s, IT adoption reduced the volatility of domestic structural shocks and, consequently, macroeconomic volatility in Peru. These findings align with Castillo et al. (2009), who argue that the adoption of the reference interest rate as the operative instrument reduced risk, and with Castillo et al. (2016), who estimate that the volatilities of AD and AS shocks fell since the 1990s.

Secondly, the volatilities of AD and MP shocks reach their maximum during the Asian-Russian crisis, while the volatilities of external, ER, and MP shocks peaked during the GFC. In these two crises, Peru experienced sudden stops and severe contractions in external variables (e.g., the S&P GSCI declined by 25% and 45% during the Asian-Russian crisis and the GFC, respectively). The volatility of MP shocks increases during both crises, but less so during the GFC, corresponding to different ex-ante and ex-post policies, such as the buildup of net international reserves (NIR), according to Velarde (2015), Rossini (2016), and Castillo and Barco (2009). In particular, the NIR/GDP ratio was 17% at the onset of the Asian-Russian crisis, so the BCRP could not provide adequate FX liquidity to mitigate the exchange rate depreciation and had to raise the interbank interest rate by almost 20 p.p. Conversely, during the GFC, the NIR/GDP ratio was 24%, so the BCRP could inject a sufficient FX amount and had to adjust the reference interest rate by just around 5 p.p.

Thirdly, external and ER shocks follow similar patterns that differ from the rest of the shocks. Among all shocks, the volatility of external shocks is the highest. Between 2002 and 2011, this volatility shows a positive trend explained by the commodity price boom, which consisted of an increasing growth rate of commodity prices and, consequently, in EMEs' activity (see Mendoza (2013) for further details for Peru). In addition, this volatility captures the uncertainty caused by the GFC, reaching its maximum of 19% on average across SV models[6]. Later, from 2011 onwards, this volatility displays a negative trend due to the end of the commodity supercycle. Meanwhile, leading up to the GFC, the volatility of ER shocks had been escalating due to heightened terms of trade, growing capital inflows, and the entry of non-residents into the Peruvian financial market in 2005, which increased the number of participants in the FX market and its volatility. After the GFC, this volatility follows a negative trend, which might be explained by an improvement in the BCRP's identification of pressures in the FX market and, consequently, its intervention in this market. For example, in periods of uncertainty, non-resident investors sought to hedge by purchasing dollars in the spot market, which increased the volatility of the exchange rate. Therefore, in 2014 the BCRP incorporated exchange rate swaps as an alternative hedging instrument.

The constant volatilities of the CVAR and TVP-VAR models respectively underestimate and overestimate those predicted by the SV models. These models fail to capture the effects of crises. For instance, during the GFC, the CVAR model estimates a constant volatility of 15%, nearly 6 p.p. lower than that estimated by SV models. Additionally, they do not accurately estimate the effects under the IT regime; e.g., the TVP-VAR model posits that the volatility of the interest rate was 1.8% in the early 2000s, thereby overlooking the gains of anchoring expectations.

From this point forward, we focus on the results of four models: TVP-VAR-R3-SV, TVP-VAR-R1-SV, CVAR-SV, and CVAR, the latter included for comparison purposes.

#### 4.3.4 Impulse Response Functions (IRFs)

This Section discusses the IRFs to MP shocks on GDP growth and inflation, along with the IRFs to external, ER, AD, and AS shocks on the interest rate. The IRFs are normalized to unity for the entire sample.

Annex 7 provides a 3D plot presenting the posterior medians of the IRFs of GDP growth and inflation for the four selected models. Both GDP growth and inflation decrease in response to a contractionary MP shock. GDP growth reacts more rapidly, reaching maximum contraction after four quarters, while inflation falls after three quarters and attains its minimum level after six quarters. These results align with those obtained by Rossini and Vega (2007), who estimate that GDP growth reaches its maximum contraction after four quarters, and Quispe (2000), who demonstrates that infla-

[6] Excluding this crisis, the average volatility for SV models is 14%.

tion hits its lowest level after five quarters. On average, all models estimate that GDP growth falls by a maximum of 0.28 p.p., which contrasts with Pérez Forero's (2015) estimate of 0.15 p.p., while inflation falls by a maximum of 0.10 p.p. The differential responses might be due to the presence of sticky prices, which reduce the impact of MP shocks on prices.

Moreover, while the IRFs of the TVP-VAR-R3-SV and CVAR-SV models are time-invariant, the TVP-VAR-R1-SV model reveals that the effect of MP shocks on GDP growth and inflation can change over time. On one hand, GDP growth reacts more robustly during recessions (the Asian-Russian crisis and the GFC), suggesting the presence of a convex supply curve, as explained by Bigio and Salas (2006). Conversely, inflation responds more vigorously when situated at the upper limit of the inflation target band. For instance, in 2006, when the average inflation was 2%, inflation decreased by a maximum of 0.02 p.p.; in 2008, when the average inflation was 2.75%, inflation declined by a maximum of 0.13 p.p.

Annex 8 presents the posterior medians of the sample and the 68% confidence bands of the IRFs to an MP shock on GDP growth and inflation. All models estimate that GDP growth declines for five quarters following the initial shock, potentially due to the year-long pass-through effect of the reference interest rate into market interest rates, as argued by Lahura (2006, 2017). On average, only the TVP-VAR-R1-SV model calculates that inflation diminishes, which might be due to this model presenting the lowest short-run price puzzle among all models, occurring only after four quarters.

Annex 9 depicts the posterior medians of the IRFs to an MP shock on GDP growth and inflation in the four previously selected models at four time periods[7]: 1998Q3, 2003Q4, 2009Q3, and 2018Q2. All models estimate that GDP growth and inflation decrease, with the TVP-VAR-R1-SV model showing both variables diminishing more under the IT regime. This could be because the signaling of MP improved under the IT regime, as explained by Rossini and Vega (2007), and that the pass-through effect of the reference interest rate into market interest rates increased. For example, during the GFC, inflation decreased by a maximum of 0.12 p.p.; however, during the Asian-Russian crisis, inflation fell by a maximum of 0.08 p.p.

Annex 10 plots the interest rate's response to external, ER, AD, and AS shocks at four different points in time: 1998Q3, 2003Q4, 2009Q3, and 2018Q2. In all models, the interest rate rises in response to AS shocks, peaking after two quarters. Additionally, SV models estimate that the interest rate escalates in response to AD shocks, presenting its highest response after four quarters. Specifically, reactions to AS shocks are stronger than responses to AD shocks, as in Portilla et al. (2022). This provides ev-

[7] 1998Q3 and 2009Q3 are the quarters of highest volatility during the Asian-Russian crisis and the GFC, respectively; while 2003Q4 and 2018Q2 represent the introduction of the reference interest rate and the end of the sample, respectively.

idence of the BCRP's anti-inflationary bias, which involves immediately mitigating the direct effects on inflation to anchor inflation expectations. Furthermore, this bias has intensified over time, as the interest rate's response to AS shocks strengthens. For instance, a 1% AS shock increases the interest rate by a maximum of 0.4% p.p. in 2009Q3, whereas, in 2018Q2, the interest rate rises by a maximum of 1.2 p.p.

Regarding external shocks, the interest rate's IRF varies between models and over time. Dancourt (2013) and Quispe et al. (2017) suggest that the interest rate rises because this shock boosts GDP growth and, consequently, inflation. However, only the TVP-VAR-R1-SV model supports this outcome. Conversely, TVP-VAR-R3-SV and CVAR models posit that the interest rate falls to mitigate the capital inflows that continuously appreciate the exchange rate and cause deflation. These two models also estimate that the reaction to external shocks increases over time, demonstrating a stronger counter-cyclical response of the BCRP to foreign factors.

Concerning ER shocks, all models indicate that the interest rate rises. This result aligns with the BCRP's mandate, which involves reducing excessive exchange rate volatility that can negatively affect economic agents' balance sheets, as explained by Castillo et al. (2011). Additionally, the interest rate's response to ER shocks intensifies over time. For instance, a 1% ER shock increases the interest rate by an average of 0.2 p.p. on average in 2009Q3, compared with 1 p.p. on average in 2018Q2. These results contradict Rodriguez et al. (2023a), who find that the interest rate does not respond to variations in the exchange rate. However, this discrepancy might be explained by the omission of FX reserves in our model. Despite this, we also find that during the IT regime, the reaction to fluctuations in the exchange rate increases.

#### 4.3.5 Forecast Error Variance Decomposition (FEVD)

Annex 11 illustrates the FEVD of GDP growth, inflation, and the interest rate over two different horizons: two ($h = 2$) and twenty ($h = 20$) quarters.

Regarding the FEVD of GDP growth, AD shocks serve as the primary source of uncertainty until 2003, when external shocks take over as the main determinant, increasing their dominance over longer horizons. This outcome aligns with Mendoza (2013), Rodriguez et al. (2018) and Rodríguez et al. (2023b), who argue that increased trade openness since 2003 and the commodity supercycle account for the significant share of external shocks in the FEVD of GDP growth. These shocks explain 50% of the FEVD of GDP growth on average. MP shocks are only relevant during the pre-IT regime, which aligns with the arguments of Rossini and Vega (2007) and Portilla et al. (2022) that these shocks became more predictable after the adoption of the interest rate as the operative instrument. The MP shocks peaked during the Asian-Russian crisis, when the BCRP unexpectedly raised the policy rate to prevent a sudden stop, as detailed by Velarde and Rodriguez (2001). In contrast, MP shocks made a minor contribution during the GFC due to the BCRP providing more liquidity to banks and intervening in the FX market. Moreover, in the long run, the share of most shocks increases, as calculated by Bringas and Tuesta (1997).

In terms of the FEVD of inflation, external and AS shocks are the most influential. Specifically, they account for approximately 85% of the FEVD on average, given that external shocks are the main source of uncertainty after 2003. Contrary to what is observed in the FEVD of GDP growth, MP shocks present a smaller share in the FEVD of inflation, which could be related to the existence of sticky prices in Peru. Furthermore, ER shocks contribute an average of 12%, which does not provide sufficient evidence of an exchange rate pass-through effect on prices in Peru, as explained by Winkelried (2003, 2012). The MS shocks become relevant over longer horizons, with their share increasing from 4% to 20% in the TPV-VAR-R3-SV model, which might indicate the existence of monetary inflation in Peru. Over longer horizons, AS and MP shocks present lower and higher shares, respectively.

In the case of the FEVD of the interest rate, MP shocks are the most significant during the pre-IT regime, as they explain almost 85% of the FEVD. However, this percentage surges to 95% during the Asian-Russian crisis because of the increase in the interbank interest rate by 19.7 p.p. in 1998. In the IT regime, external and ER shocks are the primary determinants of the FEVD of the interest rate. On one hand, external shocks have the highest share, which could suggest the high impact of these shocks on a small open commodity-exporting economy like Peru. On the other hand, the relevant share of ER shocks is due to the BCRP's intensive response to mitigate its adverse effect on the money market, as detailed by Castillo et al. (2011). During the GFC, the share of MP shocks rises, but it is lower than what was observed during the Asian-Russian crisis, since the BCRP reacted more efficiently by injecting greater liquidity via reverse repos, as detailed by Dancourt and Jiménez (2010). Over longer horizons, the participation of ER, AS, and MS shocks increases, while the participation of MP shocks decreases.

#### 4.3.6 Historical Decomposition (HD)

Annex 12 shows the HD for GDP growth, inflation, and interest rate. The HD of GDP growth shows that between the pre-IT regime (1996-2001) and the commodity price boom (2002-2011), this variable increased from 2.3% to 6.2%. All models estimate that this 3.9-p.p. increase was primarily determined by MP and ER shocks. For instance, the CVAR-SV model calculates that MP shocks explained 1.5 p.p. (around 39% of the increase), whereas ER shocks contributed 1 p.p. (around 25% of the increase).

Between the commodity price boom (2002-2011) and the following years (2012-2018), the HD of GDP growth indicates that this variable decreased by 2.2 p.p. and most models consider that ER shocks are the main cause. For example, the TVP-

VAR-R1-SV model shows that these shocks explained -0.7 p.p. (almost 34% of the decrease), while external and MS shocks contributed -0.55 p.p. (around 28% of the decrease) and -0.51 p.p. (around 26% of the decrease), respectively.

Moreover, we can quantify the effect of international crises on GDP growth. First, during the GFC, most models calculate that this variable fell from 9.2% to 1.1% and that this decrease was primarily determined by AD and MS shocks, explaining falls of -2.9 p.p. and -3 p.p., respectively During the GFC, MP shocks explained 0.1 p.p. (around -1.4% of the decrease), showing the small impact of the monetary authority. Second, during the Asian-Russian crisis, GDP growth declined from 6.4% to -0.3%, which was caused by a decrease in AD and MP shocks, explaining reductions of -7 p.p. and -1 p.p., respectively. Unlike during the GFC, MP exerted considerable influence on the dynamics of GDP growth during the Asian-Russian crisis.

In comparing the HD of inflation before and during the IT regime, most models indicate that inflation fell from 5.5% to 2.8%, with AS and MS shocks as the primary determinants, each explaining a decrease of 0.5 p.p. Regarding MP shocks, all models show that these shocks contributed 0.3 p.p. (around -10% of the decrease). In addition, external and ER shocks explained -0.2 p.p. and -0.3 p.p. of the fall in inflation, respectively. During the GFC, inflation falls from 6% to 2.3% and all models estimate this was primarily explained by AS and MS shocks. For instance, the TVP-VAR-R3-SV model estimates that AS and MS shocks explained -2.2 p.p. (59% of the decrease) and -1.1. p.p. (29% of the decrease), respectively. Moreover, all models show that MP shocks had a small positive impact on the fall in inflation during the GFC (e.g., the CVAR-SV model estimates that MP shocks explain 0.1 p.p.).

The HD of the interest rate indicates that under the IT regime, this variable decreased from 13.6% to 3.7%. The selected SV models estimate that this 9.8-p.p. decrease was mainly explained by MP shocks, e.g., the TVP-VAR-R1-SV model estimates that these explained -4.9 p.p. (around 59% of the decrease). Moreover, the selected SV models consider MS shocks as the second factor behind the interest rate fall. For instance, the TVP-VAR-R1-SV model calculates that MS shocks account for -1.2 p.p. (14% of the decrease), which might be a consequence of using the monetary base as the intermediate policy objective. Finally, external shocks have a minor share across models, as they explain -0.3 p.p. (3.4% of the decrease) at most.

In terms of the effects of crises on the interest rate, the findings are as follows. During the Asian-Russian crisis, the interest rate increased from 12.8% to 18.8%, primarily due to a rise in MS and MP shocks of 1 p.p. (around 15% of the increase) and 8 p.p. (around 130% of the increase), respectively. During the GFC, the interest rate fell from 5.9% to 3.2%. According to the selected SV models, this reduction was explained by a decrease in AD, AS, MS, and MP shocks; e.g., the TVP-VAR-R3-SV model quantifies that these four shocks contribute to a reduction of -2.5 p.p.

Among all HDs, the effects of external shocks are less significant than those obtained in Ojeda Cunya and Rodriguez (2022), Portilla et al. (2022), Alvarado et al. (2023), Chávez and Rodríguez (2023) and Rodríguez et al. (2023b). For example, Chávez and Rodriguez. (2022) calculate that external shocks explain around 89% of the increase of GDP growth under the post-IT regime. However, all these papers omit ER shocks, thereby ignoring a rapid-impact mechanism of external shocks on the economy.

## 5 Robustness Analysis

This Section discusses four robustness checks: (i) changes in the hyperparameters; (ii) changes in the recursive order (initially, inflation and money growth switch places, followed by an exchange between inflation and GDP growth); (iii) use of non-primary GDP growth instead of total GDP growth; and (iv) use of export price index (EPI) growth instead of S&P GSCI growth. Annexes 3 and 4 present the results of this Section, while the Figures are available in an Appendix upon request.

In terms of the hyperparameter changes, all outcomes are similar to the base model. The trace test, KS-test, and t-test, reported in Annex 3, indicate that all elements of $\gamma_t$ and $\mathbf{h}_t$ vary over time, with about 60% of the elements of $\boldsymbol{\beta}_t$ also changing. Furthermore, according to Annex 4, the baseline ranking stands. The BF of the TVP-VAR-SV model against the CVAR model is $2.68 \times 10^{16}$, demonstrating an improvement in fit when considering both TVP and SV. Additionally, the volatilities of all exogenous shocks are qualitatively similar. Also, the IRFs to an MP shock on GDP growth and inflation are robust, as GDP growth reacts faster, reaching its maximum contraction after four quarters, whereas inflation falls after three quarters, reaching its minimum level after six quarters. Furthermore, the IRFs to AS, AD, ER, and external shocks on the interest rate are robust. Finally, the FEVDs and HDs are alike, as external shocks are the main driver of all variable uncertainties across the sample, while MP shocks are relevant for both uncertainty and fluctuations under the pre-IT regime.

Regarding changes in the recursive order, the results also remain robust. Firstly, Annex 3 shows that the trace test, the KS-test, and the t-test present results similar to those estimated in the baseline model. In both recursive orders, all elements of $\gamma_t$ and $\mathbf{h}_t$ vary over time, while 59% of the elements of $\boldsymbol{\beta}_t$ also vary. Secondly, Annex 4 illustrates that SV models fill the top five spots. For example, in the first alternative order, the BF of the TVP-VAR-R1-SV model against the TVP-VAR-R3-SV model is $3.01$. Furthermore, in the first alternative order, the BF of the TVP-VAR-SV model against the CVAR model is $1.52 \times 10^{34}$, compared with $8.70 \times 10^{33}$ in the second alternative order, suggesting an improvement in fit when considering TVP and SV. Thirdly, all shock volatilities are identical to those in the baseline model. The volatilities of external shocks remain the highest and rise over time, like ER shocks; whereas AD, AS, and MS shocks continuously shrink, and MP shocks experience a sharp drop after IT adoption. Fourthly, the IRFs for GDP growth, inflation, and the interest rate are robust. Lastly, the FEVDs and HDs remain identical.

The results of the third exercise largely mirror those computed in the base model. Our analysis reveals that all elements of $\gamma_t$ and $\mathbf{h}_t$ vary over time, while 60% of the elements of $\boldsymbol{\beta}_t$ undergo changes. Annex 4, however, presents a few contrasting results. Although the ranking remains consistent according to the DIC, the Log-ML selection favors the TVP-VAR-R3-SV model. As with the previous two exercises, considering TVP and SV enhances fit, as the BF of the TVP-VAR-SV model against the CVAR model is $1.06 \times 10^{39}$. The volatility of all shocks remains the same except for those associated with AD shocks, which start from lower values. The IRFs to an MP shock on GDP growth and inflation are qualitatively similar. Nonetheless, the response of the interest rate to AD shocks is higher, possibly explained by the greater financial integration of the non-primary sector, enabling a more substantial pass-through effect of the reference interest rate into market interest rates. Finally, both the FEVDs and HDs estimate a more significant share for AD shocks compared to the base model.

To adequately capture the external factors impacting the Peruvian economy, the fourth exercise employs EPI growth as the external variable, yielding results akin to those in the base model. Firstly, Annex 3 indicates that the results from the trace test, the KS-test, and the t-test are robust, with all elements of $\gamma_t$ and $\mathbf{h}_t$ varying over time, while nearly 64% of the elements of $\boldsymbol{\beta}_t$ change. Secondly, according to the DIC, the model ranking remains consistent, although the Log-ML selects the TVP-VAR-R3-SV model. Consequently, the BF of the TVP-VAR-R1-SV model against the TVP-VAR-R3-SV model stands at $0.54$, while the BF of the TVP-VAR-SV model against the CVAR model is $1.39 \times 10^{39}$. Thirdly, volatilities are identical for all shocks except those associated with external shocks, which are lower than in the baseline case, but also increase during the Asian-Russian crisis and the GFC. Fourthly, the IRFs to an MP shock on GDP growth and inflation are robust; however, they show that MP shocks have a more extended but lesser impact on inflation. Fifthly, the IRFs to AS, AD, and ER shocks on the interest rate are robust, while the interest rate rises in response to positive external shocks. Lastly, the predominance of external shocks in the FEVDs and HDs of domestic variables diminishes, while the share of ER shocks increases.

## 6 Conclusions

This paper examines the time-varying impact of MP shocks in Peru during the period from 1996Q1 to 2018Q2. For this purpose, we estimate a set of time-varying parameter vector autoregressive models with stochastic volatility (TVP-VAR-SV models) as proposed by Chan and Eisenstat (2018). We used six recursively identified variables: S&P GSCI growth, exchange rate growth, GDP growth, inflation, money growth, and the interest rate.

The key findings can be summarized as follows: all volatilities, all contemporary coefficients, and approximately 75% of the parameters for lagged variables and intercepts should change over time, as indicated by the trace test, KS test, and t-test. Furthermore, SV improves model fit, according to the Log-ML and the DIC. The volatilities of AD, AS, MS, and MP shocks decrease under the IT regime. On the other hand, the volatilities of external and ER shocks rise after the GFC, suggesting that IT adoption reduced the volatility of domestic structural shocks. Particularly, the volatility of MP shocks increased more during the Asian-Russian crisis than during the GFC, due to the different policies implemented by the BCRP.

The selected models estimate that a countercyclical MP shock decreases both GDP growth and inflation, but GDP growth responds quicker and more intensively than inflation, which could be attributed to the existence of sticky prices. Moreover, the reactions of the interest rate to AS shocks are stronger than the responses to AD shocks, aligning with the BCRP's anti-inflationary bias. All models also estimate an increasing reaction of the interest rate to external and ER shocks. According to the FEVDs and HDs of GDP growth and inflation, MP shocks are only significant during the pre-IT regime, suggesting an improvement in monetary policy since IT adoption. These results collectively indicate that IT adoption contributed to stabilizing macroeconomic uncertainty in Peru.

In terms of robustness checks, we find that alternative specifications, including changes in priors, recursive order, or certain variables, reinforce the main findings. For instance, the evidence of changing variances and parameters is reaffirmed. The effects of MP shocks on GDP growth and inflation remain qualitatively similar, and the interest rate's reaction to various shocks is generally robust across different exercises.

Future research could consider alternatives such as non-recursive identifications, as suggested by Quispe (2001), or sign restrictions as detailed in Guevara and Rodríguez (2020). Including additional variables could enhance the identification of shocks and MP transmission channels. For instance, credit variables like loan supply could enhance credit channel visibility, as shown in Viladegut and Cabello (2014) and Guevara and Rodríguez (2020). Furthermore, the identification of MP shocks could be improved by incorporating other BCRP instruments, as proposed by Lahura (2010), Castillo et al. (2011), and Rodriguez et al. (2021). However, as the dimensionality of the TVP-VAR-SV model would increase, future research might consider large Bayesian VARs as suggested by Chan (2022) and Chan and Yu (2022).

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Annex 1. Tests for Time Variation in the Coefficients and Volatility

| | | | |
|---|---|---|---|
| Trace Test | | | |
| trace | 16% perc. | 50% perc. | 84% perc. |
| 0.240 | 0.166 | 0.231 | 0.344 |
| Kolmogorov-Smirnov Test | | | |
| $\boldsymbol{\gamma}_t$ | | | |
| 1993Q4-2002Q1 | 2002Q2-2018Q2 | 1996Q3-2007Q2 | 2007Q2-2018Q2 |
| 15/15 | 15/15 | 14/15 | 14/15 |
| $\boldsymbol{\beta}_t$ | | | |
| 1993Q4-2002Q1 | 2002Q2-2018Q2 | 1996Q3-2007Q2 | 2007Q2-2018Q2 |
| 58/78 | 54/78 | 63/78 | 63/78 |
| $\mathbf{h}_t$ | | | |
| 1993Q4-2002Q1 | 2002Q2-2018Q2 | 1996Q3-2007Q2 | 2007Q3-2018Q2 |
| 6/6 | 6/6 | 6/6 | 6/6 |
| t-test | | | |
| $\boldsymbol{\gamma}_t$ | | | |
| 1993Q4-2002Q1 | 2002Q2-2018Q2 | 1996Q3-2007Q2 | 2007Q3-2018Q2 |
| 15/15 | 15/15 | 15/15 | 15/15 |
| $\boldsymbol{\beta}_t$ | | | |
| 1993Q4-2002Q1 | 2002Q2-2018Q2 | 1996Q3-2007Q2 | 2007Q3-2018Q2 |
| 58/78 | 54/78 | 62/78 | 54/78 |
| $\mathbf{h}_t$ | | | |
| 1993Q4-2002Q1 | 2002Q2-2018Q2 | 1996Q3-2007Q2 | 2007Q3-2018Q2 |
| 6/6 | 6/6 | 6/6 | 6/6 |

Source: Own elaboration. $\boldsymbol{\gamma}_t$ represents the coefficients of contemporaneous relationships, $\boldsymbol{\beta}_t$ are the coefficients associated to intercepts and lagged variables and $\mathbf{h}_t$ are the variances of innovations. $\boldsymbol{\gamma}_t$ has $(n \times (n-1))/2$ elements which are under the diagonal, $\boldsymbol{\beta}_t$ has $n$ intercepts and $n \times n \times p$ parameters related to lags, and $\mathbf{h}_t$ has $n$ elements.

Annex 2. Models Selection

| Model | Log-ML$_{CE}$ | SD | Rank | DIC | SD | Rank |
|---|---|---|---|---|---|---|
| TVP-VAR-SV | -1506.455 | 0.288 | 5 | 2533.232 | 1.155 | 5 |
| TVP-VAR | -1580.195 | 0.194 | 6 | 2633.436 | 2.949 | 7 |
| **TVP-VAR-R1-SV** | **-1483.666** | **0.264** | **1** | **2411.979** | **0.514** | **3** |
| TVP-VAR-R2-SV | -1502.186 | 0.397 | 4 | 2498.542 | 1.657 | 4 |
| **TVP-VAR-R3-SV** | **-1484.715** | **0.282** | **2** | **2390.006** | **0.531** | **2** |
| **CVAR-SV** | **-1486.077** | **0.073** | **3** | **2346.120** | **6.300** | **1** |
| CVAR | -1584.832 | 0.023 | 7 | 2562.849 | 0.351 | 6 |

Source: Own elaboration. Each Log-ML$_{CE}$ estimate is based on 10,000 evaluations of the integrated likelihood using 10 parallel chains, where the importance sampling density is constructed using 10,000 posterior draws after a burn-in period of 1,000. Each DIC estimate (and the corresponding numerical standard error) is computed using 10 parallel chains; each consists of 10,000 posterior draws after a burn-inperiod of 1,000. The integrated likelihood and the DIC are evaluated every 10th post burn-in draw-a total of 10,000 evaluations.

Annex 3. Robustness Analysis: Tests for Time Variation in the Coefficients and Volatility

| Trace Test | | | | |
|---|---|---|---|---|
| Case | prior trace | 16% perc. | 50% perc. | 84% perc. |
| Alternative Priors | 0.240 | 0.164 | 0.231 | 0.338 |
| Alternative Order 1 | 0.240 | 0.163 | 0.231 | 0.339 |
| Alternative Order 2 | 0.240 | 0.164 | 0.232 | 0.344 |
| Non-Primary GDP Growth | 0.240 | 0.165 | 0.233 | 0.343 |
| EPI Growth | 0.240 | 0.437 | 0.525 | 0.642 |

| Kolmogorov-Smirnov Test | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1996Q3-2002Q1 | | | 2002Q2-2018Q2 | | | 1996Q3-2007Q2 | | | 2007Q3-2018Q2 | | |
| | $\gamma_t$ | $\boldsymbol{\beta}_t$ | $\mathbf{h}_t$ | $\gamma_t$ | $\boldsymbol{\beta}_t$ | $\mathbf{h}_t$ | $\gamma_t$ | $\boldsymbol{\beta}_t$ | $\mathbf{h}_t$ | $\gamma_t$ | $\boldsymbol{\beta}_t$ | $\mathbf{h}_t$ |
| Alternative Priors | 14/15 | 58/78 | 6/6 | 15/15 | 60/78 | 6/6 | 15/15 | 64/78 | 6/6 | 15/15 | 63/78 | 6/6 |
| Alternative Order 1 | 15/15 | 59/78 | 6/6 | 15/15 | 61/78 | 6/6 | 15/15 | 64/78 | 6/6 | 15/15 | 61/78 | 6/6 |
| Alternative Order 2 | 13/15 | 56/78 | 6/6 | 14/15 | 61/78 | 6/6 | 14/15 | 64/78 | 6/6 | 14/15 | 62/78 | 6/6 |
| Non-Primary GDP Growth | 13/15 | 57/78 | 6/6 | 15/15 | 63/78 | 6/6 | 14/15 | 65/78 | 6/6 | 15/15 | 61/78 | 6/6 |
| EPI Growth | 15/15 | 60/78 | 6/6 | 14/15 | 70/78 | 6/6 | 15/15 | 68/78 | 6/6 | 15/15 | 64/78 | 6/6 |

| t-test | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1996Q3-2002Q1 | | | 2002Q2-2018Q2 | | | 1996Q3-2007Q2 | | | 2007Q3-2018Q2 | | |
| | $\gamma_t$ | $\boldsymbol{\beta}_t$ | $\mathbf{h}_t$ | $\gamma_t$ | $\boldsymbol{\beta}_t$ | $\mathbf{h}_t$ | $\gamma_t$ | $\boldsymbol{\beta}_t$ | $\mathbf{h}_t$ | $\gamma_t$ | $\boldsymbol{\beta}_t$ | $\mathbf{h}_t$ |
| Alternative Priors | 15/15 | 61/78 | 6/6 | 15/15 | 56/78 | 6/6 | 15/15 | 62/78 | 6/6 | 15/15 | 55/78 | 6/6 |
| Alternative Order 1 | 15/15 | 56/78 | 6/6 | 15/15 | 55/78 | 6/6 | 15/15 | 61/78 | 6/6 | 15/15 | 54/78 | 6/6 |
| Alternative Order 2 | 15/15 | 55/78 | 6/6 | 15/15 | 55/78 | 6/6 | 15/15 | 61/78 | 6/6 | 15/15 | 58/78 | 6/6 |
| Non-Primary GDP Growth | 15/15 | 54/78 | 6/6 | 15/15 | 57/78 | 6/6 | 15/15 | 65/78 | 6/6 | 15/15 | 59/78 | 6/6 |
| EPI Growth | 15/15 | 57/78 | 6/6 | 15/15 | 67/78 | 6/6 | 15/15 | 64/78 | 6/6 | 15/15 | 60/78 | 6/6 |

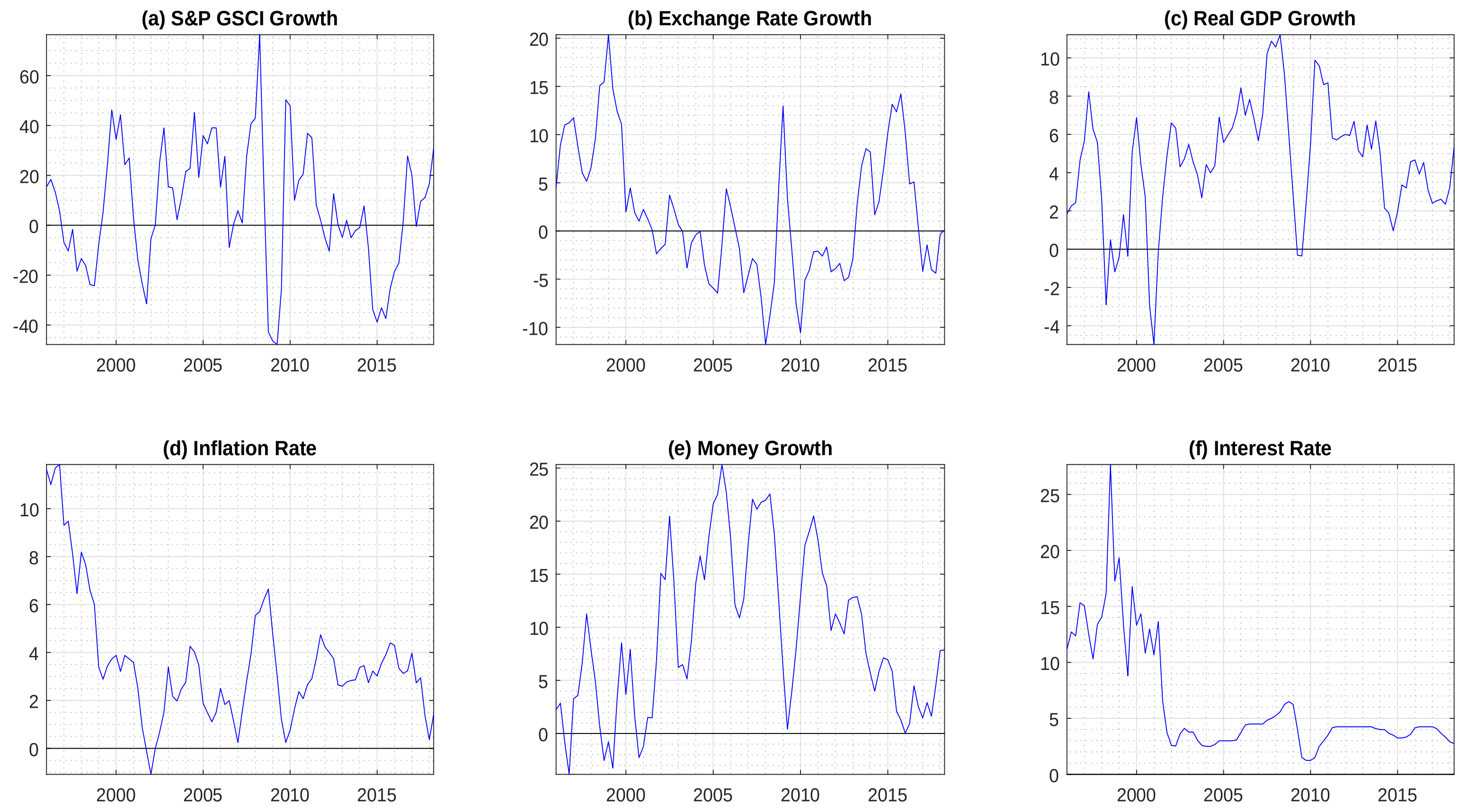
Source: Own elaboration. $\gamma_t$ represents the coefficients of contemporaneous relationships, $\boldsymbol{\beta}_t$ are the coefficients associate to intercepts and lagged variables and $\mathbf{h}_t$ are the variances of innovations. $\gamma_t$ has $(n \times (n-1))/2$ elements which are under the diagonal, $\boldsymbol{\beta}_t$ has $n$ intercepts and $n \times n \times p$ parameters related to lags, and $\mathbf{h}_t$ has $n$ elements. Alternative Order 1 refers to a change in the order between Money Supply Growth and Inflation, while Alternative Order 2 refers to a change between GPD Growth and Inflation.

Annex 4. Robustness Analysis: Models Selection

| | (i) Alternative Priors | | | | (ii) Alternative Order 1 | | | | (iii) Alternative Order 2 | | | | (iv) Non-Primary GDP Growth | | | | (v) EPI Growth | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Model | Log-ML$_{CE}$ | Rank | DIC | Rank | Log-ML$_{CE}$ | Rank | DIC | Rank | Log-ML$_{CE}$ | Rank | DIC | Rank | Log-ML$_{CE}$ | Rank | DIC | Rank | Log-ML$_{CE}$ | Rank | DIC | Rank |
| TVP-VAR-SV | -1536.295 | 5 | 2536.125 | 5 | -1508.676 | 5 | 2534.125 | 5 | -1505.273 | 5 | 2534.292 | 5 | -1498.527 | 5 | 2512.303 | 5 | -1417.976 | 5 | 2353.377 | 5 |
| | (0.210) | | (1.808) | | (0.249) | | (1.808) | | (0.373) | | (1.717) | | (0.225) | | (1.922) | | (0.288) | | (1.587) | |
| TVP-VAR | -1572.295 | 6 | 2645.197 | 7 | -1589.155 | 7 | 2640.373 | 7 | -1577.118 | 7 | 2635.119 | 7 | -1585.301 | 6 | 2631.564 | 7 | -1502.660 | 6 | 2462.609 | 7 |
| | (0.210) | | (1.602) | | (0.723) | | (6.725) | | (0.305) | | (2.269) | | (0.778) | | (7.765) | | (0.553) | | (5.941) | |
| TVP-VAR-R1-SV | -1476.532 | 1 | 2416.764 | 3 | -1487.594 | 1 | 2417.232 | 3 | -1483.021 | 1 | 2409.227 | 3 | -1481.089 | 2 | 2402.684 | 3 | -1412.237 | 3 | 2279.463 | 3 |
| | (0.315) | | (0.710) | | (0.219) | | (0.679) | | (0.321) | | (1.110) | | (0.306) | | (0.765) | | (0.269) | | (0.570) | |
| TVP-VAR-R2-SV | -1520.295 | 4 | 2505.206 | 4 | -1505.562 | 4 | 2501.206 | 4 | -1500.747 | 4 | 2499.850 | 4 | -1495.687 | 4 | 2485.108 | 4 | -1413.504 | 4 | 2326.509 | 4 |
| | (0.210) | | (1.849) | | (0.250) | | (1.849) | | (0.626) | | (1.148) | | (0.331) | | (1.783) | | (0.342) | | (1.700) | |
| TVP-VAR-R3-SV | -1479.293 | 2 | 2398.942 | 2 | -1488.263 | 2 | 2392.546 | 2 | -1483.884 | 2 | 2389.535 | 2 | -1479.541 | 1 | 2375.287 | 2 | -1411.613 | 1 | 2251.786 | 2 |
| | (0.318) | | (1.151) | | (0.319) | | (0.679) | | (0.218) | | (0.416) | | (0.255) | | (0.599) | | (0.389) | | (0.635) | |
| CVAR-SV | -1480.271 | 3 | 2346.169 | 1 | -1488.696 | 3 | 2344.169 | 1 | -1484.379 | 3 | 2338.071 | 1 | -1482.588 | 3 | 2312.340 | 1 | -1411.865 | 2 | 2174.346 | 1 |
| | (0.104) | | (8.139) | | (0.045) | | (8.139) | | (0.061) | | (6.454) | | (0.078) | | (6.333) | | (0.044) | | (9.396) | |
| CVAR | -1574.124 | 7 | 2567.320 | 6 | -1587.382 | 6 | 2563.336 | 6 | -1583.421 | 6 | 2563.461 | 6 | -1588.385 | 7 | 2571.306 | 6 | -1508.106 | 7 | 2434.973 | 6 |
| | (0.022) | | (0.202) | | (0.019) | | (0.363) | | (0.024) | | (0.198) | | (0.019) | | (0.312) | | (0.017) | | (0.239) | |

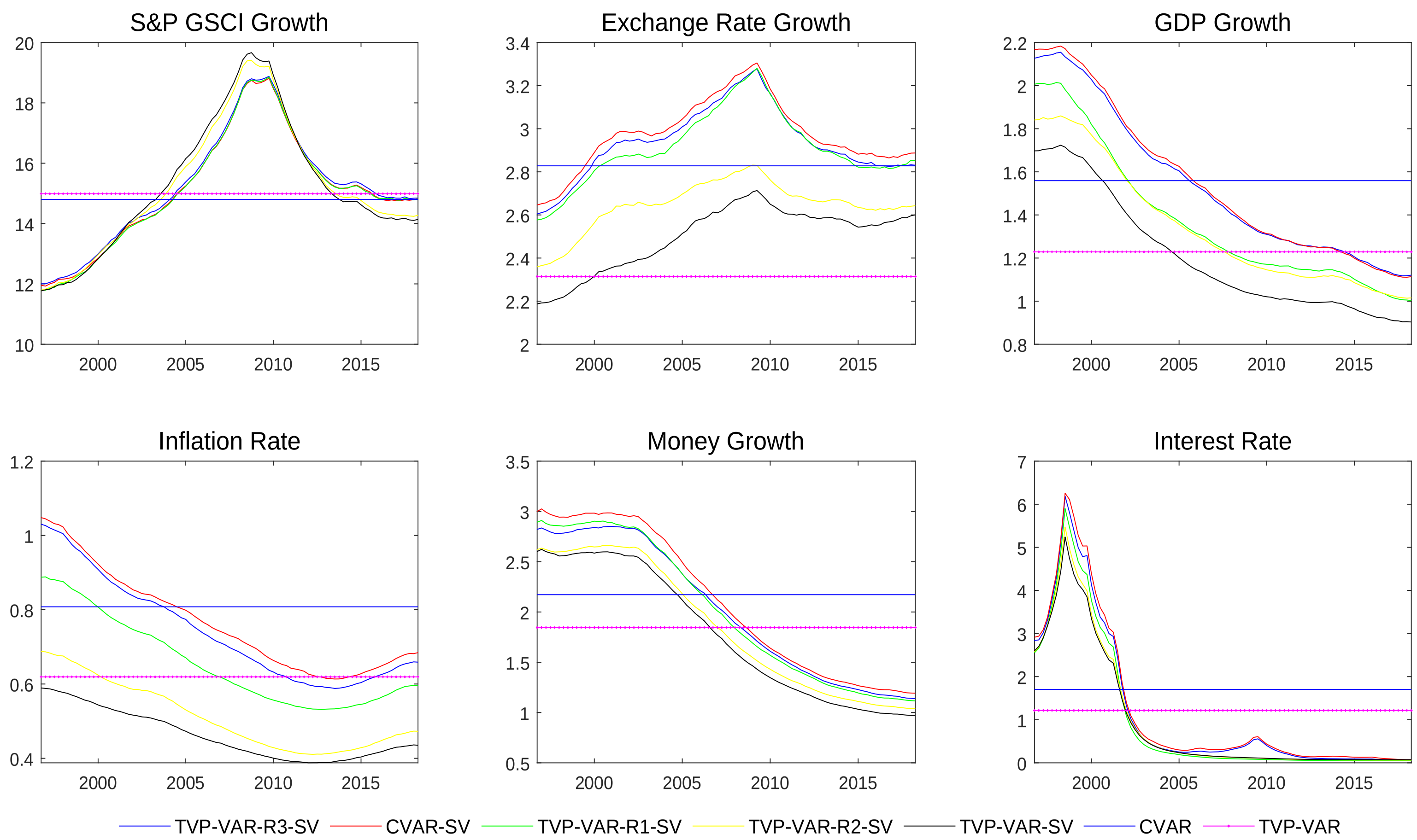
Source: Own elaboration. Each Log-ML$_{CE}$ estimate is based on 10,000 evaluations of the integrated likelihood using 10 parallel chains, where the importance sampling density is constructed using 10,000 posterior draws after a burn-in period of 1,000. Each DIC estimate (and the corresponding numerical standard error) is computed using 10 parallel chains; each consists of 10,000 posterior draws after a burn-inperiod of 1,000. The integrated likelihood and the DIC are evaluated every 10th post burn-in draw-a total of 10,000 evaluations. Alternative Order 1 refers to a change between Money Supply Growth and Inflation in the order, while Alternative Order 2 refers to a change between GPD Growth and Inflation.

Annex 5. Time Series (1996Q1-2018Q2)



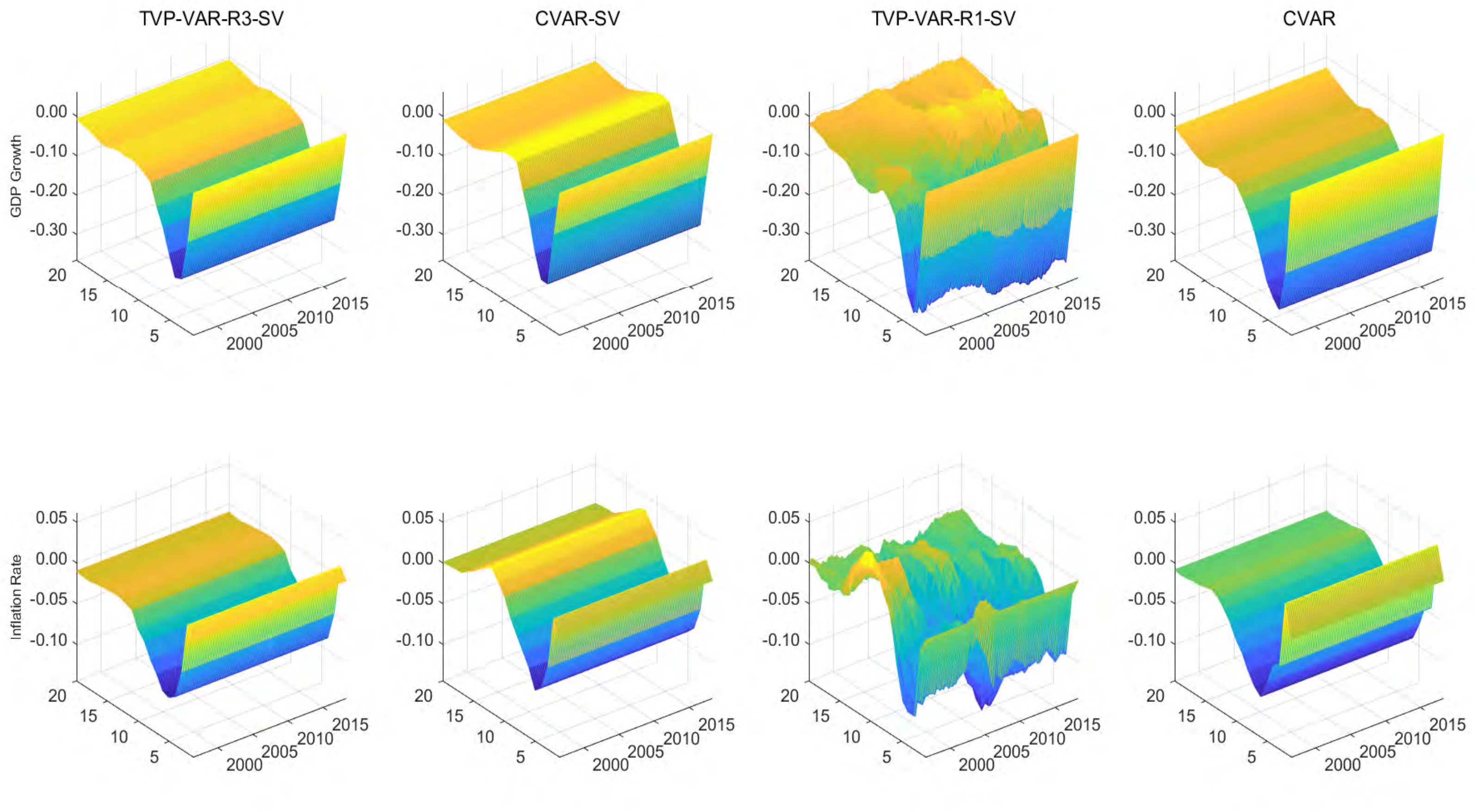

Source: BCRP and own elaboration.

Annex 6. Median Standard Deviation of the Innovations in each Equation for all Models



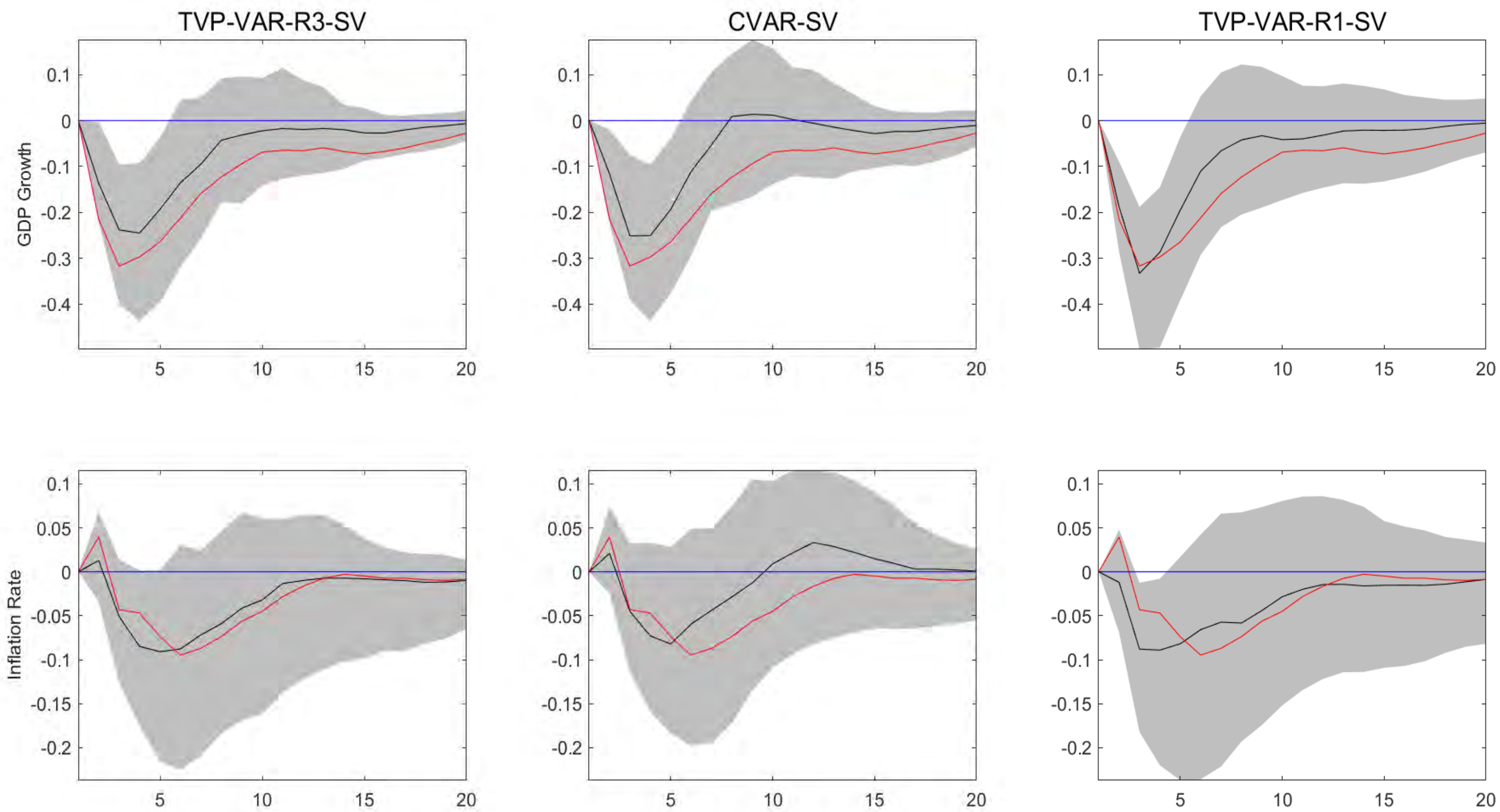

Source: Own elaboration.

Annex 7. Median Time Varying IRFs of GDP Growth and Inflation Rate to a Monetary Policy Shock



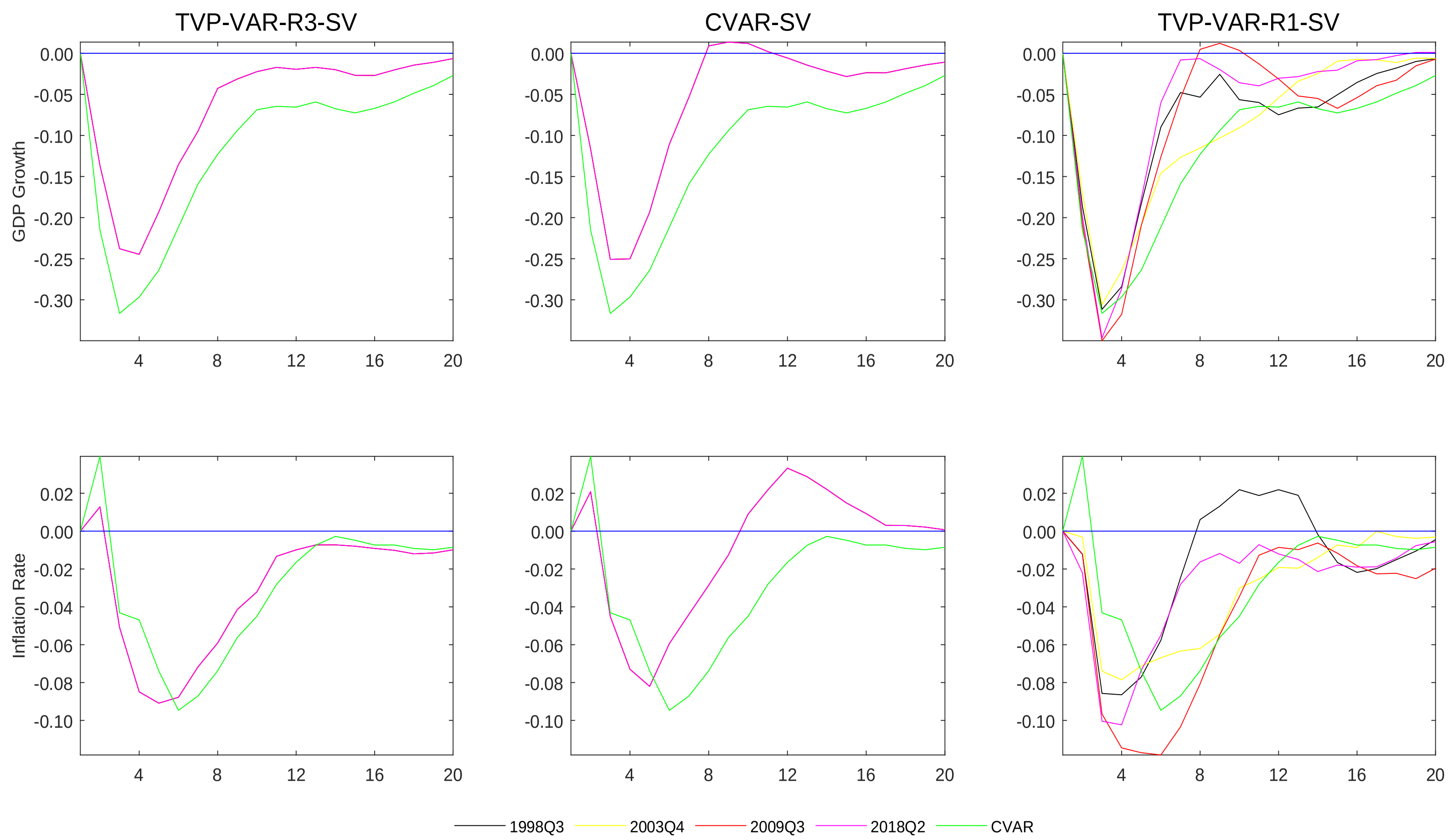

Source: Own elaboration.

Annex 8. Median Time-Varying IRFs of GDP Growth and Inflacion to a Monetary Policy Shock.



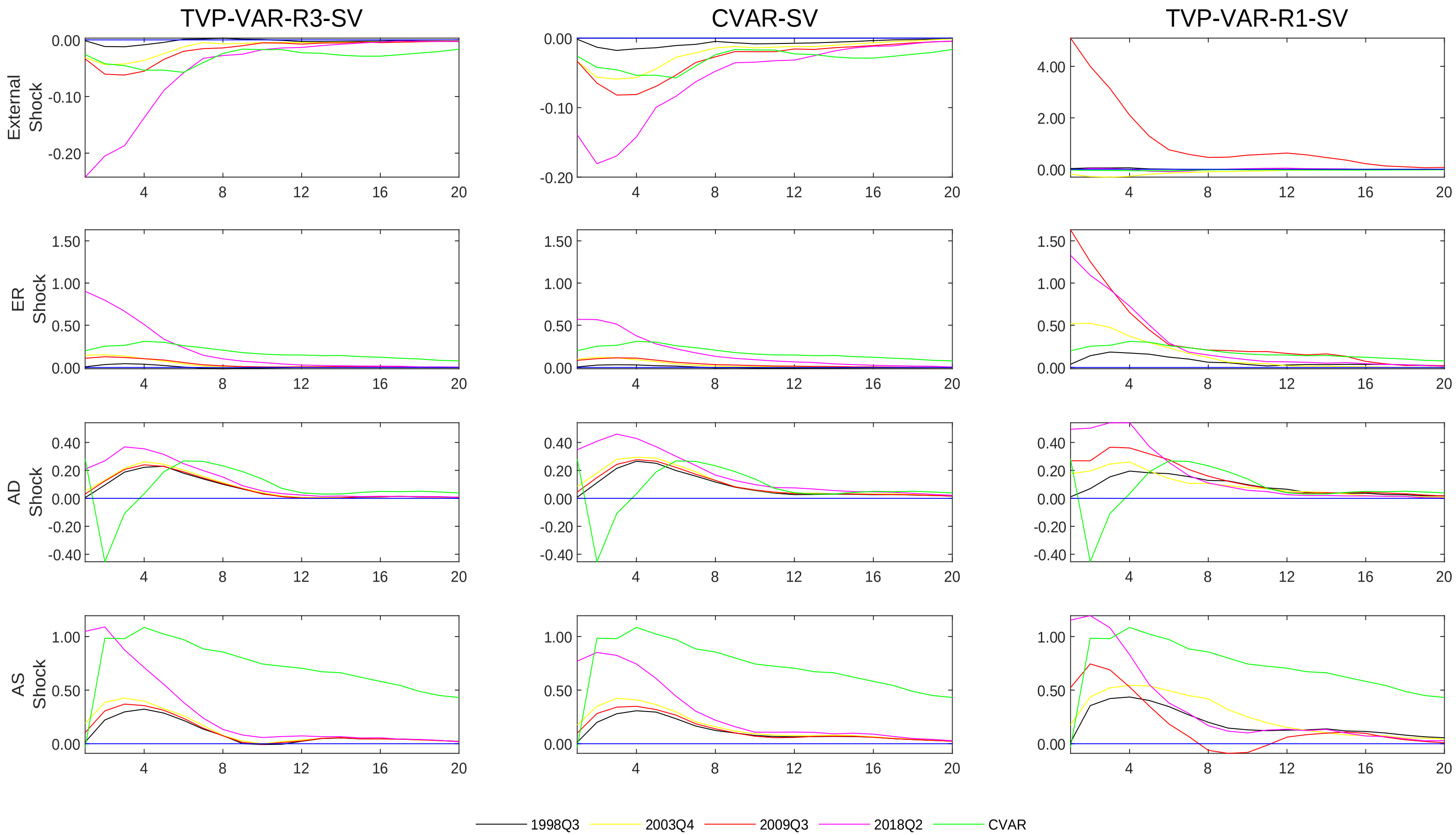

Source: Own elaboration. The solid black line represents the respective model by columns and the shaded area its 68% error band; the solid red line represent the CVAR.

Annex 9. Median IRFs of GDP Growth and Inflation Rate at Different Periods to a Monetary Policy Shock



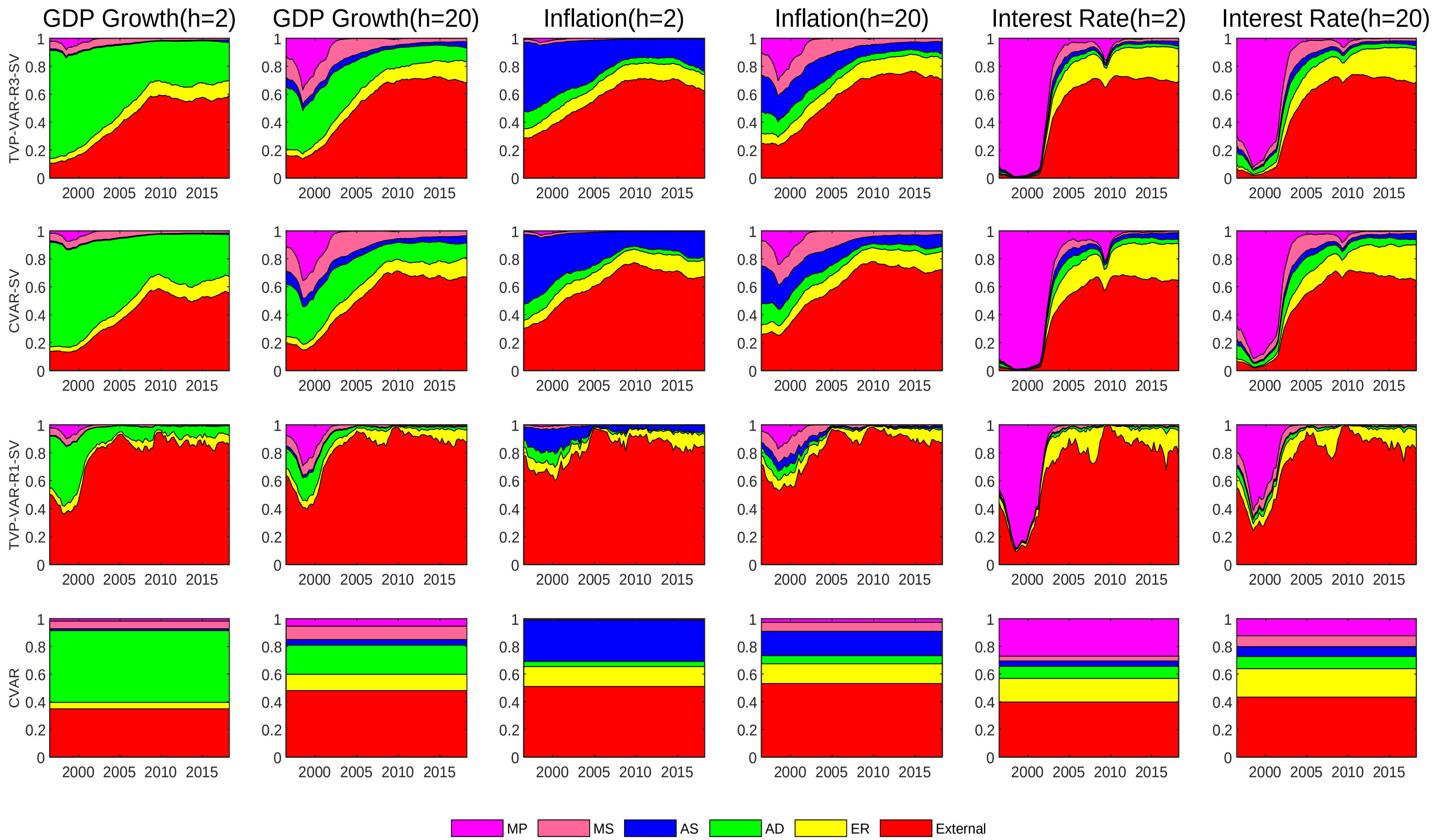

Source: Own elaboration.

## Annex 10. Median IRFs of Interest Rate at Different Periods to different shocks



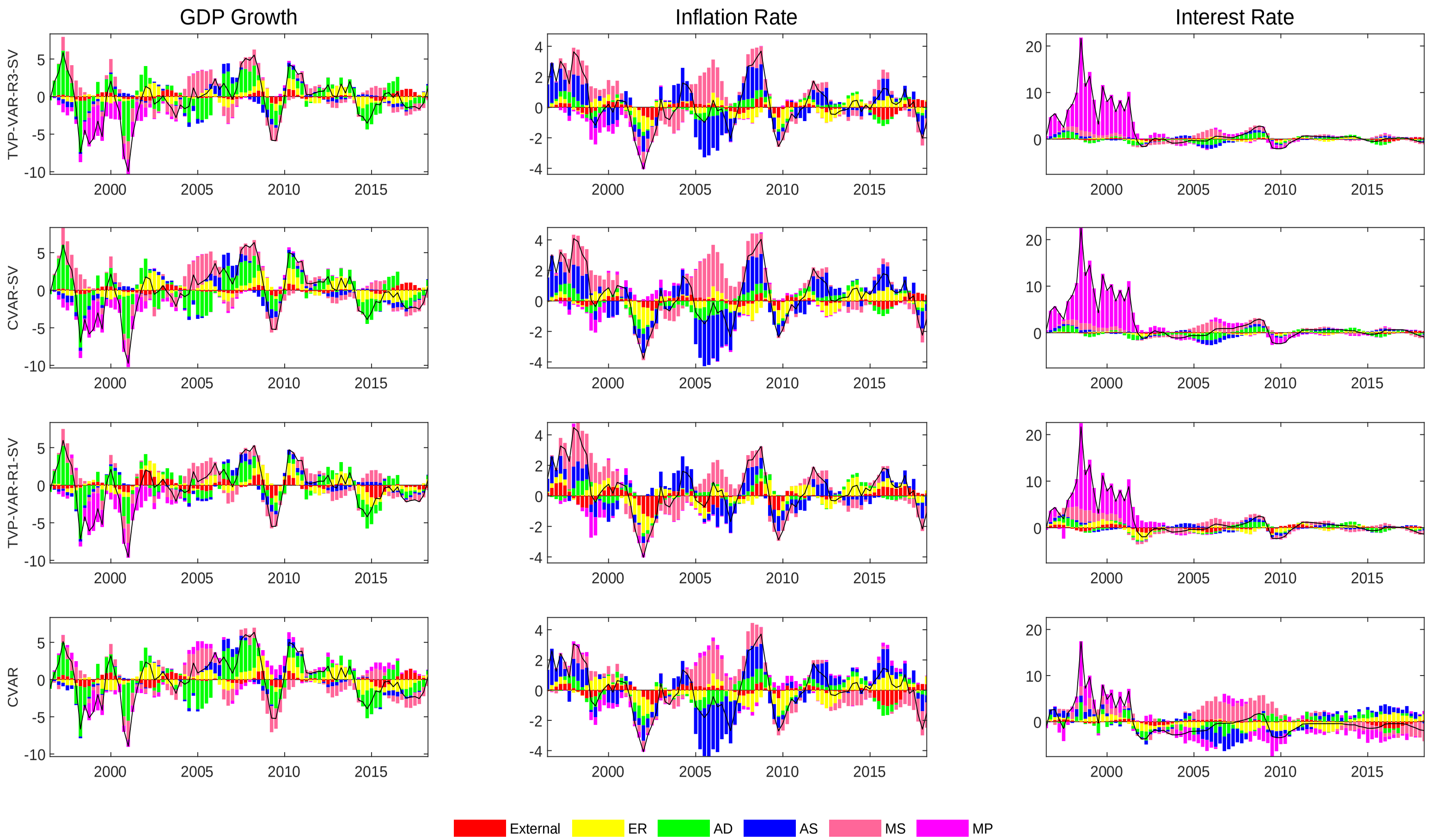

Source: Own elaboration.

Annex 11. Time Evolution of the Mean FEVD of GDP Growth, Inflation Rate and Interest Rate for various Models at $h = 2, 20$




Source: Own elaboration.

Annex 12. HD of GDP Growth, Inflation Rate and Interest Rate for various Models




Source: Own elaboration.