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Abstract

In this paper we identify different sources of nonlinearities in the Peruvian economy. For this purpose we estimate five models: i) Linear Bayesian VAR (BVAR), ii) Time-Varying BVAR with Stochastic Volatility (SV), iii) Time Varying Mean BVAR with SV, iv) BVAR with SV and Volatility feedback, v) Threshold BVAR with SV and Volatility feedback. The results obtained allow us to conclude the following: i) The inclusion of data from the Covid-19 pandemic and later (2020 onwards) can be carried out safely even for a constant coefficients model, ii) SV (especially with volatility feedback) is enough to correct the downturn of the pandemic and other episodes of higher volatility. iii) The transmission mechanism of monetary policy is stable throughout the 2002-2024 episode, and is robust across different models, even for the pre-Inflation Targeting sample (1996-2001). iv) The estimated volatility for the models with feedback can be interpreted as an aggregate macroeconomic uncertainty index. This index reaches its highest value during the Covid-19 pandemic episode (2020-2021) and, to a lesser extent, during the International Financial Crisis (2008-2009). v) Shocks in volatility resemble those of a negative and persistent supply shock, where inflation rises and the economic activity goes down. The latter triggers the response of the central bank through rising the policy interest.

JEL Classification: C53, E42, E51

Key words: Nonlinearities, Bayesian Vector Autorregressions, Stochastic Volatility

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1 Introduction

Macroeconomic analysis in a time varying and uncertain environment is clearly challenging. In particular, the task of identifying the trends and structural shocks that govern the dynamics of key macroeconomic variables, such as inflation and GDP growth, becomes much more difficult. For example, global events such as the international financial crisis, the Taper Tantrum and the Covid-19 pandemic, along with idiosyncratic events specific to each country such as political crises, which have triggered large fluctuations in recent years, make us question the validity of parameter stability of standard econometric models throughout the sample of analysis. In this context, the models that are traditionally used to perform both predictions and structural analysis have the characteristic of being linear with normally distributed errors, such as Bayesian Vector Autorregressive (BVAR) models[1]. In the case of the Peruvian economy, we can find different applications of Vector Autorregressive Models over the last twenty years such as Winkelried (2004), Llosa *et al.* (2005), Bigio and Salas (2006), Castillo *et al.* (2011), Winkelried (2012), Lahura (2012), Pérez-Forero and Vega (2014), Pérez Rojo and Rodríguez (2023), among others, which document the transmission mechanism of monetary policy and other structural shocks that are relevant for the Peruvian economy. However, none of them explore the period post Covid-19, which creates an additional research avenue[2].

Despite the solid empirical evidence for the Peruvian economy under the Inflation Targeting regime starting in 2002, it is pertinent to note that these aforementioned episodes have potentially triggered structural changes and greater macroeconomic volatility. As a result, it is convenient to evaluate whether the results supported by empirical evidence are robust to these events. At least there is evidence of structural changes in the case of some advanced economies, and other emerging ones similar to Peru (see e.g. Primiceri (2005), Canova and Pérez Forero (2015), Alessandri and Mumtaz (2019), Llosa *et al.* (2022), among others). Therefore, it is necessary to specify more flexible models that explicitly consider these non-linearities. In this paper we explore a battery of models that consider different types of non-linearities for a given

[1] See e.g. Sims (1980), Christiano *et al.* (1999), Canova (2007), Koop and Korobilis (2010), among others.

[2] See Pérez Forero (2024a) and Pérez Forero (2024b) as previous studies that include the post Covid-19 Peruvian Macroeconomic Data.

macroeconomic data set associated with the Peruvian economy. Therefore, we estimate the following models: i) Linear Bayesian VAR (M1), ii) Time-Varying BVAR with Stochastic Volatility (M2), iii) Time Varying Mean BVAR with Stochastic Volatility (M3), iv) Bayesian VAR with Stochastic Volatility and Volatility feedback (M4), v) Threshold Bayesian VAR with Stochastic Volatility and Volatility feedback (M5). All these models are estimated using the same data set, so that it is possible to compare the results across them. We also extend models M2, M3 and M5 in order to include the pre-Inflation Targeting data set (1996-2001).

The results obtained under the estimation of the different models mentioned allow us to establish the contribution of this paper and conclude the following: i) The inclusion of data from the Covid-19 pandemic and later (2020 onwards) can be carried out safely even for a constant coefficients model, since the errors from 2020 are compensated for by those from 2021. ii) However, Stochastic Volatility (especially with volatility feedback) is enough to correct the downturn of the pandemic and other episodes of higher volatility, which implies that we have statistical evidence that says that the rest of the dynamic economic relations had remained stable throughout the sample (in line with Carriero *et al.* (2024)). iii) The transmission mechanism of monetary policy is stable throughout the 2002-2024 episode, both in the case of a threshold model and in the case of continuously changing parameters, with real effects on activity that reach their peak before the first year, and with an effect on inflation between 12 and 18 months. Moreover, the transmission mechanism is robust across different models, even for the pre-Inflation Targeting Period (1996-2001). iv) The estimated volatility for the models with volatility feedback (M4 and M5) can be interpreted as an aggregate macroeconomic uncertainty index. This index reaches its highest value during the Covid-19 pandemic episode (2020-2021) and, to a lesser extent, during the International Financial Crisis (2008-2009). v) Shocks in estimated volatility (models M4 and M5) resemble those of a negative and persistent supply shock, where inflation rises and the economic activity goes down. The latter triggers the response of the central bank through rising the policy interest.

The document is organized as follows: section 2 describes the empirical models used for the analysis, section **??** describes the identification procedure for structural shocks, section 4 takes stock of the obtained results and postulates general conclusions, and section 8 makes the final remarks and sketches a future agenda.

2 The empirical setup

2.1 Peruvian Macroeconomic Data

We consider monthly macroeconomic data from Peru for the period from January-2002 to July-2024. This period coincides with the adoption of the Inflation Targeting scheme as the main monetary policy framework. In this context, the most relevant macroeconomic variables for Peru, taking into account that it is an open economy with a floating exchange rate (with Foreign Exchange Intervention in the market), which also depends on the evolution of commodity prices (especially the copper), and that implements its monetary policy through a reference interest rate together with the administration of liquidity and monetary aggregates through its balance sheet[3], is the following[4][5]:

1. **Inflation**: Is the Year-to-year growth rate in the Consumer Price Index of Metropolitan Lima (2021=100), i.e. Headline Inflation.
2. **GDP Growth**: Is the Year-to-year growth rate in the Monthly Gross Domestic Product Indicator (2007=100).
3. **Terms of Trade**: Is the Year-to-year growth rate in the Monthly Terms of Trade Indicator Index.
4. **Interest Rate**: Is the Monthly average of the Interbank Market interest rate in annual terms (in %).
5. **M1 Growth**: Is the Year-to-year growth rate in the Monthly Money Aggregate associated with Domestic Currency Liquidity: Cash + Liquid Deposits (in PEN Million).
6. **ER Depr.**: Is the Year-to-year growth rate in the Monthly end-of-period interbank market

[3]The BCRP typically carries out open market operations (OMO), with the objective of adapting liquidity based on the daily demand, and thereby reinforcing the transmission of monetary policy through the reference interest rate.

[4]All the selected variables were obtained from the Statistics Website of the Central Reserve Bank of Peru: https://estadisticas.bcrp.gob.pe/estadisticas/series/https://estadisticas.bcrp.gob.pe/estadisticas/series/

[5]We do not include variables associated with fiscal policy or the external sector, since these factors are also captured by the economic activity indicator, along with the terms of trade, and this is sufficient for the identification of the demand forces that affect the aggregate economy.

exchange rate. (PEN per USD).

All these transformed variables are depicted in Figure 1, and they will represent the vector of variables y_t with the relevant macroeconomic dataset for the Peruvian economy.

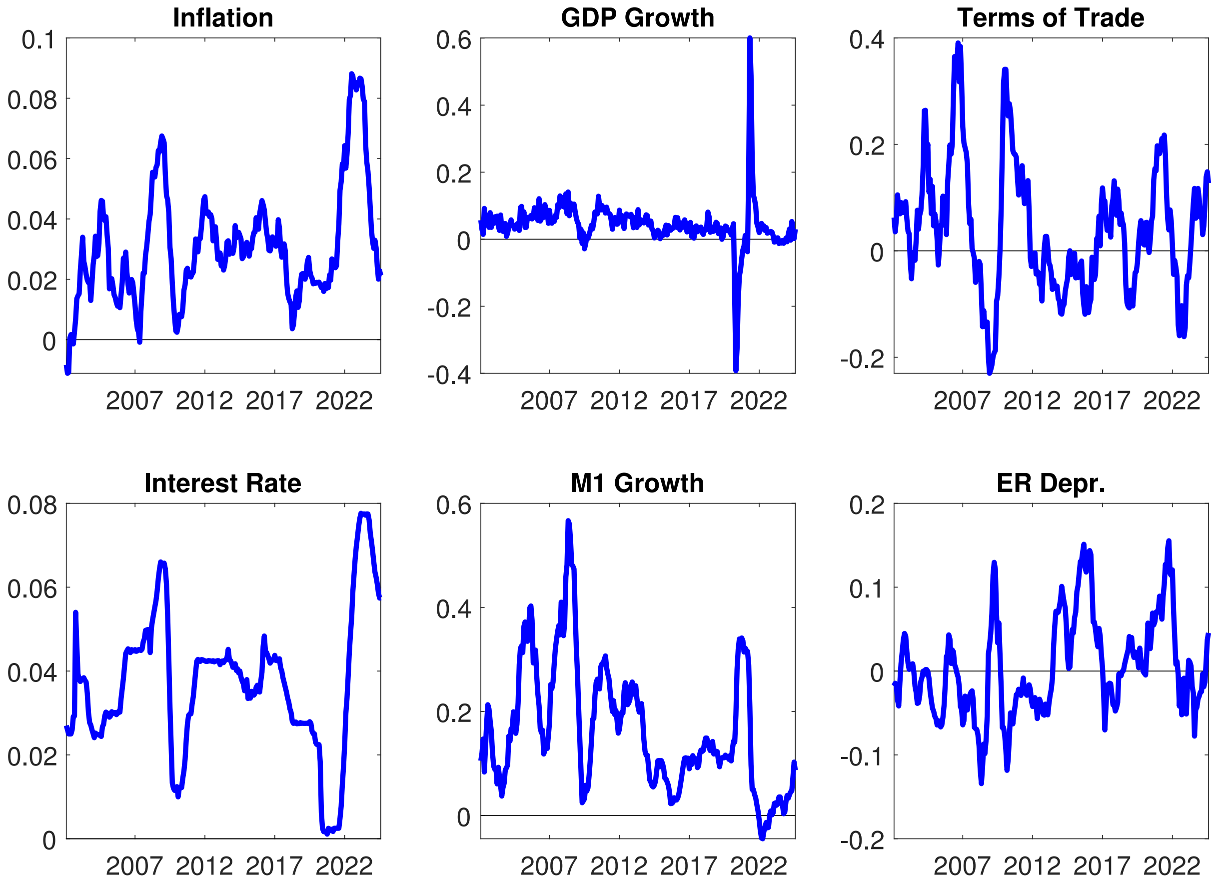

Figure 1: Macroeconomic Peruvian Data (2002-2024)

It is important to mention that the period considered (2002-2024) contains several episodes relevant for the economy under study, both global and domestic. In particular, in the case of global events it is worth highlighting: i) the commodity prices boom and bust, and the surge in the terms of trade (2004-2012), ii) the Global Financial Crisis (2008-2009), iii) the Taper Tantrum (2013), iv) the Covid-19 pandemic (2020-2021), and v) the surge and decline of inflation and geopolitical tensions (2021-2024). Regarding the relevant Peruvian domestic episodes, we can mention: i) the electoral periods of 2006, 2011, 2016 and 2021, ii) the political crisis and social instability since 2016, iii) the unconventional monetary response to the pandemic shock (2020-2021). Given the events described above, despite the macroeconomic stability that the inflation targeting scheme brings with it, we have various events that can potentially be interpreted as structural changes, which could lead to the consideration of non-linear models as perhaps the best specification. As a consequence, in the following subsections we will present different alternative models to represent the data shown in Figure 1. We will start from a basic linear model and consider some extensions towards the nonlinear field. Each model is estimated through Markov Chain Monte Carlo (MCMC) methods, with different nuances. We suggest to go to the original references in order to review the details of each case.

2.2 Model 1 (M1): A Bayesian constant coefficients VAR model

Since Sargent (1979), Sims (1980), it is very common to consider a linear specification of autorregressive vectors to represent a relevant set of macroeconomic variables for a specific country, for both forecasting and structural analysis[6]. In the case of Peru, the first model to consider is a standard Bayesian Vector Autorregressive (BVAR) model with $p \geq 1$ lags[7]:

$$y_t = c + \sum_{k=1}^{p} B_k y_{t-k} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Omega) \tag{1}$$

where y_t is a $N \times 1$ vector of macroeconomic and financial variables properly transformed such as the ones depicted in Figure 1, and we have data for $t = 1, \ldots, T$ periods. The error term ε_t is normally distributed with zero mean and covariance matrix Ω that is $N \times N$.

Following a Bayesian perspective, the posterior distribution of model 2.2 is given by:

$$P\left(\Theta \mid y^T\right) \propto P\left(y^T \mid \Theta\right) P\left(\Theta\right) \tag{2}$$

where Θ is the parameter space such that $\Theta = \{\beta, \Omega\}$, with β as a column vector that contains

[6]See also Litterman (1986), Bernanke and Mihov (1998), Christiano *et al.* (1999), among others

[7]There is a considerable amount of papers that uses vector autorregressive models to represent the Peruvian economy. The most recent ones, especially those that use Bayesian methods, are ...

all the parameters included in the lag matrices B_k for $k = 1, \dots, p$. In addition, $P(\Theta)$ is the prior distribution of parameters, $P\left(y^T \mid \Theta\right)$ is the likelihood function of the model 2.2 and y^T contains the full set of observations of the vector y_t.

Standard Bayesian simulation of the posterior distribution of the model $P\left(\Theta \mid y^T\right)$ is performed using Gibbs Sampling, which is part of the family of Markov Chain Monte Carlo (MCMC) methods (see e.g. Koop and Korobilis (2010), etc.), and also with a Minnesota-type prior (Litterman, 1986)[8]. In this context, it is crucial to consider the assumption of normal distribution for the reduced-form error term ε_t, so that β follows a normal distribution and Ω follows an Inverse-Wishart distribution.

After that, orthogonalized structural shocks are given by $u_t \sim N(0, I_N)$, and can be obtained through a matrix P such that $\varepsilon_t = Pu_t$ and $\Omega = PP'$. It is very common to assume that $P = A^{-1}\Sigma$, where A is a lower triangular matrix including the covariance parameters, and Σ is a diagonal matrix including the standard deviations of structural shocks in the main diagonal (Cholesky factorization). Given the identified structural shocks u_t and the estimated parameters Θ, then it is possible to simulate the posterior distribution of the dynamic multipliers, i.e. the well known impulse response functions, such that:

$$\frac{\partial y_{t+h}}{\partial u_t} = \Phi_h = \Psi_h P, \qquad h = 0, 1, \dots, \overline{H} \tag{3}$$

so that each column $i = 1, \dots, N$ of Φ_h represents the impact of shock $u_{i,t} \in u_t$ (e.g. the monetary policy shock) after h periods in the vector y_t, where Ψ_h is the wold decomposition matrix for period h of the model 2.2 [9]. In section **??** we will discuss how to identify these shocks for the full set of models considered in this paper.

[8] Alternatively, given that there are data available from 1996 to 2001 for the aforementioned variables, a prior distribution could be estimated from that dataset. The latter is also known as a *Training Sample*. However, for comparison purposes across models, we chose to use only the Minnesota Prior.

[9] see e.g. Hamilton (1994), etc.

2.3 Model 2 (M2): A Bayesian Time Varying VAR model with Stochastic Volatility

Consider now the extended BVAR model named the Time-Varying Bayesian $VAR(p)$ model with Stochastic Volatility (TVP-BVAR-SV):

$$y_t = c_t + B_{1,t}y_{t-1} + \cdots + B_{p,t}y_{t-p} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Omega_t) \tag{4}$$

where the vector y_t is the same as before, c_t a $N \times 1$ is a vector of time varying intercepts, $B_{i,t}$ are $N \times N$ matrices of time varying parameters for each lag $i = 1, \ldots, p$. The error term ε_t is a normally distributed vector with zero mean and a time varying covariance matrix Ω_t such that $\Omega_t = A_t^{-1}\Sigma_t^2 \left(A_t^{-1}\right)'$.

Orthogonalized structural shocks are given by $u_t \sim N(0, I_N)$ such that:

$$\varepsilon_t = A_t^{-1}\Sigma_t u_t \tag{5}$$

which means that P_t is a time-varying identification matrix, and also the diagonal matrix of structural variances is given by $\Sigma_t = diag(\sigma_t)$, where σ_t is a column vector containing the time-varying standard deviations of structural shocks. Time variation in parameter blocks is *a priori* assumed to be as random walks, so that:

$$\beta_t = \beta_{t-1} + \upsilon_t \tag{6}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \tag{7}$$

$$\log(\sigma_t) = \log(\sigma_{t-1}) + \eta_t \tag{8}$$

with

$$V = Var\left(\begin{bmatrix} \varepsilon_t \\ \upsilon_t \\ \zeta_t \\ \eta_t \end{bmatrix}\right) = \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{9}$$

All matrices Q, S and W are positive definite. Bayesian Time varying parameter estimation and the identification of structural shocks is performed in line with the recent literature (see. (Cogley and Sargent (2005), Primiceri (2005), Canova and Pérez Forero (2015)), among others. That is, the parameter set Θ in equation 2 contains $\Theta = \left\{\beta^T, \alpha^T, \sigma^T, V\right\}$, where the time-varying parameters $\left\{\beta^T, \alpha^T\right\}$ are estimated through the Kalman Filter-Smoother following Carter and Kohn (1994), and the stochastic volatility component σ^T is estimated following Kim *et al.* (1998). Finally, V follows an Inverse-Wishart distribution. Given the estimated parameters, we can now compute the time varying impulse responses according to:

$$\frac{\partial y_{t+h}}{\partial u_t} = \Phi_{h,t} = \Psi_{h,t} P_t, \qquad h = 0, 1, \ldots, \overline{H} \tag{10}$$

2.4 Model 3 (M3): A Time Varying Mean-BVAR Model with Stochastic Volatility

Consider now the modified BVAR model named Time-Varying-Mean BVAR with Stochastic Volatility (Banbura and van Vlodrop, 2018):

$$y_t - \tau_t = \sum_{k=1}^{p} B_k \left(y_{t-k} - \tau_{t-k}\right) + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \Omega_t\right) \tag{11}$$

$$\tau_t = \tau_{t-1} + \eta_t, \qquad \eta_t \sim N\left(0, V_t\right) \tag{12}$$

$$z_t = \tau_t + g_t, \qquad g_t \sim N\left(0, G_t\right) \tag{13}$$

where y_t is the column vector macroeconomic and financial variables, z_t is the column vector containing the long-term expectations data from the BCRP Survey[10] a.d τ_t is a column vector containing the time-varying means. In addition, Ω_t is the time-varying covariance matrix such that $\Omega_t = A^{-1}\Sigma_t A^{-1\prime}$, with Σ_t as the diagonal matrix containing the variances of structural shocks and A as a lower triangular matrix with ones in the main diagonal (with free parameters vector α). Finally, V_t and G_t are also diagonal time-varying matrices including the variances of the shocks η_t and g_t, respectively.

The posterior distribution is similar to equation (2), but in this case the parameter space Θ is such that $\Theta = \left\{\beta, \alpha, \tau^T, \Sigma^T, V^T, G^T\right\}$ plus the variances of the transition equations.

Moreover, impulse response functions are similar to equation 3, but in this case because of the time varying variances we consider the normalization $P = I_N$ such that:

$$\frac{\partial y_{t+h}}{\partial u_t} = \Phi_h = \Psi_h I_N, \qquad h = 0, 1, \ldots, \overline{H} \tag{14}$$

A previous application of this model to the Peruvian economy, with the BCRP's Survey of Expectations as observables in z_t, can be found in Pérez Forero (2021).

2.5 Model 4 (M4): A Bayesian VAR model with Stochastic Volatility and Volatility feedback

Consider the following BVAR with SV, in the spirit of Alessandri and Mumtaz (2019) without a threshold parameter:

$$y_t = c + \sum_{j=1}^{P} \beta_j y_{t-j} + \sum_{j=0}^{J} \gamma_j \lambda_{t-j} + \Omega_t^{1/2} \varepsilon_t \tag{15}$$

where y_t is the set of macroeconomic variables. The time varying covariance matrix Ω_t such

[10] https://www.bcrp.gob.pe/estadisticas/encuesta-de-expectativas-macroeconomicas.htmlhttps://www.bcrp.gob.pe/estadisticas/de-expectativas-macroeconomicas.html

that $\Omega_t = A^{-1}\Sigma_t A^{-1\prime}$, with A as a lower triangular matrix and Σ_t as a matrix defined by:

$$\Sigma_t = exp\left(\lambda_t\right) \times S \tag{16}$$

with S being a diagonal matrix that captures the constant heteroskedasticity:

$$S = \begin{bmatrix} s_1 & 0 & \dots & 0 \\ 0 & s_2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & s_{dim(y)} \end{bmatrix} \tag{17}$$

with $s_j > 0$ for $j = 1, \dots, dim\left(y\right)$. The matrix A is lower triangular with the main diagonal governed by ones and free parameters below the main diagonal, i.e.

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \alpha_1 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ \alpha_k & \alpha_{k+1} & \dots & 1 \end{bmatrix}. \tag{18}$$

In this context, recall also that $vec\left(A\right) = S_A\alpha + s_A$ (Amisano and Giannini, 1997), with S_A and s_A are matrices governed by 0s and 1s. The latter is a useful transformation in order to sample the full parameter vector α (Canova and Pérez Forero, 2015).

Finally, log-volatility λ_t enters both in mean (with lags) and also in the covariance matrix Ω_t. The log-volatility component can also be interpreted as an Uncertainty measure, which can be represented as a stationary $AR(1)$ process with drift:

$$\lambda_t = \mu + F\left(\lambda_{t-1} - \mu\right) + \eta_t \tag{19}$$

with $0 < F < 1$ and $\eta_t \sim i.i.d.N\left(0, Q\right)$. Notice that a single scalar process governs the time varying volatility (Carriero *et al.*, 2016; Alessandri and Mumtaz, 2019), which is a more parsimonious representation than other specifications where each shock has a different time varying variance (see e.g. Primiceri (2005), Canova and Pérez Forero (2015), (Banbura and van Vlodrop, 2018), among others).

The posterior distribution is similar to equation (2), but in this case the parameter space Θ is such that $\Theta = \left\{\beta, \gamma, \alpha, \lambda^T, S, \mu, F, Q\right\}$ plus the variances of the transition equations.

In this case, impulse response functions should be computed as the difference of two forecasts such that:

$$\frac{\partial y_{t+h}}{\partial u_t} = E\left(y_{t+h} \mid \Theta, \delta\right) - E\left(y_{t+h} \mid \Theta\right), \qquad h = 0, 1, \ldots, \overline{H} \tag{20}$$

where δ is the shock size. Equation (20) takes into account the randomization of shocks and the forecast of λ_{t+h} within the process of forecasting y_{t+h}.

2.6 Model 5 (M5): A Threshold-Bayesian VAR model with Stochastic Volatility and Volatility feedback

Consider the extended version of the BVAR presented in the previous subsection. In this opportunity we specify the following two-regime Vector Auto-regressive model (Threshold-BVAR), which closely follows Alessandri and Mumtaz (2019):

$$\begin{gathered} y_t = \left(c_1 + \sum_{j=1}^{p} \beta_{1,j} y_{t-j} + \sum_{j=0}^{J} \gamma_{1,j} \lambda_{t-j} + \Omega_{1t}^{1/2} \varepsilon_t\right) \tilde{S}_t + \\ \left(c_2 + \sum_{j=1}^{p} \beta_{2,j} y_{t-j} + \sum_{j=0}^{J} \gamma_{2,j} \lambda_{t-j} + \Omega_{2t}^{1/2} \varepsilon_t\right) \left(1 - \tilde{S}_t\right) \end{gathered} \tag{21}$$

where the vector of variables y_t is the same as in the previous models, and where the shocks are normally distributed, i.e. $e_t \sim i.i.d.N\left(0, I_{dim(y)}\right)$.

The binary regime indicator $\tilde{S}_t$ is defined by

$$\tilde{S}_t = 1 \iff F_{t-d} \leq Z^* \tag{22}$$

and where both the delay d (which follows a discrete distribution $d = 1, \ldots, d^*$) and the threshold Z^* are unknown parameters that need to be estimated.

The covariance matrix for the error term $\Omega_{it}^{1/2} e_t$ for each regime $i = 1, 2$ are similar to the previous model:

$$\Omega_{1t} = A_1^{-1} \Sigma_t A_1^{-1\prime} \tag{23}$$

$$\Omega_{2t} = A_2^{-1} \Sigma_t A_2^{-1\prime} \tag{24}$$

Finally, log-volatility λ_t and all the implied parameters are defined as in the previous case. The posterior distribution is similar to equation (2), but in this case the parameter space Θ is such that $\Theta = \left\{\beta, \gamma, \alpha, \lambda^T, S, \mu, F, Q\right\}$ plus the variances of the transition equations.

In this case, impulse response functions should be computed as the difference of two forecasts such that:

$$\frac{\partial y_{t+h}}{\partial u_t} = E\left(y_{t+h} \mid \Theta, \delta\right) - E\left(y_{t+h} \mid \Theta\right), \qquad h = 0, 1, \ldots, \overline{H} \tag{25}$$

Notice that in the threshold model the shock could cause a regime switch. Therefore, in this case is even more important to consider these two forecasts instead of a static power matrix formula.

In addition, we consider the inflation rate as the threshold variable, so that it is important to also take a look to its historical distribution for the period under analysis. The histogram is depicted in Figure 2, which reflects a bimodal distribution, suggests that there is room for a regime where inflation is above 5.0-6.0%.

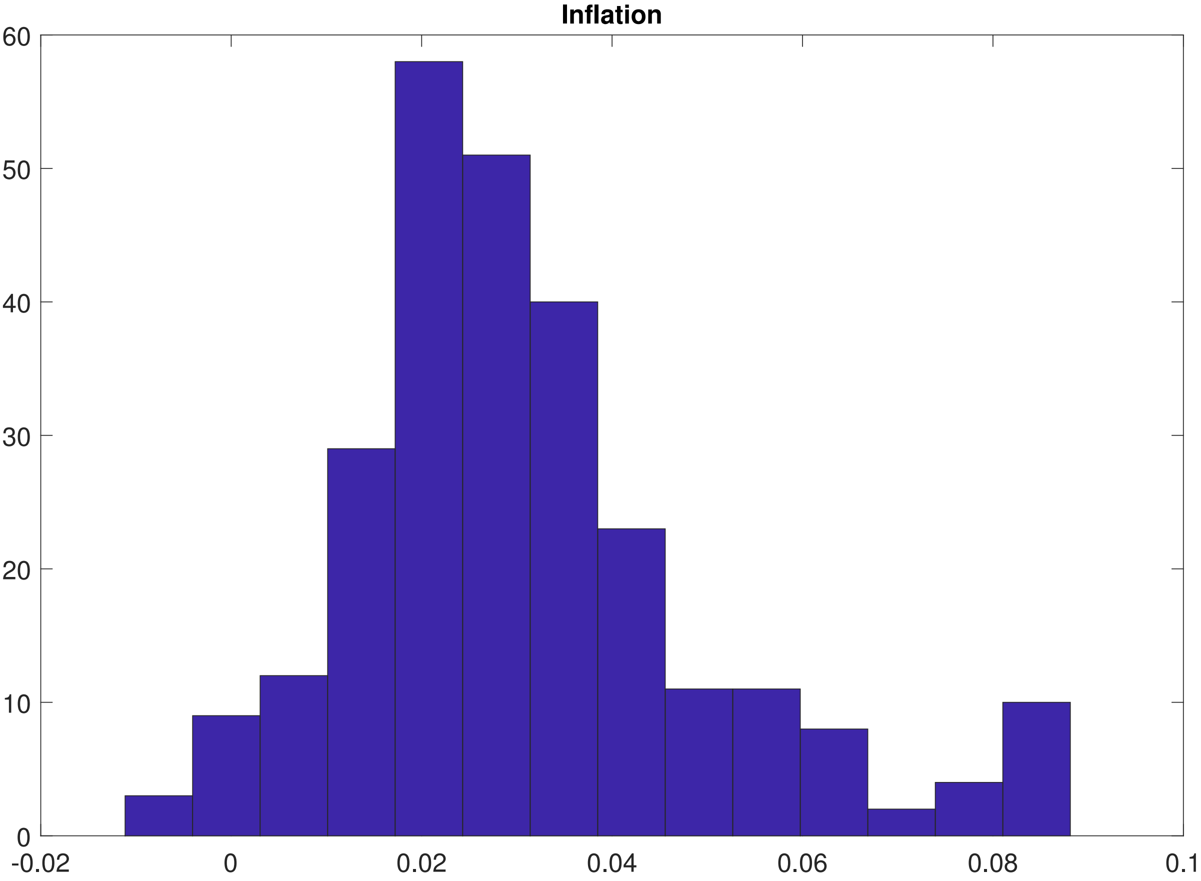

Figure 2: **Peru**: Year-to-Year Inflation Histogram (2002-2024)

2.7 The Minnesota Prior

For the BVAR coefficients $\beta = vec(B)$ we take an independent normal prior, i.e. a conjugated prior:

$$p(\beta) = N(\mu_B, \lambda_0 \Omega_B) \tag{26}$$

with μ_B as the common mean and λ_0 as the overall tightness parameter. Since me assume that the model is stationary in mean, and because the variables included in the model are transformed to be stationary, we set $\mu_B = 0_{dim(\beta)}$. The covariance matrix Ω_B takes the form of the typical Minnesota prior (Litterman, 1986), i.e. $\Omega_B = diag\left(\omega_{ij,l}\right)$ such that

$$\omega_{ij,l} = \begin{cases} \frac{1}{l^{\lambda_3}} & , i = j \\ \frac{\lambda_1}{l^{\lambda_3}}\left(\frac{\widehat{\sigma}_j^2}{\widehat{\sigma}_i^2}\right) & , i \neq j \\ \lambda_2 & , exogenous \end{cases} \tag{27}$$

where

$$i, j \in \{1, \ldots, M\} \text{ and } l = 1, \ldots, p$$

and $\widehat{\sigma}_j^2$ is the variance of the residuals from an estimated $AR(p)$ model for each variable $j \in \{1, \ldots, M\}$.

We set the parameters $\lambda_0 = 0.2$, $\lambda_1 = 0.5$, $\lambda_2 = 1$, $\lambda_3 = 2$, taking the benchmark values of Doan *et al.* (1984) (see also Canova (2007)) except the one for the exogenous component λ_2, which is typically set to $10,000$.

2.8 Model Comparison

In this section we perform the model selection using a measure of goodness of fit for each of the five presented models and for the period 2002-2024. To do so, a good practice in Bayesian Econometrics is to compute the Marginal Likelihood for each model. That is, we need to integrate out the posterior distribution across the parameter space, and the see to what extent a given model is a good representation of the data, i.e. the model with a higher marginal likelihood will be the best one. The marginal likelihood for each model M_i is

$$f\left(Y^T \mid M_i\right) = \int L\left(\psi_j \mid Y^T, M_i\right) P\left(\psi_j \mid M_i\right) dj$$

Given the scales, it is better to compute the log-marginal likelihood $\ln f\left(Y^T \mid M_i\right)$, and this is estimated using a standard harmonic mean estimator. Results are shown in Table 1. In particular, we select the model M_3 for conducting inference in the subsequent sections.

Model	Description	$\ln f\left(Y^T \mid M_i\right)$
M_1	Baseline Model $BVAR$	$-2,754.110$
M_2	TVP-BVAR-SV	$-5,372.616$
M_3	TV-MEAN-SV	$-2,194.899$
M_4	BVAR-SV-Mean	$-2,374.107$
M_5	Threshold-BVAR-SV-Mean	$-3,079.682$

Table 1: Log-Marginal Likelihood of Different models

3 Monetary Policy Shocks Identification

After computing the reduced-form parameters, we are ready to identify structural shocks. For that purpose, we impose a mixture of Zero and Sign Restrictions for for monetary policy shocks and for the Peruvian economy. The full set of restrictions are summarized in Table 3 and the algorithm to compute impulse responses can be found in Appendix A.

Now we proceed to explain the economic intuition behind the identification restrictions for each structural shocks[11]. In first place, we consider *slow* variables as the ones that do not react contemporaneously to other shocks except of their specific one. In this group of variables we include the Headline Inflation, GDP growth and the Terms of Trade. We assume that each structural shock is orthogonal (independent) of the remaining shocks in the system, so that we can interpret the associated impulse responses of each one as an estimated average causal effect for the period 2002-2024.

[11]See also a similar identification scheme in Pérez Forero (2024a) and Pérez Forero (2024b).

Var / Shock	**Mon. Policy**	**Cat.**
Inflation	≤ 0	S
GDP	≤ 0	S
Terms of Trade	?	S
Interbank Rate	> 0	F
M2	≤ 0	F
ER Depr.	≤ 0	F

Table 2: Identification Restrictions
'S' means *slow* and 'F' means *fast*

Monetary Policy Shock: A contractionary (tighter) monetary policy shock considers an hike in the interbank rate, together with a decrease in output and inflation (the traditional real interest rate channel), as well as in the money aggregate in domestic currency (liquidity effect) and a decrease in the exchange rate depreciation, which is related with the uncovered interest rate parity (UIP).

4 Discussion of main results

4.1 Identified Monetary Policy Shocks

Regarding the linear model (M1), results are in line with the empirical literature for the case of Peru (see e.g. Castillo *et al.* (2011), Pérez-Forero and Vega (2014), Aguirre *et al.* (2023), among others), with a fall in economic activity within the first 6-9 months, and with a subsequent effect on headline inflation (12-18 months peak). A detail to highlight is that the results presented in Figure 3 correspond to a linear BVAR that takes into account data including the covid-19 pandemic episode. It seems that the negative results of 2020 were offset by the rebound of 2021, and normalization began in 2022. Thus, the covid-19 pandemic can be considered as an event of large shocks, but in the long term it did not significantly alter the existing structural relationships between the relevant macroeconomic variables.

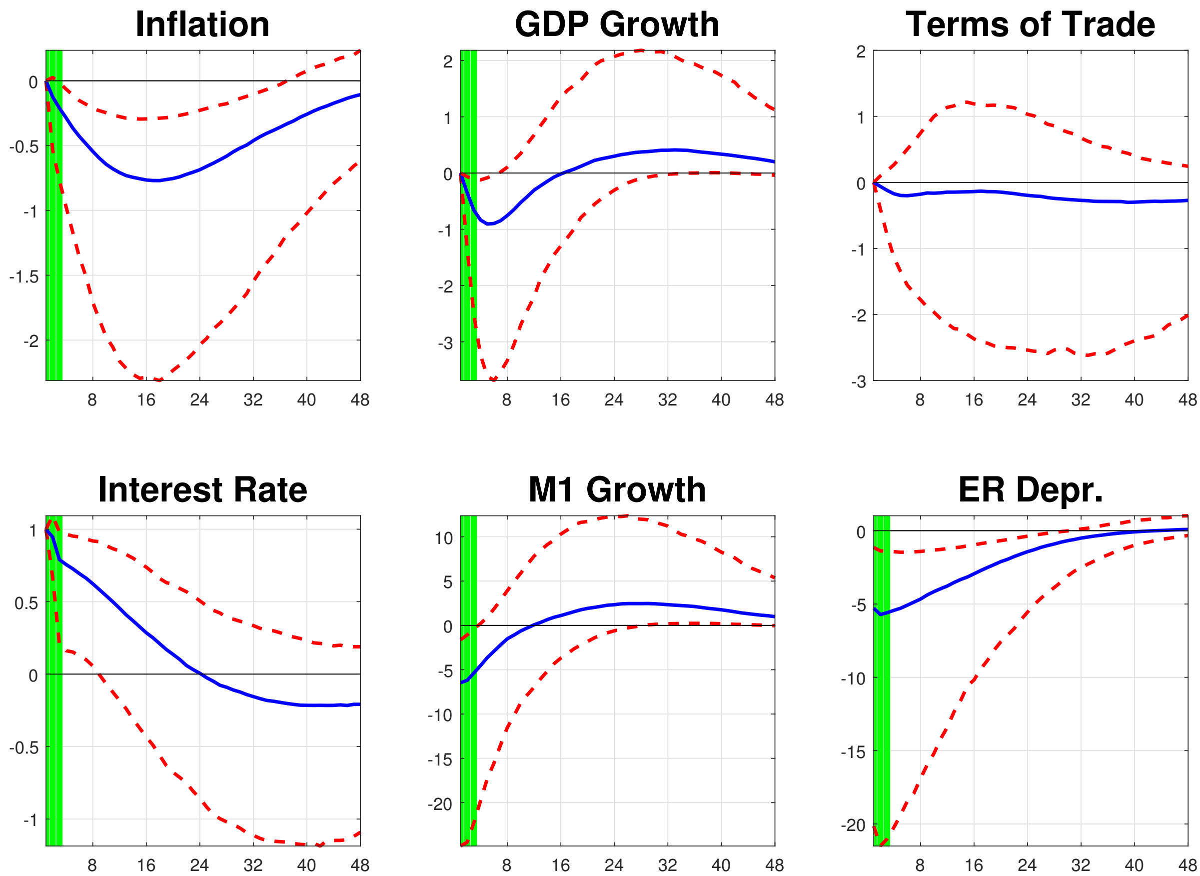

Figure 3: **M1**: Monetary Policy Shock - Median value and 68% C.I.

We now proceed to examine the results obtained from the TVP-BVAR-SV (M2) model. In particular, given the sign restrictions specified above, the results look statistically very similar to those of model M1, that is, the linear model with constant parameters. Thus, the results in Figure 4 show the transmission mechanism of the monetary policy shock in the year 2023, including its confidence bands. Although this model considers time-varying parameters, the change is extremely negligible, and therefore it can be considered that under the M2 model this mechanism is stable throughout the sample between 2002-2024 (see also appendix C.2 for the shocks in different dates.).

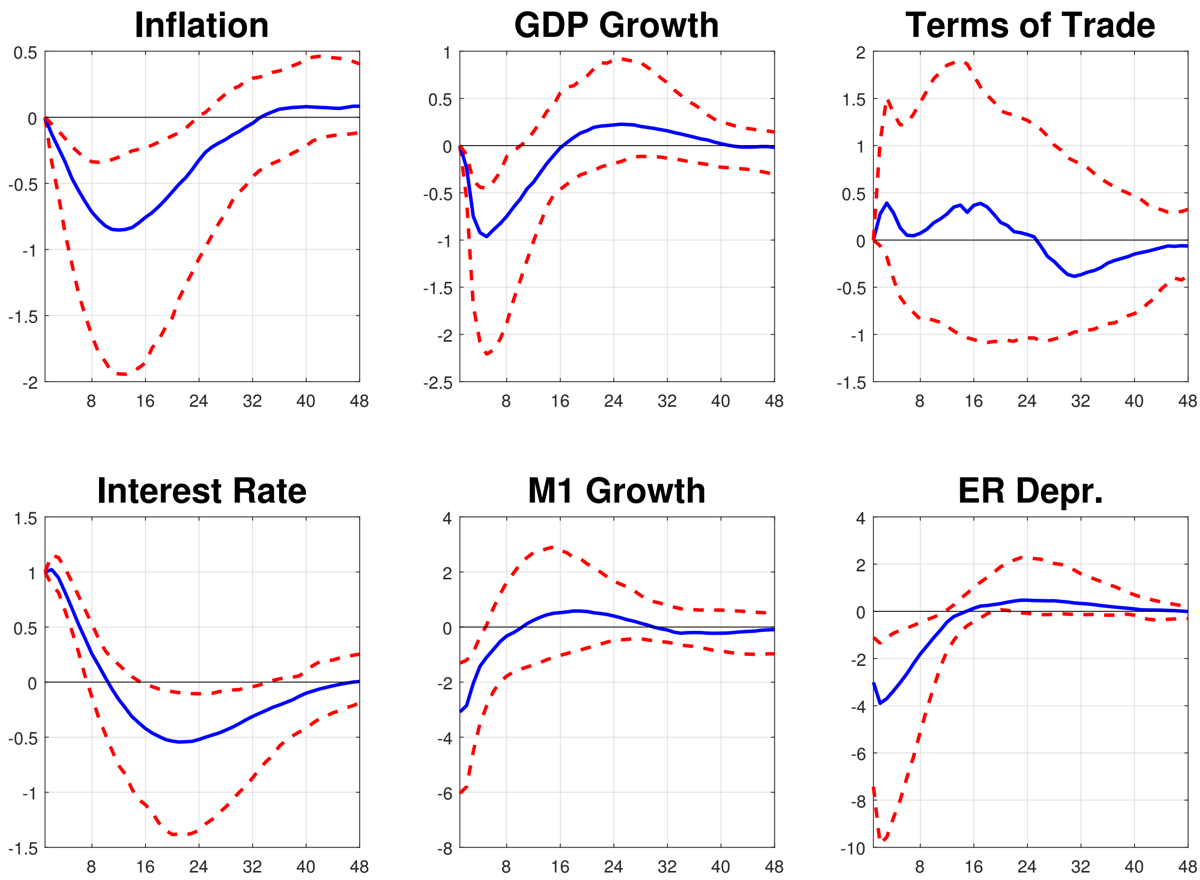

Figure 4: **M2**: Monetary Policy Shock (2023) - Median value and 68% C.I.

In addition, monetary policy shocks in the M3 model are also in line with what was previously found (see Figure 5). That is, if we consider stochastic volatility in different dimensions (both in observable and latent variables), it is possible to control for the structural breaks that are presumed to be present in the economy. As a result, even controlling for the macroeconomic expectations surveys, we find that the transmission mechanism of monetary policy shocks remains stable for the period 2002-2024.

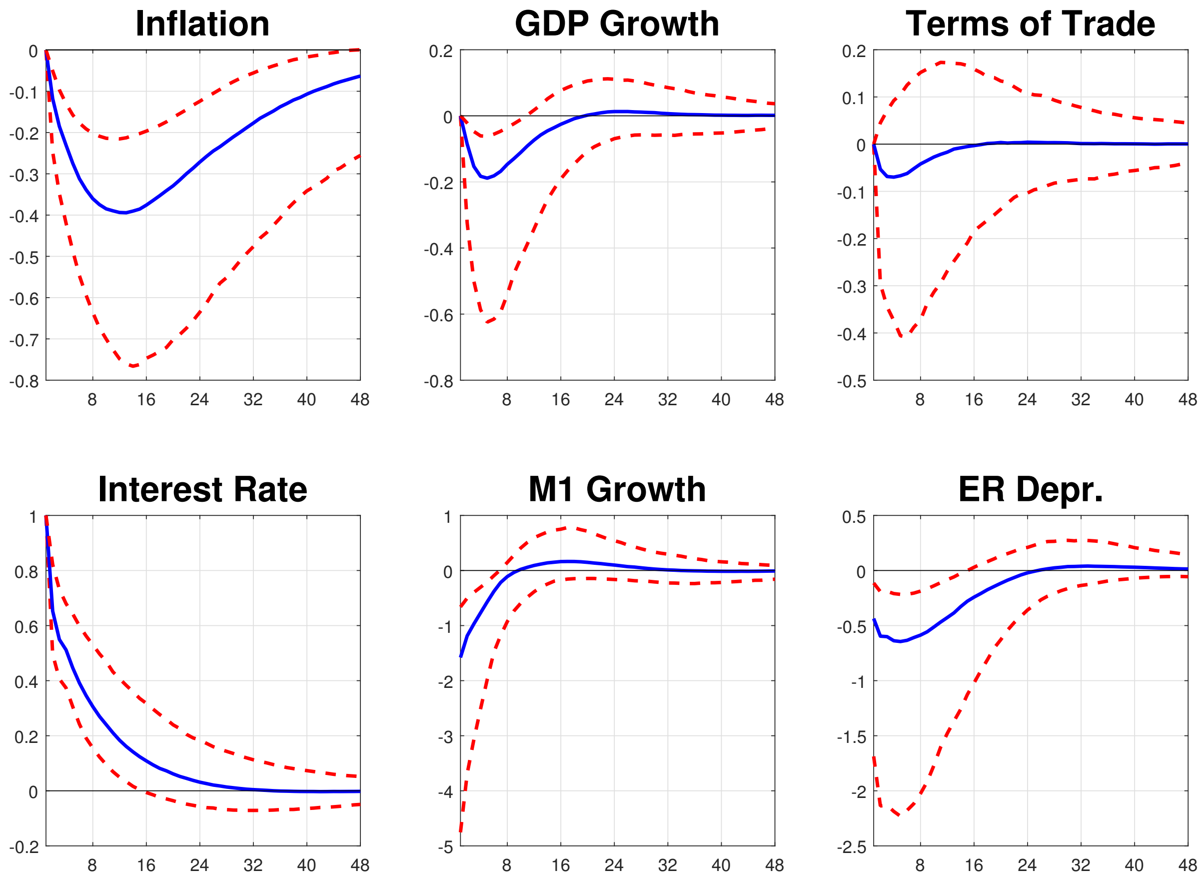

Figure 5: **M3**: Monetary Policy Shock - Median value and 68% C.I.

In the case of the model with volatility feedback, we also find a monetary policy transmission mechanism very similar to those of the previous models (see Figure **??**). This means that it is enough to correct or control for stochastic volatility in the appropriate way (in this case also in mean), in order to capture the transmission mechanism expected in a standard linear model. That is, despite the global episodes mentioned above, the transmission mechanism of monetary policy in Peru has remained stable since the inflation target scheme was adopted.

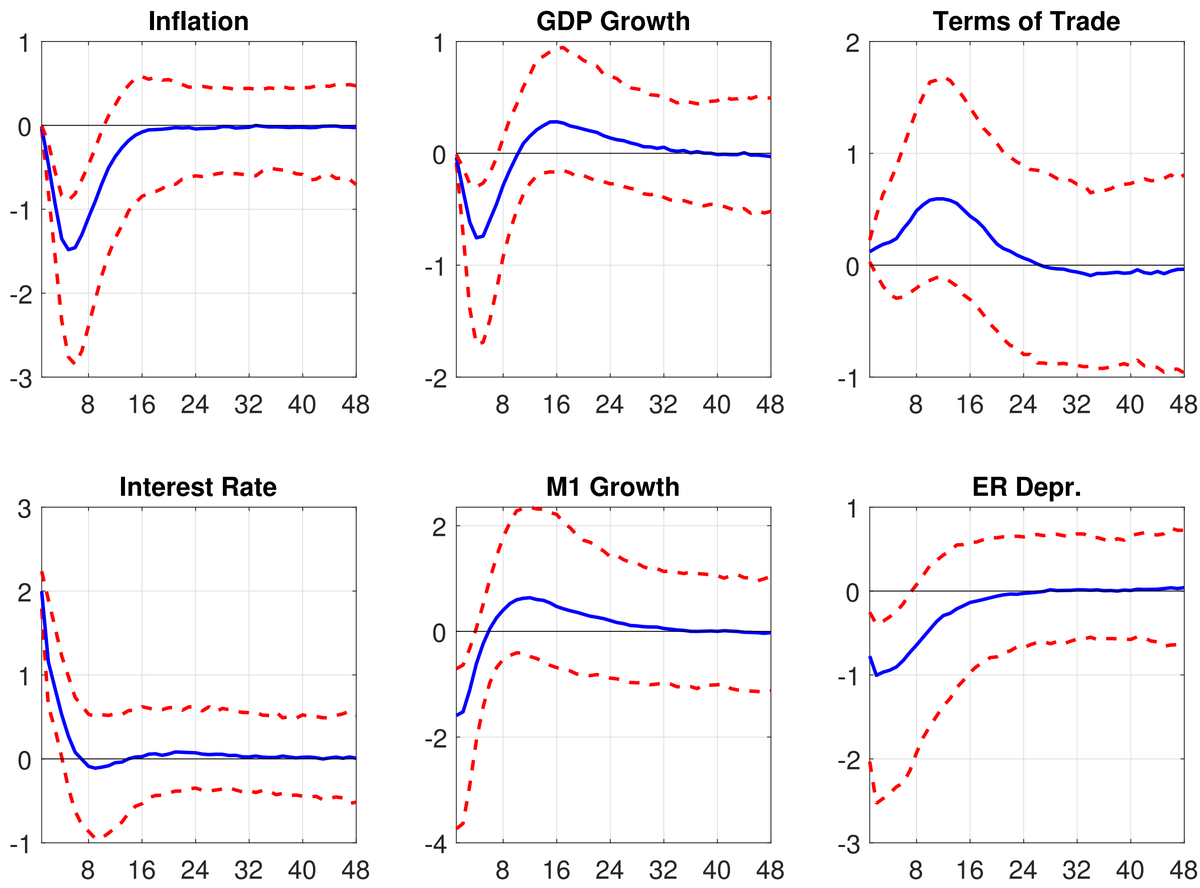

Figure 6: **M4**: Monetary Policy Shock - Median value and 68% C.I.

Finally, we can observe that in the model with a threshold variable (M5) there is no significant difference between the high and low inflation regimes (Figure 7), which means in particular that the transmission mechanism of monetary policy has remained stable despite the increase in inflation between 2021 and 2023. Thus, in general we can observe that the identified transmission mechanism of monetary policy is robust to different empirical representations using Peruvian macroeconomic data.

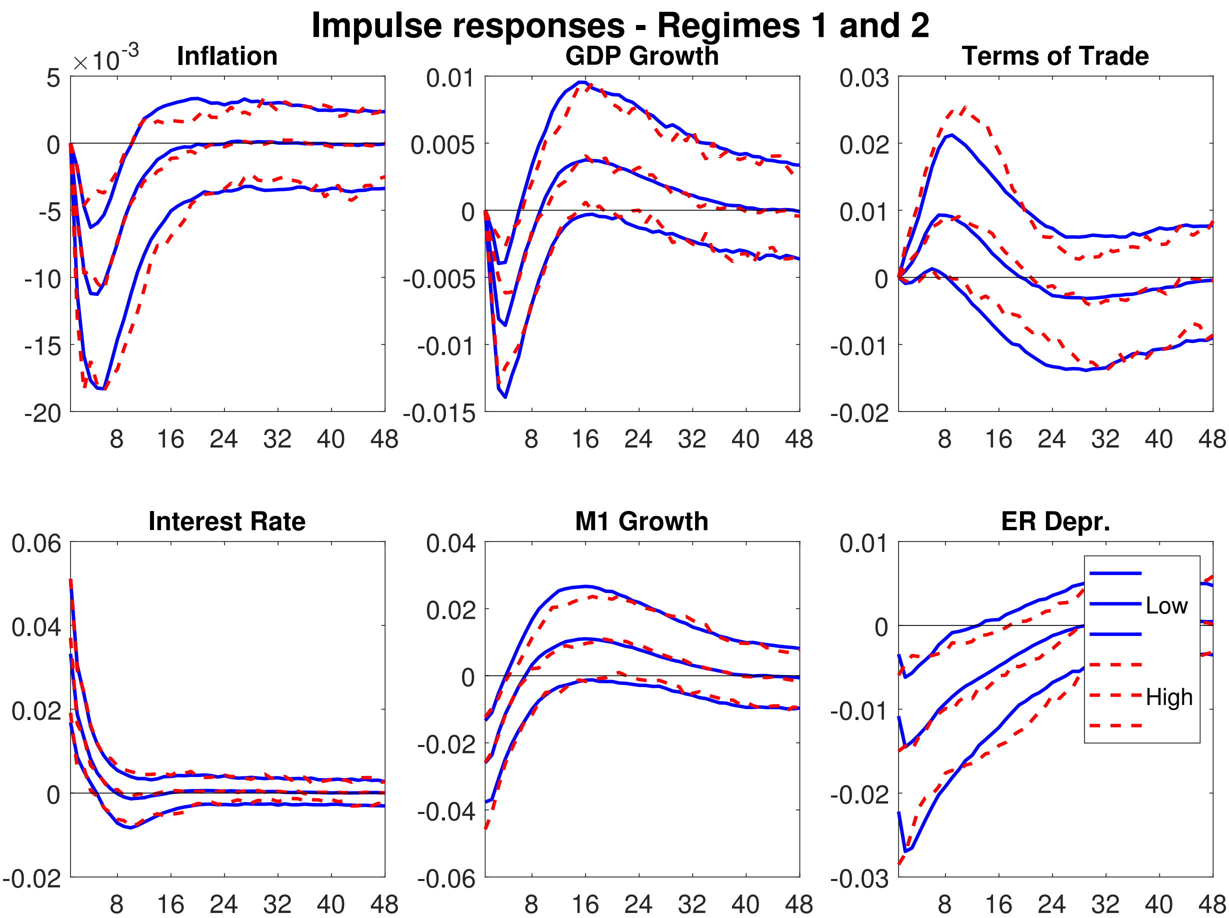

Figure 7: **M5**: Monetary Policy Shock - Median value and 68% C.I.

5 Trend Inflation Estimation

In this section we present two alternative estimated measures of Trend Inflation. In first place, using the Time-Varying BVAR model (M2), we specify the companion form following Cogley and Sargent (2005):

$$\mathbf{Y}_t = \mu_{t|T} + \mathbf{A}_{t|T}\mathbf{Y}_{t-1} + \mathbf{E}_t$$

Assuming that the model is locally stationary, we compute the time varying mean for the full system. Then, we select the inflation equation, so that the trend inflation is

$$\overline{\pi}_t = s_\pi \left(I - \mathbf{A}_{t|T}\right)^{-1} \mu_{t|T}$$

where s_π is a vector that selects current inflation (π_t) from the vector $\mathbf{Y}_t$. Results are depicted in Figure 8, where we can observe that, given the confidence interval, the trend inflation is always anchored to the inflation target range, thought the uncertainty about this value is higher for the last period of inflation surge.

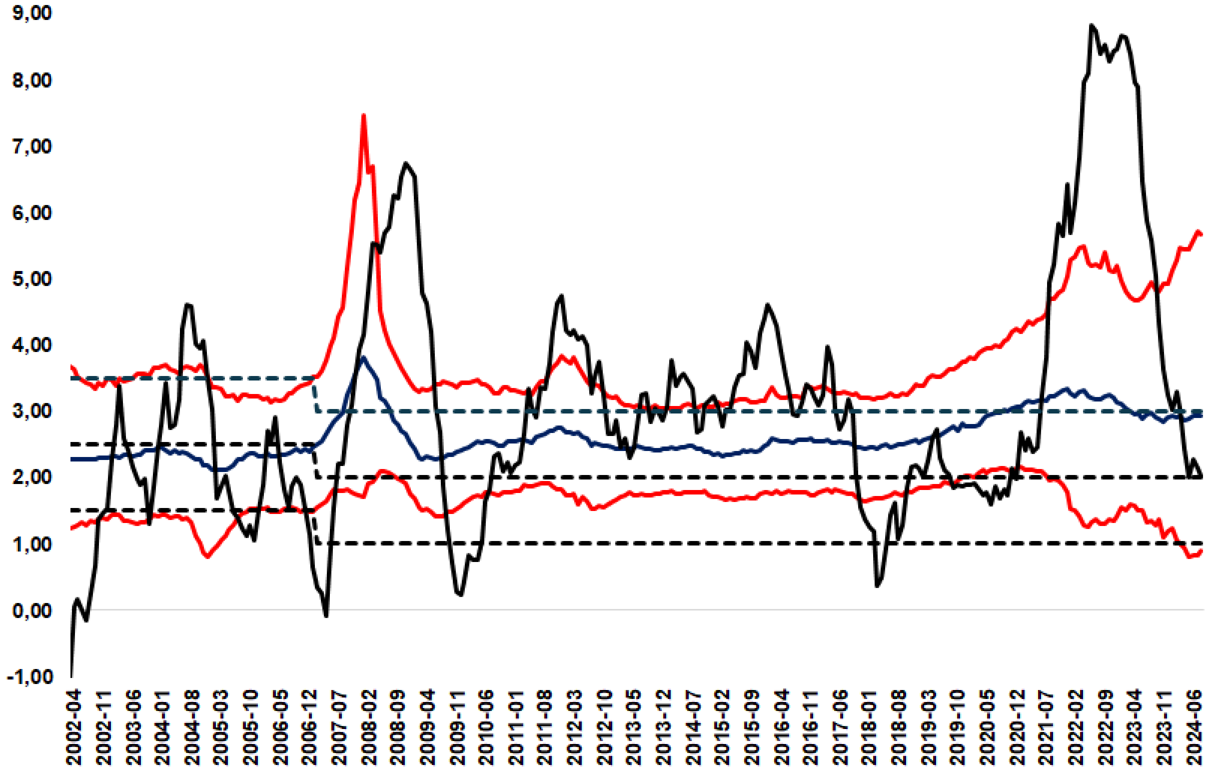

Figure 8: **M2**: Trend Inflation (median value and 68% confidence interval)

Regarding Model M3, which is the one with the best relative fit according to the marginal likelihood (see Table 1), we plot the posterior distribution of the estimated τ_t associated with inflation in equation 11, and results are depicted in Figure 9. We also observe that the inflation trend is statistically anchored to the inflation target range for the period 2002-2024, but in this case the precision is higher than model M2. All in all, we do not observe a significant deviation of the inflation trend from the target range, and this is also favorable for the credibility of the Inflation Targeting regime.

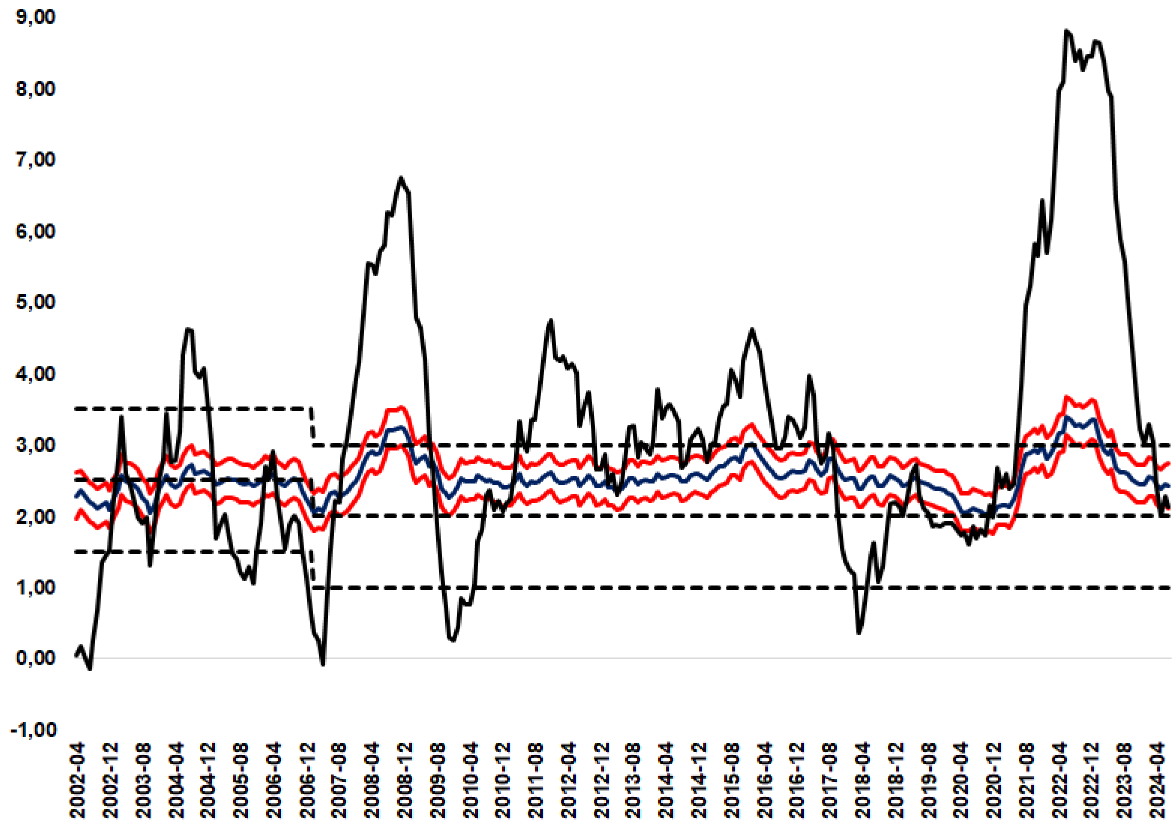

Figure 9: **M3**: Trend Inflation

6 Adding other Structural Shocks to the system - Inflation Historical Decomposition

In order to characterize the entire macroeconomic context for the Peruvian economy, we employ a similar identification scheme but for the remaining shocks. The fact that we are able to capture the posterior distribution of the mentioned shocks means that they are described by the data, and that there is room for the specification and estimation of a stylized micro-founded model with appropriate frictions.

Aggregate Supply Shock: A negative supply shock considers an increase in headline inflation, together with a fall in output, representing the typical tradeoff or Phillips curve effect, which also triggers the systematic response of the Central Bank by increasing the interest rate (Taylor

Rule effect). One of the contributions of this paper is the documentation of these supply shocks for the Peruvian economy, where we identify that the empirical literature is fairly scant about this topic. We also document that the identified macroeconomic shock does not produce any significant effect in financial variables such as credit, deposits and interest rate spreads.

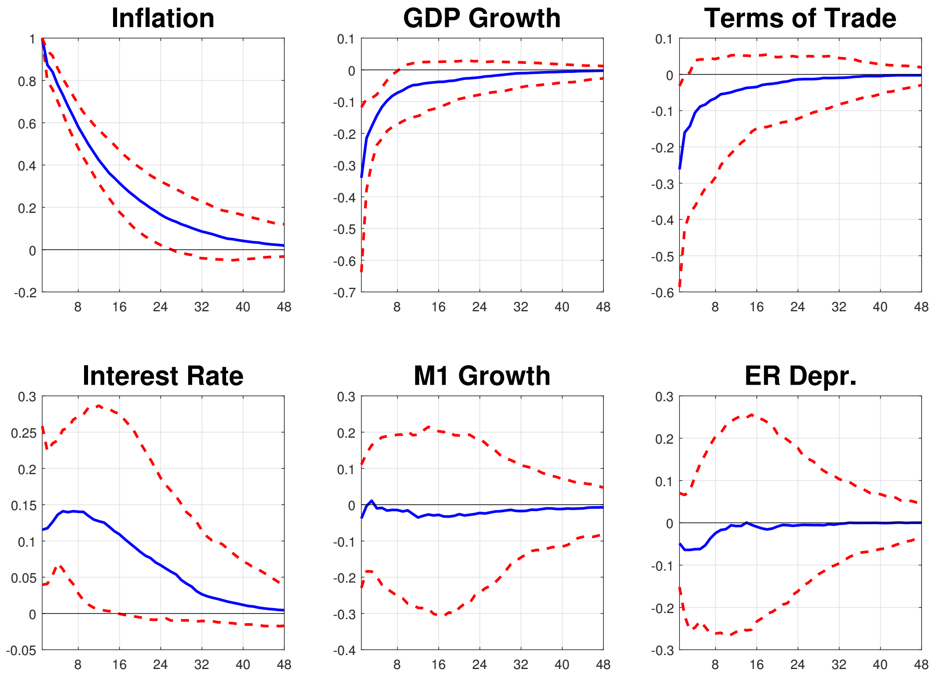

Figure 10: **M3**: Aggregate Supply shock

Aggregate Demand Shock: A positive demand shock (which is in general associated with a fiscal policy expansion) considers an impulse in GDP growth, and given the demand pressures it also delivers an increase in the inflation rate. The latter also triggers a systematic response of the Central Bank by increasing the interest rate (Taylor Rule effect). Since this an impulse in domestic currency, we impose that that it has a negative effect in the Credit in Foreign Currency. The demand impulse also produces a rise in Cash, which includes the possible transfers from the government to households, as well as an acceleration of the YOY Credit growth in soles. The last two effects fit with the demand impulse provided by the government during the Covid-19 pandemic episode. In line with the macroeconomic literature, demand shocks are part of the main determinants of inflation and economic activity, and our contribution is to document the presence of this type of shocks in Peruvian data.

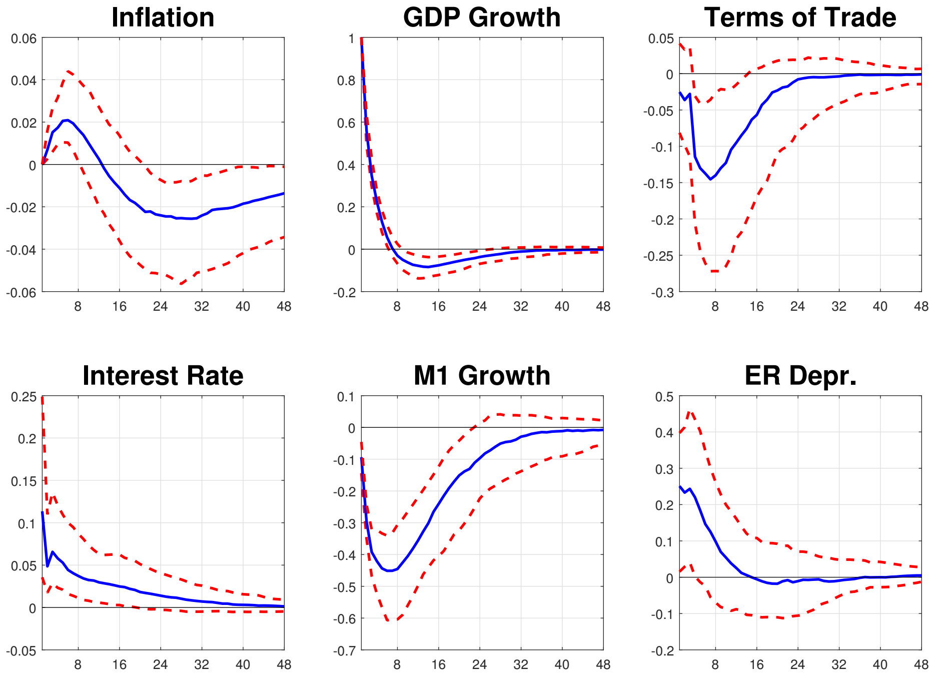

Figure 11: **M3**: Aggregate Demand shock

Exchange Rate Shock: An Exchange Rate shock produces an increase in exchange rate depreciation, which delivers an increase in inflation because of the exchange rate pass-through, and because of the latter it ultimately triggers a systematic response of the Central Bank by increasing the interest rate (Taylor Rule effect). Evidence for the exchange rate shocks in Peru can be found in Castillo *et al.* (2011). In addition, evidence of the exchange rate pass-through to inflation in Peru can be found in Pérez and Vega (2015), Winkelried (2012), and Winkelried (2003).

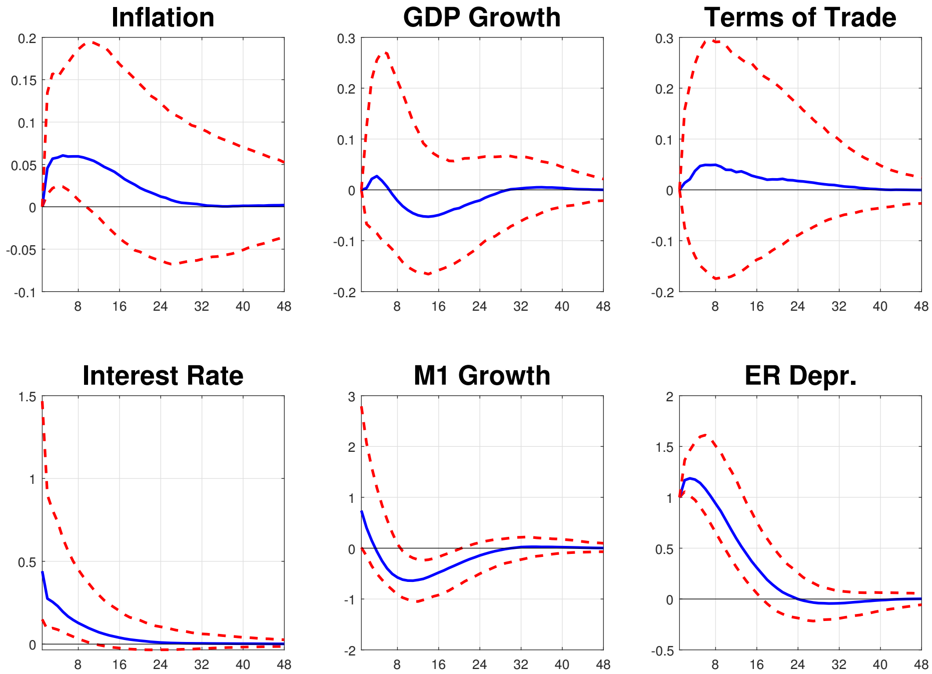

Figure 12: **M3**: Exchange Rate shock

Terms of Trade Shock: Terms of trade shocks capture the commodity boom effect, with a rise in output and an appreciation of the domestic currency.

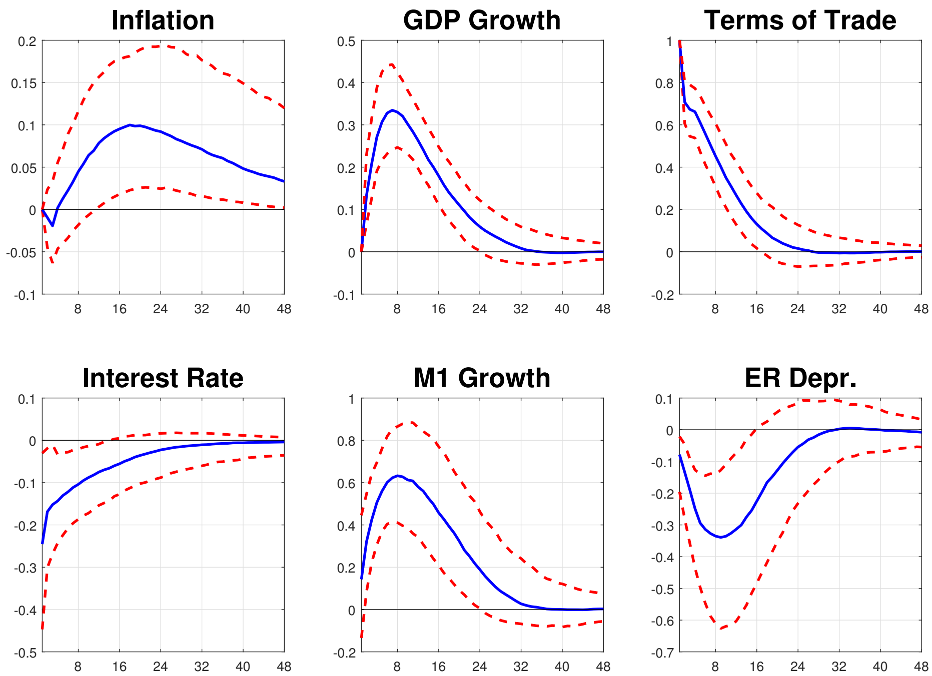

Figure 13: **M3**: Terms of Trade shock

Monet Demand Shock: Money Demand shocks will also reflect a textbook effect, with positive pressure on economic activity and interest rates.

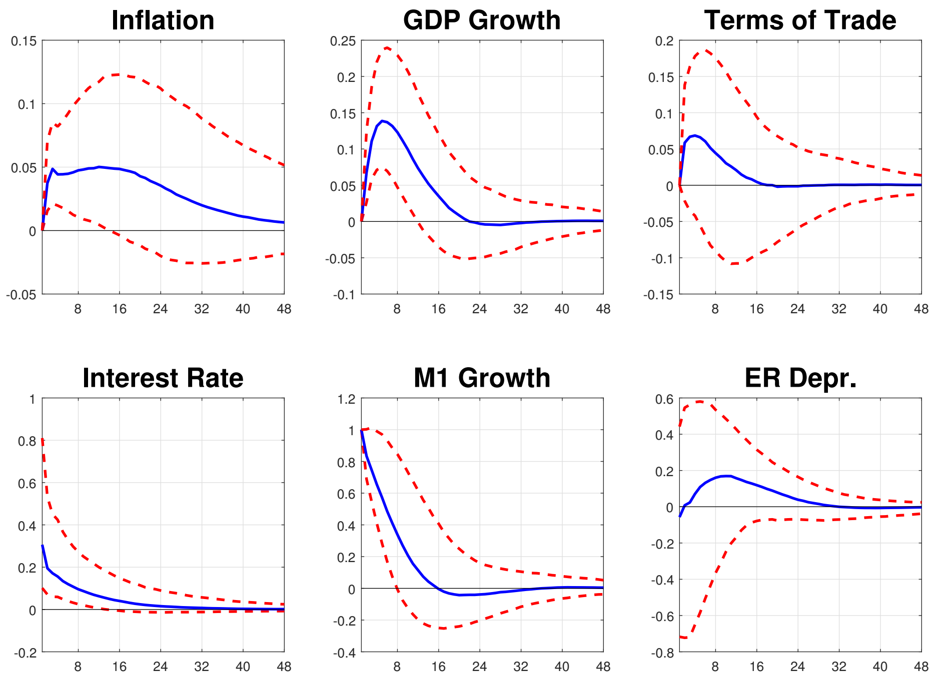

Figure 14: **M3**: Money Demand shock

It is important to mention that the effect of Central Bank actions are also reflected in the systematic component of monetary policy. That is, given a shock in e.g. aggregate demand, the policy rate rises because of the effect on inflation, and the latter also occurs for the case of the persistent supply shocks. The latter could also be considered as an empirical counterpart of a Taylor Rule. To sum up, we include the full set of zero and sign restrictions in Table 3.

Var / Shock	**Mon. Policy**	**Aggr.Demand**	**Aggr.Supply**	**Money Demand**	**Terms of Trade**	**Exch. Rate**	**Cat.**
Inflation	≤ 0	≥ 0	> 0	≥ 0	?	≥ 0	S
GDP	≤ 0	> 0	≤ 0	≥ 0	≥ 0	?	S
Terms of Trade	?	?	?	?	> 0	?	S
Interbank Rate	> 0	≥ 0	≥ 0	≥ 0	?	≥ 0	F
M2	≤ 0	?	?	> 0	?	?	F
ER Depr.	≤ 0	?	?	?	≤ 0	> 0	F

Table 3: Identification Restrictions
'S' means *slow* and 'F' means *fast*

Given the identified shocks in the Bayesian Vector Autorregressive model (M3), we compute the historical decomposition considering the time-varying mean (see Figure 15). We see that the contribution of monetary policy exogenous surprises are relatively mild, and that there is a higher contribution of both demand and supply shocks. In particular, the last episode of inflation surge (2021-2023) is basically explained by a combination of both demand and persistent supply shocks.

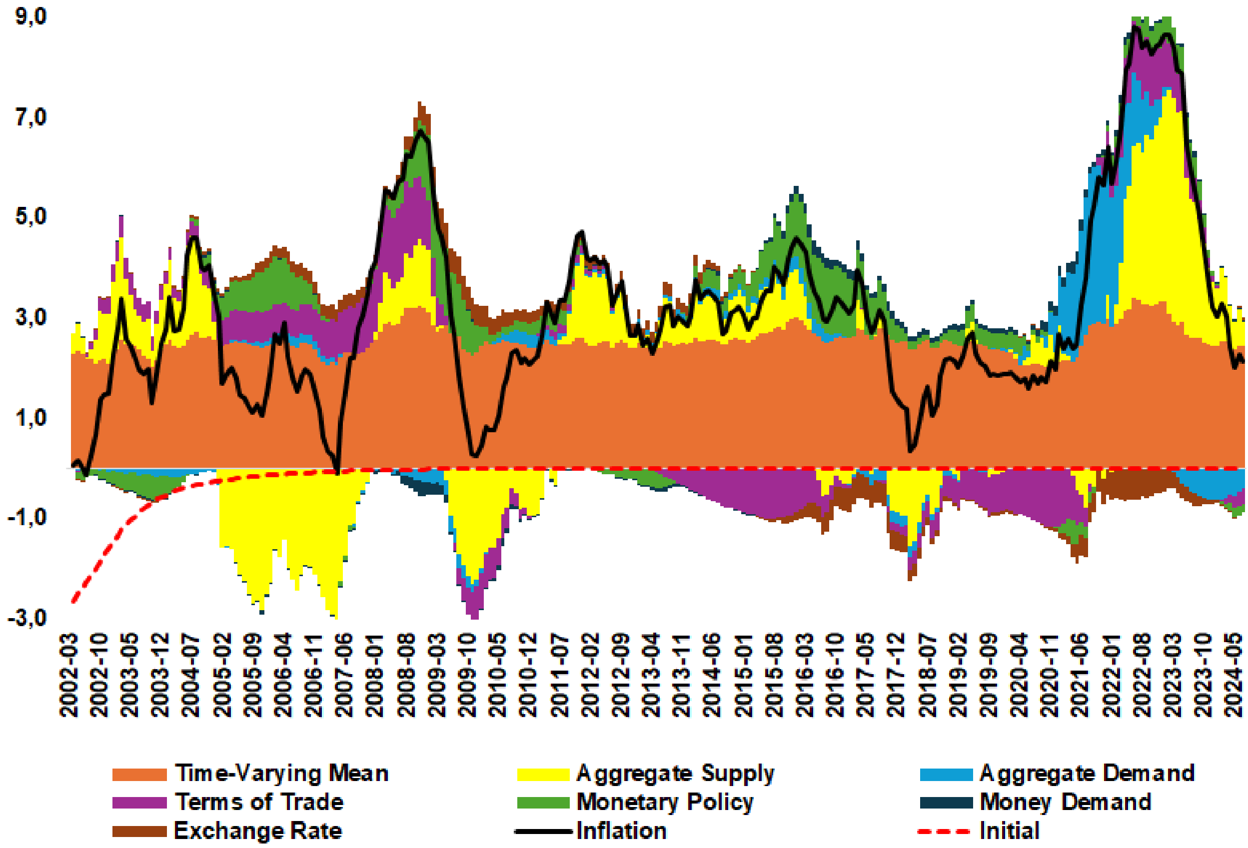

Figure 15: **M3**: Historical Decomposition of Inflation

7 Adding pre-Inflation Targeting Data (1996-2001)

In this section we take into consideration the macroeconomic data of Peru available prior to the adoption of the inflation targeting scheme. Thus, in the case of the six variables shown in figure xx, we include monthly data on year-to-year growth rates and the interest rate between October 1995 and December 2001 (see Figure 16). It is important to mention that the period prior to the adoption of the inflation targeting scheme that is going to be studied is a period in which there was already low inflation. However, as a monetary aggregate control regime was used, the recorded interbank interest rate was much more volatile at that time. Likewise, this period includes events such as the El Niño Phenomenon and the banking crisis, both recorded in 1998, which also coincides with a year-to-year depreciation of the sol (PEN) with respect to the USD of more than 20%. In short, there was a period of relative monetary contraction until 2001, with interest rates between 5 and 10 percent, and a year-to-year slowdown in liquidity in soles, which reached negative rates between 2000 and 2001. It is also worth mentioning that this period includes the first years where inflation was below 10%, that is, since February 1997. Since then and until the latest information available, total inflation in Peru has been below of said level, totaling 27 consecutive years.

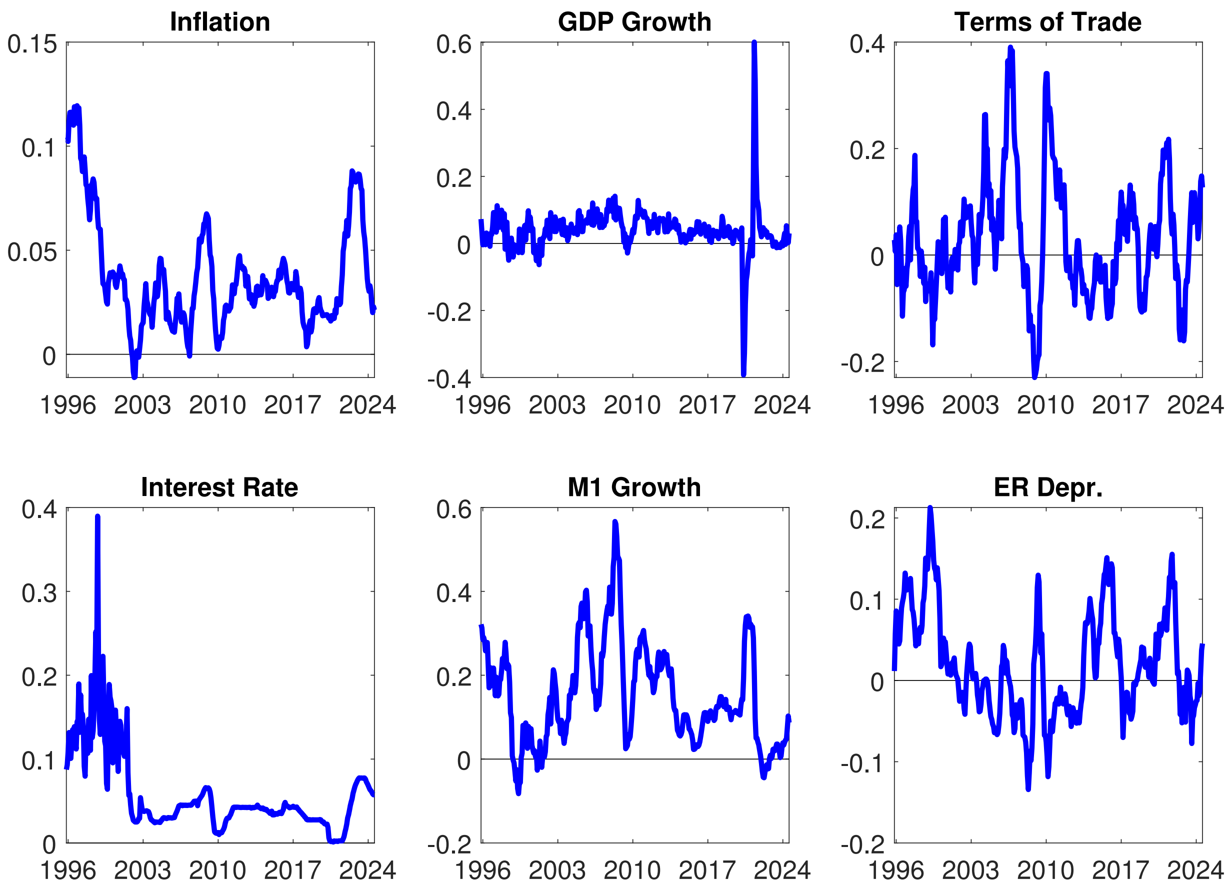

Figure 16: Peruvian Macroeconomic Data (1996-2024)

7.1 Identified Monetary Policy Shocks

Taking into account the previous data, we proceed to re-estimate models M2 and M5, associated with TVP-BVAR-SV and Threshold-BVAR-SV, respectively. We will call these **M6** and **M7**. For these cases we use the same priors structure as for the previous models (**M2** and **M5**). Likewise, it is extremely crucial to specify that the identification of monetary policy shocks in these cases is identical to that of the model that only uses the inflation targeting sample. This is possible because the sign restrictions do not consider normalization to a specific monetary policy instrument. Thus, the restrictions are valid both in the case of the use of the reference interest rate and the monetary aggregates control regime. Consequently, the results for model M6 are shown in Figure 17. The estimated dynamic effects are qualitatively similar to those obtained with the previous models (see also Figures C.36 and C.37 in the appendix). Given these results, it is possible to affirm that the transmission mechanism of BCRP's monetary policy is stable even for the years prior to the adoption of the inflation targeting scheme (see also Figure 18).

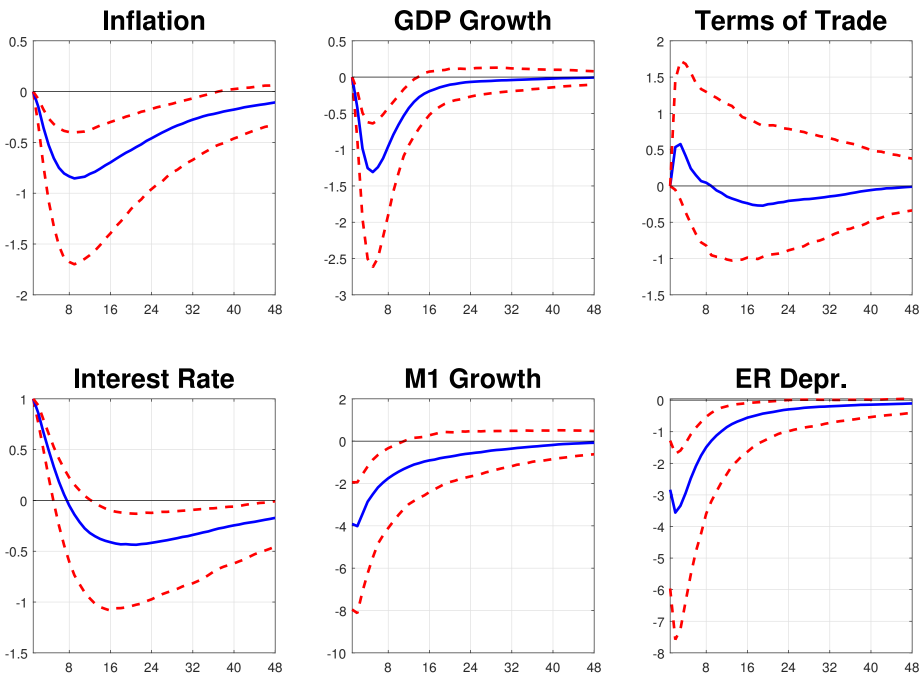

Figure 17: **M6**: Monetary Policy Shock in 1997 - Median value and 68% C.I.

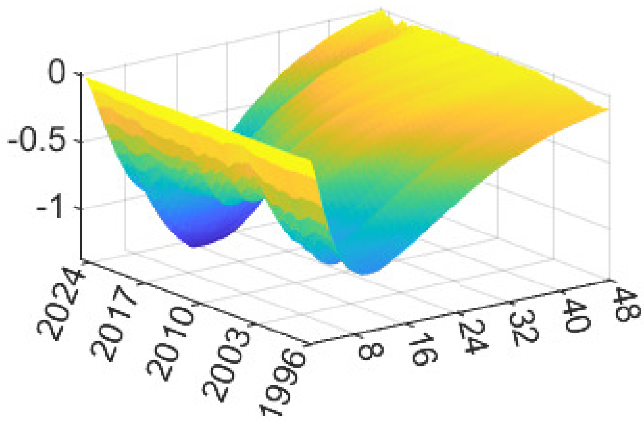

Figure 18: **M6**: Effect of Monetary Policy Shock on Inflation (1996-2024) - Median value

Moreover, regarding the remaining models: i) Threshold BVAR model with the addition pre-IT data, we also find that the impulse responses are stable over time (see Figure 19), which is also the case for the Time-varying mean model (M8) (see Figure 21), which also reinforces the evidence obtained from the previous models.

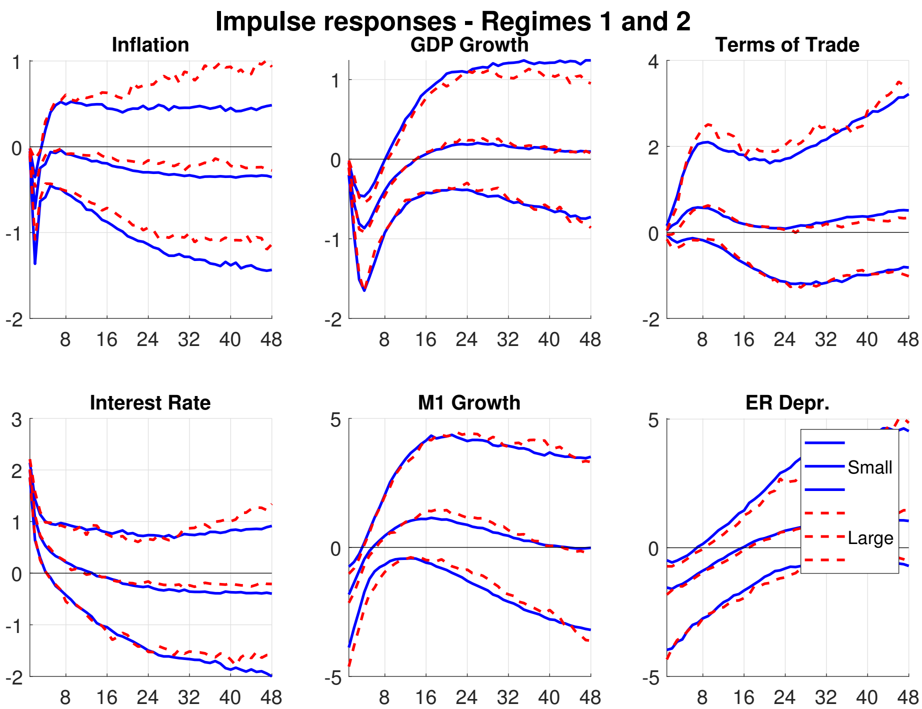

Figure 19: **M7**: Monetary Policy Shock - Median value and 68% C.I.

For this last model, the estimated inflation threshold is around 5.6%, and the regimes are depicted in Figure 20

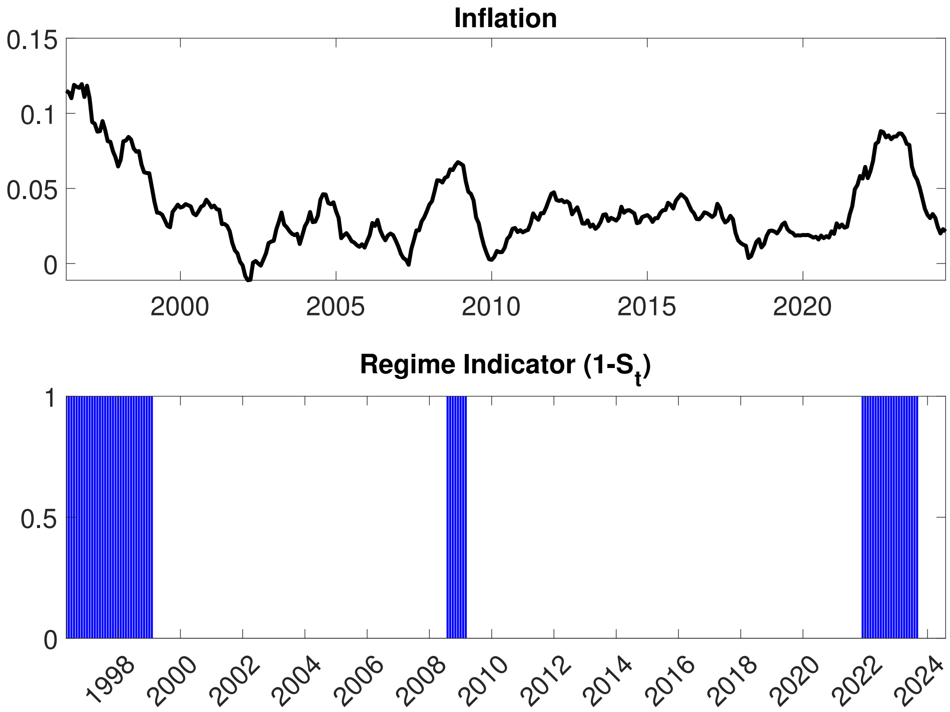

Figure 20: Inflation Data and Identified Regimes (1996-2024)

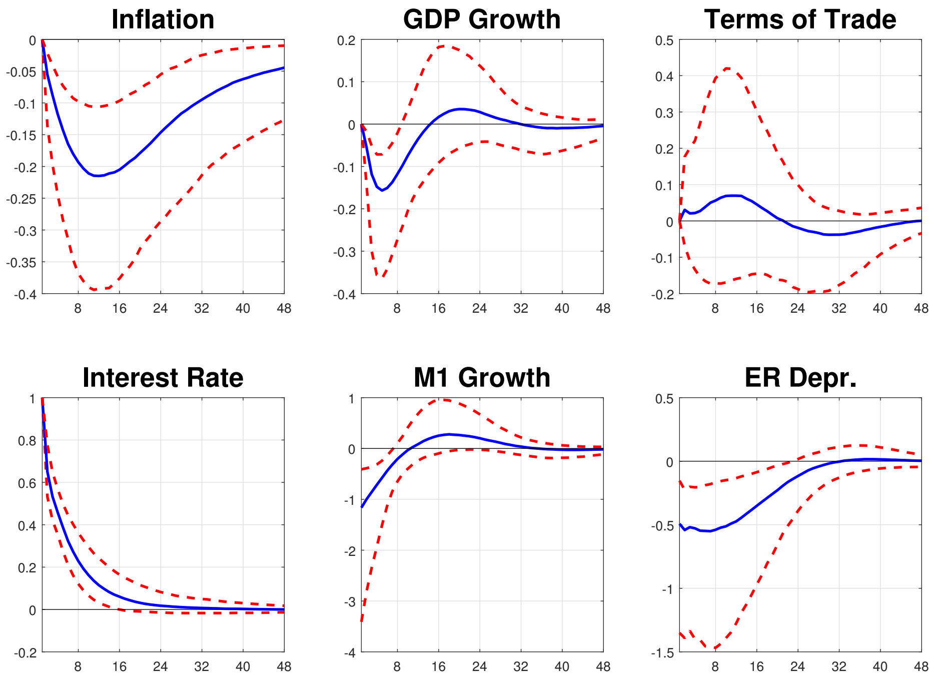

Figure 21: **M8**: Monetary Policy Shock - Median value and 68% C.I.

7.2 Identified Uncertainty Shocks

Beyond monetary policy shocks, uncertainty shocks are extremely important today in economic literature. In the case of Peru, models M4, M5 and M7 allow us to capture an uncertainty indicator associated with estimated macroeconomic volatility. In particular, volatility feedback models are capable of capturing the abrupt jump associated with the Covid-19 pandemic (2020-2021), and this is extremely useful for model specification. The macroeconomic uncertainty shown in Figure 22 indicates an abrupt adjustment in the Covid-19 pandemic, which is the result of the model that has average effect and is not captured by traditional stochastic volatility models, it is a fundamental element to explain macroeconomic fluctuations today. Thus, we also add an uncertainty shock (volatility) for model $M7$ similar to Llosa *et al.* (2022).

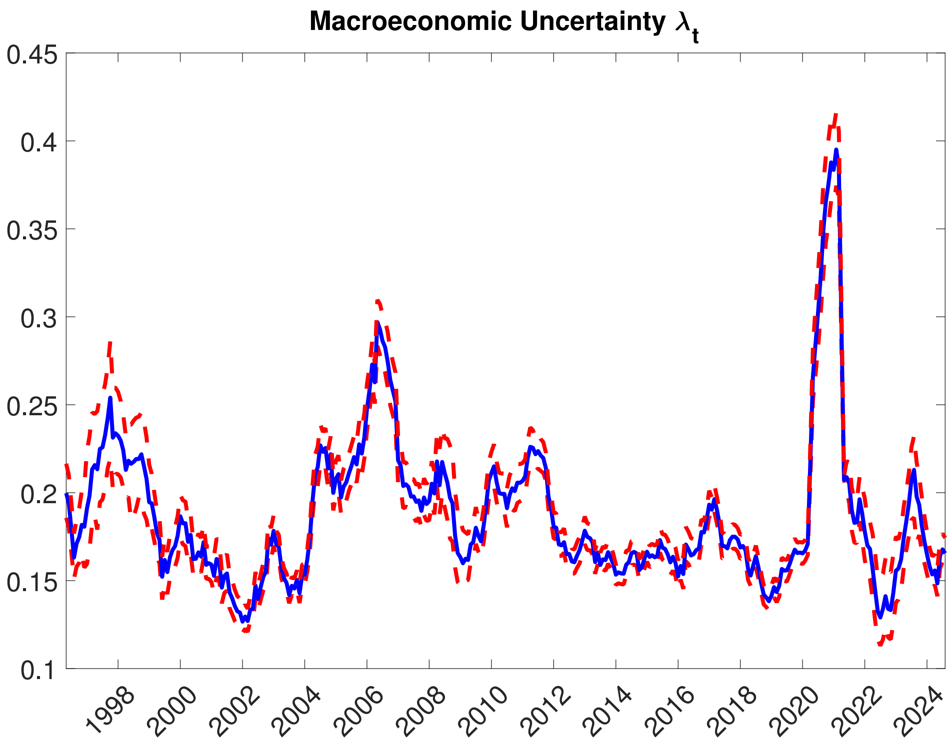

Figure 22: Macroeconomic Uncertainty Index

Regarding the impact of uncertainty shocks on the Peruvian economy, results are depicted in Figure 23. We can observe a Shocks in volatility resemble those of a negative and persistent supply shock, where inflation rises and the economic activity goes down. The latter triggers the response of the central bank through rising the policy interest.

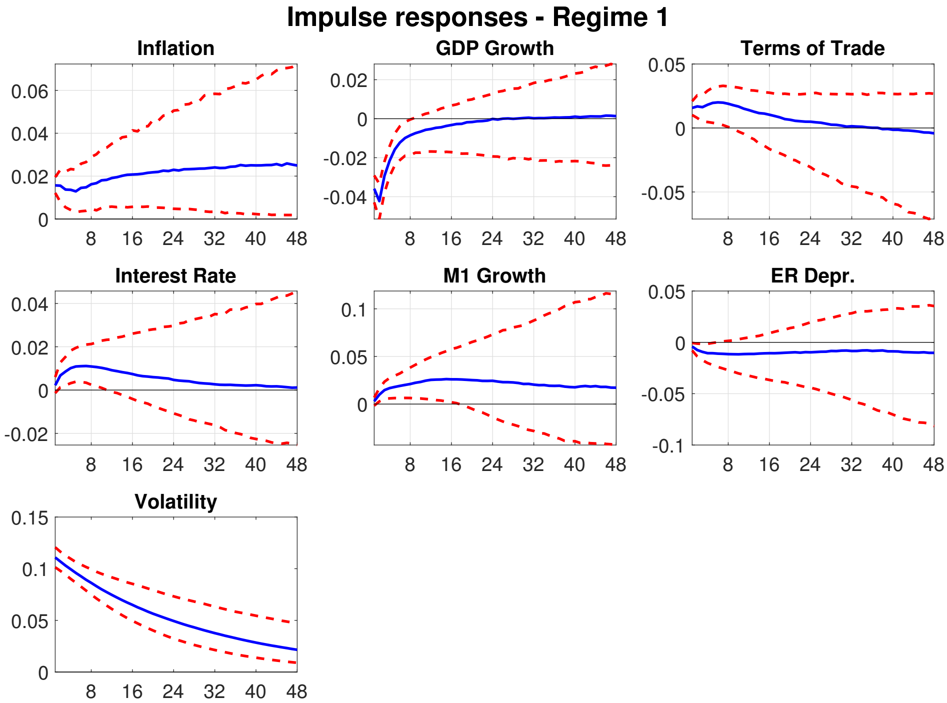

Figure 23: **M7**: Macroeconomic Uncertainty Shock - Median value and 68% C.I.

8 Concluding Remarks

In this paper we have explored the presence of non-linearities in the Peruvian economy. For this, five versions of a Bayesian vector autoregressive (BVAR) model have been estimated. The results obtained under the estimation of these models mentioned allow us to conclude the following: i) The inclusion of data from the Covid-19 pandemic and later (2020 onwards) can be carried out safely even for a constant coefficients model, since the errors from 2020 are compensated for by those from 2021. ii) However, Stochastic Volatility (especially with volatility feedback) is enough to correct the downturn of the pandemic and other episodes of higher volatility, which implies that we have statistical evidence that says that the rest of the dynamic economic relations had remained stable throughout the sample. iii) The transmission mechanism of monetary policy is stable throughout the 2002-2024 episode, both in the case of a threshold model and in the case of continuously changing parameters, with real effects on activity that reach their peak before the first year, and with an effect on inflation between 12 and 18 months. Moreover, the transmission mechanism is robust across different models. iv) The estimated volatility for the models with volatility feedback (M4 and M5) can be interpreted as an aggregate macroeconomic uncertainty index. This index reaches its highest value during the Covid-19 pandemic episode (2020-2021) and, to a lesser extent, during the International Financial Crisis (2008-2009). v) Shocks in estimated volatility (models M4, M5 and M7) resemble those of a negative supply shock, where inflation rises and the economic activity goes down. The latter triggers the response of the central bank through rising the policy interest.

In light of these results, the research agenda could go towards building a micro-founded dynamic general equilibrium model (DSGE) that takes into account explicitly the role of macroeconomic uncertainty as an important source of fluctuations. Although we have verified that the transmission mechanism of monetary policy is stable, non-linearities are still important. Thus, it remains to be explored in more detail the role of the size of the shocks and the potential asymmetries that can be generated (positive and negative shocks). The role of the formation of expectations is also extremely important, and therefore it is crucial to determine which signals matter for this, taking into account the presence of non-linearities. Finally, the agenda could also be focused on exploring the transmission mechanism of unconventional monetary policy actions, such as long-term liquidity injection, etc.

A The computation of impulse responses in the Threshold-BVAR-SV model

We calculate impulse response functions taking into account that during the horizon of interest the S_t indicator can change. Thus, we fully integrate over the path of S_t rather than condition on the initial value S_0.

After performing the MCMC simulations, we collect the posterior draws for all parameter blocks. Using the draws from each block, to get the impulse responses we perform the following steps $\overline{S}$ times:

1. **Step 1**: Set the number of periods $\overline{H}$ and select a draw for $\Theta = \left\{P^*, d, \Phi_{1:2}, \alpha_{1:2}, s_{1:N}, \lambda^T, \mu, \rho, Q\right\}$ from the estimated posterior distribution.

2. **Step 2**: Pick a random initial point t^* from $t^* \sim U(1, T)$.

3. **Step 3**: Given t^*, P^*, d and the data vector Z_{t^*}, determine the initial regime S_0 according to equation (22).

4. **Step 4**: Use the same initial value for the two regimes, $Z_0^\delta = Z_{t^*}$ and $Z_0^0 = Z_{t^*}$. Set the initial value $\lambda_0^0 = \lambda_{t^*}$.

5. **Step 5**: Repeat $\overline{L}$ times the following steps:

   (a) For each $t = 1, \ldots, \overline{H}$ forecast λ_t according to equation (19). When $t = 1$, set $e_1^\delta = \delta$ and $e_1^0 = 0$.

   (b) Given the values of e_t^δ, e_t^0, and λ_t, for each $t = 1, \ldots, \overline{H}$ forecast Z_t^δ and Z_t^0 according to equation (21) and considering for each regime i the matrix $A_i Q^*$, where A is such that $vec(A_i) = S_A \alpha_i + s_A$ and where Q^* is an orthonormal rotation matrix. Notice that it is necessary to determine the current regime in each period t, i.e. S_t^δ and S_t^0, according to equation (22).

   (c) Compute impulse responses $IRF_{1:\overline{H}} = Z_{1:\overline{H}}^\delta - Z_{1:\overline{H}}^0$.

6. **Step 6**: Take averages over $IRF_{1:\overline{H}}$.

We set $\overline{S} = 2000$, $\overline{L} = 200$. In addition, we set $\overline{H} = 36$ (three years) and $\delta = 1$. Given the number of draws $\overline{S}$, we split the complete set of impulse responses to draws in two groups, the low regime group ($S_{t^*} = 1$) and the high regime group ($S_{t^*} = 1$). To to that, we consider the initial regime determined in Step 3. Then, for each group of impulse responses we report the median value and the robust 16th and 84th percentiles.

B The algorithm for Imposing Zero and Sign Restrictions

In this stage we use as an input the estimation output from each model, i.e. the posterior distribution of the reduced-form. Then we take draws from this distribution as it is described in the following estimation algorithm[12]:

1. Set first $K = 1,000$ number of draws.
2. Draw (β, Σ) from the posterior distribution and get $(A_0) = (P)^{-1}$ from the *Cholesky* decomposition of $\Sigma_k = P\,(P)'$.
3. Draw $\mathbf{X} \sim N\left(0, I_{M_{fast}}\right)$ and get $\mathbf{Q}$ such that $\mathbf{QR} = \mathbf{X}$, i.e. an orthogonal matrix $\mathbf{Q}$ that satisfies the QR decomposition of $\mathbf{X}$. The random matrix $\mathbf{Q}$ has the uniform distribution with respect to the *Haar* measure on $O\,(n)$.
4. Construct the matrix:

$$\overline{\mathbf{Q}} = \begin{bmatrix} \mathbf{I}_{M-M_{fast}} & \mathbf{0}_{\left(M-M_{fast} \times M_{fast}\right)} \\ \mathbf{0}_{\left(M_{fast} \times M-M_{fast}\right)} & \mathbf{Q} \end{bmatrix}$$

   That is, a subset of $M - M_{fast} < M$ variables in $(\mathbf{y})$ are going to be *slow* and therefore they do not rotate. This how we impose zero restrictions in this case.
5. Compute the matrix $\overline{\mathbf{A}}_0 = (\mathbf{A}_0)\,\overline{\mathbf{Q}}$, then recover the BVAR system and compute the impulse responses.
6. If sign restrictions are satisfied, keep the draw and set $k = k + 1$. If not, discard the draw and go to next step.
7. If $k < K$, return to Step 2, otherwise stop.

[12] See e.g. Canova and Nicoló (2002) and Uhlig (2005) for previous applications. We also used an algorithm following Arias *et al.* (2018) and the results were almost identical.

C Additional Figures

C.1 Peruvian Macroeconomic Data

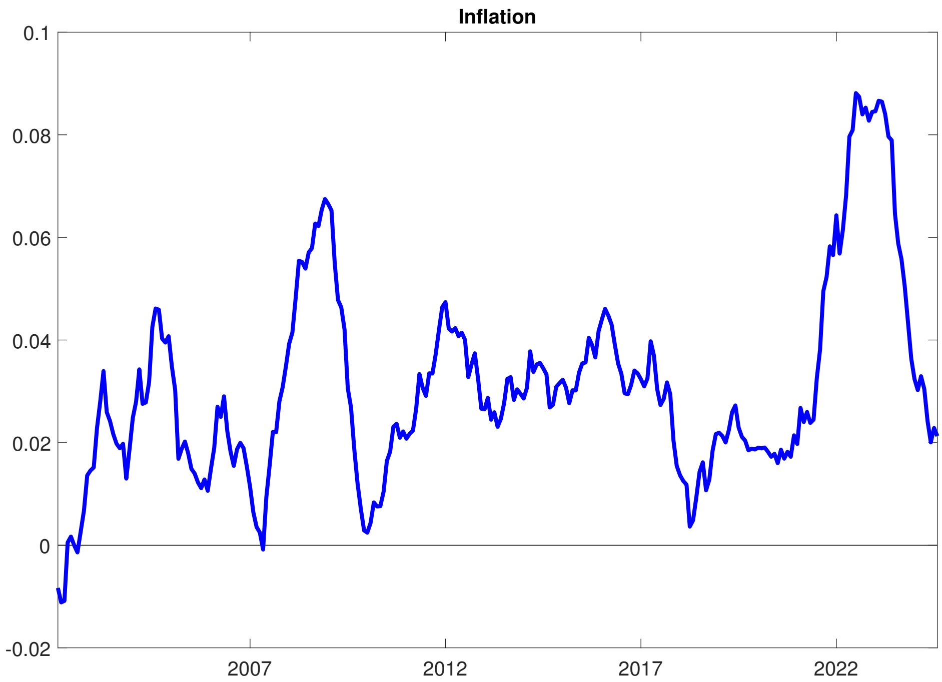

Figure C.24: Inflation YoY Rate

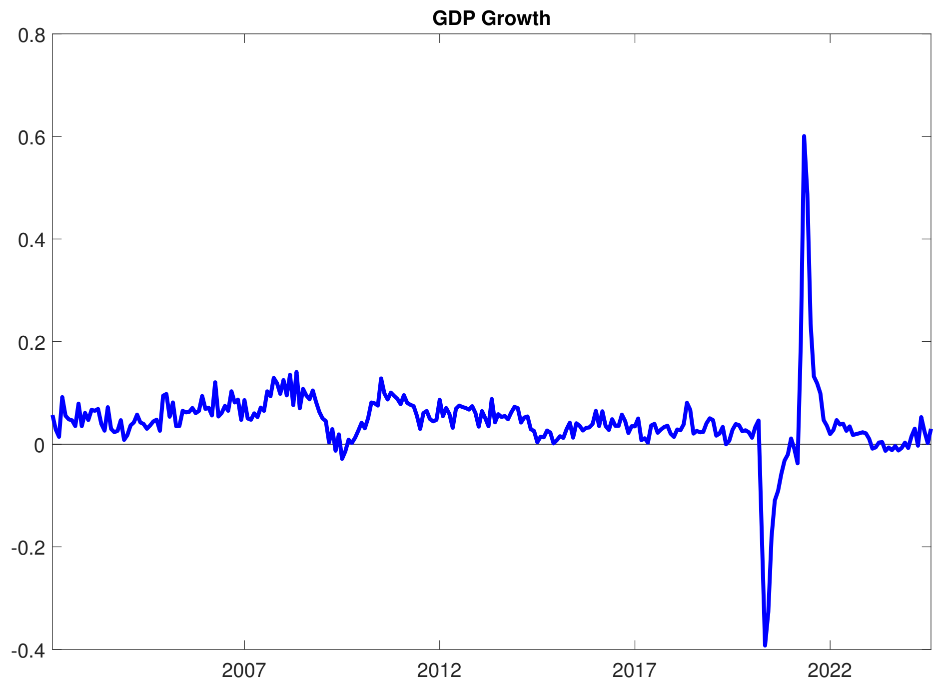

Figure C.25: GDP YoY Growth Rate

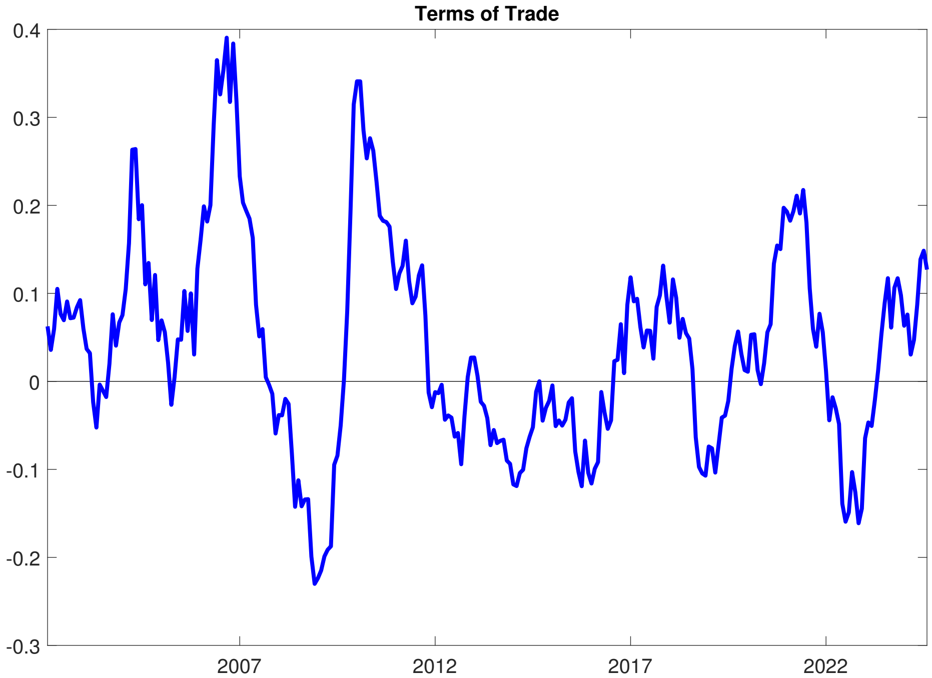

Figure C.26: Terms of Trade YoY Growth Rate

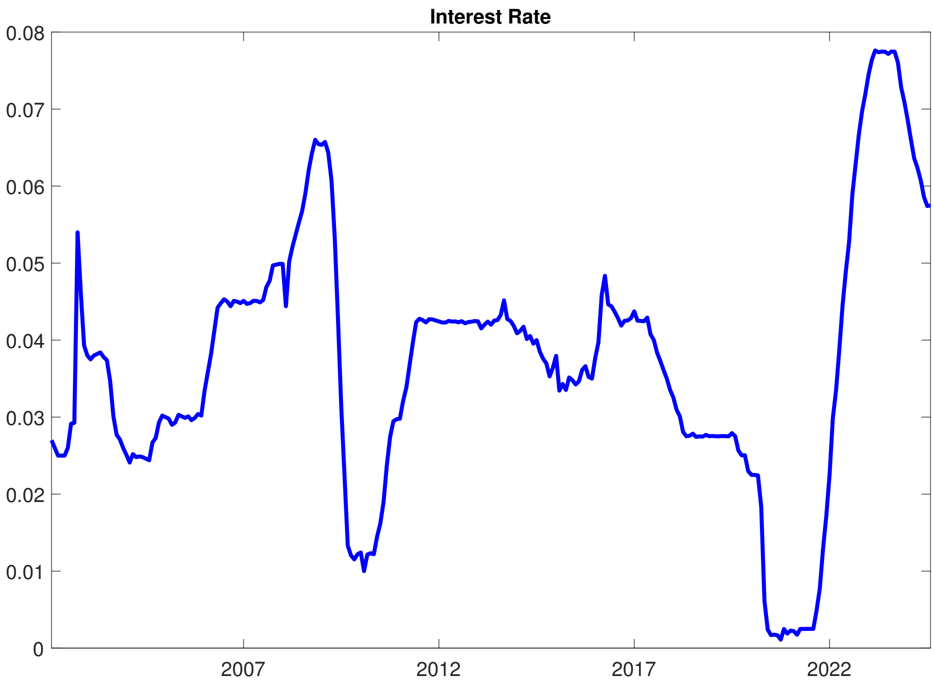

Figure C.27: Interbank Interest Rate

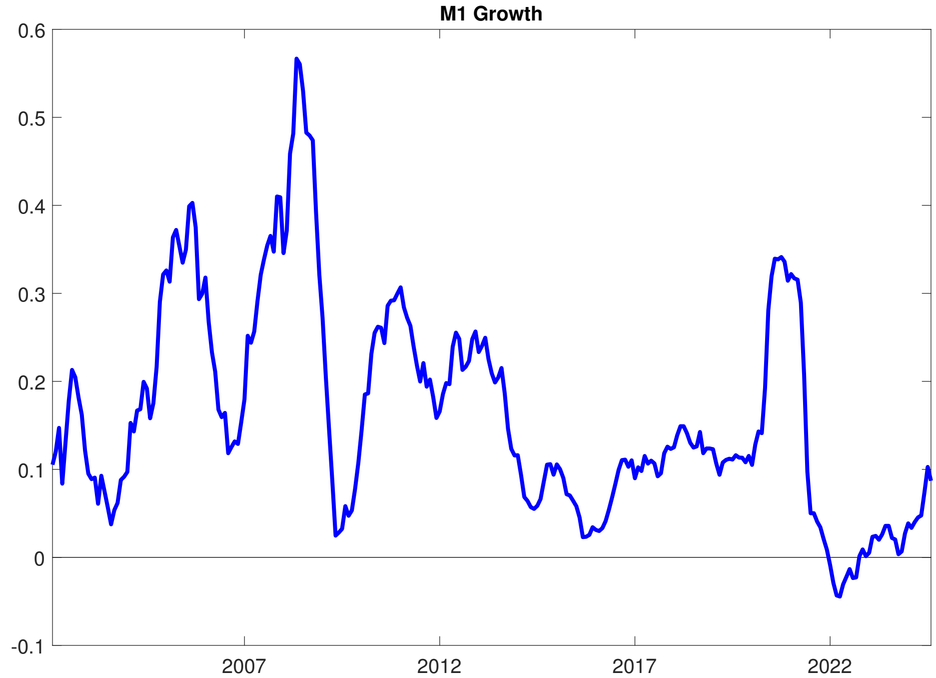

Figure C.28: M2 YoY Growth Rate

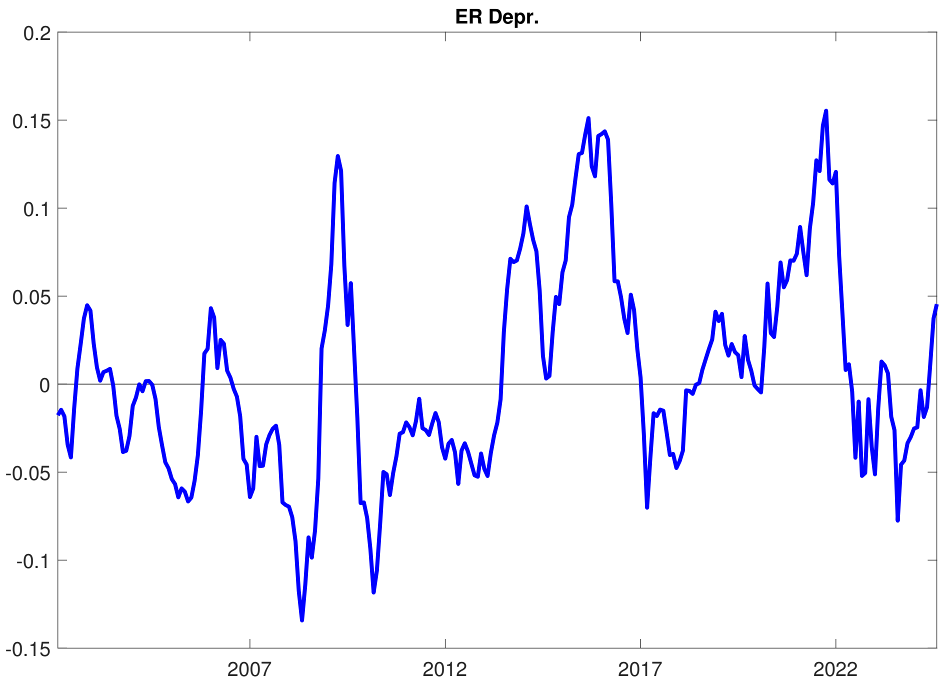

Figure C.29: PEN/USD YoY Growth Rate

C.2 Model 2 (M2)

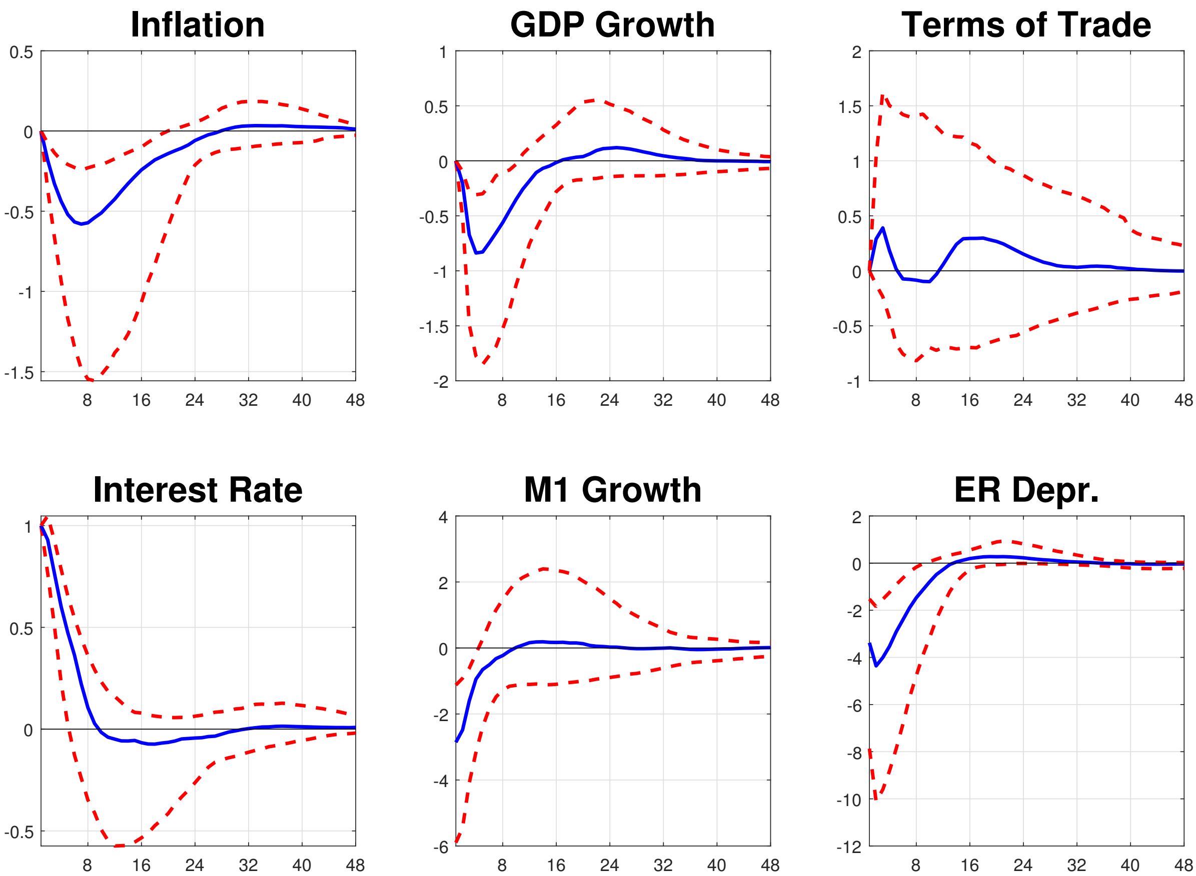

Figure C.30: **M2**: Monetary Policy Shock (2004) - Median value and 68% C.I.

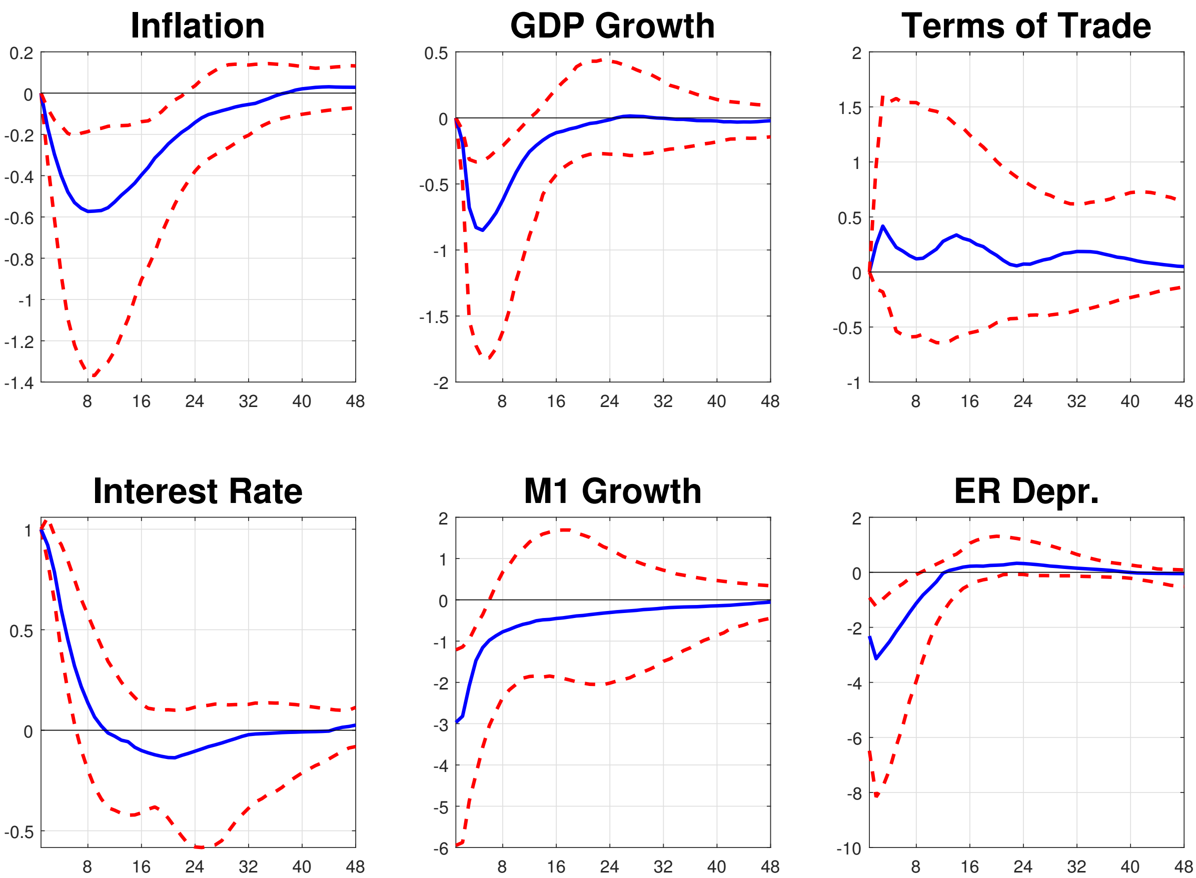

Figure C.31: **M2**: Monetary Policy Shock (2008) - Median value and 68% C.I.

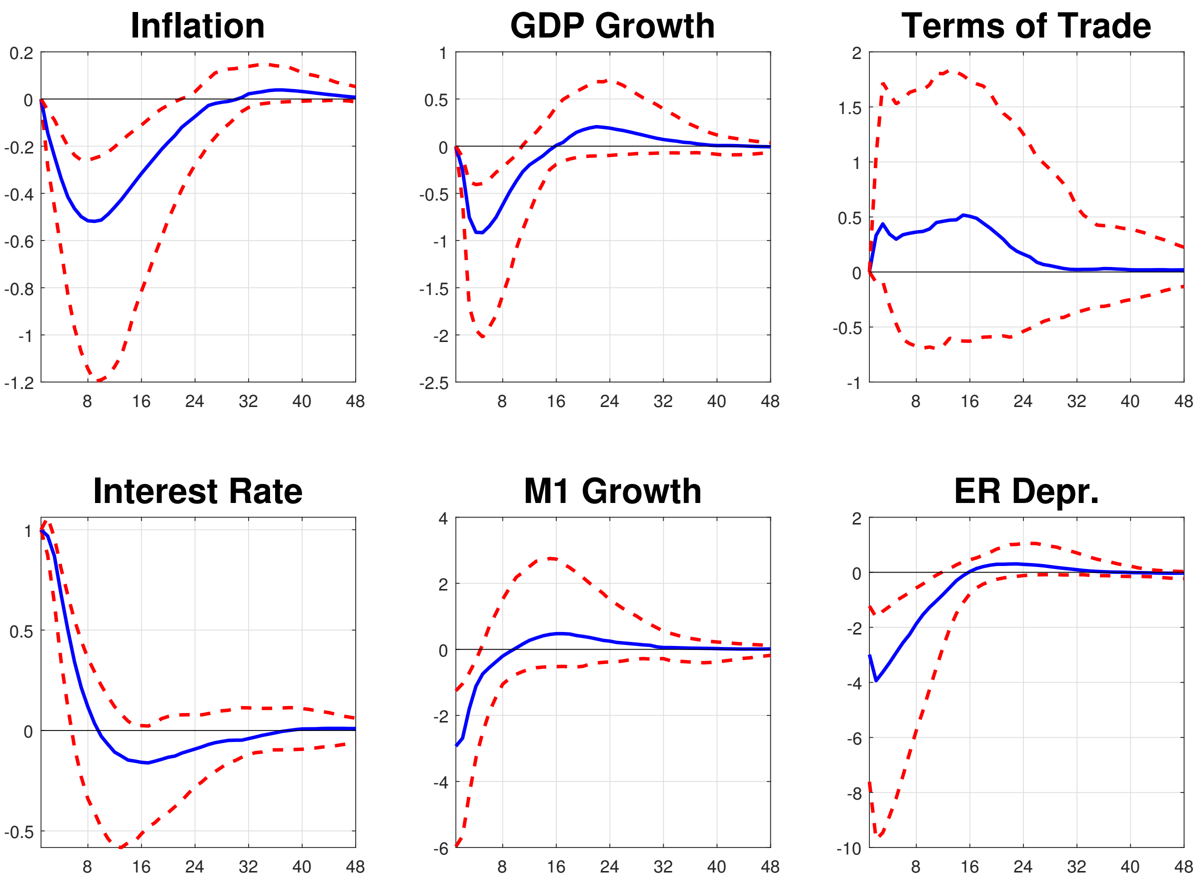

Figure C.32: **M2**: Monetary Policy Shock (2016) - Median value and 68% C.I.

C.3 Model 3 (M3)

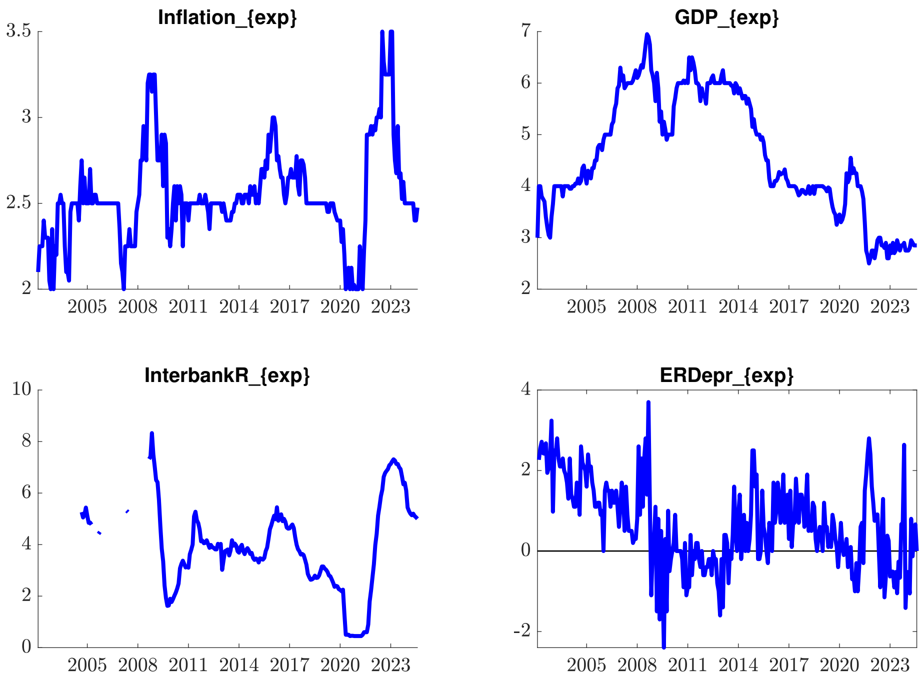

Figure C.33: Long term expectations data (2002-2024)

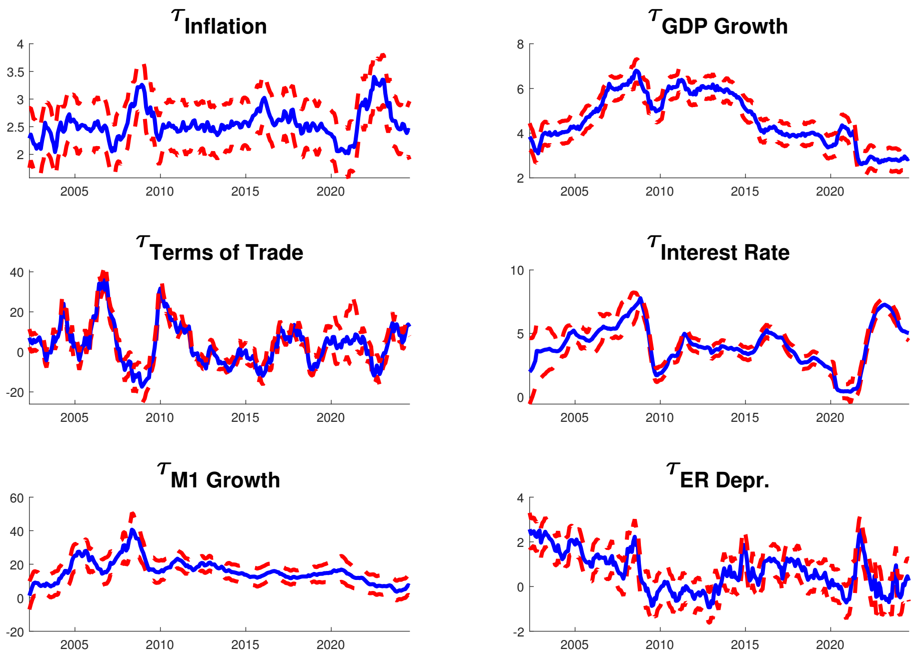

Figure C.34: Estimated Time-varying means τ_t (2002-2024)

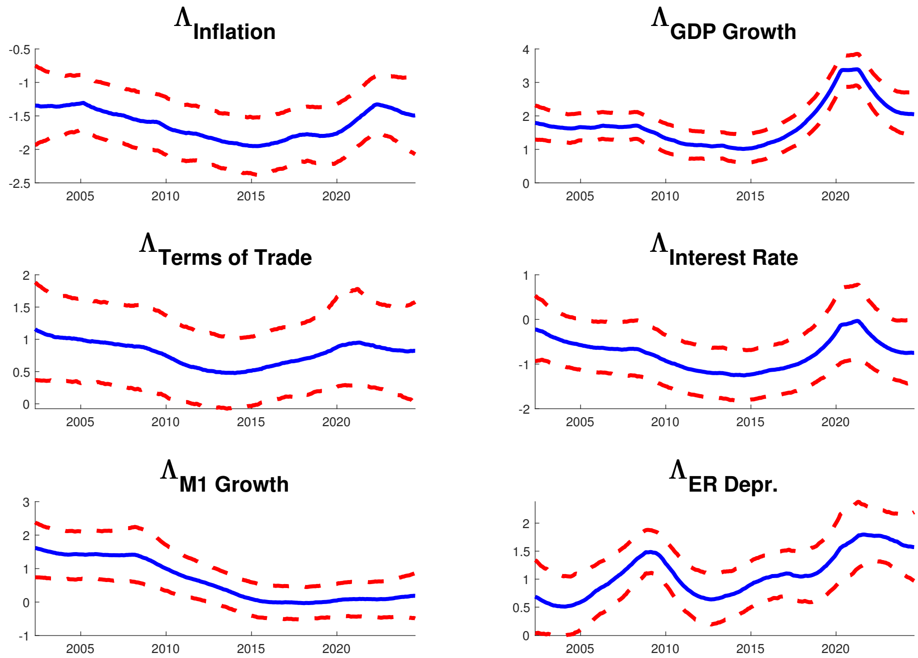

Figure C.35: Estimated Stochastic Volatility (2002-2024)

C.4 Model 6 (M6)

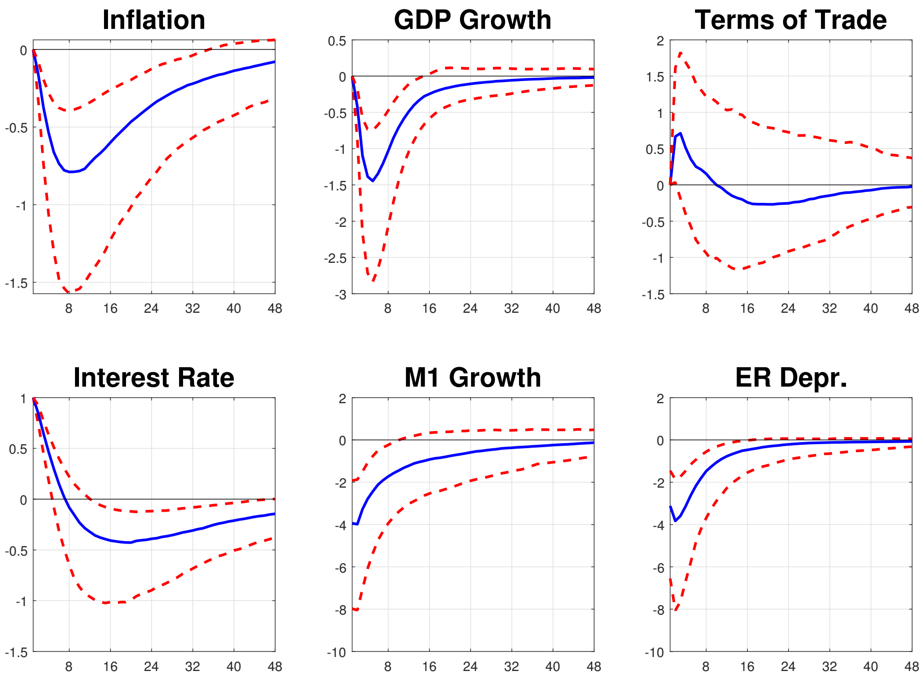

Figure C.36: **M6**: Monetary Policy Shock in 1997 - Median value and 68% C.I.

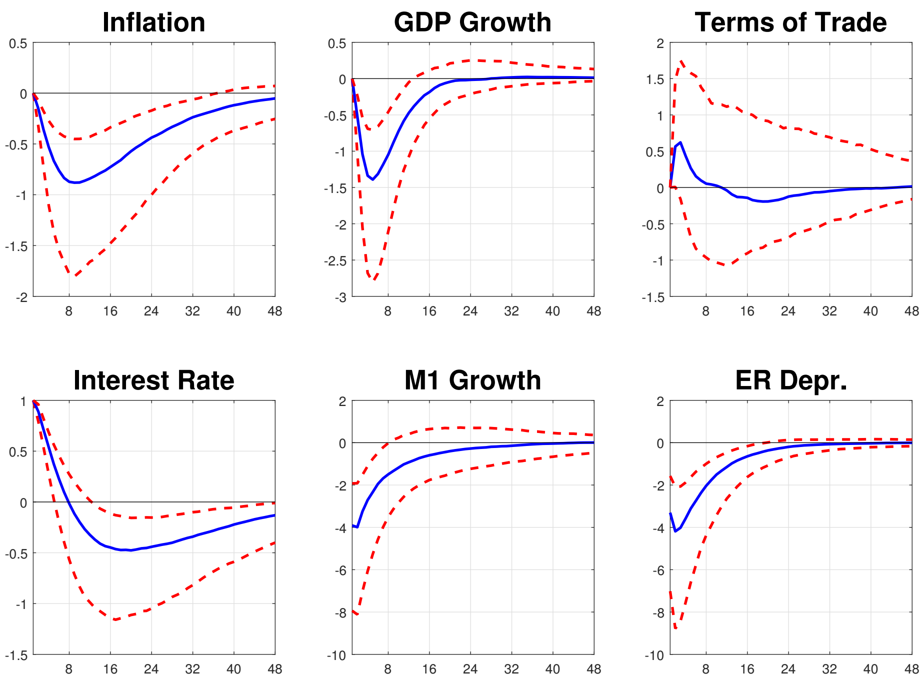

Figure C.37: **M6**: Monetary Policy Shock in 2001 - Median value and 68% C.I.

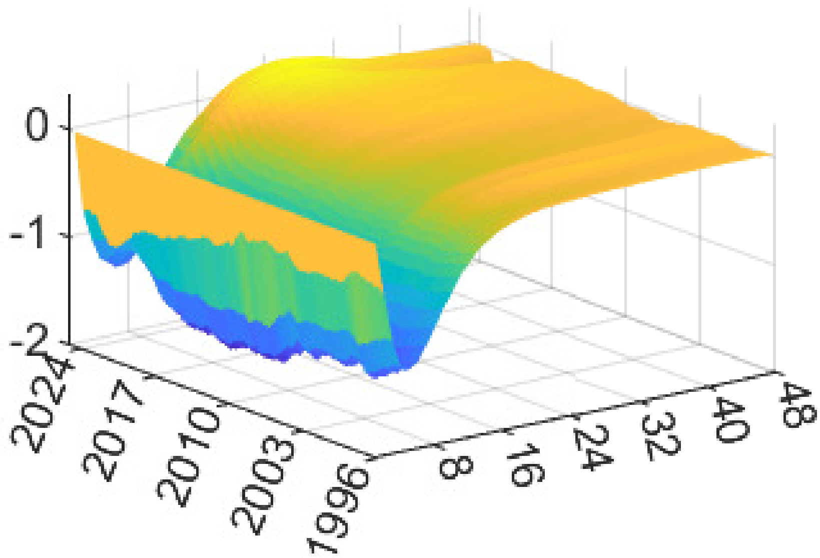

Figure C.38: **M6**: Effect of Monetary Policy Shock on GDP (1996-2024) - Median value

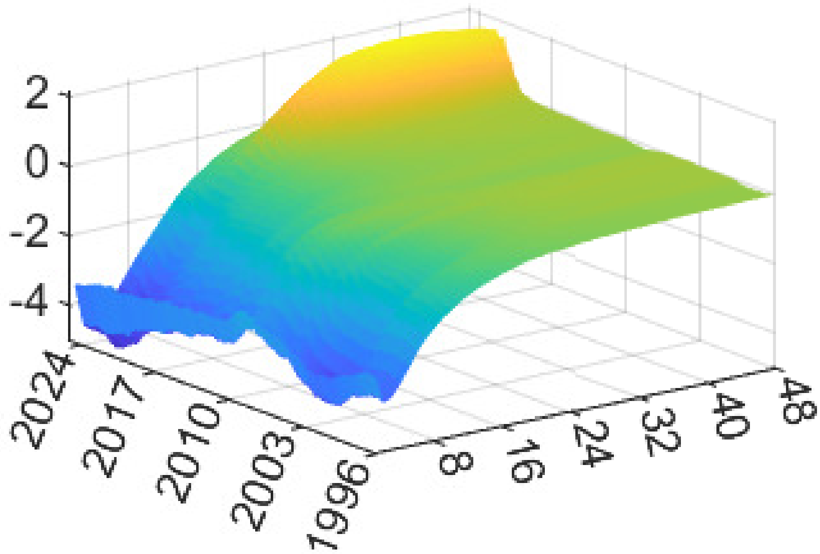

Figure C.39: **M6**: Effect of Monetary Policy Shock on ER Depr. (1996-2024) - Median value

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