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Time Changing Effects of External Shocks on Macroeconomic Fluctuations in Peru: Empirical Application Using Regime-Switching VAR Models with Stochastic Volatility[*]

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March 15, 2022

Abstract

This article quantifies and analyzes the evolving impact of external shocks on Peru's macroeconomic fluctuations in 1994Q1-2019Q4. For this purpose, we use a group of models with regime-switching time-varying parameters and stochastic volatility (RS-VAR-SV), as proposed by Chan and Eisenstat (2018). The data suggest a model with contemporaneous coefficients and constant lags and intercepts, but with regime-switching variances; and point to the existence of two regimes. The IRFs, FEVDs, and HDs show that: (i) China growth shocks have a higher impact on Peru's output growth (around 0.8%); (ii) financial shocks contract domestic output growth by 0.3% and domestic monetary policy is synchronized with Fed rate movements; (iii) external shocks explain 35% and 70% of output fluctuations under regimes 1 and 2, respectively; and (iv) China growth shocks contributed 1.0 p.p. to the 1.1-p.p. increase (around 89%) in Peru's output growth between regimes 1 and 2. Additionally, we validate these results by performing seven robustness exercises consisting in changing priors, reordering variables, changing variables, and using four different specications for the baseline model.

JEL Classification: C11, C32, C52, E32, F41.

Keywords: External Shocks, Macroeconomic Fluctuations, Regime-Switching Autoregressive Vectors, Stochastic Volatility, Model Comparison, Peruvian Economy.

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Efectos Cambiantes en el Tiempo de Choques Externos sobre Fluctuaciones Macroeconómicas en Perú: Aplicación Empírica usando Modelos VAR con Cambio de Regimen y Volatilidad Estocástica[*]

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15 de Marzo 2022

Resumen

Este artículo cuantifica y analiza la evolución del impacto de los choques externos en las fluctuaciones macroeconómicas del Perú en 1994Q1-2019Q4. Para este propósito, usamos un grupo de modelos de vectores autoregresivos con parámetros con cambio de regimen y volatilidad estocástica (RS-VAR-SV), según lo propuesto por Chan y Eisenstat (2018). Los datos sugieren la preferencia por un modelo con coeficientes contemporáneos y rezagos e intercepciones constantes, pero con varianzas dependientes del regimen; y se observa la existencia de dos regímenes. Las IRFs, FEVDs y HDs muestran que: (i) los choques de crecimiento de China tienen un mayor impacto en el crecimiento de la producción de Perú (alrededor del 0.8%); (ii) los choques financierios contraen el crecimiento de la producción interna en un 0.3% y la política monetaria doméstica se sincroniza con movimientos de la tasa de la Reserva Federal; (iii) los choques externos explican el 35% y el 70% de las fluctuaciones del producto en los regímenes 1 y 2, respectivamente; y (iv) los choques de crecimiento de China contribuyen con 1.0 p.p. de 1.1-p.p. (alrededor del 89%) del crecimiento de la producción de Perú entre los regímenes 1 y 2. Los resultados son validados utilizando siete ejercicios de robustez que consisten en cambiar las priors, reordenar las variables, cambiar las variables y usar cuatro especificaciones diferentes para el modelo de base.

Clasificación JEL: C11, C32, F41, F44, F62.

Palabras Claves: Choques Externos, Fluctuaciones Macroeconómicas, Vectores Autoregresivos con Cambio de Regimen, Volatilidad Estocástica, Estimación y Comparación Bayesiana, Economía Peruana.

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1 Introduction

External shocks on Latin American developing economies, like Peru, are considered the main source of variability in output fluctuations, according to Izquierdo et al. (2008). Greater trade and financial integration in recent years has magnified this effect in countries that depend heavily on commodity exports. Since the 1990s, several financial crises, the commodity supercycle, and China's high growth (and subsequent deceleration) have been the object of intense study and a source of concern in academia; see Cesa-Bianchi et al. (2013), Gruss (2014), and Bing et al. (2019). In this context, a crucial issue is the severity of external shock effects on macroeconomic variables in boom-bust cycles; see Calvo et al. (1993). This evolving international environment has led policymakers to revise their responses over time via new instruments or even institutional changes related to the role of monetary and fiscal authorities.

Peru's case is relevant, given its role as a major supplier of metal commodities to industrialized economies like China and the U.S. Moreover, with sound macroeconomic indicators resulting from fiscal and monetary discipline (IMF (2020)), Peru has become an attractive destination for international investors. At the same time, in this context, fluctuations in domestic aggregate variables are exposed to shocks from various sources: (i) real or external demand shocks, mainly from the U.S. and China, Peru's main trading partners; (ii) the financial channel; i.e., movements in the international interest rate affecting investment returns and financial costs; and (iii) nominal or commodity price shocks; i.e., movements in the prices of Peru's exports and imports.

The stylized facts for Peru's economy show a growing level of trade integration. Peru's trade as a percentage of GDP was around 32.5% in 1994-2002 and 49% in 2002-2018. China and the U.S. are the main destinations for Peru's exports (27% and 16% of total exports in 2018, respectively). Total exports can be broken down mainly into commodities and intermediate goods (50% and 32% in 2018, respectively).

Additionally, Peru's de facto[1] and de jure[2] financial integration indicators have performed well. Total external assets (excluding reserves and external liabilities) as percentage of GDP were around 88% in 1994-2008 and 106% in 2009-2018. The de jure financial openness indicator shows that Peru has respected free capital movements since 1997. In contrast with China's predominance in the trade channel, the U.S. is Peru's main portfolio investment destination and its main source of direct investment. In this context, movements in the Fed policy rate have implications for Peru's security market and financing costs for new investment projects.

Regarding the nominal channel, commodity prices evolved exponentially in 2000-2014, with a cumulative 72% increase in the S&P GSCI. Cumulative growth for metal commodities (mainly copper) was 235% over that period, mainly driven by the industrial push in countries like China and India. Exports of other commodities, like gold, silver, and zinc, also grew considerably.

This study seeks to examine empirically the effect and evolution of external shocks and their transmission to output growth, inflation, and the interest rate in Peru. Our specification considers three transmission channels (real demand, the financial channel, and the nominal channel). The period of analysis is 1994Q1-2019Q4, which captures a number of international events, like the 1998 and 2008 crises and the Asian and Russian financial crises, as well as episodes of high domestic

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[1] We consider the de facto financial measure proposed by Lane and Milesi-Ferretti (2007), who use the amount of external assets and liabilities as indicator.

[2] We use the index proposed by Chinn and Ito (2008), which considers information about legal restrictions on capital flows in each economy as de jure measure.

uncertainty caused by the 2001 political crisis and the 2006 and 2011 presidential elections.[3]. This period of analysis also captures the adoption of inflation targeting (IT) by the Central Reserve Bank of Peru (BCRP) in 2002. In sum, evolving developments throughout Peru's recent history tend to modify the underlying economic parameters. For instance, global financial integration has increased over time, thereby exacerbating Peru's exposure to external shocks. In our view, a VAR methodology with regime-switching and stochastic volatility (RS-VAR-SV), following Chan and Eisenstat (2018), properly addresses this issue.

The results indicate that the best fit for Peru is a VAR model with constant coefficients and regime-switching variances (RS-VAR-SV-R1) instead of a traditional VAR with constant coefficients (CVAR) and other restricted RS-VAR-SV models. Additionally, we identify two regimes before and after 2002, the pre- and post-IT regimes, where the latter is more persistent. Regarding the response of domestic variables to external shocks, China's growth has the most significant impact on domestic growth; i.e., a 1% China growth shock results in a 0.8% increase in domestic growth after one year. In contrast, a 1% surge in financial shocks has a contractionary impact on growth (a 0.3% fall after one year). Another interesting result is the increasing uncertainty around external shocks in predicting growth under regime 2; i.e., 70% of growth variability, mainly resulting from China growth shocks (34%) and commodity price shocks (30%). Regarding the historic contribution of external shocks, we underscore that the contribution of a China growth shock to the increase in domestic growth under regime 2 was considerable (89%). Moreover, the regime change shows that lower interest rates and inflation under regime 2 are explained by the moderation of monetary shocks.

The remainder of the paper is divided as follows. Section 2 provides a comprehensive review of the literature on external shocks in emerging market economies (EMEs).[4] Section 3 describes the methodology used to estimate the model, the estimation algorithm, and the selection criterion proposed by Chan and Eisenstat (2018). Section 4 presents the data, the identification scheme, the priors, the selection of models, the model's regimes, the analysis of the impulse-response functions (IRFs), the forecast error variance decomposition (FEVD), and the historical decomposition (HD). Finally, Section 5 discusses the robustness exercises and Section 6 presents the conclusions.

2 Literature Review

Mendoza (1995) uses a real business cycle (RBC) model to show that the contribution of terms-of-trade shocks on growth variability in developing countries is 50%. Hoffmaister and Roldos (1997) and Hoffmaister et al. (1997) estimate a VAR panel model with long-term restrictions; and show that terms-of-trade shocks have a greater impact on the balance of payments than on output in Asia and Latin America. Using an RBC model, Kose (2002) also finds that external trade shocks explain around 45% of aggregate output fluctuations; and that financial shocks have a lower impact on developing economies.

For Latin America, Ahmed (2003) uses a panel VAR model to estimate that terms-of-trade and

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[3] Ollanta Humala's presidential bid on a radical agenda, intended to replace the free market system with a socialist regime, created considerable domestic uncertainty in the 2006 and 2011 elections. Defeated by Alan García in 2006, Humala prevailed over Keiko Fujimori in 2011, although he became more moderate and respected the free market economy.

[4] This document focuses on EMEs, although there is also literature on developed countries; see Lubik and Teo (2005), Cesa-Bianchi et al. (2013), Charnavoki and Dolado (2014), and Dungey et al. (2020), among others.

U.S. real interest rate shocks explain 6% and 10% of output growth variability, respectively. Under the same methodology, Broda and Tille (2003) use data for 75 developing countries to show that the terms of trade explain 33% of output variability in economies with a fixed exchange rate regime, vis-à-vis less than 13% in economies with a flexible exchange rate regime.

Canova (2005) shows that U.S.-originated supply- and demand-side shocks do not have a significant influence on fluctuations in domestic variables (output, the interest rate, and the exchange rate) in Latin America; but Fed monetary shocks induce considerable responses; i.e., the financial channel plays an important role in magnifying business cycles in Latin America. Additionally, U.S.-originated shocks explain 43% of variability in monetary variables (interest rates and the exchange rate).

Using a vector error correction model (VECM), Izquierdo et al. (2008) estimate the effect of financial shocks (U.S. Treasury bills and the EMBI) and terms-of-trade shocks on output in Latin American countries for 1990-2006; and show that growth in these countries is not sustained and is conditioned by external commodity price shocks or interest rate shocks, as during the 1998 Russian Crisis and the 2002-2006 commodity boom.

For Argentina, Lanteri (2008) uses a VAR model with short-term restrictions to assess the impact of commodity price shocks on growth in output and fiscal variables; i.e., 19% and 27% of variability in real output and tax revenues, respectively. Additionally, Castillo and Salas (2010) estimate a VAR model with common stochastic trends and cointegration restrictions for Peru and Chile, evidencing that the contribution of permanent external shocks is greater for output, consumption, and investment fluctuations; and that transitory shocks are relatively more relevant for consumption and investment than for output.

Campos (2015) uses a VAR model with sign restrictions to assess the impact of terms-of-trade shocks on output and inflation in Argentina, concluding that they affect the latter to a greater extent. For the same country, Drechsel and Tenreyro (2018) use a dynamic stochastic general equilibrium (DSGE) model to find that external shocks represent 38%, 42%, and 61% of variability in output, consumption, and investment, respectively.

For several EMEs, Shousa (2016), Fernández et al. (2018) and Fernández et al. (2017, 2020) show that commodity prices create greater output and investment volatility than in advanced countries. Additionally, Pedersen (2019) concludes that a positive shock on the price of copper results in a positive impact on Chile's economic activity, as long as it originates on the demand side. On one side, Schmitt-Grohé and Uribe (2018) show that exchange rate shocks explain 10% of output variability on average in EMEs. In contrast, Fernández et al. (2020) assure that 50% of the variability of output is explained by world shocks (commodity shocks and interest rate shocks).

For Peru, Dancourt et al. (1997) identify a high correlation between recession episodes and an external shock indicator. Nolazco et al. (2016) model different external shocks and their endogenous propagation using a simultaneous equation system, showing that the impact of external shocks on output growth is around 36% and 28% in 2005-2008 and 2010-2013, respectively. Additionally, Mendoza and Collantes Goicochea (2017) use an SVAR model with long-term restrictions to show that external shocks explain over 60% of real output variability.

Rodríguez et al. (2018) use a model with common trends and cointegration to show that long-term output volatility is almost fully explained by terms-of-trade movements. They also use the HD for output growth to evidence that external factors are its main component. In the same line, Florián et al. (2018) estimate SVAR models to highlight the relevance of anticipated over unanticipated terms-of-trade shocks in explaining output variability (50% versus just 25%, respectively).

The IMF (2019) estimates the effects from the recent U.S.-China trade wars on Latin American economies. Using a global VAR (GVAR) model (Pesaran et al. (2004) and Dées et al. (2007)), they show that the effects are asymmetrical across countries, conditional on the degree of trade integration with the U.S. and China. Along these lines, Peru and Chile are affected mostly by China via the trade channel and commodity prices, while Mexico and Brazil are affected by the U.S. via the financial channel. Recently, Ojeda Cunya and Rodríguez (2022) used a family of models with time-varying parameters and stochastic volatility (TVP-VAR-SV) to explain the role of external shocks in Peru's economic fluctuations. Based on this methodology, they find further evidence of the importance of commodity price shocks and their asymmetric impact over time on output growth, inflation, and the interest rate.

Rodríguez and Vassallo (2022) expand the four-variable model proposed by Ojeda Cunya and Rodríguez (2022) to seven variables; and characterize the dynamics of external shocks via different propagation channels (the U.S.-China real demand channel, the financial channel, and the commodity price channel) on Pacific Alliance (PA) countries. Their findings show that the participation of external shocks on output variability in Peru fluctuates between 35%-80% throughout the sample. Additionally, commodity price shocks create the most uncertainty in output forecasting.

Guevara et al. (2022) use TVP-VAR-SV models with a mix of innovations to calculate the effect of external shocks on Peru's domestic dynamics. They conclude that shocks originated in its main trade partners (China and the U.S.) have the greater impact; and that volatility in domestic aggregates is explained mainly by external shocks (around 75%).

This research adheres to the methodology used initially by Rubio-Ramirez et al. (2005) and Sims and Zha (2006), who estimate RS-VAR-SV models for assessing monetary policy and its impact on the European Union (EU) and the U.S., respectively. We note that they use a Bayesian methodology (the Gibbs sampling algorithm), in contrast with the traditional approach (the expectation-maximization (EM) algorithm) used by Krolzig (1997). Along these lines, studies like Sims et al. (2008) and Lanne et al. (2010) underscore the importance of the Bayesian approach for estimating these kinds of models, in particular the efficiency in computing models that use a large number of parameters to reflect several regimes. Additionally, this approach facilitates inferences from the results; e.g., by standardizing the discussion on IRF calculation for these models (see Droumaguet (2012)). In this context, we follow the estimation methodology proposed by Chan and Eisenstat (2018), who consider a group of RS-VAR-SV models with different restrictions based on assumptions about the time variation (or constancy) of intercepts across regimes, the contemporaneous coefficients, the lagged coefficients, and the variance matrix.

In this regard, it is appropriate to use the family of RS-VAR-SV models to address the nonlinear relationship between external shocks and fluctuations in domestic macroeconomic aggregates, in contrast with the literature on external shocks described above. Additionally, we calculate and examine in detail the IRFs, FEVDs, and HDs for each RS-VAR-SV model. Another distinctive feature is the broad specification of external shocks (similar to Rodríguez and Vassallo (2022)), for which we consider three channels of transmission to the Peruvian economy (the trade, financial, and price channels). In sum, our estimations are based on a seven-variable model (four external and three domestic), validated by several robustness exercises.

3 Methodology

3.1 Models

Using the notation in Chan and Eisenstat (2018), we use a class of regime-switching VAR with heterocedasticity (RS-VAR-SV) models similar to those in Sims and Zha (2006). Let $S_t \in \{1, \ldots, r\}$ represents the regime indicator at time t and r is the number of regimes. Then, the RS-VAR-SV model is:

$$\mathbf{B}_{0_{S_t}}\mathbf{y}_t = \boldsymbol{\mu}_{S_t} + \mathbf{B}_{1_{S_t}}\mathbf{y}_{t-1} + \cdots + \mathbf{B}_{p_{S_t}}\mathbf{y}_{t-p} + \boldsymbol{\epsilon}_t, \qquad \boldsymbol{\epsilon}_t \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_{S_t}\right), \tag{1}$$

where $\boldsymbol{\mu}_{S_t}$ is an $n \times 1$ vector of intercepts, $\mathbf{B}_{1_{S_t}}, \ldots, \mathbf{B}_{p_{S_t}}$ are $n \times n$ matrices of structural coefficients, $\mathbf{B}_{0_{S_t}}$ is a triangular inferior matrix with unit values on the diagonal, also referred to as the matrix of contemporaneous relationships, and $\boldsymbol{\Sigma}_{S_t} = \mathrm{diag}(\sigma^2_{1_{S_t}}, \cdots \sigma^2_{n_{S_t}})$ is an $n \times n$ diagonal matrix containing the variances of the structural shocks. The S_t index is a non-observable state following a Markov process with transition probability $P\left(S_t = j | S_{t-1} = i\right) = p_{ij}$.

We can represent equation (1) using the three groups of parameters:

$$\mathbf{y}_t = \boldsymbol{\mu}_{S_t} + \widetilde{\mathbf{X}}_t \boldsymbol{\beta}_{S_t} + \mathbf{W}_t \boldsymbol{\gamma}_{S_t} + \boldsymbol{\epsilon}_t, \qquad \boldsymbol{\epsilon}_t \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_{S_t}\right), \tag{2}$$

where $\boldsymbol{\mu}_{S_t}, \boldsymbol{\beta}_{S_t}, \boldsymbol{\gamma}_j$ have dimensions k_μ, k_β, k_γ respectively. Additionally, the lagged variables are contained in $\widetilde{\mathbf{X}}_t = \mathbf{I}_n \otimes (\mathbf{1}, \mathbf{y}'_{\mathbf{t-1}}, \ldots, \mathbf{y}'_{\mathbf{t-p}})$, and the $n \times k_\gamma$ matrix $\mathbf{W}_t$ contains the elements of $-\mathbf{y}_t$. In order to jointly estimate the parameters, we group them as follows:

$$\mathbf{y}_t = \mathbf{X}_t \boldsymbol{\theta}_{S_t} + \boldsymbol{\epsilon}_t, \qquad \boldsymbol{\epsilon}_t \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_{S_t}\right), \tag{3}$$

where the vector of parameters $\boldsymbol{\theta}_{S_t} = (\boldsymbol{\mu}'_{S_t}, \boldsymbol{\beta}'_{S_t}, \boldsymbol{\gamma}'_{S_t})'$ has a dimension of $k_\theta = k_\mu + k_\beta + k_\gamma$.

In addition to the unrestricted model RS-VAR-SV, several restricted models similar to those used by Rubio-Ramirez et al. (2005) and Sims and Zha (2006) are considered: (i) the RS-VAR-SV-R1 model restricts all coefficients except for $\boldsymbol{\Sigma}_{S_t}$; (ii) the RS-VAR-R2 model restricts only $\boldsymbol{\Sigma}_{S_t}$; (iii) the RS-VAR-SV-R3 model restricts $(\mathbf{B}_{0_{S_t}}, \mathbf{B}_{1_{S_t}}, \ldots, \mathbf{B}_{p_{S_t}})$ and allows time-variation for $\boldsymbol{\mu}_{S_t}$ and $\boldsymbol{\Sigma}_{S_t}$; (iv) the RS-VAR-SV-R4 model restricts $\mathbf{B}_{0_{S_t}}$ and allows time-variation in the remaining coefficients; (v) the RS-VAR-SV-R5 model restricts $(\boldsymbol{\mu}_{S_t}, \mathbf{B}_{1_{S_t}}, \ldots, \mathbf{B}_{p_{S_t}})$; and (vi) the CVAR model where all parameters are constant.

3.2 Estimation Algorithm: Gibbs Sampling

To estimate the posterior parameters we use the Gibbs sampling algorithm, which consists in dividing the parameters in blocks and estimating each one separately, conditional on updating of the other blocks. We use the following notation: $\boldsymbol{\theta} = [\boldsymbol{\theta}'_1, \ldots, \boldsymbol{\theta}'_j]'$, $\boldsymbol{\Sigma} = [\boldsymbol{\Sigma}'_1, \ldots, \boldsymbol{\Sigma}'_j]'$, for $j = 1, \ldots, r$; $\mathbf{y} = [\mathbf{y}'_1, \ldots, \mathbf{y}'_T]'$, $\mathbf{S} = [S'_1, \ldots, S'_T]'$ and $\mathbf{P}$ is the transition probability matrix. According to Sims et al. (2008), the posterior distribution $p(\boldsymbol{\theta}, \boldsymbol{\Sigma}, \mathbf{S}, \mathbf{P} | \mathbf{Y}_T)$ is obtained sampling from the following conditional posterior distributions: (i) $p(\mathbf{S} | \boldsymbol{\theta}, \boldsymbol{\Sigma}, \mathbf{P}, \mathbf{y})$; (ii) $p(\mathbf{P} | \boldsymbol{\theta}, \boldsymbol{\Sigma}, \mathbf{S}, \mathbf{y})$; (iii) $p(\boldsymbol{\theta} | \boldsymbol{\Sigma}, \mathbf{S}, \mathbf{P}, \mathbf{y})$ and (iv) $p(\boldsymbol{\Sigma} | \boldsymbol{\theta}, \mathbf{S}, \mathbf{P}, \mathbf{y})$.

Before to start the step 1, in order to speed the convergence of the algorithm, we begin with at least an approximate estimate of the peak of the posterior density as Sims and Zha (2006) suggest. To initialize the Markov Chain, we set $\mathbf{S}^{(0)}$, such as it will divide the sample in symmetric subsamples, depending on the number of regimes. In each subsample, we calculate $\boldsymbol{\theta}^{(0)}$and $\mathbf{\Sigma}^{(0)}$ by OLS. Also, the value of the symmetric matrix $\mathbf{P}^{(0)}$ satisfies that $p_{ij} = 0.8$ with $i = j$ and $p_{ij} = 1/(r-1)$ with $i \neq j$.

To implement the step (i), we use a multi-move Gibbs sampling method as in Kim and Nelson (1999), Sims et al. (2008) and Bianchi and Melosi (2017). The algorithm to calculate the filtered and smoothed probabilities is: $\boldsymbol{\omega}_{t|t} = \frac{\boldsymbol{\omega}_{t|t-1} \odot \boldsymbol{\eta}_t}{\mathbf{1}'(\boldsymbol{\omega}_{t|t-1} \odot \eta_t)}$, $\boldsymbol{\omega}_{t+1|t} = \mathbf{P}\boldsymbol{\omega}_{t|t}$ where $\boldsymbol{\omega}_{t|t}$ are the filtered probabilities and η_t is the jth element of the conditional density $p(\mathbf{y}_t|S_t = j, \mathbf{y}_{t-1}; \mathbf{P}, \boldsymbol{\theta}_{S_t}, \mathbf{\Sigma}_{S_t})$, the symbol $\odot$ denotes element by element multiplication. To initialize the recursive calculation, we assume that the initial probability is 1/3. In the case of smoothed probabilities, $\boldsymbol{\omega}_{t|T}$, we consider the following algorithm: $\boldsymbol{\omega}_{t|T} = \boldsymbol{\omega}_{t|t} \odot [\mathbf{P}'(\boldsymbol{\omega}_{t+1|T}(\div)\boldsymbol{\omega}_{t+1|t})]$ where $(\div)$ denotes element by element division.

To implement step (ii), the transition probabilities are independent of $\mathbf{y}$ and the other parameters of the model and we use a Dirichlet distribution according to Chib (1996). For each row we have: $\mathbf{P}(i,:) \sim Dir(\boldsymbol{\alpha}_0 + \xi_{ij})$ where ξ_{ij} denotes the number of transitions from state i to state j, and $\boldsymbol{\alpha}_0$ is the value of the prior for this distribution. Values for $\boldsymbol{\alpha}_0$ are given in Section 4.3.

To implement step (iii), we follow Chan and Eisenstat (2018): $(\boldsymbol{\theta}_j|\mathbf{y}, \mathbf{\Sigma}, \mathbf{S}, \mathbf{P}) \sim \mathcal{N}(\widehat{\boldsymbol{\theta}}_j, \mathbf{K}_{j\theta}^{-1})$ where the mean of the normal distribution is $\widehat{\boldsymbol{\theta}}_j$= $\mathbf{K}_{j\theta}^{-1}(\mathbf{V}_\theta^{-1}\mathbf{a}_\theta + \mathbf{X}_j'\mathbf{\Sigma}_j^{-1}\mathbf{X}_j)$ and the variance is $\mathbf{K}_{j\theta}$= $\mathbf{V}_\theta^{-1}$+$\mathbf{X}_j'\mathbf{\Sigma}_j^{-1}\mathbf{X}_j$ for $j = 1, \ldots, r$. Values for $\mathbf{a}_\theta$ and $\mathbf{V}_\theta$ are define in Section 4.3.

The step (iv) is implemented using the conditional distributions of the elements on the diagonal of $\mathbf{\Sigma}_j$ for $j = 1, \ldots, r$: $(\sigma_j^2|\mathbf{y}, \boldsymbol{\theta}, \mathbf{S}, \mathbf{P}) \sim \mathcal{IG}(\boldsymbol{\nu}_0 + \frac{T}{2}, \mathbf{S}_0 + \frac{1}{2}\sum_{t=1}^{T}(\mathbf{y}_{jt} - \mathbf{X}_{jt}\boldsymbol{\theta}_j)^2)$ where $\mathcal{IG}$ represents the Inverse Gamma distribution. Values for $\boldsymbol{\nu}_0$ and $\mathbf{S}_0$ are given in Section 4.3. Lastly, the steps from (i) to (iv) should be repeated N times, where N is the sum of burnings in sample and number of iterations.

3.3 Calculation of the Marginal Likelihood

The Bayes Factor (BF) is a Bayesian measure for comparing models, defined as a ratio of marginal likelihoods $BF_{ij} = \frac{p(\mathbf{y}|M_i)}{p(\mathbf{y}|M_j)}$, where the marginal likelihood is $p(\mathbf{y}|M_m) = \int p(\mathbf{y}|\boldsymbol{\theta}_m, M_m)p(\boldsymbol{\theta}_m|M_m)d\boldsymbol{\theta}_m$ under model M_m, $m = i, j$. Chan and Eisenstat (2015) propose a more accurate and efficient way to estimate the marginal likelihood based on *importance sampling*:

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

where $\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_N$ are independent draws obtained from the importance density $g(.)$. The estimator $\widehat{p}_{IS}(\mathbf{y})$ meets the conditions of being consistent and unbiased, irrespective of the value of $g(\boldsymbol{\theta}_n)$; however, it is sensitive to its variance. Therefore, for an optimal choice of $g(.)$ with minimum variance, we use the cross-entropy method. If we denote this optimal importance density as g^* and define the posterior density as $g^* = g(\boldsymbol{\theta}) = p(\boldsymbol{\theta}|\mathbf{y}) = p(\mathbf{y}|\boldsymbol{\theta})p(\boldsymbol{\theta})/p(\mathbf{y})$, we obtain:

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

Thus, for choosing g^* we use a parametric family $\mathcal{F} = \{f(\boldsymbol{\theta}; \mathbf{v})\}$ standardized by vector $\mathbf{v}$, from which we obtain the importance density $f(\boldsymbol{\theta}; \mathbf{v}^*)$$\in$$\mathcal{F}$ that is closest to g^*. The objective is finding

$\mathbf{v}^*_{ce}$ such that it minimizes the cross-entropy distance between the optimal density and the chosen density $f(\boldsymbol{\theta};\mathbf{v})$:

$$= \arg\min_{\{\mathbf{v}\}}(\int g^*(\boldsymbol{\theta})\log g^*(\boldsymbol{\theta})d\boldsymbol{\theta} - p(\mathbf{y})^{-1}\int p(\mathbf{y}|\boldsymbol{\theta})p(\boldsymbol{\theta})\log(\boldsymbol{\theta};v)d\boldsymbol{\theta}). \tag{5}$$

As the first part of (5) does not depend on $\mathbf{v}$, solving the minimization problem is equivalent to maximizing the second part, whose estimator is:

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

where $\boldsymbol{\theta}_1,\ldots,\boldsymbol{\theta}_L$ are the draws obtained from the posteriors. In sum, the algorithm is divided into two parts: (i) obtaining the $\boldsymbol{\theta}_1,\ldots,\boldsymbol{\theta}_L$ draws from the posterior density $g^*(\boldsymbol{\theta}) = p(\boldsymbol{\theta}|\mathbf{y}) \propto p(\mathbf{y}|\boldsymbol{\theta})p(\boldsymbol{\theta})$ and seeking a solution for (6); and (ii) generating a random sample $\boldsymbol{\theta}_1,\ldots,\boldsymbol{\theta}_N$ from the $f(:;\widehat{\mathbf{v}}^*_{ce})$ density and estimating the marginal likelihood using the estimator proposed in (4).

4 Empirical Results

This Section describes the variables used, the identification scheme, the priors used in the estimations, the regimes identified, and the calculation of the IRFs, FEVDs, and HDs for the RS-VAR-SV models.

4.1 Data

Figure 1 shows the quarterly data[5] as growth rates for all variables except international and domestic interest rates. The sample covers 1994Q1-2019Q4, with data drawn from the BCRP, Bloomberg, Gruss and Kebhaj (2019), and the Federal Reserve Bank of St. Louis. The model uses two blocks of variables. The first one comprises four external variables representing trade, financial, and price shocks (see Han (2014), Nolazco et al. (2016), and Rodríguez and Vassallo (2022)): U.S. output growth (y_t^{USA}), the Fed's policy rate (i_t^*), China's output growth (y_t^{CHN}), and the export price index growth (p_t^*). The second block is made up of three domestic aggregates: Peru's output growth (y_t^{PER}), the inflation rate (π_t^{PER}), and the interest rate (i_t^{PER}).

The external variable block is modeled parsimoniously, such that trade shocks are represented by movements in y_t^{USA} and y_t^{CHN}. In this regard, Canova (2005), IMF (2014), and Kose et al. (2017) show that Peru is one of main trading partners of the U.S. among EMEs, with Peru's exports to the U.S. amounting to around 3.3% of GDP. At the same time, Han (2014), Nolazco et al. (2016) and IMF (2019) show that Peru's exports to China represent around 6.2% of GDP, twice as much as exports to the U.S. Figure 1 shows that y_t^{USA} is stable throughout the sample, with sharp falls associated with the 2001 *dot.com* crash and the 2008 Global Financial Crisis (GFC). In contrast, y_t^{CHN} is a more volatile series, particularly in 1994-2009; i.e., China's high-growth period propelled by industrial development and trade integration. From 2009, y_t^{CHN} decelerates through 2019, with lower volatility than during the first period.

We use p_t^* to model external shocks transmitted via the price channel, consisting mainly of the prices of metal commodities (copper, gold, and zinc). Peru was the world's first copper producer

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[5] The series in levels were seasonally adjusted using Tramo-Seats, as proposed by Gómez and Maravall (1996).

(12% of global production) and second zinc producer (11% of global production) in 2019. Figure 1 shows that p_t^* has a growing trend in 2000-2008, in line with the commodity supercycle, but decelerates in 2009-2019. Additionally, p_t^* volatility is lower in 1994-2002 than in 2003-2019. Along these lines, the standard deviation in the second period (around 20.5%) is twice as large as in the first one.

Finally, financial shocks are represented by i_t^*, which is subject to U.S. monetary policy and has a direct influence on Peru's short-term dollar interbank interest rate; i.e., both rates are highly correlated (0.7 in 1994-2019). The impact of this shock is directly reflected in dollar loans (27% of total credit to the private sector). We highlight that private credit has increased with greater financial development in recent years (42% of GDP). Figure 1 shows that, in the wake of financial crises, i_t^* rose to levels below 2%; in particular, i_t^* remained around zero after the GFC.

When we calculate the standard deviation of y_t^{PER}, π_t^{PER} and i_t^{PER} during the period 1994-2002 (4.5%, 7.3%, 5.3%, respectively) and the subsample 2003-2019 (2.7%, 1.3%, 1.1%, respectively), we evidenced a marked decrease in the volatility of these variables. This fact is associated with Peru's exposure, during 1994-2002, to different international crises, idiosyncratic shocks[6], and a monetary policy regime different from the current one. During 2003-2019, Peru was still exposed to external shocks, but with an IT regime adopted by the BCRP, which played a fundamental role in stabilizing the different shocks to the economy; see, for instance, Portilla et al. (2022).

4.2 Identification Scheme

The identification of the structural model involves ordering the variables recursively from the most exogenous to the most endogenous: $\mathbf{y}_t = (y_t^{USA}, y_t^{CHN}, i_t^*, p_t^*, y_t^{PER}, \pi_t^{PER}, i_t^{PER})'$. This assumes that y_t^{USA} is not affected contemporaneously by shocks from other variables. This assumption is based on Kose et al. (2017), who find evidence of the considerable influence of the U.S. on both advanced countries and EMEs. We also assume that U.S. decisions directly affect y_t^{CHN}; and that later the contemporaneous response of i_t^* is affected by y_t^{USA} and y_t^{CHN} shocks. The contemporaneous response of p_t^* is affected by y_t^{USA}, y_t^{CHN} , and i_t^* shocks, as proposed by Roache (2012). Moreover, domestic variables like y_t^{PER} are affected contemporaneously by all shocks from the external variable block; i.e., π_t^{PER} is affected by contemporaneous external shocks and by y_t^{PER}. Finally, i_t^{PER} responds contemporaneously to shocks from all variables in the system.

4.3 Priors

First, priors for estimating $\boldsymbol{\theta}$ follow a Gaussian distribution $\boldsymbol{\theta} \sim \mathcal{N}(\mathbf{a}_\theta, \mathbf{V}_\theta)$, where $\mathbf{a}_\theta = \mathbf{0}$, $\mathbf{V}_\theta = 10 \times \mathbf{I}_{k_\theta}$. Second, priors for estimating the variance follow an Inverse Gamma distribution $\boldsymbol{\Sigma}_j = \text{diag}(\boldsymbol{\sigma}_{1j}^2, \ldots, \boldsymbol{\sigma}_{nj}^2)$, for $i = 1, \ldots, n$ and $j = 1, \ldots, r$; where $\boldsymbol{\sigma}_i^2 \sim \mathcal{IG}(\boldsymbol{\nu}_0, \mathbf{S}_0)$ and $\boldsymbol{\nu}_0 = 5$, $\mathbf{S}_0 = (\boldsymbol{\nu}_0 - 1) \times \mathbf{I}_n$. Third, the transition probabilities follow a Dirichlet distribution which depends on parameter $(\boldsymbol{\alpha}_0)$, according to Sims and Zha (2006) this parameter should be settled on $\boldsymbol{\alpha}_0 = 2 \times \mathbf{1}_r$ to generate an agnostic symmetrical prior distribution.

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[6] The international crises during 1994-2002 were the Tequila crisis (1994), the Asian and Russian crises (1997-1998), and the dot.com crash (2001). On the other hand, the idiosyncratic shocks were associated with the *El Niño* Phenomenon (1998) and political crisis (2001).

4.4 Results

Following Bijsterbosch and Falagiarda (2015), Table 1 presents three tests assessing the presence of time-varying parameters in the matrix of contemporaneous relationships ($\mathbf{B}_{0_t}$), the coefficients of lags and intercepts ($\mathbf{B}_{i_t}$), and the variance matrix ($\mathbf{\Sigma}_t$) in a TVP-VAR-SV model with one lag, selected using the Bayesian Information Criterion (BIC) (as in Rodríguez and Vassallo (2022)). First, in line with Cogley and Sargent (2005), the trace test assesses whether the trace of the prior for $\mathbf{\Sigma}_t$ is significantly less than the posterior for $\mathbf{\Sigma}_t$. Second, the Kolgomorov-Smirnov test evaluates whether each set of parameters can be obtained from the same continuous distribution. Third, the t-test establishes whether the mean of the two random samples belongs to the same distribution.

In general, our results provide evidence of time-varying parameters. In particular, the trace test is estimated at 0.28, which is less than the value of the prior in the 50% and 84% percentiles. The other tests are calculated for two sub-samples, 1994Q2-2003Q4 and 2004Q1-2019Q4. The Kolgomorov-Smirnov test and the t-test show that 100% of the parameters in $\mathbf{\Sigma}_t$ change between both sub-samples. Regarding the coefficients in $\mathbf{B}_{i_t}$ and $\mathbf{B}_{0_t}$, the Kolgomorov-Smirnov test shows evidence that 90% of the parameters in $\mathbf{B}_{i_t}$ and 76% of the parameters in $\mathbf{B}_{0_t}$ vary over time. Likewise, the t-test shows that, in both sub-samples, around 87% of the parameters in $\mathbf{B}_{i_t}$ and 100% of the parameters in $\mathbf{B}_{0_t}$ vary over time.

4.4.1 Selection of the Best-Fitting Model

Table 2 shows the log-marginal likelihoods for the RS-VAR-SV models with one lag ($p = 1$)[7] and different regimes. We highlight two comments from these results. First, compared with the CVAR model, the RS-VAR-SV model provides a much inferior fit; specifically, the BF in favor of the former is 1.8×10^{24}. However, this result changes when only the volatilities across regimes are allowed to vary. Along these lines, the RS-VAR-SV-R1 model provides a better fit than the CVAR model, with a BF of 1.3×10^{25}, indicating that the highest gain in fit results from SV inclusion. Indeed, comparing a model with a constant variance matrix (RS-VAR-R2) with the RS-VAR-SV model, the BF for the latter is 1738, indicating a better fit. Additionally, the RS-VAR-SV-R1 model is a better fit than the restricted versions of the RS-VAR-SV model (RS-VAR-SV-R3, RS-VAR-SV-R4, and RS-VAR-SV-R5). Therefore, our results suggest that models with SV and constant coefficients across regimes provide a better fit compared with models where all coefficients are time-constant or time-varying. This finding is in line with Ojeda Cunya and Rodríguez (2022), Rodríguez and Vassallo (2022), and Guevara et al. (2022), who indicate that models with SV and changing intercepts fit better for Peru.

Second, the results suggest that the number of regimes estimated within each RS-VAR-SV model also affects the goodness of fit. In general, models with two regimes ($r = 2$) are largely favored by the data; e.g., comparing the RS-VAR-SV-R1 model with two regimes vis-à-vis the same model with three and four regimes ($r = 3$ and $r = 4$), the BFs favoring the first model are 5260 and 4.4×10^6, respectively.

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[7] The number of lags (p) is selected using the Schwarz Information Criterion (SIC) applied to a CVAR. We also perform a Bayesian estimation of the CVAR model with $p = 1, 2, 3$, where the BFs are 1.06×10^{32} and 3.94×10^{86} in favor of the model with $p = 1$ over those with $p = 2$ and $p = 3$, respectively.

4.4.2 Regimes in the Model

Based on the results for the RS-VAR-SV-R1 model, we calculate the standard deviation of shocks associated with regime 1 and find that domestic variable shocks under the post-IT regime are less volatile than under the pre-IT regime; in particular, y_t^{PER} and π_t^{PER} shocks are 50% less volatile and i_t^{PER} shocks are 90% less volatile. Additionally, the standard deviation of y_t^{USA}, y_t^{CHN}, and i_t^* external shocks under the post-IT regime are 10% lower than under the pre-IT regime, while the standard deviation of the p_t^* shock under the post-IT regime is 50% higher than under the pre-IT regime.

Figure 2 shows the state probability for all models with two regimes.[8] Two-regime models indicate a clear turning point between the pre- and post-IT regimes in 2002. Moreover, taking the RS-VAR-SV-R1 model as reference, we find that the duration of regimes 1 and 2 is 11 and 33 quarters, respectively, with greater persistence under the post-IT regime.

4.4.3 Analysis of Impulse-Response Functions (IRFs)

In this section we discuss the IRFs of domestic variables (mainly Peru's output growth) for external shocks (y_t^{USA}, y_t^{CHN}, i_t^* , and p_t^*); and calculate the IRFs for the pre- and post-IT regimes. To facilitate the interpretation of the results, we normalize the IRFs so that domestic variables respond to 1% external shocks.

Figure 3 shows the IRFs of y_t^{PER}, π_t^{PER}, and i_t^{PER} for different external shocks under regimes 1 and 2.[9] We note that, in all models, y_t^{PER} has a positive response to y_t^{USA}, y_t^{CHN} , and p_t^* shocks and a negative response to i_t^* shocks, in line with theory; see Kose (2002). The differences in responses between models are associated with magnitude and persistence.

Based on the above premises, we can infer four general results regarding the response of y_t^{PER}: (i) the y_t^{USA} and y_t^{CHN} shocks (real channel shocks) have a positive effect on y_t^{PER} (0.3% and 0.8% after one year, respectively) and the y_t^{CHN} shock is more persistent than the y_t^{USA} shock; (ii) the i_t^* shock (financial channel shock) has a negative and transitory impact (around 0.4%); (iii) the p_t^* shock (price channel shock) has a positive impact and the response is heterogenous depending on the model and the regime; and (iv) the responses to external shocks are more stable and similar to each other under the post-IT regime than under the pre-IT regime.

Hereinafter we will focus on the RS-VAR-SV-R1 model with two regimes, which provides the best fit according to the BF. Figure 4 shows the responses of domestic variables to y_t^{USA}, y_t^{CHN}, i_t^*, and p_t^* shocks within their respective 68% confidence bands. Additionally, we take the IRFs for the CVAR model (red lines) as benchmark.

a) U.S.-originated real external shocks: Column 1 in Figure 4 shows the response of domestic variables to a y_t^{USA} shock. The response of y_t^{PER} is positive under both regimes, with a greater impact under regime 1. The responses of π_t^{PER} and i_t^{PER} are also positive and have a greater impact under regime 1. Moreover, we note that the responses of y_t^{PER}, π_t^{PER}, and i_t^{PER} are less persistent than with the CVAR model.

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[8] We carry out the same analysis for the three-regime models (available on request). The results for these models show that the third regime in each model does not meet the rule of thumb proposed by Hamilton (1989); i.e., the estimated state probabilities do not exceed 0.5, implying that the third regime is not relevant to this study.

[9] It should be noted that we omit the IRFs for regime 1 in the RS-VAR-SV and RS-VAR-SV-R2 models, as they show an unstable behavior.

The response of y_t^{PER} indicates a 0.3% expansion resulting from a 1% increase in y_t^{USA} three quarters after the shock. However, in quarter 10 the response of y_t^{PER} contracts by 0.3% and dissipates by the fifth year. This mixed behavior is influenced by two opposing forces. The first one is associated with the trade channel; i.e., the expansion in y_t^{USA} has a positive influence on Peru's exports, the U.S. being one of its main trading partners. However, after a period of y_t^{USA} expansion, rising prices in the U.S. would result in a Fed rate increase, in turn acting as a second, opposite force with a negative effect on y_t^{PER}. The positive responses of π_t^{PER} and i_t^{PER} are associated with higher inflation expectations in response to greater economic activity; i.e., expectations of higher interest rates for countering growing inflation and external interest rate spreads.

The response of y_t^{PER} under regime 1 is greater than under regime 2 due to Peru's relatively lower post-IT trade trade dependence on the U.S., in line with Canova (2005) and IMF (2019); i.e., this lower significance is associated with a lower U.S. share as commodity importer.

b) China-originated real external shocks: Column 2 in Figure 4 indicates the IRFs of domestic aggregates for a y_t^{CHN} shock. The impact on y_t^{PER} is positive under both regimes, with a greater impact under regime 2, in contrast with the effect of a y_t^{USA} shock, as trade relations with China intensified more than with the U.S. under the post-IT regime. The responses of π_t^{PER} and i_t^{PER} are in line with the response of y_t^{PER}. We underscore that responses in the CVAR model underestimate the effects of external shocks under both regimes.

The importance of China-originated shocks grew as China became Peru's main commodity buyer in 2002 and surpassed the U.S. as main destination for Peru's exports in 2011. In this context, y_t^{CHN} shocks have a considerable impact via greater demand for metal inputs and commodities. This result is explained mainly by China's weight in the global commodity market and Peru's role as a leading exporter of metal commodities (72% of exports to China are metal commodities). Additionally, greater demand for metal commodities increases their prices, resulting in higher dollar revenues from exports and appreciation pressures on Peru's currency. Moreover, the positive outlook for the mining industry attracts investments in new exploration and exploitation projects, with China emerging as a leading investor in recent years.

The response of y_t^{PER} to a 1% expansion in y_t^{CHN} reaches 0.8% after one year under the post-IT regime (a greater effect than for y_t^{USA} shocks) and remains significant until year 2. It is worth noting that China-originated shocks also reflect an indirect effect from commodity prices, as suggested by Gruss (2014) and IMF (2019). Additionally, our results are in line with a recent report on the relevance of trade integration in Latin America and the Caribbean (World Bank (2019)), which estimates the elasticity of y_t^{PER} in response to a 1% y_t^{CHN} shock at 0.7%.

Regarding the responses of π_t^{PER} and i_t^{PER}, we find that they become inflationary starting quarter 4 as a result of greater momentum in domestic demand. In turn, this results in higher inflation expectations, which prompts an expansionary i_t^{PER} response to offset inflation pressures (Mendoza and Collantes Goicochea (2017)). Moreover, growing trade relations and integration into world commodity markets since 2002 changed the responses of π_t^{PER} and i_t^{PER} across both regimes; i.e., they are more inflationary under regime 2.

c) External financial shocks: Column 3 in Figure 4 shows the responses of domestic variables to an i_t^* shock. The contractionary response of y_t^{PER} increased under regime 2, confirming that, during that period, U.S. financial shocks have a greater effect on economic activity than U.S. real shocks. Theory predicts that this contractionary effect results from increased returns on the dollar, which in turn creates depreciation pressures on Peru's currency and promotes capital outflows. This effect raises the cost of credit, which affects financing of private investment and, therefore, y_t^{PER}. Additionally, the increase in i_t^* prompts a positive monetary policy response, which increases domestic interest rates. It should be noted that this effect is also magnified under regime 2. Moreover, the results from the selected model are more persistent than those from the CVAR model.

The 1% increase in i_t^* contracts y_t^{PER} by 0.5% in quarter 2; and is statistically significant in the short run. Our results are in line with Mendoza and Collantes Goicochea (2017), who mention that, in response to capital outflows, the price of financial securities drops; and, in turn, this wealth effect depresses demand and output. Financial shocks have a greater impact than y_t^{USA} shocks due to considerable U.S. direct and portfolio investments; see IMF (2019). Regarding the responses of monetary variables, we find that π_t^{PER} does not show a clear response; however, i_t^{PER} responds positively during the first quarters, confirming the synchronicity between Peru's monetary policy and Fed decisions. In sum, Peru's greater participation in financial markets and increased access to credit by households and companies since 2002 resulted in a greater impact of financial shocks under regime 2.

d) External commodity price shocks: Column 4 in Figure 4 indicates that the responses of y_t^{PER} to p_t^* shocks are positive (and larger under regime 2), as Peru became a leading producer of copper, zinc, silver, gold, and other minerals since the commodity price boom, coinciding with surging growth in China and the global economy (which propelled the demand for minerals since 2000).

In this context, a positive p_t^* shock will result in greater revenues from exports and enhanced mining returns, in turn encouraging other investors to develop mining projects in Peru. Higher incomes result in improved income tax revenues (mainly mining canon revenues), which creates more fiscal space to finance public investment; see IMF (2015) and Jiménez and Rodríguez (2020).

A positive 10% p_t^* impulse would increase growth by 0.5% in quarter 2 under regime 2 and then dissipate in one year; i.e., it would be a transitory shock. Its impact is comparatively low, in principle due to the presence of y_t^{CHN} in the model.[10] Other studies, like Ojeda Cunya and Rodríguez (2022), find that a 10% increase in commodity prices results in a 1%-2% expansion in y_t^{PER}; and Rodríguez and Vassallo (2022) suggest a response of around 1.1%. Despite the differences in magnitude, our results confirm the temporary nature of these shocks, as well as variation over time. We also find that the response of π_t^{PER} and i_t^{PER} is contractionary during the initial quarters. This fall is caused by greater dollar inflows caused by the price effect on exports, which in turn diminishes import prices and (via the pass-through effect of the exchange rate) reduces inflation. As the shock is temporary, monetary policy does not react significantly.

4.4.4 Analysis of the Forecast Error Variance Decomposition (FEVD)

Figure 5 shows the FEVD of y_t^{PER}, π_t^{PER}, and i_t^{PER} for 20 quarters, the two regimes in the RS-VAR-SV-R1 model, and the CVAR model. We consider y_t^{USA}, y_t^{CHN}, i_t^*, and p_t^* external shocks, as well as aggregate demand (AD), aggregate supply (AS), and monetary policy (MP) domestic shocks.

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[10] The Section on robustness exercises explains this issue in detail by comparing a model with p_t^* as sole external shock with another that considers both p_t^* and y_t^{CHN}.

The FEVD for output growth in Peru shows that, altogether, external shocks explain around 70% of y_t^{PER} fluctuations under regime 2; i.e., 40 percentage points (p.p.) higher than under regime 1. Greater uncertainty under regime 2 is associated with higher volatility in p_t^* and y_t^{CHN} shocks (30% and 34%, respectively), which increased considerably (by 19 p.p. and 16 p.p. relative to regime 1, respectively). The remaining volatility is explained by i_t^* and y_t^{USA} shocks (1% and 5%, respectively), which did not change substantially relative to regime 1. It should be noted that the y_t^{USA} shock creates less uncertainty than the y_t^{CHN}shock, as China is closely related to Peru via the trade channel. Moreover, the stylized facts show that China's output is more volatile than that of the U.S.

Our empirical results are in line with Fernández et al. (2020) and Rodríguez and Vassallo (2022). Furthermore, Ojeda Cunya and Rodríguez (2022), and Guevara et al. (2022) find values of 65% and 80% for the contribution of external shocks to y_t^{PER} variability. The increased uncertainty of external shocks under regime 2 coincides with Peru's greater trade integration with large commodity importers like China, and with the commodity price boom. Along these lines, Mendoza (2013) argues that the success of Peru's economic model is mainly associated with extraordinary international events and only partially with sound short-run policies.

We also find that AS, AD, and MP domestic shocks explain 70% of y_t^{PER} variability under regime 1, vis-à-vis 30% under regime 2. This 40-p.p. reduction is closely associated with improved monetary and fiscal policies; i.e., the BCRP adopted IT in 2002 (see Portilla Goicochea and Rodríguez (2020)) and the Ministry of Economy and Finance (MEF) implemented fiscal discipline (see Jiménez and Rodríguez (2020)).

In particular, our results indicate that the contribution of an MP shock diminishes under regime 2; i.e., it explains 1% of y_t^{PER} variability (19 p.p. less than under regime 1). This result translated into more predictable monetary policy and greater confidence in the BCRP's decisions (see Castillo et al. (2016) and Portilla Goicochea and Rodríguez (2020)).

The FEVDs for π_t^{PER} and i_t^{PER} indicate that external shocks explain 80% of variability in each variable under regime 2 (i.e., 60 p.p. and 70 p.p. increases relative to regime 1, respectively). In particular, this increase is influenced mainly by the p_t^* shock (66% and 70%, respectively), reflecting the effect of external shocks via the nominal channel on monetary variables. Additionally, i_t^* and y_t^{USA} shocks significantly affect i_t^{PER} (8% and 20%, respectively) under the post-IT regime.

In line with Canova (2005), Han (2014), and IMF (2019), our results reflect the impact of international financing costs and the greater connection with the U.S. via the financial channel. At the same time, domestic shocks introduce greater volatility in π_t^{PER} and i_t^{PER} forecasts under regime 1 (63% and 89%, respectively), vis-à-vis 20% under regime 2. This result also confirms the success of IT adoption, reflected in lower π_t^{PER} uncertainty and greater i_t^{PER} predictability under the post-IT regime.

The results for the CVAR model, vis-à-vis the RS-VAR-SV-R1 model, show that external shocks explain less than 60% of y_t^{PER} variability, 10 p.p. below the value predicted by the RS-VAR-SV-R1 model under regime 2. This result is associated with a lower contribution from the p_t^* shock (around 20 p.p.) and is replicated in the FEVDs for π_t^{PER} and i_t^{PER}. Another important result is that the contribution of the y_t^{USA} shock to i_t^{PER} variability is 20 p.p. higher than the value predicted by the RS-VAR-SV-R1 model. In general, the FEVDs for the CVAR model depart from the literature (Rodríguez and Vassallo (2022); Guevara et al. (2022)). Therefore, SV omission in traditional (CVAR) models leads to underestimating the total effect of external shocks on y_t^{PER}, π_t^{PER} , and i_t^{PER}, as well as the contribution of y_t^{CHN}, y_t^{USA}, i_t^*, and p_t^* shocks on those domestic variables.

Moreover, AS, AD, and MP shocks in the CVAR model are more influential; in particular, we identify a greater contribution of the MP shock; e.g., the latter explains 40% of i_t^{PER} variability in quarter 4; i.e., 20 p.p. higher than estimated by the RS-VAR-SV-R1 model under regime 2. Therefore, the CVAR model fails to reflect monetary policy moderation after IT adoption.

4.4.5 Analysis of Historical Decomposition (HD)

Figure 6 shows the HD for y_t^{PER}, π_t^{PER}, and i_t^{PER} for the RS-VAR-SV-R1 and CVAR models, using the methodology proposed by Wong (2017). The HD for y_t^{PER} in the RS-VAR-SV-R1 model shows that y_t^{PER} increased from 4% under regime 1 to 5.1% under regime 2. The main driver of this 1.1-p.p. increase was the y_t^{CHN} shock, which explained 1.0 p.p. (around 89%). Another determinant of the increase in y_t^{PER} under regime 2 was the y_t^{USA} shock, which contributed 0.3 p.p (around 25%). These results suggest that greater trade integration and free-trade agreements (FTAs) with Peru's main trading partners was beneficial, as they contributed to enhancing y_t^{PER} under the post-IT regime.

In contrast with real shocks, the i_t^* shock had a negative impact on the increase in y_t^{PER} between regimes (a -0.1-p.p. contribution, around -5%). Similarly, the p_t^* shock explained -0.1 p.p. of the increase in y_t^{PER} between regimes. Despite the negative contribution of both shocks, they represent just -0.2 p.p (10%) of the increase, which is relatively low compared with the total contribution of the $y_t^{CHN}$and y_t^{USA} real shocks.

Regarding domestic shocks, the MP shock contributed considerably to the increase in y_t^{PER} (0.3 p.p., around 28.5%), reflecting sound monetary policy implementation by the BCRP under regime 2. Additionally, the AS and AD shocks explained 0.5 p.p. (around 41%) of the difference in y_t^{PER} between the pre- and post-IT regimes.

The HDs for y_t^{PER} in the CVAR and RS-VAR-SV-R1 models coincide in that the y_t^{CHN} shock is the main factor explaining the increase in y_t^{PER} under regime 2. At the same time, the CVAR model estimates the contribution of the y_t^{USA} shock at 0.7 p.p. of such increase (around 66%). Additionally, the CVAR model estimates that the MP shocks contributed -0.1 p.p. to the increase in y_t^{PER} under the post-IT regime (around -7%), which is not consistent with the stylized facts about the successful implementation of monetary policy under the post-IT regime.

Using the HD for y_t^{PER} in the RS-VAR-SV-R1 model, we calculate the effect of international crises on y_t^{PER} in specific periods. For 1998, we find that the mix of external shocks had a negative effect on y_t^{PER}, coinciding with the Asian and Russian crises; see Castillo and Pereda (2009). Comparing y_t^{PER} for 1997-1998, we calculate that y_t^{PER} diminished by -6.8 p.p., of which external shocks explained -1.6 p.p. (around 23.4%). Additionally, the El Niño Phenomenon (at the beginning of 1998) destroyed fixed capital, reduced fishing production, and deteriorated exports; i.e., AS and AD shocks altogether contributed -5.3 p.p. (around 78%) to the fall in y_t^{PER} between 1997 and 1998.

In the wake of the GFC, y_t^{PER} dropped from 9.2% in 2008 to 1.1% in 2009. The main driver of this 8.1-p.p. fall was the y_t^{CHN} shock (4.7 p.p., around 58%). Another important factor was the decline in U.S. growth, which contributed 1.4 p.p. (around 17.8%) to the fall. At the same time, via U.S. expansionary policy, the i_t^* shock attenuated the fall in y_t^{PER} (a -0.6-p.p. contribution, around -7.6%).

A recent event to consider is the 2019 U.S.-China trade wars. Output growth in Peru decreased from 4.0% in 2018 to 2.2% in 2019. This 1.8-p.p. decline was explained mainly by y_t^{CHN} shocks (a

0.7-p.p. contribution, around 40%). Moreover, low commodity prices were transmitted via the p_t^* shock, representing 0.3 p.p. (around 15.4%) of the difference in y_t^{PER} between 2018 and 2019.

For its part, π_t^{PER} is 8% and 2.7% under regimes 1 and 2, respectively. The 5.3-p.p. decrease in π_t^{PER} is explained mainly by AS and MP shocks, which contributed 1.7 p.p. (around 31.6%) to the reduction. In contrast, the results for the CVAR model suggest that the MP shock was not important in reducing π_t^{PER}, which is not in line with the literature on sound monetary policy implementation in Peru; see Castillo et al. (2016) and Portilla Goicochea and Rodríguez (2020).

The HDs for i_t^{PER} in the RS-VAR-SV-R1 are 13.7% and 3.7% under regimes 1 and 2, respectively; i.e., a 10-p.p. reduction, reflecting successful IT adoption by the BCRP, and relying on the attenuation of the MP shock (4.2 p.p., around 41.5%). Like in the HD for π_t^{PER}, the CVAR model does not capture the importance of the MP shock in regime 2, as it estimates its contribution at 0.4 p.p.; i.e., around 4% of the reduction in i_t^{PER} between the pre- and post-IT regimes.

5 Robustness

We perform seven robustness exercises on the model via the following modifications: (i) use of alternative priors; (ii) changes in external variables (i_t^* and p_t^*); (iii) change in the ordering of domestic variables; and (iv)-(vii) estimation of the model using 4, 5, 6, and 8 variables. The IRFs, FEVDs, and HDs are calculated and assessed for each exercise. Table 3 shows the results.[11]

5.1 Changes in Priors

The baseline estimations use the priors proposed by Chan and Eisenstat (2018), which are non-informative. In this regard, the first robustness exercise consists in assessing the sensitivity of our results with a set of priors that use OLS estimations for a training sample covering 1994-2004 and comprising 40 observations, like Primiceri (2005). We use the information in Table 3 to calculate the BF, which clearly favors the RS-VAR-SV-R1 model with two regimes; e.g., the BFs between the RS-VAR-SV-R1 model with two regimes ($r = 2$) and the CVAR and RS-VAR-SV models with two regimes ($r = 2$) are 5.1×10^{23} and 9.3×10^{47}, respectively.

Columns 1 and 2 in Figure 7 show the IRFs of y_t^{PER} under regimes 1 and 2 in the RS-VAR-SV-R1 model for y_t^{USA}, y_t^{CHN}, i_t^*, and p_t^* shocks. The results do not indicate changes in the direction of responses relative to the baseline model. Despite this similarity, y_t^{CHN} shocks differ slightly from the baseline model; and the responses to i_t^* are non-significant for a 68% confidence interval. These results suggest that the baseline model with non-informative priors can replicate the stylized facts on the Peruvian economy.

From the FEVD analysis (Figure 8) we find that external shocks explain 60% of y_t^{PER} variability under regime 2, vis-à-vis less than 20% under regime 1. As in the baseline model, the main sources of uncertainty in predicting y_t^{PER} are the p_t^* and y_t^{CHN} shocks (although, compared with the baseline model, the latter is 20 p.p. lower in quarter 4). With the alternative priors, the differences in the CVAR and RS-VAR-SV-R1 models remain as in the baseline estimation.

Figure 9 shows the HD for y_t^{PER}, indicating that the increase in y_t^{PER} from regime 1 to regime 2 is 1.1 p.p., of which -0.5 p.p. (around -43.7%) were explained by the p_t^* shock; and the i_t^* shock

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[11] Table 3 shows only the log-marginals for the RS-VAR-SV models with $r = 2$ in each robustness exercise. We also calculated the log-marginals for the RS-VAR-SV models with $r = 3$ and $r = 4$, evidencing that the RS-VAR-SV models with $r = 2$ are the best fit in all robustness exercises. The estimations of the log-marginals with $r = 3$ and $r = 4$ are available on request.

contributed 0.1 p.p. (around 11%). Moreover, although these results differ from the baseline model, the results for the y_t^{CHN} and y_t^{USA} external real demand shocks preserve a joint contribution of 1.3 p.p. (around 119%), evidencing their importance in explaining the increase in y_t^{PER} under regime 2, as in the baseline model. As in the FEVD exercise, we find that the CVAR results with alternative priors are similar to the CVAR of the baseline estimates.

5.2 Change of Variables

The second robustness exercise consists in changing the variables for the financial and price channels. That is, i_t^* is changed for a similar variable, the shadow interest rate (i_t^{SR}), calculated by Wu and Xia (2016); and p_t^* is changed for Goldman Sachs's global commodity index, the S&P GSCI (p_t^{SP}). It should be noted that, within the empirical literature for Peru, Flores (2016) used i_t^{SR} as an alternative to i_t^*; and Ojeda Cunya and Rodríguez (2022) and Rodríguez and Vassallo (2022) used p_t^{SP} in their estimations. As in the previous exercise, the RS-VAR-SV-R1 model with two regimes is a better fit compared with the other models. Table 3 shows that the BFs between the RS-VAR-SV-R1 model with two regimes ($r = 2$) and the CVAR and RS-VAR-SV models with two regimes ($r = 2$) are 2.15 and 2.7×10^{64}, respectively.

Columns 1 and 2 in Figure 10 show the IRFs of y_t^{PER} for an i_t^{SR} shock under regimes 1 and 2. These results indicate that the response of y_t^{PER} is a 0.3% contraction in quarter 2, as in the baseline model. Regarding the p_t^{SP} shock, we find the responses of y_t^{PER} to be non-significant and without a clear direction. This result is influenced by the structure of the S&P GSCI, which includes the prices of oil and other commodities imported by Peru. Therefore, this shock involves opposite-direction export and import price effects on y_t^{PER}.

The FEVD analysis (Figure 11) indicates that external shocks contribute 78% of y_t^{PER} variability under regime 2; i.e., over 10 p.p. more than in the baseline model. However, the composition of external shocks remains similar relative to the baseline model. Regarding the i_t^{SR} shock, we find that it contributes 10% to y_t^{PER} variability under both regimes, similar to the contribution of i_t^* in the baseline model. Additionally, we find that the p_t^{SP} shock contributes 47% to y_t^{PER} variability under regime 2; i.e., 17 p.p. more than the contribution of p_t^* in the baseline model, as p_t^{SP} comprises more volatile commodities, like oil and natural gas.

Figure 12 shows the HD for y_t^{PER}, which evidences that the y_t^{CHN} shock contributed 1.4 p.p (around 122%) to the 1.1-p.p. increase in y_t^{PER} between regimes 1 and 2; and the y_t^{USA} shock contributed 0.6 p.p (around 50%). These results are in line with the baseline model, as real shocks, particularly the y_t^{CHN} shock, were the main driver of the increase in y_t^{PER} under the post-IT regime. The i_t^{SR} and p_t^{SP} shocks contributed 0.2 p.p. (around 19%) to that increase, which differs from the baseline model. However, as in the latter, these shocks made a low contribution to the increase in y_t^{PER} under regime 2.

On the other hand, the calculations of the IRFs, FEVD and HD of the CVAR model also replicate the results of the estimates of the baseline model.

5.3 Change in the Ordering of Variables

The third robustness exercise estimates the baseline model with an alternative ordering of domestic variables. Following Mendoza and Collantes Goicochea (2017), we consider y_t^{PER} and i_t as the most endogenous and most exogenous domestic variables in the system, respectively. Therefore, the ordering of the variables would be as follows: $\mathbf{y}_t = (y_t^{USA}, i_t^*, y_t^{CHN}, p_t^*, i_t^{PER}, \pi_t^{PER}, y_t^{PER})'$. As our models follow a recursive ordering, we perform this robustness exercise to verify the sensitivity of our results to a change in the ordering of variables. Despite the latter, the RS-VAR-SV-R1 model continues to be the best fit relative to the other models. Based on the results in Table 3, the BFs between the RS-VAR-SV-R1 model with two regimes ($r = 2$) and the CVAR and RS-VAR-SV models with two regimes ($r = 2$) are 3.9×10^{39} and 2.6×10^{41}, respectively.

The IRF analysis (columns 1 and 2, Figure 13) indicates that the response to y_t^{USA} preserves the same expansionary/contractionary behavior as in the baseline model. Responses to the y_t^{CHN} shock continue to be persistent. Responses to the i_t^* shock are contractionary and transitory; and responses to the p_t^* shock are expansionary and transitory. Therefore, the change in the ordering of domestic variables does not modify the results for the baseline model under either regime, and the CVAR model.

Figure 14 shows the FEVD for y_t^{PER}, which indicates that external shocks explain 70% of y_t^{PER} variability; and the composition of external shocks is similar to the baseline model; i.e., p_t^* and y_t^{CHN} shocks continue to create the most uncertainty in y_t^{PER} forecasts. Moreover, domestic (especially MP) shocks moderate under the post-IT regime; i.e., their contribution to y_t^{PER} variability decreases from 25% to 1%, in contrast with the pre-IT regime.

The HD results for y_t^{PER} (Figure 15) indicate that the contribution of external shocks does not change relative to the baseline model; and that real y_t^{USA} and y_t^{CHN} shocks contribute the most to the increase in y_t^{PER}. Regarding domestic shocks, the results are similar as for the baseline model; e.g., the AS shock contributed 0.3 p.p. (around 32%) out of 1.1 p.p. to the increase in y_t^{PER} between regimes 1 and 2.

In both the FEVD and HD of this robustness exercise, the results for the CVAR model are similar to those of the base model.

5.4 Four-Variable Model

The next robustness exercise uses only one external variable (p_t^*) while preserving the three domestic variables in the baseline model. This specification resembles the one used by Ojeda Cunya and Rodríguez (2022), except that we use p_t^* as external variable instead of p_t^{SP}. It should be noted that the RS-VAR-SV-R1 model with two regimes is widely favored by the BF relative to the other models; e.g., Table 3 shows that the BFs between the RS-VAR-SV-R1 model with two regimes ($r = 2$) and the CVAR and RS-VAR-SV models with two regimes ($r = 2$) are 4.2×10^{45} and 9.5×10^{20}, respectively.

Row 1 in Figures 16 (regime 1) and 17 (regime 2) shows the IRFs for y_t^{PER}, which are positive under both regimes; and the 1% and 2% responses of y_t^{PER} to a 10% p_t^* shock under regimes 1 and 2, respectively, are highly significant. Additionally, shocks under regime 2 are less persistent, as they dissipate in five quarters, in contrast with two years under regime 1. For this specification, the CVAR model only estimates a response similar to regimen 2.

Row 1 in Figure 18 shows the FEVD for y_t^{PER}, indicating that the p_t^* shock explains 60% of y_t^{PER} variability under regime 2, in contrast with 8% under regime 1. For their part, domestic shocks are less volatile under regime 2, particularly the MP shock, which explains less than 5% of y_t^{PER} variability, in contrast with 30% under regime 1. This result reflects the moderation of the BCRP's monetary policy; see Portilla Goicochea and Rodríguez (2020). In the results of the CVAR's FEVD model, the contribution to the variability of y_t^{PER} only reaches 50%.

The HD results for y_t^{PER} (row 1, Figure 19) show that the p_t^* shock contributed -0.02 p.p. out of a 1.1-p.p. increase in y_t^{PER} between regimes 1 and 2 (around -2%); and that domestic shocks contributed 1.6 p.p. (around 140%) of that increase. In principle, these results seem to clash with the findings for the baseline model regarding the role of external shocks. However, the model also considers that nominal external shocks have not been determinant for output growth under regime 2; and that real shocks (e.g., from y_t^{CHN}) contributed the most to y_t^{PER} growth between regimes. As this model considers p_t^* as the only external variable, it underestimates the total effect of external shocks. Moreover, the greater contribution of domestic shocks is mainly associated with MP shocks, reflecting the BCRP's sound implementation of monetary policy under regime 2; see Castillo et al. (2016) and Portilla Goicochea and Rodríguez (2020). The CVAR and RS-VAR-SV-R1 models do not have many differences to explain the contribution of external shocks through the sample.

5.5 Five-Variable Model

We modify the previous model by adding the effect of financial shocks (i_t^*), so that the external block now comprises variables p_t^* and i_t^*, and the domestic block preserves the same variables. The ordering considers i_t^* as the most exogenous variable, under the assumption that U.S. monetary policy has a more exogenous effect on commodity prices (Frankel (2014)). Similarly to the previous exercise, the BF indicates that the RS-VAR-SV-R1 model with two regimes is a better fit compared with the other models. Table 3 shows that the BFs between the RS-VAR-SV-R1 model with two regimes ($r = 2$) and the CVAR and RS-VAR-SV models with two regimes ($r = 2$) are $2.4{\times}10^{42}$ and $8.4{\times}10^{27}$, respectively.

Row 2 in Figures 16 (regime 1) and 17 (regime 2) shows the IRFs for y_t^{PER}, which indicate that the p_t^* shock is expansionary and transitory under both regimes, with a higher effect under regime 2. Additionally, the magnitude of this shock is similar as in the four-variable model. For their part, the responses of y_t^{PER} to an i_t^* shock do not show a clear direction, as the i_t^* shock picks up information form other unidentified channels. For the CVAR model, the response of y_t^{PER} to the shock of p_t^* is similar to that of regime 2; however, the response to the shock of i_t^* is negative and very persistent, different from the base model.

Column 2 in Figure 18 shows the FEVD for y_t^{PER}, which indicates that external shocks explain 60% of y_t^{PER} variability under regime 2 and less than 5% under regime 1. Moreover, most of the variability is explained by the p_t^* shock under both regimes. Regarding domestic shocks, we find that the MP shock explains 40% of y_t^{PER} variability under regime 1 (up 10 p.p. relative to the four-variable model) and 1% under regime 2. In this specification, the FEVD of the CVAR model for external shocks is similar to the 4-variable model.

The results for the HD (row 2, Figure 19) evidence that i_t^* shocks contributed -0.3 p.p. (around -25%) to the increase in y_t^{PER} between regimes 1 and 2. Additionally, the MP shock contributed 1.9 p.p. (around 172%) to the increase in y_t^{PER} , indicating that monetary policy was instrumental in offsetting the negative effects from nominal and financial shocks under regime 2. Moreover, as this exercise considers only financial and nominal shocks, monetary policy takes on a greater role in attenuating their effects under regime 2, which is in line with the BCRP's solid monetary policy implementation under the post-IT regime. For the CVAR model, the HD is similar on external shocks to the RS-VAR-SV-R1 model, but it does not capture monetary policy shocks.

5.6 Six-Variable Model

In this robustness exercise we add y_t^{CHN} to the external block and consider y_t^{CHN} as the most exogenous variable, given China's increasing role in global financial and commodity markets. Additionally, the BF results show that the RS-VAR-SV-R1 model with two regimes is the best fit (Table 3); e.g., the BFs between the RS-VAR-SV-R1 model with two regimes ($r = 2$) and the CVAR and RS-VAR-SV models with two regimes ($r = 2$) are 6.8×10^{41} and 6.8×10^{37}, respectively.

The IRFs for y_t^{PER} in row 3 of Tables 16 (regime 1) and 17 (regime 2) indicate that including the y_t^{CHN} shock reduces the impact from p_t^* under both regimes; and the marginal impact from i_t^* is identified better. This result suggests that omitting shocks from China results in an incorrect specification of the VAR model. Moreover, we find that the effects of y_t^{CHN} shocks on y_t^{PER} are expansionary and last more than two years. The elasticity of the y_t^{CHN} shock under both regimes is around 0.8%. We also find that i_t^* shocks are contractionary, with an elasticity of 0.3%; and that the responses of y_t^{PER} to a 10% p_t^* shock are 0.1% and 0.5% under regimes 1 and 2, respectively.

The FEVD results in column 3 of Figure 18 suggest that external shocks explain 70% of y_t^{PER} variability under regime 2 and 35% under regime 1. By including y_t^{CHN} we evidence that the FEVD for this model is similar to that for the baseline model. That is, the y_t^{CHN} shocks explain 32% of y_t^{PER} variability under the pre-IT regime; and y_t^{CHN}, p_t^*, and i_t^* explain 37%, 30%, and 33%, respectively, of the forecast error variance under the post-IT regime. Therefore, by adding y_t^{CHN}, the model reflects better the stylized facts of Peru's economy.

When y_t^{CHN} is included, the HD results for y_t^{PER} (row 3, Figure 19) indicate that real demand shocks were the main factor in explaining the increase in y_t^{PER} under regime 2. Specifically, the y_t^{CHN} shock contributed 0.8 p.p. (around 76%) to this increase. Additionally, the contribution of domestic shocks decreases relative to previous models; e.g., the MP shock contributed 0.3 p.p. (around 29%) to the increase, further evidencing the importance of considering y_t^{CHN} shocks to ensure an appropriate specification for the VAR model. In addition, the IRF, FEVD and HD of the CVAR model are similar to those of the baseline model.

5.7 Eight-Variable Model (with Fiscal Policy)

The last robustness exercise adds a fiscal policy channel within the domestic variable block. For this purpose, we use public investment growth (g_t^{pub}). Therefore, the model is formed by eight variables: (i) the external block (y_t^{USA}, y_t^{CHN}, i_t^* , and p_t^*) and (ii) the domestic block (g_t^{pub}, y_t^{PER}, π_t^{PER}, and i_t^{PER}). We underscore that we chose capital over current expenditure as fiscal policy instrument, as it is the main driver of Peru's output growth according to Jiménez and Rodríguez (2020). Additionally, like in previous exercises, the BF largely favors the RS-VAR-SV-R1 model with two regimes relative to the other models (Table 3). In particular, the BFs between the RS-VAR-SV-R1 with two regimes ($r = 2$) and the CVAR and RS-VAR-SV models with two regimes ($r = 2$) are 6.3×10^{66} and 3.2×10^{60}, respectively.

The IRFs for y_t^{PER} in row 5 of Figures 16 (regime 1) and 17 (regime 2) show that the y_t^{USA}, y_t^{CHN}, and p_t^* shocks are expansionary under both regimes, while i_t^* shocks are contractionary. Additionally, the magnitudes of the responses are similar to those in the seven-variable model for both regimes. Regarding the g_t^{pub} shock, we verify that the response of y_t^{PER} is expansionary and dissipates after one year. It should be noted that the evolution of the IRFs across regimes suggests that the impact increased under the post-IT regime; i.e., currently an increase in public investment has a higher return than under the pre-IT regime. Specifically, the responses of y_t^{PER} to a 1% g_t^{pub}

shock are 0.2% and 0.3% under regimes 1 and 2, respectively, in line with Jiménez and Rodríguez (2020).

The FEVD results (column 5, Figure 18) indicate that, by including g_t^{pub}shocks, the contribution of external shocks to y_t^{PER} variability diminishes under regimes 1 and 2 (25% and 38%, respectively). Therefore, our results are in line with the studies by Mendoza and Collantes Goicochea (2017), Jiménez and Rodríguez (2020), and Rodríguez and Vassallo (2022), where inclusion of g_t^{pub} shocks considerably reduces the uncertainty from external shocks. Particularly, the g_t^{pub} shock explains around 35% and 60% of y_t^{PER} fluctuations under regimes 1 and 2, respectively, as capital expenditure is a discretionary MEF decision and g_t^{pub} budget implementation by sub-national governments is largely unpredictable (around 50% according to Jiménez et al. (2020)).

Based on the HD results for y_t^{PER} in row 5 of Figure 19, we calculate that, out of the 1.1-p.p. increase in y_t^{PER} between regimes 1 and 2, the g_t^{pub} shock contributed 0.2 p.p. (around 16%), confirming the role of public investment as a major output growth buffer. Furthermore, the higher contribution under regime 2 is associated with the decentralization of capital expenditure, whereby sub-national governments can use a higher portion of mining canon revenues to finance more public works, according to Santa María et al. (2009). For its part, the MP shock contributed 0.3 p.p. (around 23%) to the increase in y_t^{PER} under the post-IT regime. These findings also confirm sound MEF and BCRP policy implementation under the post-IT regime; see Jiménez et al. (2020) and Rodríguez and Vassallo (2022).

The CVAR model for this broader specification has the same drawbacks as the CVAR baseline model, i.e., IRFs with overestimated or underestimated values. On the part of the FEVD, we find that the CVAR only captures the contributions of the second regime, and concerning the HD, it does not capture the role of monetary policy shocks explained in the baseline model.

6 Conclusions

This article studies the evolution and effect of external shocks on Peru's macroeconomic fluctuations in 1994Q1-2019Q4. For this purpose, we estimate models with regime change and stochastic volatility (RS-VAR-SV), which are identified recursively. Using four external and three domestic variables, we find that the data favor a stochastic volatility model and constant coefficients (RS-VAR-SV-R1) over a conventional VAR (CVAR) model and other restricted RS-VAR-SV models. Importantly, we identify two regimes, which divide the sample into a pre-IT regime (1994-2002) and a post-IT regime (2003-2019).

All external shocks have the expected impact on output growth (y_t^{PER}). Specifically, the U.S. real demand shock (y_t^{USA}) has a mixed impact on the response of y_t^{PER}; the China growth shock (y_t^{CHN}) and the commodity price shock (p_t^*) have a positive impact on y_t^{PER}; and the Fed interest rate shock (i_t^*) has a negative impact. Furthermore, the impact of the y_t^{CHN} and p_t^* shocks on y_t^{PER} is greater under regime 2. External shocks explain 35% and 70% of y_t^{PER} variability under regimes 1 and 2, respectively. Higher uncertainty under regime 1 is associated with y_t^{CHN} and y_t^{USA} shocks, while y_t^{CHN} and p_t^* shocks are the main source of y_t^{PER} uncertainty under regime 2. Additionally we verify a moderation in monetary policy after IT adoption.

Historical decomposition shows that the main driver of the increase in y_t^{PER} under regime 2 was the y_t^{CHN} shock, which explained around 89% of the increase. Additionally, our analysis of the Global Financial Crisis and the U.S.-China trade wars indicates that external real demand shocks had a negative impact on y_t^{PER}, while monetary policy shocks were important in offsetting the negative effect of these events.

Based on the estimation of alternative specifications (robustness exercises), we find that omitting China growth shocks alters the magnitude and significance of commodity price shocks. Moreover, including fiscal policy via public investment growth into the model does not modify the responses to external shocks, but reduces uncertainty from external shocks on output growth.

The findings in this article highlight the challenges from an evolving international environment for a small, open, commodity-exporting economy like Peru. In the face of external shock volatility, a main challenge for policymakers is implementing counter-cyclical policy tools to reduce its effects on macroeconomic stability. Additionally, the high contribution of commodity prices in output growth variability underscores the need for product diversification as a mechanism for reducing medium- and long-term growth uncertainty. Finally, MEF and BCRP policies, like IT adoption and fiscal discipline, must be preserved to secure an optimal response to shocks, as under regime 2.

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Table 1. Tests for Time Variation in Coefficients and Volatility

Trace Test			
Trace	16% perc.	50% perc.	84% perc.
0.28	0.21	0.30	0.40

Test	Matrix	Sample		
	Coefficients	1993Q2-2019Q4	1993Q2-2019Q4	1993Q2-2006Q2
Kolmogorov-Smirnov	$\mathbf{B}_{0_t}$	15/21	16/21	16/21
	$\mathbf{B}_{i_t}$	51/56	48/56	49/56
	$\mathbf{\Sigma}_t$	7/7	7/7	7/7
t-test	$\mathbf{B}_{0_t}$	20/21	19/21	21/21
	$\mathbf{B}_{i_t}$	49/56	47/56	43/56
	$\mathbf{\Sigma}_t$	7/7	7/7	7/7

The Trace test reports the trace of the prior variances matrix ($\mathbf{\Sigma}_t$). The second, third and fourth columns report the 16%, 50% and 84% percentiles of the posterior of $\mathbf{\Sigma}_t$. The Kolmogorov-Smirnov and t-test report the number of time-varying coefficients in the matrix of contemporaneous relationships ($\mathbf{B}_{0_t}$), the matrix of intercepts and lagged coefficients ($\mathbf{B}_{i_t}$) and $\mathbf{\Sigma}_t$ in three samples.

Table 2. Log-Marginal Likelihood (Log-ML$_{CE}$) estimates for Baseline Models

Model	2-Regimes	3-Regimes	4-Regimes
RS-VAR-SV	-1587.9	-1597.7	-1606.1
	(0.07)	(0.07)	(0.10)
RS-VAR-SV-R1	-1474.2	-1489.5	-1595.4
	(0.06)	(0.20)	(0.09)
RS-VAR-R2	-1595.4	-1676.9	-1680.9
	(0.09)	(0.51)	(0.44)
RS-VAR-SV-R3	-1635.9	-1664.6	-1666.7
	(0.37)	(0.01)	(0.19)
RS-VAR-SV-R4	-1608.9	-1618.9	-1627.6
	(0.60)	(0.46)	(0.69)
RS-VAR-SV-R5	-1570.2	-1579.5	-1586.9
	(0.56)	(0.57)	(0.47)
CVAR		-1532.1	
		(0.01)	

For each model, the Log-ML$_{CE}$ estimate is based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using 20,000 posterior draws after a burn-in period of 5,000. Numerical standard errors are in parenthesis.

Table 3. Log-Marginal Likelihood (Log-ML_{CE}) estimates for seven Robustness Exercises with 2-regimes

Model	Alternative Priors	Alternative Variables	Alternative Ordering	Model with 4 Variables	Model with 5 Variables	Model with 6 Variables	Model with 8 Variables (Fiscal Policy)
RS-VAR-SV	-1568.5	-1670.6	-1583.3	-1065.0	-1186.1	-1388.8	-2116.0
	(0.09)	(0.05)	(0.05)	(0.02)	(0.05)	(0.19)	(0.27)
RS-VAR-SV-R1	**-1477.6**	**-1551.1**	**-1473.0**	**-1022.0**	**-1132.2**	**-1306.8**	**-1959.0**
	(0.05)	**(0.04)**	**(0.05)**	**(0.02)**	**(0.04)**	**(0.04)**	**(0.10)**
RS-VAR-SV-R2	-1612.7	-1679.0	-1595.7	-1102.5	-1215.9	-1411.7	-2092.9
	(0.06)	(0.56)	(0.06)	(0.02)	(0.05)	(0.53)	(0.08)
RS-VAR-SV-R3	-1644.7	-1698.5	-1649.7	-1038.0	-1174.0	-1431.9	-2184.6
	(7.23)	(7.07)	(8.81)	(0.47)	(1.73)	(6.52)	(7.41)
RS-VAR-SV-R4	-1455.1	-1693.1	-1605.7	-1066.6	-1202.6	-1412.9	-2133.6
	(0.44)	(0.43)	(0.49)	(0.31)	(0.49)	(0.33)	(0.66)
RS-VAR-SV-R5	-1480.5	-1651.7	-1570.2	-1048.9	-1174.5	-1379.6	-2074.9
	(0.33)	(0.61)	(0.55)	(0.26)	(0.29)	(0.43)	(0.57)
CVAR	-1534.7	-1610.5	-1532.9	-1098.6	-1195.4	-1370.8	-1995.6
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)

For each model, the Log-ML_{CE} estimate is based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using 20,000 posterior draws after a burn-in period of 5,000. Numerical standard errors are in parenthesis.

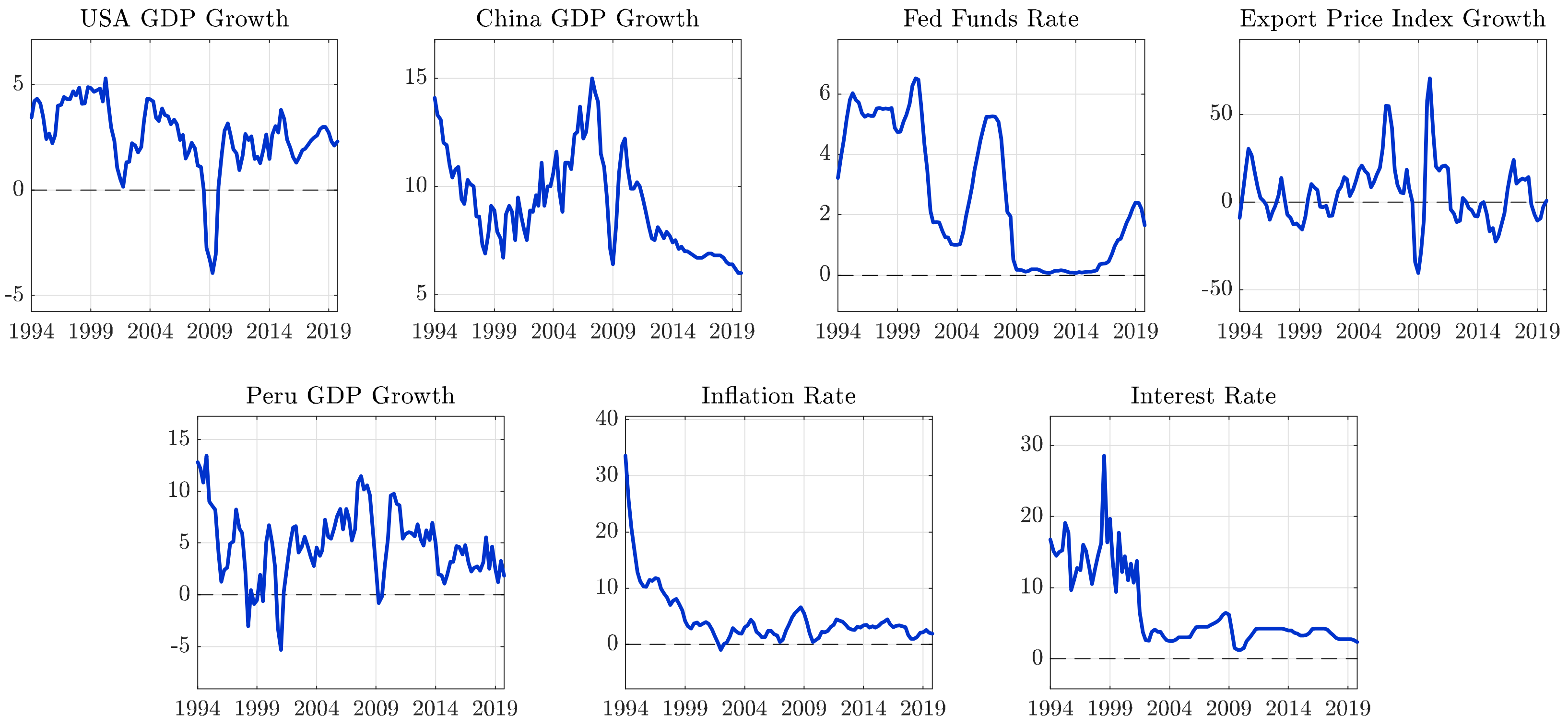

Figure 1. Time Series in Growth Rates 1994Q1-2019Q4

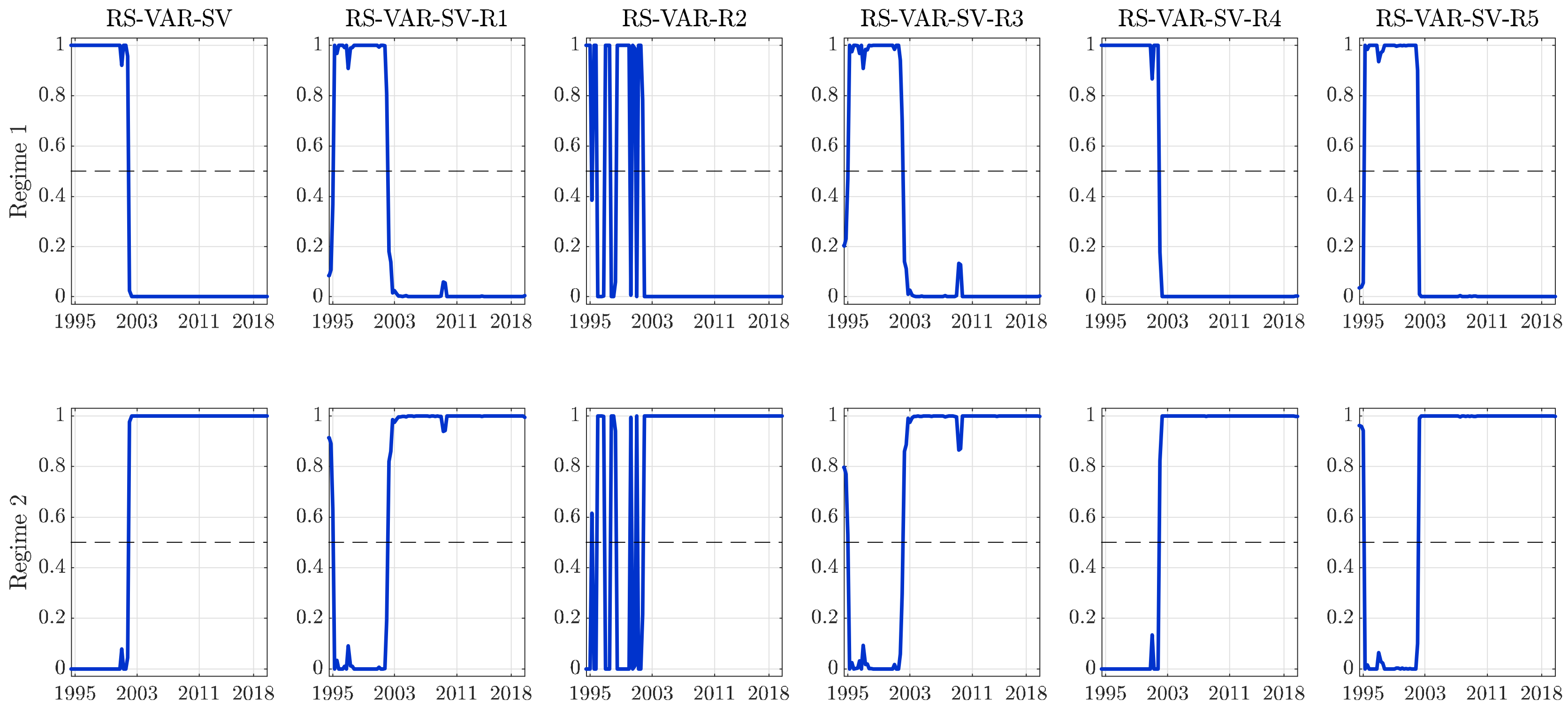

Figure 2. State-Probabilities for Baseline Models, 2-State Regime-Switching. The columns indicate the Baseline Models, and rows report the two Regimes of each Model.

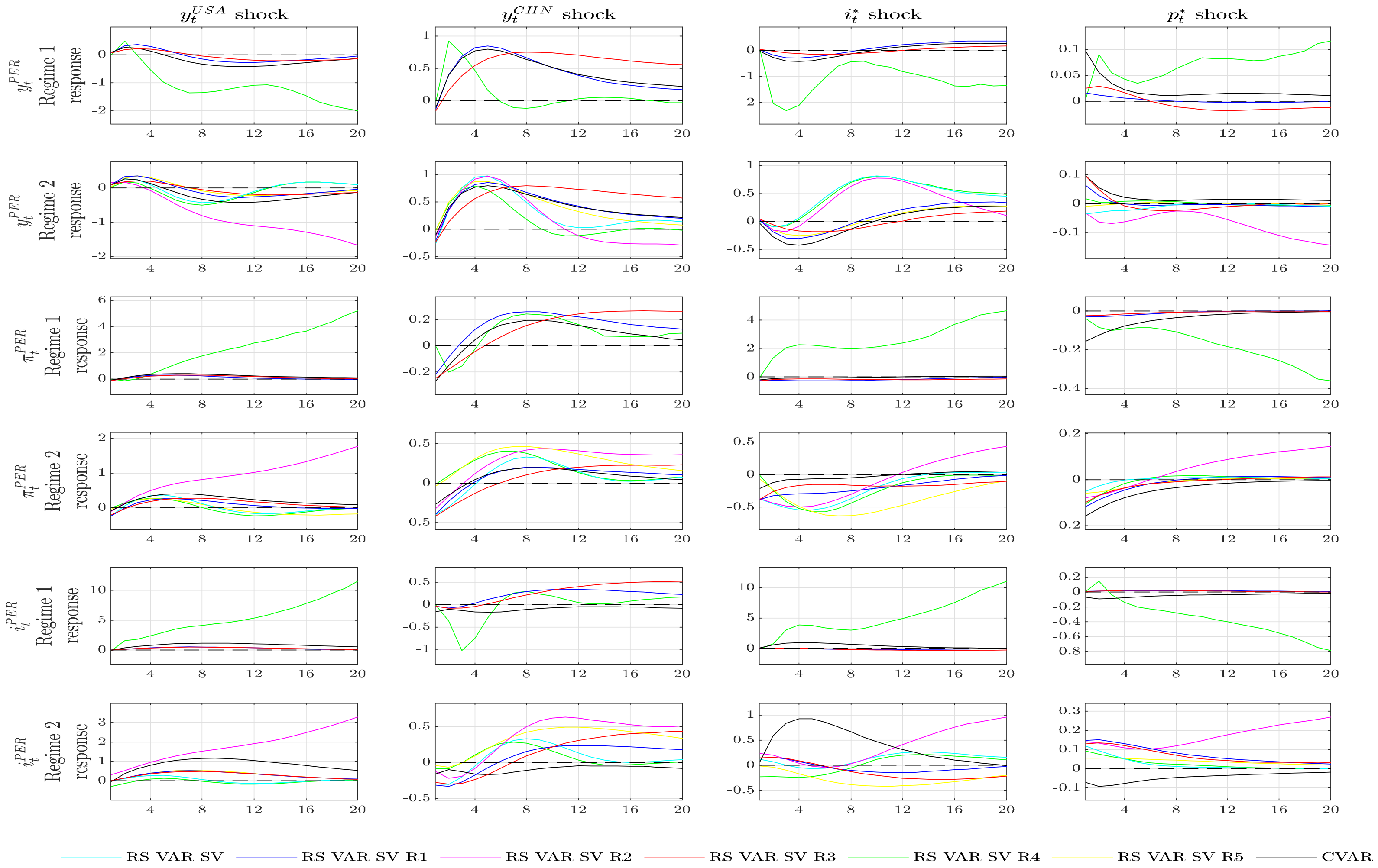

Figure 3. First and Second Regime IRFs to different External Shocks. Rows represent the response of Domestic GDP Growth, Inflation and Interest Rate in the Regime 1 and Regime 2 to a set of External Shocks, ordered in each column. We omit the IRFs of RS-VAR-SV and RS-VAR-SV-R2 Models in the First Regime, due to they are unstable.

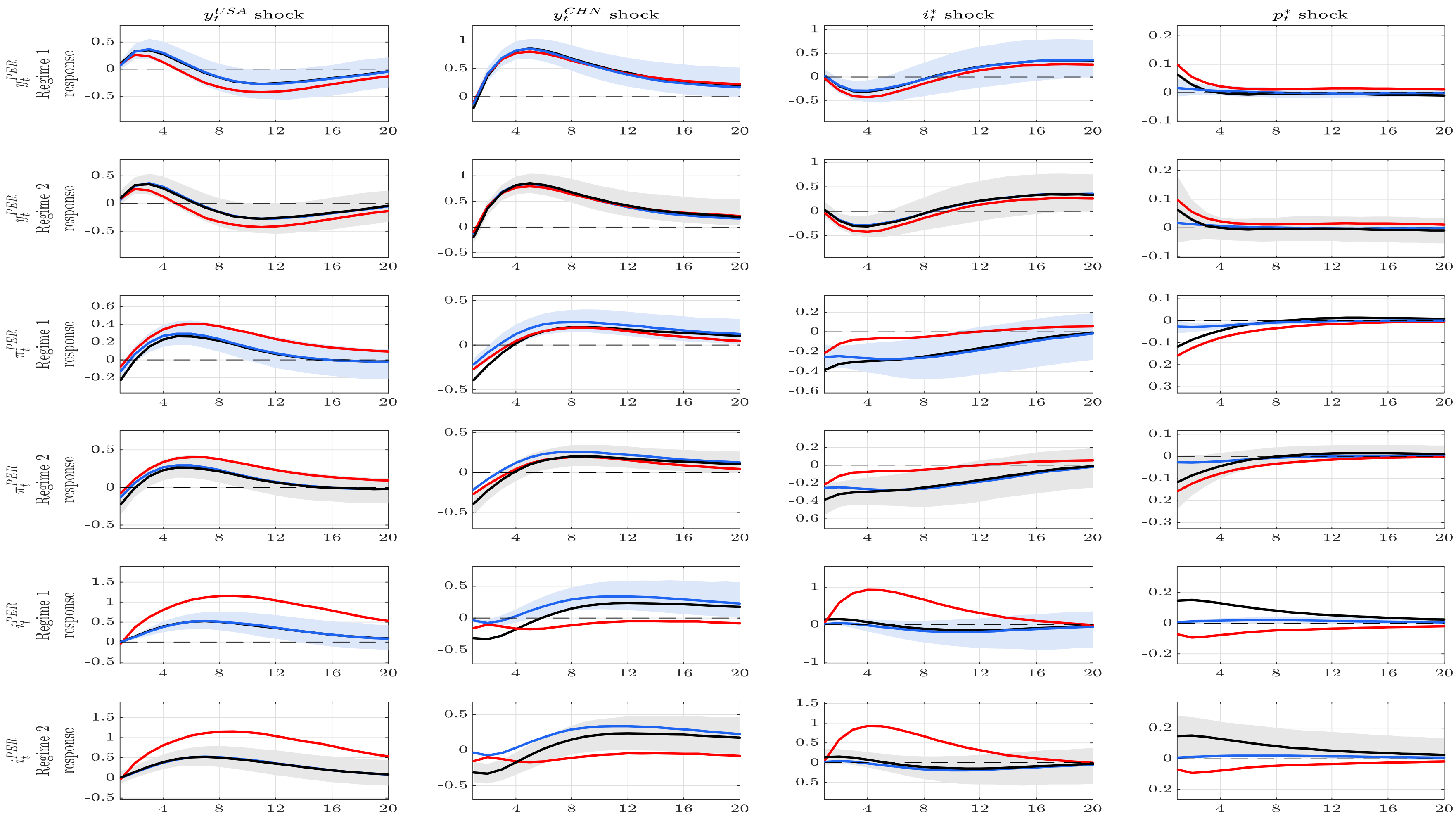

Figure 4. First and Second Regime IRFs of Domestic Variables to different External Shocks. The solid blue line: RS-VAR-SV-R1 Model First Regime; the solid black line: RS-VAR–SV-R1 Model Second Regime; the solid red line: CVAR Model. The blue shaded area is the 68% error band in the First Regime; the grey shaded area is the 68% error band in the Second Regime. Rows represent the response of Domestic GDP Growth, Inflation and Interest Rate to Regime 1 and Regime 2 to a set of External Shocks, ordered in each column.

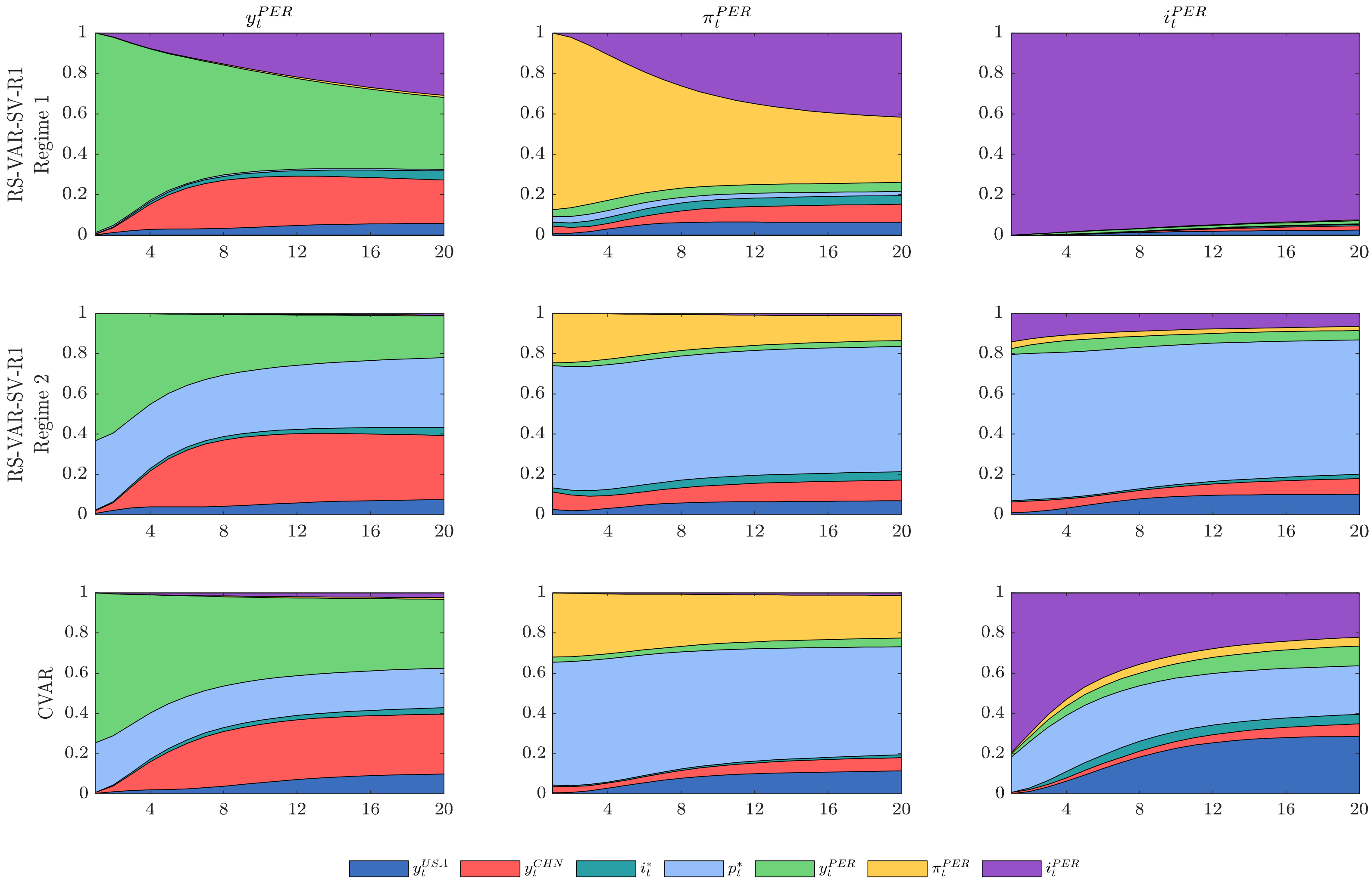

Figure 5. FEVD of Domestic GDP Growth, Inflation and Interest Rate for the RS-VAR-SV-R1 Model by Regime and the CVAR Model, 20 periods.

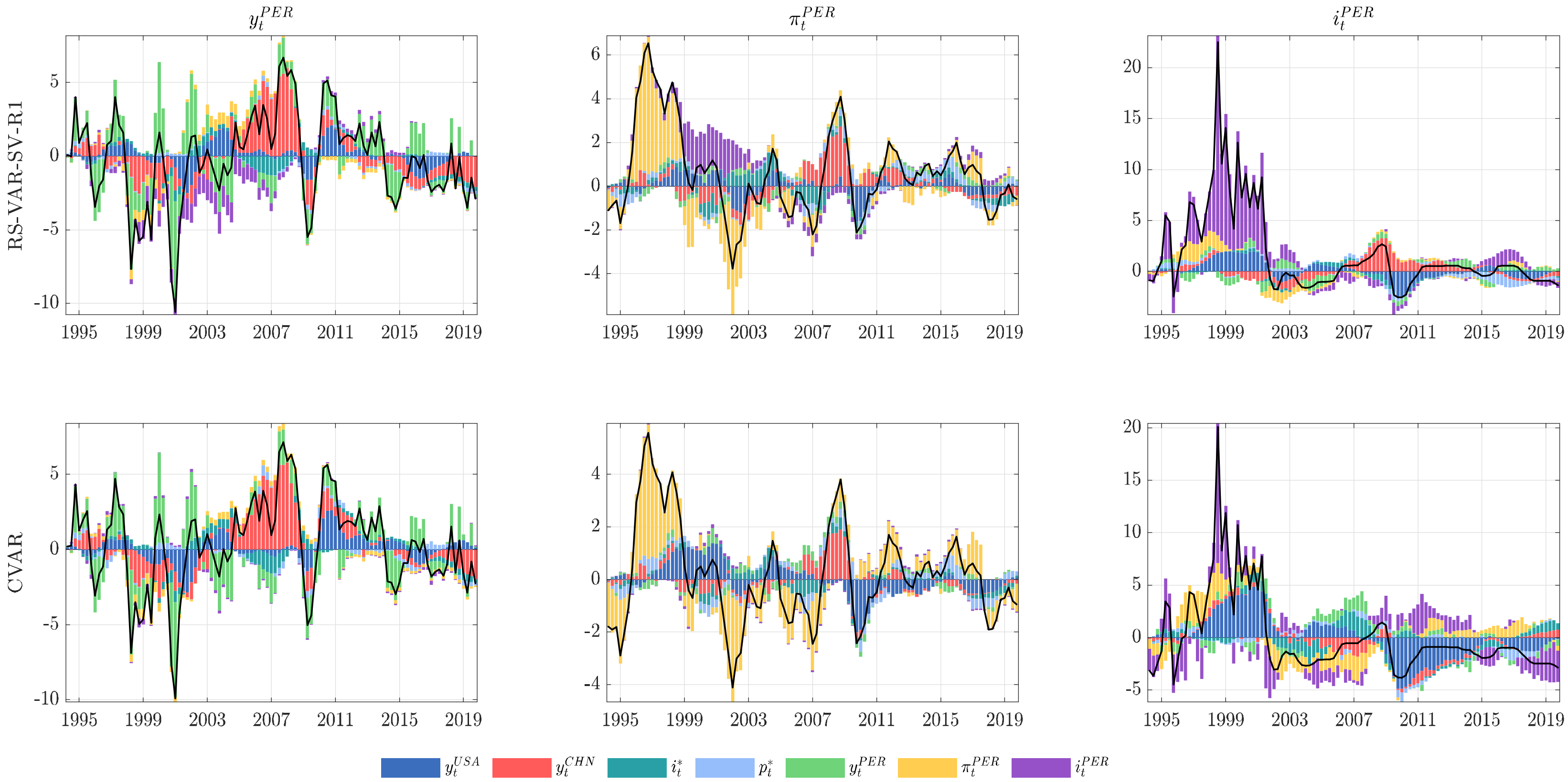

Figure 6. Historical Decomposition of Domestic GDP Growth, Inflation and Interest Rate for the RS-VAR-SV-R1 Model and CVAR Model.

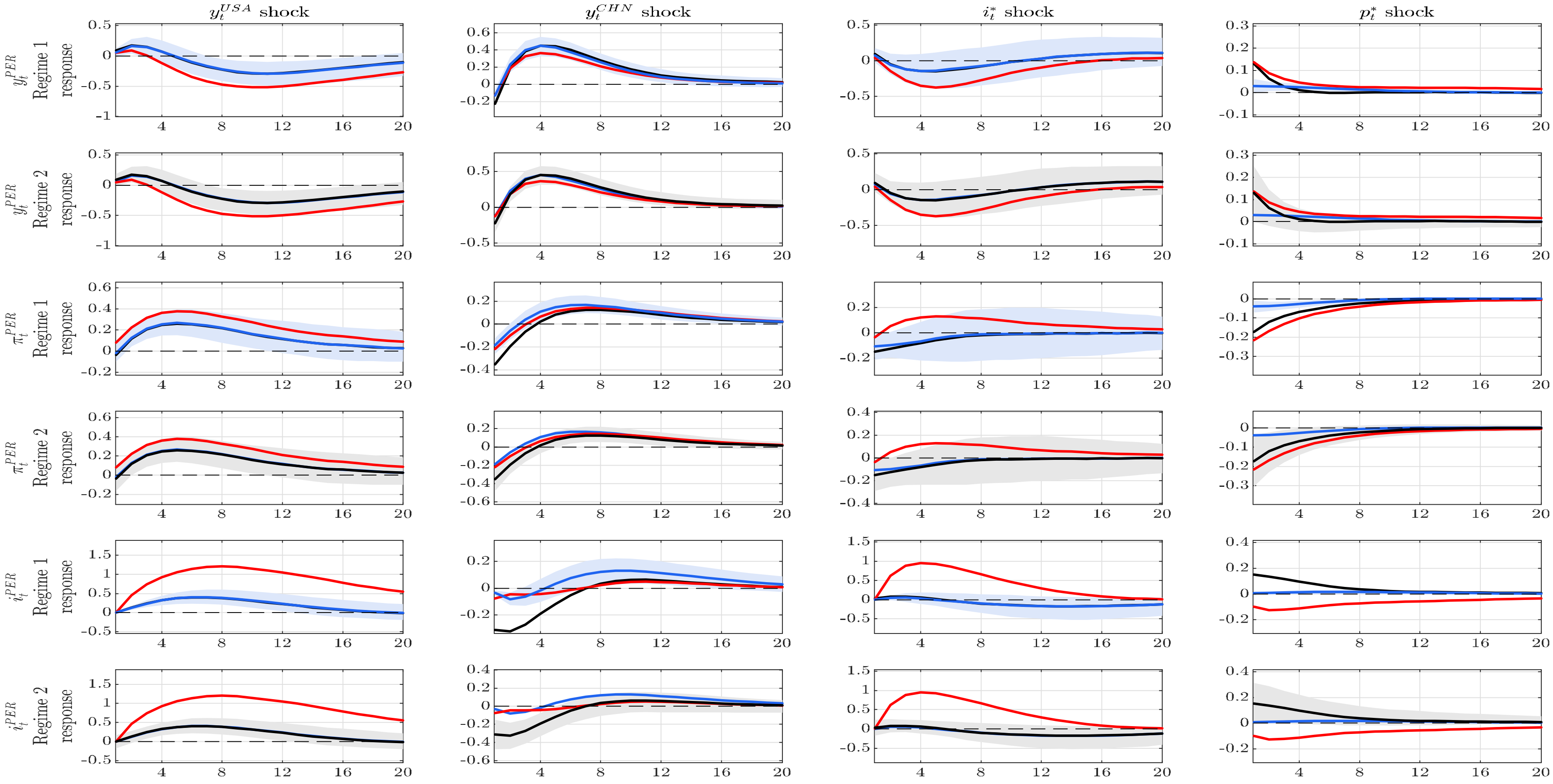

Figure 7. Robustness Analysis 1: Alternative Priors for First and Second Regime IRFs of Domestic Variables to different External Shocks. The solid blue line: RS-VAR-SV-R1 Model First Regime; the solid black line: RS-VAR–SV-R1 Model Second Regime; the solid red line: CVAR Model. The blue shaded area is the 68% error band in the First Regime; the gray shaded area is the 68% error band in the Second Regime. Rows represent the response of Domestic GDP Growth, Inflation and Interest Rate to Regime 1 and Regime 2 to a set of External Shocks, ordered in each column.

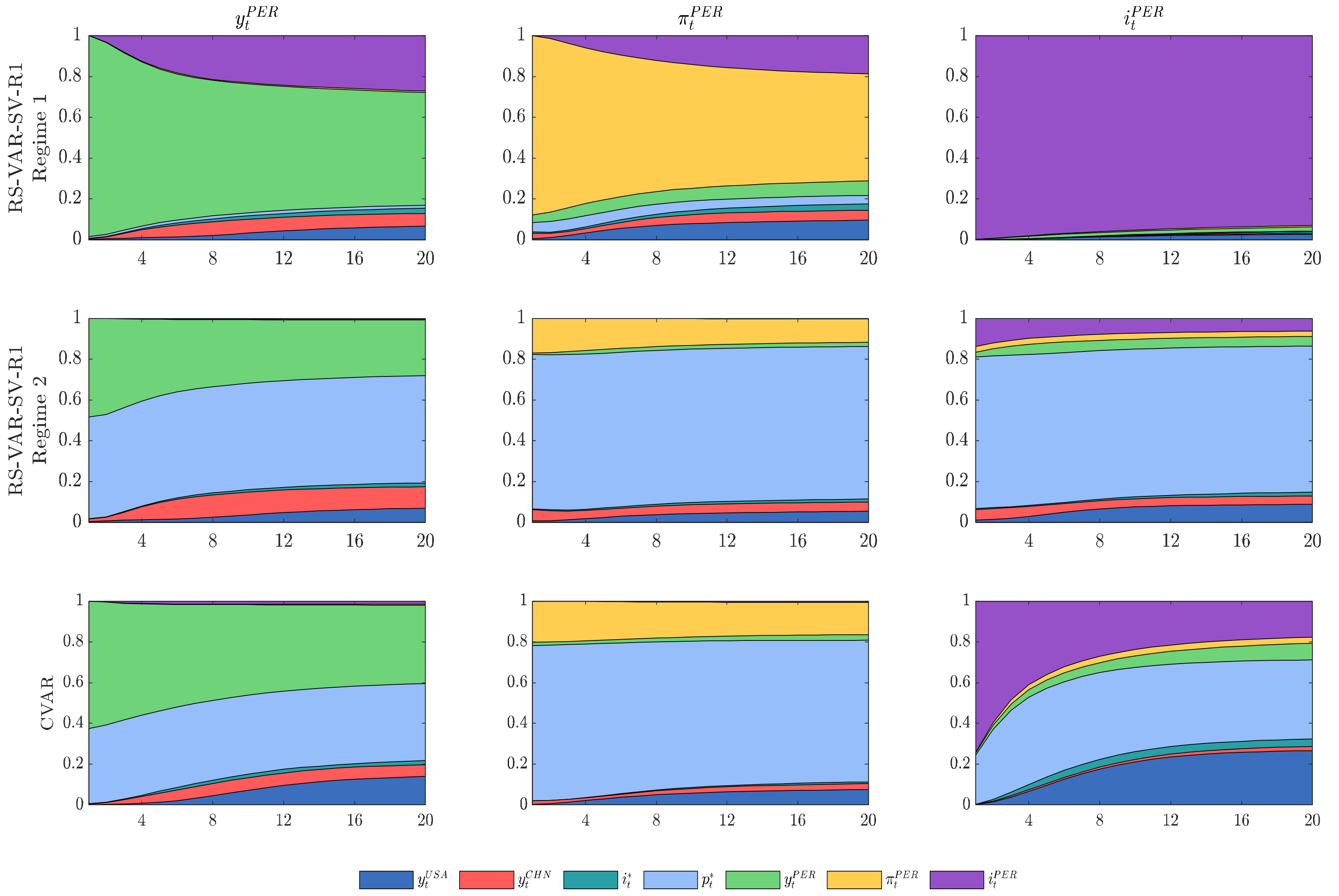

Figure 8. Robustness Analysis 1: Alternative Priors for FEVD of Domestic GDP Growth, Inflation and Interest Rate for the RS-VAR-SV-R1 Model by Regime and the CVAR Model (20 periods).

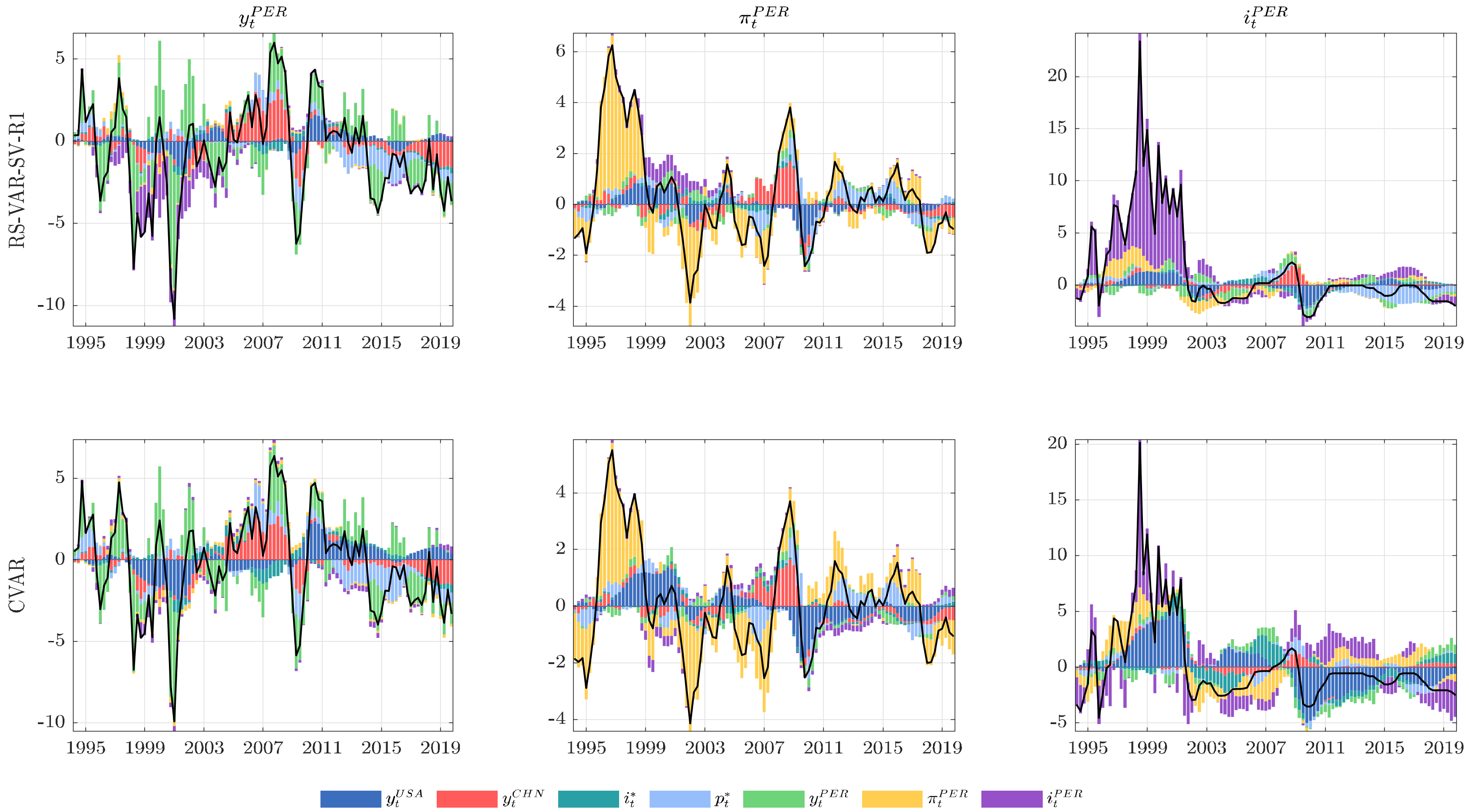

Figure 9. Robustness Analysis 1: Alternative Priors for Historical Decomposition of Domestic GDP Growth, Inflation and Interest Rate for the RS-VAR-SV-R1 Model and the CVAR Model.

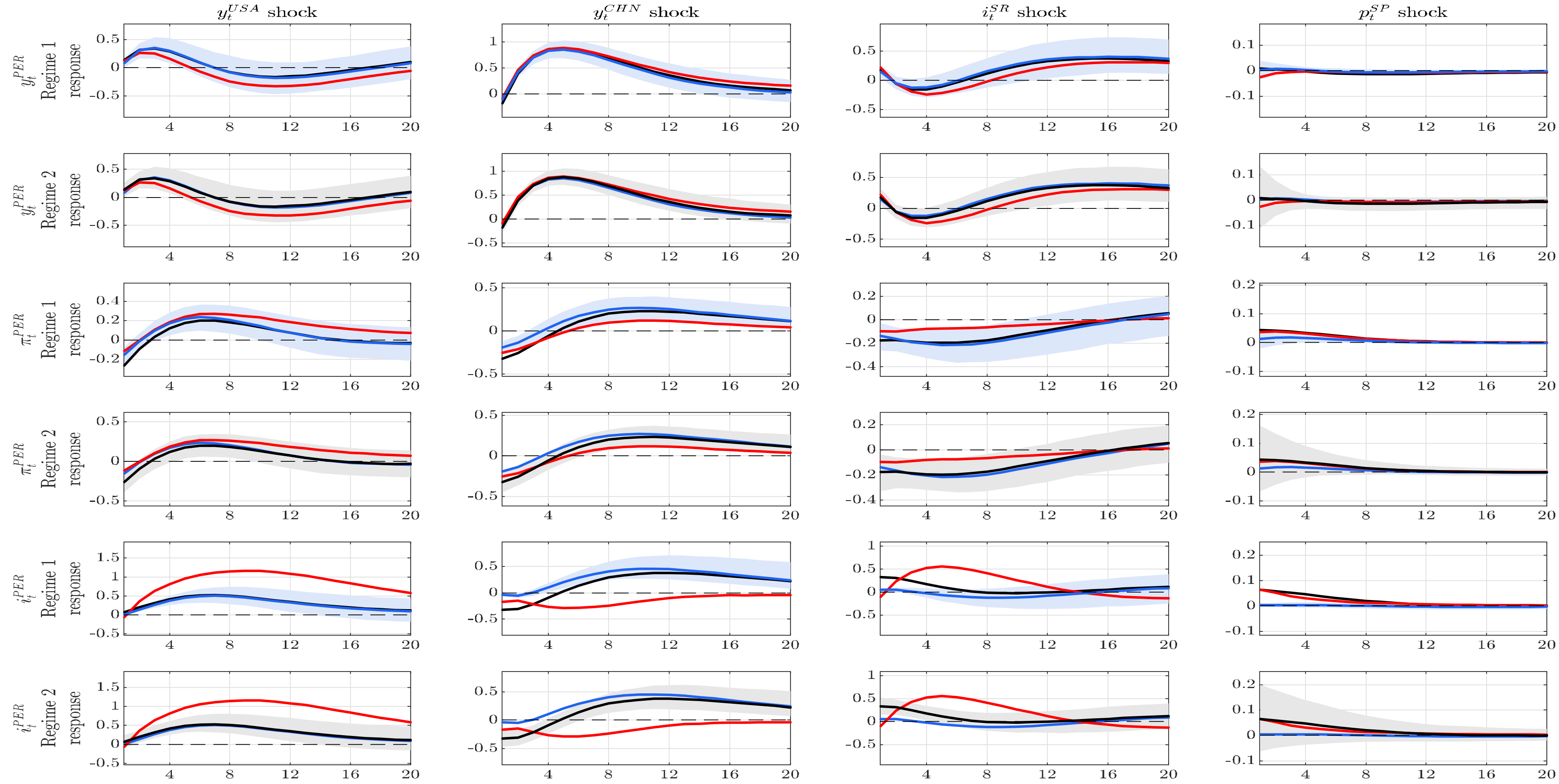

Figure 10. Robustness Analysis 2: Alternative External Shocks for First and Second Regime IRFs of Domestic Variables to different External Shocks. The solid blue line: RS-VAR-SV-R1 Model First Regime; the solid black line: RS-VAR–SV-R1 Model Second Regime; the solid red line: CVAR Model. The blue shaded area is the 68% error band in the First Regime; the gray shaded area is the 68% error band in the Second Regime. Rows represent the response of Domestic GDP Growth, Inflation and Interest Rate to Regime 1 and Regime 2 to a set of External Shocks, ordered in each column.

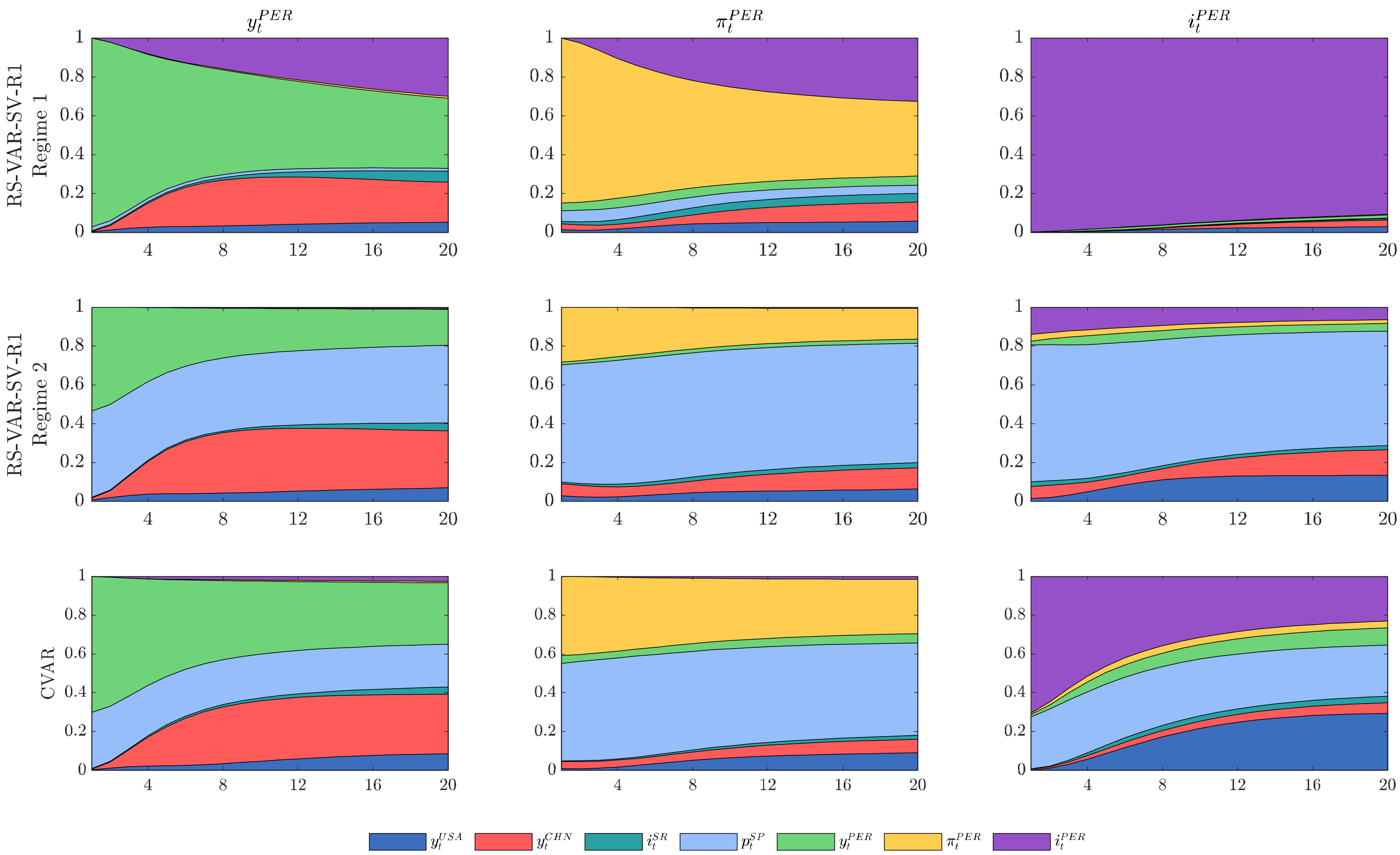

Figure 11. Robustness Analysis 2: Alternative External Shocks for FEVD of Domestic GDP Growth, Inflation and Interest Rate for the RS-VAR-SV-R1 Model by Regime and the CVAR Model (20 periods).

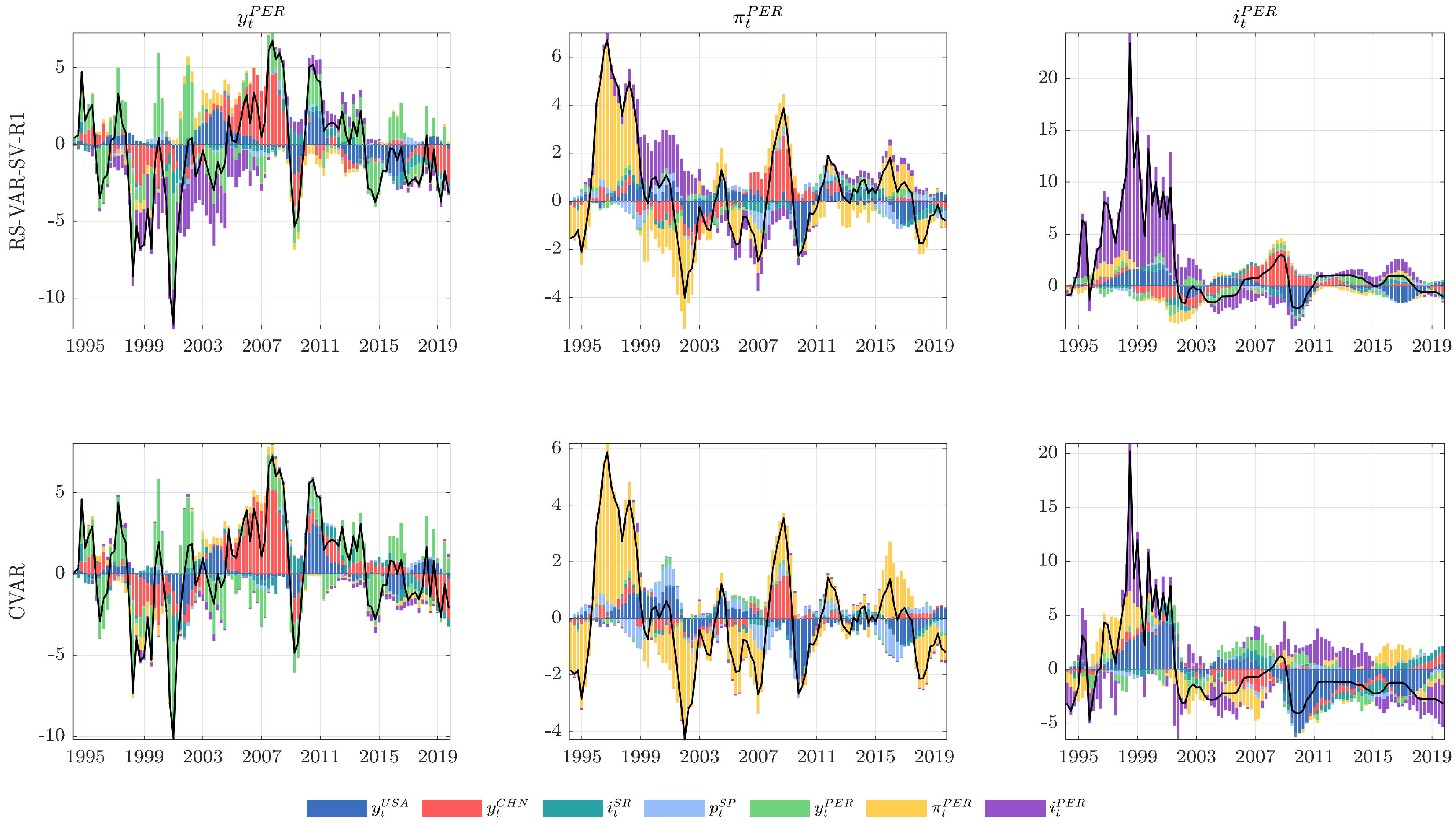

Figure 12. Robustness Analysis 2: Alternative External Shocks for Historical Decomposition of Domestic GDP Growth, Inflation and Interest Rate for the RS-VAR-SV-R1 Model and the CVAR Model.

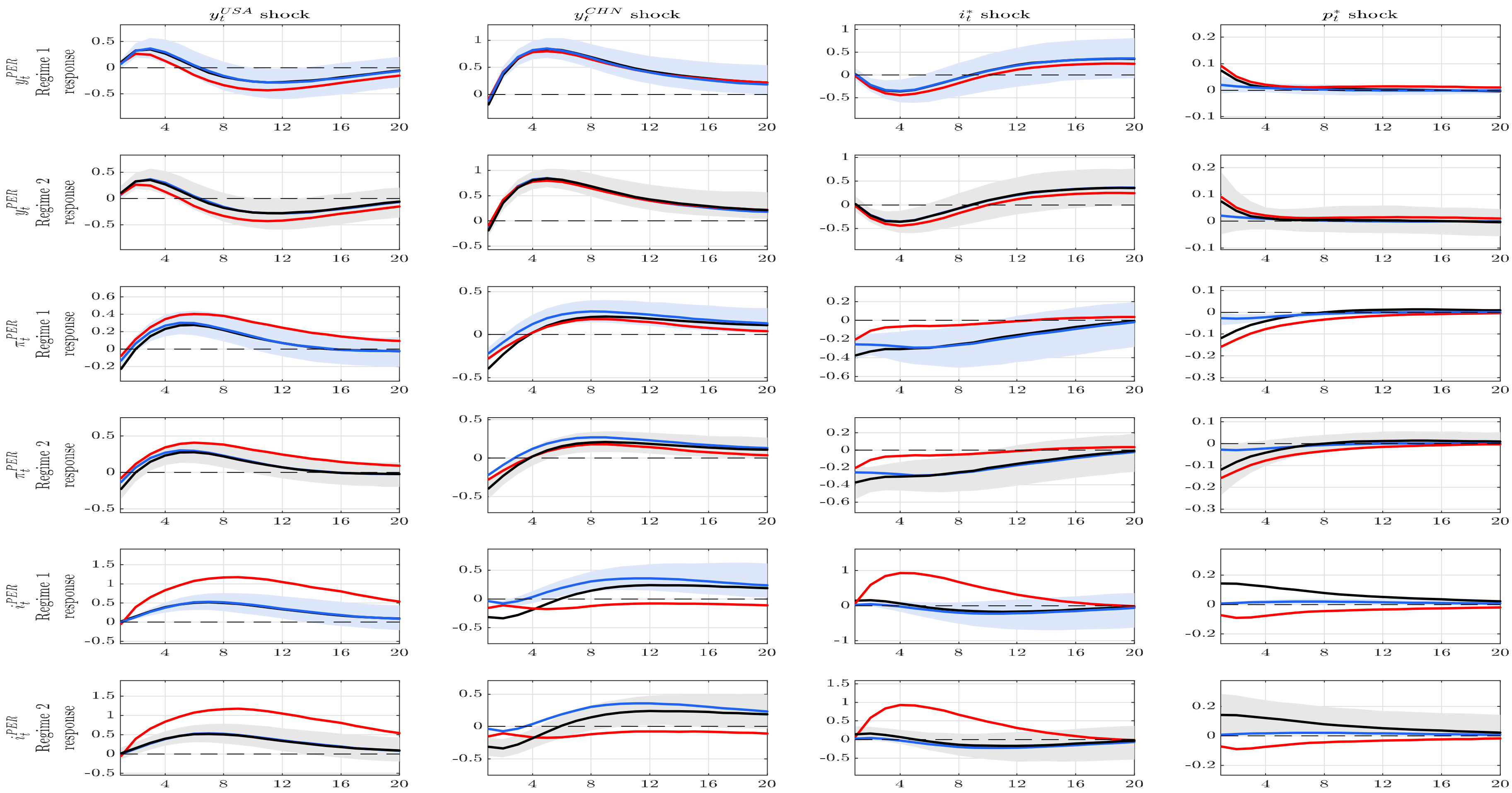

Figure 13. Robustness Analysis 3: Different Ordering of Domestic Variables for First and Second Regime IRFs of Domestic Variables to different External Shocks. The solid blue line: RS-VAR-SV-R1 Model First Regime; the solid black line: RS-VAR–SV-R1 Model Second Regime; the solid red line: CVAR Model. The blue shaded area is the 68% error band in the First Regime; the gray shaded area is the 68% error band in the Second Regime. Rows represent the response of Inflation, Interest Rate and Domestic GDP Growth to Regime 1 and Regime 2 to a set of External Shocks, ordered in each column.

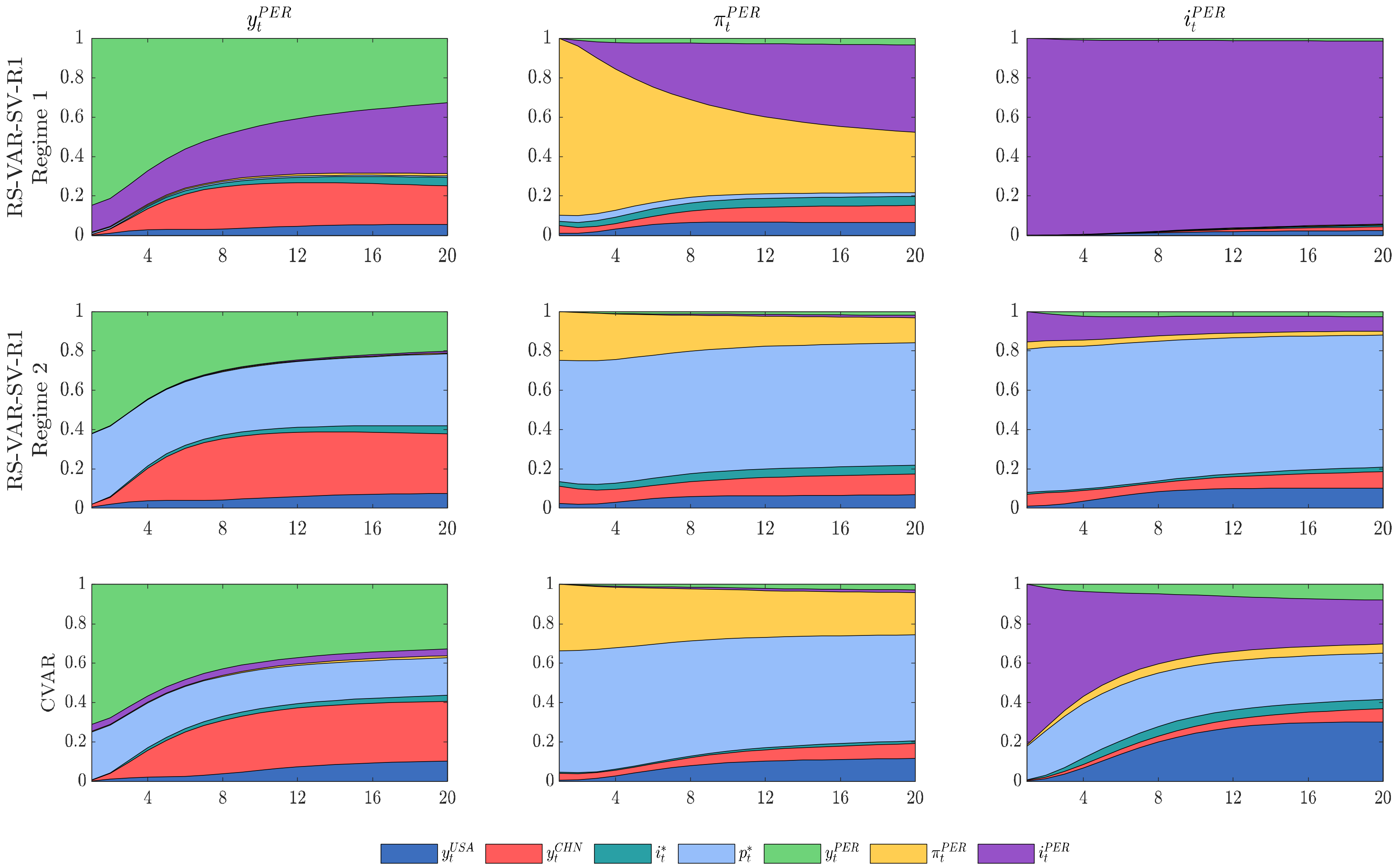

Figure 14. Robustness Analysis 3: Different Ordering of Domestic Variables for FEVD of Inflation, Interest Rate and Domestic GDP Growth for the RS-VAR-SV-R1 Model by Regime and the CVAR Model (20 periods).

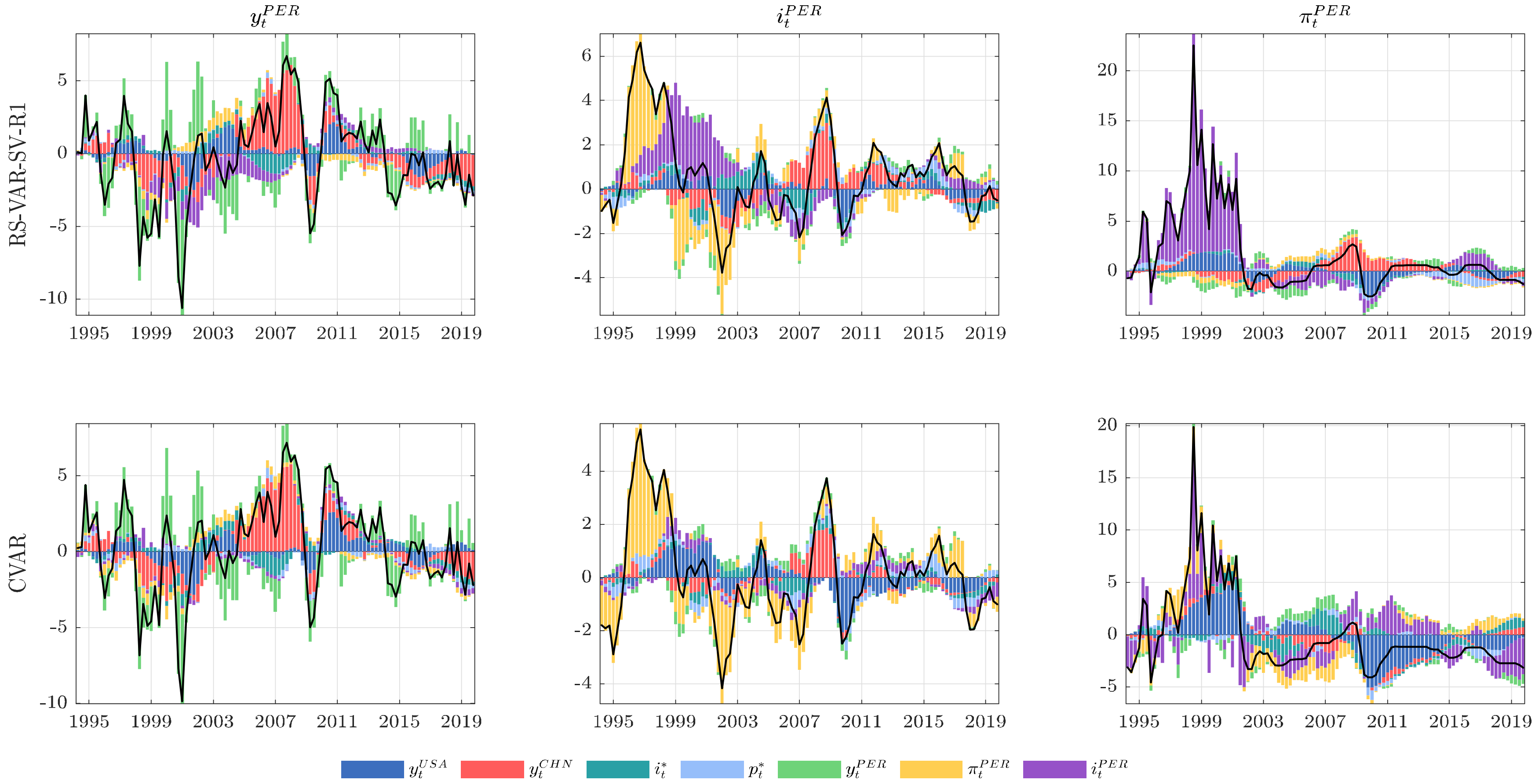

Figure 15. Robustness Analysis 3: Different Ordering of Domestic Variables for Historical Decomposition of Inflation, Interest Rate and Domestic GDP Growth for the RS-VAR-SV-R1 Model and the CVAR Model.

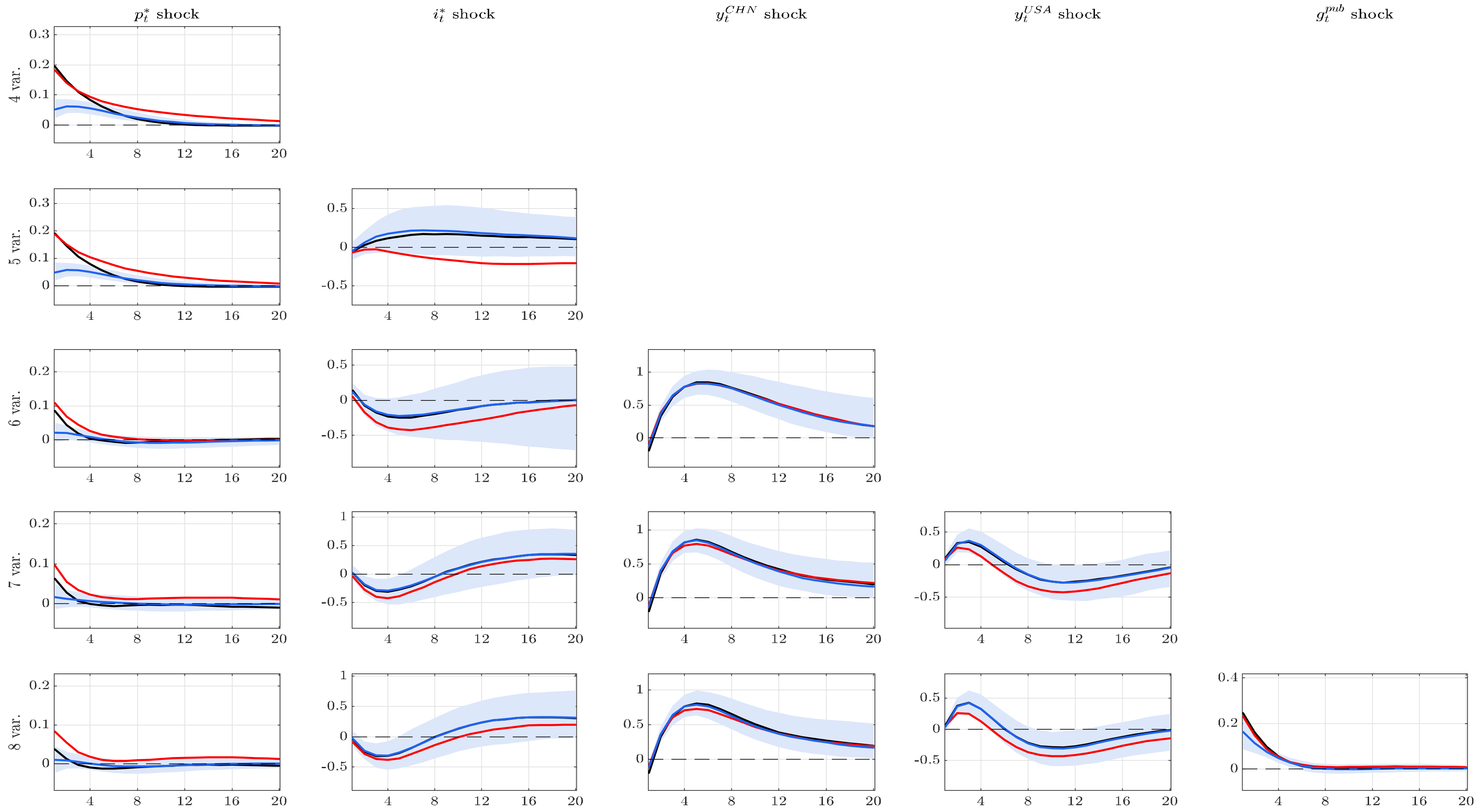

Figure 16. Robustness Analysis 4-7: First Regime IRFs of Domestic GDP Growth to different External Shocks. The 4-variable Model considers the XPI Growth as the unique External Variable; the 5-variable Model adds the Fed Funds Rate; the 6-variable Model adds China's GDP Growth; the 7-variable Model is the Baseline Model; and the 8-variable Model incorporates Public Investment Growth. The solid blue line: RS-VAR-SV-R1 Model First Regime; the solid black line: RS-VAR–SV-R1 Model Second Regime; the solid red line: CVAR Model. The blue shaded area is the 68% error band in the First Regime.

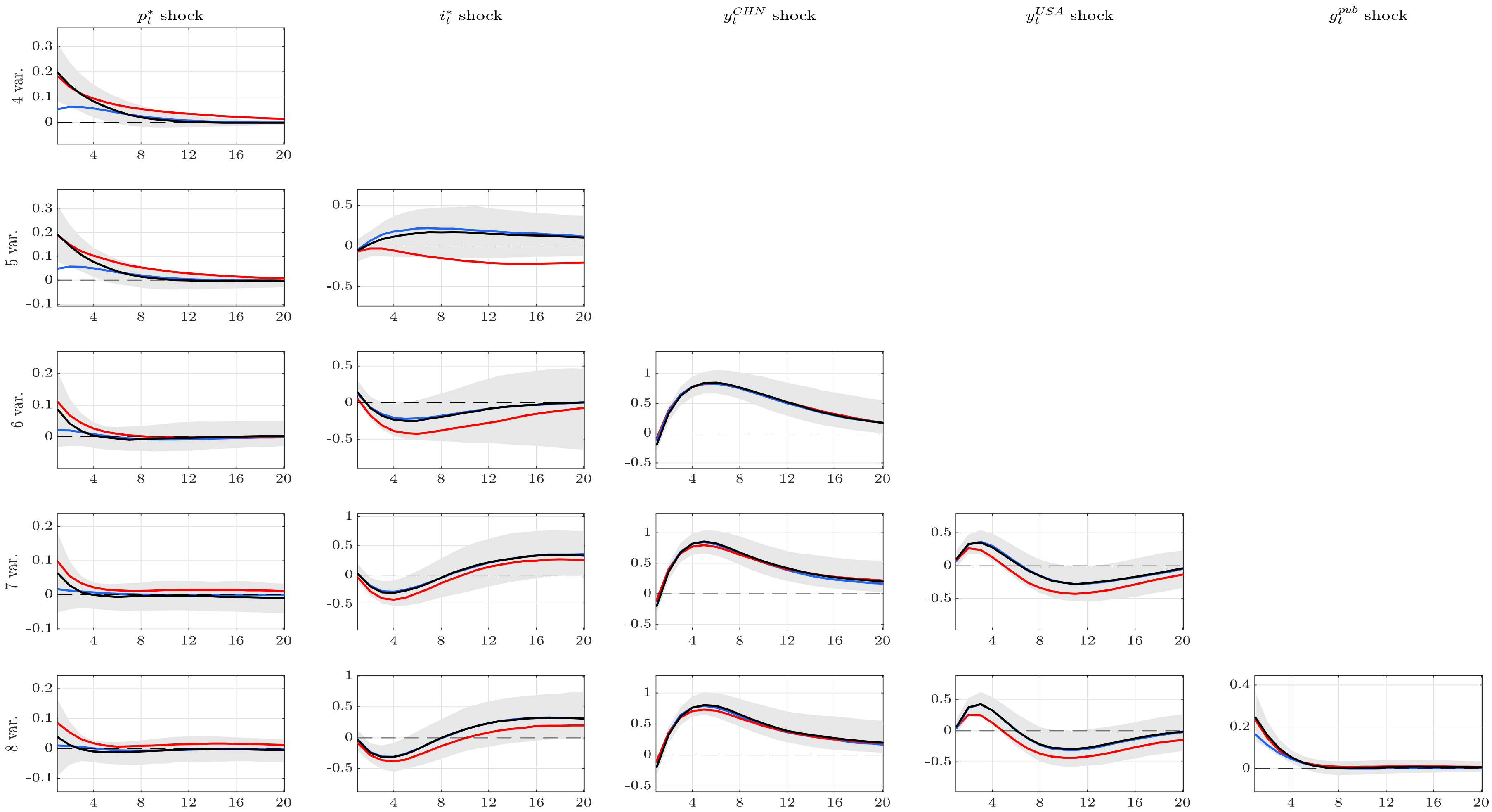

Figure 17. Robustness Analysis 4-7: Second Regime IRFs of Domestic GDP Growth to different External Shocks. The 4-variable Model considers the XPI Growth as the unique External variable; the 5-variable Model adds the Fed Funds Rate; the 6-variable Model adds China's GDP Growth; the 7-variable Model is the Baseline Model; and the 8-variable Model incorporates Public Investment Growth. The solid blue line: RS-VAR-SV-R1 Model First Regime; the solid black line: RS-VAR–SV-R1 Model Second Regime; the solid red line: CVAR Model. The gray shaded area is the 68% error band in the Second Regime.

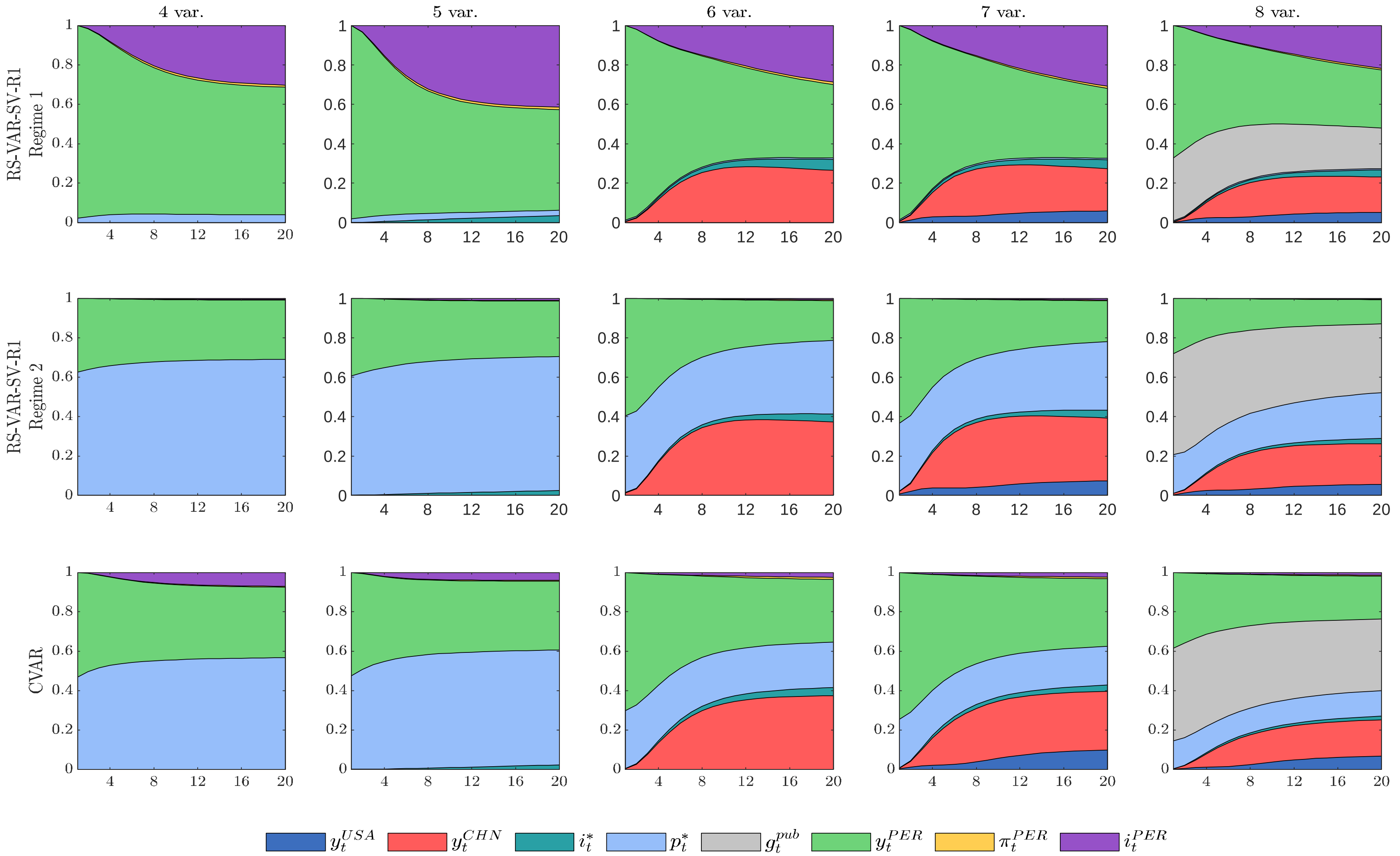

Figure 18. Robustness Analysis 4-7: FEVD of Domestic GDP Growth for the RS-VAR-SV-R1 Model by Regime and CVAR Model, 20 periods. The 4-variable Model considers the XPI Growth as the unique External Variable; the 5-variable Model adds the Fed Funds Rate; the 6-variable Model adds China's GDP Growth; the 7-variable Model is the Baseline Model; and the 8-variable Model incorporates Public Investment Growth.

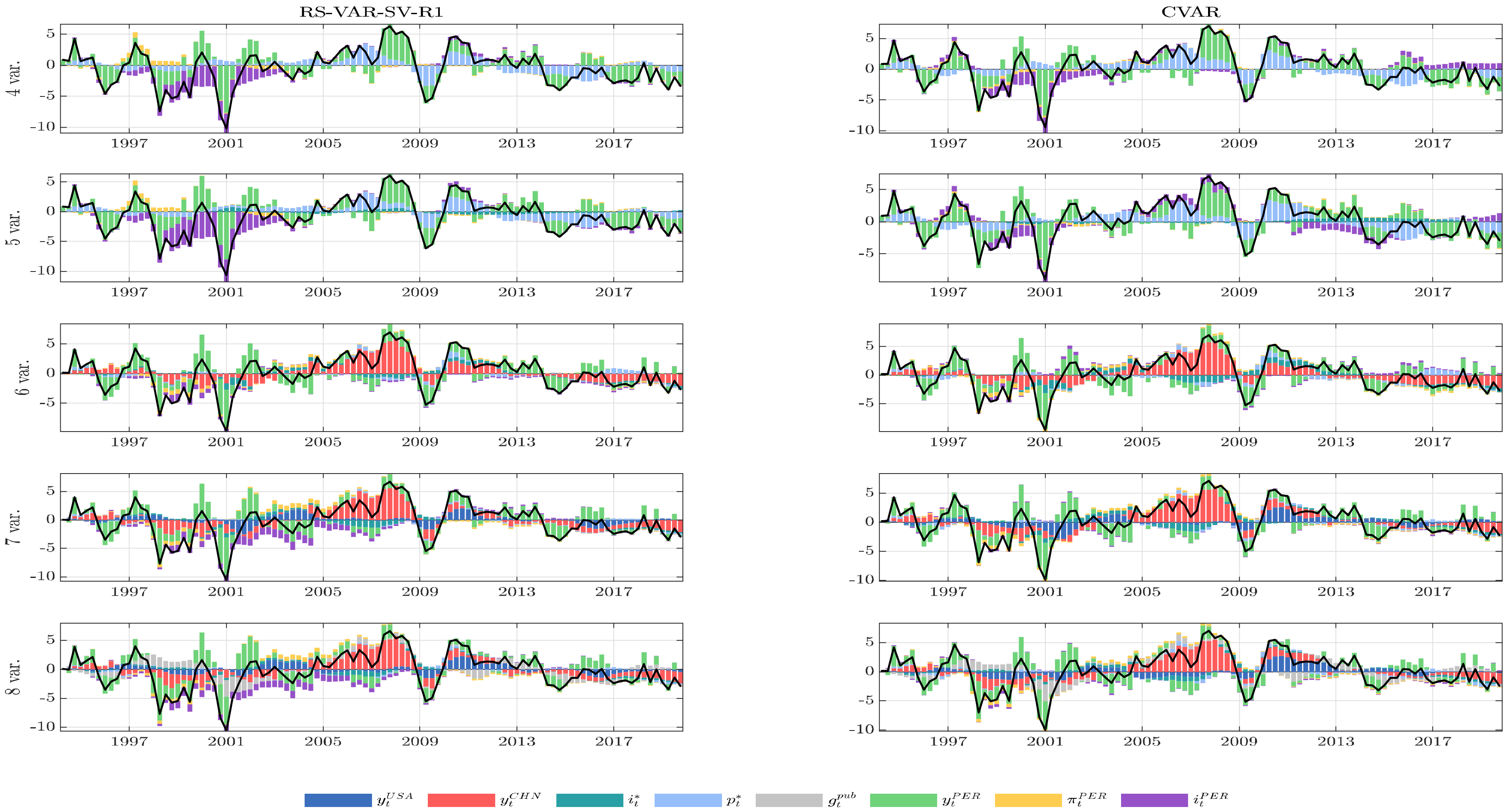

Figure 19. Robustness Analysis 4-7: Historical Decomposition of Domestic GDP Growth for the RS-VAR-SV-R1 Model and CVAR Model. The 4-variable Model considers the XPI Growth as the unique External Variable; the 5-variable Model adds the Fed Funds Rate; the 6-variable Model adds China's GDP Growth; the 7-variable Model is the Baseline Model; and the 8-variable Model incorporates Public Investment Growth.

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