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TIME-VARYING EFFECTS OF EXTERNAL SHOCKS ON MACROECONOMIC FLUCTUATIONS IN PERU: AN EMPIRICAL APPLICATION USING TVP-VAR-SV MODELS

Junior A. Ojeda Cunya y
Gabriel Rodríguez

Departamento
Académico de Economía

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Teléfono: (51-1) 626-2000 anexos 4950 - 4951
econo@pucp.edu.pe
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Departamento de Economía – Pontificia Universidad Católica del Perú
Barrantes.r@pucp.edu.pe
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Time-Varying Effects of External Shocks on Macroeconomic Fluctuations in Peru: An Empirical Application using TVP-VAR-SV Models*

Junior A. Ojeda Cunya†
Pontificia Universidad Católica del Perú

Gabriel Rodríguez‡
Pontificia Universidad Católica del Perú

March 15, 2022

Abstract

This study uses a family of VAR models with time-varying coefficients and stochastic volatility (TVP-VAR-SV) to analyze the impact of external shocks on output growth and inflation in Peru in 1992Q1-2017Q1. The statistical relevance of the models is assessed using the deviance information criterion (DIC) and the marginal log-likelihood calculated using the cross-entropy (CE) method. The results show that: (i) it is more relevant to introduce SV than TVP; i.e., the best fitting model admits only varying intercepts and SV; and TVP-VAR and CVAR are the least performing models; (ii) the models impulse response functions indicate that the impacts from external shocks are different under high inflation, economic crisis, and monetary policy change, with a greater impact in episodes of high uncertainty; (iii) the impact and importance of external shocks has increased over time; and (iv) the results are robust to changes in the priors, the lag structure, order of the variables, the external variable, and the variable for domestic economic activity.

JEL Classification: C11, C32, E32, F41, F62.

Keywords: Macroeconomic Fluctuations, External Shocks, Autoregressive Vectors with Time-Varying Parameters, Stochastic Volatility, Bayesian Estimation and Comparison, Peruvian Economy

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†Department of Economics, Pontificia Universidad Católica del Perú, Av. Universitaria 1801, Lima 32, Lima, Perú, E-Mail Address: jaojedac@pucp.pe.

‡Address for Correspondence: Gabriel Rodríguez, Department of Economics, Pontificia Universidad Católica del Perú, 1801 Universitaria Avenue, Lima 32, Lima, Perú, Telephone: +511-626-2000 (4998). E-Mail Address: gabriel.rodriguez@pucp.edu.pe, ORCID ID: https://orcid.org/0000-0003-1174-9642.

Efectos Variantes en el Tiempo de los Choques Externos en las Fluctuaciones Macroeconómicas en Perú: Una Aplicación Empírica utilizando Modelos TVP-VAR-SV*

Junior A. Ojeda Cunya†
Pontificia Universidad Católica del Perú

Gabriel Rodríguez‡
Pontificia Universidad Católica del Perú

15 de Marzo 2022

Resumen

Este estudio utiliza una familia de modelos VAR con coeficientes cambiantes en el tiempo y volatilidad estocástica (TVP-VAR-SV) para analizar el impacto de los choques externos en el crecimiento de la producción y la inflación en el Perú en 1992Q1-2017Q1. La relevancia estadística de los modelos se evalúa utilizando el criterio de información de desviación (DIC) y la verosimilitud marginal calculada utilizando el método de entropía cruzada (CE). Los resultados muestran que: (i) es más relevante introducir SV que TVP; es decir, el mejor modelo de ajuste admite solo interceptos variables y SV; y TVP-VAR y CVAR son los modelos menos favorecidos por los datos; (ii) las funciones impulso respuestas de los modelos indican que los impactos de los choques externos son diferentes bajo alta inflación, crisis económica y el cambio de política monetaria, con un mayor impacto en los episodios de alta incertidumbre; (iii) el impacto y la importancia de los choques externos ha aumentado con el tiempo; y (iv) los resultados son robustos a los cambios en las priors, la estructura de rezagos, el orden de las variables, la variable externa y la variable para la actividad económica doméstica.

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

Palabras Claves: Fluctuaciones macroeconómicas, Choques Externos, Vectores Autorregresivos con Parámetros Cambiantes en el Tiempo, Volatilidad Estocástica, Estimación y Comparación Bayesiana, Economía Peruana.

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†Departamento de Economía, Pontificia Universidad Católica del Perú, Av. Universitaria 1801, Lima 32, Lima, Perú, Correo Electrónico: jaojedac@pucp.pe.

‡Dirección de Correspondencia: Gabriel Rodríguez, Departamento de Economía, Pontificia Universidad Católica del Perú, Av. Universitaria 1801, Lima 32, Lima, Perú, Teléfono: +511-626-2000 (4998). Correo Electrónico: gabriel.rodriguez@pucp.edu.pe, ORCID ID: https://orcid.org/0000-0003-1174-9642.

1 Introduction

An established fact for small open economies is that economic fluctuations are strongly dependent on external shocks. The latter can be partially measured through movements in the terms of trade, export prices or commodity prices. A basic analysis of a positive external shock on a mainly primary-exporting country like Peru indicates that it leads to increased investment and production of primary industries, in turn resulting in higher economic activity. Additionally, higher international prices favor exports and dollar inflows into the economy, in turn diminishing the exchange rate and inflation.

Much of the literature on the impacts of external shocks is based on the use of VAR models introduced by Sims (1980) and related variants of identification schemes when it comes to structural VAR (SVAR) models. This type of model assumes that the parameters and innovations are constant throughout the sample. However, this approach can underestimate or overestimate the impacts of external shocks given the different fluctuations experienced by small and open economies oriented or dependent on the export of raw materials, with Peru being a representative case in this regard. Therefore, in order to introduce greater flexibility and examine the impact of external shocks over time, following Chan and Eisenstat (2018), we estimate a set of SVAR models with time-varying parameters with stochastic volatility (TVP-VAR-SV) for 1992Q2-2017Q1. Time-varying parameters are instrumental in assessing the impact of shocks under different monetary and fiscal regimes, which is relevant given that the latter may change due to economic or political reasons, thereby altering the interaction between the main economic variables. Towards this end, we use Bayesian techniques to estimate a family of seven TVP-VAR-SV models, which are discriminated through the Deviance Information Criterion (DIC) proposed by Spiegelhalter et al. (2002) and improved by Chan and Grant (2016) for latent variable models; and the marginal log-likelihood calculated using the cross-entropy method proposed by Chan and Eisenstat (2015).

The results show that the best fitting models are those with stochastic volatility and a certain variability of coefficients (especially the intercepts) over time. The estimations are used to analyze the impulse response functions (IRFs) for an external shock measured by an increase in the growth of the commodity price index. The effect of a positive external shock is positive on output growth and negative on inflation. At the same time, the magnitude of these responses varies according to the point in time for which they are calculated, with larger responses during the last 15 years, in contrast with the first 10 years of the sample. Additionally, the constant VAR model underestimates the magnitude of the response of output growth and inflation to a positive external shock in recent years, especially under global uncertainty such as in 2008 and 2010. The share of external shocks in the forecast error variance decomposition (FEVD) of the main economic variables also changes over time, drastically increasing from the beginning of the century. Moreover, monetary shocks predominate in the first 10 years of the sample, but later decrease in importance in favor of external and aggregate demand shocks. The results are robust to different prior selections, other external sector variables (terms of trade, export prices, an copper price), changes in the lag structure, the order of variables, and domestic variables (domestic demand and non-primary GDP).

The rest of the document is organized as follows. Section 2 presents a brief revision of the literature. Section 3 discusses the models and methodologies used to estimate them, as well as the selection criteria. Section 4 analyzes the estimations through IRFs, FEVD, historical decomposition (HD), and robustness exercises. Section 5 presents the conclusions.

2 Brief Literature Review

The study of the impact of external shocks (e.g., changes in the terms of trade and commodity prices) on economic variables (e.g., output growth and inflation) has taken on greater importance since the last decade of the previous century[1] due to the fast development of VAR models promoted by Sims (1980) and of dynamic stochastic general equilibrium (DSGE) models pioneered by Kydland and Prescott (1982). The studies yield mixed results. Some conclude that external shocks have limited influence on fluctuations of aggregate variables in emerging and developing economies, while others suggest that external shocks, especially movements in trade-related variables (i.e., commodity prices, terms of trade, and import/export prices) are important in explaining economic fluctuations.

Specifically, the study by Ahmed and Murthy (1994) shows that external shocks are not relevant in explaining economic fluctuations; and attempts to explain macroeconomic variable cycles in Canada using an SVAR model. The analysis shows that domestic shocks are more important than external shocks (e.g., terms of trade variations) in explaining short-term output fluctuations.

Along these lines, Hoffmaister and Roldós (1997) use an SVAR model to show that external shocks do not play an important role in explaining output fluctuations in Asian and Latin American countries. Using a similar technique, Hoffmaister et al. (1998) assess the influence of external shocks on output movements in African countries; and conclude that, irrespective of whether a group of countries have a common currency, the impact of such shocks is low and does not explain macroeconomic fluctuations.[2]

Lubik and Teo (2005) use a DSGE model with Bayesian estimation for Australia, Canada, New Zealand, Chile, and Mexico to analyze the influence of both foreign interest rate and terms of trade shocks. Their results show that real external shocks explain less than 5% of fluctuations in the economic cycles of those economies; and that foreign monetary policy shocks explain 40%-75% of fluctuations.

Aguirre (2011) and Schmitt-Grohé and Uribe (2018) conducted research works in this field more recently. The former uses a sample of 15 emerging economies from Asia, Africa, Europe, and Latin America for 1994-2009 to show that terms of trade shocks explain only 5% of output movements. Similarly, Schmitt-Grohé and Uribe (2018) show that external shocks explain less than 10% of economic fluctuations.

For their part, works suggesting that external shocks are important for macroeconomic fluctuations are more numerous. In this line, Mellander et al. (1992) analyze the terms of trade, consumption, and real investment in Sweden in 1875-1986 using a VAR model with cointegration restrictions. The authors show that permanent external shocks are important in explaining output fluctuations.

Mendoza (1995) conducted a well-known study on the impact of terms of trade shocks on small open economies. The study uses a DSGE model to show that such shocks explain 50% of output

[1] Studies done before this period, such as the works by Obstfeld (1982) and Svensson and Razin (1983), assess the possible impact of the terms of trade (as part of an external shock) on the current account and domestic output (known as the HLM effect), as suggested by Harberger (1950) and Laursen and Metzler (1950). The authors conclude that the effects estimated depend on the duration of shocks: while a negative and transitory shock deteriorates the current account, a permanent external shock does not have a relevant impact on the current account.

[2] Among others, Broda (2004) uses a VAR model to establish that the impact of the terms of trade on output fluctuations depends on the exchange rate regime. Under a fixed exchange rate regime the impact is strong and positive (around 33%), while with a flexible exchange rate the response is not significant and below 13%.

fluctuations in a sample of 7 industrialized economies and 23 developing countries. The works by Kose and Riezman (2001) and Kose (2002) also use a DSGE approach to show that real external shocks through fluctuations in commodity prices, imported capital goods, and intermediate goods explain 45% of output fluctuations in a representative African economy. Additionally, Kose (2002) concludes that international price shocks explain 90% of output fluctuations in developing countries.

Blattman et al. (2004) and Becker and Mauro (2006) study the impact of terms of trade shocks on economic fluctuations according to the level of economic development. Using a sample of 35 countries divided into two groups (central and peripheral countries), Blattman et al. (2004) show that changes in the long-term trends of the terms of trade result in a positive and significant effect on growth in central countries, while greater volatility in such shocks diminishes output growth in peripheral countries. For their part, Becker and Mauro (2006) use a multivariate probit model to analyze the impact of external shocks on emerging and developing economies, showing that external shocks play an important role in output falls in most countries. Moreover, they show that financial and macroeconomic shocks reduce output the most, while terms of trade shocks are the most relevant for developing countries. Collier and Goderis (2008) use global GDP and commodity price data for 1963-2003 to show a high influence of commodity price movements on economic activity in developing countries.

More recent works by Fernández et al. (2015), Shousha (2016), and Fernández et al. (2017, 2020) underscore the importance of real external shocks on aggregate economic variables. Using different methodological approaches (e.g., SVAR and panel VAR models), the authors show that commodity price shocks are important in explaining output variability in emerging and developing economics. Finally, Tiawara (2015), Kamber et al. (2016), and Farias and Alves da Silva (2017) use DSGE models to show the impact of external shocks on economic activity in African countries, New Zealand, and Brazil, respectively. Tiawara (2015) and Güneş et al. (2016) show that an increase in commodity prices results in a 3.6% average increase in per capita GDP in African countries; 0.3% and 2% increases in consumption and investment, respectively; and a -0.8% fall in tradable inflation. Farias and Alves da Silva (2017) examine the influence of commodity price movements considering whether they are anticipated or not. Both kinds of positive external shocks increase real GDP, although anticipated shocks have a greater impact on GDP, consumption, and investment.

Several works study the impact of external shocks on economic fluctuations in Latin America. Canova (2005) uses a TVP-VAR model to examine the transmission of external exogenous shocks (originating in the U.S.) to Latin American economies (i.e., Mexico, Panama, Brazil, Chile, Ecuador, Argentina, Uruguay, and Peru). The author concludes that U.S.-related disturbances explain 58% and 38% of output and price fluctuations on average in Latin America, respectively. At the same time, shocks are transmitted mainly via the interest rate channel, while the real channel, associated with commodity prices and the terms of trade, does not play an important role.

Misas et al. (2004) use a VAR model with cointegration restrictions to show that terms of trade shocks (particularly permanent ones) are important in explaining the behavior of output, consumption, and investment in Colombia. Hernández (2013) obtains similar results, concluding that terms of trade shocks have a positive and significant effect on GDP in Colombia, explaining around 33% of short-term output fluctuations in 1994-2011.

Lanteri (2008) applies an SVAR model to output and fiscal variables in Argentina; and finds that external shocks have a 19% positive impact on output. Campos (2015) uses the same methodology to conclude that terms of trade shocks have a positive impact on output and fiscal variables. Drechsel and Tenreyro (2018) use a DSGE model to describe the impact of commodity price shocks on output, consumption, investment, and the trade balance, concluding that external shocks explain 38%, 42%, and 61% of output, consumption, an investment growth, respectively.

For the case of Chile, Pedersen (2015) shows that a positive shock on the price of copper (Chile's main export commodity) has a positive impact on economic activity, as long as it is a demand-side shock, whereas the effect of supply-side or speculative shocks is unclear.

Dancourt et al. (1997) discuss whether economic fluctuations in Peru are explained by a given development strategy or external disturbances. The authors conclude that, out of six recession cycles in 1950-1996, five coincide with adverse shocks on terms of trade, international interest rates, or credit.

Castillo and Salas (2010) identify two cointegration relationships and two common trends in a system of variables including terms of trade, output, consumption, and investment; and conclude that the terms of trade explain 33%-95% of fluctuations in output, consumption, and investment. Recent works by Mendoza and Collantes Goicochea (2017) and Rodríguez et al. (2018) also address the impact of terms of trade shocks on fluctuations of aggregate economic variables. Mendoza and Collantes Goicochea (2017) show that terms of trade shocks are the most important component in output fluctuations, concluding that external factors explained around 66% of output movements in 2001-2016. For their part, Rodríguez et al. (2018) use a common trends and cointegration model to assess the role of terms of trade and domestic productivity in economic fluctuations. Their results show that long-term output volatility is almost fully explained by terms of trade movements. Moreover, they use a historical decomposition to show that external factors are the main component in output, consumption, private investment, and public expenditure growth (thereby explaining, for instance, the potential output fall in 2000, 2008, and 2013). Finally, Rodríguez and Vassallo (2022), Guevara et al. (2022), and Chávez and Rodríguez (2022) use extensions of the TVP-VAR-SV model to show that external shocks are important in Peru's economic activity. This document is part of this type of literature with the aim of providing evidence on the time-varying impact of external shocks on output growth, inflation and interest rate; as well as the role played by the volatility of these shocks.

3 Models and Methodology

In order to reflect evolving economic dynamics, we use a TVP-VAR-SV model, which allows coefficients of lagged and contemporaneous variables, and intercepts, as well as innovation variance, to change over time. We also describe briefly the algorithm used to obtain the parameters, as well as the method used to calculate the two metrics for comparing the models: the marginal log-likelihood and the DIC.

3.1 The TVP-VAR-SV Model

Based on Koop and Korobilis (2010) and Chan and Eisenstat (2018), the TVP-VAR-SV model in structural form is as follows:

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

where μ_t is an $n \times 1$ vector of time-varying intercepts, $\mathbf{B}_{1,t}...\mathbf{B}_{p,t}$ are the $n \times n$ matrices of coefficients associated with the vector of lagged endogenous variables, $\mathbf{B}_{0,t}$ is the $n \times n$ lower triangular matrix of contemporary effects with diagonal unit values, and $\mathbf{\Sigma}_t = diag(\exp(h_{1,t}), ..., \exp(h_{n,t}))$. The movement law for the logs of all variables $\mathbf{h}_t = (h_{1,t}, ..., h_{n,t})'$ is specified as an independent random walk:

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

where the initial conditions $\mathbf{h}_0$ are also parameters to be estimated.

As the system in (1) is in structural form and the variance matrix $\boldsymbol{\Sigma}_t$ is diagonal, the estimation can be carried out recursively. For this purpose, we rewrite the model. We consider the $k_\beta \times 1$ vector of intercepts and coefficients associated with the lagged observations $\boldsymbol{\beta}_t = vec((\boldsymbol{\mu}_t, \mathbf{B}_{1,t}, ..., \mathbf{B}_{p,t})')$. The second $k_\gamma \times 1$ vector, containing the time-varying coefficients that characterize contemporaneous relationships between variables, is denoted by $\boldsymbol{\gamma}_t$. It should be noted that $k_\beta = n(np+1)$ and $k_\gamma = n(n-1)/2$. Therefore, equation (1) can be rewritten as:

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

where $\widetilde{\mathbf{X}}_t = \mathbf{I}_n \otimes (1, \mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-p})$ and $\mathbf{W}_t$ is an $n \times k_\gamma$ matrix that contains the appropriate elements of $-y_t$[3]. If $\mathbf{X}_t = (\widetilde{\mathbf{X}}_t, \mathbf{W}_t)$, we can simplify the above model to obtain a generic space-state representation:

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

where $\boldsymbol{\theta}_t = (\boldsymbol{\beta}'_t, \boldsymbol{\gamma}'_t)'$ has a $k_\theta = k_\beta + k_\gamma$ dimension and the coefficients have a random walk behavior:

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\eta}_t, \qquad \boldsymbol{\eta}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_\theta), \tag{4}$$

where the initial conditions $\boldsymbol{\theta}_0$ are also parameters to be estimated.

The priors of the initial conditions $\boldsymbol{\theta}_0$ and $\mathbf{h}_0$ are both Gaussian: $\boldsymbol{\theta}_0 \sim \mathcal{N}(\mathbf{a}_\theta, \mathbf{V}_\theta)$ and $\mathbf{h}_0 \sim \mathcal{N}(\mathbf{a}_h, \mathbf{V}_h)$. We also assume that the error covariance matrices for the state equations are diagonal, that is: $\boldsymbol{\Sigma}_\theta = diag(\sigma^2_{\theta_1}, \ldots, \sigma^2_{\theta_n})$ and $\boldsymbol{\Sigma}_h = diag(\sigma^2_{h_1}, \ldots, \sigma^2_{h_n})$. The elements of $\boldsymbol{\Sigma}_\theta$ and $\boldsymbol{\Sigma}_h$ are independently distributed as $\sigma^2_{\theta_i} \sim \mathcal{IG}(\nu_{\theta_i}, S_{\theta_i})$, $i = 1, \ldots, k_\theta$, $\sigma^2_{h_j} \sim \mathcal{IG}(\nu_{h_j}, S_{h_j})$, $j = 1, \ldots, k_h$ where $\mathcal{IG}$ represents the Inverse Gamma distribution. The values of hyperparameters $\mathbf{a}_\theta$, $\mathbf{V}_\theta$, $\mathbf{a}_h$, $\mathbf{V}_h$, ν_{θ_i}, S_{θ_i}, ν_{h_j}, and S_{h_j} are defined in Section 3.2.

3.2 Restricted Versions

We use the general TVP-VAR-SV model in (1) to estimate restricted models resulting from each set of parameters we chose to restrict. We estimate six additional models: (i) TVP-VAR, which assumes homoscedastic variance ($\mathbf{h}_t = \mathbf{h}_0$); (ii) TVP-VAR-R1-SV, which assumes constant parameters for the lagged variables and the intercepts ($\boldsymbol{\beta}_t = \boldsymbol{\beta}_0$); (iii) TVP-VAR-R2-SV, which assumes constant coefficients for the contemporaneous relations ($\boldsymbol{\gamma}_t = \boldsymbol{\gamma}_0$); (iv) TVP-VAR-R3-SV, which assumes

[3] For example, when $n = 3$, $\mathbf{W}_t$ has the form:

$$\mathbf{W}_t = \begin{bmatrix} 0 & 0 & 0 \\ -y_{1,t} & 0 & 0 \\ 0 & -y_{1,t} & -y_{2,t} \end{bmatrix}$$

where y_{it} is the ith element of $\mathbf{y}_t$ for $i = 1, 2$.

that only the intercepts and variances are time-varying; (v) CVAR-SV, which assumes constant parameters for the lagged variables, the intercepts, and the contemporaneous relations ($\boldsymbol{\theta}_t = \boldsymbol{\theta}_0$), but has stochastic volatility; and (vi) CVAR, which assumes everything constant.

3.3 Estimation Algorithm: Gibbs Sampling[4]

We estimate the posterior parameters using the Gibbs sampling method, which consists in dividing the parameters in blocks and estimating each one separately, conditional on updates in the other blocks. The draws are based on the precision sampling proposed by Chan and Jeliazkov (2009) and developed by Chan and Eisenstat (2018). The algorithm for estimating the TVP-VAR-SV models is described as follows: (i) the draws are obtained from $(\boldsymbol{\theta}|\mathbf{y}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{N}(\widehat{\boldsymbol{\theta}}, \mathbf{K}_\theta^{-1})$, where $\mathbf{K}_\theta = \mathbf{H}_\theta' \mathbf{S}_\theta^{-1} \mathbf{H}_\theta + \mathbf{X}' \boldsymbol{\Sigma}^{-1} \mathbf{X}$ and the mean $\widehat{\boldsymbol{\theta}} = \mathbf{K}_\theta^{-1}(\mathbf{H}_\theta' \mathbf{S}_\theta^{-1} \mathbf{H}_\theta \boldsymbol{\alpha}_\theta + \mathbf{X}' \boldsymbol{\Sigma}^{-1} \mathbf{y})$, with $\boldsymbol{\alpha}_\theta = \mathbf{H}_\theta^{-1} \widetilde{\boldsymbol{\alpha}}_\theta$. The matrices $\mathbf{H}_\theta$, $\mathbf{S}_\theta$, $\boldsymbol{\Sigma}$ and $\widetilde{\boldsymbol{\alpha}}_\theta$ are described in Appendix A of Chan and Eisenstat (2018); (ii) using the conditional distributions of the diagonal elements in $\boldsymbol{\Sigma}_\theta$, the draws are obtained from $(\sigma^2_{\theta_i}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}(\nu_{\theta_i} + \frac{T}{2}, S_{\theta_i} + \frac{1}{2}\sum_{t=1}^T (\theta_{it} - \theta_{i,t-1})^2)$ for $i = 1, \ldots, k_\theta$ and the hyperparameters ν_{θ_i} and S_{θ_i} are defined in Section 4.2; (iii) the draws are obtained from the diagonal elements in $\boldsymbol{\Sigma}_h$ with the form $(\sigma^2_{h_j}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}(\nu_{h_j} + \frac{T}{2}, S_{h_j} + \frac{1}{2}\sum_{t=1}^T (h_{jt} - h_{j,t-1})^2)$ for $j = 1, \ldots, k_h$ and the hyperparameters ν_{h_j} and S_{h_j} are defined in Section 4.2; (iv) the draws are obtained for the initial condition θ_0 from $(\boldsymbol{\theta}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\widehat{\boldsymbol{\theta}}_0, \mathbf{K}_{\theta_0}^{-1})$, where $\mathbf{K}_{\theta_0} = \mathbf{V}_\theta^{-1} + \boldsymbol{\Sigma}_\theta^{-1}$ and $\widehat{\boldsymbol{\theta}}_0 = \mathbf{K}_{\theta_0}^{-1}(\mathbf{V}_\theta^{-1}\mathbf{a}_\theta + \boldsymbol{\Sigma}_\theta^{-1}\boldsymbol{\theta}_1)$ and values for $\mathbf{a}_\theta$ and $\mathbf{V}_\theta$ are given in Section 4.2; (v) the draws are obtained for the initial condition $\mathbf{h}_0$ from $(\mathbf{h}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\widehat{\mathbf{h}}_0, \mathbf{K}_{h_0}^{-1})$, where $\mathbf{K}_{h_0} = \mathbf{V}_h^{-1} + \boldsymbol{\Sigma}_h^{-1}$ and $\widehat{\mathbf{h}}_0 = \mathbf{K}_{h_0}^{-1}(\mathbf{V}_h^{-1}\mathbf{a}_h + \boldsymbol{\Sigma}_h^{-1}\mathbf{h}_1)$ and values for $\mathbf{a}_h$ and $\mathbf{V}_h$ are given in Section 4.2; (vi) steps (i)-(v) are repeated N times.

3.4 Comparison of Models

For comparing the above models and choosing the best one we use the Bayes factor (BF) with the log-likelihood calculated via the cross-entropy method ($\log ML_{CE}$) and the DIC.

3.4.1 Calculation of Marginal Log-Likelihood ($\log ML_{CE}$)[5]

Chan and Eisenstat (2015) propose a better alternative for estimating the marginal likelihood using the cross-entropy method (ML_{CE}). This estimation is based on the importance sampling density $g\left(\boldsymbol{\theta}_n\right)$:

$$\widehat{p}_{IS}\left(\mathbf{y}\right) = \frac{1}{N}\sum_{n=1}^{N} \frac{p\left(\mathbf{y}|\boldsymbol{\theta}_n\right) p\left(\boldsymbol{\theta}_n\right)}{g\left(\boldsymbol{\theta}_n\right)}, \tag{5}$$

where $\boldsymbol{\theta}_1, ..., \boldsymbol{\theta}_N$ are the independent draws obtained from the importance sampling density. The $\widehat{p}_{IS}$ estimator is consistent and unbiased irrespective of the value of $g\left(\boldsymbol{\theta}_n\right)$, but is sensitive to the $g\left(\boldsymbol{\theta}_n\right)$ variance. If the importance sampling is denoted by g^*, and using the posterior density to represent it, we infer that $\widehat{p}_{IS}\left(\mathbf{y}\right)$ is equivalent to $p(\mathbf{y})$. Therefore, the solution is choosing a g

[4] Complete details about the algorithm for estimating the TVP-VAR-SV model and other restricted models can be found in Section 4 and Appendix A of Chan and Eisenstat (2018).

[5] Complete details may be found in Section 4 and Appendix B of Chan and Eisenstat (2018).

similar to g^* such that the variance of the estimator is minimized. We obtain g via the cross-entropy method, which is used to measure the distance between two densities.

Given the parametric family $\mathcal{F} = \{f(\boldsymbol{\theta}, \mathbf{v})\}$ indexed by vector $\mathbf{v}$, we need to select the importance sampling $f(\boldsymbol{\theta}, \mathbf{v}) \in \mathcal{F}$ that is closer to g^*. Therefore, it is necessary to choose the density $f(\boldsymbol{\theta}, \mathbf{v}^*_{ce}) \in \mathcal{F}$ that minimizes the cross-entropy distance between the optimal density g^* and the chosen density $f(\boldsymbol{\theta}, \mathbf{v})$ as follows:

$$\begin{aligned}
\mathbf{v}^*_{ce} &= \arg\min_{\{\mathbf{v}\}} \left(\int g^*(\boldsymbol{\theta}) \log g^*(\boldsymbol{\theta})\, d\boldsymbol{\theta} - p(\mathbf{y})^{-1} \int p(\mathbf{y}|\boldsymbol{\theta})\, p(\boldsymbol{\theta}) \log f(\boldsymbol{\theta}, \mathbf{v})\, d\boldsymbol{\theta} \right), \\
\mathbf{v}^*_{ce} &= \arg\max_{\{\mathbf{v}\}} \int p(\mathbf{y}|\boldsymbol{\theta})\, p(\boldsymbol{\theta}) \log f(\boldsymbol{\theta}, \mathbf{v})\, d\boldsymbol{\theta},
\end{aligned}$$

whose estimator is:

$$\widehat{\mathbf{v}}^*_{ce} = \arg\max_{\{\mathbf{v}\}} \frac{1}{R} \sum_{r=1}^{R} \log f(\boldsymbol{\theta}_r, \mathbf{v}), \tag{6}$$

and we obtain the draws $\boldsymbol{\theta}_1, ..., \boldsymbol{\theta}_R$ using the posterior density[6].

3.4.2 Deviance Information Criterion (DIC)

The deviation information criterion (DIC) was proposed initially by Spiegelhalter et al. (2002). Based on Chan and Grant (2016), the deviance of the model's goodness of fit is defined as:

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

where $f(\mathbf{y}|\boldsymbol{\theta})$ is the model's likelihood function and $h(\mathbf{y})$ is a function of the data. Additionally, we use a measure of model complexity via the effective number of parameters, defined as:

$$p_D = \overline{D(\boldsymbol{\theta})} - D(\widetilde{\theta}), \tag{8}$$

where $\overline{D(\boldsymbol{\theta})} = -2E_{\boldsymbol{\theta}}[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2 \log h(\mathbf{y})$ is the posterior mean deviance and $\widetilde{\boldsymbol{\theta}}$ is an estimate of $\boldsymbol{\theta}$ (posterior mean or mode). Using these definitions, the DIC can be represented as the sum of the mean posterior deviation and the effective number of parameters; i.e., $DIC = \overline{D(\boldsymbol{\theta})} + p_D$. Assuming $h(\mathbf{y}) = 1$ and substituting the previous definitions, we obtain:

$$DIC = -4E_{\theta}[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2 \log f(y|\widetilde{\boldsymbol{\theta}}), \tag{9}$$

where the estimate $\widetilde{\boldsymbol{\theta}}$ of $\boldsymbol{\theta}$ is set as the posterior mode $\widehat{\boldsymbol{\theta}}$ and the first term of (9) can be estimated by averaging the log-integrated likelihoods $\log f(\mathbf{y}|\boldsymbol{\theta})$ over the posterior draws of $\boldsymbol{\theta}$. In order to approximate the posterior mode $\widehat{\boldsymbol{\theta}}$, we obtain the parameter set that yields the maximum value for $f(\mathbf{y}|\boldsymbol{\theta})f(\boldsymbol{\theta})$, where $f(\boldsymbol{\theta})$ is the prior density. Finally, the version used is the following:

$$DIC = -4E_{\theta}[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2 \log f(\mathbf{y}|\widehat{\boldsymbol{\theta}}).$$

[6] Gelfand and Dey (1994), Chib (1995) and Chib and Jeliazkov (2001), among others, propose alternative methods for calculating the marginal likelihood. However, Frühwirth-Schnatter and Wagner (2008) show that using the conditional likelihood or the complete data likelihood obtained through the method suggested by Chib (1995) results in an incorrect choice of models. Moreover, Chan and Eisenstat (2015) use empirical results to show that the CE method is faster and more accurate that the three mentioned before.

There are other versions of this selection criterion based on complete-data likelihood or conditional likelihood[7]. However, in this study we used the DIC based on integrated likelihood, taking into consideration the results obtained by Chan and Grant (2016), since other DIC forms favor over-parameterized models and yield high standard errors.

4 Empirical Results

4.1 Data

The variables used are the S&P GSCI index, real GDP, inflation, and the interest rate for 1992Q2-2017Q1. The series were obtained from the Central Reserve Bank of Peru (BCRP) database. The commodity index and seasonally-adjusted GDP are expressed in annual variations; and inflation is calculated as the annual variation of the Consumer Price Index (CPI). The interest rate is a combination of the interbank interest rate until 2003Q3 and the reference interest rate since 2003Q4.

Figure 1 shows the commodity index, real GDP, the CPI, and the interest rates, both as logarithms and annual growth rates. Column 1 shows an upward trend in GDP and prices, with some episodes of stagnation or decline during economic or political crises. Commodity prices followed a growing trend in 2000-2013, with an abrupt fall in the third and fourth quarters of 2008, together with a slight decrease in output, suggesting a dependence between these variables. Additionally, column 2 shows that the rate of growth of the commodity index and output move similarly, although not in the same proportion, over the sample, suggesting that the influence of commodity prices on GDP varies over time.

4.2 Priors

The priors of the initial conditions $\boldsymbol{\theta}_0$ and $\mathbf{h}_0$ are both Gaussian: $\boldsymbol{\theta}_0 \sim \mathcal{N}(\mathbf{a}_\theta, \mathbf{V}_\theta)$ and $\mathbf{h}_0 \sim \mathcal{N}(\mathbf{a}_h, \mathbf{V}_h)$. We also assume that the error covariance matrices for the state equations are diagonal; i.e., $\boldsymbol{\Sigma}_\theta = diag(\sigma^2_{\theta_1}, \ldots, \sigma^2_{\theta_n})$ and $\boldsymbol{\Sigma}_h = diag(\sigma^2_{h_1}, \ldots, \sigma^2_{h_n})$. The elements of $\boldsymbol{\Sigma}_\theta$ and $\boldsymbol{\Sigma}_h$ are independently distributed as $\sigma^2_{\theta_i} \sim \mathcal{IG}(\nu_{\theta_i}, S_{\theta_i})$, $i = 1, \ldots, k_\theta$, $\sigma^2_{h_j} \sim \mathcal{IG}(\nu_{h_j}, S_{h_j})$, $j = 1, \ldots, k_h$ where $\mathcal{IG}$ represents the Inverse Gamma distribution. The priors established for the hyperparameters are non-informative in all models. For the general TVP-VAR-SV, we establish that $\mathbf{a}_\theta = \mathbf{0}$, $\mathbf{V}_\theta = 10 \times \mathbf{I}_{k_\theta}$, $\mathbf{a}_h = \mathbf{0}$, $\mathbf{V}_h = 10 \times \mathbf{I}_n$, and $\nu_{\theta_i} = \nu_{h_j} = 5$. We also assume that $S_{\theta_i} = 0.01^2$ for the coefficients of the lagged variables and $S_{\theta_i} = 0.1^2$ for the intercepts. Additionally, we fix $S_{h_j} = 0.1^2$. The priors for restricted models follow the same criteria according to the restrictions imposed on them.

4.3 Results

The models are estimated with 2 selected lags according to the information criteria of Schwarz (SIC) and Hannan-Quinn (HQIC)[8]. We performed 11 thousand simulations for all models and discarded

[7] Spiegelhalter et al. (2002) provide the DIC expressions presented here; and Celeux et al. (2006) propose up to eight DIC versions, each with a different calculation method for likelihood according to the treatment of latent variables.

[8] Akaike's information criterion (AIC) selects 4 lags. However, this may imply an over parameterization and loss of efficiency in the estimates. Therefore, in terms of parsimony, we choose 2 lags. Furthermore, we follow Ivanov and Kilian (2005) who recommend using SIC and HQIC for quarterly series.

the first thousand in 10 parallel chains. Therefore, 100 thousand simulations remained, of which one in 10 where chosen, resulting in a total of 10 thousand simulations, which were used to calculate the DIC and the $\log ML_{CE}$.

As preliminary evidence, Table 1 shows three statistics used to assess time variability in the parameters. The results show that the first test (Trace test), which evaluates whether the trace of the matrix of prior variances is significantly different from the trace of the matrix of posterior variances, takes a value of 0.16; i.e., below the lower bound (0.17) of the interval calculated for the trace of matrix of posterior variances. Therefore, there are grounds to suggest the possibility of time-varying volatility. The next two statistics in Table 1 assess, in two different points in time, whether each parameter can be obtained from the same continuous distribution (Kolmogorov-Smirnov) or from two distributions with the same mean (t-test). In a first exercise, we divided the sample into two regimes, 1993Q4-2002Q4 and 2003Q1-2017Q1. The results show that almost all parameters are time-varying in both periods. Additionally, we apply the tests after changing the intermediate date to 2005Q2; i.e., the date at the middle of the sample. The results confirm that very few parameters are constant over time.

Table 2 shows the $\log ML_{CE}$ and the DIC for the TVP-VAR-SV model and its six restricted versions.[9] The results show that the least fitting models are those with constant VAR coefficients and variances. Comparing the $\log ML_{CE}$ for the CVAR model with that for the more general model (TVP-VAR-SV), the BF is 2.8×10^{39} for the latter and 5.6×10^{47} for the best fitting model (TVP-VAR-R3-SV). This evidence in favor of time-varying parameters is also verified when comparing the TVP-VAR and CVAR models, where the BF favors the former with a value of 365. However, the improved fitting is not due mainly to the time-varying VAR coefficients, but rather to the inclusion of the SV in the model. This can be verified by comparing the $\log ML_{CE}$ in the CVAR-SV model vis-à-vis the homoscedastic variance models. El BF in favor of the CVAR-SV model is 1.3×10^{44} and 4.7×10^{46} vis-à-vis the TVP-VAR and CVAR models, respectively. Moreover, the BF in favor of the TVP-VAR-SV model vis-à-vis the TVP-VAR model is 7.8×10^{36}.

Table 2 also shows the selection of models based on the DIC. We verify that TVP-VAR-R3-SV is the best fitting model. The least fitting models are TVP-VAR and CVAR, both with a matrix of constant variances. Along these lines, we argue that including the SV is more important than considering time-varying coefficients for lagged variables. Comparing the CVAR and CVAR-SV models, we verify that the inclusion of the SV improves the DIC. The same happens when comparing the TVP-VAR and TVP-VAR-SV (or the unrestricted TVP-VAR-SV) models; i.e., introducing the SV considerably improves the DIC.

Therefore, examining the variance's behavior over time is important for understanding the forthcoming results. Figure 2 shows the evolution over time of the standard deviation of innovations in each equation for the seven models estimated. The results show that the standard deviation of external shocks grows until mid-2008 and then changes its trend, declining until 2015 and remaining constant thereafter. The volatility of shocks on output growth declines (with slight fluctuations)

[9] We also estimated regime-switching (RS) VAR models with SV, three with 2 regimes ($r = 2$) and three with 3 regimes ($r = 3$). The only RS models that are better than the main ones (TVP-VAR and CVAR) are those that allow a change in volatility between regimes, with a log-ML_{CE} of -1059.717 and -1067.507 for $r = 2$ and $r = 3$, respectively. However, both TVP-VAR-SV and CVAR-SV are preferred over the best RS model (RS-VAR-R1-SV, $r = 2$), as they show a BF of 1.7×10^{21} and 2.8×10^{28}, respectively. This indicates that a smooth and continuous change in the variance, the VAR coefficients, and the intercepts are preferable to an abrupt and discrete change, as in the RS models, and therefore we discard them in this study. Chávez and Rodríguez (2021) estimate an extension of the RS-VAR-SV models, with similar results as ours.

in 1998-2001 and 2008-2009. The volatility of inflation shocks is constant until the middle of the second half of the 1990s and then declines. In the interest rate equation, the volatility of monetary policy (MP) shocks grows until mid-1998 and then declines rapidly since 2003 due to inflation targeting (IT) adoption.

Figure 3 shows the median of the IRFs for output growth, inflation, and the interest rate in response to an external shock. The results for output show the different impact of commodity price shocks pre- and post-IT adoption. We identify a weak response in the first years of the sample, during which domestic issues limited openness to international trade and foreign investment. However, the impact of the external shock becomes larger as domestic and political variables become more stable.

Regarding inflation, the negative impact of the external shock tapers out as we approach the maximum horizon (20 quarters). At the same time, the decline is lower in the pre-IT period; i.e., the impact on inflation pre-2002 is around -0.05%, and increases thereafter to a median of -0.15%. The negative response of inflation can be explained by the positive effect of improved international prices on exports, leading to greater dollar inflows, a fall in the exchange rate and, via the pass-through effect, lower inflation. The IRFs differ between the other models in Figure 3: the two best models after the TVP-VAR-R3-SV according to the $\log ML_{CE}$ (CVAR-SV and TVP-VAR-R1-SV) show a similar behavior, although with larger responses.

Figure 4 shows the IRFs for the TVP-VAR-R3-SV model, calculated as the median over time for the whole sample (1993Q4-2017Q1); and compares them with the IRFs for the other models. The goal is showing whether the other six models estimated remain within the confidence bands of the TVP-VAR-R3-SV model, reflecting a lower variability. We also considered shorter periods for calculating the median to examine its variations over time. The results show that the responses of output growth, inflation, and the interest rate in the six models, while differing somewhat in the median, are mostly within the confidence bands of the TVP-VAR-R3-SV model for the entire sample (1993Q4-2017Q1). At the same time, we note that the least fitting models, like TVP-VAR, TVP-VAR-SV, and TVP-VAR-R2-SV, lie outside the confidence bands, in line with the results detailed in the tables.

Additionally, output growth responses reach a maximum increase of 0.15% in the median and 0.25% in the confidence bands. It is important to compare the IRF for the CVAR model vis-à-vis the TVP-VAR-R3-SV model. The results show that the response of output growth to an external shock in the CVAR model is similar to the average response of the TVP-VAR-R3-SV model for the entire sample. However, when the same process is performed for 1993Q4-2002Q1, the CVAR model overestimates the response of this variable. Therefore, the CVAR model can only be used to calculate an average response for the sample, but not to identify responses in different (crisis or boom) periods.

Moreover, we use the IRFs for 1994Q1, 1999Q1, 2003Q1, 2008Q4, 2010Q1, and 2017Q1 in Figure 5 to examine the responses of output growth and inflation to a positive commodity price shock. We chose periods in which economic crises (the 1998 Asian and Russian crises, the 2007-2008 sub-prime crisis, and the 2010 European debt crisis), monetary regime changes (IT in 2003) and stability episodes took place. The IRFs for 1994Q1 show a mild impact on output growth, as Peru's trade integration was low and the main problem was inflation control. In the 1999Q1 crisis, which stemmed from the foreign financial sector and affected mainly the interest rate, the external price shock is not important enough to influence output growth considerably. In 2003Q1, in a context of domestic political stability, moderate global growth, and greater trade integration, IRFs are larger and last longer. The latter result is the most similar to the IRF calculated using the CVAR model, suggesting that it captures only the impact of an external shock in that period, rather than its magnitude at different points over the sample.

The 2007-2008 sub-prime crisis, while originated in the financial sector, had implications for the real sector, given its links with the real estate and construction industries. The impact on inflation is more negative that for other periods; and the response of output growth is much larger than in 2003, with a peak (above 0.2%) in the second quarter and zero after the sixth quarter.

In 2010Q1, an external shock increases output growth by close to 0.25% (similar to the result for the 2008 crisis) in a context of optimism due to global recovery after the 2009 slowdown, but also uncertainty caused by debt problems in some European countries. This response of output growth confirms the result for the previous crisis period; i.e., external shocks have a significant impact on economic activity in a context of domestic and international turbulence.

Finally, we calculate the IRFs for 2017Q1, a period of moderate global growth and rising commodity prices. As anticipated above, the results show that, during periods of moderate global growth, Peru's output growth increases moderately in response to a real external shock, in a way comparable to the response calculated for 2003Q1 and for the CVAR model. Therefore, output growth responses calculated using the CVAR model do not reflect accurately the effect of real external shocks in moments of global or domestic uncertainty, but rather only capture the impact of shocks in periods of economic calm (average effects).

Figure 6 shows the FEVD results for forecast horizons $h = 2$ and $h = 20$ using the TVP-VAR-R3-SV and CVAR models for output growth, inflation, and the interest rate. We note that, in the short run (horizon 2), external shocks (red area) explain less than 40% of output growth fluctuations using the TVP-VAR-R3-SV model only until IT adoption. Over the remaining periods, the share of external shocks increases and stabilizes at values close to 80%; i.e., for longer forecast horizons, external shocks become more relevant in explaining uncertainty regarding output growth. However, the behavior described above persists: before 2002 their share in the FEVD is low and then increases drastically to values close to 80%.[10] In terms of magnitudes, the share of external shocks in output variability is low (6%-17%) prior to the change in the monetary regime (1994Q1 and 1999Q1), while post-IT adoption the share increases to 72.96% and 79.56% on average in the short and long run, respectively.[11] In the case of the CVAR model, the share of external shocks is constant over both the short and long run (around 70%).

The results regarding the time-varying influence of external shocks are in line with the studies by Jiménez (2009) and Mendoza (2013) on the increase in trade openness after 2001. Jiménez (2009) argues that the Peruvian economy became more sensitive to external shocks since 2001 due to a reduction in effective tariffs, especially on commodities and intermediate goods. Mendoza (2013) shows that Peru's degree of trade openness as a percentage of GDP has increased over time, from below 30% until 2003 to close to 50% in 2009 and 2012. This suggests that greater trade openness after 2000, together with the IRFs and the FEVD, provide evidence of a time-varying impact of external shocks.

[10] In some cases the share is close to 100% (TVP-VAR-SV, TVP-VAR-R1-SV, and TVP-VAR-R2-SV models).

[11] The share of AD shocks is more important in explaining output fluctuations before IT adoption; and drops to around 20% more recently. In contrast, the share of AS shocks is not important (always below 5%). Additionally, the share of MP shocks is high in the first years of the sample, especially since 1997 due to the interest rate increase caused by the Asian crisis, as suggested by Velarde and Rodríguez (2001), until 2002. This result is in line with Castillo et al. (2009) regarding the high interest rate variability in 1994-2001 and stabilization since 2002.

Columns 3 and 4 in Figure 6 show the results for inflation. The TVP-VAR-R3-SV model suggests that, in the short run, external shocks explain 20%-60% until before 2002. From then on, their share increases to values above 80%. For longer horizons, the importance of external shocks rises to 60%-100%. The share of real external shocks in inflation variability rises from 16.64% in 1994Q1 to 74.90% in 2017Q1.

Regarding inflation, the share of MP shocks is greater in 1997-2002. Specifically, the share of MP shocks is important for inflation variability in the long-term forecasts of 1999Q1 (23.10%), but decreases to 0.12% on average in later periods (2002-2017). Additionally, the share of AD shocks in inflation is small, indicating that this variable reacts mainly to international price movements rather than to domestic variables; and the share of AS shocks on average is around 33% in the short run and 23% after 20 quarters.

The results obtained by Ahmed (2003) are similar to those in Figure 6; i.e., the share of AD shocks is not high in inflation variation: 7% in the short run (one year) and 12% after five years. The same study shows that the share of AS shocks in the FEVD for output growth is also not significant. These results are in line with Armas and Grippa (2008), who mention that in the period between IT adoption and the sub-prime crisis, inflation fluctuations were driven mainly by AS shocks and imported inflation associated with movements in the international prices of imports.

The last two columns in Figure 6 show that the FEVD for the interest rate in the short and long run is similar to the above results. In the short run, the share of MP shocks is close to 100% in the TVP-VAR-R3-SV model, in contrast to 50% in the CVAR model. Additionally, over longer forecast horizons the share of MP shocks decreases and external shocks predominate. The results for the CVAR model are similar, although very different in magnitude; i.e., in the long run the share of MP shocks decreases to 40% and that of external shocks increases to close to 50%.

Figure 7 shows the historical decompositions[12] (HDs) for output growth, inflation and the interest rate for the TVP-VAR-R3-SV and CVAR models. The column 1 shows similar results as for the FEVD. The results of the TVP-VAR-R3-SV model suggest that external real and AD shocks are important for output growth fluctuations (at some points almost fully explaining them); MP shocks are important only until IT adoption; and AS shocks are not significant throughout the sample. In contrast, the CVAR model indicates that, until 2000, MP shocks maintain a high share but, unlike in other models, the latter does not decrease abruptly since then, but rather remains high until the end of the sample. We verify this by examining the share of each kind of shock in output fluctuations throughout the sample. For instance, the 1994-1995 output growth variation was -4.9%, 44.7% of which was caused by the MP shock; while the 1997-1998 output growth variation of -6.7% was due mainly by the AD shock (71.2%), followed in importance by the MP and external shocks (10.0% and 14.6%, respectively). The opposite holds post-2002: the 2004-2005 growth output variation was 1.3%, 64.3% of which was due to the external shock. Similarly, 80.8% of the 2015-2016 difference was also caused by the external shock. The impact of the commodity price boom on growth in 2004-2014 can be examined in a similar manner. Over 30% of growth acceleration from 2002 to 2007Q3-2008Q2 (from 5.5% to 10.7%) is due to an external shock (commodity prices). Moreover, close to 20% of the -9.0% difference between the highest and lowest growth periods (2007Q3-2008Q2 and 2014Q2-2015Q1, respectively) is due to commodity shock prices.

Column 2 in Figure 7 shows the HD of inflation in the TVP-VAR-R3-SV and CVAR models. In

[12] HD calculation is based on the method suggested by Wong (2017) for non-linear models.

the TVP-VAR-R3-SV model, AS shocks are significant for inflation until 2003 and lose importance thereafter relative to more recent commodity price shocks. The share of MP shocks is also important until 2003, but later diminishes compared to other shocks. AD shocks maintain a low and constant share throughout the sample. The other models yield the same conclusions as our best model. The share of AS shocks is high until 2000 and later decreases to similar levels as external and AD shocks.

Finally, the last column in Figure 7 shows the HD for the interest rate. The TVP-VAR-R3-SV model suggests that the share of MP shocks is high until 2002; and from then on, mirroring the path of this variable (Figure 2), diminishes compared to external and AD shocks in the last 15 years. In the CVAR model, the share of MP shocks remains constant throughout the sample and does not reflect either a natural fall or the higher share of external shocks in more recent periods.

The results for the share of external factors are in line with the findings by Rodríguez et al. (2018); i.e., external shocks explain almost 100% of long-term output variability. These conclusions show that inflation control via IT and use of the Taylor rule to determine interest rate movements proved beneficial, as they reinforced credibility in the BCRP's capacity to keep inflation within target; and made interest rate movements more predictable, such that they can be internalized by market participants. Along these lines, AS shocks have a low and short-term impact, as markets envisage that they will be swiftly controlled by the BCRP; and MP shocks via interest rate cuts or hikes become fully predictable. Therefore, the economy can only be affected by unanticipated shocks, mostly external; see also Portilla et al. (2022).

4.4 Robustness Exercises

We performed three robustness exercises:[13] (i) the models are reestimated with the same variables but subject to three different conditions: alternative priors, a different number of lags, and a different order in the variables; (ii) the models are estimated with a different external variable: terms of trade, export prices, and copper price; (iii) the models are estimated with a different variable for domestic economic activity: domestic demand, non-primary GDP, employment, and private investment.

Table 3 shows the results for the first robustness exercise. Panel (a) shows the results using alternative priors. We use more diffuse priors for the mean of the error variance in the VAR ($\mathbf{\Sigma}_\theta$) coefficients. Towards this end, the priors for S_i change from 0.01^2 to 0.1^2 for the lagged coefficients and from 0.1^2 to 1^2 for the intercepts. The results confirm that differentiation and fit improvement are mainly due to SV inclusion. Additionally, making the hyperparameters more diffuse and favoring coefficient variability does not yield good results for the $\log ML_{CE}$ and the DIC. In this case, the ranking of the models changes slightly, especially for the one based on the $\log ML_{CE}$; however, the change is not drastic and the best model identified previously (TVP-VAR-R3-SV) falls one position and the CVAR-SV model, which is quite similar, takes its place; and TVP-VAR remains among the least fitting models. Moreover, the IRFs keep similar trends. However, the responses to some shocks (AD shocks) become non-significant; or the confidence intervals become narrower (AS shocks). Regarding the FEVD and the HD, the share of external shocks increases, especially in the short run.

Panel (b) in Table 3 shows the results for a larger number of lags ($p = 3$). The selection criteria

[13] We calculate the IRFs, FEVD, and HD for each robustness exercise. The Figures are in an Appendix available upon request.

worsen in magnitude and standard errors, especially for the $\log ML_{CE}$. However, the results preserve to a great extent the ranking of models for the main estimations: TVP-VAR-R3-SV as the best model and non-SV models as the least fitting. Estimations for the IRFs are similar to the main one, except for the AS shock, where output growth experiences a sharp short-run fall, unlike the main estimation. The share of shocks remains the same for both the FEVD and the HD.

Panel (c) in Table 3 shows the results for an alternative order of the variables; i.e., we exchange the position of the output growth and interest rate variables. The results show that the main estimations are robust to changes in the order of variables, both for the selection of models and the IRF, FEVD, and HD results.

Table 4 shows the results of the second robustness exercise, which confirm that non-SV models are the least fitting. TVP-VAR-R2-SV is selected according to the $\log ML_{CE}$, while TVP-VAR-R3-SV is selected according to the DIC for the terms of trade (panel (a)) and export prices (panel (b)); but, according to both selection criteria, TVP-VAR-R3-SV is the best model for copper price (panel (c)). Figure 8 shows the median for the IRFs calculated using the TVP-VAR-R3-SV model for each external variable. With the terms of trade, the IRFs maintain similar results for output growth and inflation in the face of an external shock. The response of output growth to a terms of trade shock is less than 0.1% during the pre-2003 period and increases to around 0.14% thereafter, while the response to export prices is 0.17% on average over the last 15 years. In contrast, the response to copper price are low and inconclusive. For a terms of trade shock, inflation falls by around -0.1% from the beginning of the sample until 2003 and later falls as much as -0.3%. The response of inflation to export prices and copper price is the lowest throughout the sample.

Figure 9 shows the IRFs using the terms of trade, export prices, and copper price as medians over time and with confidence intervals to compare whether the other models estimated are within those bands. Column 1 in Figure 9 shows that output growth increases in response to a terms of trade shock, although less than in response to a commodity price shock. Inflation falls -0.2% on average, while the interest rate shows a positive response. Column 2 shows that the response of output growth to export prices is similar to the response to the terms of trade throughout the sample. In contrast, inflation shows a negative response of around -0.10% and is overestimated by the CVAR model, which forecasts a fall close to -0.20%. The last column in Figure 9 shows that the response of output growth and inflation to copper price is not significant.

Figure 10 shows the results for specific dates, where each row corresponds to the shock on each alternative variable. Output growth shows a positive response to the terms of trade and export prices; but its response to copper price is not significant. The fall in inflation in response to an external shock is low for the first years of the sample, but increases for recent years to up to -0.25%. The results using export prices follow the same trend but with lower magnitudes.

Figure 11 shows the FEVD for output growth, inflation, and the interest rate for each external variable used. It is worth noting that these variables yield the lowest share of external shocks identified in this study (30% and 50% in the short and long run, respectively). Similarly, using export prices and copper price, the share of external shocks in output growth reaches 40% and 60% in the short and long run, respectively. These results are in line with the study by Florián et al. (2018), which shows that the share of terms of trade shocks in output growth variability is 50%. The share of MP shocks is high (40%) until 2002 and then falls to less than 1%, as in the baseline model.

The share of external shocks in inflation grows with all external variables, although in different magnitudes. The share of external shocks reaches a peak of 70% from 2010 onwards when using the terms of trade and copper price; and is slightly lower when using export prices. The share of AD shocks is similar using the three external variables (10%-20%). MP shocks reach a peak of 20% in 1998 and fall below 1% more recently.

The FEVD for the interest rate yields similar results as the main ones, where the share of the MP shock, using the TVP-VAR-R3-SV, is around 100% pre-2002 and decreases abruptly thereafter, with a maximum mean of 25%. This shift in the share of the MP shock is not captured by the CVAR model, which shows a constant share (around 50%) throughout the sample.

Figure 12 shows the HD for output growth and inflation corresponding to each external variable used. The results are similar as for the baseline model; i.e., the share of MP shocks is the highest in output growth until 2003; but drops thereafter (even becoming null in certain periods) while the shares of external and AD shocks become predominant. The shares of AS and MP shocks are the highest for inflation until 2003; but AS shocks drop since then and external shocks gain importance.

Table 5 shows the selection of models according to the $\log ML_{CE}$ and the DIC for the third robustness exercises, where we perform estimations considering other variables for economic activity: domestic demand, non-primary GDP, employment, and private investment (using the S&P Index and the terms of trade). For all variables, TVP-VAR-R3-SV is the best fitting model. Additionally, except for slight differences in the magnitude of the responses, the IRFs show the same trend as the main results; i.e., external shocks have a positive impact on the variable for economic activity, especially in recent years; and reduce inflation significantly, leading to a short-run drop in the interest rate. However, this effect becomes non-significant if the confidence bands are kept around zero. Moreover, the share of external shocks in the FEVD and the HD grows over time and even more so after IT adoption; and the share of MP shocks decreases as the variables for inflation and the interest rate stabilize.

5 Conclusions

We estimate a group of seven SVAR models to establish the impact of external shocks on output growth and inflation fluctuations in Peru in 1992Q1-2017Q1. The models include from a CVAR, frequently used in the literature, to a TVP-VAR-SV, where both the parameters and the variance of shocks are time-varying. The empirical evidence shows that, using Bayesian selection criteria, a model with time-varying parameters and stochastic volatility adjusts better to Peru's economy than maintaining a homoscedastic variance and constant parameters. TVP-VAR-SV estimations (including with restrictions on the parameters for contemporaneous and lagged variables, intercepts, and variances) show that the best fitting model is TVP-VAR-R3-SV, which considers only time-changing intercepts in each equation and stochastic volatility.

The calculation and assessment of IRFs suggests that there are differences in the responses of output growth and inflation for each model and at each point in time. There is a considerable difference in the responses of output growth and inflation before and after IT adoption. Additionally, the response of output growth to commodity price shocks is larger during domestic or international crisis episodes. However, under conditions of stability and moderate growth, the response of output growth is lower and shorter.

The FEVD for output growth shows that the share of external shocks is less than 30% for pre-2002 fluctuations in this variable and increases to above 80% thereafter. The share of external shocks is high for inflation and shows the same behavior as for output growth: a low magnitude pre-2002 and up to 100% thereafter in some models. The results for the HD are similar to those for the FEVD: a large share of external shocks for output growth and inflation; and a significant influence of MP shocks until before IT adoption.

We also show that the results are robust to changes in priors, the number of lags, the order variables, the external variable, and the variable for domestic economic activity. We find that TVP-VAR-R3-SV is the best fitting model; and the IRFs, as well as the FEVD and the HD, are similar as for the main results. Specifically, we verify that the importance of external shocks grows over time, especially since 2002.

We conclude that models with constant parameters do not adequately capture the time variability of shocks; and therefore the latter's calculated share in the fluctuation of economic variables is not consistent with the evolving conditions in Peru's economy. Therefore, it is important for policymakers to consider the economic context in measuring the impact of an external shock and implementing the necessary fiscal and monetary rules.

Possible extensions to this study can consider sign restrictions or additional variables than may provide further information on external developments and their influence on the domestic economy.

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Table 1. Tests for Time Variation in Coefficients and Volatility

Trace Test			
trace	16% perc.	50% perc.	84% perc.
0.16	0.17	0.25	0.38
Kolmogorov-Smirnov test			
$\boldsymbol{\gamma}_{it}$			
1993Q4-2002Q4	2003Q1-2017Q1	1993Q4-2005Q2	2005Q3-2017Q1
6/6	6/6	6/6	6/6
$\boldsymbol{\beta}_{it}$			
1993Q4-2002Q4	2003Q1-2017Q1	1993Q4-2005Q2	2005Q3-2017Q1
28/36	30/36	28/36	30/36
$\mathbf{h}_{it}$			
1993Q4-2002Q4	2003Q1-2017Q1	1993Q4-2005Q2	2005Q3-2017Q1
4/4	4/4	4/4	4/4
t-test			
$\boldsymbol{\gamma}_{it}$			
1993Q4-2002Q4	2003Q1-2017Q1	1993Q4-2005Q2	2005Q3-2017Q1
6/6	6/6	6/6	6/6
$\boldsymbol{\beta}_{it}$			
1993Q4-2002Q4	2003Q1-2017Q1	1993Q4-2005Q2	2005Q3-2017Q1
25/36	28/36	26/36	26/36
$\mathbf{h}_{it}$			
1993Q4-2002Q4	2003Q1-2017Q1	1993Q4-2005Q2	2005Q3-2017Q1
4/4	4/4	4/4	4/4

$\boldsymbol{\gamma}_{it}$ represents the coefficients of contemporaneous relationships, $\boldsymbol{\beta}_{it}$ are the coefficients associate to intercepts and lagged variables and $\mathbf{h}_{it}$ are the variances of innovations.

Table 2. Models Selection

Model	log-ML_{CE}	SD	Rank	DIC	SD	Rank
TVP-VAR-SV	-1010.853	0.114	5	1783.718	1.423	4
TVP-VAR	-1095.801	0.380	6	1890.801	5.657	7
TVP-VAR-R1-SV	-998.719	0.200	3	1715.435	0.235	2
TVP-VAR-R2-SV	-1000.631	0.233	4	1751.257	1.301	3
TVP-VAR-R3-SV	**-991.749**	**0.082**	**1**	**1687.990**	**0.679**	**1**
CVAR-SV	-994.226	0.034	2	1801.402	1.441	5
CVAR	-1101.700	0.027	7	1888.423	0.115	6

For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML_{CE} estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains; in each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, i.e., a total of 10,000 evaluations.

Table 3. Robustness Check: Alternative Priors, Different Lags and Different Ordering

Model	log-ML$_{CE}$	SD	Rank	DIC	SD	Rank
(a) Alternative Priors						
TVP-VAR-SV	-1228.753	0.080	6	2285.831	0.971	6
TVP-VAR	-1255.24	0.016	7	2299.703	0.237	7
TVP-VAR-R1-SV	-1102.254	0.149	4	1933.515	0.763	4
TVP-VAR-R2-SV	-1179.147	0.082	5	2168.418	1.079	5
TVP-VAR-R3-SV	-1028.309	0.318	2	**1774.16**	**0.821**	**1**
CVAR-SV	**-994.226**	**0.034**	**1**	1801.402	1.441	2
CVAR	-1101.700	0.027	3	1888.423	0.115	3
(b) $lag = 3$						
TVP-VAR-SV	-1054.849	0.206	5	1802.033	1.912	5
TVP-VAR	-1125.233	0.209	6	1874.737	3.546	7
TVP-VAR-R1-SV	-1036.037	0.101	3	1700.667	0.533	2
TVP-VAR-R2-SV	-1047.714	0.309	4	1770.765	1.518	4
TVP-VAR-R3-SV	**-1027.066**	**0.224**	**1**	**1667.881**	**0.366**	**1**
CVAR-SV	-1028.667	0.027	2	1741.610	3.565	3
CVAR	-1129.430	0.013	7	1862.938	0.112	6
(c) Alternative Ordering						
TVP-VAR-SV	-1007.141	0.140	5	1777.458	0.616	4
TVP-VAR	-1096.173	0.450	6	1898.793	8.944	6
TVP-VAR-R1-SV	-997.075	0.214	3	1713.155	0.468	2
TVP-VAR-R2-SV	-998.245	0.153	4	1748.964	1.274	3
TVP-VAR-R3-SV	**-988.550**	**0.103**	**1**	**1687.129**	**0.365**	**1**
CVAR-SV	-991.127	0.032	2	1777.780	1.095	5
CVAR	-1102.288	0.010	7	1888.216	0.140	7

For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML$_{CE}$ estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains; in each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, i.e., a total of 10,000 evaluations.

Table 4. Robustness Check: Using Terms of Trade, Export Prices and Copper Price as Foreign Variable

Model	log-ML_{CE}	SD	Rank	DIC	SD	Rank
(a) Terms of Trade						
TVP-VAR-SV	-945.442	0.078	2	1647.148	0.746	4
TVP-VAR	-1023.676	0.296	6	1760.123	5.754	6
TVP-VAR-R1-SV	-952.254	0.127	5	1620.448	0.367	2
TVP-VAR-R2-SV	**-942.885**	**0.094**	**1**	1629.244	0.817	3
TVP-VAR-R3-SV	-949.759	0.090	3	**1607.707**	**0.387**	**1**
CVAR-SV	-950.314	0.029	4	1660.650	1.758	5
CVAR	-1056.454	0.010	7	1819.778	0.143	7
(b) Export Prices						
TVP-VAR-SV	-967.044	0.066	2	1692.073	0.736	4
TVP-VAR	-1053.053	0.309	6	1812.489	5.331	6
TVP-VAR-R1-SV	-975.115	0.149	5	1662.900	0.488	2
TVP-VAR-R2-SV	**-964.968**	**0.203**	**1**	1673.352	1.256	3
TVP-VAR-R3-SV	-971.835	0.146	3	**1645.973**	**0.317**	**1**
CVAR-SV	-973.025	0.036	4	1747.359	3.207	5
CVAR	-1087.783	0.009	7	1874.603	0.163	7
(c) Copper Price						
TVP-VAR-SV	-1078.364	0.143	5	1910.590	0.878	5
TVP-VAR	-1167.490	0.436	6	2038.118	7.860	6
TVP-VAR-R1-SV	-1076.765	0.117	4	1864.187	0.603	2
TVP-VAR-R2-SV	-1071.381	0.171	3	1882.748	0.520	3
TVP-VAR-R3-SV	**-1065.942**	**0.099**	**1**	**1829.559**	**0.514**	**1**
CVAR-SV	-1067.142	0.045	2	1901.496	2.230	4
CVAR	-1193.501	0.009	7	2064.151	0.194	7

For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML_{CE} estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains; in each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, i.e., a total of 10,000 evaluations.

Table 5. Robustness Check: Using Domestic Demand, Non-Primary GDP, Employment and Private Investment as Economic Activity Variable

Model	log-ML$_{CE}$	SD	Rank	DIC	SD	Rank	Model	log-ML$_{CE}$	SD	Rank	DIC	SD	Rank
(a) Domestic Demand							(b) Non-Primary GDP						
TVP-VAR-SV	-1036.146	0.233	1	1888.250	0.654	4	TVP-VAR-SV	-1018.221	0.165	5	1796.929	0.909	4
TVP-VAR	-1154.420	0.489	6	1998.935	8.606	6	TVP-VAR	-1116.759	0.750	7	1912.601	5.540	6
TVP-VAR-R1-SV	-1050.863	0.110	4	1816.546	0.567	2	TVP-VAR-R1-SV	-1007.231	0.145	3	1730.153	0.496	2
TVP-VAR-R2-SV	-1055.403	0.151	5	1859.746	1.154	3	TVP-VAR-R2-SV	-1008.890	0.176	4	1765.496	0.902	3
TVP-VAR-R3-SV	-1044.127	0.131	2	1790.065	0.586	1	TVP-VAR-R3-SV	-996.986	0.092	1	1697.514	0.498	1
CVAR-SV	-1047.782	0.055	3	1998.731	4.053	5	CVAR-SV	-1001.392	0.053	2	1931.429	4.839	7
CVAR	-1161.995	0.009	7	2000.266	0.161	7	CVAR	-1112.960	0.009	6	1908.342	0.203	5
(c) Employment							(d) Private Investment - S&P Index						
TVP-VAR-SV	-676.985	0.256	5	1113.798	0.570	4	TVP-VAR-SV	-1139.036	0.164	5	2034.393	0.484	4
TVP-VAR	-752.992	0.306	7	1234.779	1.689	7	TVP-VAR	-1241.956	0.626	6	2150.090	8.469	7
TVP-VAR-R1-SV	-672.243	0.140	4	1068.560	0.551	2	TVP-VAR-R1-SV	-1124.164	0.120	3	1964.066	0.450	2
TVP-VAR-R2-SV	-668.921	0.223	3	1086.242	0.931	3	TVP-VAR-R2-SV	-1128.108	0.131	4	1999.532	1.141	3
TVP-VAR-R3-SV	-663.922	0.210	1	1040.076	0.700	1	TVP-VAR-R3-SV	-1113.164	0.091	1	1927.604	0.400	1
CVAR-SV	-667.641	0.040	2	1156.490	5.969	5	CVAR-SV	-1118.030	0.030	2	2108.538	4.846	5
CVAR	-739.696	0.011	6	1173.790	0.175	6	CVAR	-1242.959	0.005	7	2146.772	0.157	6
(e) Private Investment - Terms of Trade													
TVP-VAR-SV	-1070.360	0.073	2	1897.807	1.036	4							
TVP-VAR	-1163.977	0.238	6	2012.813	3.812	6							
TVP-VAR-R1-SV	-1075.378	0.092	5	1864.888	0.433	2							
TVP-VAR-R2-SV	-1066.316	0.172	1	1877.782	0.688	3							
TVP-VAR-R3-SV	-1072.739	0.087	3	1849.738	0.425	1							
CVAR-SV	-1074.831	0.024	4	1938.582	2.694	5							
CVAR	-1199.756	0.007	7	2081.959	0.146	7							

For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML$_{CE}$ estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains; in each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, i.e., a total of 10,000 evaluations.

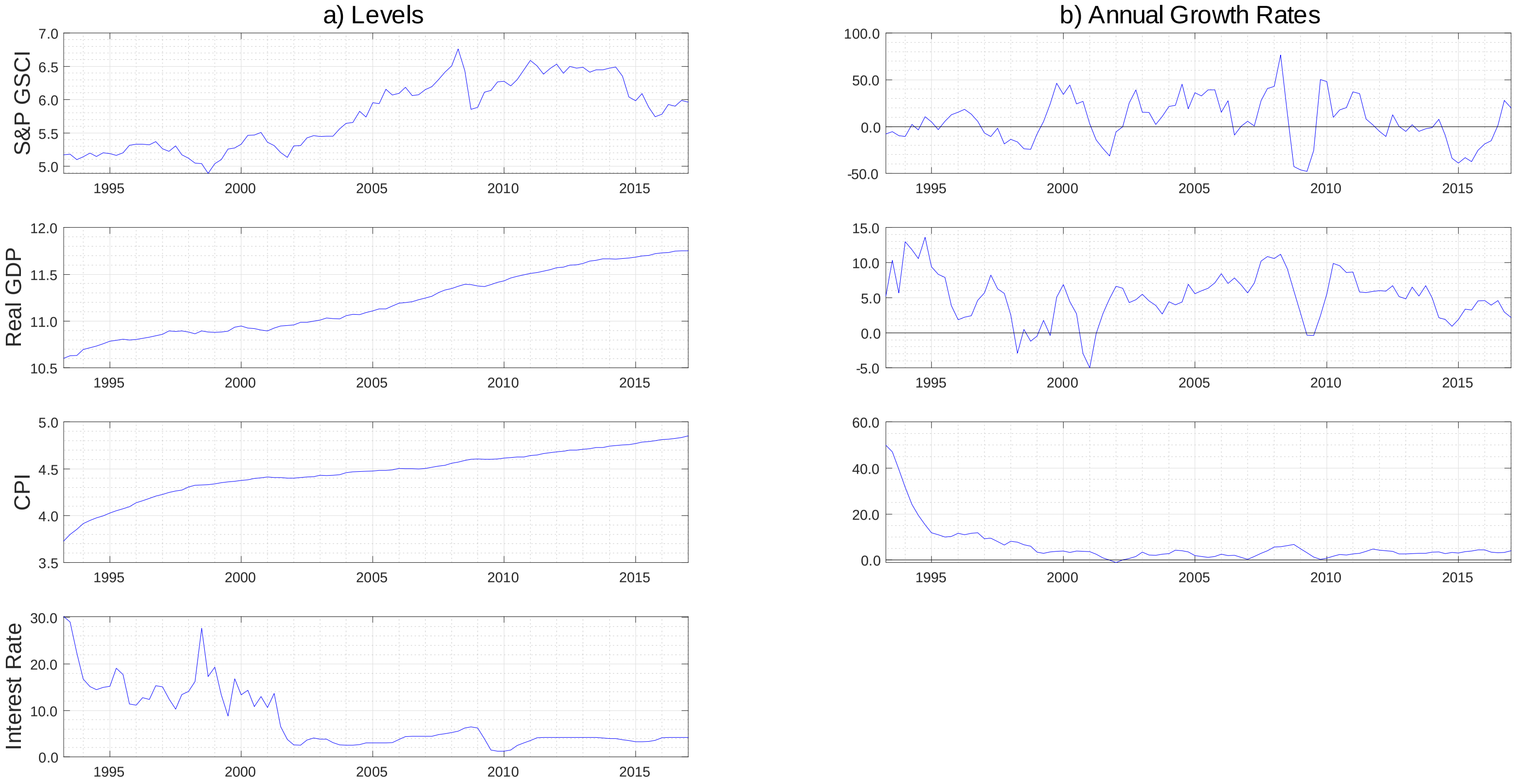

Figure 1. Time Series in Levels and Annual Growth Rates: Sample 1992Q2-2017Q1.

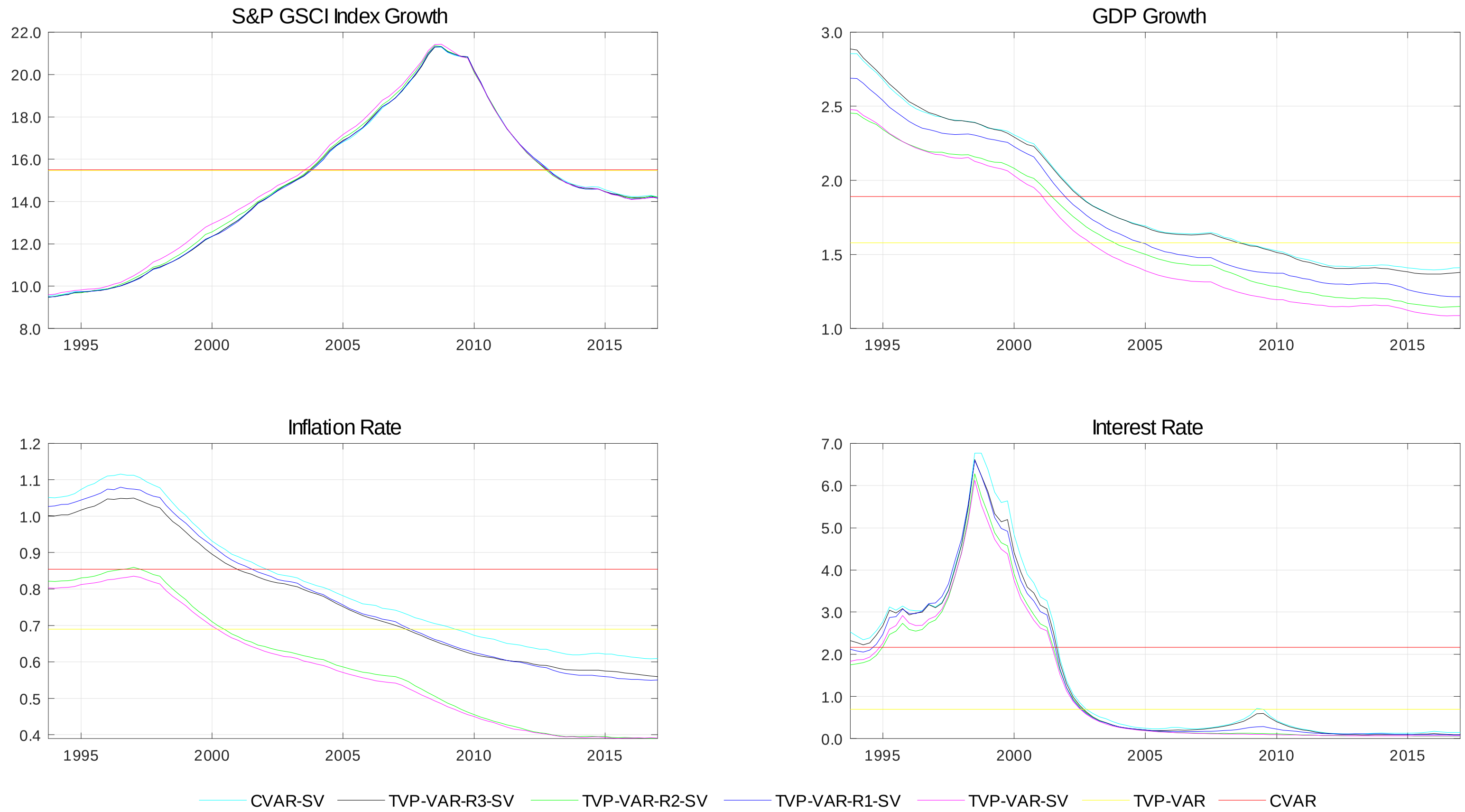

Figure 2. Standard Deviation (Median values) of the Innovations in each Equation for all Models.

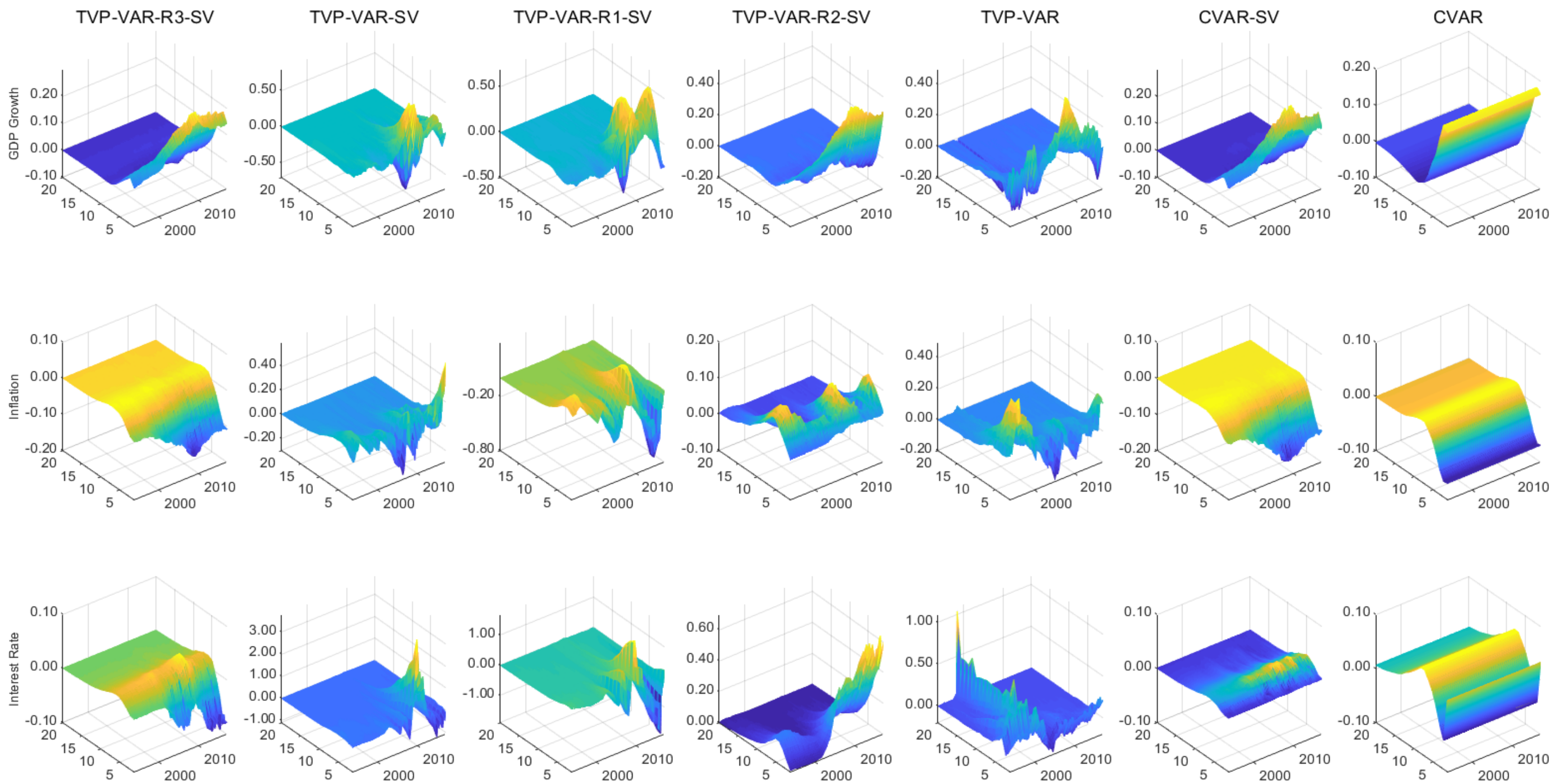

Figure 3. Median Time-Varying IRF to an External Shock. The shock is normalized to increase the Terms of Trade growth by 1% at each point in the sample period.

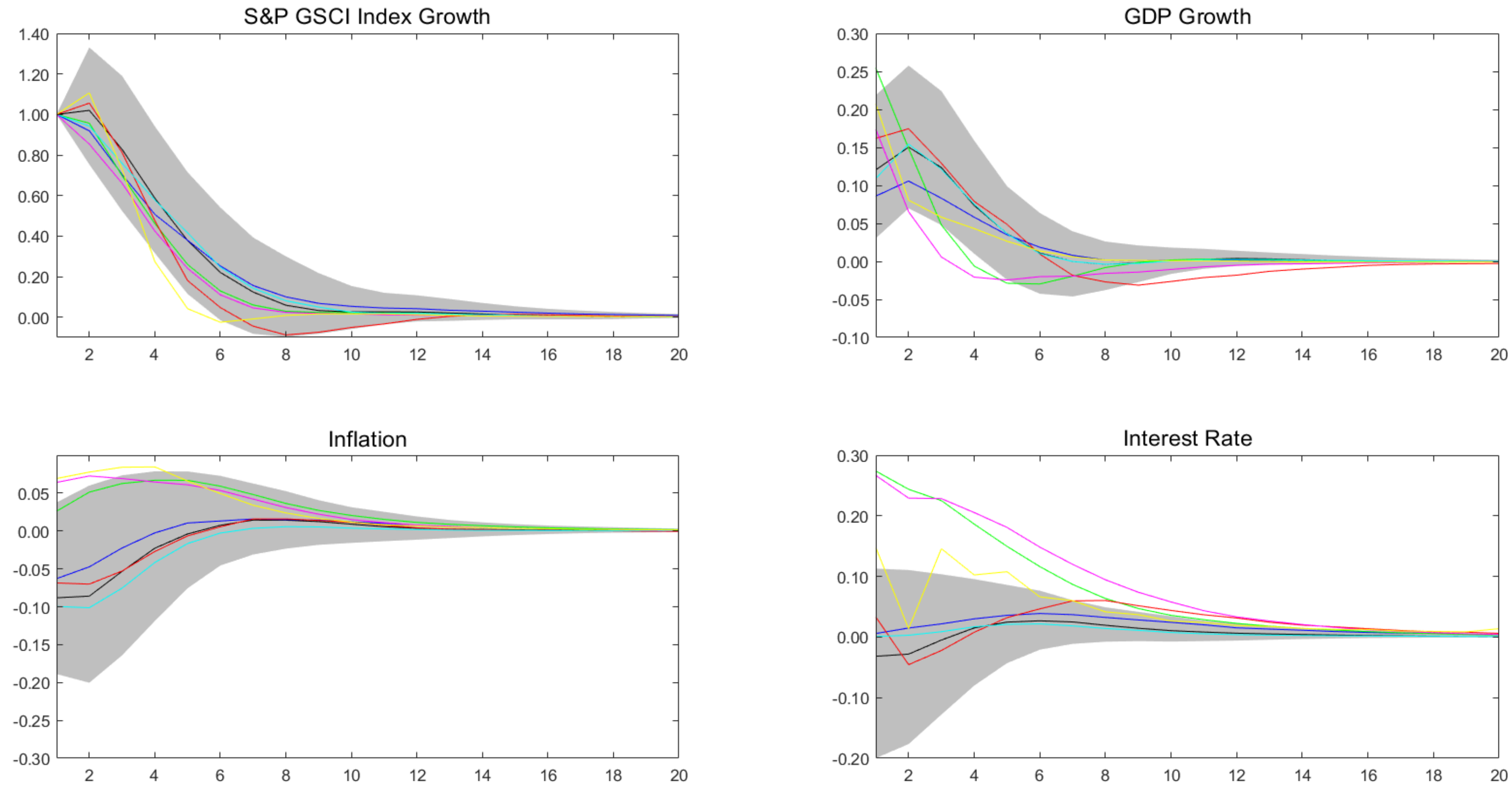

Figure 4. Time-Varying Impulse Responses to an External Shock. The black line represents the TVP-VAR-R3-SV model and the shaded area its 68% error band; the blue line represents the TVP-VAR-R1-SV model; the green line represents the TVP-VAR-R2-SV model; the red line represents the CVAR model; the cyan line represents the CVAR-SV model; the magenta line represents the TVP-VAR-SV model; and the yellow line represents the TVP-VAR model.

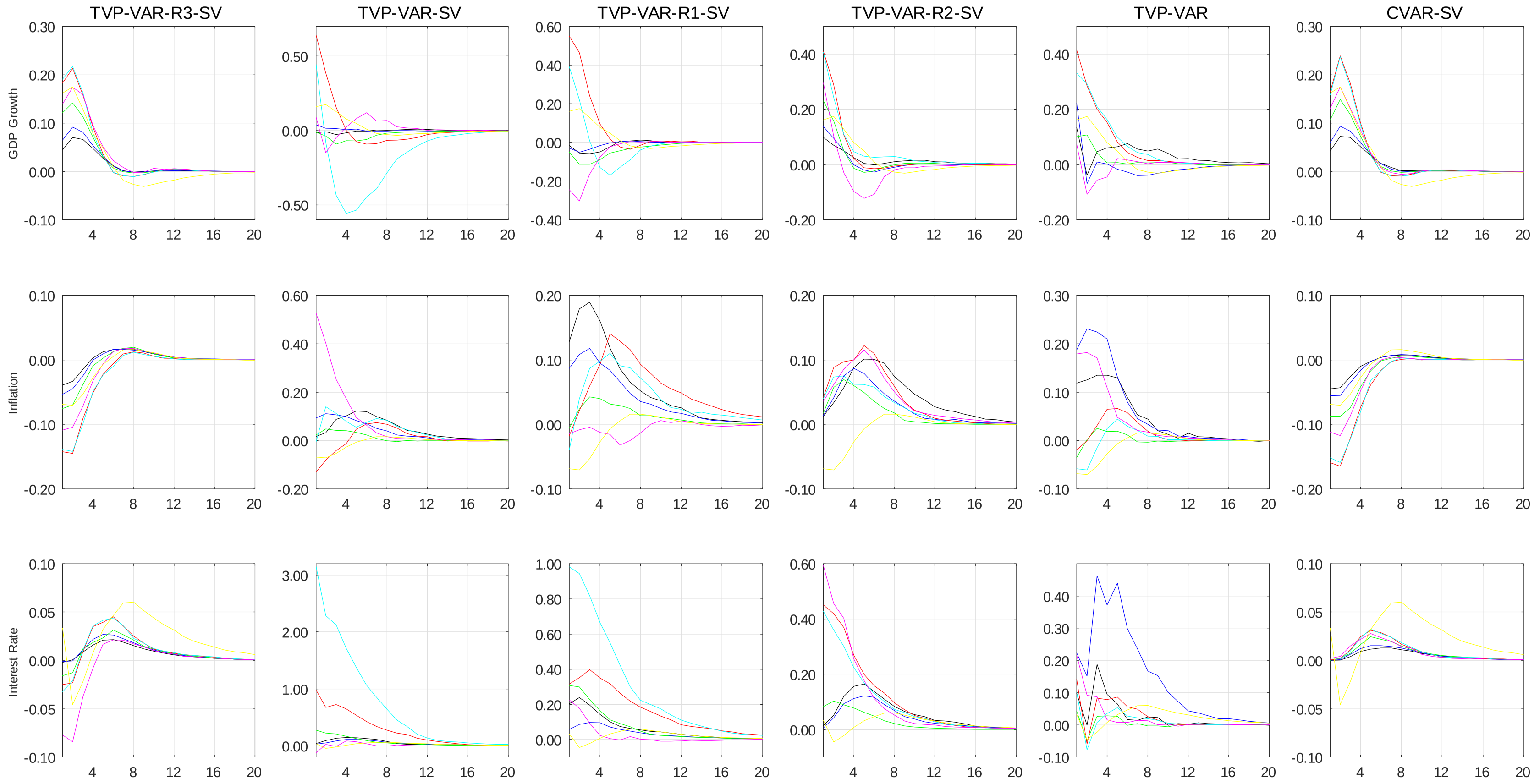

Figure 5. Impulse Responses at Different Time Periods to an External Shock (Median Values). 2017Q1 - magenta line; 2010Q1 - cyan line; 2008Q4 - red line; 2003Q1 - green line; 1999Q1 - blue line; 1994Q1 - black line; CVAR Model - yellow line.

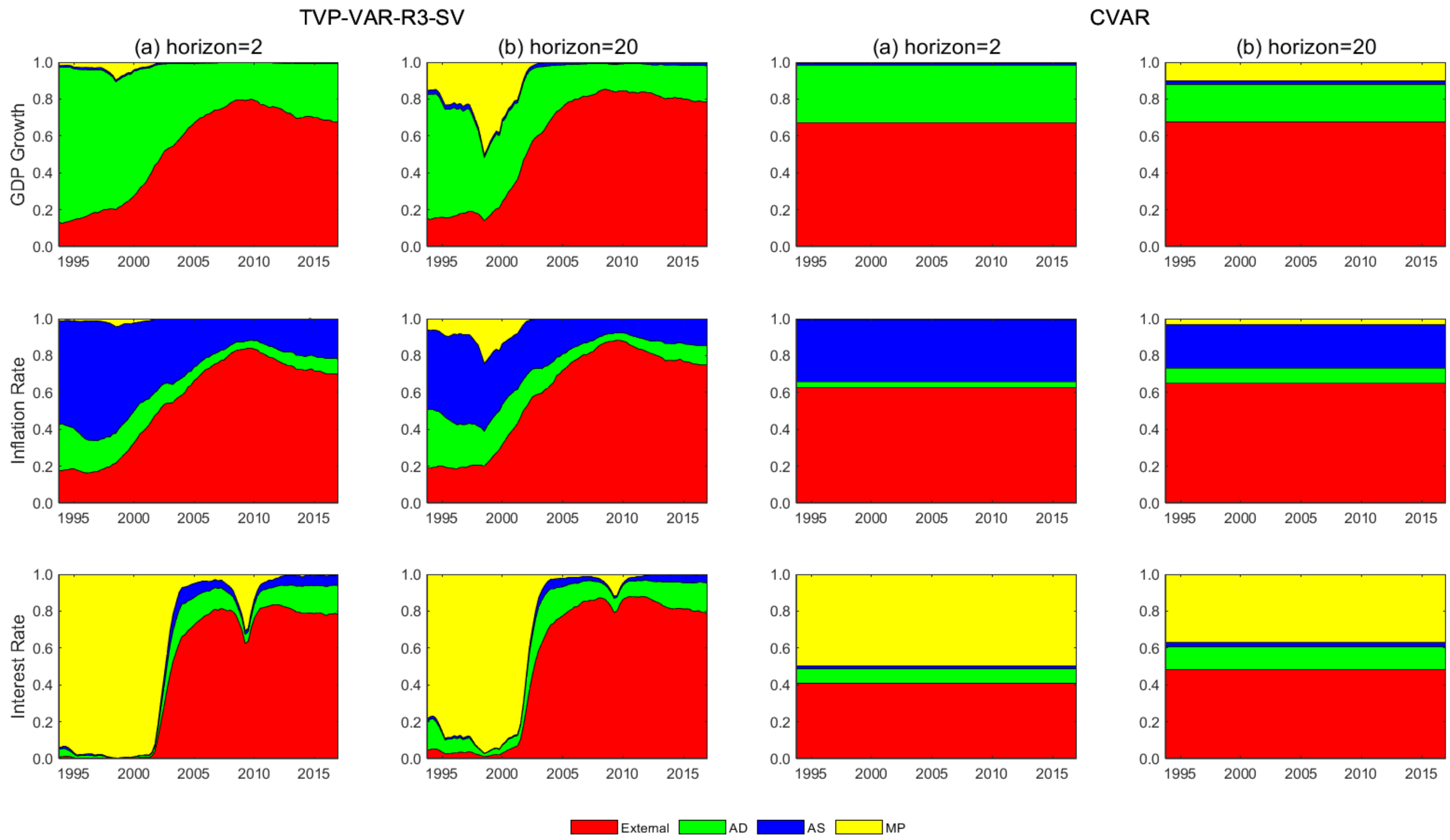

Figure 6. Time Evolution of the Variance Decomposition of GDP Growth, Inflation Rate and Interest Rate for the TVP-VAR-R3-SV and CVAR Models at Different Horizons.

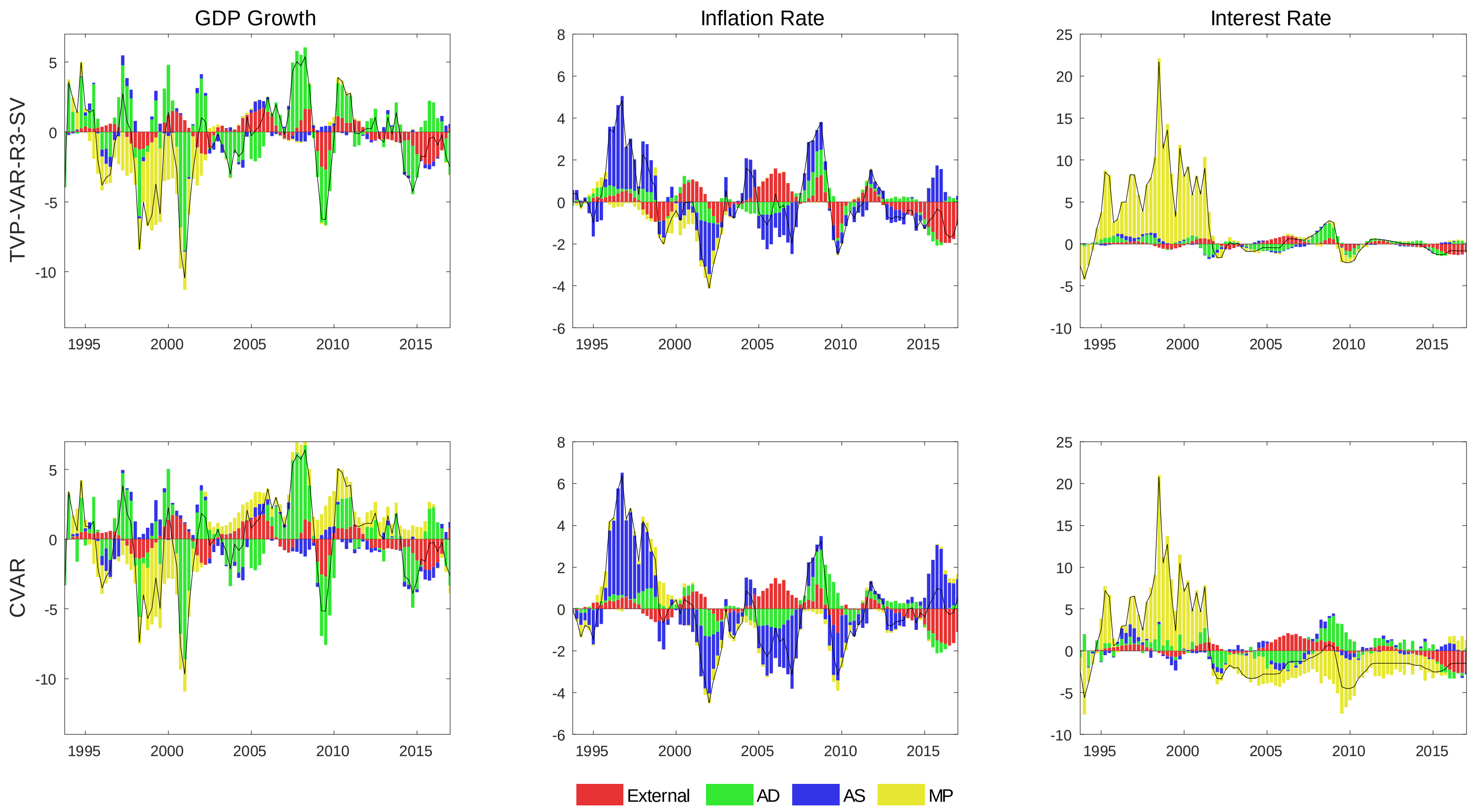

Figure 7. Historical Decomposition of GDP Growth, Inflation Rate and Interest Rate for the TVP-VAR-R3-SV and CVAR Models.

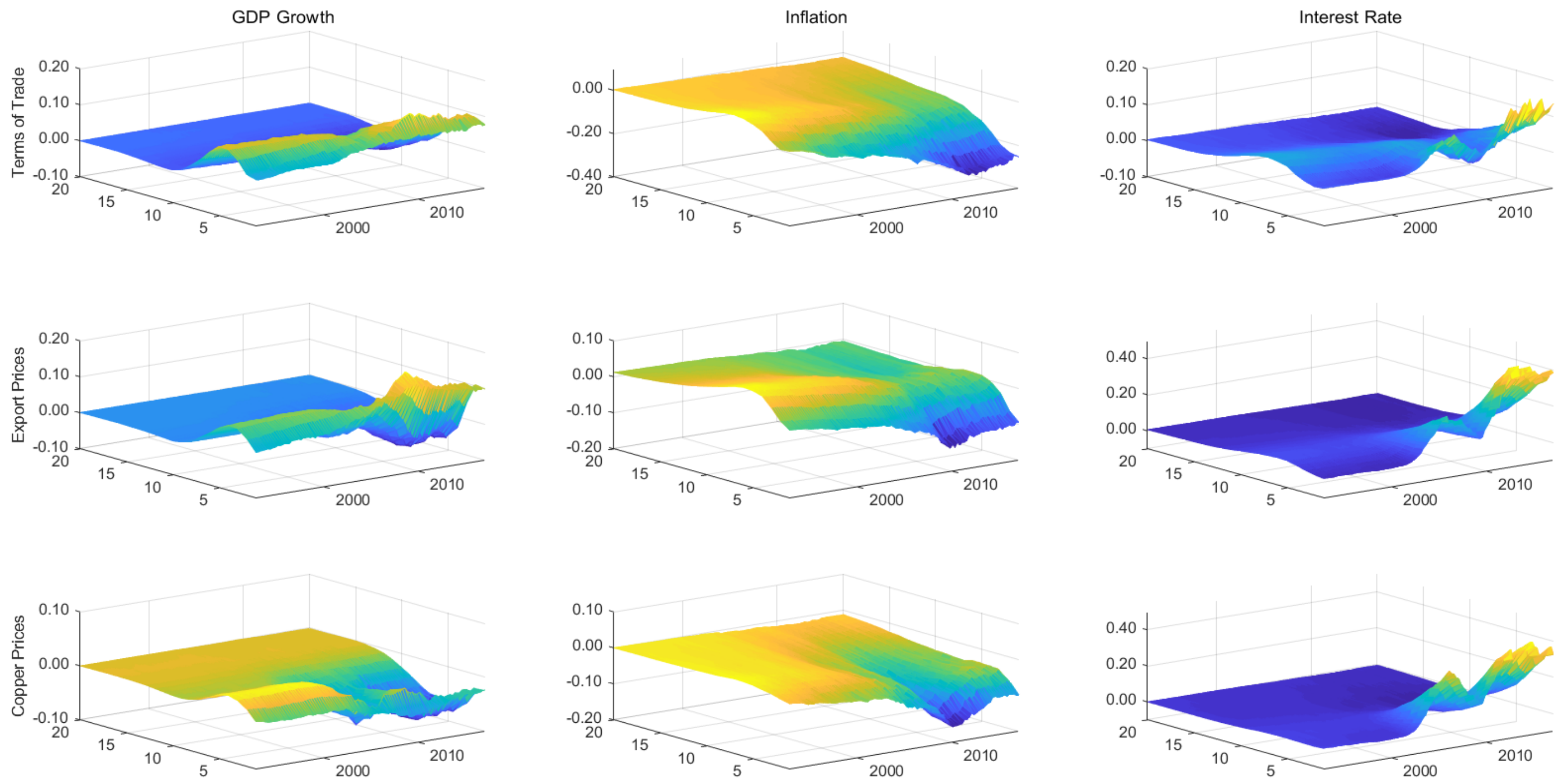

Figure 8. Median Time-Varying IRF to an External Shock for alternative External Variable: Terms of Trade, Export Prices and Copper Prices, for the TVP-VAR-R3-SV Model. The shock is normalized to increase the external variable by 1% at each point in the sample period.

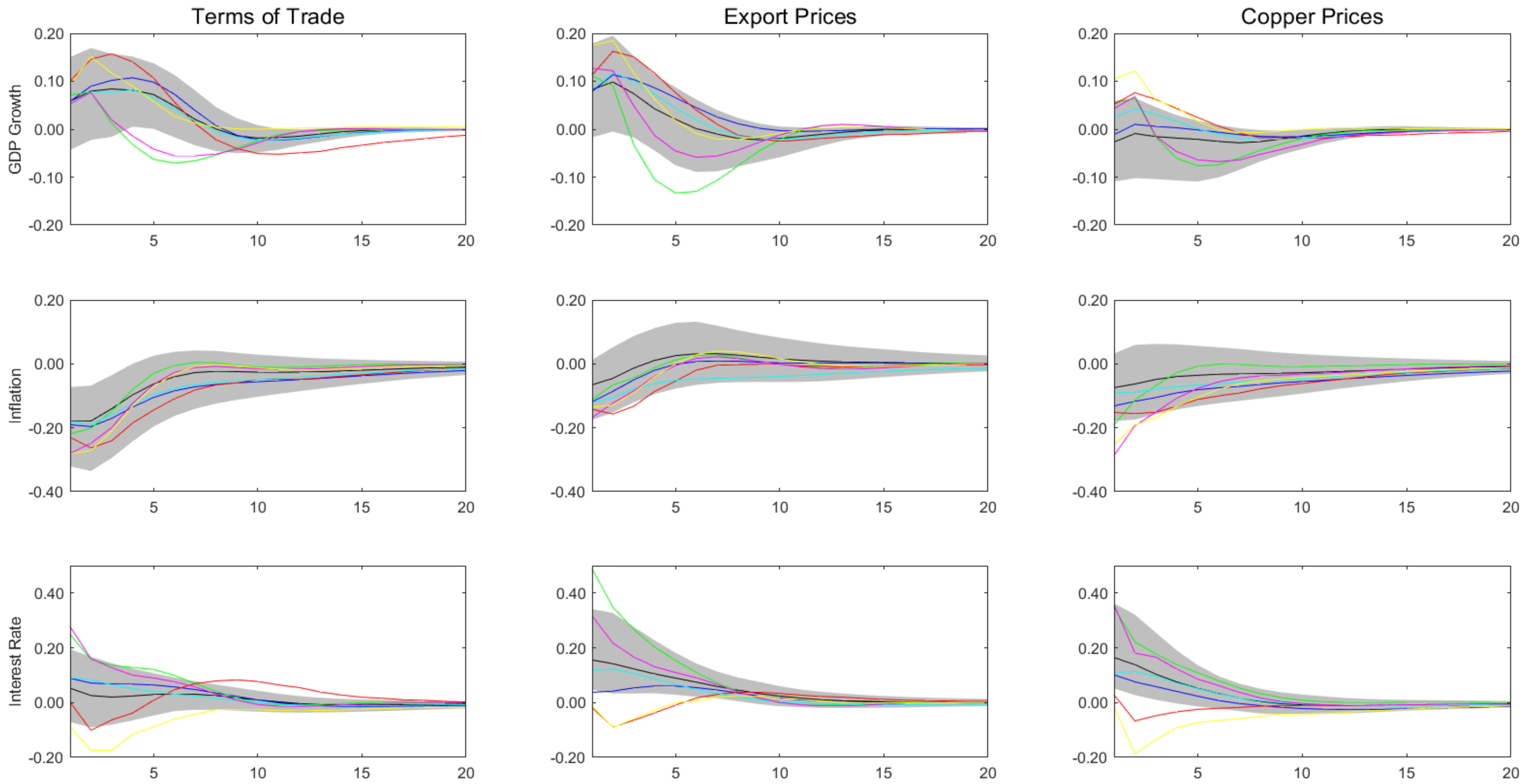

Figure 9. Time-Varying Impulse Responses to an External Shock using Terms of Trade, Export Prices and Copper Prices. The black line represents the TVP-VAR-R3-SV model and the shaded area its 68% error band; the blue line represents the TVP-VAR-R1-SV model; the green line represents the TVP-VAR-R2-SV model; the red line represents the CVAR model; the cyan line represents the CVAR-SV model; the magenta line represents the TVP-VAR-SV model; and the yellow line represents the TVP-VAR model.

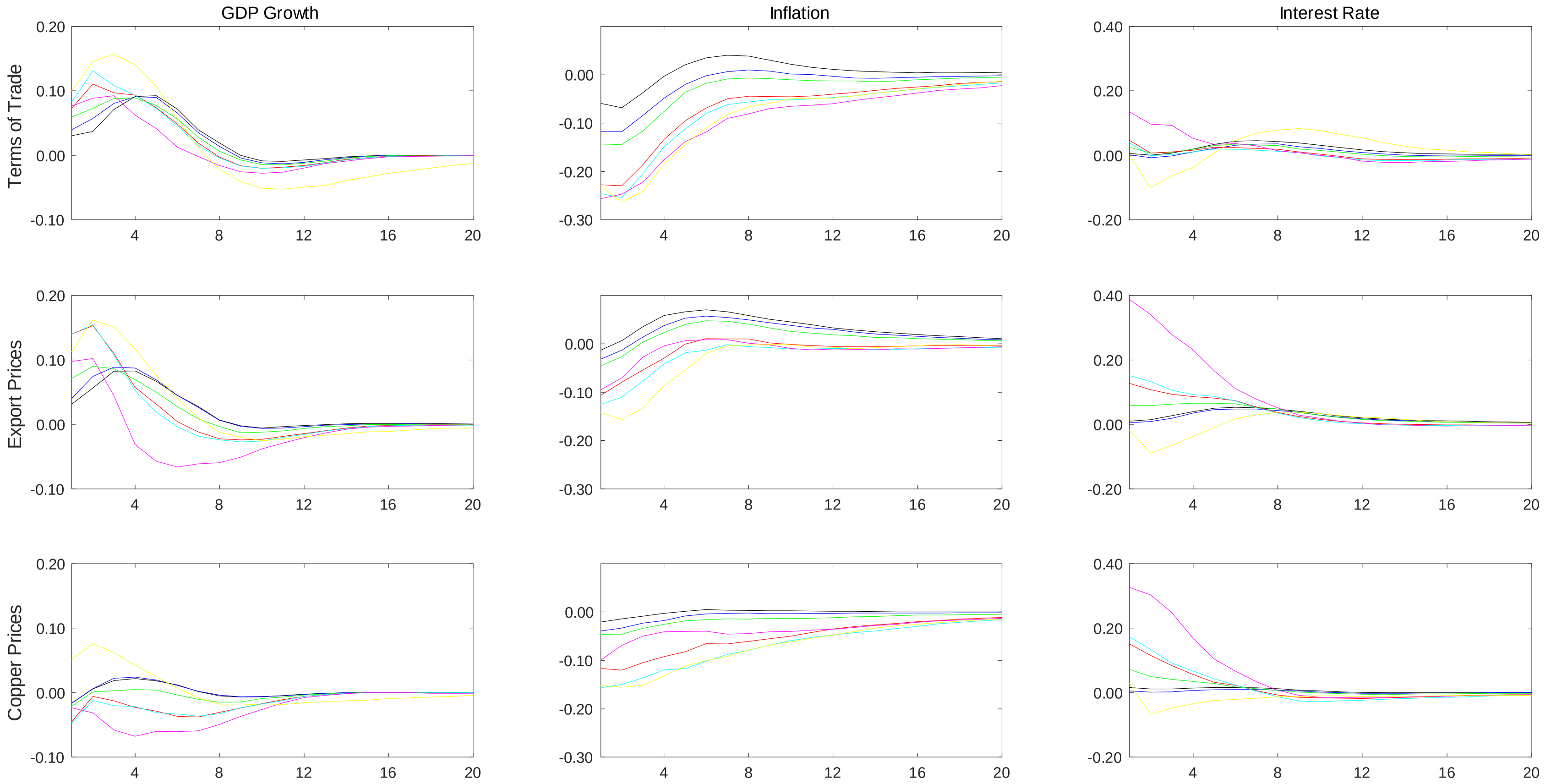

Figure 10. Impulse Responses at Different Time Periods to an External Shock in the TVP-VAR-R3-SV Model for alternative External Variable: Terms of Trade, Export Prices and Copper Prices (Median Values). 2017Q1 - magenta line; 2010Q1 - cyan line; 2008Q4 - red line; 2003Q1 - green line; 1999Q1 - blue line; 1994Q1 - black line; CVAR Model - yellow line.

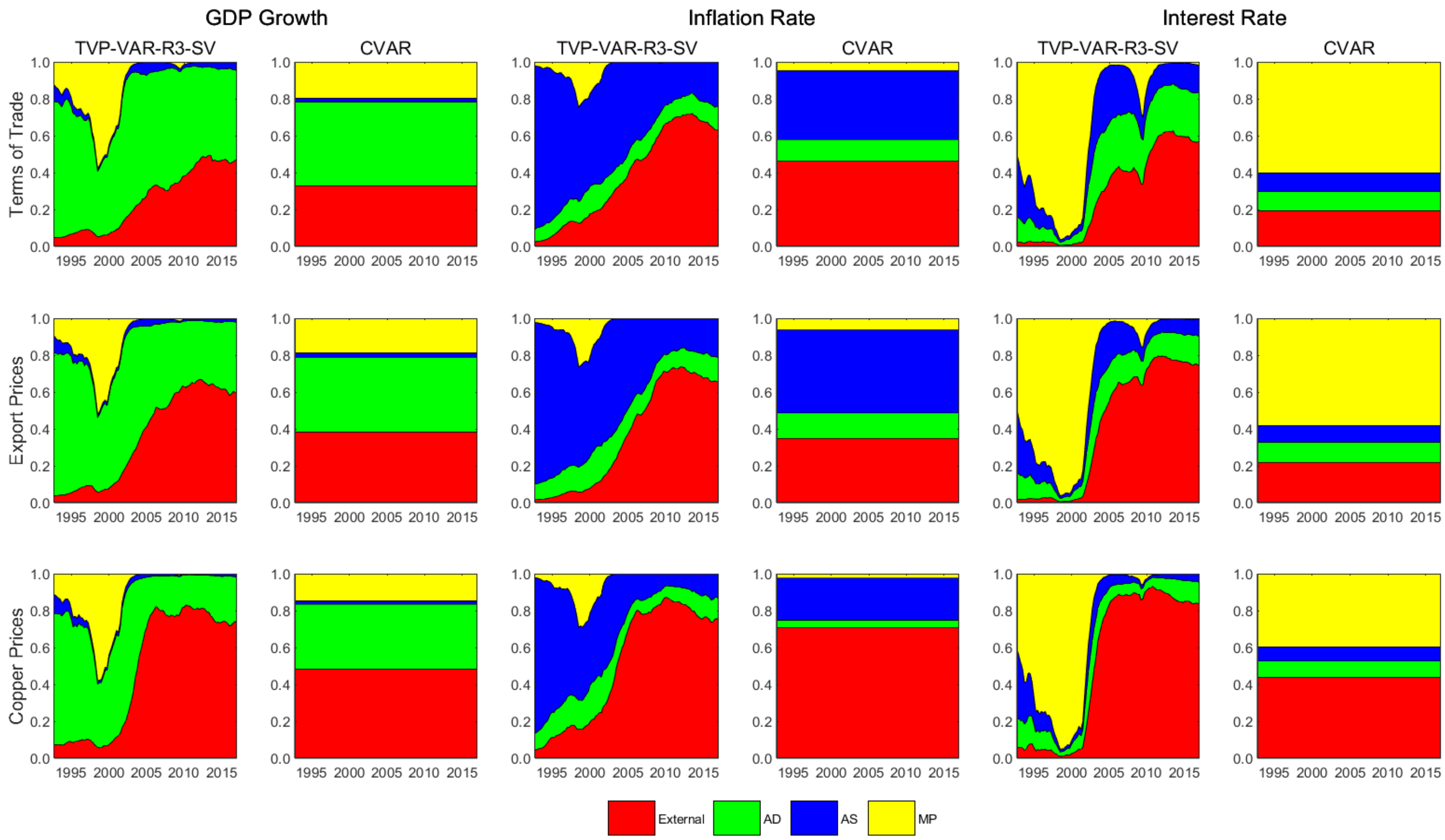

Figure 11. Time Evolution of the Variance Decomposition of GDP Growth in the TVP-VAR-R3-SV and CVAR Models for alternative External Variables for $h = 20$.

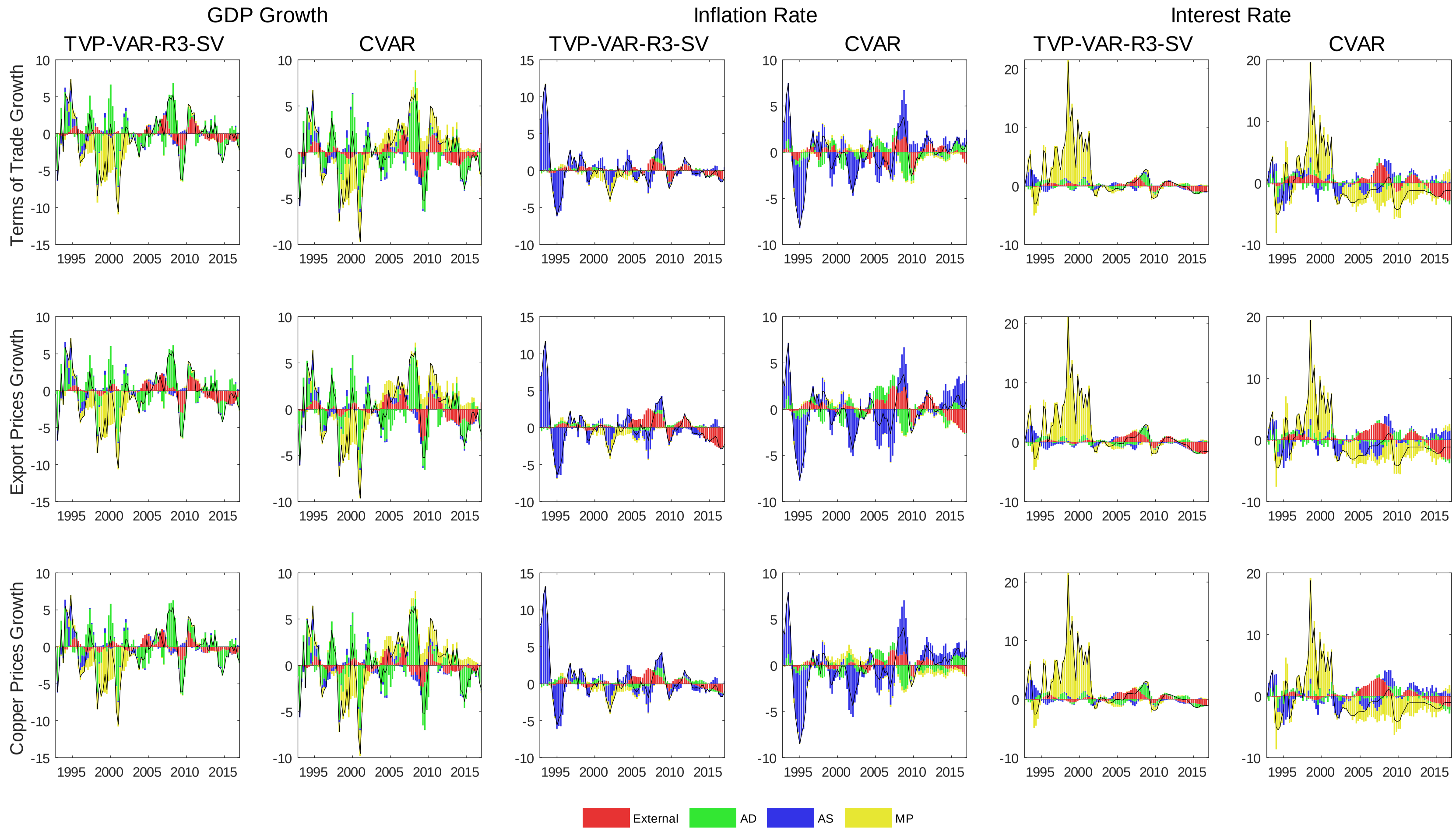

Figure 12. Historical Decomposition of GDP Growth, Inflation Rate and Interest Rate for the TVP-VAR-R3-SV and CVAR Models for various External Variables.

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