PONTIFICIA UNIVERSIDAD CATÓLICA DEL PERÚ

FACULTAD DE CIENCIAS SOCIALES

Evolution over Time of the Effects of Fiscal Shocks in the Peruvian Economy: Empirical Application Using TVP-VAR-SV Models

Tesis para obtener el título profesional de Licenciado en Economía que presenta:

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Lima, 2022

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Agradecimientos

Con cariño a mi padre Félix que siempre me alentó y al que le mando un beso al cielo. Sé que desde donde te encuentras estás muy orgulloso de mis logros, y con la ayuda de Dios se vienen muchos más. Con amor a mi madre Jenny, que día a día me muestra su apoyo incondicional. Sin ustedes nada de esto sería posible.

A mi hermana Claudia y a mis tíos maternos por el afecto y la ayuda.

A todas las personas que me acompañaron a lo largo de mi vida universitaria. Gracias por su amistad, las risas y los buenos momentos vividos; especialmente a María Paz, Airton y Carlos.

A mi asesor Gabriel por la disciplina y perseverancia inculcada, y por ser un ejemplo a seguir en el mundo académico.

Resumen

Esta investigación evalúa el impacto y la evolución de la política fiscal sobre la actividad económica peruana en el periodo 1993T4-2018T2 usando modelos TVP-VAR-SV irrestrictos y restrictos siguiendo el enfoque de Chan y Eisenstat (2018a). Los resultados señalan que la inclusión de volatilidad estocástica es indispensable y que no hay una clara evidencia de parámetros cambiantes según dos criterios de selección bayesianos. Los choques del crecimiento del gasto corriente y del crecimiento del gasto de capital impactan positivamente sobre el crecimiento del PBI (0.2% y 0.3%, respectivamente, ante un incremento de 1% de cada variable), y son importantes en la descomposición de la varianza del error de predicción (23% y 45%, respectivamente) y en la descomposición histórica del mismo (14% y 25%, respectivamente). El impacto de los choques del crecimiento de los ingresos fiscales es débil en todo el periodo de estudio. Los multiplicadores de gasto corriente y de gasto de capital se incrementan entre 1995T1-2007T4, pero luego muestran valores menores entre 2008T1-2018T2. Adicionalmente, se encuentra que los choques externos tienen un impacto fuerte y positivo sobre el crecimiento de los ingresos fiscales (0.4%). Por último, se realizan diferentes ejercicios de robustez en los que se observan pocos cambios respecto a los resultados obtenidos en el modelo baseline.

Palabras clave: Política fiscal, multiplicador fiscal, modelo VAR con parámetros variables en el tiempo y volatilidad estocástica, estimación bayesiana, economía peruana.

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1 Introduction

Peru's public debt and fiscal deficit have been among the lowest in the LATAM region over recent years. Notably, fiscal consolidation efforts between 1995-2018 turned Peru into one of the most attractive investment destinations in the region, as emphasized by Mendoza and Anastacio (2021). Therefore, it is important to assess the impact of fiscal consolidation measures on economic activity.

Theoretically, fiscal policy is a fundamental tool for affecting production through aggregate demand. Additionally, fiscal mechanisms for affecting GDP makes them a potential instrument for economic stabilization. Along these lines, it transpires from the long debate between Keynesian and neoclassical theory about the impact of fiscal policy on economic activity that its effectiveness depends on key structural economic features, such as trade liberalization, credit restrictions, the size of domestic industry, the exchange rate regime, inflation, and public debt, as indicated by Ilzetzki et al. (2013). As these variables have evolved considerably in Peru over the last three decades, it is reasonable to argue that the impact of fiscal instruments on economic activity in Peru has varied over time due to economic structure and fiscal policy changes.

During this period, the evolution of Peru's economic activity suggests that fiscal instruments, especially government expenditure, were important to explain the macroeconomic dynamics described by Mendoza and Anastacio (2021). The empirical evidence suggests procyclical and moderately countercyclical behaviors in government expenditure in 1995-2008 and 2009-2018, respectively; i.e., the fiscal stance did not remain constant, implying heterogenous impacts of fiscal shocks on economic activity over the period under study. In this regard, Rojas and Vassallo (2018) highlight the differentiated fiscal stance in 2000-2017, when Peru implemented new fiscal rules, especially for the government deficit.

Additionally, Peru is a small, open, and partially dollarized economy, affected by evolving global conditions as a commodity exporter, as indicated by Mendoza and Collantes Goicochea (2018) and Rodríguez et al. (2018). This dependence may be partially measured via indicators like export prices, terms of trade, and commodity prices, among others; e.g., positive external shocks can propel mining investment, in turn resulting in greater economic activity, as pointed out by Vtyurina and Leal (2016). At the same time, fiscal collection dynamics depends on tax revenues from commodity exports, in turn affecting the government's spending capacity, as described by Rossini et al. (2012).

Against this backdrop, this study analyzes the impact of the evolution of fiscal policy (expenditures and revenues) on GDP growth using quarterly data for 1993Q4-2018Q2. We use the methodology of time-varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV) proposed by Chan and Eisenstat (2018a) to assess the evolving effect of fiscal shocks on economic activity for each quarter in the period of the study. It should be noted that, due to the nature of this approach, the model could be over-parameterized. Therefore, we use unrestricted and restricted TVP-VAR-SV models to obtain a more detailed assessment of parameter variability and innovation heteroscedasticity. In this way, it is possible to identify more parsimonious and efficient models for calculating the impact of shocks via impulse-response functions (IRFs), forecast error variance decompositions (FEVDs), historical decompositions (HDs), and fiscal multipliers.

With an aim to identify a model for representing the behavior of fiscal policy in Peru, we establish which parameters must remain constant or vary over time. Towards this end, we use the log marginal likelihood calculated by cross-entropy (log-ML$_{CE}$) and the Deviance Information Criterion (DIC) as selection criteria for Bayesian models, as explained by Chan and Eisenstat (2015) and Chan and Grant (2016), respectively. The estimations indicate that the inclusion of stochastic volatility (SV) is determinant, but there is no clear predominance between models including parameter variability. Therefore, we study the models that include SV and discuss which one relates more closely to the stylized facts.

The results indicate that the impacts of shocks from current and capital spending on GDP growth are positive (0.2% and 0.3%, respectively, from a 1% increase in each variable) and show important percentages in the FEVDs (23% and 45%, respectively) and HDs (14% and 25%, respectively) for GDP growth. In contrast, shocks from fiscal income growth are negative and weak over most of the period of the study. Therefore, both spending multipliers are greater in magnitude to that for fiscal income. Additionally, we estimate that the impact of external shocks on fiscal income growth is positive (0.4% in response to a 1% increase in the external variable); and that the external variable plays a determinant role in the FEVDs (34%) and HDs (39%).

This article is organized as follows. Section 2 reviews the literature about empirical studies on fiscal policy. Section 3 describes the models and the two Bayesian selection criteria. Section 4 details the data and analyzes the empirical results. Section 5 explains the robustness exercises. Finally, Section 6 presents the conclusions.

2 Literature Review

The point of reference for the empirical literature on this subject is Barro (1981), who proposes a reduced-form model to estimate the effect of fiscal shocks on economic activity in the U.S., finding a fiscal spending multiplier close to zero. Later, Ramey and Shapiro (1998) use a narrative analysis approach to suggest that an expansionary fiscal policy creates a positive effect on GDP, although private consumption diminishes.

Blanchard and Perotti (2002) measure the impact of fiscal policy on GDP using a VAR/mixed-event structural approach; and find that an increase in public spending and a tax hike have a positive and negative impact, respectively, on the level of economic activity. Kuttner and Posen (2002) use a structural vector autoregressive model (SVAR) to analyze fiscal policy in Japan over 1976-1999; and find that expansionary fiscal policy has positive and significant effects on GDP. Moreover, they find that the tax-cut multiplier is around 25% higher than that for fiscal spending after four years; and that both are greater than one. Additionally, Perotti (2005) studies fiscal policy in five OECD countries using a SVAR model; and explains that the fiscal spending multiplier is positive but shows a declining trend, especially after 1980, when it was less than one. Mountford and Uhlig (2009) use a SVAR model to estimate fiscal shocks on U.S. economic activity using sign restrictions, as proposed by Uhlig (2005). The results indicate that the scenario where tax cuts are deficit-financed provides the greater economic stimulus. Moreover, the spending multiplier is less than one because the increase in fiscal spending discourages domestic and foreign investment.

For their part, Kirchner et al. (2010) use a TVP-VAR-SV model, as proposed by Primiceri (2005); and find that the fiscal spending multiplier in the Eurozone is positive, although with a declining trend. Furthermore, the multiplier diminishes as credit and debt as a percentage of GDP growth. Later, Berg (2015) used a TVP-VAR-SV model, including expenditure forecasts, which captures both unanticipated and anticipated shocks, as the latter are previously announced by the authorities. The author suggests that fiscal sustainability is the main determinant of Germany's fiscal spending multiplier (around two at the beginning and the end, although less than one at the middle of the sample).

Boiciuc (2015) studies the effects of fiscal policy (government income and spending) on Romania's GDP using a TVP-VAR-SV model. The results show that fiscal policy has a weak impact on economic activity and that the parameters do not change significantly. In the same line, Glocker et al. (2019) explore the behavior of the fiscal spending multiplier in the UK over 1966-2015 using a factor-augmented VAR model with time-varying parameters (TVP-FAVAR). The results indicate that the multiplier is positive and less than one in expansions, and greater than one in recessions, implying that the impact of fiscal spending shocks depends on the economic cycle.

Other approaches that also differentiate the impact of fiscal shocks according to the economic cycle include Auerbach and Gorodnichenko (2012), who use a smooth transition VAR model (ST-VAR) for the U.S. with control for predictable components. Their results indicate that fiscal spending multipliers are greater in recessions than in expansions; and increase when control for expectations is included. Auerbach and Gorodnichenko (2013) expand their previous research to cover a group of OECD countries. Using a univariate panel data model, the results confirm their previous findings. Furthermore, Auerbach and Gorodnichenko (2017) assess Japan's fiscal policy in 1960-2012 and obtain similar results using the same methodology. At the same time, they find that the effectiveness of fiscal policy in stimulating the economy has declined in recent years.

Regarding LATAM, Restrepo and Rincón (2006) use SVAR and structural vector error correction (SVEC) models for Chile and Colombia. The authors find that when public finances are under control, like in Chile, fiscal policy is more effective than if they lack stability and credibility, like in Colombia since the mid-1990s. For their part, Canavire-Bacarreza et al. (2013) study the effect of different kinds of taxes on GDP growth in Argentina, Brazil, Mexico, and Chile using an SVAR model; and find that the personal income tax does not have the expected negative impact on GDP growth. In contrast, the tax on corporate profits has moderately negative effects, especially in Argentina, Chile, and Mexico.

Additionally, Garry and Rivas (2017) estimate an SVAR model for selected Central American countries. They find that the contribution of public spending to GDP growth is significant in most of them over 2005-2014; and that the economic growth IRFs for current spending shocks are greater than for capital spending shocks (the latter are even negative in some countries). In the cases of Mexico, Costa Rica, and Panama, the spending multipliers reach values of 2.9, 2.6, and 2.3, respectively, when adding up the effects of current and capital spending. For their part, Holland et al. (2020) assess the effectiveness of public spending in Brazil using multiple approaches, including the threshold VAR (TVAR) model and the SVAR model with sign restrictions. They find that, irrespective of the approach taken, the public spending multiplier is small (0.01-0.26).

There are few studies about the effect of fiscal policy shocks on economic activity over time in Peru. Mendoza and Melgarejo (2006) use a SVAR model to find that a 1% increase in public spending has a positive 0.22% impact on GDP. Furthermore, they divide the sample in two sub-periods, 1980-1989 and 1990-2006; and find that the GDP IRF for a fiscal spending shock in the second sub-sample shows a stronger impact due to the strengthening of fiscal stability. Sánchez and Galindo (2013) estimate a logistic smooth transition VAR (LSTVAR) model and show that the effect of the spending multiplier is greater in recessions than in booms. For their part, Salinas and Chuquilín (2013) use a SVAR model decomposing public spending into current and capital spending. The results show that the latter has a greater effect on economic activity. For their part, Vtyurina and Leal (2016) study the effectiveness of Peru's fiscal policy in recession and boom periods over 1995-2015 using a TVAR model. They find that the current and capital spending multipliers are greater in recessions, especially the latter, although both are less than one.

From different approaches, Santa María et al. (2009) and Martinelli and Vega (2018) show different fiscal policy stylized facts over 1960-2018, highlighting the importance of fiscal responsibility in Peru's economic growth. Additionally, Lahura and Castillo (2018) and Ganiko and Montoro (2018) study specifically the behavior of fiscal income until 2017. For their part, Mendoza and Anastacio (2021) explore the history of fiscal policy over 1980-2020 and estimate a SVAR model using fiscal income, the public deficit, public debt, and multiple external variables. The results show that fiscal variables depend heavily on external shocks. Additionally, Rodríguez and Santisteban (2022) assess the impact of fiscal shocks on GDP growth using regime-switching VAR models with SV (RS-VAR-SV) over 1994Q4-2018Q4. They find that the effect of fiscal shocks and spending multipliers are positive and increase over the second part of the sample (2003Q1-2018Q4), while the impact of revenue shocks is moderately negative.

All the above-mentioned articles explore the impacts of fiscal policy, but none of them use the TVP-VAR-SV methodology. The first one to adopt this approach was Guevara (2018), who finds that the impact of fiscal spending showed a growing trend in 1993-1998, in contrast with a declining pattern in 1999-2017. However, the study does not decompose public spending into capital and current spending. Additionally, the author finds that the public debt-to-GDP ratio is the variable with the highest influence on the variability of the spending multiplier. Later, Jiménez and Rodríguez (2020) use the methodology proposed by Chan and Einsestat (2018b) to estimate hybrid TVP-VAR-SV models, with restrictions applied to certain equations, with an aim to analyze the impact of fiscal shocks on GDP growth. The authors find that the impact of expenditure shocks is positive, while the impact of revenue shocks is negative and limited. Moreover, they indicate that the current and capital spending multipliers are positive and show a growing trend over the last 20 years.

The above discussion shows that the TVP-VAR-SV methodology has been used to assess fiscal policy mainly in developed countries, with very few articles applying it to LATAM and emerging economies. In particular, there are no empirical studies on the evolution of fiscal policy and its impact on Peru's economic activity applying the restricted TVP-VAR-SV models used in this article, at the same time dividing public spending into current and capital spending. Moreover, we assess the evolution of external shocks and their impact on fiscal income over the period of the study, thereby enhancing the article's analytical value.

3 Methodology

3.1 The Empirical Model

This subsection describes the empirical model based on Chan and Eisenstat (2018a). Initially we consider the more general model and, subsequently, we specify models that include certain restrictions on the parameters and the SV. If $\mathbf{y}_t$ is an $n \times 1$ vector, the following equation describes a TVP-VAR-SV model:

$$\mathbf{B}_{0,t}\mathbf{y}_t = \boldsymbol{\mu}_t + \sum_{i=1}^{p} \mathbf{B}_{i,t}\mathbf{y}_{t-i} + \boldsymbol{\epsilon}_t, \tag{1}$$

where $\boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_t)$, $t = 1, 2..., T$, $\boldsymbol{\mu}_t$ is an $n \times 1$ vector of time-varying intercepts; $\mathbf{B}_{0,t}$ is an $n \times n$ triangular inferior matrix containing the coefficients of contemporaneous effects, with diagonal elements equal to one; $\mathbf{B}_{i,t}$ is an $n \times n$ matrix containing the parameters of the lagged variables; and $\boldsymbol{\epsilon}_t$ is the heteroscedastic innovation, such that $\boldsymbol{\Sigma}_t = diag(\exp(h_{1t}), \exp(h_{2t}), \ldots, \exp(h_{nt}))$. The logs of volatilities $\mathbf{h}_t = (h_{1t,}..., h_{nt})'$ are modeled as a random walk:

$$\mathbf{h}_t = \mathbf{h}_{t-1} + \boldsymbol{\zeta}_t, \tag{2}$$

where $\boldsymbol{\zeta}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_h)$, considering that the initial condition $\mathbf{h}_0$ must be estimated jointly with the parameters. Thus, we define a $k_\beta \times 1$ vector $\boldsymbol{\beta}_t = vec((\boldsymbol{\mu}_t, \mathbf{B}_{1t}, \mathbf{B}_{2t}, ...\mathbf{B}_{nt})')$ containing the intercepts and coefficients of the VAR model related to the variables' lags. Additionally, $\boldsymbol{\gamma}_t$ is a $k_\gamma \times 1$ vector that characterizes the contemporaneous relations between the variables. Note that $k_\beta = n(np+1)$ and $k_\gamma = n(n-1)/2$. Once the matrices have been defined, we can rewrite (1) as follows:

$$\mathbf{y}_t = \widetilde{X}_t\boldsymbol{\beta}_t + \mathbf{W}_t\boldsymbol{\gamma}_t + \boldsymbol{\epsilon}_t, \tag{3}$$

where $\widetilde{\mathbf{X}}_t = \mathbf{I}_n \otimes (1, \mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-p})$, the operator $\otimes$ is the Kronecker product, and $\mathbf{W}_t$ is an $n \times k_\gamma$ matrix containing the appropriate elements of$-y_t$.[1]

[1] For example, when $n = 3$, $\mathbf{W}_t$ has the following form: $\mathbf{W}_t = \begin{pmatrix} 0 & 0 & 0 \\ -y_{1t} & 0 & 0 \\ 0 & -y_{1t} & -y_{2t} \end{pmatrix}$

where y_{it} is the i-th element of y_t for $i = 1, 2$.

Finally, we rewrite the model in space-state form:

$$\mathbf{y}_t = \mathbf{X}_t\boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t. \quad (4)$$

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\eta}_t \quad (5)$$

where $\boldsymbol{\eta}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_\theta)$, $\mathbf{X}_t =$ $(\widetilde{X}_T, \mathbf{W}_t), \boldsymbol{\theta}_t = (\boldsymbol{\beta}'_t, \boldsymbol{\gamma}'_t)$ considering that the initial condition $\boldsymbol{\theta}_0$ must be estimated jointly with the parameters.

3.2 Competing Models

The competing models restrict a certain group of parameters in the TVP-VAR-SV model as follows: (i) the TVP-VAR model shows homoscedastic innovations; (ii) the TVP-VAR-R1-SV model keeps $\boldsymbol{\beta}_t$ constant (i.e., $\boldsymbol{\beta}_t = \boldsymbol{\beta}_0$); (iii) the TVP-VAR-R2-SV model restricts the variability of $\boldsymbol{\gamma}_t$ (i.e., $\boldsymbol{\gamma}_t = \boldsymbol{\gamma}_0$); (iv) the TVP-VAR-R3-SV model limits the change in $\boldsymbol{\theta}_t$, except for the intercepts; (v) the CVAR-SV model restricts the variability of $\boldsymbol{\theta}_t$ (i.e., $\boldsymbol{\theta}_t = \boldsymbol{\theta}_0$); (vi) the traditional CVAR model keeps $\boldsymbol{\theta}_t$ constant, and the innovations are homoscedastic.

3.3 Estimation Algorithm: Gibbs Sampling[2]

The algorithm consists in separating each group of parameters to estimate them individually, subject to updates in all other groups. The draws are based on Chan and Jeliazkov (2009), later further elaborated by Chan and Eisenstat (2018a). The TVP-VAR-SV models are estimated according to the following algorithm: (i) we obtain the draws via sequential sampling of $(\boldsymbol{\theta}|\mathbf{y}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{N}\ (\hat{\boldsymbol{\theta}}, \mathbf{K}_\theta^{-1})$, where the mean is $\hat{\boldsymbol{\theta}} = \mathbf{K}_\theta^{-1}(\mathbf{H}'_\theta\mathbf{S}_\theta^{-1}\mathbf{H}_\theta\boldsymbol{\alpha}_\theta + \mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{y})$ and the inverse variance matrix is denoted as $\mathbf{K}_\theta^{-1} = \mathbf{H}'_\theta\mathbf{S}_\theta^{-1}\mathbf{H}_\theta + \mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{X}$, where $\boldsymbol{\alpha}_\theta = \mathbf{H}_\theta^{-1}\hat{\boldsymbol{\alpha}}_\theta$. The $\mathbf{H}_\theta$, $\mathbf{S}_\theta$, $\boldsymbol{\Sigma}$, and $\hat{\boldsymbol{\alpha}}_\theta$ matrices are described in Appendix A of Chan and Eisenstat (2018a); (ii) we obtain the draws for $(\mathbf{h}|\mathbf{y}, \boldsymbol{\theta}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{N}\ (\widetilde{\mathbf{h}}, \mathbf{K}_\mathbf{h}^{-1})$, where the elements in $\boldsymbol{\Sigma}_\theta$ and $\boldsymbol{\Sigma}_h$ are conditionally independent and follow inverse gamma distributions $(\sigma^2_{\theta_i}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}$ $(v_{\theta_i} + \frac{T}{2}, S_{\theta_i} + \frac{1}{2}\Sigma_{t=1}^T(\theta_{it} - \theta_{i,t-1})^2)$ and $(\sigma^2_{\theta_i}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}\ (v_{\theta_i} + \frac{T}{2}, S_{\theta_i} + \frac{1}{2}\Sigma_{t=1}^T(\theta_{it} - \theta_{i,t-1})^2)$, respectively; (iii) we obtain the draws for $(\boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_\theta|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0)$; (iv) we obtain the draws for the initial conditions $\boldsymbol{\theta}_0$, given by $(\boldsymbol{\theta}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\widetilde{\boldsymbol{\theta}}_0, \mathbf{K}_{\boldsymbol{\theta}_0}^{-1})$, where $\mathbf{K}_{\boldsymbol{\theta}_0} = \mathbf{V}_\theta^{-1} + \boldsymbol{\Sigma}_\theta$ and $\widetilde{\boldsymbol{\theta}}_0 = \mathbf{K}_{\theta_0}^{-1}(\mathbf{V}_\theta^{-1}\mathbf{a}_\theta + \boldsymbol{\Sigma}_\theta^{-1}\boldsymbol{\theta}_1)$, as well as the draws for the initial conditions $\mathbf{h}_0$, given by $(\mathbf{h}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\widetilde{\mathbf{h}}_0, \mathbf{K}_{\mathbf{h}_0}^{-1})$, where $\mathbf{K}_{h_0} = \mathbf{V}_h^{-1} + \boldsymbol{\Sigma}_h$ and $\widetilde{\mathbf{h}}_0 = \mathbf{K}_{h_0}^{-1}(\mathbf{V}_h^{-1}\mathbf{a}_h + \boldsymbol{\Sigma}_h^{-1}\mathbf{h}_1)$; (v) we repeat steps (i) - (iv) N times.

3.4 Cross-Entropy Method[3]

Chan and Eisenstat (2015)[4] present the estimator for the log-ML$_{CE}$, which is based on importance sampling:

$$\hat{p}_{IS}(\mathbf{y}) = \frac{1}{N}\sum_{n=1}^{N}\frac{p(\mathbf{y}|\boldsymbol{\theta}_n)p(\boldsymbol{\theta}_n)}{g(\boldsymbol{\theta}_n)}, \quad (6)$$

[2] Section 4 and Appendix A of Chan and Eisenstat (2018a) provide complete details of the algorithm for estimating the TVP-VAR-SV and other restricted models.

[3] The complete details can be found in Section 4 and in Appendix B of Chan and Eisenstat (2018a).

[4] The advantages of using the cross-entropy method are explained in this document.

where $\boldsymbol{\theta}_1, ..., \boldsymbol{\theta}_N$ are the independent draws obtained from a density of importance $g(.)$. We use the cross-entropy method to choose $g(.)$ optimally, which involves selecting an importance density that can be used to identify an estimator with variance equal to zero. If we express this importance density as $g^*(.)$ and use the posterior density as $g^*(.) = g(\boldsymbol{\theta}) = p(\boldsymbol{\theta}|\mathbf{y})$ $=p(\mathbf{y}|\boldsymbol{\theta})p(\boldsymbol{\theta})/p(y)$, we obtain:

$$\hat{p}_{IS}(\mathbf{y}) = \frac{1}{N}\sum_{n=1}^{N}\frac{p(\mathbf{y}|\boldsymbol{\theta}_n)p(\boldsymbol{\theta}_n)}{g(\boldsymbol{\theta}_n)} = \frac{1}{N}\sum_{n=1}^{N}\frac{p(\mathbf{y}|\boldsymbol{\theta}_n)p(\boldsymbol{\theta}_n)}{p(\mathbf{y}|\boldsymbol{\theta}_n)p(\boldsymbol{\theta}_n)/p(y)} = p(y). \tag{7}$$

Therefore, the solution is choosing $g(.)$ similar to $g^*(.)$, such as to minimize the variance of the estimator. Given a parametric family $F = \{f(\boldsymbol{\theta}; \boldsymbol{v})\}$, indexed by a vector of parameters $\boldsymbol{v}$, we must select importance sampling $f(\boldsymbol{\theta}; \boldsymbol{v}^*) \in F$ close to $g^*(.)$. To this end, we must choose a density $\boldsymbol{v}$ that minimizes the cross-entropy distance between the optimal density and the chosen density $f(\boldsymbol{\theta}; \boldsymbol{v})$ as follows:

$$\boldsymbol{v}^*_{ce} = \arg\min_{\{v\}}\left(\int g^*(\boldsymbol{\theta})\log g^*(\boldsymbol{\theta})d\boldsymbol{\theta} - p(\mathbf{y})^{-1}\int p(\mathbf{y}|\boldsymbol{\theta})p(\boldsymbol{\theta})\log f(\boldsymbol{\theta}; \boldsymbol{v})d\boldsymbol{\theta}\right), \tag{8}$$

whose estimator is:

$$\boldsymbol{v}^*_{ce} = \arg\max_{\{\boldsymbol{v}\}}\frac{1}{L}\sum_{l=1}^{L}\log f(\boldsymbol{\theta}_l; \boldsymbol{v}), \tag{9}$$

where draws $\boldsymbol{\theta}_1; ...; \boldsymbol{\theta}_L$ are obtained through the posterior density.

3.5 Deviance Information Criterion (DIC)

Spiegelhalter et al. (2002) introduce a new selection criterion for Bayesian models, called Deviance Information Criterion (DIC), which balances the trade-off between complexity and model fit. Later, Chan and Grant (2016) improve the DIC as follows:

$$D(\boldsymbol{\theta}) = -2\log f(\mathbf{y}|\boldsymbol{\theta}) + 2\log h(\mathbf{y}), \tag{10}$$

where the first term is the likelihood function and the second one is solely a function of the data. The complexity of the model is defined as the effective number of parameters, denoted as $p_D = \overline{D(\boldsymbol{\theta})} - D(\widetilde{\boldsymbol{\theta}})$, where $\overline{D(\boldsymbol{\theta})} = -2E_\theta[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2\log h(\mathbf{y})$ is the posterior mean deviation and $\widetilde{\boldsymbol{\theta}}$ is an estimator of $\boldsymbol{\theta}$. Thus, the sum of the posterior mean deviation and the effective number of parameters can be expressed as $DIC = \overline{D(\boldsymbol{\theta})} + p_D$. As $h(\mathbf{y})$ does not depend on the parameters, we assume that $h(\mathbf{y}) = 1$ to simplify the estimation. Therefore, we obtain:

$$DIC = -4E_\theta[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2\log f(\mathbf{y}|\widetilde{\boldsymbol{\theta}}), \tag{11}$$

where the first term denotes the average of the log-likelihoods $f(\mathbf{y}|\boldsymbol{\theta})$ over the posterior draws of $\boldsymbol{\theta}$.

4 Empirical Results

4.1 Data

The variables considered in the analysis are the Export Price Index (XPI), general government current spending (GC), general government capital spending (GK), Gross Domestic Product (GDP) at constant 2007 prices, and general government non-financial income (FI). All variables for 1993Q4-2018Q2 were obtained from the Central Reserve of Peru (BCRP) website. The fiscal variables were deflated using the consumer price index (2009 = 100). We then used the Tramo-Seats methodology proposed by Gómez and Maravall (1996) to seasonally adjust the series, except for XPI. We choose the latter as foreign variable, as it captures, to a great extent, the external shock impact on GDP growth; see Ojeda Cunya and Rodríguez (2022). Moreover, according to Gániko and Montoro (2018), this variable captures practically all FI fluctuations. Additionally, we disaggregate general government non-financial spending to distinguish the impact of GC and GK on GDP growth, as in Rossini et al. (2012), BCRP (2012), Salinas and Chuquilín (2013), BBVA Research (2014), MEF (2015), Vtyurina and Leal (2016), Consejo Fiscal (2018), Jiménez and Rodríguez (2020), and Rodríguez and Santisteban (2022).

Column 1 in Figure 1 shows the evolution of the XPI, GDP, GC, GK and FI logs. The last four variables show a positive trend, with some deceleration during crisis episodes. The XPI also shows a positive trend; however, it does not show a clear pattern since the Global Financial Crisis (GFC). Column 2 in Figure 1 shows the series in annual growth rates. Hereafter, any mention of XPI, GC, GK, GDP and FI will refer to their respective annual growth rates. The behaviors of GC and GK are very similar to that of GDP until the 2009 international crisis. Additionally, FI has a similar behavior as XPI. However, in some periods they move in different directions since, unlike XPI, FI also depends on domestic demand fluctuations.

The series are fed into the TVP-VAR-SV model in annual growth rates and ordered as follows: $y_t = (XPI_t \; GC_t \; GK_t \; GDP_t \; FI_t)'$. This ordering assumes that all domestic variables respond contemporaneously to XPI shocks, as Peru is a small open economy. Moreover, the expenditure variables do not respond over the same period to GDP movements, as the fiscal budget is determined previously. Additionally, GC has a contemporaneous impact on GK, as the latter is an adjustment variable for meeting the deficit target, as highlighted by Jiménez (2003). Finally, FI adjusts automatically to changes in GDP, as tax collections depend on the level of economic activity.

4.2 Priors and Hyperparameters

The priors for initial conditions $\boldsymbol{\theta}_0$ and $\mathbf{h}_0$ are normally distributed: $\boldsymbol{\theta}_0 \sim \mathcal{N}(\mathbf{a}_\theta, \mathbf{V}_\theta)$ and $\mathbf{h}_0 \sim \mathcal{N}(\mathbf{a}_h, \mathbf{V}_h)$. We also assume, like Chan and Eisenstat (2018a), that the disturbance covariance matrices for the state equations are diagonal; i.e., $\boldsymbol{\Sigma}_\theta = diag(\sigma^2_{\theta_1}, \sigma^2_{\theta_2}, ..., \sigma^2_{\theta k_\theta})$ and $\boldsymbol{\Sigma}_h = diag(\sigma^2_{h_1}, \sigma^2_{h_2}, ..., \sigma^2_{h_n})$. The diagonal elements of $\boldsymbol{\Sigma}_\theta$ and $\boldsymbol{\Sigma}_h$ are independently distributed as follows: $\sigma^2_{\theta_i} \sim \mathcal{IG}(\upsilon_{\theta_i}, S_{\theta_i})$, $\sigma^2_{h_j} \sim \mathcal{IG}(\upsilon_{h_j}, S_{h_j})$, $i = 1, ..., k_\theta$, $j = 1, ..., k_h$, where $\mathcal{IG}$ is the inverse gamma distribution.

The set of parameters has the following means and variances: $\mathbf{a}_\theta = \mathbf{0}$, $\mathbf{V}_\theta = 10 \times \mathbf{I}_{k_\theta}$, $\mathbf{a}_h = \mathbf{0}$, $\mathbf{V}_h = 10 \times \mathbf{I}_n$. We impose small values on the degrees of freedom: $\upsilon_{\theta_i} = \upsilon_{h_j} = 5$; and establish the scale parameters so that the prior mean of σ^2_{hj} is 0.1^2. Additionally, we assume that $S_{\theta_i} = 0.01^2$ for the coefficients of the lagged variables, $S_{\theta_i} = 0.1^2$ for the intercepts, and $S_{h_j} = 0.1^2$.

4.3 Evidence of Time-Varying Parameters

Table 1 shows two statistics on the variability of coefficients and innovations in the TVP-VAR-SV model. After estimating the model, the coefficients for the intercepts, the matrix of contemporaneous effects, and the matrix of lagged variables, as well as volatility, are evaluated using the Kolgomorov-Smirnov and t statistics, as in Bijsterbosch and Falagiarda (2015) and Guevara (2018).

The Kolgomorov-Smirnov test assesses whether each coefficient comes from the same distribution; and the t statistic evaluates whether each coefficient comes from distributions with the same mean in two different periods over the sample.

We selected four specific dates in the period under study and compare the coefficient distributions in 1995Q1 (beginning of the sample) with those in 2005Q4 (middle of the sample); and then the coefficient distributions in 2006Q1 with those in 2018Q2 (end of the sample). The results indicate that all volatilities vary over time. Regarding the coefficients in the matrix of contemporaneous effects, the Kolgomorov-Smirnov and t statistics indicate that 75% and 100% of coefficients must be modeled as time-varying, respectively. For the intercepts and coefficients in the matrix of lagged variables, both statistics yield similar results: around 75% of parameters are time-varying. We also performed a robustness exercise consisting in changing one of the comparison dates: we replaced 2005Q4 with 2003Q4 and the results were very similar.

4.4 Model Selection

Considering the results from the estimation of the Akaike and Schwarz selection criteria, we estimated all models using a lag. We used 10 parallel chains and performed 11,000 simulations in each one of them, resulting in the elimination of the first 1,000. We chose 1 in every 10 simulations, resulting in a total of 10,000 simulations. We then used the latter to estimate the log-ML$_{CE}$ and the DIC.

Table 2 shows the ranking of models sorted according to the estimations of the two selection criteria. The log-ML$_{CE}$ indicates that the least-performing models are TVP-VAR and CVAR[5] (ranked 6 and 7, respectively), which reinforces the results of the Kolgomorov-Smirnov and t statistics. However, it remains unclear whether modeling time-varying parameters is indispensable, as we obtain a BF (Bayes Factor) of 2.23 in favor of the TVP-VAR model when compared with the CVAR model.

The importance of SV becomes clearer when examining the results for the CVAR-SV and TVP-VAR-SV models (ranked 2 and 3, respectively), which depart considerably from the opposite models (i.e., not including SV), with BFs favoring them by $3.1 \times (10)^{29}$ and $1.1 \times (10)^{29}$, respectively. According to the log-ML$_{CE}$, TVP-VAR-R1-SV is the best-performing model. However, the difference between the models ranked first and fifth is just 3.32 according to the BF, and therefore no model can be clearly singled out.

The results of the DIC are like those obtained from the log-ML$_{CE}$. However, there are important ranking changes. The best-fitting model is CVAR-SV, which is ranked second according to the log-ML$_{CE}$. However, the TVP-VAR-R3-SV and TVP-VAR-R1-SV models come very close, indicating, like the log-ML$_{CE}$, that there is no clear pick. For this reason, we assess the first five models according to the log-ML$_{CE}$: TVP-VAR-R1-SV, CVAR-SV, TVP-VAR-SV, TVP-VAR-R2-SV, and TVP-VAR-R3-SV. It should be noted that four of these five models are also among the first five models according to the DIC.

4.5 Evolution of the Standard Deviation of Innovations

Figure 2 shows the evolution of the standard deviation of innovations in each equation. Among the SV models, we establish that the standard deviation in the XPI equation shows a growing trend and peaks between 2008Q1-2009Q4. This continuous increase in volatility begins in 2004Q1 with the

[5] The TVP-VAR and CVAR models are not analyzed later, but are used for comparison purposes.

commodity price boom, as pointed out by Radetzki (2006), and peaks during the GFC. However, volatility declines subsequently until the end of the sample period, coinciding with the end of the commodity price cycle, as highlighted by Gruss (2014). However, we identify a slight increase in volatility when comparing its magnitude at the beginning and end of the sample. For their part, non-SV models underestimate the standard deviation between 2006Q1-2013Q4 and overestimate it for the rest of the sample.

The volatility of errors in the GC and GK equations follow differing patterns. The standard deviation in the GC equation declines until 2010Q1-2011Q4, increases until 2017Q1, and shows no clear trend thereafter. Non-SV models underestimate the standard deviation in 1995Q1-2003Q4 and subsequently overestimate it almost to the end of the sample. Meanwhile, the volatility of disturbances in the GK equation was higher and peaked immediately after the Russian-Asian crisis and the GFC. The reason is that the government boosted capital spending to offset external negative shocks, although the latter operated with a lag due to red tape and regulatory restrictions, as analyzed by Vtyurina and Leal (2016). In this context, GK is more volatile than GC, as current spending is used as an adjustment variable; i.e., its discretionary nature magnifies its fluctuations; see Jiménez (2003). It should be noted that non-SV models overestimate the standard deviation between 2003Q1-2008Q4 and underestimate it during the rest of the period.

The volatility of errors in the GDP equation shows a declining trend throughout the sample, although in 1997Q1-2000Q2 it increases slightly due to the El Niño Phenomenon (ENP) and the Russian and Asian crises. Starting in 2002Q4, when the BCRP adopted an Inflation Targeting (IT) regime, the decrease in volatility until the end of the sample becomes more evident. Additionally, the non-SV models underestimate the standard deviation in 1995Q1-2003Q4 and overestimate it in 2004Q1-2018Q2.

For its part, the volatility of disturbances in the FI equation declines during the 1998Q1-1999Q4 crisis but increases slightly between 2003Q1-2009Q4 due to the transmission of volatility from commodity prices to tax collections. It declines again during the GFC, although from 2012 it shows a positive trend. Additionally, the TVP-VAR model underestimates the standard deviation throughout the sample. Meanwhile, the CVAR model overestimates the standard deviation in 1995Q1-1997Q4, 2003Q1-2008Q4, and 2015Q1-2018Q4.

4.6 Impulse-Response Functions (IRFs)

Each model presents five different shocks: XPI (external), GC, GK, aggregate demand (AD) and FI. Figure 3 shows the median of GDP responses to GC, GK, and FI shocks normalized to 1% in each quarter. The GDP IRFs for GC shocks show positive values in all models and in each quarter. At the same time, the dynamics of the TVP-VAR-R1-SV and TVP-VAR-SV models show certain differences relative to the CVAR-SV, TVP-VAR-R2-SV, and TVP-VAR-R3-SV models.

Between 1997Q1-2008Q2, the impact of GC on GDP increased gradually in all models, reflecting the structural reforms implemented by the authorities in the 1990s, as pointed out by Mendoza and Melgarejo (2006). Starting 2012Q1, the effect begins to decline in the TVP-VAR-R1-SV and TVP-VAR-SV models, which may be associated with a considerable expansion of less flexible expenditure, resulting in a less efficient GC level, as analyzed by Consejo Fiscal (2016). However, the CVAR-SV, TVP-VAR-R2-SV, and TVP-VAR-R3-SV models suggest that the response of GDP continues to grow through the end of the sample.

Likewise, the impact of GK shocks on GDP is positive in all models throughout the period under study. The IRFs show a growing trend until 2013Q2 in all models, but subsequently it changes and becomes somewhat unclear. Additionally, the TVP-VAR-R1-SV and TVP-VAR-SV models show high values in 1997Q2-1998Q4, 2008Q1-2009Q4, and 2017Q1-2018Q2. The increase in 2008Q1-2009Q4 was caused by the GFC, while those in 1997Q2-1998Q4 and 2017Q1-2018Q4 were due to ENP episodes in those periods, which caused considerable physical capital destruction. The IRFs peak in 2013Q2, associated with substantial changes in public investment, as highlighted by Jiménez et al. (2018). However, the impact began to recede since 2014Q1, with the end of the economic stimulus plan led by the Ministry of Economy and Finance. Since 2017Q2 the IRFs show a growing trend created by an expansionary fiscal stance aimed at financing ENP-related reconstruction expenditure, as pointed out by Consejo Fiscal (2018).

Regarding FI shocks, the GDP IRFs in most models show negative and small values;[6] and the impact reaches a peak in the medium term. In some models the sign of the effect is unexpectedly positive from certain periods onwards. Guevara (2018) and Jiménez and Rodríguez (2020) find similar results, which can be explained by high tax non-compliance, as emphasized by MEF (2019), or because the FI series captures the dynamics of GDP, as indicated by Ganiko and Merino (2018). Therefore, the results found so far point to a clearer relation between empirical evidence and IRF behavior for the TVP-VAR-R1-SV and TVP-VAR-SV models. Therefore, the analysis of the following results focuses on these two models.

Figure 4 shows the median of the GDP IRFs throughout the sample for GC, GK, and FI shocks, as well as their respective confidence bands for percentiles 16 and 84. In this case we use the CVAR model for comparison (IRF in red). The GDP IRFs for a GC shock are between 0.20%-0.27% in the first quarter and cease to be significant starting the fifth-sixth quarter. Additionally, the response of GDP is underestimated by the CVAR model, although it falls within the confidence bands in all models, except for the CVAR-SV model from the fourth quarter onwards.

The GDP IRFs for a GK shock are between 0.25%-0.32% in the first quarter. Moreover, the CVAR model shows a very similar IRF, at least during the first four quarters, subsequently underestimating the impact. Like Salinas and Chuquilín (2013), BBVA Research (2013), Vtyurina and Leal (2016), Guevara (2018), and Jiménez and Rodríguez (2020), the GDP IRFs for a GK shock are higher than for a GC shock.

For their part, FI shocks do not impact GDP contemporaneously, but subsequently create a negative response, with minimum values over the medium term (between -0.02% and -0.05%), although most IRFs are non-significant. Additionally, the CVAR model shows a similar evolution, but with less negative values, thereby remaining within the confidence bands of the other models.

Figure 5 shows the responses of GDP to GC, GK, and FI shocks for 1995Q1, 1999Q1, 2003Q1, 2008Q4, and 2018Q2, when economic crises (the 1998-1999 Rusian-Asian crises and the 2007-2008 GFC), a key monetary policy change (IT adoption at end-2002) and a macroeconomic stability episode (2018) took place. The IRFs for GC and GK shocks in 1995Q1 show positive and small impacts, explained by the fact that the country was rebuilding its public finances, as pointed out by Mendoza and Melgarejo (2006). For the second period analyzed (1999Q1), the IRFs for GC and GK shocks are greater compared with the IRFs in the previous period, although the effect remains moderate. This increase is explained by the maintenance of fiscal discipline, which continued to be an important element in developing the stabilization program, thereby reinforcing the effectiveness of fiscal instruments.

Regarding the third selected period (2003Q1), in most models the GDP IRFs for GC and GK

[6] The contemporaneous effect is zero due to the identification of the models.

are greater than in the two previous dates. This is associated with a context where inflation has been controlled under IT, and therefore the impacts of GC and GK shocks on GDP are greater. Moreover, in 2003 fiscal policy aimed to reinforce public budget consolidation, as emphasized by Rossini et al. (2012).

During the GFC (2008Q4), the GDP IRFs for GC and GK shocks are the highest in most models. This ability to attenuate external shocks was due to Peru's good macroeconomic conditions (low public debt, high international reserves, and considerable capital inflows) and implementation of countercyclical fiscal policies, as pointed out by Mendoza and Anastacio (2021). Moreover, the demand for Chinese domestic goods[7] remained almost unaltered. These results indicate that fiscal expenditure plays an important role in attenuating the impact of negative external shocks on GDP.

Finally, during 2018Q2, a period of macroeconomic stability, the IRFs for GK shocks are higher, as a considerable part of public investment was dedicated to recovering the physical capital destroyed by the 2017 ENP, as indicated by Mendoza and Anastacio (2021).

For their part, the IRFs for FI shocks have an opposite sign to that expected for IRFs in 2008Q4. However, in this period we observe negative values, which become more persistent in subsequent quarters, suggesting that FI shocks have a more recessionary effect on economic activity in crisis episodes over the medium term, although in small magnitudes.

4.7 Forecast Error Variance Decomposition (FEVD)

Figure 6 shows the evolution of GDP FEVDs for horizons 2, 12, and 20. GDP FEVDs can be disaggregated according to the uncertainty associated with each one of the five shocks.

The contribution of XPI shocks was important during 2004Q1-2010Q2 as a consequence of the commodity price boom and the GFC, as pointed out by Ojeda Cunya and Rodríguez (2022), Rodríguez and Vassallo (2022), and Chávez and Rodríguez (2022). However, the importance of external shocks is considerably lower over the rest of the sample. Their contribution may have been absorbed by GC and GK shocks, as FI depends strongly on XPI and, under a cap on the fiscal deficit, the uncertainty from this variable is transferred to government expenditure, as discussed by Mendoza and Anastacio (2021). Particularly, the CVAR model indicates that XPI shocks explain 20% of GDP fluctuations, with an underestimation in 2004-2010.

For 1995Q1-1999Q4, the TVP-VAR-R1-SV and TVP-VAR-SV models show that the contribution of GC shocks is close to 35% of GDP fluctuations, due to the implementation of structural fiscal reforms. This contribution declines in 2000Q1-2010Q4, to a minimum at the end of the decade (10%), due to the increasing contribution of external shocks. Later the contribution of GC shocks grows and becomes important by the end of the sample, which is explained by an increase in public consumption in 2011Q1-2016Q4, as indicated by Consejo Fiscal (2016). Additionally, according to Mendoza and Anastacio (2021), a surge in current expenditure in 2014-2015 prevented compliance with the fiscal deficit rule (Law 30099). This greater spending flexibility can explain the greater uncertainty associated with GC. The evolution of the importance of GC shocks is similar in the CVAR-SV, TVP-VAR-R2-SV, and TVP-VAR-R3-SV models, but their contributions range between 5-15 percentage points (p.p.), above those obtained using the other two models. For its part, the CVAR model suggests that GC shocks explain 25% of fluctuations.

At the same time, GK shocks in the TVP-VAR-R1-SV and TVP-VAR-SV models are the most important in 1995Q1-2003Q2 due to systematic changes in fiscal policy. It should be noted that

[7] China moved from Peru's second (BCRP, 2009) to first trade partner, surpassing the U.S. in 2012.

GC and GK contributions decline since 2000Q1 due to the Fiscal Prudence and Transparency Law, which decelerated expenditure growth, as indicated by Mendoza and Anastacio (2021). Additionally, considering the increasing importance of external shocks since 2003Q1, the contribution of GK shocks declines to a minimum of 28% by the end of the decade. Since 2010Q1 the contribution of GK shocks increases, to 50% of GDP variability on average in 2010Q1-2018Q2. This is explained by the rise (2010-2011) and fall (2014-2015) of public investment implemented by sub-national governments; the exhaustion of the natural resources that underpinned financing, as pointed out by Jiménez et al. (2018); and an important drop in public expenditure in 2016Q4, as detailed by BCRP (2017). Moreover, the behavior of the CVAR-SV, TVP-VAR-R2-SV, and TVP-VAR-R3-SV models is similar to that of the two previous models, but their contributions are lower (5-15 p.p. less). For its part, the CVAR model suggests that GK shocks explain 45% of fluctuations.

The importance of FI shocks in GDP fluctuations has been very limited in all models and across quarters, which is probably associated with a lack of structural tax reforms; see Mendoza and Anastacio (2021). At the same time, AD shocks explain 20%-25% of GDP uncertainty throughout the 1990s, as the Peruvian economy was recovering from a crisis situation at the end of the 1980s and beginning of the 1990s, and from the 1997-1998 ENP. However, since the 2000s AD shocks declined to irrelevance by the end of the sample.

It should be noted that the FEVD for the CVAR model is similar to that for the TVP-VAR-R1-SV and TVP-VAR-SV models. In the CVAR model, GC and AD shocks take on more importance, and XPI shocks lose relevance, only at the end of the sample.

4.8 Historical Decomposition (HD)

Following the methodology proposed by Wong (2017), Figure 7 shows the GDP HDs for each shock, with an aim to measure their contributions in real values. In addition to XPI and AD shocks, GC and GK shocks also play important roles. In relative terms, the TVP-VAR-R1-SV and TVP-VAR-SV models give more relevance to XPI and GK shocks, while other models attach more importance to GC and AD shocks. For their part, FI shocks show minor contributions in all models.

In 1995Q1-2001Q4, AD shocks are mostly negative because of the 1998-1999 ENP and political tensions in 2000-2001. XPI shocks also contribute negatively due to the 1998Q1-1999Q4 Russian-Asian crises (-28% on average). At the same time, GK shocks in 1995Q1-1999Q2 were positive, explaining 10% of GDP variability, against a negative contribution from GK shocks (-20%) caused by a reduction in public investment and an increase in remunerations, as pointed out by Santa María et al. (2009).

In 2003Q1-2008Q2, XPI shocks were positive (40%) in association with the global economic boom. In contrast, GC and GK shocks had a negative contribution in 2000-2004 (-12% and -41%, respectively) due to a decentralization process that devolved expenditure competencies to sub-national governments, which were less efficient than the national government, as indicated by Jiménez et al. (2018).

In 2008Q3-2010Q4, XPI shocks deteriorated GDP (-57%) in the context of the GFC. Additionally, GC shocks have a negative (although limited) contribution in 2008-2010. For their part, GK shocks contribute positively (45%), in association with a significant increase in investment by sub-national governments and the fiscal stimulus plan, aimed at offsetting the adverse effects from the GFC.

In 2012Q3-2016Q4, XPI shocks had a negative effect on GDP (-23%) due to global deceleration and the fall in commodity prices. In contrast, the contribution of GC shocks is positive (20%) due to greater expenditure flexibility, as discussed by Consejo Fiscal (2016). However, GC shocks had negative contributions after this period. GK shocks also contribute negatively (-19%) from 2014 to the end of the sample due to the fiscal consolidation effort explained by MEF (2017).

In 2009, FI shocks have positive contributions in the CVAR-SV, TVP-VAR-R2-SV, and TVP-VAR-R3-SV models. The same holds for 2017Q3-2018Q2 in the first two models, due to the implementation of fiscal measures to stimulate the economy and promote formalization. However, these contributions are quite small throughout the sample (6%).

For its part, the evolution of the HD for the CVAR model is similar to that for the TVP-VAR-R1-SV and TVP-VAR-SV models. The contributions of GC and GK shocks are small relative to those in the first model, but greater than those in the second one, while the opposite happens with FI shocks.

4.9 Fiscal Multipliers

This subsection presents the current spending, capital spending, and fiscal income multipliers, obtained as follows:

$$m_{t,H} = \frac{\sum_{h=0}^{H} \frac{\partial \Delta y_{t+h}}{\partial \epsilon_{t,\Delta g_t}}}{\sum_{h=0}^{H} \frac{\partial \Delta g_{t+h}}{\partial \epsilon_{t,\Delta g_t}}} \times \frac{Y_t}{G_t} \times (\sigma_{\Delta g_t})^{-1}, \tag{12}$$

where $m_{t,H}$ is the fiscal multiplier in period t over H horizons; $\frac{\partial \Delta y_{t+h}}{\partial \epsilon_{t,\Delta g_t}}$ is the IRF of GDP growth in period $t+h$ for a fiscal shock in period t; $\frac{\partial \Delta g_{t+h}}{\partial \epsilon_{t,\Delta g_t}}$ is the IRF of growth in the fiscal variable in period $t+h$ for a shock on itself in period t; $\frac{Y_t}{G_t}$ is the inverse of the ratio of the fiscal variable to GDP (in levels) in period t, both seasonally adjusted and in nominal values; and $\sigma_{\Delta g_t}$ is the standard deviation of innovations in the equation for growth in the fiscal variable in period t.

Figure 8 shows the evolution of the one-year cumulative current spending, capital spending, and fiscal income multipliers. The blue line shows the multipliers obtained following (12), the black lines are the confidence bands (percentiles 16 and 84), the orange line represents the multipliers obtained using the CVAR model, and the red line shows the multipliers obtained using average ratios ($\frac{\overline{Y}}{\overline{G}}$) as in Jiménez and Rodríguez (2020). Since the multipliers reflect IRF dynamics, this subsection focuses on the multipliers for the TVP-VAR-R1-SV and TVP-VAR-SV models, as they are more consistent with empirical evidence.

In the TVP-VAR-R1-SV and TVP-VAR-SV models, current spending multipliers show a growing trend until 2007Q3, peaking at PEN 0.59 and 0.74, respectively. After this period, they decline to around PEN 0.34 and 0.39, respectively, in recent years. Thus, the average multipliers are PEN 0.34 and 0.43, respectively; i.e., close to the values estimated by BCRP (2012), Salinas and Chuquilín (2013), and BBVA Research (2014), who obtain values of PEN 0.46, 0.53 (average) and 0.30, respectively; and by Jiménez and Rodríguez (2020) (who calculate a value between PEN 0.25-0.75). It is worth mentioning that the upper band reaches PEN 0.75 in the TVP-VAR-R1-SV model between 2006Q2-2008Q4 and PEN 1.00 in the TVP-VAR-SV model between 2007Q2-2008Q3, close to the multiplier values of PEN 0.85 and 0.90 obtained by MEF (2015) and Consejo Fiscal (2018), respectively. For its part, the CVAR model underestimates the GC multiplier (PEN 0.30) throughout most of the period of the study.

The capital spending multipliers show values between PEN 0.16-0.88 throughout the period of the study. The capital spending multipliers in the TVP-VAR-R1-SV and TVP-VAR-SV models show a growing trend until 2004Q1-2005Q1 (to 0.67 and 0.88, respectively), in line with Mendoza and Melgarejo (2006). Subsequently they contract until 2009Q1-2010Q2, but subsequently resume a positive trend through the end of the period of the study, to around PEN 0.50. On average, the multipliers reach values of PEN 0.44 and 0.48, respectively; i.e., close to the boom and recession multiplier values of PEN 0.35 and 0.50 estimated by Vtyurina and Leal (2016). At the same time, these values are far from the multiplier values of PEN 0.90 (average), 1.74, and 1.08 estimated by Salinas and Chuquilín (2013), MEF (2015) and Consejo Fiscal (2018), respectively. This is due to the fact that the impact of GK on the same variable takes time to dissipate; i.e., $\frac{\partial \Delta GK_{t+h}}{\partial \epsilon_{t,\Delta g_t}}$ is high and diminishes the value of the multiplier. It is important to stress that in 2002Q3-2005Q2 the upper band in the TVP-VAR-R1-SV model is around PEN 0.90 (above PEN 1.00 in the TVP-VAR-SV model). Additionally, using average ratios, the capital spending multipliers show a growing trend, as in Jiménez and Rodríguez (2020). Moreover, the CVAR model yields a capital spending multiplier of PEN 0.37; and underestimates it throughout most of the period of the study.

For their part, most FI multipliers are negative, small, and non-significant, except for that obtained using the TVP-VAR-R1-SV model. The multipliers for the TVP-VAR-R1-SV and TVP-VAR-SV models are negative up to 2015Q1 and 2012Q1, respectively. Subsequently the sign changes, as in Guevara (2018) and Jiménez and Rodríguez (2020), resulting in average multipliers close to PEN -0.08 throughout the sample. These results are similar to those obtained by Rossini et al. (2012), Sánchez and Galindo (2013), BBVA Research (2014), and MEF (2015), who calculate the FI multiplier at PEN -0.20-0.00. Moreover, the CVAR model yields an FI multiplier of PEN -0.21; and underestimates it throughout the period of the study.

4.10 Sensitivity of FI Growth to External Shocks

This subsection analyzes the evolving impact of external shocks on FI.

4.10.1 Impulse-Response Functions (IRFs)

Figure 9 shows the median of FI responses to external shocks normalized to 1% for each quarter. IRF values in the models analyzed (TVP-VAR-R1-SV and TVP-VAR-SV) are positive and show a growing trend up to 2007Q4 (prior to the GFC), associated with the considerable surge in the average price of Peru's main export goods in 2002-2007, as mentioned by Santa María et al. (2009). However, from 2008Q1 they show a declining trend up to 2016Q4, associated initially with the GFC (2008-2009) and later with global deceleration (2012-2016), both discussed by Mendoza and Anastacio (2021). IRF values increase slightly in the last two years due to an improved international context (2017-2018).

Figure 10 shows the median of the FI IRFs for the entire sample. The TVP-VAR-R1-SV and TVP-VAR-SV models show that contemporaneous FI responses to XPI shocks are close to 0.40% and increase to around 0.50% in the two following quarters. This result coincides with the behavior of the IRF for tax revenues in the presence of a positive mineral price shock, estimated by Mendoza and Anastacio (2021). Additionally, IRF values from the CVAR model are similar to those from other models in the short run, but lower in the medium and long run. This indicates that the CVAR model is instrumental in capturing the impact of external shocks on FI during the first quarters, but loses precision in the following quarters.

4.10.2 Forecast Error Variance Decomposition (FEVD)

Figure 11 shows the evolution of the FI FEVDs throughout the sample. The contribution of XPI shocks increased from 20% to 35% between 1995Q1-2002Q4, which is associated with Peru's increasing integration into the world economy, as detailed in IDB (2006). Subsequently, in 2003Q1-2009Q3 it increases from 35% to close to 70%, due to the commodity price boom and global economic momentum, as emphasized by Santa María et al. (2009). However, after the GFC the contribution of XPI shocks diminishes gradually due to the end of the commodity price boom and the beginning of global deceleration, as pointed out by Gruss (2014). By the end of the sample, XPI shocks explain 25% of FI fluctuations. For their part, XPI shocks explain 55% of FI fluctuations in the CVAR model.

At the same time, in 1995Q1-2002Q4 the contribution of AD shocks to FI variability is explained by economic uncertainty associated with the persistent effects of the domestic crisis during the previous years, the 1998-1999 ENP, and political tensions in 2000-2001. However, the uncertainty associated with these shocks is minor (5%-10%) and practically disappears since 2005Q3. This is explained by the high level of informality, as described by Saldarriaga (2017), caused by a combination of deficient public services and weak government supervision and implementation, as indicated by Loayza (2007).

For their part, fiscal (GC, GK and FI) shocks in 1995Q1-1999Q4 represented a considerable part of FI variance (70%), which is associated with the implementation of fiscal structural reforms, as pointed out by Mendoza and Melgarejo (2006). However, in 2000Q1-2009Q4 these shocks lose relevance against the increasing contribution of external shocks.

Starting in 2010Q1, GC and GK shocks show greater contributions (especially the latter). Uncertainty associated with GC shocks is due to the increase in non-flexible expenditure, as discussed by Consejo Fiscal (2016), which may have had an impact on FI through valued added (IGV) and personal income (IR) tax collections. As a result, GC shocks explain 20% of FI variability in 2010Q1-2018Q2. For their part, GK-related FI fluctuations are explained by the impact of investment expenditure on the capital stock, which in turn has a multiplier effect on current and future productivity; i.e., this mechanism triggers shifts in the dynamics of IGV and IR collections. Thus, GK shocks explain around 35.0% of FI fluctuations by the end of the sample. It should be noted that XPI uncertainty is partially absorbed by GC and GK shocks, as pointed out in subsection 4.7. Additionally, fiscal shocks explain 40% of FI fluctuations in the CVAR model.

4.10.3 Historical Decomposition (HD)

Figure 12 shows the FI HDs for each shock, with an aim to measure their contribution to real values. Again, the TVP-VAR-R1-SV and TVP-VAR-SV models are best aligned with empirical evidence. External shocks had a significant and negative contribution in 1998Q1-1999Q4 during the Russian-Asian crises (-46% on average), which depressed export prices and, in turn, export tax revenues, as described by Santa María et al. (2009). Moreover, AD shocks show negative contributions in 1998Q2-1999Q3 during the ENP (-14%) and in 2000Q2-2001Q2 due to political tensions[8] (-20%), which discouraged domestic demand growth. Subsequently, the participation of AD shocks practically disappears, as was the case with the FI FEVD.

[8] Due to allegations of fraud in the 2000 presidential election, bribery of public officials, and other forms of misconduct, President Alberto Fujimori resigned in November 2000, and was replaced by interim President Valentín Paniagua until July 2001.

In 2004Q1-2008Q1, the contribution of XPI shocks to FI variability was positive and predominant (52%) in a context of booming commodity prices and global activity, as indicated by Mendoza and Anastacio (2021), which propelled private investment, exports, and economic activity. Especially, growing mining royalties and tax collections led to a considerable increase in FI. In contrast, GK shocks had a negative contribution in 2000Q3-2006Q4, in the context of the decentralization of the national budget, due to implementation deficiencies at the subnational level, which limited public investment growth, as described by Jiménez et al. (2018). Therefore, GK shocks decelerated growth and, in turn, FI.

In 2008Q3-2009Q4, the contribution of external shocks to FI variability was negative and predominant (-65%) due to the GFC and the fall in exports. In contrast, GK shocks had a positive contribution (19%), which offset the fall in FI by 4.0 percent points under a fiscal stimulus plan geared to attenuate negative external impacts on economic activity.

In 2010Q1-2011Q3, XPI shocks had a positive contribution (16%) due to the second commodity price boom. In 2012Q1-2016Q2, external shocks explained 50% of the fall in FI caused by global deceleration, as pointed out by Gruss (2014). At the same time, GC shocks have limited importance throughout the sample; and the contribution of FI shocks is not as relevant as that of XPI shocks.

For its part, HD dynamics in the CVAR model is similar to that in the TVP-VAR-R1-SV and TVP-VAR-SV models. However, the value of the contribution of XPI shocks is relatively lower in the CVAR model.

5 Robustness Exercises[9]

We perform three robustness exercises;[10] and Table 3 shows the results for the log-ML$_{CE}$ and the DIC. As in the case of the baseline estimation, no model is clearly superior. For comparison, in each robustness exercise we calculate the BF between the models ranked first and second according to the log-ML$_{CE}$. In each robustness exercise the DIC indicates that the CVAR-SV model is the best, confirming the baseline estimation. Moreover, the CVAR model is used solely for the sake of comparison, as it ranks poorly according to the log-ML$_{CE}$ and the DIC, as in the baseline estimation.[11]

In exercise (i) we use an alternative ordering, exchanging the positions of GC and GK, as changes in public investment can have a contemporaneous impact on current expenditure; e.g., more road, hospital, or school building projects require more workers and logistics staff, resulting in higher payroll expenditure (a considerable portion of GC).

The two best models according to the log-ML$_{CE}$ are TVP-VAR-R1-SV and TVP-VAR-SV, with a BF of 1.22 in favor of the former. All seven models show that the impacts of GC and GK shocks on GDP are positive, but the magnitudes of GC and GK shocks diminish and increase, respectively. As for the GDP FEVDs, GK shocks are the main source of uncertainty, although fluctuations are

[9] All figures for the results of the robustness exercises are available on request.

[10] Additionally, we performed a robustness exercise by changing the number of lags to $p = 2$. However, the impact of GC shocks is greater than that of GK shocks, which is inconsistent with the literature. We also perform a robutsness exercise using more diffuse priors. The results for the CVAR-SV and TVP-VAR-R3-SV models do not show significant changes relative to the baseline model, while the remaining models show distortions in their results. It should be noted that the priors proposed by Chan and Eisenstat (2018a) are already sufficiently diffuse, suggesting that even more diffuse priors do not contribute to improving the results.

[11] For example, comparing the TVP-VAR-R1-SV and CVAR models under robustness exercise (i) yields a BF of $1.4 \times (10)^{30}$ in favor of the former. Likewise, comparing the TVP-VAR-SV and CVAR models yields a BF of $1.1 \times (10)^{30}$ in favor of the former.

absorbed to a considerable extent by XPI shocks during the commodity price boom and the GFC. For their part, the fiscal multipliers show a similar behavior, although the magnitude of the current spending multiplier diminishes, while the capital spending multiplier increases slightly. The CVAR model shows equivalent changes across robustness exercises.

To assess the impact of fiscal variables on other economic activity indicators, in exercise (ii) we replace GDP with non-primary GDP growth (NPGDP) and with private investment growth (PI), respectively. When using NPGDP, the two best models according to the log-ML$_{CE}$ are TVP-VAR-R1-SV and TVP-VAR-SV, with a BF of 6.05 in favor of the former. Like Jiménez and Rodríguez (2020), we find that the impacts of GC and GK shocks on NPGDP are greater across all models, especially in the last part of the period of the study; and that the contributions of these shocks to the NPGDP FEVDs and HDs also increase. For their part, external shocks lose some relevance in the NPGDP FEVDs and HDs. These results indicate that external shocks have a greater impact on GDP than on NPGDP, as the latter does not consider mining and hydrocarbons, which are highly dependent on the international context. At the same time, the impact of FI shocks continues to be limited. Moreover, capital spending and fiscal income multipliers behave in a similar way as in the baseline estimation, while the current spending multipliers show a growing trend.

Additionally, when replacing GDP with PI, the two best models according to the log-ML$_{CE}$ are TVP-VAR-R1-SV and TVP-VAR-SV, with a BF of 4.06 in favor of the former. In all seven models the median of the PI IRFs for GC shocks throughout the sample is close to -0.20% in the first quarter, thereby generating a crowding out effect, but loses importance thereafter. In contrast, the median of the PI IRFs for GK shocks throughout the sample is close to zero over the initial horizon and reaches higher values (0.13%-0.20%) in subsequent quarters, thereby generating a crowding in effect. Vtyurina and Leal (2016) indicate that private investment has been complemented with Public-Private Partnerships (PPPs). However, the impact of infrastructure projects on private investment often takes time to materialize due to red tape and regulatory burdens; and therefore IRFs reach their peak values between quarters 3-4 instead of the initial quarter. For their part, XPI shocks lose relevance in the PI HDs and FEVDs, mainly in the first quarters, although they grow in importance in the medium and long term starting from 2012Q1. Moreover, contrary to expectations, FI shocks have a positive impact on PI.

Moreover, the contributions of fiscal variables to PI FEVDs show a growing trend; and, by the end of the sample, GK shocks play an important role in fluctuations due to the increase in the number of PPPs in recent years. At the same time, XPI shocks are important in the FEVDs (especially in the medium and long term) and HDs for PI, which capture the dynamics of external shocks, as explained by Mendoza and Collantes Goicochea (2018). Additionally, GK shocks affect the HDs for PI less directly, while FI shocks are more relevant, as they depend strongly on XPI.[12]

In exercise (iii) we replace XPI with the rates of growth of the S&P GSCI (SP), the terms of trade (TT), and the price of copper (PC), respectively. When using SP, the two best models according to the log-ML$_{CE}$ are TVP-VAR-R1-SV and TVP-VAR-R2-SV, with a BF of 2.23 in favor of the former. Additionally, when using TT the two best models according to the log-ML$_{CE}$ are TVP-VAR-SV and TVP-VAR-R1-SV, with a BF of 1.65 in favor of the former. Moreover, when using PC, the two best models according to the log-ML$_{CE}$ are CVAR-SV and TVP-VAR-R3-SV, with a BF of 2.23 in favor of the former. In contrast with the baseline estimation, the GDP IRFs

[12] It should be stressed that robustness exercises (i) and (ii) included an estimation of the evolving impact of XPI shocks on FI. The IRFs, FEVDs, and HDs do not show substantial changes relative to the baseline estimation. The results are available on request.

for FI shocks are positive across all seven models when using SP, like in Guevara (2018); and the same happens in some models when using PC.

Especially, when using SP and PC, the GDP FEVDs reveal a considerably greater importance of external shocks in all seven models, especially since 2000, as these variables are more related to the variability of commodities, which propelled rapid economic growth in Peru during that period. In contrast, when using TT, variability is almost entirely due to GC and GK in all seven models, while the contribution of external shocks is minor, probably due to the fact that export price fluctuations are compensated by import price fluctuations. The evolution of fiscal multipliers does not show changes but, when using SP and PC, the current spending multiplier diminishes and the capital spending multiplier increases. In contrast, when using TT, the current spending multiplier increases, even surpassing the capital spending multiplier.

For its part, the impact of external shocks on FI diminishes by around 50% in the seven models when using SP, but the evolution of IRFs and their contribution to FEVDs are similar to those for the baseline estimation, while the HDs show distortions. Additionally, when replacing XPI with TT, the effect of external shocks on FI is similar to that observed in the baseline estimation, although the positive and negative trends in 1995Q1-2008Q4 and 2009Q1-2018Q2, respectively, are less pronounced. Moreover, the median of the impact remains virtually unaltered, as well as the result for the HDs; and the contribution of TT shocks on the FI FEVDs diminishes drastically. Finally, when using PC, the impact of external shocks on FI is more perceptible during the commodity price boom and the GFC across all seven models (a similar behavior is noticeable in the FI FEVDs). Additionally, the results for the HDs are similar to those in the baseline regression.

In general, there are no significant changes under the robustness exercises. With the exception of the scenario with the terms of trade as external variable, all robustness exercises confirm the importance of external shocks in the FEVDs and HDs for GDP during the global boom (2003Q1-2007Q4) and the GFC (2008Q1-2009Q4), while GC and GK shocks are more important in the rest of the period of the study. Additionally, the impact of GC and GK shocks on GDP are similar in most scenarios, although with different magnitudes. For its part, the impact of FI shocks on GDP depends on the model, the ordering of variables, and the external variable used. At the same time, we confirm that external shocks remain important throughout the sample, especially in 2003Q1-2009Q4.

6 Conclusions

This study assesses the evolving and heterogenous impact of fiscal shocks (GC, GK, and FI) on Peru's economic activity in 1993Q4-2018Q2 using unrestricted and restricted TVP-VAR-SV models, which are compared through the log-ML_{CE} and DIC to identify the most efficient one. The results indicate that SV inclusion is essential, although there is no clear evidence of parameter variability. However, it is possible to establish that the most relevant models are TVP-VAR-R1-SV and TVP-VAR-SV.

The IRFs indicate that expenditure (GC and GK) shocks have an important and positive effect on GDP, while FI shocks have weak and negative impact throughout most of the period of the study. Regarding the GDP FEVDs, expenditure shocks contribute considerably to the variance of economic activity, although they lose importance in the 2000s. For their part, FI shocks remain irrelevant throughout the period of the study. Additionally, the results for the GDP HDs reveal that, up to the middle of the sample, fiscal expenditure has been procyclical, followed by a moderately countercyclical behavior.

The current spending multiplier shows a declining trend up to 2007Q3, while the capital spending multiplier reaches peak values in 2004Q1-2005Q1. For its part, the fiscal income multiplier remains at negative and low levels until 2015Q1 and subsequently changes sign and remains at values close to zero. Additionally, we find that the impact of external shocks on FI is high and positive.

A policy recommendation that transpires from the study is the need to ensure careful public expenditure implementation. Since we find that GC and GK multipliers are less than one, fiscal spending policy in Peru would be inefficient. Additionally, while the Fiscal Council now issues opinions on fiscal policy, this study recommends giving it greater powers to assess expenditure- and revenue-related draft laws exhaustively via a cost-benefit analysis, with an aim to improve the quality of government expenditure and enhance revenue collection capacities.

Finally, future research building on this study may incorporate or combine different restrictions on the parameters of TVP-VAR-SV models; e.g., restrictions on parameter variability for selected equations, like Chan and Eisenstat (2018b). It might also be of value to use the sign restriction methodology to obtain contemporaneous GDP responses to FI shocks; and to include additional variables that can provide more information on the domestic economy. In addition, the document presents a limitation because it does not incorporate the effect of anticipated fiscal shocks on economic activity, as in Ramey (2011), because there are no exogenous government spending series available for Peru in the frequency and the sample period used in this work.

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Table 1. Tests for Time Variation Coefficients and Volatility

Kolmogorov-Smirnov test			
$\boldsymbol{\gamma}_t$			
1995Q1-2005Q4	2006Q1-2018Q2	1995Q1-2003Q4	2004Q1-2018Q2
8/10	7/10	8/10	7/10
$\boldsymbol{\beta}_t$			
1995Q1-2005Q4	2006Q1-2018Q2	1995Q1-2003Q4	2004Q1-2018Q2
24/30	21/30	22/30	21/30
$\mathbf{h}_t$			
1995Q1-2005Q4	2006Q1-2018Q2	1995Q1-2003Q4	2004Q1-2018Q2
5/5	5/5	5/5	5/5
t-test			
$\boldsymbol{\gamma}_t$			
1995Q1-2005Q4	2006Q1-2018Q2	1995Q1-2003Q4	2004Q1-2018Q2
10/10	10/10	10/10	10/10
$\boldsymbol{\beta}_t$			
1995Q1-2005Q4	2006Q1-2018Q2	1995Q1-2003Q4	2004Q1-2018Q2
24/30	18/30	22/30	21/30
$\mathbf{h}_t$			
1995Q1-2005Q4	2006Q1-2018Q2	1995Q1-2003Q4	2004Q1-2018Q2
5/5	5/5	5/5	5/5

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

Source: Own elaboration.

Table 2. Log Marginal Likelihood and DIC estimates

Model	log-ML$_{CE}$	s.e.	Rank	DIC	s.e.	Rank	p_D	s.e.
TVP-VAR-SV	-1594.0	0.06	3	2991.0	0.52	6	43.6	0.25
TVP-VAR	-1660.9	0.05	6	3012.2	0.52	7	42.0	0.22
TVP-VAR-R1-SV	**-1593.5**	**0.11**	**1**	**2971.7**	**0.46**	**3**	**46.0**	**0.22**
TVP-VAR-R2-SV	-1594.2	0.12	4	2980.8	0.59	4	43.,4	0.29
TVP-VAR-R3-SV	-1594.7	0.07	5	2968.9	0.44	2	47.6	0.18
CVAR-SV	**-1593.8**	**0.01**	**2**	**2961.9**	**0.29**	**1**	**47.4**	**0.14**
CVAR	-1661.7	0.01	7	2983.0	0.20	5	44.0	0.10

Note: Each log marginal likelihood estimate is based on 10,000 evaluations of the integraded likelihood, where the importance sampling density is constructed using 10,000 posterior draws after a burn-in period of 1,000. Each DIC estimaded and the corresponding numerical standard error (s.e.) are computed using 10 parallel chains; each consists of 10,000 posterior draws after a burn-in period of 1,000. The integrated likelihood is evaluated every 10th post burn-in draw – a total of 10,000 evaluations.

Source: Own elaboration.

Table 3. Models Selection under Robustness Exercises

Model	log-ML$_{CE}$	Rank	DIC	Rank	Model	log-ML$_{CE}$	Rank	DIC	Rank
Exercise 1: Alternative Order					Exercise 2.A: Non-Primary Real GDP				
TVP-VAR-SV	−1594.1 (0.05)	2	2986.7 (0.56)	6	TVP-VAR-SV	−1558.1 (0.04)	2	2916.3 (0.57)	6
TVP-VAR	−1660.9 (0.06)	6	3009.8 (1.09)	7	TVP-VAR	−1623.1 (0.03)	6	2939.4 (0.49)	7
TVP-VAR-R1-SV	−1593.9 (0.08)	1	2970.2 (0.36)	3	TVP-VAR-R1-SV	−1556.3 (0.14)	1	2895.7 (0.34)	2
TVP-VAR-R2-SV	−1594.9 (0.17)	4	2980.3 (1.32)	4	TVP-VAR-R2-SV	−1561.3 (0.09)	5	2915.1 (0.71)	5
TVP-VAR-R3-SV	−1595.9 (0.08)	5	2968.7 (0.61)	2	TVP-VAR-R3-SV	−1559.9 (0.08)	4	2898.0 (0.36)	3
CVAR-SV	−1594.9 (0.02)	3	2960.8 (0.21)	1	CVAR-SV	−1559.1 (0.02)	3	2890.4 (0.18)	1
CVAR	−1663.3 (0.01)	7	2982.5 (0.16)	5	CVAR	−1624.9 (0.01)	7	2910.5 (0.21)	4
Exercise 2.B: Private Investment					Exercise 3.A: S&P GSCI Index				
TVP-VAR-SV	−1810.2 (0.06)	2	3415.9 (0.54)	5	TVP-VAR-SV	−1682.2 (0.05)	3	3164.6 (0.94)	6
TVP-VAR	−1900.8 (0.03)	6	3442.9 (0.40)	7	TVP-VAR	−1760.5 (0.06)	7	3191.5 (0.94)	7
TVP-VAR-R1-SV	−1808.8 (0.11)	1	3399.5 (0.28)	3	TVP-VAR-R1-SV	−1680.7 (0.08)	1	3141.9 (0.24)	3
TVP-VAR-R2-SV	−1812.5 (0.10)	5	3412.9 (0.57)	4	TVP-VAR-R2-SV	−1681.5 (0.08)	2	3152.1 (0.68)	4
TVP-VAR-R3-SV	−1811.6 (0.05)	4	3399.0 (0.49)	2	TVP-VAR-R3-SV	−1682.9 (0.09)	5	3139.4 (0.42)	2
CVAR-SV	−1811.3 (0.03)	3	3394.4 (0.17)	1	CVAR-SV	−1682.5 (0.01)	4	3133.2 (0.19)	1
CVAR	−1902.9 (0.01)	7	3423.4 (0.12)	6	CVAR	−1760.2 (0.01)	6	3157.5 (0.26)	5
Exercise 3.B: Terms of Trade					Excercise 3.C: Copper Price				
TVP-VAR-SV	−1571.5 (0.05)	1	2946.0 (0.86)	6	TVP-VAR-SV	−1743.0 (0.14)	5	3270.9 (0.88)	5
TVP-VAR	−1627.7 (0.03)	6	2951.0 (0.76)	7	TVP-VAR	−1864.5 (1.15)	7	3338.9 (0.75)	7
TVP-VAR-R1-SV	−1572.0 (0.11)	2	2929.7 (0.39)	4	TVP-VAR-R1-SV	−1737.8 (0.07)	3	3240.4 (0.45)	4
TVP-VAR-R2-SV	−1572.1 (0.12)	3	2940.9 (0.41)	5	TVP-VAR-R2-SV	−1740.3 (0.10)	4	3251.7 (1.37)	3
TVP-VAR-R3-SV	−1573.3 (0.07)	5	2929.2 (0.53)	3	TVP-VAR-R3-SV	−1736.4 (0.13)	2	3225.2 (0.37)	2
CVAR-SV	−1572.2 (0.01)	4	2922.1 (0.18)	1	CVAR-SV	−1735.6 (0.02)	1	3218.1 (0.35)	1
CVAR	−1631.0 (0.01)	7	2928.6 (0.16)	2	CVAR	−1842.2 (0.01)	6	3297.8 (0.21)	6

Note: Same as Table 2. Standard errors are reported in parentheses.

Source: Own elaboration.

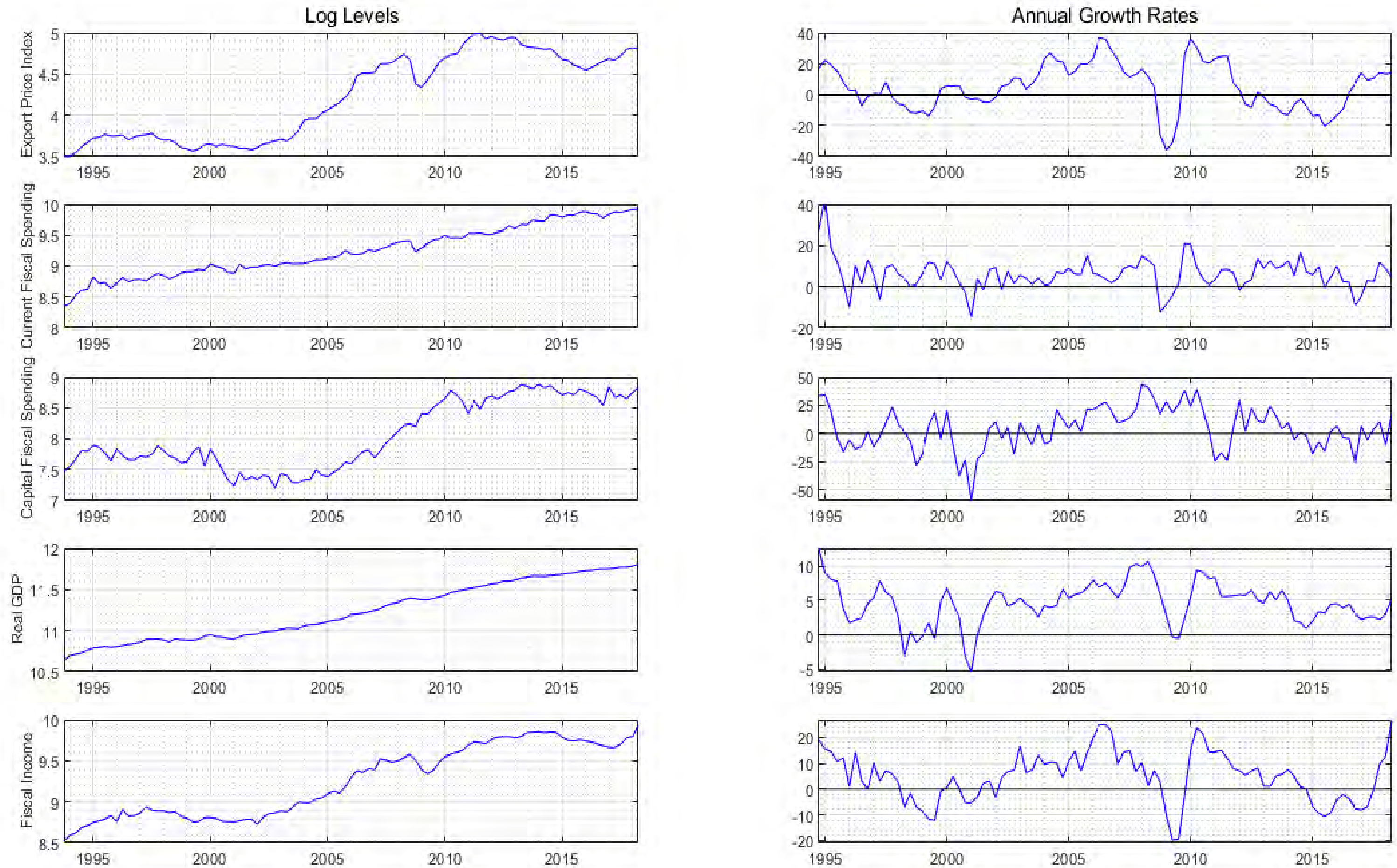

Figure 1. Time Series in Log Levels (1993Q4-2018Q2) and Annual Growth Rates (1994Q4-2018Q2).
Source: Central Reserve Bank of Peru. Own elaboration.

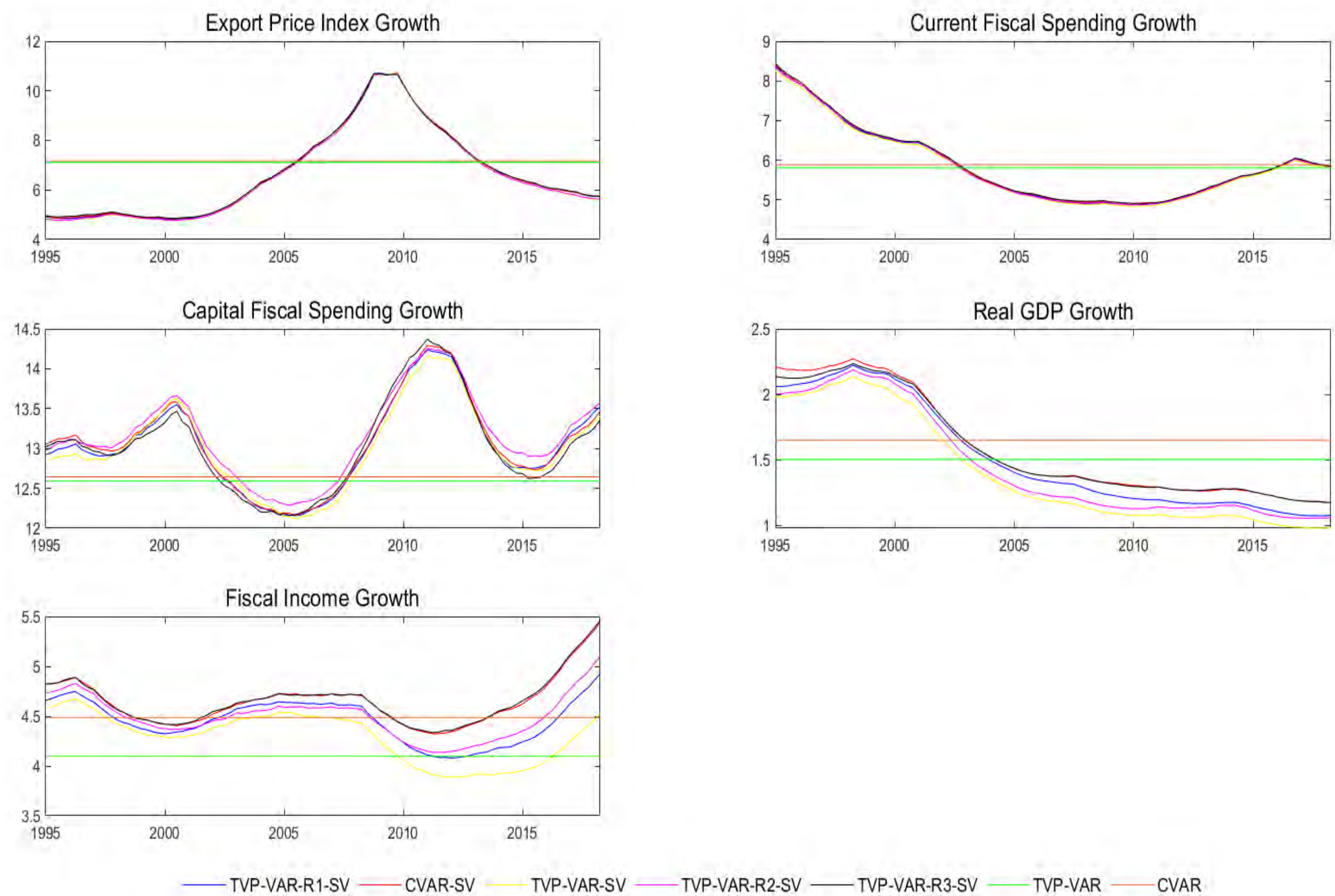

Figure 2. Standard Deviation of the Innovations in each Equation.
Source: Own elaboration.

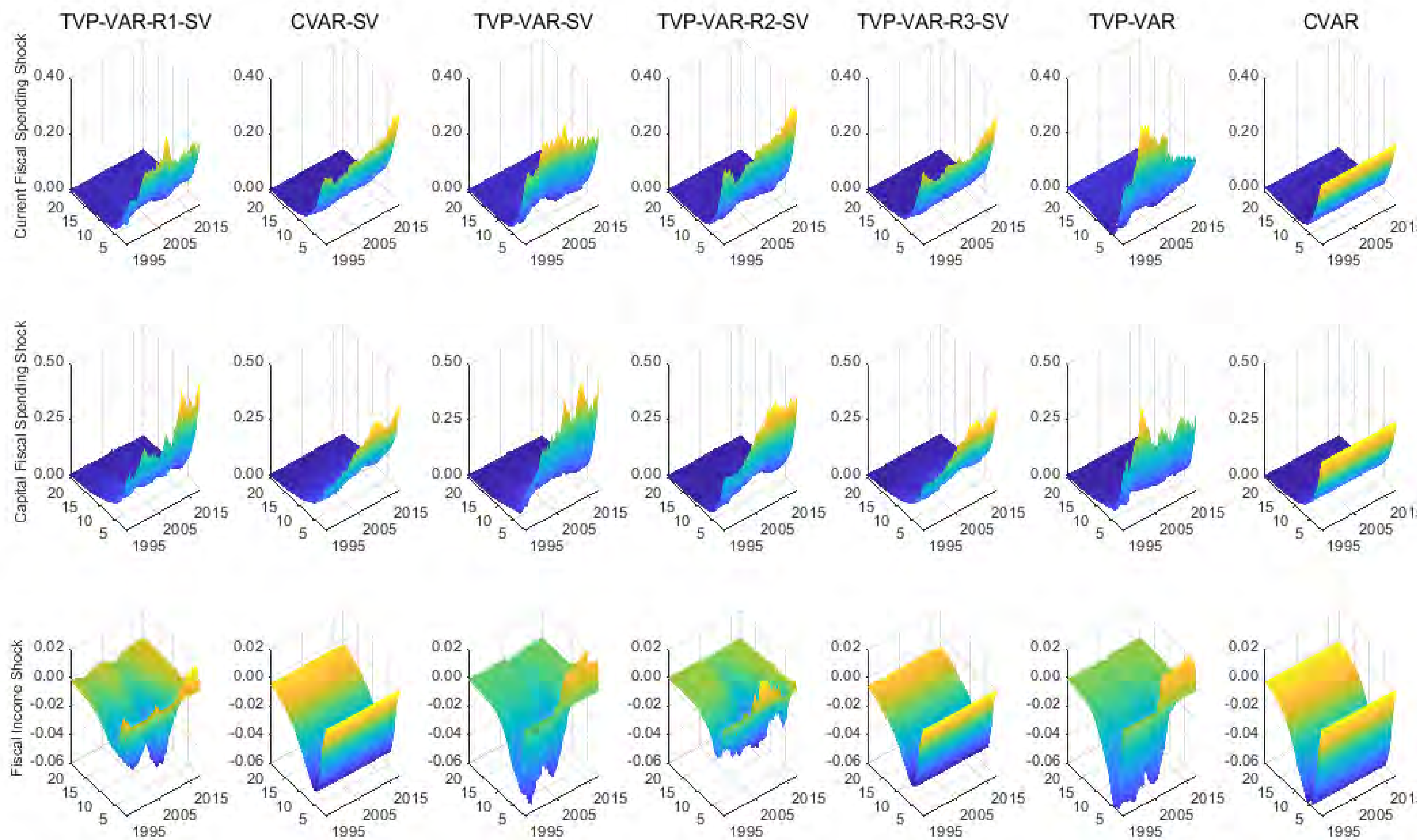

Figure 3. Median Time-Varing IRFs of Real GDP Growth to a Fiscal Current Spending Shock, a Fiscal Capital Spending Shock and a Fiscal Income Shock. The shock is normalized to increase the Fiscal Current Spending Growth, Fiscal Capital Spending Growth and Fiscal Income Growth by 1%, respectively, at each point in the sample.
Source: Own elaboration.

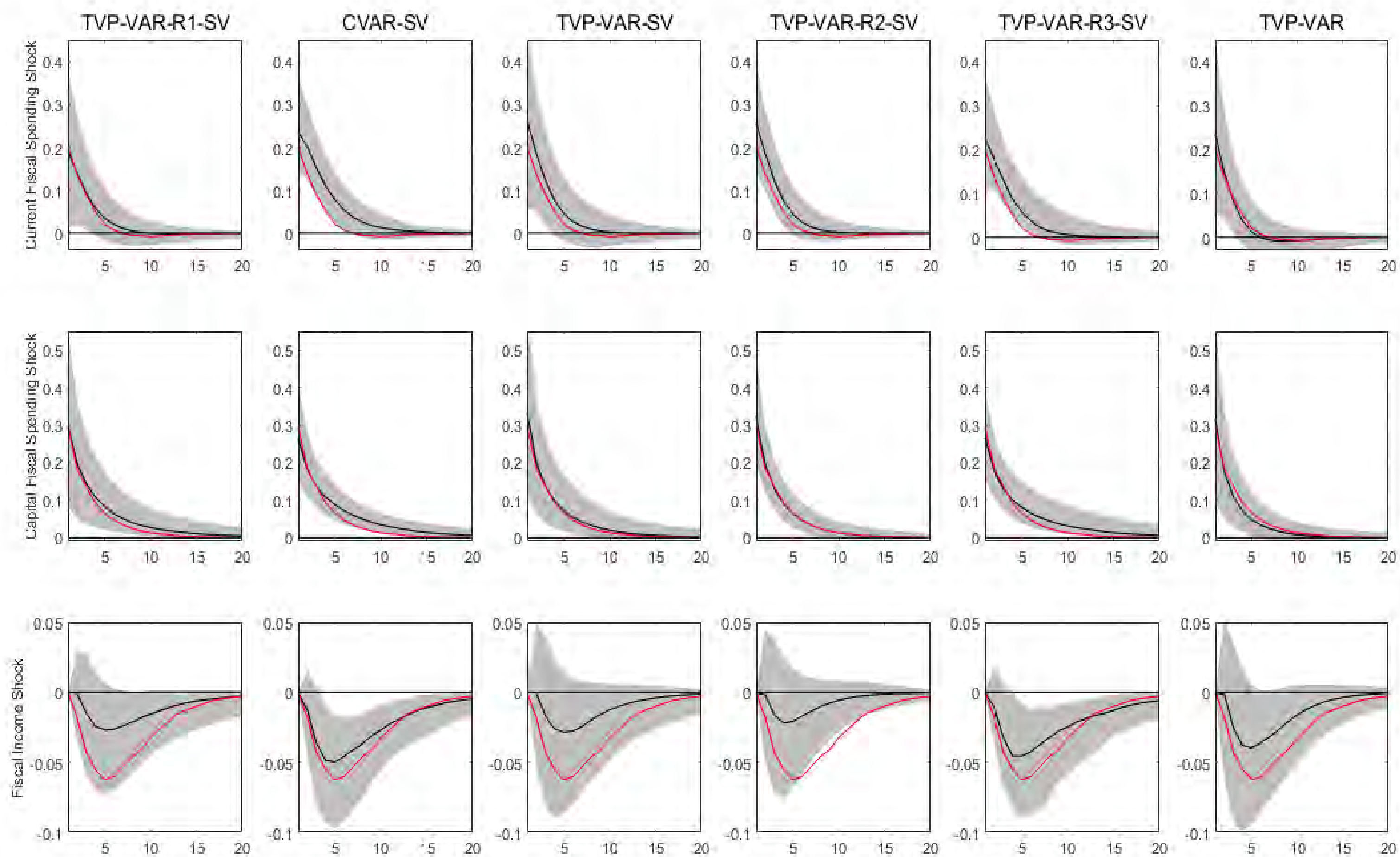

Figure 4. Median IRF of the Real GDP Growth to a Current Fiscal Spending Shock, a Capital Fiscal Spending Shock and a Fiscal Income Shock. The solid black line represents the model and the shaded area its 68% error band; as a benchmark, the solid red line represents the CVAR Model.

Source: Own elaboration.

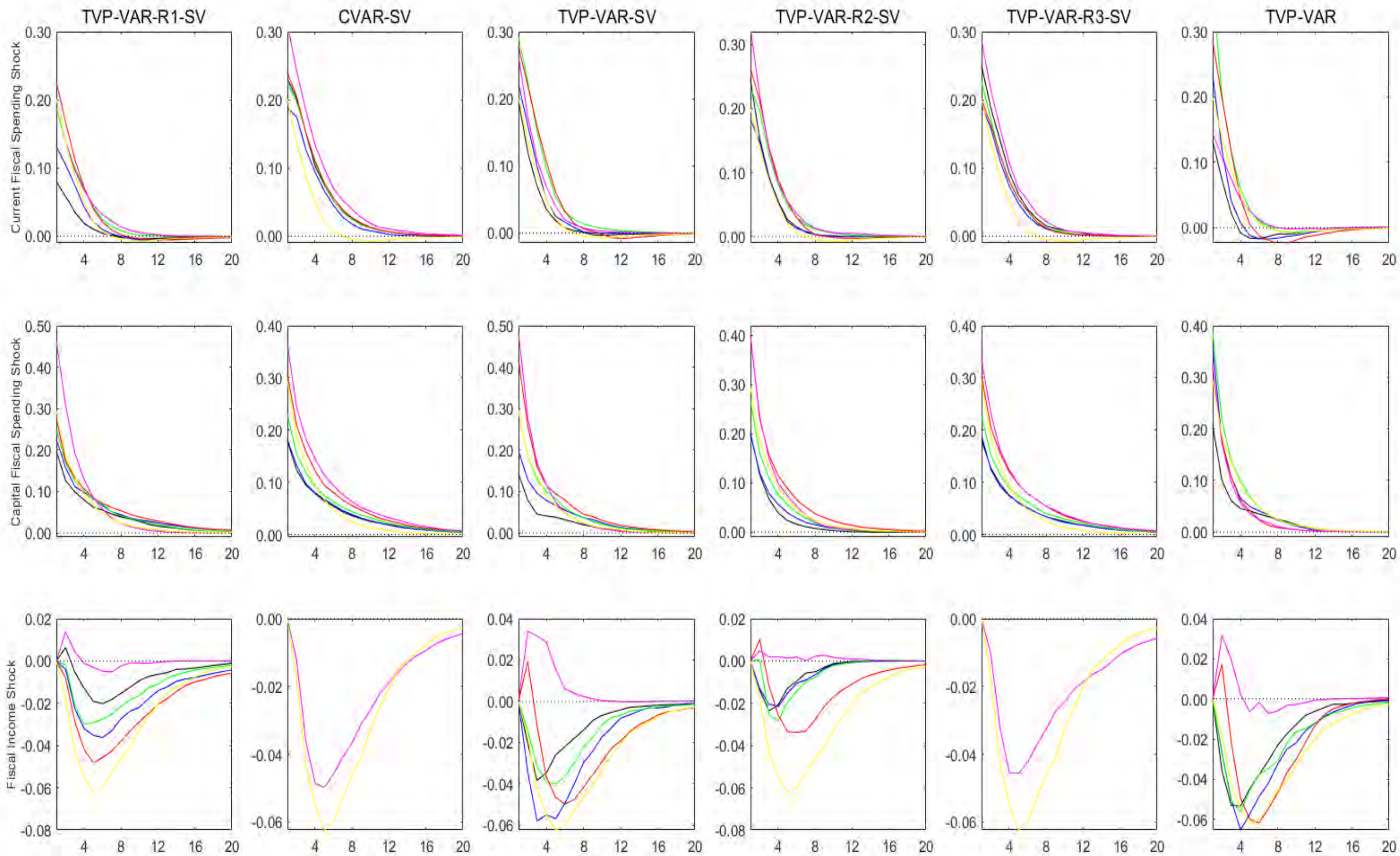

Figure 5. Median IRFs at Different Time Periods of the Real GDP Growth to a Current Fiscal Spending Shock, a Capital Fiscal Spending Shock and a Fiscal Income Shock: 2018Q2 - magenta line; 2010Q1 - cyan line; 2008Q4 - red line; 2003Q1 - green line; 1999Q1 - blue line; 1995Q1- black line; CVAR Model - yellow line.

Source: Own elaboration.

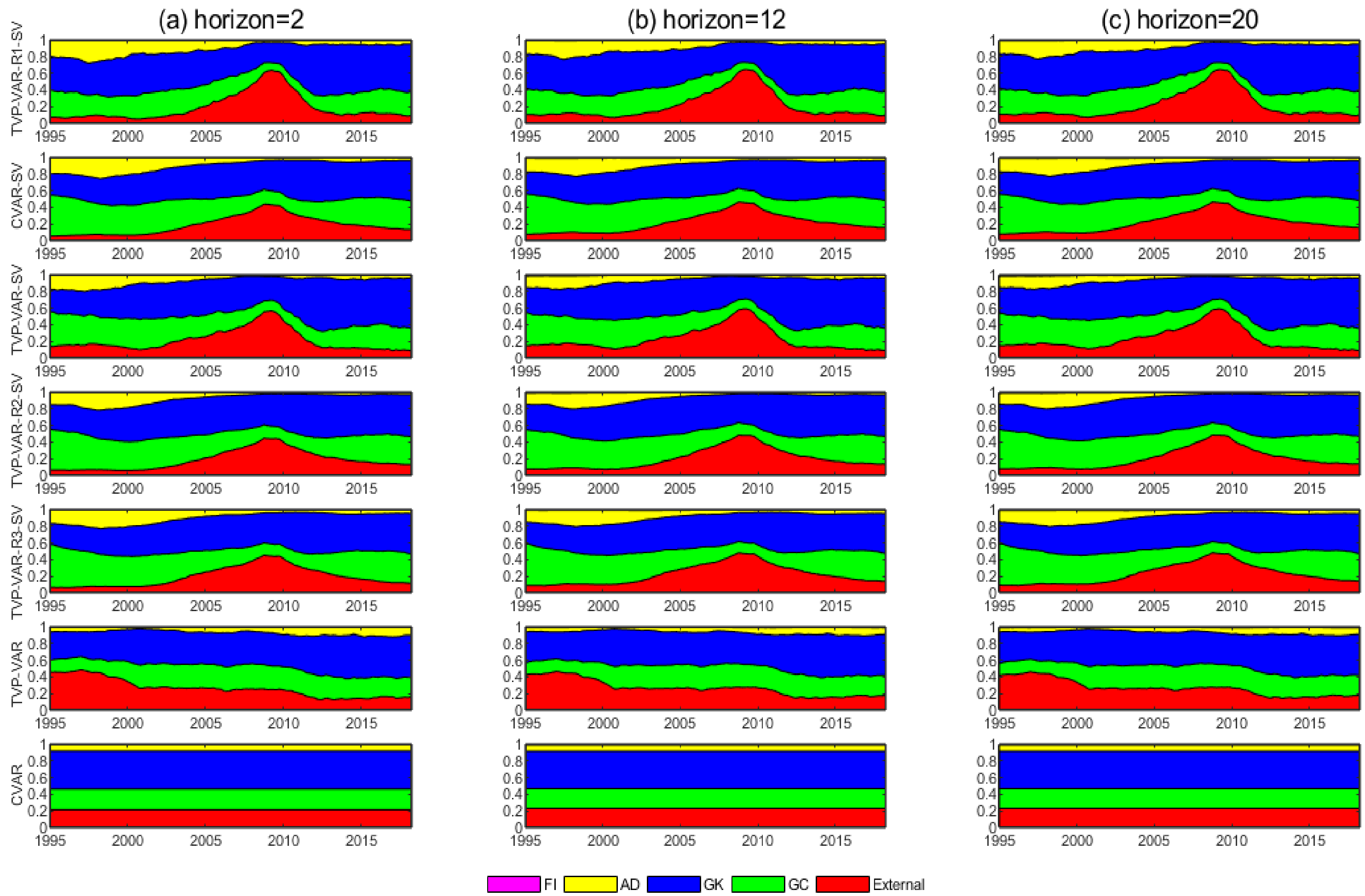

Figure 6. Time Evolution of the FEVD of the Real GDP Growth for all Models at Different Horizons. Source: Own elaboration. Source: Own elaboration.

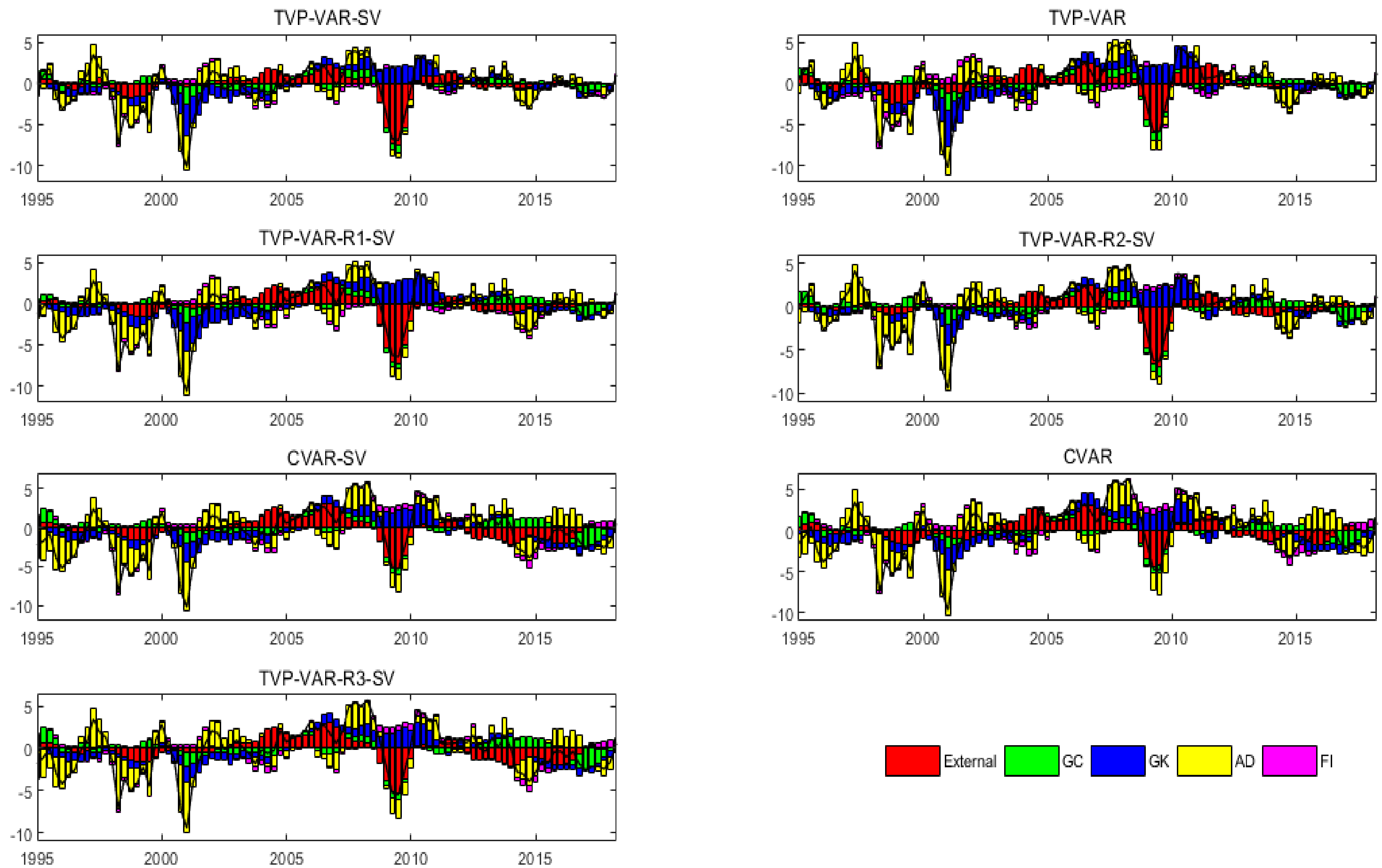

Figure 7. Historical Decomposition of the Real GDP Growth for all the models.
Source: Own elaboration.

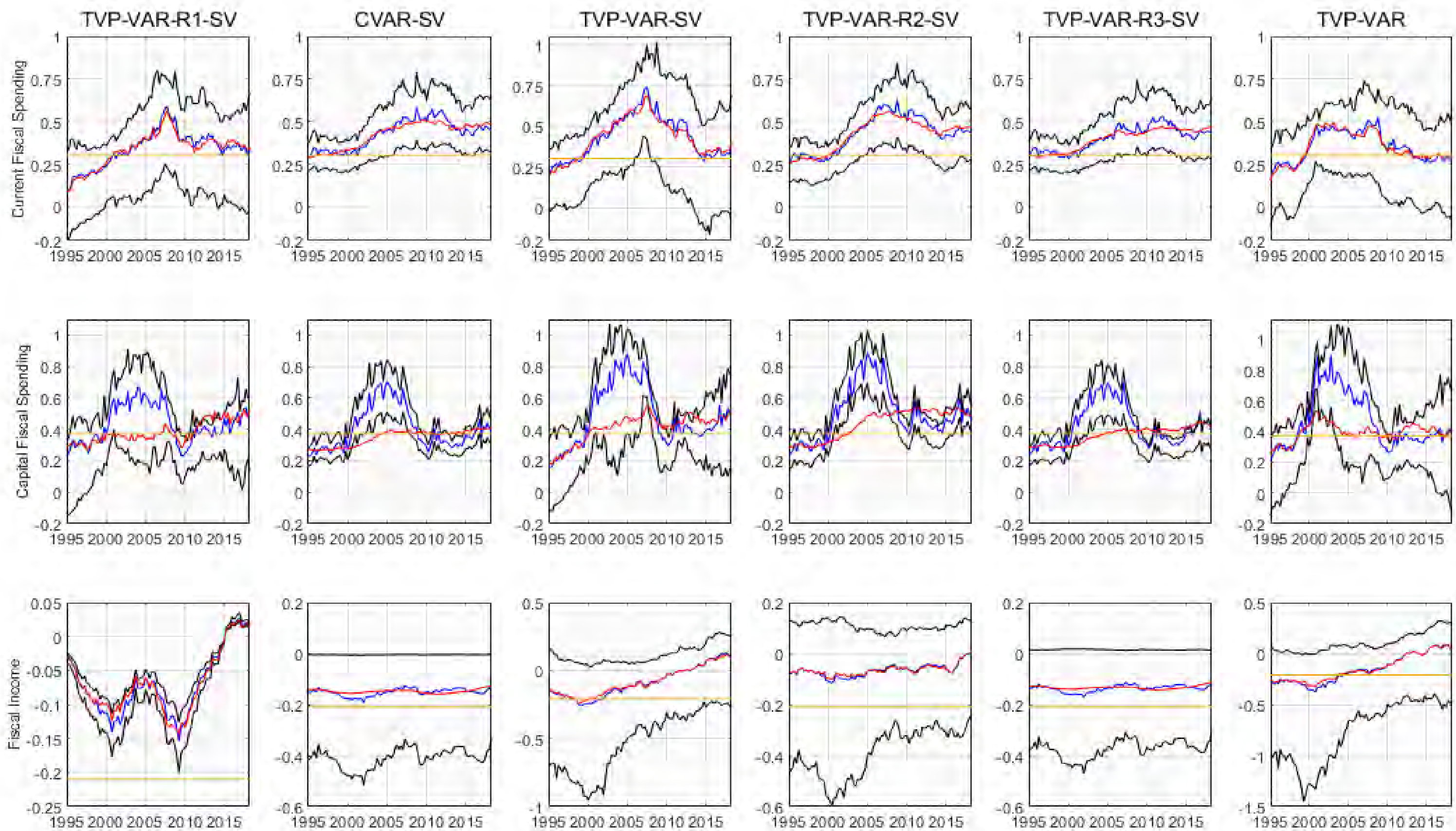

Figure 8. Time Evolution of the Cumulative for One Year Current Fiscal Spending Multiplier, the Capital Fiscal Spending Multiplier and the Fiscal Income Multiplier. The orange line represents the multipliers obtained from the CVAR Model. The blue line represents the multipliers using time-varying ratios, the black lines represents its 68% error band and the red line represents the multipliers using the period average ratios.

Source: Own elaboration.

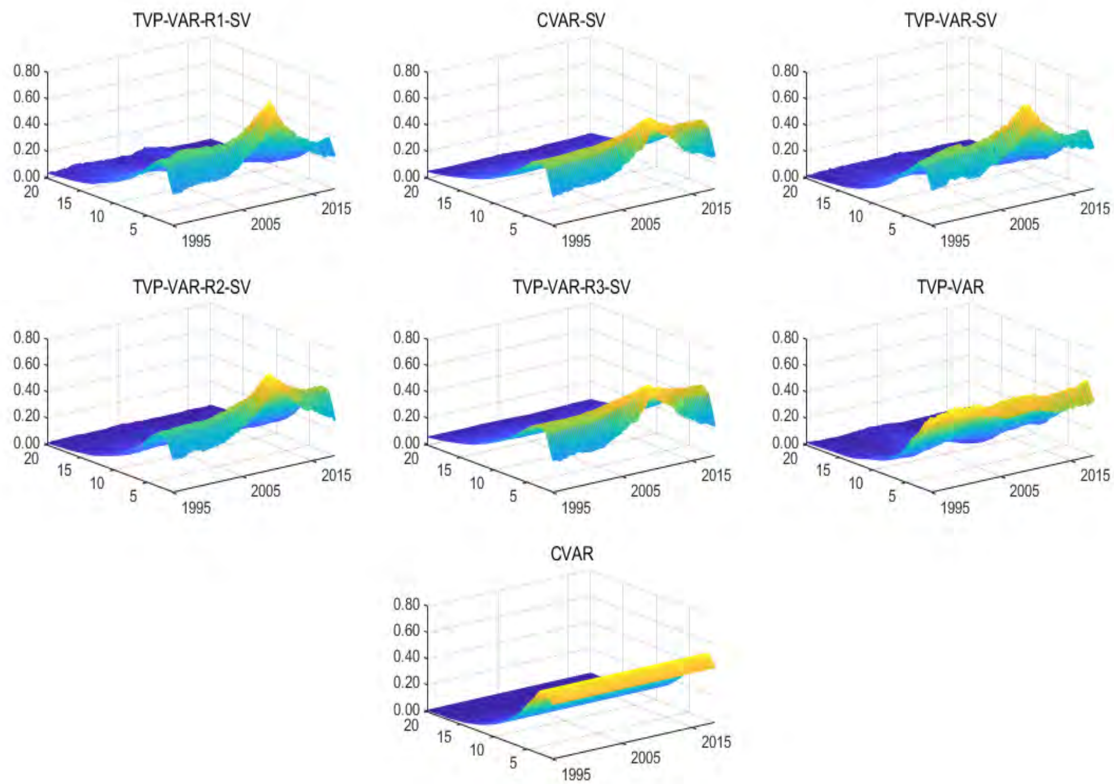

Figure 9. Median Time-Varyng IRFs of Fiscal Income Growth to an External Shock. The shock is normalized to increase Fiscal Income Growth by 1% at each point in the sample.
Source: Own elaboration.

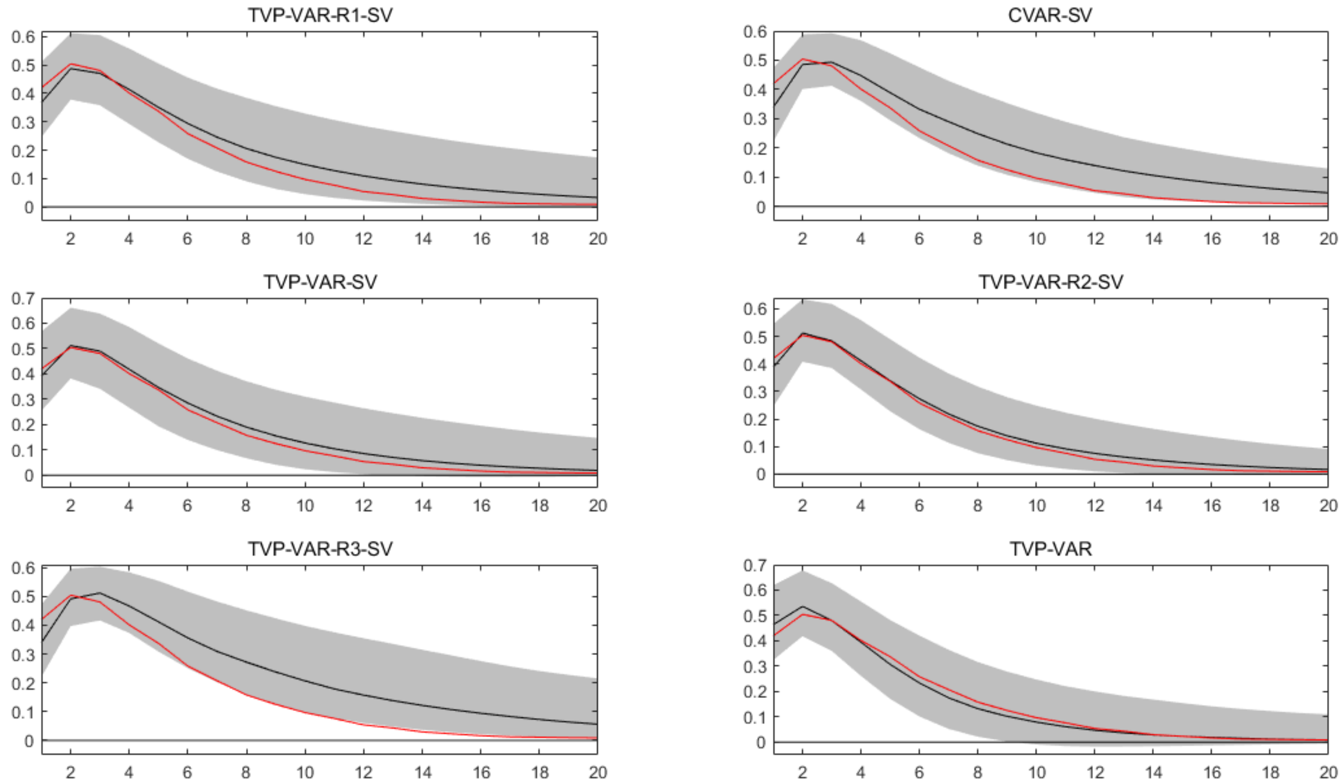

Figure 10. Median IRF Fiscal Income Growth to an External Shock. The solid black line represents the model and the shaded area its 68% error band; as a benchmark, the solid red line represents the CVAR Model.
Source: Own elaboration.

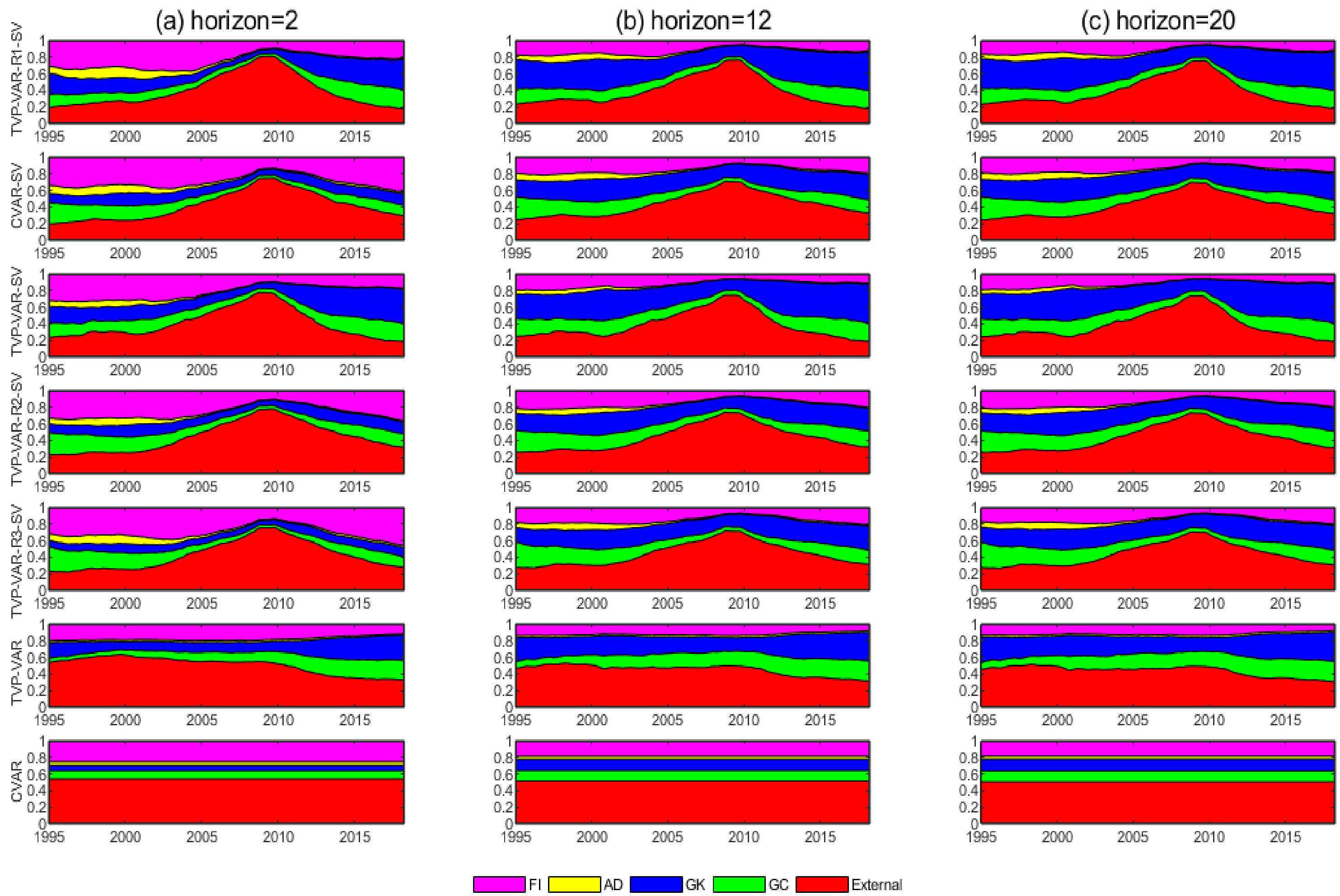

Figure 11. Time Evolution of the FEVD of the Fiscal Income Growth for all Models at Different Horizons.
Source: Own elaboration.

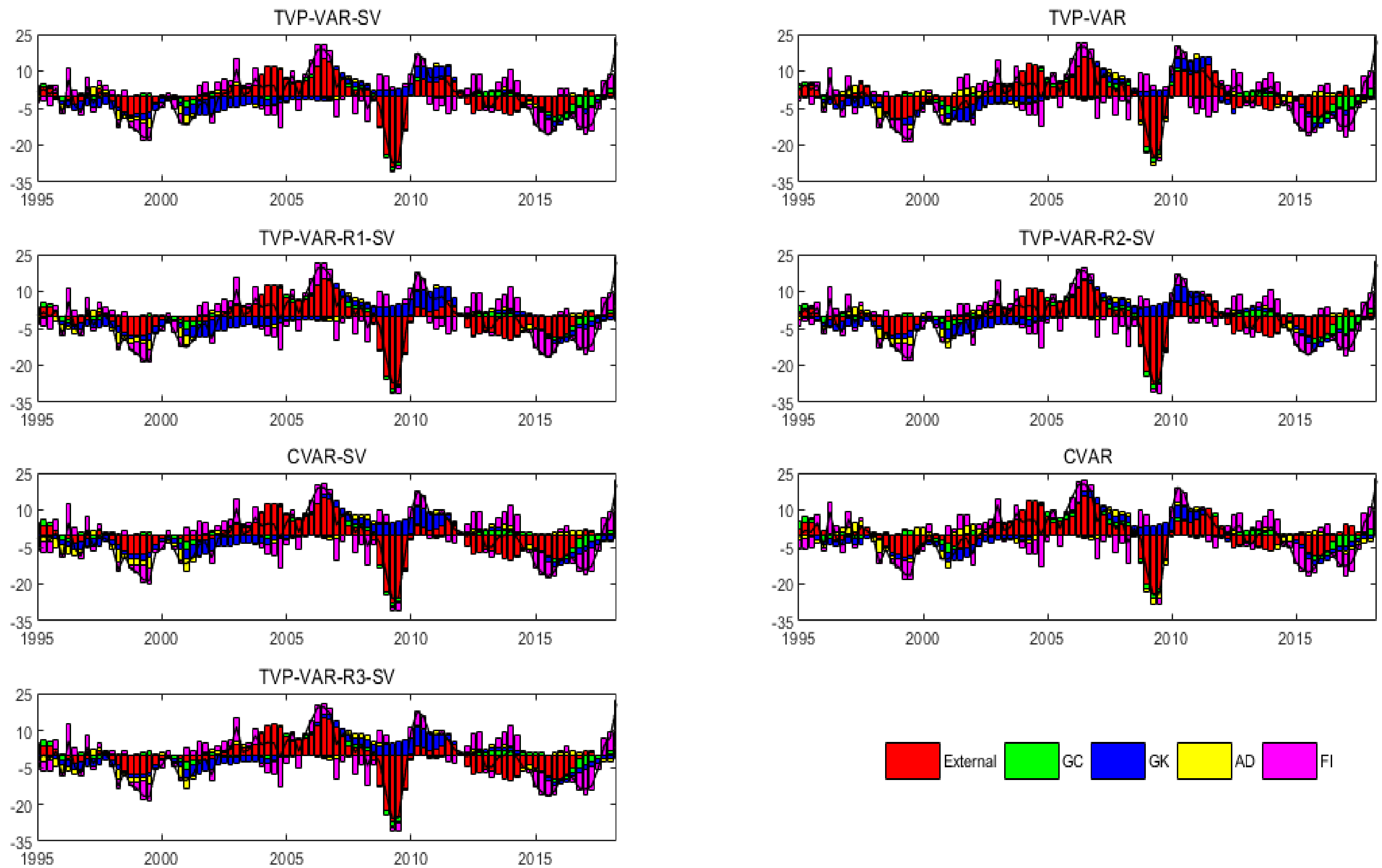

Figure 12. Historical Decomposition of the Fiscal Income Growth for all the models.
Source: Own elaboration.